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Research

Price Elasticity of Electricity Demand in the Mining Sector: South Africa

by

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Abstract

This study estimates the price and income elasticity coefficients of electricity demand in the mining sector of South Africa for the period ranging from April 2006 to March 2019. A time varying parameter (TVP) model with the Kalman filter is applied to monitor the evolution of the elasticity estimates. The TVP model can provide a robust estimation of elasticities and can detect any outliers and structural breaks. The results indicate that income and price elasticity coefficients of electricity demand are lower than unit. The income elasticity of demand has a positive sign and it is statistically significant. This indicates that mining production – used as a proxy for mining income – is a significant determinant of electricity consumption in the mining sector. In its final state income elasticity is estimated at 0.15 per cent. On the contrary, price does not play a significant role in explaining electricity demand. In fact, the price elasticity coefficient was found to be positive which is contrary to normal economic convention. This lack of response is attributed mainly to the mining sector's inability to respond, rather than an unwillingness to do so.

A fixed coefficient model in a form of Ordinary Least Squares (OLS) is used as a benchmark model to estimate average price and income elasticity coefficients for the period. The results of the OLS regression model confirm that price does not play a significant role in explaining electricity consumption in the mining sector. An average price elasticity coefficient of -0.007 has been estimated. Income elasticity was estimated at 0.11 for the period under review. The CUSUM of squares test indicate that parameters of the model are unstable. The Chow test confirms 2009 as a breakpoint in the data series. This means that elasticity coefficients of electricity demand in the mining sector are time variant. Thus the OLS results cannot be relied upon for inference purposes. The Kalman filter results are superior.

This study cautions policy makers not to interpret the seeming lack of response to price changes as an indication that further prices increases could be implemented without hampering electricity consumption in the sector. Furthermore, it recommends that the electricity pricing policy should take into account both the negative impacts of rapid price increases and the need to invest in long-term electricity infrastructure in order to improve the security of energy supply. A long term electricity price path should be introduced in order to provide certainty and predictability in the price trajectory. This would allow all sectors of the economy sufficient time and space to make investment and operational decisions that would have the least adverse effects on economic growth and job creation.

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Abbreviations and Acronyms

ARDL	Autoregressive Distributive Lag
BLUE	Best Linear Unbiased Estimator
CLRM	Classical Linear Regression Model
CPP	Critical Peak Pricing
DoE	Department of Energy
DME	Department of Minerals and Energy
DSM	Demand Side Management
EAF	Energy Availability Factor
ECM	Error Correction Model
EIFR	Eskom Integrated Financial Report
FMOLS	Fully Modified Ordinary Least Squares
GDP	Gross Domestic Product
GMTN	Global Medium Term Note Programme
IBR	Incentive Based Response
IPPs	Independent Power Producers
IRP	Integrated Resource Plan
IV	Instrumental Variable
KWh	Kilowatt Hour
ML	Mega-liters
MWH	Megawatt Hour
MYPD	Multi Year Price Determination
NERSA	National Electricity Regulator of South Africa
OECD	Organization for Economic Cooperation and Development
OLS	Ordinary Least Squares
PAM	Partial Adjustment Model
PBR	Price Based Response
PGMS	Platinum Group Metals
PPI	Producer Price Index

PRF	Population Regression Function
RTP	Real Time Pricing
SRF	Sample Regression Function
STSM	Structural Time Series Model
TOU	Time of Use
TVP	Time Variable Parameter
UCLF	Unplanned Capability Loss Factor
VIF	Variance Inflation Factor

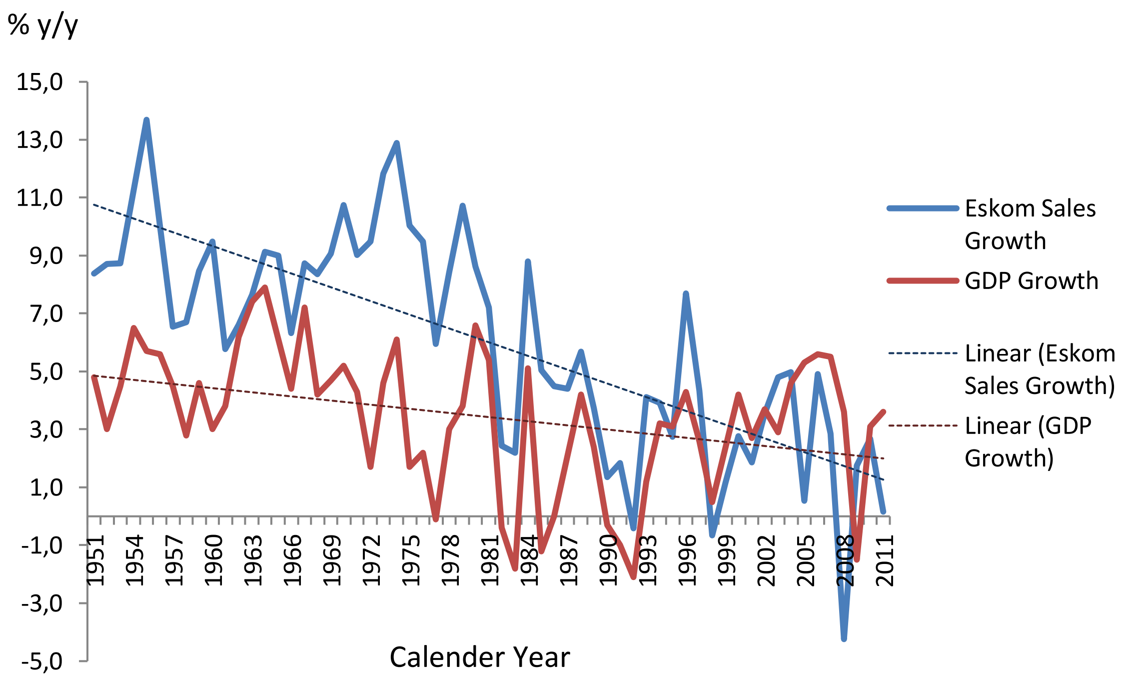
Chapter 1
Introduction

1.1 Background

Energy security is one of the most important components of a successful economic development programme (Blignaut, 2009:696). It is a fundamental input for both a country's social and economic development. Ferguson *et al.* (2000) found a strong positive correlation between increases in wealth over time and increases in energy consumption in most developed countries. In general, countries with a high per capita income also have a high per capita energy consumption. Consequently, a high level of energy consumption, in particular commercial energy like electricity, could signify a high economic status of a country. It is in this context that developing countries, and in particular Sub- Saharan Africa, invested significantly in the development of its electricity infrastructure. This investment is aimed at improving efficiencies and fostering higher economic growth (Wolde-Rufael, 2004:1108).

In recent years, the global demand for electricity has outpaced the demand for energy as a whole. For the period 2000 to 2010, overall energy usage increased by 26 percent while electricity consumption grew by 40 percent (Kwon *et al.,* 2016:324). The rapid increase in electricity consumption during this period contributed to the power shortages in several countries across the world, including in North America and Europe (Kwon *et al.,* 2016:324). In 2007 and 2008, South Africa experienced periods of significant shortages in electricity supply. This resulted in the rolling blackouts commonly referred to as load shedding. This was particularly concerning as there is an observable long-term correlation between GDP growth and electricity sales in South Africa. As the economy grows, the productive sector of the economy requires more energy and electricity to support its growth, since more machinery will be required to enable capacity expansion and higher production at company level. When household income increases, household electricity consumption also rises. Higher income levels in a country result in higher household expenditure. Typically, a rise in household expenditure includes expenditure on household capital goods such as refrigerators, television sets, geysers and heaters. Consequently, higher income leads to greater electricity consumption by households. When the economy grows and per capita income increases, electricity consumption is likely to increase in the productive sectors of the economy, as well as in households. Figure 1 illustrates the relationship between GDP growth and electricity sales in South Africa from 1951 to 2011. A casual observation indicates that, for the most part, electricity sales grew more rapidly than GDP. This indicates that for every additional unit of output produced, the economy consumed a higher amount of electricity than in the preceding period. This is to be expected in an economy that was dominated by electricity-intensive sectors like mining and manufacturing. It shows that the availability of cheap and abundant electricity has at the very least been an enabler for growth in the economy. However, since 1998, GDP growth has overtaken growth in electricity sales. The long-term trend lines of the two indicators intersected in 2005. This development reflects a change in the growth composition of the economy. The economy is now growing faster in sectors that do not require a lot of electricity to function. This would consist mainly of the services orientated sectors like retail, finance and tourism. It is also plausible that over time, as technologies improve and production processes become modernised, the primary sectors of the economy have improved their efficiencies, thereby reducing the amount of electricity they need per unit of output. Nevertheless Figure 1 depicts a close relationship between economic growth and electricity sales growth.

Figure 1: Electricity Sales Volume and Real GDP Growth



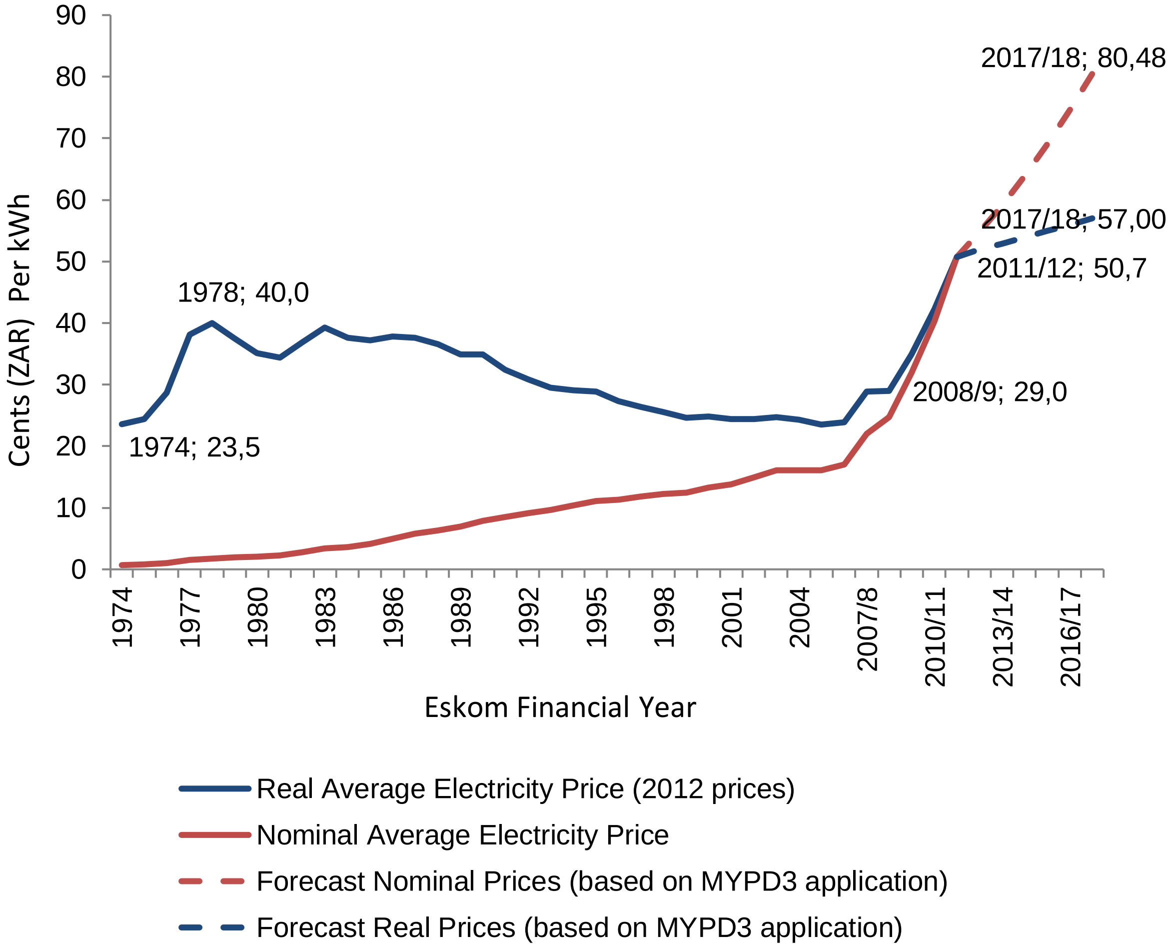
Source: Eskom Integrated Financial Report (various issues), Statistics South Africa: GDP publication series

This relationship between electricity consumption and economic growth informed government's policy to make electricity cheap and abundant. In 1991 Eskom, South Africa's power utility, announced a national price compact which was underpinned by the assertion that cheap electricity prices were essential for faster economic growth (Van Hoeren, 1996:9). The objective of this price compact was to keep electricity prices as low as possible for as long as possible, in an effort to provide South Africa with an international competitive edge.

Following this compact, the *real* price of electricity declined substantially over time. Research by Doppegieter *et al*. (1999:52) found that electricity tariffs in South Africa were amongst the lowest in the world during the 1990's. The real average tariff declined from 40.0 cents (2012 constant prices) per kilowatt hour (KWh) in 1978 to 23.50 cents in 2005. This pricing strategy was an implied subsidy for the economy, with a view to stimulating economic growth and development. It is important to note that this favourable pricing outlook was not always in place. In the decades leading to the 1991 price pact, electricity price increases were quite steep. Figure 2 depicts the historical electricity price trajectory in real and nominal terms. From 1974 to 1978 the real electricity price almost doubled from 24 cents per KWh to 40 cents. This means that electricity prices increased by 60 per cent from 1974 to 1978 after accounting for inflation. This rapid increase in electricity prices was occasioned by the infrastructure expansion programme that Eskom had embarked on at the time. It was busy with the construction of its flagship projects, including the construction of new power stations. This significant increase in the generation capacity necessitated an increase in the electricity distribution network such that more industries, mines and farms could be connected to the electricity network.

This aggressive electricity infrastructure expansion programme was based on an assumption that economic growth would continue at a rapid pace, thus providing demand for more electricity power in the future. However, by the late 1970's and early 1980's the South African economy had slowed down materially. This slowdown was occasioned by political unrest and international financial sanctions that were imposed on the country. By the late 1980's Eskom was left with excess capacity and sluggish electricity demand. It was in this context that the 1991 national price compact was formulated. According to this agreement, annual electricity price increases were deliberately set below the inflation rate in order to encourage electricity consumption and stimulate economic growth. This meant that every year, electricity became relatively cheaper as compared to other goods and services. This strategy encouraged growth in the electricity-intensive industries as the low electricity price was effectively a subsidy to these industries. Subsidising energy use involves providing it at a price below its opportunity cost. This happens when the regulated electricity price does not reflect the long run marginal cost of supply. Such a policy may encourage an inefficient use of electricity, resulting in the country becoming more energy intensive. Furthermore, the low electricity tariff may discourage new investment in the electricity sector, thereby limiting the scope for further capacity expansion. It follows that this strategy could only be sustained for as long as Eskom had excess capacity. It also follows that this implicit electricity price subsidy would result in a depletion of Eskom's financial reserves, increased borrowings and / or more equity bailouts from the shareholder(s). The strategy was inherently unsustainable.

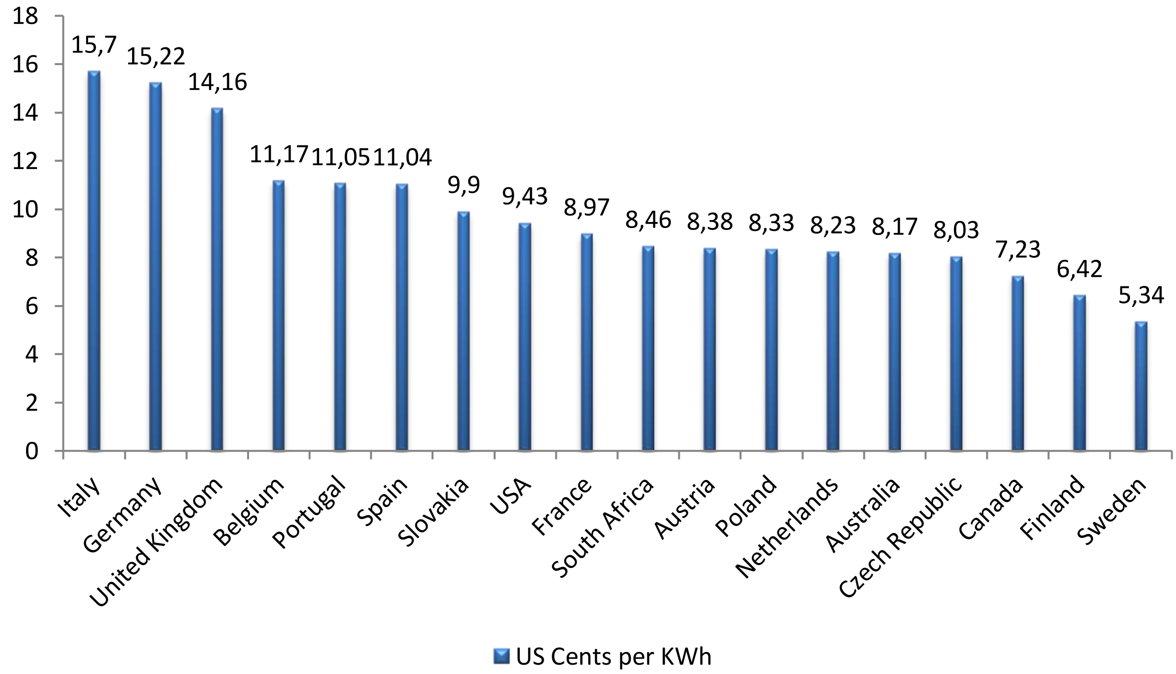
Figure 2: Historical Aggregated Electricity Prices



Source: Eskom MYPD 3, 2013.

After almost two decades of declining real prices, an aging generation fleet and no new capacity additions to speak of, electricity demand began to outstrip supply. This resulted in load-shedding or blackouts in 2008 (Eskom GMTNP, 2013:3). The short supply threatened the integrity of the grid as generation could not keep up with demand. At this point it was clear that the utility needed to expedite its generation capacity expansion programme. It needed significant increases in revenue to build a sizeable balance sheet, which could be used as leverage for borrowing the capital required to finance urgent and crucial capital expansion. Given this background, electricity tariffs were bound to increase faster than they had in preceding years. As it can be observed on Figure 2, real electricity prices begun to increase in 2006 and were rapidly escalating by 2011. This indicates that nominal price increases were substantially higher than the inflation rate during this period. The National Energy Regulator of South Africa (NERSA) awarded Eskom tariff increases of 24.8 per cent, 25.8 per cent and 25.9 per cent for the financial years ending 31 March 2011, 2012 and 2013, respectively (Eskom GMTNP, 2013:51). However, after considering the impact of the higher tariff on the economy in general and large power users in particular, NERSA revised the 2013 tariff increase downwards to 16 per cent (Eskom GMTNP, 2013:51). Nevertheless, this signified a new pricing regime. In 2012, Eskom submitted its application for the third Multi-Year Price Determination. It requested an average annual price increase of 16 per cent over the five-year period ending on 31 March 2018. Eskom argued that it needed these increases to support investment and expansion in the sector, while enhancing the quality of the electricity supply and diversifying its generation capacity. The requested price increase consisted of 13 per cent to cover Eskom's operational inputs and debt-servicing costs. The remaining 3 per cent was requested to cover the costs of procuring power from independent power producers (Eskom MYPD 3, 2013:8). Notwithstanding the high tariff increases, electricity prices in South Africa remained relatively low by international standards.

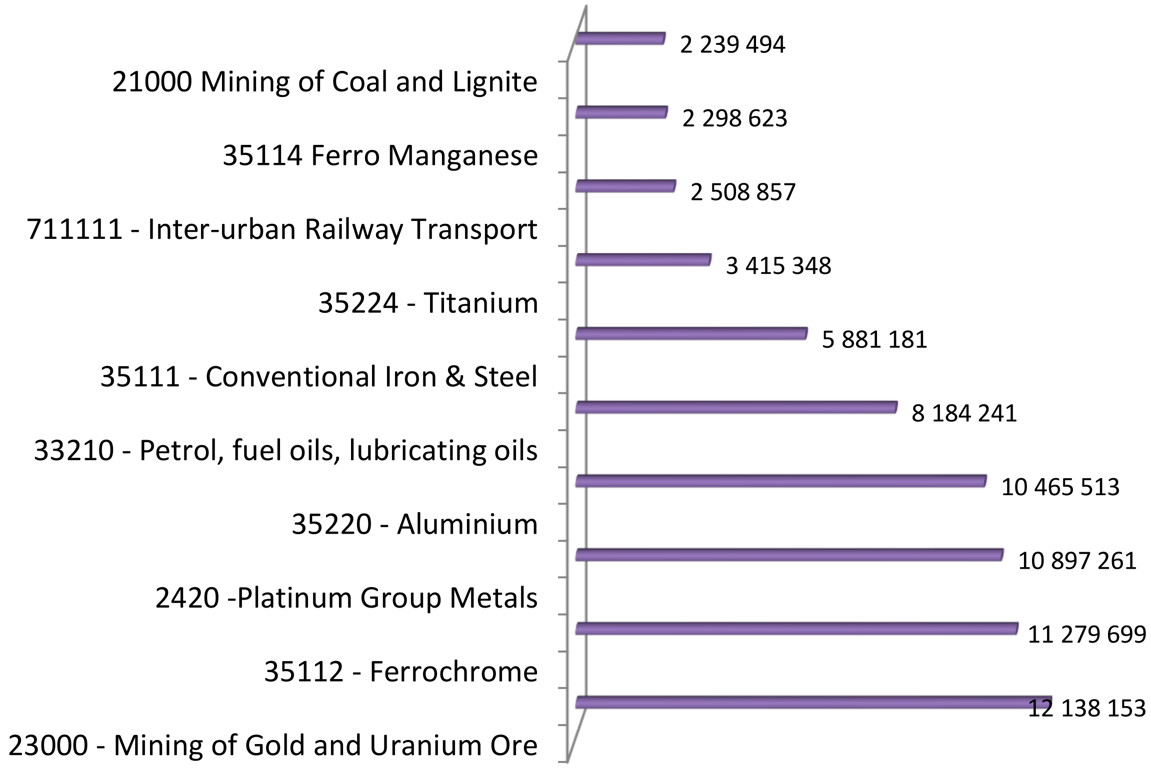
Figure 3: International Electricity Price Survey - 2015



Source: International Electricity and Natural Gas Survey, NUS Consulting Group, 2015.

Figure 3 indicates that in 2015 South Africa's average electricity price was 8.46 US cents per Kwh. This was still below the mean for the group of 18 countries that were sampled by the NUS consulting group. In 2016, the World Bank undertook an analysis of electricity utilities in 39 African countries. The study found that Eskom's average unit price was relatively low as compared to most utilities in other countries (Kojima & Trimble, 2016:8). The authors noted that most utilities, including Eskom, were pricing their product at an unsustainably low level. They cautioned that unless this was rectified, these utilities would run into significant financial distress in the future. These studies suggest that at least at the time when they were conducted, there was still scope for further tariff increases without adversely affecting the country's international competitiveness. However, it could be argued that the recent rapid increase in electricity prices could have a negative impact on the sectors that consume most of the electricity in the economy.

Figure 4: Electricity Consumption (MW/h) per Standard Industry Classification

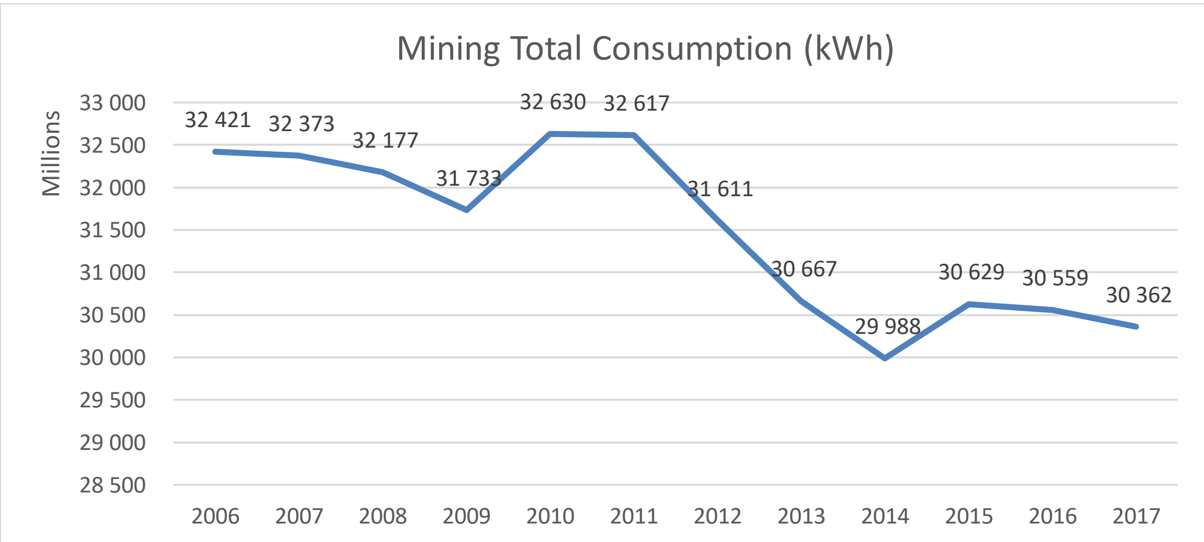


Source: Eskom Integrated Financial Report (2012/13)

Figure 4 depicts electricity consumption per standard industry classification in South Africa. The gold mining industry is the largest consumer of electricity in the country. This is followed closely by the ferrochrome and the platinum group metals (PGMs) sub-sectors. This means that the top three largest consumers of electricity per standard industry classification are all within the mining sector. It is evident that the mining sector is a large consumer of electricity in South Africa. Therefore, the electricity demand response in this sector could have a significant impact on the aggregate level of electricity consumed in the country as a whole. If the mining sector is experiencing financial strain, this could result in a reduction in electricity consumption by the sector. If this reduction in consumption is not compensated by an increase in sales in another sector, it could result in a significant drop in revenue for the electricity utility. By extension, the performance of the commodities market may have a significant impact on the level of electricity consumption in this sector. If there is a boom in the commodities market and the level of mining production increases, electricity consumption may increase. Similarly, if mining output decreases, electricity consumption is expected to decline.

South Africa has large reserves of chrome, gold, platinum group metals, vanadium and other minerals (DoE, 2010:72). The mining of these natural resources has played a pivotal role in the development of the electricity industry in South Africa. The vast nature of mining activity across the country forms a significant customer base for Eskom. In the 2012/13 financial year, electricity sales to the mining sector accounted for 14.5 per cent of Eskom's total sales (Eskom, 2012/13:62). The mining sector has historically been dominated by the gold sub-sector. However, its dominance has declined over the years as the old gold mines closed down and fewer new operations were opened. As a result gold production has decreased significantly. In 1970, 1 000 tonnes of gold were produced, in comparison to only 253 tonnes in 2007 (DoE, 2010:72). Similar developments have befallen other sub-sectors although not to the same extent.

Figure 5: Electricity Consumption in the Mining Sector



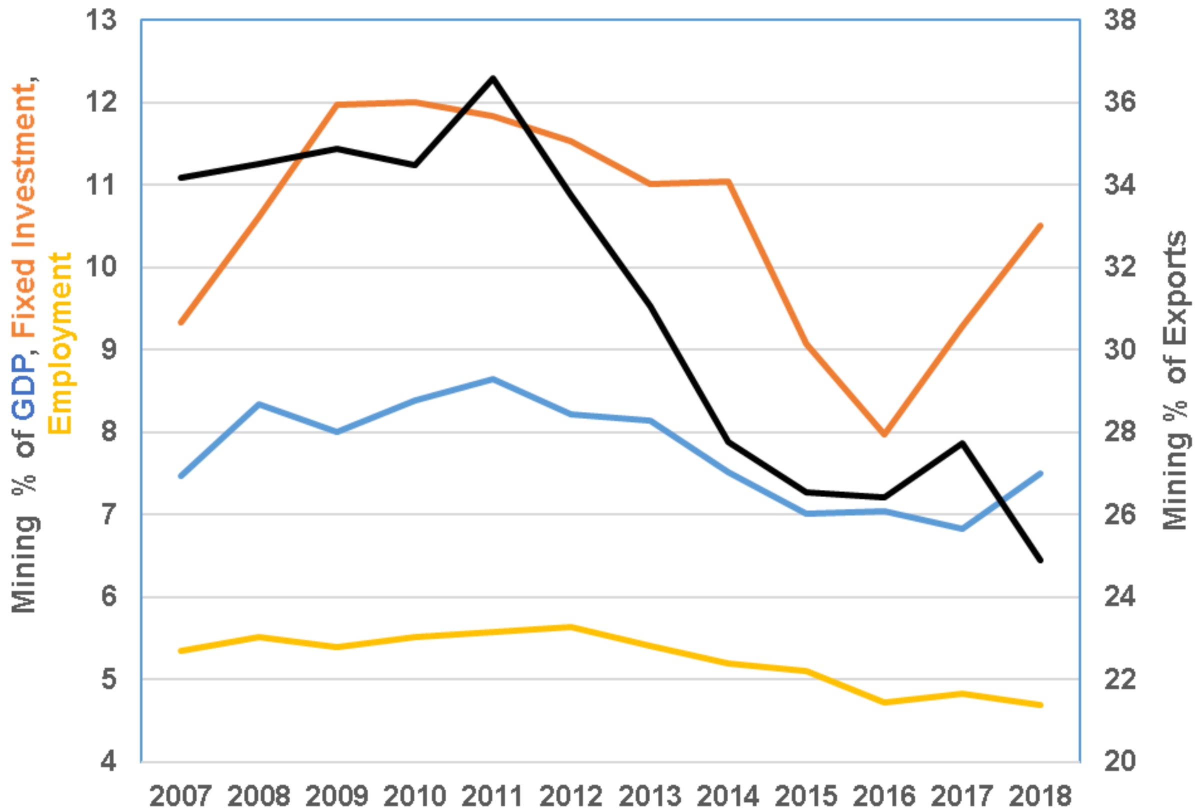
Source: Eskom Sales report 2017/18

Figure 5 indicates that electricity consumption in the mining sector has been on a downward trend over the last decade or so. This may be an indication that the mining sector in South Africa has entered its twilight years. Mineral resources are finite in nature, therefore all mines have a finite lifespan. At some point any mining operation has to cease, either because the resources have been depleted or because it is no longer commercially viable to continue with it. It follows that as mining production declines, electricity consumption could decline with it. The decline in consumption could, however, also be interpreted as evidence that electricity prices have become too high for the mining sector, suggesting that certain operations cease to be commercially viable. The high electricity price increases during the last decade may have encouraged the sector to scale down its electricity usage and seek alternative mining strategies in an effort to contain its operating costs. This may have stifled growth and investment in the sector.

The declining electricity consumption in the mining sector should be of concern to Eskom for several reasons. Firstly, the mining sector and Eskom are joined at the hip. The discovery of a gold reef in Langlaagte, Johannesburg in 1886 sparked a rush that had an immense impact on the city as well as on the electricity sector as a whole. The soaring demand for electricity occasioned by a booming mining sector hastened the need for network integration, regulations and a greater electricity supply at an affordable price. Prior to this, electricity was generated by private or municipality-owned generators, which operated in a disintegrated network (Amusa *et al.*, 2009: 4168). Given these new requirements, Parliament approved the 1922 Electricity Act in terms of which Eskom was established and given the task of supplying a large amount of electricity at relatively low prices to the mining sector in particular and the broader economy in general (Marquard, 2006:126). It follows that from the onset the mining sector always provided a significant customer base for Eskom. The sector creates a significant level of stable and predictable electricity consumption. Unlike other sectors which have peak and off peak demand during the day, the mining sector's demand profile is fairly static throughout the day. This creates an essential level of around the clock minimum demand which is crucial for operating the electricity network efficiently. Eskom also depends on the mining sector for the supply of coal which is used as fuel for its power stations. South Africa has vast coal reserves, which serve as a source of cheap primary energy. Coal-fired power stations produce most of the country's electricity. In 2006, coal-fired power stations generated about 92 per cent of all electricity produced in South Africa (DoE, 2010:52).

The mining sector plays a critical role in the economy of South Africa. It is a significant source of foreign exchange earnings and a critical creator of job opportunities, especially for semi-skilled and unskilled labour. Figure 6 depicts, amongst other indicators, the sector's share of total employment in the country. This dropped from about 5.5 per cent in 2007 to below 4.6 per cent in 2018. Most notably, the sector's share of total exports has plummeted from 36 per cent in 2011 to 25 per cent. As a proportion of GDP, the mining sector has been on a gradual decline. In the past decade, the mining sector in South Africa has been under considerable pressure. This pressure emanated from internal and external factors. Internal growth in the sector has been curtailed by limited export capacity infrastructure in the form of ports and the rail network. The intermittent electricity supply disruptions have also undoubtedly disturbed production processes in the sector. The sector has also experienced tenuous industrial relations, which have often resulted in output losses. All these bottlenecks have constrained growth and investment. Policy uncertainty with respect to ownership and local procurement rules have contributed to the decline in fixed investment in the mining sector. This further exacerbated the reduction in electricity consumption by the sector.

Figure 6: Mining Sector contribution to the SA economy



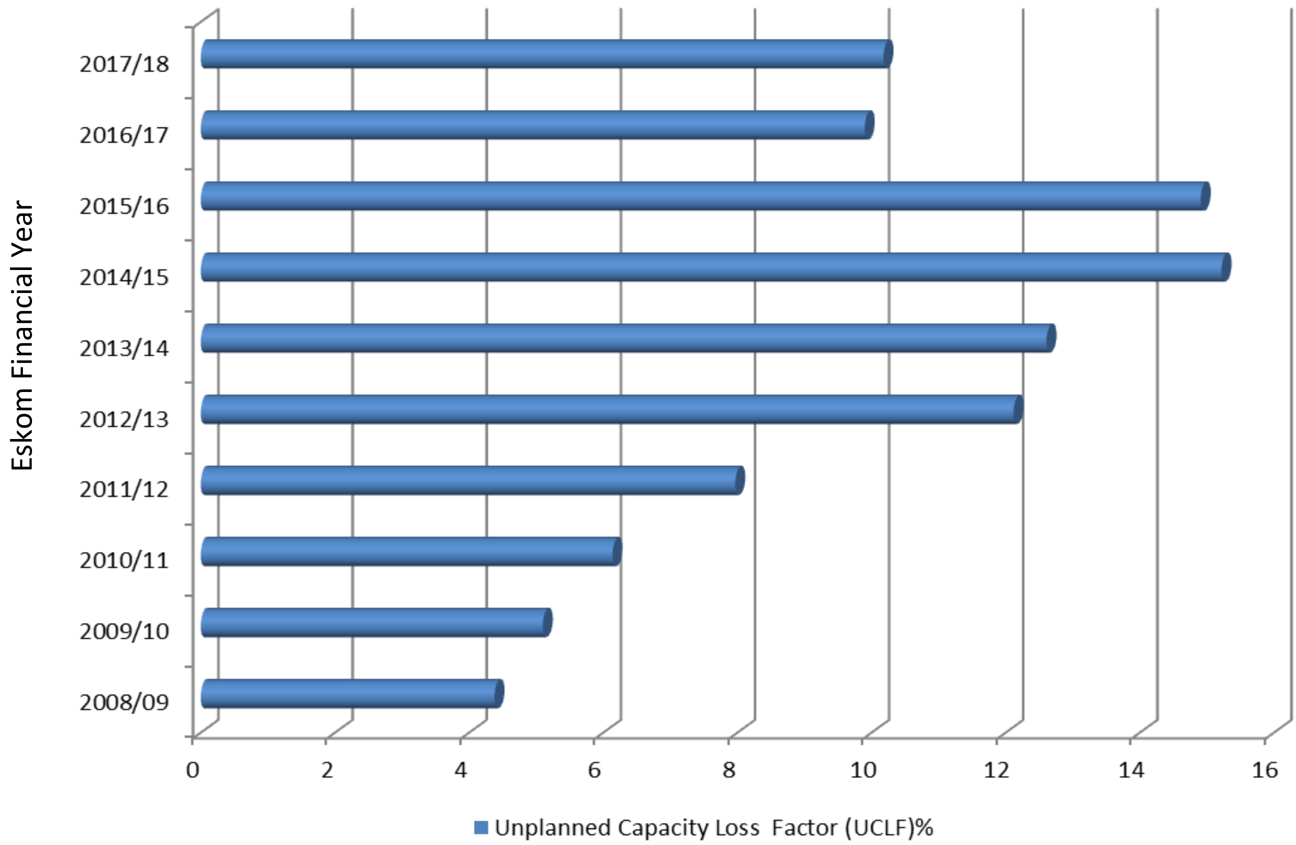
Source: Mineral Council South Africa, 2019

The mining sector also serves as a strategic line of defence for the electricity network. Electricity consumption in the mining sector is highly concentrated. As a result, in times of emergencies it is relatively easy to identify several electricity supply points and switch them off in order to save the rest of the network. This tactic proved to be effective when Eskom declared a national emergency in 2009. It compelled its large customers, especially the mining houses, to cease operations because it could not guarantee supply. This act saved the network from a national blackout which would have an untold impact on the economy and security of the country. Since then, the mining sector has been called upon on numerous occasions to curtail its level of electricity consumption when the network is deemed to be vulnerable. This electricity supply crisis highlighted the pressing need for capital investment in the country's electricity generation and reticulation capacity (Maroga, 2009:4). It also demonstrated the risk that the electricity generation capacity constraint posed for the country's economic growth in the short to medium term. In an effort to resolve this crisis, the South African government established a long term plan of how the country will meet its electricity generation requirements going forward. This plan is commonly referred to as the Integrated Resource Plan (IRP). It is a 20-year plan that gives an estimate of South Africa's electricity demand and possible ways of catering for it. In its latest version, the IRP 2019 (DMRE, 2019) identifies key generation and reticulation projects, including the completion of Medupi and Kusile power stations. It also envisages an increasing bias towards renewable energy, mainly in the form of solar and wind power, as part of the country's response to the challenge of climate change. The urgency of this infrastructure expansion is demonstrated in most stark terms by a decreasing electricity generation reserve margin. The reserve margin refers to the spare capacity that could be called upon should there be a breakdown in one of the generators. During 2007, the utility's reserve margin for generation capacity reduced to about 6 per cent of peak demand (Eskom GMTNP, 2013:3). This was significantly below the recommended global practice of maintaining a reserve generation capacity of 15 percent. The main reason for this low level of reserves can be ascribed to the increase in electricity demand by 50 percent between 1994 and 2007 (Inglesi-Lotz & Blignaut, 2011:452). Notwithstanding the substantial increase in electricity demand, there were no material additions made to the generation capacity during this period. This happened despite the Energy Policy white paper of 1998 indicating government's intention to make decisions about large public sector electricity generation investments in response to rapidly increasing electricity demand (DME, 1998). As it was anticipated, since 2008 electricity demand has frequently outstripped supply, thereby severely restraining the electricity grid.

The other contributing factor towards a low reserve margin had to do with the age of the Eskom generation plant fleet itself. The average age of these plants was 30 years, with the oldest power station being over 50 years old (Eskom, 2012/13:58). As power stations get older, they are more likely to break down. In addition, very old stations will face challenges when sourcing their spare parts due to their outdated technology (Eskom, 2012/13:71). This adds to the downtime that is required each time the plant breaks down. In general, older plants require maintenance more frequently, resulting in longer and more frequent downtime. The increase in downtime means that the generation plants have become less reliable. The Unplanned Capability Loss Factor (UCLF) measures the lost energy caused by unplanned production interruptions as a result of equipment failures and other plant conditions (Eskom, 2012/13:58). It measures the amount of production lost due to system breakdowns as a percentage of total production capacity available.

Figure 7 indicates that the UCLF percentage has been on a gradual increase since 2008. On average, Eskom lost 15.22 percent of its generation capacity due to unplanned breakdowns during 2014/15 as compared to 4.4 per cent during 2008/9. The increase in UCLF starkly reflects the decreasing reliability of the Eskom generation fleet. Ordinarily if the generation fleet becomes more prone to breakdowns it would require an even higher level of a reserve margin. In addition, an increasing unplanned capacity loss factor limits the downtime that is made available for normal maintenance work. Ultimately, the lack of adequate space to do scheduled maintenance, plus the pressure to always keep the lights on, resulted in an even weaker plant performance, in turn resulting in a sustained deterioration in UCLF from 2008 to 2016.

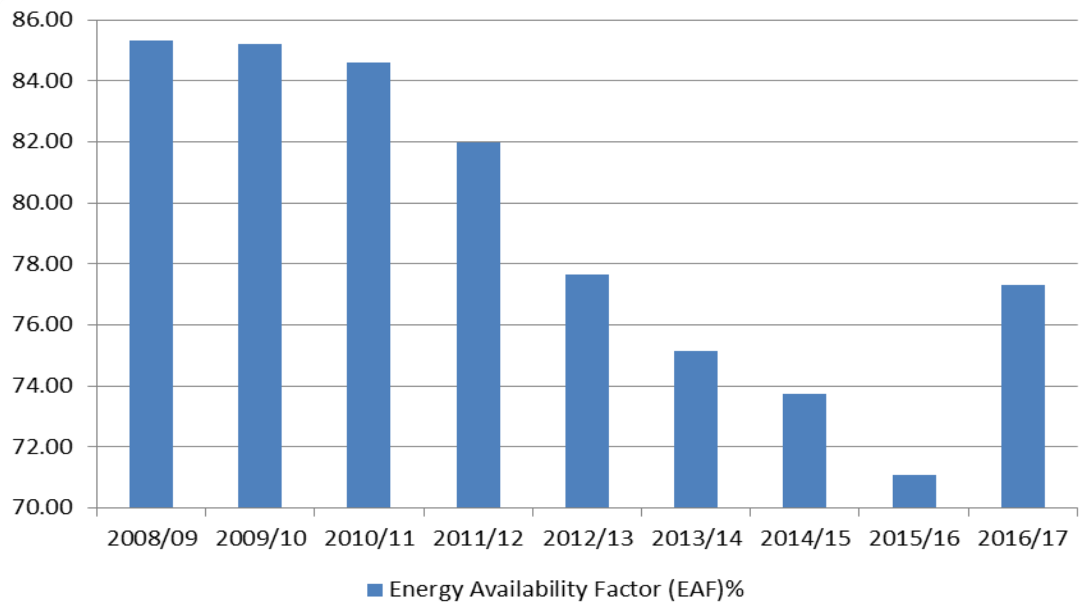
Figure 7: Unplanned Capacity Loss Factor (UCLF)



Source: Eskom Integrated Annual Financial Report (2017/18)

In the absence of any meaningful additions to the generation capacity, an increasing UCLF percentage means that there is even less energy available to be supplied into the electricity network. The Energy Availability Factor (EAF) measures plant availability plus energy losses not under the control of plant management (Eskom, 2012/13: 58). In the year which ended in March 2016, Eskom had an average EAF of 71.07 percent as compared to 85.3 percent in 2008/9 (Eskom, 2017/18: 58). This means that for the 2015/16 financial year Eskom had on average 71.07 percent of its installed generation capacity available for electricity generation. The other 29 percent of its generation capacity was unavailable due to breakdowns and planned maintenance. Figure 8 illustrates that the EAF has been weak for most of the period under review. This indicates that, notwithstanding an impressive amount of installed generation capacity, a significant portion of it was not available to generate electricity when needed. In view of these supply constraints, Eskom had to cut the electricity supply to some customers, leading to rolling blackouts across the country. The failure to cater for the rising electricity demand of the grid in 2007 emphasised the urgent requirement for investment in new generation capacity. The deterioration in plant performance, which resulted in a lower EAF percentage, further added to the urgency for investment in electricity infrastructure. Hence, it is important to replace the old power stations, which have become susceptible to breakdowns, and add new generation capacity to cater for the rising demand. To respond to this supply shortfall, the government has estimated that the country needs 40 000 MW of new capacity by 2030 (IRP, 2019:42). This includes 10 500 MW to replace some of the existing power stations that will be decommissioned at the end of their useful lives.

Figure 8: Energy Availability Factor (EAF)



Source: Eskom Integrated Financial Report (2017/18)

It is mainly because of this infrastructure expansion programme that electricity prices in South Africa have increased sharply in recent years. Eskom has invested an average of R40bn per year over the last ten years in electricity generation and reticulation infrastructure (Eskom, 2017/18:74). This investment is aimed at alleviating the electricity supply shortage and improves the reliability of electricity supply in the country. As a consequence of this investment drive, Eskom has accumulated significant amounts of debt. The utility's gross debt has increased almost tenfold from R36bn in 2007/08 to R358bn by end of March 2018 (Eskom, 2017/18:81). Most of this debt has been guaranteed by the South African government. This high level of debt has, however, become a source of risk for the South African economy. Eskom is an effective monopoly in the generation and transmission of electricity in South Africa. It supplies approximately 95 per cent of South Africa's electricity and approximately 45 per cent of the total electricity consumed on the continent (Eskom GMTNP, 2013:94). It follows that if Eskom is in financial distress and it cannot fulfil its electricity supply role, it would have a devastating effect on the economy. It was with this background that Eskom submitted its tariff application to NERSA for the fourth multi-year price determination (MYPD 4). As part of this application, it requested an average annual price increase of 15 percent over the three year period ending in March 2022 (Eskom MYPD 4, 2019:15), arguing that the new electricity price level would allow it to complete its infrastructure investment drive and service its debt. This would alleviate any pressure on the government for further bailouts, thereby reducing the risk that Eskom poses to South Africa's fiscal strength.

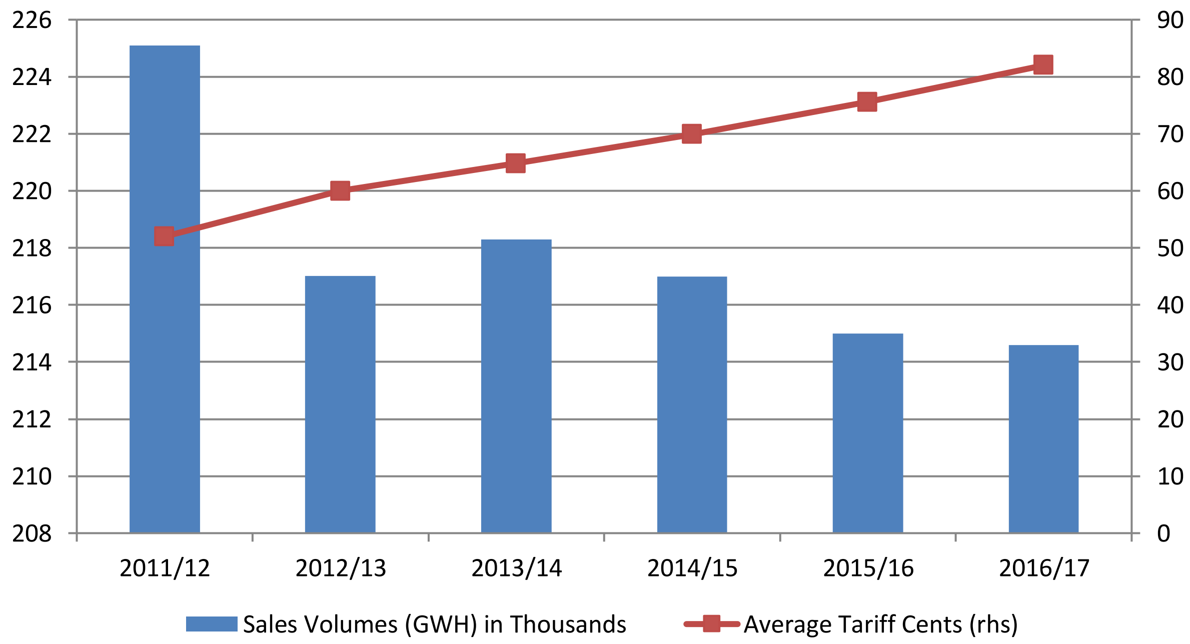
The Minerals Council of South Africa strongly opposed the proposed electricity tariff increases. They impressed upon the regulator that any significant further price increases would have negative economic and social consequences. Questions were raised about how this price trajectory would affect electricity demand in the mining sector. The Minerals Council argued that electricity consumption in the sector was on a downwards trend partly due to the high price increases that were allowed in the recent past. In their view, any further increases in price would result in a significant decrease in electricity consumption, thereby resulting in lower revenues for Eskom. NERSA indicated that it had to strike a balance between the two competing views. The regulator awarded an effective price increase of 13.87 percent, 7.81 percent and 5.05 percent for the years 2019, 2020 and 2021, respectively. This decision was lauded as a victory for the end users, as only a portion of the requested tariff increase had been awarded. As part of its reasons for decision, NERSA argued that an above inflation price increase would result in a decrease in electricity sales volume (RFD: 115). NERSA concluded that higher prices were not a viable long term solution for Eskom's revenue shortage as they would incentivise consumers to look for alternative energy sources and defect from the national electricity grid. This would result in a reduction in sales revenue which would in turn cause Eskom to increase its electricity tariffs even further. However, Eskom indicated that this decision would have negative financial implications for it. It indicated that its shareholder would be required to support it financially if it were to survive. If NERSA did not allow the consumer to pay a cost reflective tariff then the tax payer would have to fund the resultant revenue shortfall. To this end the government of South Africa has announced a financial rescue package for Eskom. A total of R138bn has been allocated in a form of equity injections into the entity (MTBPS 2019). However the minister indicated that the government was itself in a dire financial position and it could no longer afford to rescue Eskom or any other state owned enterprise in the future. This raises questions about the long-term sustainability of the entity if it has to rely on the government for continued financial support. Therefore until cost reflective electricity tariffs are achieved, the financial health of Eskom is bound to remain fragile.

In essence the regulator was caught between a rock and hard place. On the one hand there is sufficient evidence that Eskom’s generation fleet is underperforming. This is to be expected given the average age of its power stations. It also means that an increasing amount of costs and downtime will be incurred as more maintenance work is required owing to the age of the fleet. The need to build new generation capacity to cater for new demand and to replace old generators is undeniable. Without this investment programme, the utility will produce a diminishing amount of electricity as the years go by and the existing generation plant becomes older and more unreliable. This would increase the risk of electricity shortages in the country. An inadequate supply of electricity will have negative economic and social welfare implications. From that perspective, the upwards pressure on electricity prices is understandable. On the other hand, electricity consumption by key customers like the mining sector has been declining over time. The assertion that additional price increases will result in a further reduction in electricity sales volume in the mining sector must be tested. It is crucial to determine what the impact of past electricity price increases have been on this sector. The regulator cannot be seen to be awarding price increases that may stifle economic growth and investment in the country. The socio-economic ramifications of that could be too disastrous to contemplate. At the same time the regulator cannot be seen to be stifling investment and development in the electricity sector by denying Eskom a cost reflective tariff. The consequences of such an outcome would also be devastating on the economy and could undermine the government’s efforts to develop the country and create more job opportunities for its citizens. Thus the regulator is required to strike a fine balance between the two competing policy requirements.

1.2 Statement of the Problem

Concerns have been raised that the higher rate of electricity price increases in the recent years may have a dampening effect on electricity demand. The demand response to these price increases is therefore a crucial aspect to consider when making electricity price decisions. Over the years, Eskom has been criticised for not incorporating the potential demand response to price increases on its electricity demand projections (Inglesi & Pouris, 2010:4). It has been argued that although demand response may have been subdued over the years, especially prior to 2006, it cannot be assumed that the same lack of response will be observed in the future. It is entirely plausible that the level of demand response following the materially higher price increases which commenced in 2006 could be more pronounced than in the earlier years. Therefore, it is important to ascertain how electricity demand has responded to changes in electricity prices over time, especially in electricity intensive sectors like mining. This will inform policy makers on whether or not the electricity demand projections, on which the Eskom generation capacity expansion programme is based, are reasonable. This assessment must be performed keeping in mind the markedly different rates of price increases that were recorded during the period under review. This is important because if these electricity sales projections do not take into account the consumer response to changes in electricity prices, then there is a risk that expected future electricity demand could be overstated. This could result in lower than projected electricity sales.

Figure 9: Eskom Electricity Sales Volume



Source: Eskom Integrated Report (Various issues).

This concern is especially heightened by the marked reduction in Eskom's electricity sales volumes over the last few years. The decline in sales has not been confined to the mining sector alone. Figure 9 indicates that Eskom's sales volume has decreased by over ten thousand gigawatt hours from 2012 to 2017. Sales volume decreased by an average of 0.9% per annum from 2015 to 2017. This happened while the average tariff increased from 69 cents to 82 cents in the same period. The lower sales volume could be attributed to a number of factors, including the downturn in economic growth and demand response to tariff changes. There is an emerging risk that Eskom could price itself out of the market, as cheaper and usually more environmentally friendly means of electricity generation come into effect. This would be bad for Eskom as it could be left with idle or excess generation capacity. Eskom could be left with assets that are not generating any sales or revenue for it. This has raised the spectre that Eskom could be caught up in a utility death spiral. A utility death spiral occurs when additional generation and distribution of electricity makes the electricity grid more expensive for the remaining consumers thus making alternatives even more economically attractive (Felder & Athawale, 2014:10). If a death spiral occurs an electricity price increase would be futile in raising sufficient revenues to cover the utility's total costs. This happens because after a price increase is introduced, lower sales volumes follow. Hence fewer units of electricity are used to cover the utility's fixed costs thus a further price increase becomes necessary. This higher price results in an even greater sales decline, which requires yet another price increase. It is apparent that as the utility tries to recover its total costs through higher prices it actually makes less profit due to the decline in its sales volume. Historically the death spiral related to price increases resulting from high utility costs. However, the proliferation of Distributed Generation (DG), particularly end-user solar panels, has resulted in an erosion of electricity utility sales across the world. Most of the costs in the generation and transmission of electricity are fixed. The utility recovers these costs through charges that are allocated to customers. These costs are volumetric in nature (Hledik, 2014: 83). This means that the higher the volume of sales achieved, the lower the component of fixed costs is allocated per unit of electricity. With more DG systems in place, electricity demand falls, which forces utilities to raise prices in order to compensate for a drop in sales and help to recover costs. However, this increase in prices accelerates the adoption of more DG systems and further electricity price increases, thereby inducing a utility death spiral. The utility death spiral in this context includes the phenomena of retail customers migrating from a full-requirements utility service to a partial service or moving towards self-sufficiency. Like in an operational cost-induced death spiral, any attempts to recover the lost revenue through higher prices could aggravate the problem, resulting in fewer customers on the utility network and even more revenue being lost.

Therefore, cost recovery is threatened whenever a major decrease in sales volume occurs. The starting point of a utility death spiral is either a drop in the sales volume or a rapid cost increase or both occurring at the same time. These events could be occasioned by the increased attractiveness of new technologies, a depressed economy or other major shocks to the electricity network. Although it is theoretically possible, some scholars have argued that a utility death spiral is unlikely to occur as both utilities and regulators are likely to adopt measures that will avert such eventuality (Costello & Hemphill, 2014). In particular the tariff structure of electricity utilities is criticised for being too dependent on energy flows while the majority of the actual costs of supplying electricity are capacity based. Capacity costs are fixed in nature. They do not vary depending on the level of energy flow at a particular point in time. Thus a tariff structure that is mainly dependent on energy flows is unlikely to be cost reflective. The penetration of DGs simply exacerbates this problem. In order to avoid a utility spiral, regulators must migrate towards a tariff structure that is capacity based rather than energy usage orientated (Eid et al., 2014:253). This will allow the tariffs to be better aligned to the utilities' underlying cost structure. For example, a tariff structure that charges electricity users based on their respective observed maximum capacity usage improves cost-causality as compared to charges that are simply levied on energy flows under a volumetric tariff regime. Another proposed measure that a utility could take to avert a death spiral is to shift more of the fixed costs of its operation to its price inelastic customers (Costello & Hemphill, 2014:19). This would result in the utility being able to increase its revenue by increasing its average tariff. This requires the utility to be able to anticipate the demand response of each key customer segment before implementing a price increase such that only the customers with the least demand response are targeted. On the other hand, some economists argue that the long run demand response to a utility price change is extremely large such that a utility which raises its price will probably lose more revenue on the back of a reduced sales volume (Lovins, 1988:155). They argue that the only way for a utility to increase its revenue in the long run is to lower its unit price. This inherently requires the utility to cut its operational costs such that a downwards shift in the marginal cost and the average cost curves can be realised. Notwithstanding these varied opinions, it is crucial to establish what the demand response to an electricity price change is. If the demand response is inelastic, an increase in price would likely result in an increase in revenue from electricity sales. However, if the demand response is elastic, an electricity price increase could result in a decrease in revenue, further straining the utility's financial position. Once this has been established a utility can determine whether or not an increase in its price would result in a reduction in its revenue base. This is crucial to ensure the financial sustainability of the utility. This will also contribute towards understanding how a customer is likely to react to changes in the tariff structure as articulated earlier.

Another consideration to be made is to establish whether or not there is a causality relationship between electricity consumption and economic growth. There is a difference of opinion on whether or not such a relationship exists. If it is established that some form of a causality relationship exists between electricity consumption and economic growth, an assessment of the impact of the electricity price increase should not be limited to the revenue implications for the utility only. It should also take into account the impact that a reduction in the utility's sales volumes could have on the broader society. There is a risk that electricity price increases could slow economic growth. In turn sluggish economic growth could reduce future electricity consumption. Therefore higher electricity prices could drag the economy into a recession or a low growth trajectory. This makes it even more important to estimate the demand responses of key sectors of the economy. Decisions to increase electricity prices, either in the form of general increases or targeted increases should be informed at least in part by how consumers would respond, and how their response would impact the utility's revenue base and the economy at large. This study seeks to shed light on these considerations and provide policy makers with some information in order to adequately address these concerns.

1.3 Objective of the Study

The primary objective of this study is to estimate the price elasticity coefficient of electricity for the mining sector. It provides insight into the sector's electricity demand response to price changes between April 2006 and March 2019. During this period, electricity price increases in South Africa were higher than the inflation rate. This sent a signal to the economy that real electricity prices in South Africa were on an upward trajectory, thereby moving away from a prolonged period of nominal price increases that were below the inflation rate. This feature distinguishes this study from other South African studies, as most of them were conducted during periods when nominal prices were increasing, while real prices were decreasing. Several empirical studies, such as Inglesi-Lotz and Blignaut (2011), found that price did not play a significant role in determining electricity consumption in South Africa. However, it can be argued that the declining real electricity price during those studies probably resulted in a somewhat subdued response, thereby presenting relatively low price elasticity coefficients. Therefore the point of contention is the magnitude of the elasticity coefficients, especially given the price increases that were implemented during the period under review. It cannot be assumed that the elasticity coefficients have remained unchanged while the sector was experiencing significant price adjustments. The new estimations of price elasticity coefficients will be useful to provide some insights into the impact that price increases have on electricity demand. It will bring clarity on whether or not the reduction in electricity sales was a consequence of price increases during this period. This would contribute towards assessing the veracity of the claim that the utility is in the clutches of a death spiral. This study could assist policy makers in formulating an appropriate electricity pricing policy in South Africa.

The results of this study should be interpreted in conjunction with the existing findings on the nature of the causality relationship between electricity consumption and economic growth as well as other related information. Firstly, the study discusses existing findings on the energy intensity of the South African economy and the implications that this may have on the price elasticity of electricity demand. Secondly, it provides an overview of the various schools of thought about the causality relationship between electricity consumption and economic growth. Thirdly, the study assesses the theoretical aspects of demand response in general and price elasticity in particular. Lastly, the study undertakes a review of the outcomes of the empirical studies that have been conducted in South Africa and internationally. This approach lays the ground for making inferences about the elasticity coefficients that are derived from the demand response during the period under review. Overall, the study draws from the findings of other related studies to provide a proper context within which the newly estimated price elasticity coefficients can be interpreted.

1.4 Significance of the Study

This topic is relevant and timely given that Eskom's electricity sales have been steadily declining over the last few years while electricity prices have been increasing. On the one hand, the utility argues that electricity prices in South Africa are relatively low and must be gradually increased towards a truer cost reflective tariff. This would be achieved when the price of electricity equals its long run marginal cost of production. This implies that cost reflective prices must be used to indicate to the electricity consumers the true economic cost of supplying electricity so that supply and demand can be matched efficiently (Munasinghe, 1981:333). On the other hand, there are preliminary indications that the consumer may be experiencing considerable pressure due to the high rate of electricity price increases. The reduction in electricity sales volumes over the last several years suggests that consumers are responding negatively to price increases. This could have an adverse effect on the utility's revenue base which could threaten its long term sustainability. There is a risk that further price increases could spark a utility death spiral. This would severely undermine the developmental objectives of supplying cheap and reliable electricity to most segments of society. Therefore a study that seeks to establish the demand response to price increases in this environment is crucial. It will assist policy makers in determining the most effective price path.

Authors like Satchwell *et al.* (2015) downplay the possibility of a utility death spiral however, they recognise the revenue erosion brought about by solar DG penetration. They propose changes in the tariff designs to avoid cross subsidisation or implied subsidies. Nevertheless, they caution that demand sensitivity to tariff structure changes could contribute to the adoption of solar-plus-battery systems. This would exacerbate the revenue erosion experienced by utilities. A study by Picciariello *et al.* (2015) concluded that in order to avert a death spiral, utilities should design a tariff structure based on the cost-causality principle to better reflect costs based on the electricity network usage. Once again the success of such a policy shift would depend mainly on the demand sensitivity to changes in the structure of the electricity tariff. It is apparent that irrespective of how a utility chooses to respond to a declining revenue base, demand sensitivity remains a key aspect for consideration. Once the elasticity coefficients have been estimated, a utility can choose a most efficient tariff structure for itself. This study therefore forms the basis on which a plethora of alternatives could be considered going forward. Last but not least, this study reviews the existing literature on the causality relationship on electricity consumption and economic growth. This will help to locate the debate about price increases or changes in the tariff structure within the context of the developmental and socio-economic objectives that an electricity utility may have.

1.5 Methods and Data

This study uses monthly aggregate data for the mining sector as a whole. It follows Arisoy & Ozturk (2014) and Wang & Mogi (2017) by using value added in a particular sector as a proxy for income in that sector. Thus, mining production is used to estimate income elasticity. The mining production data is obtained from Statistics South Africa. The electricity consumption data is obtained from the Eskom sales department. The electricity price has to be treated carefully. Firstly the electricity price in the mining sector is not uniform. The price that the mines face varies according to the customer category, high season or low season, peak or off-peak. For the purposes of this study, average monthly prices are used for the industry as a whole. It is acceptable to use these monthly average prices since this study is less concerned about the absolute level of the electricity price itself but more about the rate of change of the price. However this approach has been criticised before. In economic theory firms and consumers face marginal price rather than the average price. Following this idea some studies use marginal price data when estimating price elasticity. However, Shin (1985) and Ito (2014) found strong evidence that residential consumers respond to average electricity prices. This approach was also adopted by Wang & Mogi (2017).Thus in this study average price, rather than marginal price, is used. The average electricity price is obtained by dividing the monthly sales revenue by the number of electricity units sold during a particular month. This has an added advantage of effectively smoothing the electricity price for a particular month. The daily and sometimes hourly price variations are accounted for as part of a simple average. The monthly electricity price is derived as follows:

$$\text{Cents per kilowatt hour } = \frac{\text{Sales Revenue}}{\text{Kilowatt Hours Sold}}$$

This study employs a time-varying parameters (TVP) model based on the Kalman filter technique. This technique provides the evolution of price and income elasticity coefficients over time. The model enables the detection of any exogenous shocks and structural breaks that may have occurred during the period under review. For comparison purposes, an Ordinary Least Squares (OLS) regression is also performed. The elasticity coefficients estimated by this model are averages for the period under review and may not be relied upon in the presence of breakpoints. This study uses the Chow Test to ascertain whether or not there are any breakpoints in the data.

The research hypotheses of this study are the following:

- Electricity prices have a negative relationship with electricity consumption in the mining sector.
- Mining production (income) has a positive relationship with electricity consumption in the sector.

The alternative hypotheses of this study are the following:

- Electricity prices have a positive or no relationship with electricity consumption in the mining sector.
- Mining production (income) has a negative or no relationship with electricity consumption in the sector.

This study uses the 5 per cent critical value for all the tests that are performed. In instances where a different critical value is considered, this is clearly indicated with the rationale for that decision provided.

1.6 The Scope and Limitation of the Study

This study focuses on the mining operations that receive their electricity supply directly from Eskom and are located inside the borders of South Africa. It excludes the electricity supplied to the sector by the redistributors and the electricity consumption that emanates from self-generation by the mining sector itself. Eskom sells electricity directly to nearly 1 000 mining customers. This represents a significant majority of all the mining customers in the country. This customer base accounts for a large and concentrated amount of Eskom's electricity sales. The sales data to this client base is fairly accurate as it is monitored by both Eskom and the mines for the purposes of smart metering and billing processes. The mining sector is arguably the most valuable customer base for Eskom. It provides a large stable and predictable demand of electricity all day, every day. This profile makes it one of the cheapest and easiest customer categories to cater for. In addition, electricity prices in the mining sector are used to provide a cross subsidy towards other customer categories, especially the lower income households and rural customers. If Eskom loses significant portions of its most valued – and perhaps its most profitable – client base, then its entire business model will be in serious jeopardy. It is for this reason that the study focusses on this customer base. The study focuses on the period from April 2006 to March 2019 as this was a period when the industry experienced significantly high electricity price increases. The price trajectory during this period has moved away from a sustained period of increases that were below the inflation rate. The rapid rise in electricity prices during the period under review provides an ideal platform from which an unbiased price response can be assessed. This will provide sufficient insight into how the sector has responded to this price trajectory albeit the increases were from a small base.

1.7 Organisation of the Study

This study is organized in five chapters. Following the introductory chapter, chapter two commences by discussing the electricity intensity of the South African economy, and how it relates to the causality relationship between electricity consumption and economic growth. It then presents a review of the literature on the price elasticity of electricity demand, both theoretically and empirically. Chapter three discusses the methodology and the econometric modelling. This chapter provides a detailed discussion of the econometric techniques that are used in this study. Chapter four analyses the data using the methods explained in chapter three and interpret the results obtained from E-views. The final chapter concludes the study and provides policy implications.

Chapter 2
Literature Review

2.1 Introduction

This chapter has three main sections. It starts with the review of the energy and electricity intensity in South Africa. It proceeds by discussing the theories on the causality relationship between electricity consumption and economic growth. The second part discusses the theory of demand response in general and price elasticity in particular. The last part focusses on the empirical literature on the price elasticity of electricity demand in South Africa and across the globe.

2.2 Energy Intensity

It could be argued that an unintended consequence of the 1991 electricity price pact or any other similar pricing strategy would be the over-allocation of electricity as a factor of production. The sustained lower-than-inflation price increases could result in electricity being cheaper as compared to other factors of production. This could result in an over-allocation of electricity in the production process. Capital intensive sectors like mining would find it attractive to automate their production processes and use more units of electricity per unit of output. Once such automated processes are in place, the sector would become less responsive to electricity price increases. This would result in a relatively subdued price elasticity coefficient. It is therefore important to ascertain whether or not South Africa uses energy and electricity in particular, efficiently.

Energy studies have received considerable attention, not only because of the increasing awareness of energy shortages, but also because of the adverse effects that all energy consumption has on the environment (Inglesi-Lotz & Blignaut, 2011:450). Energy intensity is directly related to the emission of greenhouse gases such that an improvement in energy efficiency may result in a reduction in emissions. The pure concept of energy intensity is defined as the ratio between energy consumption and economic activity (Silva & Guerra, 2009:2590). The value of energy intensity shows how many units of energy are consumed in order to produce one unit of economic output. The literature differentiates between global energy intensity and added energy intensity (Silva & Guerra, 2009: 2590). Global energy intensity is the total amount of energy consumed per production activity. The added level of energy intensity is the level of energy consumption per activity after taking into account the relative changes in production. Energy intensity is therefore inversely related to energy efficiency, where energy efficiency refers to a reduction in the amount of energy consumed in order to render a certain level of service or economic activity. This improvement in energy efficiency can be achieved through technological improvements in the production process, better organisational structure or an improvement in the economic environment. As in other countries, the government of South Africa has identified energy supply as a critical element of economic growth and social development. The allocation of free basic electricity to impoverished segments of the population is aimed at ensuring universal access to electricity in the country (Inglesi-Lotz & Pouris, 2012:114). This will contribute positively towards the social wellbeing of all citizens with improved productivity being a potential spinoff from this programme. The electrification programme underpins the government's policy towards access to energy as part of the country's socio-economic developmental plan.

Inglesi-Lotz & Pouris (2012) found that energy intensity in South Africa gradually declined between 1993 and 2006. Even though both economic output and total energy consumption increased during the period, the increase in economic output was higher than the increase in energy consumption. Notwithstanding the improvement, energy intensity in South Africa was estimated to be much higher than in other comparable countries. For the year 2000, South Africa's energy intensity was estimated to be about 3.3 times the average of OECD countries (Sebitosi, 2008:1591). This was the case despite the fact that energy consumption per capita in South Africa was about half the average of the OECD countries (Sebitosi, 2008:1591). A combination of a high energy intensity and a low energy consumption per capita caused South Africa to be ranked amongst the top seven emitter of greenhouse gases per capita (Sebitosi, 2008:1591). A similar study by Kohler (2014) observed that even though the energy intensity level in South Africa has been gradually improving in recent years, the improvement compared unfavourably to the reductions in both OECD and non-OECD countries. The author calculated that in 2010, South Africa was amongst the highest energy intensive countries in the world at 0.13 tonnes of oil equivalent (toe) per thousand 2005 dollars of GDP. This is in contrast to the energy intensity of 0.09 and 0.15 (toe) for OECD and non-OECD countries respectively (Kohler, 2014: 524).

Inglesi-Lotz & Pouris (2012) ascertained that the industrial consumers accounted for the biggest proportion of energy consumption in South Africa. In addition, they found that the mining sector was amongst the most energy intensive sectors in the economy. They found that the energy intensity in this sector increased by twenty-one per cent from 1993 to 2006, even though the national energy intensity declined during the period (Inglesi-Lotz & Pouris, 2012:117). Energy intensity in the mining sector had defied the national trend over the period of their study. Energy efficiency improvements provide an opportunity to realise economic value and meet energy demands in a sustainable and cost effective manner (Sebitosi, 2008:1591). It was against this background that the Department of Minerals and Energy published the country's first energy efficiency strategy in 2005. The objective of this strategy is to increase access to affordable energy sources, accelerate energy efficiency gains and reduce greenhouse gas emissions. Therefore, energy efficiency represents the cheapest available prospect of energy supply. By becoming more energy efficient, an economy can achieve higher levels of production with the same amount of energy that is currently available to it, thereby eliminating, or at least reducing, the need for investment in additional energy supply infrastructure.

2.3 Electricity Intensity

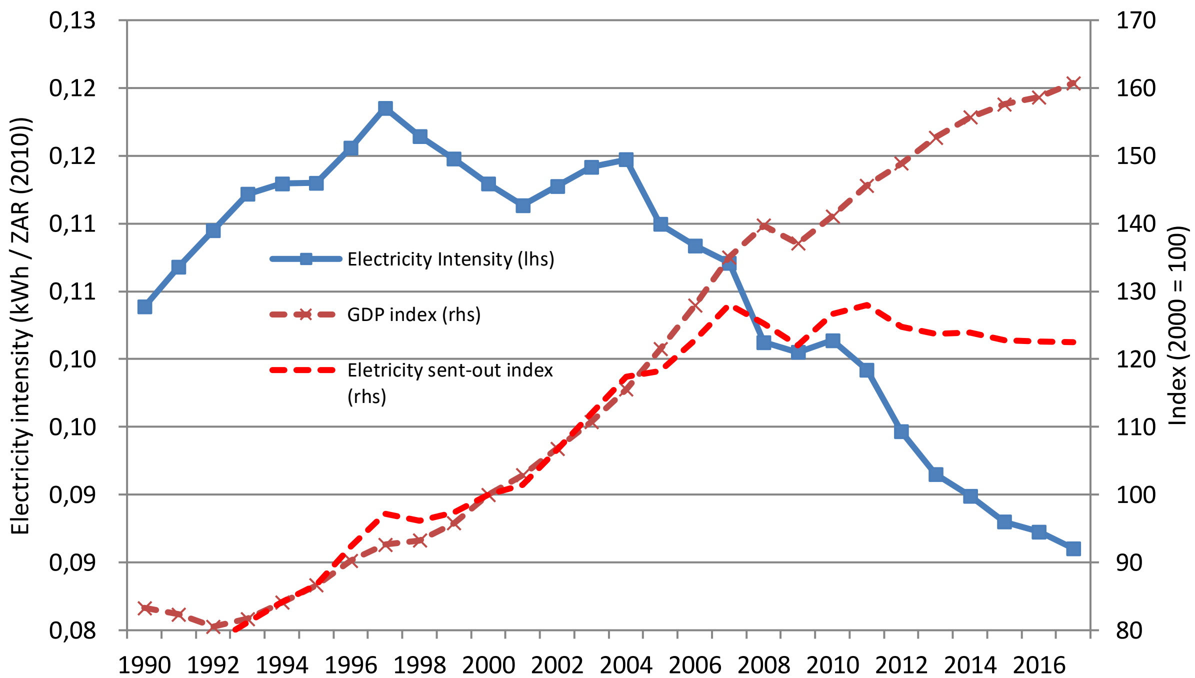
The lower electricity prices emanating from the 1991 national electricity price pact inadvertently contributed to the South African economy becoming very energy intensive. Notwithstanding the fact that the character of the South African economy was already energy intensive, the historically low electricity prices had provided little incentive to save energy (Inglesi-Lotz & Pouris, 2012:113). Inglesi-Lotz & Blignaut (2012) found that there was a large variation of electricity intensity between various sectors in the economy. According to their calculations, the three most electricity intensive sectors in the economy in 2006 were basic metals, mining and quarrying, and non-metallic minerals. By contrast, the transport, construction, food and tobacco sectors were amongst the most electricity efficient sectors in the economy. Furthermore, the study found that the economy-wide total electricity intensity had been on an upward trend during the period 1994 to 2006. Electricity intensity more than doubled from 0.329 in 1990 to 0.713 in 2007 (Inglesi-Lotz & Blignaut, 2012:4495). The alarming rate of increase in electricity intensity since 1994 is attributed to the resource-based nature of the South African economy and the local abundance of coal. The historical domestic under-pricing of coal and electricity has led to a heavily capital and electricity intensive developmental path (Kohler, 2014:525). In addition, the government programme for universal access to electricity for households following the dawn of democracy in 1994 has also contributed to increased intensity.

Inglesi-Lotz & Blignaut (2012:4494) found that electricity intensity in South Africa was significantly higher than the average of the OECD developing countries. Electricity intensity in the OECD countries has remained relatively constant at 0.35 GWH/$ million over the period 1990 to 2007, whereas South Africa's electricity intensity has increased from 0.329 in 1990 to 0.713 during the same period (Inglesi-Lotz & Blignaut, 2012: 4495). Between 1971 and 2010, electricity intensity in South Africa was on average 43 per cent and 30 per cent higher than in OECD and non-OECD countries respectively (Kohler, 2014:525). Overall nine out of thirteen sectors in South Africa were more electricity intensive than their OECD counterparts (Inglesi-Lotz & Blignaut, 2012). A common feature is that in both South Africa and the OECD countries, the basic metals sector had the highest electricity intensity. However, the electricity intensity of this sector was significantly higher in South Africa. In as far as the mining and quarrying sector is concerned, electricity intensity in South Africa is significantly higher than the OECD average (Inglesi-Lotz & Blignaut, 2012:4496). A further study by Inglesi-Lotz & Blignaut (2014) aimed at creating a theoretical benchmark-and-trade carbon system collaborated the findings of the earlier studies. The authors found that the differences between sectoral electricity intensities of South Africa and the OECD countries were substantial. The study used three different standards of electricity intensity to benchmark against. In all three scenarios, the mining and quarrying sectors were deemed to be purchasers of carbon credits as their electricity intensity was higher than the OECD benchmark (Inglesi-Lotz & Blignaut, 2014:837). Even in a more generous scenario where the benchmark was set at 20 times the OECD level, the South African mining sector was found short of at least 20 carbon credits. This is in contrast to the construction sector for example, which would be a seller of up to 100 carbon credits if such a system were introduced. This indicates that the construction sector is more efficient and less electricity intensive than its OECD counterparts.

According to the various studies reviewed in this chapter, it is evident that while South Africa's *energy* intensity has been on a gradual decline, *electricity* intensity was on the rise from 1990 to 2007. This is partly because South Africa has historically enjoyed favourable electricity tariffs. It can also be argued that this was a direct consequence of the 1991 electricity price pact. This price pact encouraged automation and made electricity intensive processes attractive. Electricity had become cheaper over time, which resulted in its over-allocation in the production sectors of the economy. By 2011, South Africa still had electricity tariffs that were amongst the lowest in the world (Kohler, 2014:525). The cheap and abundant electricity propelled the mining sector to be one of the top electricity intensive industries in the economy. The electricity intensity in this sector rose sharply from 1994 to 2006 with no indication of changing course (Inglesi-Lotz & Blignaut, 2012:4497). The increasing electricity intensity coupled with electricity shortages pose a threat to the country's sustainable development.

It follows that electricity price reform, consumer education and other efficiency enhancement programmes, amongst other initiatives, will have to be implemented in order to safeguard the country's energy security into the future. A range of options is available for South Africa to implement in order to have a successful energy efficiency and conservation programme. These measures include the use of more efficient electrical appliances, the use of more renewable energy and extensive consumer education. Although the government has introduced credible policy documents to improve energy efficiency, it is the implementation of these policies that remain a problem (Sebitosi, 2008:1595). Consequently, electricity tariffs had to increase in order to provide the correct price signal in the market. A further analysis of the electricity intensity in South Africa indicates that there has been a gradual improvement in the intensity level during the period under review. Figure 10 indicates that after a marked increase following the 1991 electricity price pact, electricity intensity levels have been on a downward trend since 2004. The improvement in the intensity levels coincided with an increase in electricity prices. This suggests that a sustained correction in the price level may have played a role in improving electricity efficiency in the economy.

Figure 10: Electricity Intensity



Source: Integrated Resource Plan (IRP 2019)

In addition to a general price increase, some scholars have suggested that differential pricing can be used as a tool to encourage efficiency gains and reduce electricity intensity in the economy. It is argued that the negative effects of an electricity price increase could be minimised if these increases are diversified amongst high electricity consuming industries like mining (Kohler, 2014:531). A differential tariff structure which is punitive to high electricity intensive sectors would raise the cost of energy inefficiency and induce a rearrangement of the production processes such that an efficient allocation of electricity is achieved. It follows that in the long term a differential electricity pricing regime would drive out the least electricity efficient industries, thereby making the economy less electricity intensive. Such a system is similar to what was applied in China in 2004. The government of China instituted special pricing policies for electricity intensive sectors in an effort to improve energy efficiency and reduce demand pressure on the electricity network. Electricity intensive industries that did not meet specific energy efficient targets were taxed through higher differential electricity tariffs (Price *et al.,* 2010:6498). The primary objective of the system was to drive electricity inefficient sectors out of the market or force innovation in those sectors. Another proposed system involves penalising electricity intensive sectors through the use of carbon tax. The carbon benchmark-and-trade system as envisaged by Inglesi-Lotz & Blignaut (2014) is one such system. In such a regime electricity intensive sectors would be compared against an agreed benchmark. If these sectors perform worse than the benchmark then they would have to purchase carbon credits in order to continue operating. However, if they outperform the benchmark they earn carbon credits which could be sold in the market. This is a carrot and stick system whereby electricity users are rewarded for efficiencies and are penalised for inefficiencies.

The available literature suggests that South Africa and in particular the mining sector is very electricity intensive as compared to its counterparts. Policy makers should implement corrective measures to improve the electricity and energy efficiency of the country in the long run. The introduction of the Carbon Tax Act No 15 of 2019, which became effective from June 2019, is one of the policy initiatives aimed at reducing the country's carbon footprint. It gives effect to the polluter-pays-principle for large emitters and helps to ensure that firms and consumers take the negative externalities (including those emanating from electricity consumption) into account when evaluating their future production processes. It is clear that policy makers have several policy options available to them when trying to reduce electricity intensity. However any efforts to reduce electricity usage in any sector should take into account the potential causality relationship between electricity consumption and economic growth.

2.4 Causality: Electricity Consumption and Economic Growth

Several studies indicate a high correlation between electricity consumption and economic growth. In a study that encompassed over one hundred countries, which collectively accounted for more than ninety-nine per cent of the global economy, Ferguson *et al.* (2000) established that there is a highly-correlated relationship between electricity consumption and economic growth. However, the correlation between electricity consumption and economic growth was stronger than the correlation between total energy consumption and economic growth (Ferguson *et al.,* 2000:934). In addition, the correlation factor for electricity consumption was higher in wealthier countries than in poorer ones. In a similar way Rosenberg (1998) showed that electricity supply played an integral role in the economic development of the United States of America. Electricity supply was crucial both as a factor of production during the country's industrial development and as a key factor in improving the quality of life of its citizens (Rosenberg, 1998:7). Therefore, electricity consumption is beneficial for the production processes in an economy and it has a positive utility impact on the welfare of the consumers. However, a high correlation between electricity consumption and economic growth does not imply causality. The main question that economists are concerned with is whether electricity consumption stimulates, retards or is neutral to economic growth. From an economic planning perspective, it is important to establish whether economic development takes precedence over electricity consumption, or whether electricity supply itself is a stimulus for economic growth. The literature concerning the relationship between electricity consumption and economic growth has led to the emergence of two opposite views, namely the *neutrality* view and the *institutional* view.

The neutrality hypothesis assumes that there is no causality between electricity consumption and economic growth (Ghali & El-Sakka, 2004:225). It is based on a neo-classical assumption that electricity plays a relatively minor role in influencing economic growth. The main reason for the neutrality hypothesis is that the cost of energy is usually very small as a proportion of GDP, thus it is not likely to have a material impact on overall economic growth. The proponents of this hypothesis argue that the possible impact of a change in electricity consumption on economic growth depends mainly on the structure of the economy and the stage of economic development of the country concerned (Ghali & El-Sakka, 2004:226). It is argued that as the economy develops, its production structure becomes more service orientated and less energy intensive.

The neutrality hypothesis is likely to hold in instances where energy intensity is low and / or energy costs are relatively low. As a result, the neutrality hypothesis is more likely to be supported by studies that are conducted in high income countries which are at an advanced stage of development. It follows that this hypothesis may fall short in instances where an energy intensive sector is being assessed irrespective of the state of development of the country concerned. The impact of a change in electricity consumption in the sector might have a material impact on its output growth, even though the impact on overall economic growth may be insignificant. What is more, if this hypothesis is proven it may have serious implications for the optimal use of different factors of production in the economy. This is essentially the case for countries that have an abundance of energy sources like oil, natural gas or coal where electricity prices are likely to be distorted by some form of subsidies. The lack of causality between electricity and economic growth could lead to an inefficient use of electricity as a factor of production. This inefficient allocation of resources could lead to an inappropriate growth of some sectors of the economy, thereby resulting in an imbalanced economy. The incorrect pricing and subsequently inefficient use of electricity as a factor of production may result in an economy that is skewed towards more capital-intensive means of production. This may result in the displacement of labour, as the economy becomes more capital intensive. Such an outcome could result in less job opportunities been created. Typically, this would not be good for an economy that is still in a developing stage.

On the other hand, the institutional economists consider energy and electricity in particular as a limiting factor to GDP growth. They argue that there is a causality relationship between electricity consumption and economic growth (Ghali & El-Sakka, 2004:225). They consider electricity as a critical component of the production process in any modern economy. Thus, its unavailability could limit the productivity of other factors of production. There are three distinct views in the literature about the direction of the causality between electricity consumption and economic growth. The first view is known as the *growth* hypothesis. This hypothesis assumes that there is a unidirectional causality that runs from electricity consumption to economic growth (Ozturk, 2010:341). The growth hypothesis asserts that electricity supply has a significant impact on economic growth both directly as part of the energy sector and indirectly as a complement to labour and capital in the production process. The proponents of this view argue that governments should encourage an increase in electricity consumption, as it will inevitably result in an increase in economic growth and an improved standard of living for its citizens. If the growth hypothesis holds then all electricity conservation initiatives should be halted, as this would have negative implications for economic growth. This is in sharp contrast to the *conservation* hypothesis. This hypothesis stipulates that electricity consumption is driven by economic growth (Apergis & Payne, 2011:770). As a result, unidirectional causality flows from economic growth to electricity consumption. Therefore, if the economy achieves a different level of electricity consumption this would not affect economic growth. It follows that if this hypothesis holds, electricity conservation policies can be implemented without any negative implications for economic growth. The economy will simply become more energy efficient without any adverse effects on income growth or the general standard of living. The third view is the *feedback* hypothesis. This hypothesis advocates that there is an interdependent relationship between electricity consumption and economic growth (Ozturk, 2010:342). This suggests that there is a bidirectional causality relationship between the two variables. The feedback hypothesis implies that a reduction in electricity consumption will have negative implications for economic growth and vice versa.

The idea that electricity supply is essential for economic growth and development has been well established (Blignaut & De Wet, 2001:360). If electricity is accepted as a limiting factor to GDP then any shortages in electricity supply could hinder economic growth. Similarly, any tampering with electricity consumption could have an effect on economic development. It is crucial for economists and policy makers to ascertain whether economic development takes precedence over electricity consumption or whether electricity consumption serves as a stimulant to economic development in a particular country. This involves establishing the direction of the causality relationship between the two variables in order to formulate appropriate energy policies that can achieve the intended outcomes.

To sustain a high economic growth rate when the unidirectional causality effect runs from economic growth to electricity consumption, the economy should be able to cater for a rapidly increasing level of electricity consumption. This requires a country to maintain an adequate level of electricity generation capacity reserves at all time. A failure to cater for the increasing level of electricity consumption may have negative economic repercussions. This direction of the unidirectional causality effect makes it possible to consider energy conservation strategies without jeopardising prospects of economic growth. In a similar way, this argument is relevant to the neutrality hypothesis. In such a scenario, electricity conservation strategies can be implemented safely as it will only cause energy efficiency gains with little or no effect on economic growth. Such policies should be pursued, as they will result in a better allocation of resources and / or a reduction in the country's carbon footprint. On the other hand, if the unidirectional causality effect flows from electricity consumption to economic growth, a reduction in electricity consumption will lead to a fall in economic growth. In this scenario, policies promoting an increase in the availability of electricity will have positive economic growth implications. This will also improve the standard of living of communities who did not have previous access to electricity. In the case of the feedback hypothesis, the bi-directional relationship between the two variables creates a possibility that energy conservation policies that are aimed at reducing electricity consumption may curtail economic growth. In a similar way, a reduction in economic growth should have a dampening effect on electricity consumption while an increase in economic growth should cause a surge in consumption. Policy makers should keep this in mind when seeking more effective policy solutions.

There is still no consensus on either the existence of the causality relationship between electricity consumption and economic development or its direction. Various studies found different results for different countries. For example, a study by Wolde-Rufael (2006) found different causality results for seventeen African countries. The study found a positive unidirectional causality running from economic growth to electricity consumption for six countries, an opposite causality for three, and bidirectional causality for another three. There was no causality detected for the remaining five countries, including South Africa. The results on South Africa were in sharp contrast to the results of the study by Odhiambo (2009), which found a long run bidirectional causal relationship between electricity consumption and real gross domestic product. The lack of consensus on the empirical results may be attributed to differences in model specifications, variable selection and time horizon between the two studies. Furthermore, the different findings for different countries by Wolde-Rufael (2004) indicate that there is no uniformity on the existence or the direction of causality between electricity consumption and economic growth. A possible reason may be that these countries are at different stages of development, which results in different scenarios and hypotheses.

In an effort to bring clarity on this, a study by Apergis & Payne (2011) used a sample of eighty-eight countries to examine the causal relationship between electricity consumption and economic growth. The countries were divided into four panels according to the World Bank's income classification for high income, upper middle income, lower middle income and low income countries. The study revealed the presence of bi-directional causality for high and upper middle income countries (Apergis & Payne, 2011:779). In the case of lower middle income countries, there was unidirectional causality running from electricity consumption to economic growth in the short run while bidirectional causality was detected in the long run. Finally, the study indicated unidirectional causality running from electricity consumption to economic growth for the low income panel (Apergis & Payne, 2011:780). This means policies aimed at improving the accessibility and affordability of electricity in the low income countries will also improve their economic growth prospects. What is more, these policies will also improve the quality of life of their citizens, especially in the rural and remote areas where access to electricity is inadequate. The results for the high and upper middle income country panels provide support for the feedback hypothesis. In these countries, higher economic growth may stimulate demand for more electricity consumption while higher electricity demand may induce faster economic growth. The interdependence between electricity consumption and economic growth suggests that electricity conservation measures may affect economic growth negatively.

South Africa was included amongst the upper middle income panel in the study. These findings suggest that electricity consumption and economic growth have an interdependent relationship in the country. Therefore, the electricity policy in the country must be guided by this relationship. Firstly, all measures of electricity conservation or the restriction of electricity consumption must be implemented with caution as they might restrain economic growth. Secondly, it is important for the country to have an adequate supply of electricity, as it is a stimulant of economic growth. In addition the results indicate that there is merit for improving the availability and accessibility of electricity across the country. This will yield positive developmental and social results. Therefore, investment in the electricity sector is paramount for long-term economic development. It should be noted that given the bidirectional nature of the causality between electricity consumption and economic growth in South Africa, the demand response to any electricity policy should be taken into account. This includes assessing the demand response to any proposed electricity price increases. If a price change results in a material change in the level of electricity consumption, it could have an impact on economic growth and social welfare. A price change that results in lower electricity consumption might restrain economic growth.

2.5 Theoretical Literature Review – Demand Response

Demand response refers to a change in the behaviour of consumers in lieu of a change in the scarcity of supply (Albadi & El-Saadany, 2008:1990). It includes all intentional modifications to the consumption profile with respect to the timing and the level of total consumption. This change in behaviour can be realised as a result of an Incentive Based Response (IBR) and/ or a Price Based Response (PBR).

2.5.1 Incentive and Price Based Response

Incentive based programmes involve rewarding consumers for reducing their consumption during a particular time of the day or season of the year. On the other hand *price based* programmes involve flattening the demand curve by introducing price variations between one period and the next. In the electricity sector, IBR includes measures like Direct Load Control, Interruptible Load, Emergency Demand Reduction and Ancillary Services Market (Albadi & El-Saadany, 2008:1990). Participants in these programmes give consent to their supplier to curtail their electricity supply for some time if certain conditions in the electricity network are met. This can be an inconvenience to the consumer as supply curtailment can happen at short notice or without any warning at all, depending on the nature of the programme. For this inconvenience, consumers who enlist on these programmes are compensated either through a rebate on their electricity bill, a favourable tariff or direct cash payments.

Electricity price response refers to a consumer's change in electricity consumption in response to a change in the price that it pays for electricity (Neenan & Eom, 2007:4). A price change can be either explicit or implicit. An explicit price change occurs when the posted price of a unit of electricity that a consumer pays increase or decrease. If the posted price remains unchanged, but a consumer is offered a financial incentive to alter its consumption profile this will in effect be an implicit price change. The literature broadly refers to three main pricing schemes that have been implemented to promote a greater demand response in the electricity market (Fan & Hyndman, 2011:3710). The *Time of Use* (TOU) tariff is the most commonly used price scheme. This refers to a tariff structure where pre-determined but different unit prices are applied for usage during different blocks of time within a twenty-four-hour day. The difference in price serves as an incentive for consumers to use electricity during the time slots when it is cheaper to do so. In South Africa, some large power users get incentivised to use more electricity at night than during the day by virtue of a cheaper night tariff (Eskom GMTNP, 53). This is done to reduce electricity demand during the day in order to provide some relief to the network. The second category is the *Critical Peak Price* (CPP). This tariff is used only during peak demand periods, while a flat tariff or TOU tariff is used for the rest of the day. This tariff is designed to discourage consumers from using electricity during peak periods. It is essentially the most expensive tariff of the day. The third category is *Real Time Pricing* (RTP). Where an integrated wholesale electricity market exists, prices can be determined on an hourly basis, thereby reflecting the changing demand and supply dynamics. In such a market, customers face hourly price changes each day. These hourly prices are usually announced a day in advance (Niemeyer, 2001:1).

Currently South Africa does not have an integrated wholesale market whereby consumers and suppliers interact to determine prices. To date real time pricing in its purest form does not exist in the country. However, a weaker form of RTP can be observed in Eskom's seasonal pricing mechanism. For example, in winter electricity demand increases as temperatures drop and the demand for heating energy increase. This often puts pressure on the electricity network. In response to this supply constraint Eskom charges its key customers a higher tariff during this period (Eskom GMTNP, 2013:53). This is done in an effort to curtail demand during winter. The higher winter tariff is implemented in order to reflect the unique supply and demand dynamics of that season. After winter, the tariff is adjusted back to where it was before.

These three price schemes are to various degrees a departure from the traditional flat tariff structure whereby a consumer would be charged a flat tariff irrespective of the time of day or season of use. It follows that a successful implementation of such schemes requires smart meters that are able to record the required additional information over and above the amount of energy used. In South Africa, the use of smart meters has historically been reserved for large power users and it has only recently been rolled out to some households.

2.5.2 Demand Transformation vs Demand Shifting

A price change, whether explicit or implicit, can encourage a consumer to change its demand profile. A consumer could alter its demand profile within a one day or one season cycle while keeping its total electricity consumption relatively unchanged. This is referred to as *demand shifting* (Neenan & Eom, 2007:5). This is typical of a situation where a consumer 'shifts' its electricity consumption from a high tariff period to a low tariff period within a day. Thus, the objective of 'shifting' is to substitute electricity usage in a higher tariff time period with usage in a cheaper tariff time period. The objective of demand 'shifting' is not to reduce overall demand by substituting electricity with another factor of production, but it is to take advantage of lower tariffs by shifting demand during the course of the day. In contrast, *demand transformation* refers to modifying the total electricity consumption in a particular period in response to a change in the relative price of electricity as compared to other factors of production (Neenan & Eom, 2007:6). A consumer that is facing an electricity price change may decide to substitute electricity with other forms of energy like natural gas, solar power or any other form of self-generation, thereby reducing its total electricity consumption.

It is important to note that for demand transformation to occur in the electricity sector, the consumer should have access to other forms of energy supply. Furthermore, the relative price of the substitute energy should be cheaper than the new electricity price, otherwise any demand transformation would not be profit maximising. Similarly, for demand shifting to happen in a sustainable manner, the opportunity costs of doing it should not be prohibitive to the consumer. Nevertheless, the distinction between the two demand responses is critical as it explains the impact of a price change on the demand profile and on total electricity consumption. Both elements have crucial implications for the revenue expectations of a power utility. If sufficient demand shifting occurs (i.e. from a high tariff time block to a low tariff period), it will have negative revenue implications for the utility, even though total electricity consumption may remain relatively unchanged. However, a total reduction in electricity consumption, which is what is observed in the case of demand transformation, could have either a negative, neutral or positive impact on revenue depending on price elasticity.

2.5.3 Price Elasticity

Demand response is a component of the neoclassical theory of demand. This theory forms the basis of the demand curve. The demand curve shows how much of a good or service consumers are willing to buy as the price per unit changes. The law of demand states that there is an inverse relationship between quantity demanded of goods or services and their unit price, *ceteris paribus*. This means that holding all other factors constant, an increase in a price of a good or service will result in a reduction in the quantity demanded of that good, and vice versa. Goods that comply with this rule are known as normal goods. Electricity is a normal good, thus it should have a negatively sloped demand curve in accordance with the law of demand. An increase in its unit price should therefore result in a reduction in its quantity demanded.

The magnitude of the demand response or price sensitivity can be measured by the coefficient of price elasticity. Price elasticity is the relative change in quantity demanded which is caused by a change in price, *ceteris paribus* (Neenan & Eom, 2007:15). It is defined as the ratio of the percentage change in quantity demanded to the percentage change in price while holding all other factors of demand unchanged (Niemeyer, 2001:2). Price elasticity seeks to isolate the percentage change in the quantity demanded, following a one percent change in price.

A good is considered to be price-*elastic* if its elasticity coefficient is greater than 1, in absolute terms. This means that a 1% increase in price will result in a greater than 1% decrease in the quantity demanded. By the same measure, if a 1% increase in price results in less than a 1% decrease in quantity demanded, then the good is considered to be price-*inelastic*. If the ratio between the percentage price change and percentage quantity change equals 1, then elasticity is *unitary*. This means that a particular percentage change in price will result in an equal percentage change in the quantity demanded. Figure 11A illustrates the demand curve of a price-elastic good. A small increase in price results in a large decrease in the quantity demanded. This means that the elasticity coefficient is greater than 1 in absolute terms. Figure 11B illustrates the opposite. The elasticity coefficient in this case is less than 1 in absolute terms. This means that a large price increase will result in a relatively small decrease in the quantity demanded. The good is therefore price-inelastic.

Figure 11A: Elastic Demand

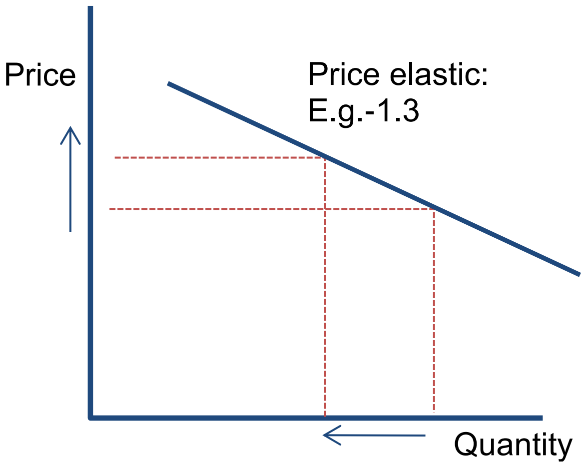
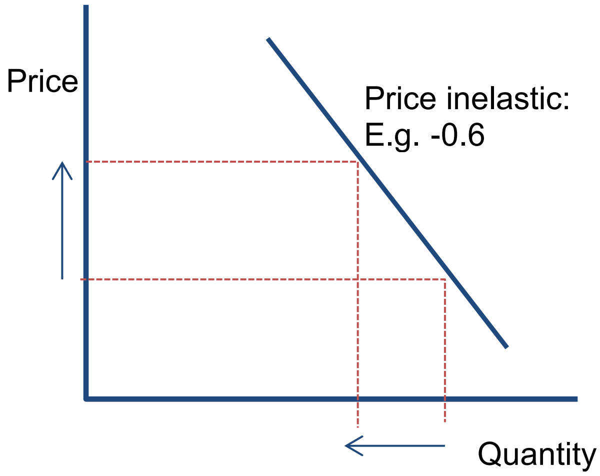


Figure 11B: Inelastic Demand



Price elasticity is useful because it reflects the relationship between the change in the price of a good and the change in the consumers' expenditures on that good (Niemeyer, 2001: 2). If the demand is price elastic, a price increase will lead to lower total expenditure on that good. If the demand is price inelastic a price increase will result in a higher total expenditure. In the case of unitary price elasticity, the percentage price change is offset by an equal percentage change in quantity demanded thereby neutralising each other's impact on total expenditure (Niemeyer, 2001:2). The underlying consumer behaviour, which underpins the theory of demand, stipulates that a consumer with a fixed budget constraint essentially has only three options when faced with a price increase: Firstly, the consumer can buy another good as a substitute. Secondly, the consumer can buy less of the good with no corresponding purchase of a substitute. Lastly, the consumer can continue to purchase the same amount of the good and reduce expenditures on other goods in his or her consumer bundle. It is therefore essential for elasticity coefficients to be specific about which kind of demand response they are measuring.

Academic literature refers to two kinds of electricity price elasticity coefficients, namely own-price elasticity and substitution elasticity (Fan & Hyndman, 2011:3709). The *own-price elasticity* of electricity is defined as a percentage change in total electricity usage as a result of a one percentage change in the unit price of electricity (Bernstein & Griffin, 2006:6). Therefore own-price elasticity is a measure of electricity demand transformation in response to a one per cent price change. If the electricity price varies from one time block to the next in a single a day or season, as in the case of TOU and RTP tariff schemes, consumers may treat electricity usage in different time blocks as substitute goods (Neenan & Eom, 2007: 17). Electricity usage in peak periods may be substituted with usage in off-peak periods if tariffs are materially different between the two periods. When there is a price change in one of the “goods” (e.g. peak period electricity), it will not only affect demand of that good, but it will also affect demand of the substitute “good” (off-peak electricity). The *substitution elasticity* thus measures the percentage change in the ratio of electricity consumption between two time periods following a price change in either of the two periods (Neenan & Eom, 2007:17). Thus, price elasticity coefficients play a pivotal role in explaining the revenue implications of any price change.

Own-price elasticity and substitution elasticity are somewhat similar in a sense that they both measure the magnitude of demand response following a price change. If the coefficient of either of the two is elastic, it indicates a relatively large change in electricity consumption in response to a price change. However, since each one of these elasticity calculations measures a different demand response, they should each be used in their appropriate context. Own-price elasticity should be used where total electricity consumption has been reduced, whereas substitution elasticity should be used where the price response is mainly characterised by shifting consumption from one period to the other (Fan & Hyndman, 2011:3717).

2.5.4 Short-run vs Long Run Price Elasticity

The magnitude of a demand response to a particular price change will differ over time. The consumers’ ability to respond to price changes is likely to increase as more time passes following the announcement of a price change. In the short-run, which is usually considered to be less than two years, consumers have limited capacity to respond to a price change. Since capital stock is fixed in the short-run, the consumers’ only available response is to reduce the intensity of use of their current stock of equipment or shift their consumption to off-peak periods (Fillipini, 2011: 5817).

In the long-run, which is considered to be greater than five years, consumers have both the time and motivation to respond to a price change (Niemeyer, 2001: 2). In the long-run new technologies and new production processes are introduced. This creates scope for the consumers to migrate from their current capital equipment into more energy efficient stock as part of their business recapitalisation processes. With the benefit of time, consumers could also re-engineer their production processes such that they become more energy-efficient and more cost-effective. They could even consider other options, which were not available to them in the short-term. For example, they could install their own electricity generators for their own consumption and/or adjust their work schedules such that most of their production activities – and subsequently consumption – are shifted from peak to off-peak periods. As a result, price elasticity coefficients tend to be higher in the long-run than in the short-term (Niemeyer, 2001: 2).

Price elasticity is a vital measure of the quantum of the demand response following a price change. It provides insight into what the impact of a potential price change could be. Elasticity coefficients are useful in estimating the effects of an electricity levy or subsidy on overall electricity demand. Price elasticity estimates are an important tool for policy-makers, energy-planners and managers of power utilities. Consider, for example, a public utility requesting an electricity price hike from the regulator. The regulator needs to consider how the price adjustment will affect demand both in the short-run and in the long-run. It is crucial that the appropriate form of price elasticity is used to measure the expected demand response. The substitution elasticity is useful to measure demand shifting, while own-price elasticity is useful to measure demand transformation. Since the focus of this study is to ascertain whether price increases have resulted in the transformation of electricity demand in the mining sector (i.e. a change in aggregate electricity demand), it pays attention to own-price elasticity only, and not to substitution elasticity. For simplicity's sake and in keeping with convention, henceforth this study refers to 'price elasticity' instead of 'own-price elasticity'.

2.6 Empirical Literature Review – Price elasticity

Price is an important factor for electricity consumption. This highlights the need for understanding its demand sensitivities (Inglesi-Lotz & Blignaut, 2011:458). A review of the empirical estimates of price elasticity of electricity demand can be broadly categorised as long-term and short-term elasticity estimates. The main objective of this section is to discuss the key findings of the various elasticity studies that have been conducted in different countries. These findings are then compared to the elasticity coefficients that have been estimated for South Africa. In addition, the South African studies are critiqued in order to identify potential areas of improvement that could be incorporated into this study.

2.6.1 International Studies

A number of studies found that the price elasticity of electricity demand is generally very low and insignificant, especially in the short run. Although electricity demand is indeed price-inelastic, some studies indicate that price plays a significant role in determining electricity demand in the long run. Irrespective of the econometric techniques used, the findings among different studies were fairly similar.

Bose & Shukla (1999) examined the econometric relationship between electricity consumption and variables like income, price of electricity and price of diesel for five major customer categories in India. These categories were residential, commercial, agriculture, small and medium industries, and large industries. Income and price elasticities of electricity consumption were estimated at the national level by pooling data across 19 states spread over a nine-year period. The results showed that short run price elasticities varied from -1.35 in agriculture, -0.65 in residential, -0.45 in large industry, -0.26 in commercial and insignificant in small and medium industries. Electricity demand in the commercial and large industrial sectors were found to be income elastic while the residential, agricultural and small and medium industries were inelastic. On the whole, income was found to play a more critical role than electricity prices in determining electricity demand. With all industries taken together the income elasticity coefficient was estimated to be 0.73. Using a slightly different approach, a study by Al-Faris (2002) resorted to identifying the main economic fundamentals that influenced the behaviour of electricity consumption in the Gulf States (Saudi Arabia, United Arab Emirates, Kuwait, Oman, Bahrain and Qatar) from 1970 to 1997. According to the study, both income and prices affect demand. The average price elasticity for the countries under review was -0.09, with estimates ranging from -0.04 for Saudi Arabia to -0.18 for Qatar. The author found that for any price policy to be an effective demand reduction tool, given the low elasticity and overall electricity prices, a substantial upward adjustment of electricity tariffs would be required (Al-Faris, 2002:123).

A sectoral and regional study by Egorova *et al.* (2004) on Russia's industrial sectors, produced similar findings. The study showed that even though price is an important factor when determining electricity demand, output is more significant. For the period from 1998 to 2002, the estimated price elasticity of electricity demand in Russian industries ranged from -0.2 to -0.4. The authors noted that these estimates were fairly close to the European and American estimates (Egorova *et al.,* 2004:8). In the United States of America, a study by Kamerschen and Porter (2004) used the simultaneous equation model to estimate the price elasticity coefficient of electricity demand for the residential and industrial sectors for the 26 years ending in 1998. The study found that the residential customers were more price sensitive than the industrial customers. It also confirmed the view that weather plays a greater role in explaining electricity consumption in the residential sector than in the industrial sector. The residential price elasticity estimates ranged between -0.085 and -0.94 whereas the industrial estimates ranged between -0.34 and -0.55. Total electricity demand appeared to be the least sensitive with its price elasticity estimate ranging between -0.13 and -0.15. The authors noted that these elasticity values were in line with the findings of other previous studies in the United States (Kamerschen & Porter, 2004:97).

In Sweden, a study was conducted by Lundberg (2009) to determine the demand functions for Swedish industrial electricity consumption for the periods from 1960 to 1992 and from 1993 to 2002. Lundberg found that the coefficients for price elasticity and the cross-price elasticity of electricity demand were insignificant in the first period, but significant in the second period. The author indicated that after the deregulation of the electricity market which effectively commenced in 1992, firms had been induced to expand their flexibility in energy usage, which in turn made substitution between electricity and oil much easier (Lundberg, 2009:31). This made electricity demand more sensitive to price, although it was still rather price-inelastic. Bianco *et al.* (2010) analysed non-residential electricity consumption in Romania for the period from 1975 to 2008, to forecast consumption up to 2020. According to the authors' findings the price elasticity of electricity demand was -0.0752 in the short-run and -0.274 in the long-run (Bianco *et al.,* 2010:3587). This indicated higher demand response in the long run than in the short run. In a similar way, Dilaver & Hunt (2010) assessed the relationship between electricity consumption, industrial value-added and electricity prices, to forecast the future industrial demand for electricity in Turkey. Their study provided projections for electricity demand in 2020 by applying a structural time series technique to annual data covering the period from 1960 to 2008. According to their findings the price elasticity of electricity demand in Turkey for the period was -0.16. However, the underlying demand for energy showed an increasing trend (Dilaver & Hunt, 2010:17), suggesting a potentially higher demand response in the long run.

Ghaderi *et al.* (2006) examined the electricity demand functions of the industrial sector in Iran. The authors estimated the electricity demand for 17 subgroups from 1980 to 2002. They used different variables to measure the electricity demand sensitivity in the industrial sector. These variables included a number of industrial customers representing components of the demand function and dummy variables to control for the Iran-Iraq war. The results indicated that the coefficients of price elasticity are significant in most subgroups, such as food, furniture and basic metals, whereas the overall electricity demand was still price-inelastic (Ghaderi *et al.*, 2006:403). Muazzam *et al.* (2013) assessed the growth trends of electricity consumption in Pakistan's industrial sector for the period from 1975 to 2008. The authors found that price is a significant variable in this equation, with an increase in electricity tariffs causing a decrease in the demand for electricity. The study also showed that an increase of one percentage point in the price of electricity would result in a 0.28 per cent decrease in the demand for electricity. Although the authors found that electricity demand is price-inelastic, they still recommend, for the purpose of fostering industrial growth, policies that ensure price control on 'future demand' as well as efficient compensation to cover any 'shortages of electricity' (Muazzam *et al.,* 2013:643).

De Vita *et al.* (2006) used an autoregressive distributive (ARDL) bounds testing approach to co-integration to estimate the long-run elasticity of the Namibian energy demand for the period from 1980 to 2002. The authors estimated the long-run elasticity coefficients for the aggregate energy consumption levels for electricity, petrol and diesel. Their finding showed that energy consumption has a negative correlation with the price of electricity, while the price elasticity coefficients vary for the different fuel types. While the price elasticity of electricity demand was estimated at -0.30, the authors found no significant cross-price elasticity outcomes for the various fuel types (De Vita *et al.,* 2006:3462). Similarly, Ziramba & Kavezeri (2012) also used the bounds testing approach to estimate the long-run price elasticity of aggregate electricity demand for Namibia from 1993 to 2010. Their findings showed that electricity demand is price-inelastic, with a long-run elasticity estimate of -0.32 (Ziramba & Kavezeri, 2012:208).

Wasantha-Athukorala & Wilson (2010) investigated the short run dynamics and long run equilibrium relationship between residential electricity demand and the factors influencing demand in Sri Lanka for the period 1960 to 2007. Their study used co-integration and error correction models to capture the long run as well as short run relationships among the relevant variables. The results showed that electricity demand is both price and income inelastic. However, electricity demand was more responsive in the long run than in the short run. The long run demand elasticities of income, own price and price of kerosene oil (a substitute source of energy) were estimated to be 0.78, -0.62 and 0.10 respectively. The short run elasticities for the same variables were estimated to be 0.32, -0.16 and 0.10 respectively. The study concluded that increasing the electricity price would not be the most effective way of reducing electricity demand. It surmised that given the low price elasticity level the government could remove the existing price subsidies without it having a significant impact on sales revenue. It also noted that the long run income elasticity of demand showed that any future increase in household incomes would likely result in a significant increase in electricity consumption. Therefore, income played a more significant role than price in determining electricity demand in the Sri Lankan residential market. The study concluded that any power generation expansion plans should take into account the potential impact of future income increases on electricity demand if the country were to avoid power shortages in the future.

In Japan, price elasticity of electricity demand had long been assumed to be as small as -0.1 or 0 without any proper examination of the empirical validity of such an assumption (Hosoe & Akiyama, 2009:4313). This assumption was based on the outcomes of earlier studies that were conducted elsewhere in the developed world. These included studies by Taylor (1975) and Anderson (1971) that had analysed industrial and commercial electricity demand and found small elasticity coefficients which were close to zero. As more reforms were introduced in the Japanese electricity market, it became crucial to test such a *priori* assumptions, particularly because these reforms were aimed at changing the behaviour of customers who consumed a large part of the electricity generated in the country. Hosoe & Akiyama (2009) estimated the price elasticity of electricity demand in the industrial and commercial sectors in nine of the ten electricity supply regions in Japan. The regional power demand function was estimated using the ordinary least squares as well as the panel estimation method. The price elasticity coefficient was found to be significant and negative in all the regions. It ranged between -0.086 in Tokyo and -0.297 in Shikoku in the short term. Long term price elasticity estimates ranged between -0.120 in Kansai and -0.564 in Hokkaido. An analysis of the results revealed that urban regions had lower price elasticity than their rural counterparts. They attributed this to the difference among regions in the availability of suitable plant sites for self-owned power plants. The industrial and commercial users analysed in this study were large scale users. Some of them are equipped with their own power plants in order to substitute the electricity they purchased from the regional power company. The authors noticed that as the share of power supplied by their own power plants increases, electricity demand became more price elastic. The availability of physical space and more accommodative environmental regulations in the rural regions make it more likely for customers in those areas to have their own electricity generating power plants. As articulated in section 2.5.2, the availability of options makes demand transformation more easily attainable. Thus electricity demand by customers with alternative sources of energy is typically more sensitive to price changes than by customers who are wholly dependent on the electricity grid.

In a fairly unique approach, a study by He *et al.* (2011) used the Computable General Equilibrium (CGE) model to simulate the impact of electricity price adjustments on demand for electricity in China. The simulation results show a range of electricity elasticities for different consumer categories. The price elasticity coefficient for residential customers was found to be -0.30, while the price elasticity estimate for coal mining and agriculture were -0.12 and -0.06 respectively. On the whole the short run price elasticities of electricity demand of each sector were small. The price elasticity of electricity demand for the total economy was estimated at -0.037. However, the elasticity values of the electricity intensive sectors like mining, metal product industry, metal smelting and rolling processing were relatively larger than the less intensive sectors. Based on this, the authors argued that increasing electricity prices in the industries which are characterized by high energy consumption and high pollution should be considered in order to adjust the structure of the

Chinese economy in the long run. The authors also noted that the absolute value of price elasticity of electricity demand of the agricultural sector was relatively small. This meant that the impact of electricity price changes in this sector was relatively benign. Therefore cheap electricity prices would not provide sufficient stimuli for the sector.

In Spain, Balzquez *et al.* (2013) conducted an empirical analysis on residential demand for electricity. The study used aggregate panel data at the province level for 47 Spanish provinces for the period 2000 to 2008. A dynamic demand function was estimated using a two-step system based on the general method of moments (GMM) estimator. The study found the residential sector to be price inelastic with an estimated coefficient of -0.07 in the short run and -0.19 in the long run. Income elasticity was estimated at 0.23 and 0.61 for the short run and long run respectively. This meant that electricity demand in Spain was more responsive to price and income in the long run than in the short run. Furthermore, the study confirmed that weather variables have a significant impact on electricity consumption by the residential customers.

A study by Lim *et al.* (2014) examined the electricity demand function in the Korean service sector by using data covering the period 1970 – 2011. The study used a co-integration and error correction model to estimate the short and long run elasticities of electricity demand in this sector. The short and the long run price elasticities were estimated to be -0.421 and -1.002 respectively. The income elasticity values were estimated to be 0.855 in the short run and 1.090 in the long run. These findings were rare because they indicated that electricity demand in the service sector was inelastic to changes in both price and income in the short run, but elastic in the long run. Therefore, a pricing policy strategy would be effective in limiting electricity demand in the long run. Furthermore, policy makers should encourage electricity efficiency strategies as income growth in this sector is likely to result in even faster growth in electricity demand in the long run.

In Jamaica a study by Campbell (2018) used the bounds testing approach to co-integration to obtain long run price elasticity of demand estimates for the period 1970 – 2014. The study focussed on aggregate demand and three different consumer categories, namely residential, commercial and industrial customers. The main results of the study suggest that price is a significant determinant of electricity demand at the aggregate level with an own-price elasticity of -0.40. The price elasticity coefficients of -0.82, -0.15, and -0.25 were estimated for the residential, commercial and industrial sectors respectively. Given these findings, the authors concluded that price based approaches were more likely to be successful in slowing electricity demand growth in the residential sector than in the other two customer categories.

On the other hand, the commercial and industrial consumers were found to be very responsive to changes in income with an income elasticity coefficient of 0.77 and 1.22 respectively. These findings indicate that the residential customer is more price sensitive than its commercial or industrial counterparts. It also supports the hypothesis that for the most part, electricity demand is more responsive to income changes than price changes.

The majority of international studies found that electricity demand is price-inelastic, and that income plays a more significant role in determining electricity demand as compared to price. However, demand responsiveness seems to be more pronounced in the long-term than in the short-term. As a result, elasticities of electricity demand are generally higher in the long-term than in the short-term. This is consistent with economic theory as both consumers and producers are expected to have greater flexibility in changing their behaviour over the long-term than in the short-run. It is more probable for industrial users of electricity to change their production processes and acquire more energy efficient equipment in the long-term than in the short-run. In some cases, price is deemed to play an insignificant role in determining electricity demand in the short-term, but it plays a pivotal role in the long-term. It is also evident that elasticities of electricity demand are different in different countries. These differences could be occasioned by the differences in the developmental level, pricing mechanism and climate in these countries (He *et al.,* 2011:116). Another observation is that a sector-specific analysis may yield different elasticity estimates to those of the economy as a whole. In some cases electricity intensive sectors were found to have higher price elasticity values (in absolute terms) than the less intensive sectors. In other cases, price is significant in the macro-economic analysis, but insignificant in the sector-specific analysis. Therefore, even in the same country, the elasticities of electricity demand may differ from one sector to the other and from one jurisdictional or electricity supply region to the next.

2.6.2 Critique of International Studies

The introduction of Distributed Generation (DGs) will serve as a structural change in the electricity markets, especially in the developed world. The *a priori* assumption that there are no structural breaks in the electricity demand function in these markets may not hold anymore. This is especially the case in advanced markets like Europe, where a customer is also simultaneously a seller with the capacity to sell their excess self-generated electricity back into the national grid. As seen in Hosoe & Akiyama (2009), the ability of the customers to generate their own electricity has a significant impact on the price elasticity of electricity demand. These customers are generally more sensitive to the changes in the grid electricity price since they have an option to install or increase their own generation, and can therefore substitute away the more expensive electricity for their own generated supply. This is likely to become a stronger feature in the electricity demand equation as the price of installing DGs reduces. It therefore follows that markets that have experienced a high penetration of DGs, or that have potential to do so, may present different elasticity values than what was inferred by most studies that have been reviewed thus far.

There is sufficient evidence from the studies that were reviewed that weather conditions play a significant role in explaining electricity demand in the residential sector. In some studies the weather was found to have the greatest impact on the residential sector (Kamerschen & Porter, 2004:98). Therefore studies that focus on residential customers but fail to account for climate conditions in their models may be found wanting.

2.6.3 South African Studies

An earlier study conducted by Pouris (1987) on the price elasticity of electricity demand in South Africa examined the effect of price on the demand for electricity from 1950 to 1983. It placed considerable emphasis on the estimation of the long-run price elasticity of electricity demand. The coefficients were estimated by using an unconstrained distributed lag model. Over a 12-year period, the price elasticity of electricity demand was estimated at -0.90 (Pouris, 1987:1269). According to the author, more than 70 per cent of electricity in South Africa was consumed by the industrial and mining sectors over this period.

Blignaut & De Wet (2001) examined electricity consumption in the manufacturing sector with regard to price, by estimating the price elasticity coefficients for the various subsectors during the period from 1976 to 1996. The authors found that even though the electricity intensity was particularly high in the manufacturing sector, there was a weak relationship between price and consumption. For most subsectors, an increase in price did not result in a decrease in consumption, and the price elasticity coefficients were positive. This emphasized the insignificance of price. All price elasticity coefficients were small and between 1 and -1, indicating that electricity consumption was price-inelastic (Blignaut & De Wet, 2001:367). Similarly, Ziramba (2008) analysed residential electricity demand by using the bounds testing approach to cointegration. The study found that price did not have a significant impact on the residential sector during the period from 1978 to 2005. The author found that the price elasticity coefficients were negative and statistically insignificant in both the short and the long run. The long-run price elasticity was -0.04, whereas the short-run value was -0.02. According to Ziramba (2008:3465) “in the long run, income is the main determinant of electricity demand, while electricity price is insignificant”. Amusa *et al.* (2009) applied a similar methodology as Ziramba (2008), in order to analyse the aggregate demand for electricity in South Africa for the period from 1960 to 2007. The results showed that electricity prices have an insignificant impact on electricity demand in the long run while income is actually the main determinant of electricity demand.

In contrast to the findings of Ziramba (2008), Blignaut & De Wet (2001) and Amusa *et al.* (2009), Inglesi (2010) found that electricity prices have a significant impact on total electricity demand in the long run at a macro-economic level. Inglesi (2010) analysed the relationship between electricity demand, income, prices and population for the period from 1980 to 2005. The results show that the "long run impact of income and price is significant although both estimates are inelastic at 0.42 and -0.55 respectively" (Inglesi, 2010:202). The results also indicated that the consumption of electricity can be explained by growth in the gross domestic product and that price is insignificant in the short-term. In an effort to expand on the work of Inglesi (2010) and Blignaut & De Wet (2001), Inglesi-Lotz & Blignaut (2011) examined the electricity consumption of various economic sectors in response to changes in price and economic output for the period from 1993 to 2006. The authors determined the overall relationship between price, output and consumption. Their pooled effect model showed that price and output are significant factors in the overall or aggregate electricity demand of industries. The fixed effects model on the other hand accounted for cross-sector dynamics and showed that electricity prices are insignificant, while output becomes less significant (Inglesi-Lotz & Blignaut, 2011:458). An analysis of the results indicates that cross-section heterogeneity in the sample data might be the cause of price insignificance. A Seemingly Unrelated Regression (SUR) model was used to estimate separate elasticity coefficients for the various economic sectors. The results for the individual sectors showed that price is insignificant in determining electricity demand for most economic sectors, with the exception of the industrial and transport sectors. The price elasticity coefficients of the industrial and transport sectors were -0.869 and -1.220 respectively (Inglesi-Lotz & Blignaut, 2011:458).

Kohler (2014) estimated the price and income elasticities of electricity demand in different economic sub-sectors which were collectively classified as the industrial sector. The study employed the ARDL bounds testing procedure to estimate the demand function of each economic sub-sector using OLS. The sample period covered was 1993 to 2006. The results showed that for most sub-sectors price did not play a significant role in determining electricity demand. Only the iron and steel, paper and print, and construction sub-sectors showed a negative price elasticity value. These sectors yielded relatively high price elasticity values with the iron and steel at -0.586, paper and print at -1.774 and the construction sector at -

7.765. The rest of the sectors, including mining and non-ferrous metals, did not reflect any significant response to price changes. On the other hand income was found to be a significant determinant of electricity demand in almost all the economic sub-sectors under review. Sectors like non-ferrous metal, iron and transport equipment were found to be income elastic with an estimate of 1.797 and 2.578 respectively. At an aggregate level, total industry electricity demand was found to be price inelastic at -0.939 and income inelastic at 0.628.

2.6.4 Critique of South African Studies

Even though the findings of the South African studies are in line with international studies, there are three key concerns about their validity. Firstly, electricity prices declined in real terms from 1978 to 2005. On average, the real price declined by 0.43 per cent per annum from 1960 to 2007 (Amusa et al., 2009:4172). The decrease in the real price of electricity during this period could result in a somewhat subdued demand response, thereby presenting relatively low price elasticity coefficients. This could nullify the significance of the effect of prices on consumption during the various periods covered by these studies.

Secondly, the historically low levels of electricity prices induced a lack of demand responsiveness to price changes (Blignaut & De Wet, 2001:373). In addition to this low base, the decline in real prices led to the cost of electricity accounting for a significantly low percentage of the total input costs. For the period from 1976 to 1996, the electricity costs accounted for less than 10 per cent of the total operating costs for most of the sectors in the economy (Blignaut & De Wet, 2001: 367). According to the calculations by Inglesi-Lotz & Blignaut (2011: 459), this low electricity cost ratio was still firmly in place by 2005. The low ratio of electricity costs to total operating expenditure and a declining trend in real prices indicate that changes in electricity tariffs were of limited concern to consumers at that time. Consequently, it is plausible to find subdued price elasticity estimates during this period. However, this might not hold from 2006 onwards, when real prices began to rise. It is therefore crucial to have a study that covers a period when real prices were increasing.

Lastly, most of the studies make an implicit assumption that price elasticity estimates did not change materially during the periods under review in the respective studies. The elasticity estimates are therefore effectively averages over these periods. Given the long periods covered by most studies, the structural changes in the South African economy over the course of time and the material changes in electricity intensity levels, this assumption does not seem plausible. Inglesi-Lotz (2011) duly challenged this assumption. She used the

Hansen test to determine whether or not the estimated parameters in the electricity demand function in South Africa for the years 1980 to 2005 had remained static. The results suggest that the parameters had changed over time. Therefore it must be assessed whether or not the price elasticity coefficient has remained static during the period under review. If it has remained unchanged, then models that assume as such can be used to estimate long term elasticity averages and make inferences about demand response in the future. However, if there is parameter instability during the period under review, efforts must be made to highlight this structural change as long term averages would be misleading. It would be prudent to ascertain this fact so that policy makers can make more informed demand projections.

2.7 Review - Modelling Techniques

The literature review indicates that there is no single preferred approach for estimating econometric models (Beenstock *et al.,* 1999:168). However, fixed coefficient models are among the most commonly used modelling techniques. These models range from Engle-Granger co-integration, Johansen co-integration, error correction (ECM) to autoregressive distributed lag (ARDL) models. As time passes, new models are introduced with the view to improve the old ones or to serve as alternatives to the existing ones. Consequently, there is no uniform approach to modelling electricity demand and estimating its price and income elasticity coefficients (Jamil & Ahmad, 2011: 5520).

Some studies have compared various methodologies of energy demand modelling and ended up with different results (Beenstock *et al.,* 1999:182). For example, a study by Amarawickrama & Hunt (2008) used six different techniques to highlight the variation in elasticity estimates emanating from using different econometric techniques. Their findings indicate that the long run elasticity coefficients obtained while using the different techniques were dissimilar even though the same data set was being used. The estimated long run income elasticity coefficients ranged from 0.99 for the Static Engle–Granger (EGII) method to 1.96 for the Structural Time Series Model (STSM). This represented a wide range in the income elasticity estimates depending on the technique that was used. The estimated long run price elasticity coefficients ranged from 0 for the Static EGII, Dynamic EG, the Pesaran, Shin and Smith (PSS) method and FMOLS methods to -0.06 for the STSM method. The Johansen method gave an estimate of -0.04 and the Static EGI gave an estimate of -0.02. This indicated that even at the largest (in absolute terms) estimated coefficient, price elasticity would have a limited effect on the demand of electricity in Sri Lanka. Therefore all models supported the conclusion that the price elasticity of electricity demand in Sri Lanka was inelastic.

A similar exercise was conducted by Alberini & Filippini (2011). They conducted an empirical analysis of the residential demand for electricity using annual aggregate data of 48 US states from 1995 to 2007. They used the LSDVC and the "system" GMM estimator proposed by Blundell & Bond (1998). Unlike in the other studies, their results indicated that the estimated price elasticities differed significantly depending on the technique that was used. Short run elasticities varied between -0.08 and -0.15 while long run price elasticities varied between -0.45 and -0.75. Therefore changing the estimation technique alone resulted in a 70 to 88 per cent variation in the elasticity coefficient. The wide range in the income elasticity coefficient observed from different models would be of some concern to electricity demand forecasters and policy makers. This study highlights the importance of using different techniques if there is no clear statistical rationale for favouring one over another, rather than just having a blind faith in one technique.

These differences in outcomes owing to differences in techniques, has led to criticisms and counter-criticisms amongst researchers (Fan & Hyndman, 2011:3711). Questions have been raised about which models are more appropriate in which circumstances. There is a growing acknowledgment that elasticities of electricity demand are not static (Wang & Mogi, 2017:233). This raises the question whether or not, given the structural and technological changes that the electricity sectors the world over are undergoing, the fixed parameter models are the best approach to model electricity demand and its elasticities. The aim of this section is to discuss the modelling techniques that have been widely used over time and discuss the evolution of the literature in this regard.

2.7.1 Fixed Coefficient Demand Models

The Ordinary Least Squares (OLS) method, or variations thereof, is most renowned for estimating elasticity coefficients. Historically, the "simple" Error Correction Model (ECM) has also been widely used in electricity demand analysis (Jamil & Ahmad, 2011:5520). More recently, studies show that models that represent special cases of the general autoregressive distributed lag (ARDL) model impose very implausible *a priori* restrictions on the relationship between short and long run elasticity estimates (Cuddington & Dagher, 2015:189). For example, the exclusion of contemporaneous price as an explanatory variable in the ECM model forces short-run elasticity estimates to be zero. Although this may be the case in some instances, the condition seems unreasonable, especially if annual data is used. Similarly, the Partial Adjustment Model (PAM) also has *a priori* restriction on the magnitude of the elasticity estimates. In essence, the PAM and ECM models force the short-term elasticity estimates to be lower than their long-term counterparts (Cuddington & Dagher, 2015:189). This restriction applies to all forms of elasticity estimates, including price and income elasticity. Although this outcome is consistent with economic theory, ideally it should be derived from the data and not be forced as a condition in the model.

The AR(1) model, on the other hand imposes *a priori* restriction that short-run elasticity must be equal to long run elasticity (Cuddington & Dagher, 2015:192). This condition is often found wanting, especially if the purpose of the study concerned is to compare the short-run and the long run elasticity estimates. To avoid any *a priori* restrictions on the magnitude of the elasticity coefficients, some researchers found the Autoregressive Distributed lag (ARDL) model to be more useful for energy demand studies (Jamil & Ahmad, 2011:5520). A study by Fatai *et al.* (2003:119) found that the ARDL approach is better to forecast performance in comparison to the other approaches. The authors highlight the particular fact that ARDL does not require pre-testing for the order of integration of the variables as a key advantage over the other models.

Rao (2007) came to a different conclusion. The author examined alternative techniques to estimate time series models and concluded that the ECM specification has an advantage over the alternative approaches. The study suggests that the general to specific (GTS) approach adequately forecasts data and could be used for inference purposes (Rao, 2007:1620). Cuddington & Dagher (2015) addressed this contradiction by using a vector error correction model that reduces a single-equation conditional ECM with no loss of information. Following this assertion they suggest that ARDL or its corresponding specific ECM can be employed as a dynamic demand specification model. Cuddington & Dagher (2015:202) also conclude that the PAM and AR(1) process should not be employed owing to the implausible *a priori* restrictions that these models place on short and long-run elasticity estimates. In conclusion, the authors found that these restrictions can be easily avoided when a general to specific modelling approach is employed.

Studies by Huntington (2007) and Inglesi-Lotz & Blignaut (2011) use OLS regressions that allow for contemporaneous effects in order to estimate short-run and long-run elasticity coefficients. Cuddington & Dagher (2015) found that the OLS estimates of the dynamic demand coefficients will be consistent when the data series contains only stationary and lagged regression variables. If the model allows for contemporaneous effects, as in the case of Huttington (2007), all variables must be weakly or strictly exogenous in order for OLS estimates to be consistent. Once this is established, conditional inference from the OLS estimators is valid. If the variables are endogenous the OLS estimators could result in biased and inconsistent parameters (Cuddington & Dagher, 2015:188).

Consequently a critical shortcoming in research is the failure to test for the weak exogeneity condition which is required to validate parameter estimation when using OLS. Quite often, the variables are simply assumed to be weakly exogenous, as in the case of the research by Huttington (2007). This may seem like a reasonable assumption to make, especially in South Africa where electricity tariffs are not determined by the market but are imposed by the regulator. However, Cuddington & Dagher (2015:196) argued that while it may be reasonable to assume that this assumption holds when dealing with income and substitute price effects in a dynamic demand model, it is typically not reasonable for own-price effects. It may be tempting to exclude contemporaneous price from the demand model in an effort to legitimise the use of OLS; however, this would make the model susceptible to omitted variable bias (Cuddington & Dagher, 2015:188). It follows that all the necessary OLS conditions must be met before any inference can be made from the OLS estimators. If a study fails to indicate that all the relevant tests have been performed and does not disclose the results thereof, there is no assurance that the findings of the empirical work are valid. In fact, there is no reason to trust that the conclusions of that particular study are correct. When a researcher uses the OLS model, the conditional data testing that is a prerequisite for a valid deployment of OLS is just as important as the results of the study itself. Another shortcoming is that for most studies the authors fail to disclose the standard errors of their elasticity coefficients. This makes it difficult to ascertain whether there is any statistical difference between the short-term and long run elasticity estimates of the same study. More importantly, it makes it impossible to establish whether elasticity coefficients across different studies are statistically different from each other.

2.7.2 Time-Varying Coefficient Demand Models

More recently there has been a growing trend of supporting time-varying coefficients, considering the parameter instability due to outliers and structural breaks in the electricity sector. The introduction of new electricity generation technologies, the restructuring of the sector and incidences of electricity supply shortages in different electricity supply jurisdictions and other related disruptions have encouraged researchers to seek demand models that are able to handle any such disruptions or break points. To achieve this, time-varying parameter models are often estimated and analysed by using state space methods.

A key advantage of state space models is that they can be analysed by using the Kalman filter.

Wang & Mogi (2017) estimated the price and income elasticities of industrial and electricity demand in Japan using annual data from 1989 to 2014. A time-varying parameter model (TVP) with the Kalman filter was applied to test the evolution of consumer behaviour given the exogenous shock (i.e. the 2008 Asian economic crisis) and the structural breaks (i.e. electricity deregulation: 1995 and Fukushima Daiichi nuclear disaster: 2011). The results suggest that both industrial and residential consumers became less sensitive to price after the electricity deregulation and the economic crisis. However, both sectors became more sensitive to price after the nuclear crisis. In particular, price elasticity of electricity demand by the industrial sector customers fluctuated considerably during the period under review. It declined dramatically from -0.797 in 1995 to -0.289 in 2007 during the industry deregulation period. After the financial crisis of 2008, price elasticity further declined to -0.020 in 2010 which was the lowest estimated value (in absolute terms) for the period. Following the Fukushima Daiichi disaster, price elasticity began to recover and reached -0.16 in 2014 which was its final state. On the other hand the sectors income elasticity of electricity demand was estimated at 1.024 in its final state. It barely changed during the period under review. A somewhat similar result was observed for the residential sector customers. Income elasticity of residential demand remained stable from 1989 to 2015 at 1.206 and 1.219 in those years, while price elasticity increased from -0.48 in 1989 to -0.64 in 1994. Following the electricity sector deregulation in 1995 price elasticity decreased marginally from -0.72 to -0.61 in 2007. From 2008 it further declined and dropped to -0.3107 in 2010. Similarly to the case of the industrial sector, price elasticity in this sector recovered after the 2011 nuclear disaster and reached its final state at -0.511 in 2014. The authors of this study also estimated an OLS model on the same data and made several observations. For income elasticity, the results of the OLS model were reasonably close to the final values as derived by the Kalman filter. This made sense as there was not much variation observed in this parameter during the period. However, the OLS price elasticity estimates were materially higher than the Kalman filter final estimates at -0.341 and -0.681 for the industrial and residential customers respectively (Wang & Mogi, 2017:238). Therefore, if long term forecasts were to be made based on the OLS results, there could potentially be an over-estimation of demand response. This seems to validate the opinions of Morisson & Pike (1977). They argued that if the elasticity coefficients do not vary over time, the Kalman filter and the OLS approach are expected to produce similar results. However, in the presence of parameter instability, the Kalman filter can be proven superior to the least squares model.

Arisoy & Ozturk (2014) estimated the price and income elasticity of industrial and residential electricity demand in Turkey for the period 1960 to 2008. A time-varying parameters model based on the Kalman filter was used. The results showed that the price and income elasticities of electricity demand in both the industrial and residential sectors were inelastic. The income elasticity of electricity demand was estimated at 0.979 and 0.955 for the industrial and residential sectors respectively. The price elasticity estimates were very low for both sectors. The price elasticity of the industrial electricity demand was estimated at -0.014, while the residential sector was at -0.0223. The authors observed the varying estimates of price and income elasticity of electricity demand in both these sectors had not changed significantly since the 1970s. The study concluded that electricity price increases in Turkey would not discourage electricity consumption in either sector as there was limited demand response.

A similar study by Inglesi-Lotz (2011) applied the Kalman filter model to estimate the evolution of income and price elasticities of electricity demand in South Africa from 1983 to 2005. The study found that income elasticity experienced a downward trend from 1986 to 1990 where it was close to zero. However, it increased sharply from the beginning of the 1990's with its final state estimated at 1.002 in 2005. On the other, hand price elasticity was close to unitary elastic during the 1980s and beginning of 1990s. The results showed that from 1991/92, price elasticity decreased sharply (in absolute terms) from -1.077 in 1986 to -0.045 in 2005. The study showed that the price elasticity of electricity demand became inelastic since the beginning of the 1990s. From then onwards, electricity prices did not play a significant role in determining electricity demand. This was at the time when the national electricity price pact became effective. The low electricity prices (in real terms) following this price pact resulted in a declining price elasticity. The price pact was therefore a disruption or a structural break in the electricity demand equation. As it was built to do, the Kalman filter model detected this structural change and pointed it out. The author noted how the elasticity values of electricity demand at different times seemed to match with the findings of other South African studies which focussed specifically on the corresponding time periods (Inglesi-Lotz, 2011:3694).

2.7.3 Specification of the Electricity Demand Model

A further challenge in modelling electricity demand is with respect to choosing the explanatory variables. Different studies use different variables to explain the variation in electricity demand (Jamil & Ahmad, 2011:5520). In general, the explanatory variables that have been used for analysing electricity demand can be broadly classified as demographic, economic, and weather related. For instance, Amusa *et al.* (2009:4170) expresses electricity demand as a function of electricity price, the price of electricity substitutes, production output, and the prices of electrical machinery. This model requires a fair amount of data for all explanatory variables in a format that best reflects the sector under review and therefore poses significant data challenges. For example, different mining operators use different technologies and different equipment for their operations. Consequently it is difficult to standardise the electrical machinery prices in every sector or subsector. Such constraints resulted in almost all studies modelling electricity demand as a function or combination of output/income, temperature, population, substitute price and own-price (Narayan *et al*., 2007:4489).

Al-Faris (2002:120) expressed electricity demand as a function of own-price, price of substitute (e.g. natural gas) and real income. In contrast, a study by De Vita *et al.* (2006:3454) analysed electricity demand in Namibia by incorporating variables on marginal electricity prices, real income and minimum temperatures into its demand model. Inglesi-Lotz & Blignaut (2011:456) modelled electricity demand as a function of price and output. In their model electricity consumption is dependent on only two explanatory variables, namely electricity price and output.

2.8 Discussion

A wide range of studies that were reviewed in this chapter indicate that electricity demand across different countries and most economic sectors is both price and income inelastic. It is also apparent that electricity demand responds more to changes in income than in price. Although electricity demand has generally been income inelastic, the elasticity estimates are usually higher than the price elasticity estimates. In some studies income elasticity was estimated close to unitary, while price elasticity was fairly subdued. It can be observed that elasticity coefficients are higher in the long run than in the short term. This means that electricity demand is more responsive to price changes in the long run than in the short run. However, there is no clear convergence of elasticity estimates of electricity demand across different countries. The electricity industry is undergoing material structural changes the world over. These changes emanate from within the individual countries in a form of internal reforms (i.e. industry restructure) and at a global level (i.e. changes in technology). There is already evidence emerging in the literature that shows that these changes may have an impact on the elasticities of electricity demand. Therefore, for the purposes of making long term electricity demand projections, the results of these studies should be viewed with this potential shortcoming in mind.

The South African studies have by and large yielded similar results to their international counterparts. Electricity demand was found to be price inelastic and income inelastic. In most cases income or output was found to play a more significant role in determining electricity demand. The role of price in this regard was always limited or insignificant. A unique feature in the South African context is how different studies have estimated significantly varied elasticity values depending on the period under review. The literature indicates that prior to the 1991 electricity pact; price played a significant role in determining demand. In the mid to late 1990s, prices became an insignificant variable in the electricity demand equation. As a result, the electricity intensity in the country increased dramatically. Nevertheless the economy benefited (especially the energy-intensive sectors) from this cheap and abundant electricity given the bi-directional causality relationship that exists between economic growth and electricity consumption in South Africa. Since 2006, however, electricity prices in South Africa have increased sharply. Unsurprisingly, calculations done in this study indicate that electricity intensity has improved markedly, even reaching some pre-1991 levels. There is a reasonable chance that elasticity coefficients of electricity demand have been markedly different during this period as compared to the periods that were assessed in the literature review. This evolution of elasticities of electricity demand, from pre-1991 to post-2006 illustrates the importance of time variant coefficient demand models.

Notwithstanding the growing recognition of time-varying coefficients, there are still a lot of studies that use fixed-coefficient regressions in energy modelling. The prominent techniques encountered in the literature review range from OLS, ECM, Engle-Granger co-integration, Johansen co-integration and the ARDL bounds testing approach. The literature is still evolving on the superiority of the time-varying or fixed-coefficient approach. Therefore there is no reason to doubt the integrity of the results that have been produced by these models. Nevertheless, it may be necessary to evaluate the underlying statistical behaviour of the energy demand parameters before any long term inference can be drawn from elasticity estimates produced by these models.

It should be noted that there is a limited amount of literature on the price elasticity of electricity demand in the mining sector both in South Africa and Internationally. Historically, electricity demand in this sector has been considered to be inflexible. However the advent of DGs has ushered in new flexibility in the sector's electricity demand profile. This study is an early contribution towards a body of knowledge that will be acquired as the proliferation of self-generation technologies increases and the sector becomes more sensitive to the grid electricity price. It is aimed at filling some of the research gap that currently exists and lays the foundation for future work that will be required as the sector's demand profile changes.

Chapter 3
Methodology and Econometric Modelling

3.1 Introduction

This chapter consists of three sections. The first section discusses the electricity demand model which has been adopted in this study. The second section focusses on the various diagnostic tests that are aimed at ensuring that the data is compliant with the classical linear regression model (CLRM) assumptions. This makes it permissible to perform linear estimations. The last section discusses the Kalman filter as the preferred econometric modelling technique for estimating elasticity coefficients of electricity demand. It also provides the rationale for this choice.

3.2 Model Specification

A number of determinants of electricity demand have been considered in the empirical literature. In broad terms, the demand for electricity has usually been specified as a function of, among others, real income and the price of electricity. This study follows a similar approach to Arisoy & Ozturk (2014), where electricity demand is approximated by electricity consumption and the income variable is approximated by monthly mining production. It could be argued that more variables, including but not limited to the price of commodities, the exchange rate, global economic growth and domestic interest rates, could play some role in determining the level of electricity consumption in the mining sector. However, these variables are likely drivers of mining production itself. Thus, their inclusion and other similar macro-economic variables are likely to give rise to challenges of multicollinearity as their impact is already encapsulated by including mining production as an explanatory variable.

The electricity demand function in the mining sector can thus be denoted in a form of a generalized two-variable population regression function such that:

$$Y_t = \alpha_1 + \alpha_2 X_{2,t} + \alpha_3 X_{3,t} + u_t, \quad \forall i = 1, \dots, N \wedge t = 1, \dots, T \qquad (1)$$

where:

- Y_t is the dependent variable (i.e. electricity consumption),
- $X_{2,t}$ and $X_{3,t}$ are the time-variant explanatory variables (i.e. electricity price and mining production, respectively) and
- u_t is the error term which is assumed to be white noise and which is normally distributed.

In equation (1), α_1 is the intercept or constant term. It provides the average autonomous electricity consumption when prices and output are at zero. It gives the mean effect which all the other excluded variables from the model have on the dependent variable Y_t. The coefficients α_2 and α_3 are partial regressors. The coefficient α_2 measures the change in the mean value of electricity consumption *Y* per unit change in production, holding electricity price constant. Likewise, α_3 measures the change in the mean value of *Y* per unit change in price while production remains constant. This equation represents a population regression function (PRF). It would be appropriate if the entire population data was available for regression analysis. However, this is rarely the case. As it was indicated earlier, the sample data that has been made available for the purpose of this study is not exhaustive of the population data. Therefore, the task at hand is to estimate the PRF on the basis of the available sample data.

A sample regression function (SRF), which corresponds with the PRF of Equation (1) can be denoted as follows:

$$LnCons_t = \hat{\beta}_1 + \hat{\beta}_2 LnPrice_t + \hat{\beta}_3 LnProduction_t + \hat{\varepsilon}_t \qquad (2)$$

The subscript Ln indicates that all the variables are in their natural logarithms such that $LnCons$ is the natural logarithm of electricity consumption, $LnOutput$ is the natural logarithm of mining output and $LnPrice$ is the natural logarithm of electricity price. $\hat{\beta}_1$ is the constant and $\hat{\varepsilon}_t$ is the error term. The demand function has been transformed into a double log form. Transforming variables into their natural logarithm form has two basic advantages. Firstly, the natural logs enable the slope coefficients to be interpreted as the elasticity of the dependent variable with respect to the percentage change in the independent variables. Therefore $\hat{\beta}_2$ and $\hat{\beta}_3$ represent estimates of price and income elasticities respectively. Secondly, the log transformation reduces the problem of heteroscedasticity which is discussed later in this chapter.

The OLS estimators of the population partial regression coefficients $\hat{\beta}_2$ and $\hat{\beta}_3$ can be derived as follows:

$$\hat{\beta}_2 = \frac{(\sum y_i x_{2it})(\sum x_{3i}^2) - (\sum y_i x_{3i})(\sum x_{2i} x_{3i})}{(\sum x_{2i}^2)(\sum x_{3i}^2) - (\sum x_{2i} x_{3i})^2} \qquad (3)$$

and

$$\hat{\beta}_3 = \frac{(\sum y_i x_{3i})(\sum x_{2i}^2) - (\sum y_i x_{2i})(\sum x_{2i} x_{3i})}{(\sum x_{2i}^2)(\sum x_{3i}^2) - (\sum x_{2i} x_{3i})^2} \qquad (4)$$

3.3 Unit Roots and other Time Series Issues

In a time series analysis, one of the main concerns is to establish whether or not the variables are stationary so as to avoid obtaining spurious regressions. It is often stated that macro-economic data and financial market variables follow a random walk. This makes such data susceptible to unit root behaviour. However, a random walk process can be stationary if its mean and variance are found to be constant across time and the covariance between any time periods is dependent on the lag between them (Tsay 2002:56). A random walk time series can be broadly defined by the following properties:

$$Mean: E(Y_t) = \mu$$

$$Variance: Var\ (Y_t) = E(Y_t - \mu)^2 = \sigma^2$$

$$Covariance: = \gamma(k) = E[(Y_t - \mu)\ (Y_t + k - \mu)$$

where –

Y_t is a series of a random walk
$\gamma(k)$ is the auto covariance at lag k

A random walk time series would be considered to be stationary if all of the above conditions are satisfied. If one or more conditions are not met, then the time series would have a unit root thus making the series non-stationary. Non-stationary series violate the classical OLS assumptions, giving rise to spurious regression. The concern for stationarity of time series variables gives rise to unit root tests. In this study, the stationarity of the time series is tested using the unit root test, as originally suggested by Dickey & Fuller (1981). Therefore this study uses the Augmented Dickey Fuller test. In order to understand this test it is useful to consider the original Dickey Fuller test and acknowledge its shortcomings.

A random walk economic data time series that resembles the Markov first-order auto-regressive model can be given as follows:

$$Y_t = \theta Y_{t-1} + \varepsilon_t \qquad (5)$$

where –
Y_t is a given time series and
ε_t is the white noise error term

If θ =1 then every data observation will be highly dependent on its immediate predecessor barring the impact of any white noise. That means that the time series has a unit root. If a time series has unit root (i.e. non-stationary), it cannot be used in its current form as it would result in spurious outcomes. A common remedy to addressing this problem is to take the first difference of the time series and use it instead. There is a possibility that this first difference data series becomes stationary (Dickey & Fuller 1981: 1058). Therefore, taking the first difference of equation (5),

$$\begin{aligned} Y_t - Y_{t-1} &= \theta Y_{t-1} - Y_{t-1} + \varepsilon_t \\ &= (\theta - 1)\, Y_{t-1} + \varepsilon_t \end{aligned} \tag{6}$$

Equation (6) can be re-written as:

$$\Delta Y_t = \gamma Y_{t-1} + \varepsilon_t \tag{7}$$

where –

γ = $(\theta - 1)$,

Δ is the first difference operator.

It now becomes possible to estimate equation (7) by using the sample time series data. This can be achieved by taking the first differences of Y_t and regress them against Y_{t-1}. If the estimated slope coefficient (i.e. the estimated γ) is negative, then it can be concluded that Y_t is stationary. If the estimated slope coefficient is zero then the series can be considered to be non-stationary (Gujarati 2003: 814).

Testing the null hypothesis that γ = 0 or turns out to be slightly complicated since the *t* value of the estimated coefficient of Y_t does not follow a normal distribution even in large samples (Gujarati 2003: 814). Under the null hypothesis γ = 0, the estimated *t*-value follows the tau (τ) statistic. The tabular values of the τ statistic distribution are given by Dickey and Fuller (1979). The τ test is commonly referred to as the Dickey Fuller (DF) test in honour of its discoverers. A key feature of the τ statistic is that its distribution is wider than that of a normal *t* statistic. Therefore the critical points in the τ statistic distribution are larger (in absolute terms) than those of the t statistic. This makes it possible to accept a null hypothesis (i.e. there is unit root - data series is nonstationary) under τ test that would have otherwise been rejected under the normal t test. In that sense the τ test is a more stringent test than the normal *t* test. For example, the border line of rejection of the null hypothesis at the 95 per cent confidence level with a sample size T =100 for a one-tailed *t* test is -1.658.

The corresponding critical value for the τ test is -1.95. This makes it more likely for the τ test to accept the null and deem the data series to be nonstationary.

A random walk process may or may not have a drift. It may also have both deterministic and stochastic trends (Gujarati 2003: 802). In light of this the Dickey Fuller test considers three possible deterministic structures for each individual time series. The model considers a structure where the data series has a constant and a trend, no constant but a trend, or neither a constant nor a trend.

The equations can be denoted as follows:

$$\Delta Y_t = \gamma Y_{t-1} + \varepsilon_t$$

$$\Delta Y_t = a_0 + \gamma Y_{t-1} + \varepsilon_t \tag{8}$$

$$\Delta Y_t = a_0 + a_2 t + \gamma Y_{t-1} + \varepsilon_t \tag{9}$$

where –

t is a time trend variable

The first equation is a repetition of equation (7) where Y_t is a pure random walk. Equation (8) adds a drift term (or intercept) a_0 to the random walk. In equation (9) Y_t is a random walk which has both a drift term and a linear time trend $a_2 t$. Thus, the difference between the three regressions is the presence of the deterministic elements a_0 and $a_2 t$. For all three equations, the key parameter is γ. In each case the null hypothesis is that γ = 0, meaning there is a unit root and thus the time series is nonstationary. The alternative hypothesis is that that γ is less than zero, therefore there is no unit root and the time series is stationary. If the null hypothesis is rejected it means that the time series (Y_t) is stationary with a zero mean, non-zero mean and around a deterministic trend for equations (7), (8) and (9), respectively (Gujarati 2003: 815).

The Dickey Fuller unit root test involves estimating one (or more) of the equations above, by using OLS in order to obtain the estimated value of γ and dividing it by its associated standard error to compute its τ statistic. If the computed absolute value of the τ statistic exceeds the Dickey Fuller τ -value, we reject the hull hypothesis that γ = 0, in which case the time series is stationary. However if the computed absolute value of the τ statistic is less than the Dickey Fuller tau value, then the null hypothesis will not be rejected meaning the time series is non-stationary. It is important to note that the critical values of the tau test to test the null hypothesis are different for each of the three random walk specifications referred to in equations (7), (8) and (9). It is therefore critical to make sure that the appropriate critical tau values are used. The main shortcoming of the Dickey Fuller (DF) test is that it assumes that the error terms ε_t in equations (7), (8) and (9) are uncorrelated. However, in the event that this is not the case, the test loses its power significantly, thereby making its results less credible. To deal with this shortcoming Dickey and Fuller augmented their test such that the number of lags of the independent variable is included to the regression in order to whiten the errors (Gujarati 2003: 817).

3.3.1 Augmented Dickey Fuller Test

The Augmented Dickey Fuller (ADF) test augments the three Dickey Fuller (DF) diagnostic specifications by adding the lagged values of the dependent variable. For example, equation (9) has been augmented as follows:

$$\Delta Y_t = \beta_1 + \beta_{2t} + \gamma Y_{t-1} + \sum_{i=1}^{k} \psi_i \Delta Y_{t-1} + \varepsilon_t \qquad (10)$$

Where –

ε_t is the white noise error term,

$\Delta Y_{t-1} = (Y_{t-1} - Y_{t-2}), \Delta Y_{t-2} = (Y_{t-2} - Y_{t-3}),\ etc.$

In equation (10), *k* refers to the number of lagged difference terms included in the model. This is often determined empirically until enough terms are included so that the error term becomes serially uncorrelated. By so doing, the model ensures that error terms are white noise with a zero mean and a constant variance across different time periods. The Schwarz Information Criteria (SIC) is automatically used to select the maximum lag length for *k*. The ADF test uses the same critical τ -statistics that are used in the original DF test as both tests follow the same asymptotic distribution. Similarly to the DF test, the null hypothesis of the ADF test is that the data has a unit root which means the series is not stationary. The rejection of the null hypothesis that γ = 0 implies that the time series does not have a unit root and is therefore stationary. If the null hypothesis is not rejected, then the time series is not stationary. A common shortcoming of both the ADF and the DF tests is that there is no way of knowing upfront which one of the three equation specifications (i.e. equations (7), (8) and (9)) is applicable. This raises the risk of committing a specification error. To avoid this, some trial and error may be required until the correct specification is identified. In this study all three equation specifications are tested on E-views until the correct one is identified.

3.3.2 Normality Test

This study uses a data sample of less than 150 observations. Given this sample size, it is imperative to ensure that the error term in the model follows the normal distribution. Otherwise the testing procedure that is conducted will not be valid, given the relative size and finite nature of the sample data. The Jarque–Bera test for normality is employed in this research. This test is based on OLS residuals analysis. It computes the skewness and kurtosis of the OLS residuals. It uses the following statistic:

$$JB = n\left(\frac{s^2}{6} + \frac{(k-3)^2}{24}\right) \tag{11}$$

Where, *n* is the sample size,
s is the skewness coefficient and
k is the kurtosis of the coefficient.

The null hypothesis is that the residuals are normally distributed, while the alternative hypothesis is that residuals are not normally distributed. The null hypothesis is rejected if the ρ value of the statistics is lower or equal to the level of significance. If the ρ value is found to be reasonably high, which will happen if the value of the statistic is close to zero, the normality assumption is not rejected. The Jarque-Bera test statistic asymptotically follows the chi square distribution with two degrees of freedom (Gujarati 2003: 148).

3.3.3 Serial Correlation Test

Autocorrelation, also known as serial correlation, may exist if the error term of one period is related to the error term in another period of the same data series. If such a relationship exists, it would be a violation of one of the assumptions of classical linear regression model (CLRM) which states that the error term which relates to any observation should not be influenced by the error term relating to any other observation. That means that the expected relationship between the error terms of different time periods is non-existent (Gujarati 2003: 442). This can be denoted as:

$$E(\varepsilon_t \varepsilon_{t+1}) = 0, \qquad t \neq t+1 \tag{12}$$

where E is the expected or average value of the error term ε_t over time.

Autocorrelation can be either positive or negative. Positive autocorrelation refers to a scenario where autocorrelation is already established and the error term, which is of a particular sign (i.e. a positive or negative sign), is followed by another error term with the same sign throughout the time series.

This can be denoted as follows:

$$cov(\varepsilon_t, \varepsilon_{t+1}) > 0, \qquad \forall t \neq t+1 \tag{13}$$

where:

cov is the covariance of the error term ε_t over time.

When autocorrelation exists, the error term is approximated by assuming that it is generated through the following process:

$$\varepsilon_t = \rho\varepsilon_{t-1} + u_t, \qquad -1 < \rho < 1 \tag{14}$$

where:

ρ is the first order autocorrelation coefficient, and

u_t is a stochastic error which satisfies the standard OLS and CLRM assumptions.

Therefore, u_t is white noise. This means that the value of the error term ε_t is equal to rho times its value in the preceding period plus a random error term. Equation (14) is known as the Markov First Order Autoregressive Scheme, usually denoted as AR(1). It is the regression of ε_t on itself lagged for one period. It is referred to as the first order regression because ε_t and its immediate predecessor is involved in the regression.

Given the AR(1) scheme, the following dynamics can be derived:

$$var(\varepsilon_t) = E(\varepsilon_t^2) = \frac{\sigma_u^2}{1-\rho^2} \tag{15}$$

$$Cov(\varepsilon_t, \varepsilon_{t+1}) = E(\varepsilon_t\varepsilon_{t-1}) = \rho^2\frac{\sigma_u^2}{1-\rho^2} \tag{16}$$

$$Cor(\varepsilon_t, \varepsilon_{t+1}) = \rho^2 \tag{17}$$

where:

$Cov(\varepsilon_t, \varepsilon_{t+1})$ refers to covariance between error terms which are 1 period apart and

$Cor(\varepsilon_t, \varepsilon_{t+1})$ refers to the correlation between error terms which are 1 period apart.

In Equation (15) and Equation (16), σ_u^2 represents the homoscedastic variance of the error term u_t. Since ρ is a constant between -1 and 1, Equation (15) shows that under the AR(1) scheme, the variance of ε_t is still homoscedastic. If ρ is 1, the variances and co-variances above will be undefined. The covariance of the error term is always greater than zero for all observations. On the other hand, negative autocorrelation occurs when an error of a specified sign tends to be followed by an error of the opposite sign. It can be denoted as follows:

$$cov(\varepsilon_t, \varepsilon_{t+1}) < 0, \qquad \forall t \neq t+1 \tag{18}$$

It follows that in the presence of autocorrelation the OLS estimators are still linear unbiased as well as consistent and asymptotically normally distributed; however, they are no longer efficient (Gujarati 2003: 454). This means that the estimated parameter $\hat{\beta}$ is still a true estimate of β. However, its variance is no longer efficient. (i.e. minimum variance). Thus, $\hat{\beta}$ is not a Best Linear Unbiased Estimator (BLUE). In addition, the estimated standard errors of the coefficient are biased which results in unreliable hypothesis tests (t-statistic).

There are several ways to detect autocorrelation. This thesis uses the Durbin Watson Test. The Durbin Watson Test uses the AR(1) process to detect autocorrelation. In essence, the Durbin Watson Test is concerned with estimating ρ. Given Equation (14), it is observable that if ρ is equal to 0, then there is no autocorrelation. In the AR(1) scheme, the value of ρ is unknown. The Durbin Watson Test uses the estimated correlation between the error term in period *t* and the error term in period *t-1* to calculate it. The value given by the DW Test is known as the *d*-statistic and it is calculated as follows:

$$d = \frac{\sum_{t=2}^{T}(\hat{\varepsilon}_t - \hat{\varepsilon}_{t-1})^2}{\sum_{t=1}^{T}\hat{\varepsilon}_t^2} \tag{19}$$

where *T* represents the last observation in the time series.

From Equation (19) the *d*-statistic can be derived such that:

$$d \approx 2(1 - \hat{\rho}) \tag{20}$$

where $\hat{\rho}$ is the estimator of the first order coefficient of autocorrelation ρ. $\hat{\rho}$ is denoted as follows:

$$\hat{\rho} = \frac{\sum \hat{\varepsilon}_t \hat{\varepsilon}_{t-1}}{\sum \hat{\varepsilon}_t^2} \tag{21}$$

The DW Test has no unique critical value defining the point at which one can reject the null hypothesis of no autocorrelation. However, it has a zone of indecision which is defined by a lower bound (d_l) and upper bound (d_u). These bounds are dependent on the number of observations in the sample data and the number of explanatory variables in the original model. The *d*-statistic ranges from zero to four (0 to 4) (Gujarati 2003: 469). The closer the *d*-statistic is to 2, the stronger the evidence that there is no autocorrelation. The closer the statistic is to 0, the more likely it is that there is positive autocorrelation. The closer the statistic is to 4, negative autocorrelation is likely to be present in the data.

3.3.4 Heteroscedasticity Test

The error term is a vital component of the classical linear regression model (CLRM). One of the CLRM assumptions is that the variance of the error term is constant (homoscedastic). This assumption refers to a situation where the error term has the same variance regardless of the values(s) taken by the independent variable(s). Mathematically this can be denoted as such:

$$var(\varepsilon_t \vee X_t) = E\big(\varepsilon_t - E(\varepsilon_t \vee X_t)\big)^2 \qquad (22)$$

$$E(\varepsilon_t^2 \vee X_t) = \sigma^2 \qquad \forall t = 1, \dots, T$$

where X_t represents a vector of values for each individual and for all independent variables.

Contrary to this, heteroscedasticity occurs when the error term does not have a constant variance. This takes place when the variance of the error term changes in response to a change in the value(s) of the independent variable(s). Mathematically this can be denoted as follows:

$$var(\varepsilon_t \vee X_t) = E\big(\varepsilon_t - E(\varepsilon_t \vee X_t)\big)^2 \qquad (23)$$

$$E(\varepsilon_t^2 \vee X_t) = \sigma_t^2 \qquad \forall t = 1, \dots, T$$

The presence of heteroscedasticity in the time series will result in the OLS estimators to not be efficient; i.e. not to achieve the smallest variance of the error term. The variance of the error term will be different from one observation to the next. Thus, the estimated errors of the coefficients could be biased. As a result, the hypothesis tests (t-statistics) will be unreliable. Nevertheless, the OLS estimates will remain unbiased.

In the presence of heteroscedasticity, the variance of the OLS parameter estimators $\hat{\beta}_2$ and $\hat{\beta}_3$ are given by:

$$var(\hat{\beta}_2) = \frac{\sigma_t^2}{\sum x_{2t}^2(1 - r_{23}^2)} \quad (24)$$

and

$$var(\hat{\beta}_3) = \frac{\sigma_t^2}{\sum x_{3t}^2(1 - r_{23}^2)} \quad (25)$$

where σ_t^2 is the time varying variance of the error term.

Unlike in a homoscedastic variance where $\hat{\sigma}^2$ is constant throughout the time series, σ_t^2 changes over time (represented by the subscript *t*).

It is important to note that, if one fails to appropriately account for the presence of heteroscedasticity, the calculation of the variances and standard errors of the slope coefficients will be misleading. The t-statistic which is calculated as

$$t = \frac{estimated\ \beta - hypothesized\ \beta}{standarderror}$$

and the conclusions of the statistical significance will be misleading because of the bias in the calculation of the standard errors.

Although heteroscedasticity does not cause OLS coefficient estimates to be biased, it can cause the estimates of the variance and thus the standard errors to be biased. As a consequence thereof, the OLS estimators may no longer be BLUE (best linear unbiased estimators). This could compromise the integrity of the hypothesis testing by invoking type II errors. A type II error is an incorrect failure to reject a false null hypothesis. This happens when the model fails to detect an effect that is present in the data series.

This study uses White's general heteroscedasticity test to assess if the sample data is characterised by heteroscedasticity or homoscedasticity. The test allows for one or more independent variable to have a non-linear and interactive effect on the error variance. The step process of the test can be illustrated while using a three variable regression model which is denoted in Equation (1):

Step 1: Given Equation (2), run the regression analysis and obtain the residual error term(s) $\hat{\varepsilon}_t$.

Step 2: Estimate the following auxiliary regression:

$$\hat{\varepsilon}_t^2 = \theta_1 + \theta_2 X_{2t} + \theta_3 X_{3t} + \theta_4 X_{2t}^2 + \theta_5 X_{3t}^2 + \theta_6 X_{2t} X_{3t} + v_t$$

In Step 2, the squared residuals from the original regression are regressed on the original regressors, their squared values and the cross product(s) of the regressors. Then an R^2 from this auxiliary regression is obtained.

Step 3: Under the null hypothesis that there is no heteroscedasticity, it can be shown that sample size (n) times the R^2 obtained from the auxiliary regression asymptotically follows the chi-square distribution with degrees of freedom (df) equal to the number of regressors (excluding the constant term) in the auxiliary regression. That is:

$$n \cdot R^2 \; \widetilde{asy} X_{df}^2$$

Step 4: If the chi-square value obtained exceeds the critical chi-square value at the chosen level of significance, the conclusion is that there is heteroscedasticity. If it does not exceed the critical chi-square value, there is no heteroscedasticity, which is to say that the parameter coefficients in Step 2 are simultaneously equal to zero. This can be represented as:

$$\theta_2 = \theta_3 = \theta_4 = \theta_5 = \theta_6 = 0$$

In this case, the error variance is the homoscedastic constant which is θ_1.

3.3.5 Misspecification Test

One of the assumptions of the classical linear regression model (CLRM) is that the regression model used in the analysis is correctly specified. If this is not the case, the model could results in spurious results emanating from the specification error in the model. There are several techniques that are available for testing specification errors. This study uses the Regression Specification Error Test (RESET) as suggested by Ramsey (1969) to test for specification error in the regression. The RESET technique is based on three steps. The first step is assuming Y to be dependent variable and X to be an explanatory variable such that:

$$Y_t = \lambda_1 + \lambda_2 X_t + \mu_i \tag{26}$$

and obtain the estimated value of $\tilde{Y}_t$.

The second step is to again regress equation (26) by including the estimated $\tilde{Y}_t$ as an explanatory variable in the reconfigured regression such that:

$$Y_t = \alpha_1 + \alpha_2 X_t + \alpha_3 \tilde{Y}_t^2 + \mu_i \tag{27}$$

The last step entails using the *F* test to find out if the increase in R^2 from equation (26) to equation (27) is statistically significant. Let R^2 obtained from equation (26) be R^2_{old} and R^2 obtained from equation (27) be R^2_{new}. The *F* value can be calculated as follows:

$$F = \frac{\left[\dfrac{(R^2_{new} - R^2_{old})}{number\ of\ new\ regressors}\right]}{\left[\dfrac{(1 - R^2_{new})}{(n - number\ of\ paramters\ in\ the\ new\ model)}\right]} \tag{28}$$

If the computed *F* value is significant, one can accept the hypothesis that the regression model as stated in equation (26) is mis-specified. The main advantage of RESET is that it is easy to implement and it does not require an alternative model to be constructed. However this can also be viewed as a weakness. After asserting that a particular model has been mis-specified, the test does not assist in anyway in building an alternative one.

3.3.6 Parameter Stability Test

A fixed-coefficient model requires that the parameters should be stable throughout the time series. An inherent assumption made in such a model is therefore that parameter coefficients do not change substantially during the study period. A fixed-coefficient model is not able to highlight any significant changes that may be unfolding in the elasticity estimates as time passes. Such variations would be suppressed by long-term averages. Therefore, if the assumption of parameter stability is violated, the elasticity coefficients which are estimated by this model may be somewhat misleading as they will essentially be averages over the entire sample instead of dynamically evolving. It is therefore crucial to determine whether or not there are any structural changes or breakpoints in the data series. A data series may contain a structural break, due to a change in policy or sudden shock to the economy. This study uses the cumulative sum (CUSUM) of squares of the recursive residuals test to assess whether or not parameters of the model have remained stable. The Chow Test is employed to confirm any breaks that may be identified by the CUSUM test.

The null hypothesis of the CUSUM of squares of recursive errors test is that there is parameter stability in the model. The recursive errors are standardised one-step ahead of the prediction errors. This makes them homoscedastic. The CUSUM of squares statistic is computed as follows:

$$CUSUM\ of\ Squares_t = \frac{\sum_{i=k+1}^{t} w_i^2}{\sum_{i=k+1}^{T} w_i^2} \qquad (29)$$

Where

w_i are the recursive residuals, k is the number of explanatory variables in the model.

The upper and lower critical values of $CUSUM\ of\ Squares_t$ are given by:

$$\pm a + \frac{(t-k)}{T-k} \qquad (30)$$

The critical values of CUSUM of squares of residuals test can be obtained from Edgerton and Wells (1994). Once the CUSUM of squares statistic and the lower and upper bounds are calculated, a graph can be created such that if the plot of the residuals crosses any of the bounds, it would indicate parameter instability. Thus the null hypothesis can be rejected. This is a convenient way of visually ascertaining where break-point(s) occur in the time series.

Once a potential breakpoint is identified, the Chow Test is used to confirm it. This test in effect uses an *F*-test to determine whether a single regression is more efficient than two separate regressions which are created by splitting the data into two sub-periods. Following this logic, there are essentially three different regressions. There are two regressions for the sub-periods (i.e. sub-period 1 and sub-period 2) and one regression for the entire period.

Assuming that March 2009 is a suspected breakpoint, the three regressions can be denoted as follows:

$$\text{Time period April 2006 - March 2009: } Y_t = \varphi_1 + \varphi_2 X_{2t} + \varphi_3 X_3 + \varepsilon_{1t} n_1 \quad (31)$$

$$\text{Time period April 2009 - March 2019: } Y_t = \omega_1 + \omega_2 X_{2t} + \omega_3 X_3 + \varepsilon_{2t} n_2 \quad (32)$$

$$\text{Time period April 2006- March 2019: } Y_t = \beta_1 + \beta_2 X_{2t} + \beta_3 X_3 + \varepsilon_{3t} n_3 \quad (33)$$

Equation (36) assumes that there is no difference between the two sub-periods, such that the autonomous consumption (i.e. intercept) and the elasticity coefficients remain the same throughout the entire period. If the sector has not undergone any structural change between sub-period 1 and sub-period 2, then:

$$\varphi_1 = \omega_1 = \beta_1,$$

$$\varphi_2 = \omega_2 = \beta_2 \text{ and}$$

$$\varphi_3 = \omega_3 = \beta_3$$

It follows that Equation (32) and Equation (33) assume that there has been a structural change between the two periods, which explains the difference in the parameter notations. The Chow test essentially tests whether the single regression line or the two separate regression lines fit the data best. The stages in running the Chow test can be summarised as follows:

1) Estimate the regression using all the data, before and after the structural break, collect the Residual Sum of Squares (RSS_C) for the complete data.

2) Estimate two separate regressions on the data before and after the structural break, collecting the RSS in both cases, giving RSS1 and RSS2.

3) Using these three values to calculate the test statistic from the following formula:

$$F = \frac{RSS_C - (RSS_1 + RSS_2)/k}{(RSS_1 + RSS_2)/n - 2k}$$

4) Find the critical values in the F-test tables, in this case it has F(k,n-2k) degrees of freedom.

5) Reject or fail to reject the null hypothesis that there is no structural break in the data series.

If the null hypothesis of a breakpoint is not rejected, it means that are two or more sub-periods within the research scope where the results of the regression analysis are distinctly different from the other(s). This would mean that the elasticity values that are estimated by the regression in one sub-period are significantly different to the values that are estimated in another sub-period within the same research scope. This variation may be caused by differences in autonomous consumption, changes in the parameter coefficients, or both. It follows that just blindly using averages for the entire period may be problematic.

3.4 Modelling Technique

The consideration of time-varying coefficients is increasingly gaining prominence over the constant or fixed coefficients in energy modeling owing to the growing evidence of parameter instability in energy demand (Salisu & Ayinde, 2016:1472). Income and price elasticities of electricity demand vary over time due to a number of reasons, such as the level of economic activity, the regulation of prices, structural changes and the price level. As discussed earlier in this study, these factors had an impact on electricity demand in South Africa at different stages during the period under review. Unless a study finds evidence that parameters have remained stable during the period under review, the results from a fixed-coefficient model would be misleading. To avoid this pitfall, it is useful to consider a model which allows parameters to be a function of time. To this end, this study makes use of a time-varying parameters (TVP) model based on the Kalman filter approach. Given the potential shortcomings of the fixed-coefficient models, the TVP approach is equipped to provide more reliable results with regard to the price and income elasticities of electricity demand (Arisoy & Ozturk, 2014:961). The model specification as presented in equation (2) refers to a constant coefficient model based on Ordinary Least Squares (OLS). As articulated above, it would be difficult to capture the diverse and dynamic nature of electricity demand in the mining sector using this model. Therefore, this demand specification has to be converted into a state-space format so that the estimated coefficients can be allowed to vary over time.

3.4.1 Linear Gaussian State-Space Model

The state-space format provides a general framework for representing a wide range of time series models. It is similar to OLS regression, but it does not assume that the coefficients are constant over the regression window. Instead, state-space models incorporate variability of the coefficients owing to the impact of various factors over time. The general form of a state-space multi-factor can be denoted as follows:

$$y_t = \alpha_t + \sum_{i=1}^{k} \beta_{it} X_{it} + \varepsilon_t \tag{34}$$

where:

y_t: Electricity consumption at time *t*.

X_{it}: Factors affecting electricity consumption (i.e. electricity prices and mining production)

α_t: Autonomous electricity consumption, when there is no mining production activity.

β_{it}: Exposure of the dependent variable (electricity consumption) to the factor *i* at time *t*.

ε_t: Random disturbances of electricity consumption at time t.

k: The number of factors. A positive integer larger than zero.

The statistical noise ε_t, is a zero mean random variable. It is generally assumed that the covariance between ε_t and X_{it} is zero. This means that the explanatory variables should not contain any information about the error terms. Equation (34) is commonly referred to as the *measurement equation*. It measures the relationship between the dependent variable (i.e. electricity consumption) and the independent variables (i.e. electricity price and mining production). In order to allow for time variability of the coefficients, the state-space model should have the capability to estimate the coefficients at every time interval. For this purpose, a *state equation* is utilized. This equation uses the observed information from the past in order to describe the dynamics of the state variables such that the future behavior of these variables can be predicted given the current state. The outcome of the equation is incorporated into the measurement equation at every future input. It follows that a complete state-space model essentially consists of two equations, namely the *measurement* equation and a *state* (or transition) equation. This can be denoted as follows:

$$Measurement\ equation\colon\ y_t = \alpha_t + \sum_{i=1}^{k} \beta_{it} X_{it} + \varepsilon_t \tag{35}$$

$$State\ equation: \beta_{it} = M_{it}\beta_{i,t-1} + \epsilon_{it}$$

$$\alpha_t = M_2\alpha_{t-1} + \xi_t$$

where $\varepsilon_t \sim \aleph(0, \sigma^2_{\varepsilon_t})$, $\epsilon_{it} \sim \aleph(0, \sigma^2_{\epsilon_{it}})$, $\xi_t \sim \aleph(0, \sigma^2_{\xi_t})$ and are independent. M_{it} and M_2 are the transition matrices, which allow coefficients to evolve based on their past values. In this study a first-order autoregressive process is assumed. Let $M_{it} = \phi_{1i}$ and $M_2 = \phi_2$. Therefore equation (35) can be abbreviated as follows:

$$y_t = Z_t\Gamma_t + \epsilon_t \qquad (36)$$

$$\Gamma_t = \phi\Gamma_{t-1} + \Psi_t$$

where $i = 1, \dots, k$ is the number of factors in the model, $\Gamma_t = (\alpha_t\ \beta_{1t}\ \beta_{2t} \dots \beta_{kt})'$, $Z_t = (1\ X_{1t}\ X_{2t} \dots X_{kt})$, $\Psi_t = (\xi_t\ \epsilon_{1t}\ \epsilon_{2t} \dots \epsilon_{kt})'$ and $\phi_t = (\phi_2\ \phi_{1t}\ \phi_{2t} \dots \phi_{kt})'$. Therefore Γ_t represents the estimated coefficient values for the autonomous consumption, price and income at a specific time *t*. Z_t represents price and mining production observations at a specific time *t*. Ψ_t represents the estimated error terms of the measurement equation and the error terms of the transition equation at every time period *t*. ϕ_t is the correlation factor between elasticity coefficients are every time period and their immediate preceding observations.

The error is assumed to be distributed with conditional expectation of zero and covariance matrix H_t, $E(\epsilon_t) = 0$ and $Var(\epsilon_t) = H_t$. In our case we assume that $\mathrm{H_t}$ is constant over time, i.e. $H_t = H = \sigma^2_\epsilon$

Furthermore, $E(\Psi_t) = (0\ \ 0)'$ and $Var(\Psi_t) = \begin{bmatrix} R_t & 0 \\ 0 & Q_t \end{bmatrix}$ where Q_t and R_t are diagonal matrices with the variance of ξ_t and $(\epsilon_{1t}\ \epsilon_{2t} \dots \epsilon_{kt})'$, respectively, as

$$R_t = \begin{bmatrix} \sigma^2_{\xi_1} & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & \sigma^2_{\xi_t} \end{bmatrix} \qquad Q_t = \begin{bmatrix} \sigma^2_{\epsilon_{1t}} & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & \sigma^2_{\epsilon_{kt}} \end{bmatrix}$$

In our study, we take $R_t = R = \sigma^2_\xi$ as constant for any *t* and $Q_t = Q$ is a vector depending on $i = 1, \dots, k$ the number of factors in the model. Vector *Q* contains the constant variance for each factor in our model, i.e $Q = (\sigma^2_{\epsilon_1}, \dots, \sigma^2_{\epsilon_k})$.

The challenge with solving equation (36) is that it has two sets of unknowns, namely the coefficient of the state vectors Γ_t and the parameter coefficient of the measurement equation. One of the ways of addressing this challenge is by using the Kalman filter technique.

3.4.2 Kalman Filter Technique

The Kalman filter technique is the best linear estimator as it minimizes the sum of the squared difference between the observed responses in the data set and the predicted outcome (Grewal & Andrews, 2001:117). This can be denoted as follows:

$$\begin{aligned}\epsilon_t &= y_t - \hat{y}_t \\ &= y_t - Z_t \hat{\Gamma}_{(t|t-1)}\end{aligned} \tag{37}$$

Where $\hat{\Gamma}_{(t|t-1)}$ is the estimator at time t given the information up to time t-*1.* Therefore ϵ_t is the prediction error.

Let a_t be the optimal estimator of Γ_t based on all the observed information at time t. Then, the estimator could be written as $a_t = E_t(\Gamma_t)$, i.e. the conditional expectation of the state variables up to time t. The covariance of the estimators, denoted as P_t, is given by $P_t = E_t[(a_t - \Gamma_t)(a_t - \Gamma_t)']$. Therefore, the optimal estimator of Γ_t, based on all the observations at time t-*1*, could be denoted by $a_{t-1} = E_{t-1}(\Gamma_t)$; consequently the covariance of this estimator is defined by $P_{t|t}$.

Given the above denotation, the Kalman filter consists of the following recursive equations:

$$\begin{aligned}
a_{t|t-1} &= \phi a_{t-1} && \text{(state prediction)} \\
P_{t|t-1} &= \phi P_{t-1}\phi' + (R\ \ Q)' && \text{(prediction dispersion)} \\
y_{t|t-1} &= z_t a_{t|t-1} && \\
\eta_t &= y_t - y_{t|t-1} && \text{(prediction error)} \\
F_t &= z_t P_{t|t-1} z_t' + H && \text{(error dispersion)} \\
G_t &= P_{t|t-1} z_t' F_t^{-1} && \text{(Kalman gain)} \\
a_t &= a_{t|t-1} + P_{t|t-1} z_t' F_t^{-1} \eta_t && \text{(state estimate)} \\
P_t &= (I_2 - K_t z_t) P_{t|t-1} && \text{(estimate dispersion)}
\end{aligned} \tag{38}$$

Where $P_{t|t-1}$ is the covariance matrix of the error of $a_{t|t-1}$. η_t, is an innovation function which is a one-period prediction error for y_t. F_t^{-1} is the inverse of the covariance matrix of the innovation at time t. G_t is the Kalman gain.

The Kalman filter gain vector depends on $\phi, (R\ \ Q), H = \sigma_\epsilon^2$ and the past data vector z_t. The Kalman gain function plays an important role in updating the estimates because it determines how heavily the innovations are weighted. When the system is linear and the normality assumptions are valid, this specific form of the Kalman gain function optimally weighs the innovations, which makes $a_t = \hat{\varGamma}_t$ (the expectation of the conditional distribution of $\varGamma_t$ given the information y_t). This is the Minimum Mean Square Estimator (MMSE) of $\varGamma_t$ based on the information up to t. If the assumptions mentioned above are violated, then the Kalman filter estimator is no longer the MMSE (Tsay 2002:410).

In other words, the Kalman filter method gives unbiased and efficient estimators of the state vector $E(\varGamma_{t|t}) = E(\varGamma_{t|t-1}) = E(\varGamma_t) = a_t$, when the initial conditions a_0 and P_0 and the matrices $\phi, (R\ \ Q), H$ are known. The objective of this modelling technique is to infer properties of the state $\beta_{it}, i = 1, \dots, k$, from the data series y_t (Tsay 2002:411). There are three important types of inferences made. These are:

- Filtering for $t = N$, to recover the state variable given the information available at time t in order to remove the measurement errors from the data.
- Prediction for $t > N$, to forecast $\beta_{i,t+m}$ or y_{t+m} for $m > 0$ given the information available at time t, where t is the forecast origin.
- Smoothing for $t < N$, to estimate β_{it} given the information available at time T, where $T > t$

where: N is the length of the data series.

The key advantage of the Kalman technique is that the model is “learning” in real time as each additional data point is observed. That means that for any value observed in the time series, the model can forecast the next observation with minimum error. This agility allows the model to observe disturbances in the evolution of the parameter coefficients as time progresses. It updates its predictions or forecasts of the future points given the variance between its latest observation and what it had previously estimated. This allows the estimated coefficients to be time-variant, thereby providing the Kalman filter with a significant advantage over the conventional constant coefficient models.

3.5 Summary

The research questions of this study are addressed using the methodologies described in this chapter. This study uses the ordinary least squares method as a benchmark model only and not as a primary research model. Nevertheless, all the relevant pre-requisite tests for the use of this model are discussed. Crucially, tests for parameter stability are conducted. The CUSUM of squares and the Chow test have been chosen to ascertain whether or not the parameters in the model are time variant. In the event that parameter instability is established, a more robust model must be employed. This study chooses a space state model based on the Kalman filter technique for this purpose. It has also been established that if the parameters of the model are static, the OLS and Kalman filter results should be fairly similar. However, if there is significant time-variation in the parameters, the Kalman filter technique will provide more superior results. The added advantage of the Kalman filter technique is that it presents the evolution of the elasticity coefficients over time. The next chapter analyzes the data and interprets the results of the various analyses done using these methodologies. All the estimations and diagnostic tests are carried out using Econometric Views (E-views) version 7.2 statistical software.

It is important to note that both the explanatory variables that are used in this study are assumed to be exogenous. This is in line with the assumption that was made by Arisoy & Ozturk (2014) and Wang & Mogi (2017) while using a TVP model to estimate elasticity coefficients of electricity demand in the industrial sector in Turkey and Japan respectively. If endogeneity is proven, it would require a marginal adjustment of the Kalman gain in the TVP model. As discussed in section 2.7.1, this assumption is one of the common shortcomings observed in studies that use the OLS as their primary regression model. If the variables are endogenous then its estimators are not BLUE. Theoretically, there is a potential bi-directional relationship between electricity consumption and mining production albeit with some lag. This is consistent with the feedback hypothesis that was discussed in section 2.4. Nevertheless this does not qualify as evidence. When using the OLS model, endogeneity concerns can be addressed through an instrumental variables (IV) technique known as the Two Stage least Squares (TSLS). This technique requires the modeller to find a genuinely exogenous variable (instrument) that is strongly correlated with the potential endogenous variable. If mining production is suspected to be endogenous, another variable that is highly correlated to it has to be found. However this instrument must not have any direct impact on electricity consumption in its own right except through its influence on mining production. The difficulty in establishing the presence of endogeneity in an OLS model is in finding a variable or instrument that fits these criteria.

Chapter 4
Data Analysis and Interpretation of Results

4.1 Introduction

In the preceding chapter methods of analysing the elasticity estimates of electricity demand were discussed. Econometric techniques discussed in the previous chapter are employed here, and the results are discussed in detail. This chapter consists of three sections. The first section deals with the description of the data and the results of the stationarity tests. The second part discusses the results of the OLS regression as a benchmark model in conjunction with its requisite diagnostic tests and the proposed remedies thereof. These results are discussed within the limitations of a fixed-coefficient model as articulated in the previous chapter. The last section focusses on the main results of the study which are obtained from the Kalman filter technique. The evolution of the elasticity coefficients is assessed and the observed structural breaks are explained.

4.2 Data Description

This study uses electricity consumption, electricity price and mining production as the variables in estimating electricity demand. All equations are estimated in the natural logarithm form since it enables the interpretation of coefficients in terms of elasticity. These variables, their respective sources and their assigned code names are presented in Table 1. Electricity consumption and price figures are obtained from Eskom's sales department. As discussed in section 1.5, this study uses average monthly prices and not marginal prices. The mining production figures are obtained from Statistics South Africa.

Table 1: Denotation of Variables

Variable	Source	Logarithmic Transformation	Code-name
Electricity Consumption	Eskom Sales Department	Log(consumption)	Logcon
Electicity Price	Eskom Sales Department	Log(price)	logprice
Mining Production	Stats SA	Log(production)	Logprod

The maximum, mean and minimum values for these three variables are presented in Table 2. For ease of presentation, electricity consumption has been converted into gigawatt hours. Electricity price is presented in cents per kilowatt hours, while mining production is kept in its index form. The data shows that price has a minimum of 14 cents and a maximum of 121 cents. Mining production has ranged from a minimum of 78.7 index points to a maximum of 115.8 points. Consumption ranges from a maximum of 2800 GWH to a low of 2200 GWH with the mean and median at 2570 GWH. The period under review spans April 2006 to March 2019, and consists of a total of 156 observations.

Table 2: Summary of Actual Values

	Consumption(GWh)	Price (c/kwh)	Production
Mean	2,570	53.8610	99.5192
Median	2,570	55.8062	100.8500
Maximum	2,800	121.5064	115.8000
Minimum	2,200	14.4599	78.7000
Observations	156	156	156

The first and the second rows in Table 2 show the mean and median values of the respective variables. It can be observed that the mean and the median values for all the variables are close to each other. However, in the case of both the independent variables the median is larger than the mean. The difference between the mean and the median is particularly noticeable in the case of price. This indicates that electricity price was relatively low at the beginning of the series but increased at some considerable rate as time progressed. On the whole the data is skewed to the left with a long tail of low observations pulling the mean down more than the median

Table 3: Descriptive Summary

	Logcon	Logprice	logprod
Mean	21.6646	3.8163	4.5968
Median	21.6687	4.0219	4.6136
Maximum	21.7512	4.8000	4.7519
Minimum	21.5131	2.6714	4.3656
Std Dev.	0.0526	0.6222	0.0845
Skewness	-0.7385	-0.4487	-0.5812
Kurtosis	3.2812	1.9409	2.7812
Jarque-Bera	14.6944	12.5252	9.0945
Probability	0.0006	0.0019	0.0106
Observations	156	156	156

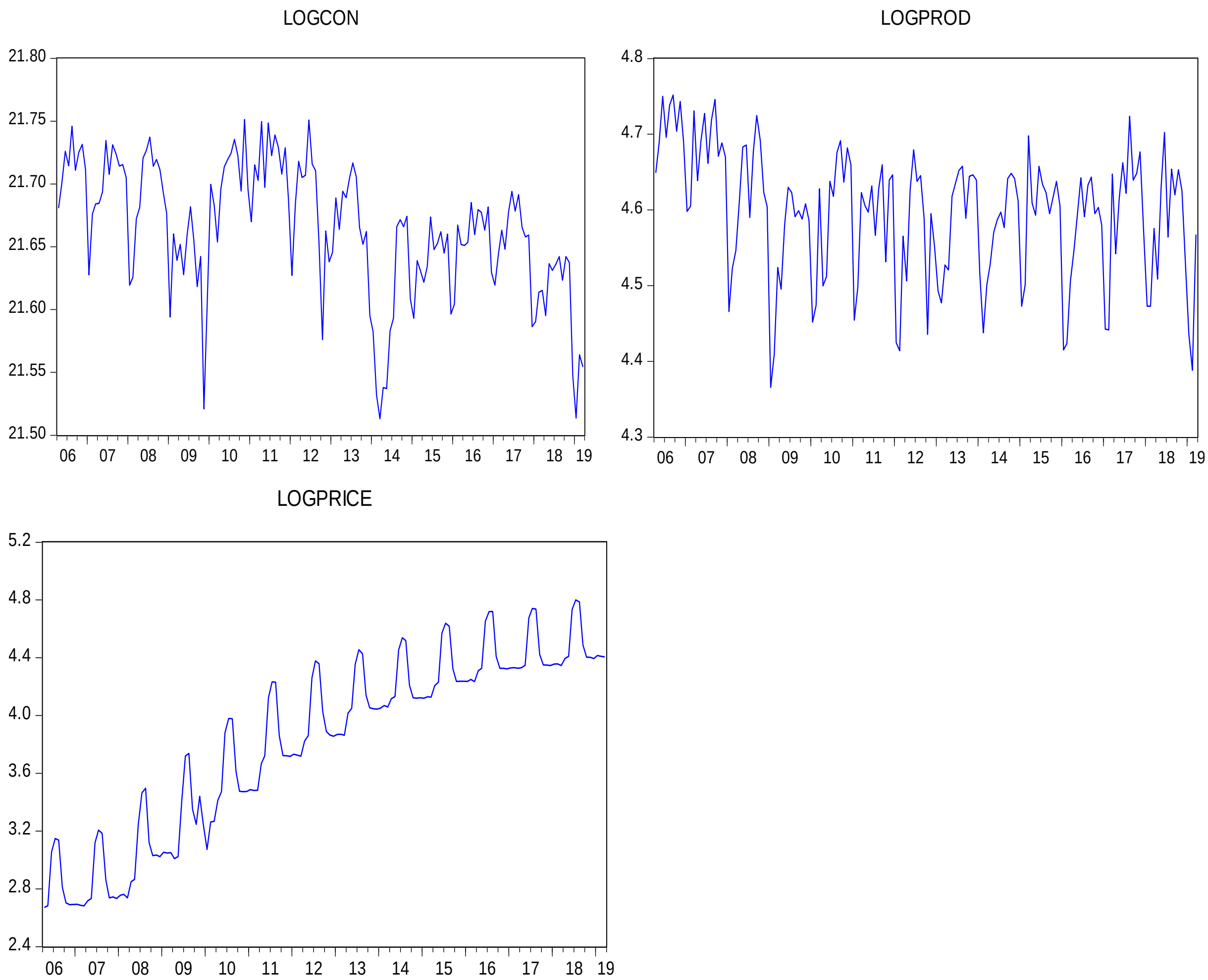
Table 3 presents the same variables in their logarithmic forms. Other indicative values such standard deviation and skewness are also presented. The standard deviation measures the dispersion around the mean in the series. Accordingly log of consumption is a less dispersed with the standard deviation of 0.0526 while log of price is highly dispersed with a value of 0.6222. The relatively high level of dispersion observed in the log of price series pays credence to the observation that electricity price changed materially during the period under review.

Skewness measures the asymmetry of the distribution of the series around the mean. A symmetric distribution has a zero skewness value. Thus none of the series is close to symmetric distribution with log of consumption having a value of -0.73851, log of price with a value of -0.44866 and log of production with a value of -0.58122. All variables exhibit a negatively symmetric distribution which is a further indication that these distributions have left tails. Also included in Table 3 are values for kurtosis. This measures the flatness and the peak of the distribution of the series. A normal distribution has a kurtosis value of 3. Log of consumption has a peaked (leptokurtic) distribution relative to the normal, since it has a kurtosis value higher than 3. On the other hand, log of price and log of production have flatter distributions (platykurtic) with kurtosis values that are less than 3. The skewness and kurtosis values suggest that none of the three variables are normally distributed. Nevertheless, these indicative values are not sufficient evidence that the data is not normally distributed. A more rigorous econometric test is required for this purpose.

This study employs the Jarque-Bera (JB) test of normality for this purpose. The results of this test are enclosed in Table 3 for each variable. The null hypothesis of the JB test is that the series follows a normal distribution. The JB statistic follows a chi-squared (χ^2) distribution with two degrees of freedom. The null hypothesis of a normal distribution is rejected for all three series due to the low probability values of the JB statistic. Therefore, according to the JB test none of the three variables is normally distributed. It follows that the *t*- and the *f*-statistics that may be derived from this data could be misleading, thus making any hypothesis testing less robust.

In Figure 12 the graph of log of price shows that it has a positive growth rate albeit with pronounced oscillations. These oscillations are attributable to the fact that electricity prices in the mining sector increase significantly during the winter months. This variation in price during the year is done to encourage the sector to reduce its electricity consumption during the peak demand periods. In winter, residential electricity demand is higher. This puts significant pressure on the national grid. Higher winter tariffs for the mining sector are aimed at incentivizing the sector to shift demand to summer in order to lower pressure on the grid. This further demonstrates the critical role that the mining sector plays in stabilizing overall country electricity demand as seasons change and demand patterns change accordingly.

Figure 12: Time plots of variables in natural logarithmic forms



The graphs of log of consumption and log of production exhibit fluctuations from time to time. In general both these series show a dip in December and January of every year. This can be attributed to the fact that the mining sector in South Africa generally operates with skeleton staff during significant portions of these months as most workers take their end of year leave of absence. Therefore both mining production and electricity consumption during these months are generally lower than during other months of the year. The most basic method of detecting stationarity depends on plotting the data and visually assessing whether or not the series presents some known properties of stationarity (or non–stationarity). It can be observed that all variables especially log of price, present prominent seasonality. However in order to ascertain whether or not the data series is stationary, a proper econometric test has to be performed.

4.3 Unit Root Tests

As mentioned in the previous chapter, one of the challenges encountered when studying time series relationships is spurious regressions. The problem can be partly avoided by checking if the observations in a particular time series are related in such a manner that a long run relationship exists between them. In this study the Augmented Dickey Fuller (ADF) test is used to test for stationarity. There is no way of knowing upfront which deterministic structure is the most relevant for each series. This requires some trial and error. Therefore the results of the unit root tests while using all the deterministic structures are presented.

Table 4: Results of the Unit Root Tests

Variable	Possible Deterministic Structure	Statistic	P-Value	Level of Significance	Conclusion
Log Consumption	None	-0.3941	0.5405	-	-
	Intercept	-4.2533	0.0008	***	stationary
	Intercept and trend	-5.1980	0.0002	***	stationary
Log Price	None	2.4714	0.9968	-	-
	Intercept	-2.7218	0.0728	*	stationary
	Intercept and trend	0.3262	0.9986	-	-
Log Production	None	-1.0751	0.2545	-	-
	Intercept	-2.9469	0.0426	**	stationary
	Intercept and trend	-2.6459	0.2609	-	-
Note: *, **, and *** denote 10%, 5% and 1% levels of significance respectively					

The results of ADF unit root test are enclosed in Table 4. They reveal that all variables have a unit root when neither the intercept nor the trend is included in the test equation. When both intercept and trend are included in the deterministic structure, still log of price and log of production have unit roots; however, log of consumption becomes stationary at a one per cent significance level. When only the intercept is included in the test equation all variables are stationary with log of consumption, log of production and log of price being stationary at one per cent, five per cent and ten per cent significance levels respectively.

4.4 OLS Regression

The OLS regression provides average price and income elasticity coefficients for the period under review. The regression is estimated such that log of price and log of production are explanatory variables for log of consumption. The results of the regression are presented in Table 5. The price elasticity coefficient is estimated at -0.02 while income elasticity is estimated at 0.30. Therefore both price and income elasticities of electricity demand are inelastic, as they are smaller than 1 in absolute terms. Nevertheless, both variables are deemed to play a statistically significant role in explaining electricity consumption in the mining sector. However, before these results can be relied upon, the requisite OLS diagnostic tests should be performed to ensure that the data is compliant with key CLRM conditions. Already there are some worrying signs that can be observed from the table of results. For example, the relatively low d-statistic is a cause for concern. These results could be spurious. In addition, the relatively low R^2 of 34 per cent suggest that our explanatory variables do not sufficiently explain changes in electricity consumption. This necessitates further scrutiny.

Table 5: Results of the Ordinary Least Squares Regression

Dependent Variable: LOGCON
Method: Least Squares
Date: 09/28/19 Time: 16:53
Sample: 2006M04 2019M03
Included observations: 156

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	20.34315	0.194480	104.6030	0.0000
LOGPRICE	-0.021180	0.005608	-3.776743	0.0002
LOGPROD	0.305049	0.041279	7.389859	0.0000

R-squared	0.344257	Mean dependent var	21.66459
Adjusted R-squared	0.335685	S.D. dependent var	0.052561
S.E. of regression	0.042840	Akaike info criterion	-3.443630
Sum squared resid	0.280800	Schwarz criterion	-3.384979
Log likelihood	271.6032	Hannan-Quinn criter.	-3.419809
F-statistic	40.16160	Durbin-Watson stat	0.710706
Prob(F-statistic)	0.000000		

4.5 Residual Diagnostics

The integrity of the error terms is crucial in ensuring that spurious regressions are avoided. To this end the results of the diagnostic tests in the form of heteroscedasticity and serial correlation are discussed in this section.

4.5.1 Heteroscedasticity Test

There are several ways of testing for heteroscedasticity. This study employs White's Test for this purpose. As articulated in the previous chapter, this test provides a flexible functional form that is useful for identifying almost any pattern of heteroscedasticity. It does so by allowing the independent variables to have a non-linear effect on the variance of the error term. This flexibility is particularly crucial in this case as we have already established that the data is not normally distributed. The null hypothesis of White's Heteroscedasticity Test is that the data series is homoscedastic. A five per cent level of significance is chosen such that the decision matrix is as follows:

- If p-value < level of significance (alpha); then null hypothesis is rejected
- If p-value > level of significance (alpha); then we fail to reject the null hypothesis.

Table 6: Results of White's Test

Heteroskedasticity Test: White

F-statistic	3.496587	Prob. F(5,150)	0.0051
Obs*R-squared	16.28427	Prob. Chi-Square(5)	0.0061
Scaled explained SS	21.43801	Prob. Chi-Square(5)	0.0007

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 09/28/19 Time: 13:51
Sample: 2006M04 2019M03
Included observations: 156

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.947571	0.647617	-1.463166	0.1455
LOGPRICE	0.026647	0.022336	1.193000	0.2348
LOGPRICE^2	-0.001785	0.000731	-2.443482	0.0157
LOGPRICE*LOGPROD	-0.002909	0.004708	-0.617816	0.5376
LOGPROD	0.399846	0.278082	1.437873	0.1526
LOGPROD^2	-0.043176	0.029872	-1.445389	0.1504

R-squared	0.104386	Mean dependent var	0.001800
Adjusted R-squared	0.074533	S.D. dependent var	0.002988
S.E. of regression	0.002874	Akaike info criterion	-8.828435
Sum squared resid	0.001239	Schwarz criterion	-8.711133
Log likelihood	694.6179	Hannan-Quinn criter.	-8.780792
F-statistic	3.496587	Durbin-Watson stat	1.513952
Prob(F-statistic)	0.005105		

It can be observed from Table 6 that the observed R^2 from the auxiliary regression has been calculated as N X R^2 = 156 x 0.104386 = 16.28427. The observed R^2 asymptotically follows a chi-squared distribution with five degrees of freedom. The corresponding *p*-value is calculated to be 0.0061. This is below the five per cent level of significance. Therefore the null hypothesis that the data is homoscedastic can be rejected, thereby inferring the presence of heteroscedasticity. This means that variances of the series are not constant throughout the period under review. Therefore linear regressions based on this data may not be suitable for inferences into the future.

4.5.2 Serial Correlation Test

This study uses the Durbin Watson Statistic to detect serial correlation. This statistic can be observed in Table 5. It is calculated at 0.710706. As articulated in the previous chapter, the *d*-statistic ranges from zero to four (0 to 4). The closer the *d*-statistic is to 0, the more likely it is that there is positive autocorrelation. At 0.710706 the *d*-statistic indicates that there is likely to be negative correlation as the figure is closer to zero than to two which is a point where no autocorrelation can be confirmed. In order to further confirm that there is serial correlation in the residuals, the Breusch-Godfrey Serial Correlation LM Test is employed. The null hypothesis of the test is that there is no serial correlation in the residuals. The results of this test are enclosed in Table 7. The observed R^2 shows that there is a zero probability that there is no serial correlation in the error terms. Therefore the null hypothesis is rejected.

Table 7: Results of the Breusch-Godfrey LM Serial Correlation Test

Breusch-Godfrey Serial Correlation LM Test:

F-statistic	63.54276	Prob. F(2,151)	0.0000
Obs*R-squared	71.29225	Prob. Chi-Square(2)	0.0000

Test Equation:
Dependent Variable: RESID
Method: Least Squares
Date: 09/28/19 Time: 17:05
Sample: 2006M04 2019M03
Included observations: 156
Presample missing value lagged residuals set to zero.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.415911	0.148903	2.793167	0.0059
LOGPRICE	-0.001953	0.004164	-0.469082	0.6397
LOGPROD	-0.088957	0.031620	-2.813314	0.0056
RESID(-1)	0.562404	0.080253	7.007916	0.0000
RESID(-2)	0.201244	0.079418	2.533988	0.0123

R-squared	0.457002	Mean dependent var	-7.06E-15
Adjusted R-squared	0.442618	S.D. dependent var	0.042563

S.E. of regression	0.031777	Akaike info criterion	-4.028638
Sum squared resid	0.152474	Schwarz criterion	-3.930886
Log likelihood	319.2338	Hannan-Quinn criter.	-3.988936
F-statistic	31.77138	Durbin-Watson stat	1.998834
Prob(F-statistic)	0.000000		

A popular remedy to serial correlation is to introduce another independent variable in the model. In this study this is done by introducing a one period lag of the dependent variable as another explanatory variable. Therefore the new model includes three explanatory variables namely, log of price, log of production and lag-log of consumption. The results of this regression are enclosed in Table 8.

Table 8: Results of Ordinary Least Squares (Regression 2)

Dependent Variable: LOGCON
Method: Least Squares
Date: 09/28/19 Time: 17:50
Sample (adjusted): 2006M05 2019M03
Included observations: 155 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	7.153936	1.281020	5.584561	0.0000
LOGPRICE	-0.007363	0.004567	-1.612230	0.1090
LOGPROD	0.119964	0.036444	3.291711	0.0012
LOGCON(-1)	0.645608	0.062281	10.36598	0.0000

R-squared	0.617461	Mean dependent var	21.66448
Adjusted R-squared	0.609860	S.D. dependent var	0.052715
S.E. of regression	0.032927	Akaike info criterion	-3.963602
Sum squared resid	0.163709	Schwarz criterion	-3.885062
Log likelihood	311.1791	Hannan-Quinn criter.	-3.931700
F-statistic	81.24353	Durbin-Watson stat	2.005098
Prob(F-statistic)	0.000000		

A *d*-statistic of 2.005098 is obtained from this regression. This value is close to 2. It indicates that there is no serial correlation in the residuals of this regression. An added advantage of this regression model is the noticeable improvement in the value of the R^2 from 34 per cent in the original regression to 61 per cent in the latter. This means that the explanatory variables as arranged in the second regression have greater explanatory power over electricity consumption. Crucially, the elasticity coefficients that are estimated by the new regression are significantly different from the initial estimates. The price elasticity coefficient has diminished somewhat (in absolute terms) to -0.007 as compared to -0.02 earlier. Price is no longer deemed to be a significant determinant of electricity demand in the sector. The income elasticity coefficient is now estimated at 0.11 as compared to 0.30 previously. However income remains a significant determinant of electricity consumption. The statistical significance and relatively large coefficient on lagged electricity consumption supports the view that electricity consumption is strongly path-dependent. This inertia results from the inability of mines to drastically change their electricity consumption patterns, once production processes are locked in.

4.6 Stability Diagnostics

It is crucial to ensure that any regression model used in the analysis has been correctly specified. Otherwise the explanatory power of the independent variables in the model would be questionable. Another condition for the results of a fixed coefficient model to be reliable is for the estimated parameter coefficients to remain relatively unchanged throughout the period under review. This allows the averages that are estimated by this model to be a correct representation of the true outcome.

4.6.1 Results of Misspecification Test

The explanatory variables that are included in a regression model must sufficiently explain movements in the dependent variable. Otherwise the model could present spurious results owing to a non-existent relationship between the independent variables and the dependent variable. This is of particular concern since the OLS model was expanded to include the lag of log of consumption in an effort to remedy serial correlation. This study employs Ramsey's Regression Specification Error Test (RESET) to test for misspecification. The null hypothesis of this test is that the model has been correctly specified. The results of Ramsey's RESET test are enclosed in Table 9. The *p*-value is calculated as 0.84. Therefore we fail to reject the null hypothesis thereby inferring that the regression model has been correctly specified.

Table 9: Ramsey RESET Test

Ramsey RESET Test
Equation: OLS
Specification: LOGCON C LOGPRICE LOGPROD LAGLOGCON
Omitted Variables: Squares of fitted values

	Value	df	Probability
t-statistic	0.199213	150	0.8424
F-statistic	0.039686	(1, 150)	0.8424
Likelihood ratio	0.041003	1	0.8395

F-test summary:

	Sum of Sq.	df	Mean Squares
Test SSR	4.33E-05	1	4.33E-05
Restricted SSR	0.163709	151	0.001084
Unrestricted SSR	0.163665	150	0.001091
Unrestricted SSR	0.163665	150	0.001091

LR test summary:

	Value	df
Restricted LogL	311.1791	151
Unrestricted LogL	311.1996	150

Unrestricted Test Equation:
Dependent Variable: LOGCON
Method: Least Squares
Date: 09/29/19 Time: 18:30
Sample: 2006M05 2019M03
Included observations: 155

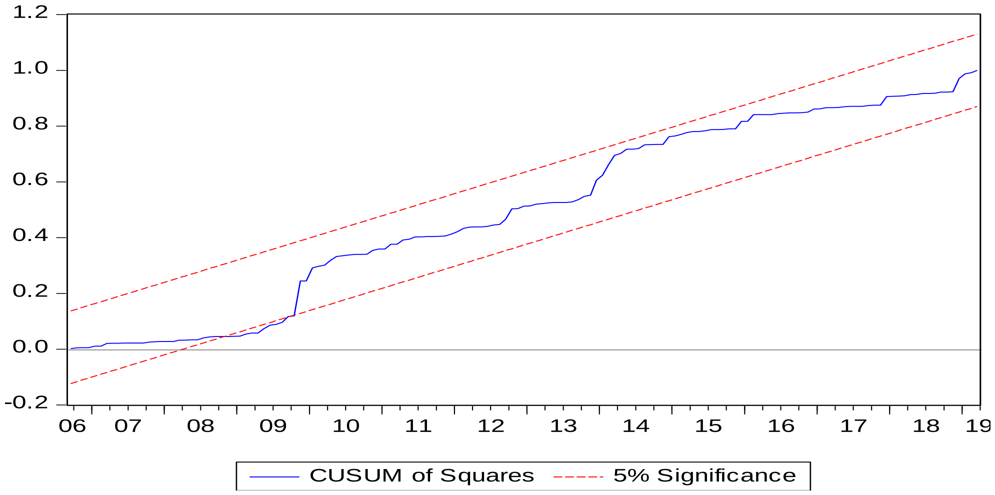
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-32.90968	201.1124	-0.163638	0.8702
LOGPRICE	-0.088045	0.405027	-0.217381	0.8282
LOGPROD	1.431393	6.583114	0.217434	0.8282
LOGCON(-1)	7.695208	35.38711	0.217458	0.8281
FITTED^2	-0.252237	1.266158	-0.199214	0.8424

R-squared	0.617562	Mean dependent var	21.66448
Adjusted R-squared	0.607363	S.D. dependent var	0.052715
S.E. of regression	0.033032	Akaike info criterion	-3.950963
Sum squared resid	0.163665	Schwarz criterion	-3.852788
Log likelihood	311.1996	Hannan-Quinn criter.	-3.911086
F-statistic	60.55505	Durbin-Watson stat	2.006261
Prob(F-statistic)	0.000000		

4.6.2 Determining breakpoints in the Data Series

In order to ensure that the model is stable, it is crucial to ascertain whether or not there are any breakpoints in the data series. This study employs two separate tests for this purpose. Firstly, the Cumulative Sum (CUSUM) of Squares is employed. A graphical representation of recursive residuals, and the upper and lower bounds of the critical value have been plotted in Figure 13. The null hypothesis of the test is that the parameters of the model are stable. Therefore, if the CUSUM of squares of the variation of the error term stays within the five per cent significance level then parameters are stable. It follows that if CUSUM of squares deviates outside the five per cent significance level then the parameters are time variant. The results indicate that in 2009 the CUSUM sum of squares veered outside the five per cent level of significance, therefore the null hypothesis is rejected. The results indicate that 2009 was a breakpoint in the data. In 2009 the South African economy went through a deep recession following the global economic meltdown occasioned by the sub-prime crisis. This global economic crisis had a significant impact on the South African mining sector as global demand slowed and commodity prices plummeted. Therefore, it is probable that 2009 was indeed a breakpoint in the data series.

Figure 13: Cumulative Sum of Squares



As a secondary confirmation, the Chow test is employed to ascertain whether or not this specific time period represents a breakpoint. The results of the Chow Test are presented in Table 10. The *F*-statistic has a probability that is close to zero. That means that there is a zero probability that there are no breaks at the specified point in the data series. Therefore the Chow Test confirms that a breakpoint in the series occurred in April 2009. Thus we reject the null hypothesis that there are no breakpoints. It is possible that there are more breakpoints than what has been ascertained here. Be that is it may, the confirmation of at least one break point is sufficient proof that the parameter coefficients have been time variant. The elasticity estimates are not static throughout the period under review.

Table 10: Results of the Chow Breakpoint Test

Chow Breakpoint Test: 2009M04
Null Hypothesis: No breaks at specified breakpoints
Varying regressors: All equation variables
Equation Sample: 2006M05 2019M03

F-statistic	4.292290	Prob. F(4,147)	0.0026
Log likelihood ratio	17.12204	Prob. Chi-Square(4)	0.0018
Wald Statistic	17.16916	Prob. Chi-Square(4)	0.0018

Therefore, it would be more beneficial to employ a model that allows for the time variation of parameter coefficients instead of relying on a single average fixed coefficient models like OLS. As articulated in the previous chapter, the essence of the Chow test is to show that there is at least one sub-period where the elasticity coefficient(s) is materially different from the average of the total period under review. To illustrate this point, two more OLS regressions are performed in line with the period specifications as articulated in section 3.3.6. Therefore the first sub-period ends in March 2009 while the second sub-period commences in April 2009 and ends in March 2019. The results of the regression of the first sub-period are presented in Table 11. The income elasticity coefficient is estimated at 0.34 while price elasticity is estimated at 0.05. This indicates that for this sub-period, income played a more significant role in explaining electricity consumption. The income elasticity coefficient for this period is substantially higher than the estimate for the entire period of 0.11 as presented in Table 8. On the other hand, price elasticity is close to zero but positive. This is not a significant departure from the estimates that were presented earlier. Nevertheless, this outcome is contrary to economic theory. As discussed in section 2.5.3 if electricity is a normal good, then electricity demand must have a *negative* relationship with price. However, a small but positive price elasticity coefficient indicates that price had a limited impact in determining electricity consumption during this period.

Table 11: OLS Regression Sub-period 1

Dependent Variable: LOGCON
Method: Least Squares
Date: 10/13/19 Time: 17:26
Sample (adjusted): 2006M05 2009M03
Included observations: 35 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	21.58198	2.291391	9.418728	0.0000
LOGPRICE	0.051285	0.013785	3.720283	0.0008
LOGPROD	0.346411	0.040460	8.561810	0.0000
LOGCON(-1)	-0.075866	0.111543	-0.680150	0.5015

R-squared	0.800312	Mean dependent var	21.69588
Adjusted R-squared	0.780987	S.D. dependent var	0.037320
S.E. of regression	0.017465	Akaike info criterion	-5.149989
Sum squared resid	0.009456	Schwarz criterion	-4.972235
Log likelihood	94.12480	Hannan-Quinn criter.	-5.088628
F-statistic	41.41398	Durbin-Watson stat	2.276241
Prob(F-statistic)	0.000000		

In sharp contrast, the results of second sub-period indicate that income elasticity of electricity demand became more inelastic during this period thereby playing a less significant role in explaining changes in electricity consumption. On the other hand electricity demand became marginally more sensitive to changes in price albeit still very inelastic. The results of this regression are presented in Table 12. Income elasticity is estimated at 0.08. This is not substantially lower than the total period average of 0.11 as presented earlier. In as far as price elasticity is concerned, a coefficient of -0.01 is estimated. This is marginally higher (in absolute terms) than the total period estimate of -0.007. However, price is still not considered to be a statistically significant determinant of electricity demand. The regression results for these two periods present two crucial findings. Firstly, there was significant variation in the income elasticity coefficient over time. As time progressed electricity demand became even more income inelastic. Secondly, price elasticity has not played a significant role in determining electricity demand. Electricity demand has remained relatively non-responsive to price changes. However, there is some evidence of increased demand sensitivity to price changes in the second period, albeit still very low.

Table 12: OLS Regression Sub-period 2

Dependent Variable: LOGCON
Method: Least Squares
Date: 10/13/19 Time: 17:30
Sample: 2009M04 2019M03
Included observations: 120

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	6.031537	1.427868	4.224155	0.0000
LOGPRICE	-0.010505	0.008066	-1.302379	0.1954
LOGPROD	0.084175	0.048728	1.727438	0.0868
LOGCON(-1)	0.705624	0.069863	10.10005	0.0000

R-squared	0.591921	Mean dependent var	21.65533
Adjusted R-squared	0.581367	S.D. dependent var	0.053140
S.E. of regression	0.034383	Akaike info criterion	-3.869763
Sum squared resid	0.137132	Schwarz criterion	-3.776846
Log likelihood	236.1858	Hannan-Quinn criter.	-3.832029
F-statistic	56.08627	Durbin-Watson stat	2.060830
Prob(F-statistic)	0.000000		

4.7 Implications of the various diagnostic tests

The results of the various tests highlight the downside of using OLS or any other fixed-coefficient model for the purpose of estimating elasticity coefficients. The first challenge is that the data is not normally distributed. The second challenge is the presence of heteroscedasticity. This violation of the Classical Linear Regression Model (CLRM) conditions means that the parameter estimators may not be BLUE. Nevertheless, the elasticity coefficients as estimated by the OLS model can be utilised notwithstanding their shortcomings. After correcting for serial correlation, the price elasticity coefficient is estimated at -0.007, but price is found to play an insignificant role in explaining electricity consumption. The inclusion of lagged consumption reduces the role of prices in explaining electricity consumption, to the point that the price variable is not statistically significant. This suggests significant inertia in electricity consumption, supporting the notion that electricity consumption is driven by long-term production processes and infrastructure, and slow to adjust to price changes. On the other hand income elasticity is estimated at 0.11. Mining production is deemed to play a more significant role in explaining electricity demand.

It should be noted that these figures are averages for the period under review. Given the presence of break points in the data, as confirmed by the Chow Test, these estimates cannot be relied upon for inference purposes. There is no evidence of significant variation in the price elasticity coefficient. Therefore, the OLS price elasticity estimate is likely to be reflective of a true state of affairs at any point during the time series. However, there is significant variation in the income elasticity coefficient. This is demonstrated by the vastly different elasticity coefficients that were estimated in sub-period 1 (0.34) and sub-period 2 (0.08). This shows that the income elasticity coefficient for the mining sector is time variant. Therefore it would not be prudent to rely on the OLS average for the purpose of making inferences with respect to income elasticity. The variation of this parameter coefficient dictates that a more adoptive model should be used in order to reflect the latest state of affairs. This makes a time-varying parameter (TVP) model more relevant.

4.8 Time-varying parameter model

Following the confirmation that the mining sector underwent a structural change during the period under review, it is beneficial to use a methodology that allows for the elasticity coefficients to vary stochastically over time. Firstly, a graphical depiction of this varying elasticity coefficient may be more meaningful than a single average figure. This allows the modeller to identify breakpoints and provide clarity on the events that caused it. This would put the researcher in a better position to make inferences. Secondly, the final state of the elasticity coefficients is more useful than the long term averages. They are a better reflection of what the demand response is estimated to be at the final stage. It removes any bias that may be caused by a particular event or a specific period in the series. This study uses the Kalman Filter technique for this purpose. In cases where parameter instability has been ascertained, the Kalman Filter model can be proven to be superior to the least squares model (Morisson & Pike, 1977: 773). The Kalman Filter provides a more informed assessment of the elasticity coefficients. The results of the Kalman Filter are presented in Table 13. In this table, C(1) and C(2) represent the constant parameters of the estimation, whereas SV1 and SV2 represent the final estimates for price and production/income elasticity respectively. SV3 relates to the value of the remaining factors not included in the model that have an impact on electricity consumption in the sector. The results indicate that electricity demand in the mining sector is both price and income inelastic. In its final state, price does not play a significant role in explaining electricity demand. In fact, the price elasticity coefficient was found to be positive. On the contrary, mining production was found to be a significant determinant of electricity demand. An income elasticity coefficient of 0.15 was estimated for its final state.

Table 13: Kalman Filter Results

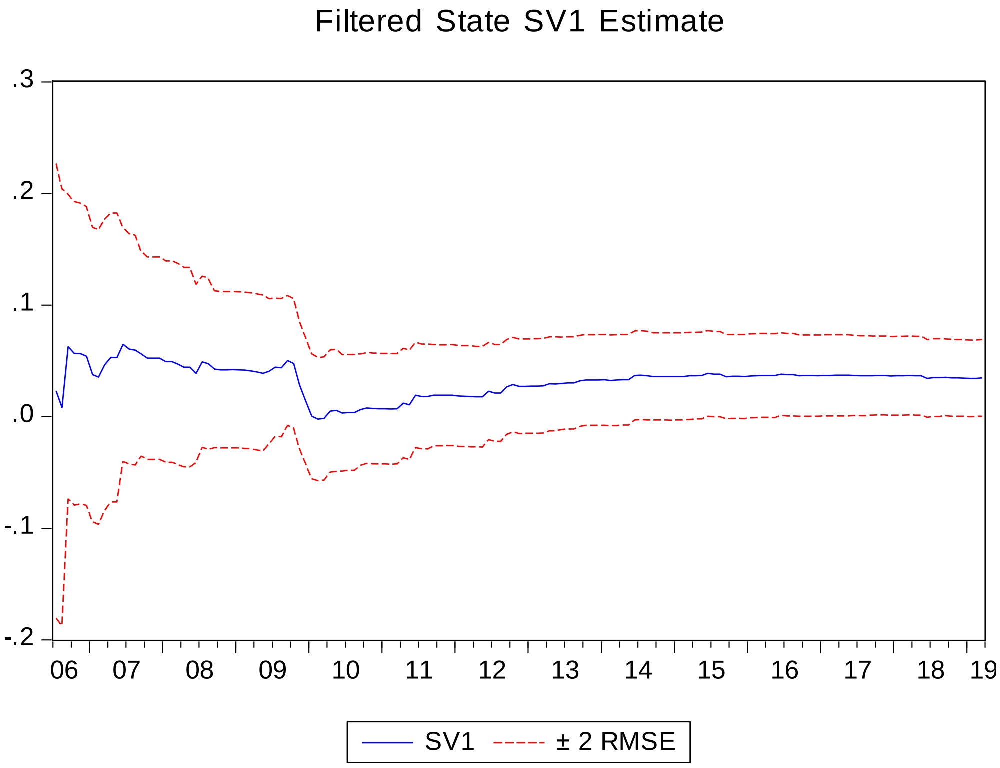
Sspace: KALMAN
Method: Maximum likelihood (Marquardt)
Date: 09/15/19 Time: 11:09
Sample: 2006M04 2019M03
Included observations: 156
Convergence achieved after 4 iterations

	Coefficient	Std. Error	z-Statistic	Prob.
C(1)	-6.809697	0.080835	-84.24185	0.0000
C(2)	0.999945	0.000131	7640.825	0.0000
	Final State	Root MSE	z-Statistic	Prob.
SV1	0.034780	0.017163	2.026479	0.0427
SV2	0.153788	0.033575	4.580468	0.0000
SV3	20.69754	0.166422	124.3677	0.0000
Log likelihood	279.7009	Akaike info criterion		-3.560268
Parameters	2	Schwarz criterion		-3.521167
Diffuse priors	3	Hannan-Quinn criter.		-3.544387

The evolution of the price elasticity coefficient is depicted in Figure 14. The price elasticity coefficient was fairly static at 0.05 during the three years leading to 2009, and in line with the OLS estimate of the same period. The structural break owing to the 2009 global financial crisis can be observed in the evolution of the coefficient. During that year the elasticity coefficient abruptly turned negative, showing some increased sensitivity to changes in electricity prices, albeit still at a very low level. As the global economy recovered and commodity prices improved, price elasticity reverted back to almost pre-crisis levels. From 2011 to 2013 the elasticity coefficient gradually turned marginally positive, indicating a reduction in price sensitivity. From 2013 to 2019 the coefficient plateaued at around 0.03.

A positive, but very small, price elasticity coefficient indicates that electricity consumption in the mining sector is by and large *not responsive* to changes in electricity price. Notwithstanding the variation of the price elasticity coefficient over the period under review, it can be observed that electricity demand has remained very price inelastic. This suggests that electricity price sensitivity in the mining sector has remained fairly subdued. Towards the latter parts of the period the coefficient gradually declined towards relatively low positive figures, although it turned negative on some occasions. Notwithstanding the detected breakpoint, the change in the price elasticity coefficient during this period was fairly marginal. The elasticity coefficient has remained at or close to zero for most of the period.

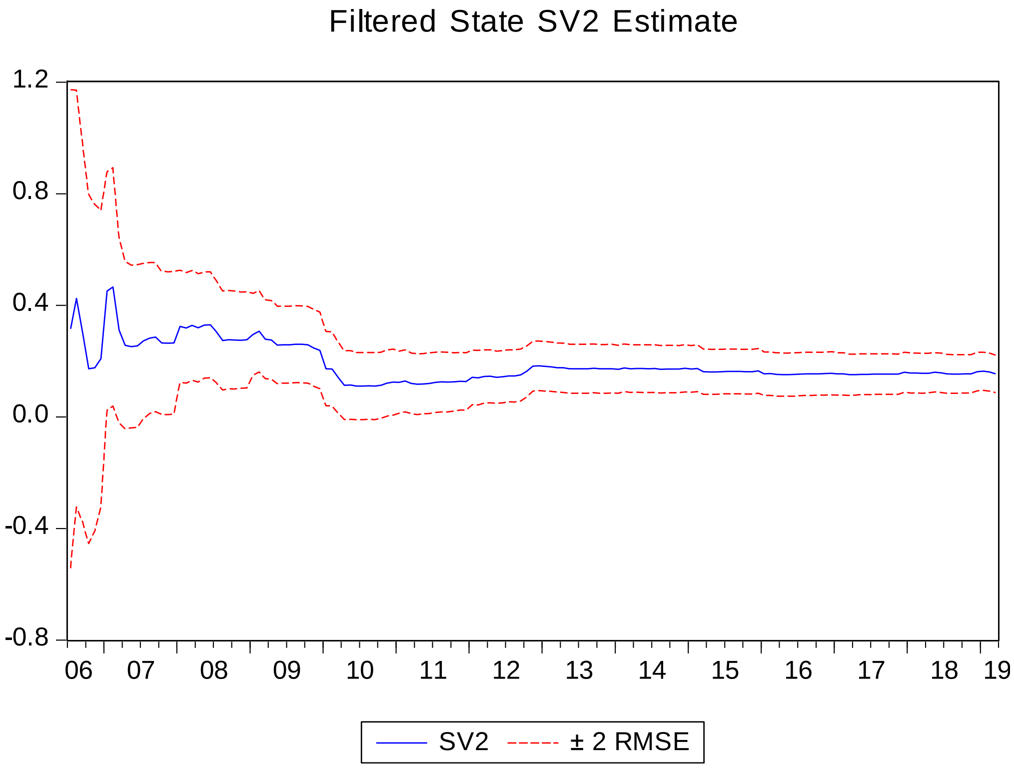
Figure 14: Evolution of price elasticity coefficient



In contrast, the changes in the income elasticity coefficient were considerably more pronounced. The evolution of income elasticity is depicted in Figure 15. It registered a high of 0.46 in 2007, lows of 0.11 in 2010, and 0.15 in its final state. This means that at its final state, a one per cent increase in mining production would result in 0.15 per cent increase in electricity consumption. On the whole, income elasticity showed a gradual decline during the period under review. This means that changes in production are having less impact on electricity consumed in the sector. Electricity consumption remained income-inelastic throughout the study period. However, mining production continued to play a significant role in determining electricity demand.

The positive relationship between production and electricity consumption was maintained for the entire period. This further pays credence to the existence of causality between economic growth and electricity consumption. The positive income elasticity coefficient indicates that an increase in mining production will result in an increase in electricity consumption. The gradual decline in the elasticity coefficient indicates some electricity efficiency gains in the sector. The sector is using fewer units of electricity to produce a single additional unit of production. Nevertheless, mining production remains a significant determinant of electricity demand in the sector.

Figure 15: Evolution of income elasticity coefficient



4.9 Discussion

The Kalman Filter is the primary model that is used to address the research questions of this study. It is a more robust forecasting technique than the OLS approach. It allows for the algorithmic forecasting to proceed even though some of the CLRM conditions are not met. For example, the observed seasonality of the data used in this study would have to be corrected before the results of the OLS could be fully relied upon. However these limitations are not encountered in the case of the Kalman filter. In fact this technique does not require the data series to be stationary before model estimations are performed (Arisoy & Ozturk, 2014:961). Crucially, this study makes the point that the results of the OLS regression cannot be relied upon due to the existence of breakpoints in the data. For these reasons, the Kalman filter results are the primary focus of the study while the OLS results are referred to solely for benchmarking purposes and are considered within the limitations of this model.

In addition, the Kalman filter provides greater insight into the evolution of Income elasticity. As in the OLS model, it affirms that mining output is a significant determinant of electricity consumption in the mining sector. It also indicates that electricity consumption in the mining sector is income-inelastic. A casual observation of the evolution of the income elasticity coefficient indicates that it is gradually declining over time. However, there has been a significant variation in the income elasticity coefficient during the period under review. An analysis of the evolution of the income elasticity coefficient indicates that elasticity estimates at various time periods by and large correspond with the OLS averages that were calculated for those respective periods. Therefore if there was no variation in the parameter over time, the OLS average and the Kalman filter estimate would be similar. It could be tempting to surmise that the difference between the Kalman filter estimate (0.15) and the OLS average (0.11) is not material, therefore either of the two models would be appropriate. However, this would be incorrect. The fact that these two models have yielded fairly similar results is simply by chance and not by design. For example, if elasticity outcomes in period 1 and period 2 were swapped around such that income elasticity was increasing over time and not decreasing as it is currently the case, the OLS average would remain the same but the Kalman filter final state estimate would be materially higher. The higher Kalman filter estimate would be more appropriate for inference purposes as it would reflect the higher level of income elasticity at that point. On the other hand, the OLS average would be misleading at best. In this scenario, the models would be exactly the same, but the vulnerabilities of the OLS model would be exposed in a more emphatic way.

The variation in the income parameter means that long term elasticity averages cannot be relied upon to make accurate inferences about demand responsiveness to changes in production. In this case, a long term elasticity average could understate the anticipated electricity consumption response to changes in mining production albeit by a small margin. If such a coefficient is used it could result in an inaccurate electricity demand projection. Therefore, the Kalman filter is crucial in providing a more reliable elasticity coefficient in this circumstance. Policy makers should be conscious of this variation. The income elasticity coefficient has plateaued around the current level for several years. There is no evidence to suggest that it could go through another change in the near future. Therefore the final state of 0.15 can be used as a reliable income elasticity estimate for the short to medium term. Therefore, the research hypothesis that mining production has a positive relationship with electricity consumption in the mining sector cannot be rejected.

Another point of convergence between the Kalman filter technique and the OLS regression is the fact that electricity price does not play a significant role in determining electricity consumption. However, the Kalman filter provides an added advantage of depicting how the elasticity estimate has evolved over time such that the impact of key events can be detected. It is clear that the 2009 global financial crisis had a significant impact on the sector. The lower commodity prices that ensued as a consequence of the crisis put the financial viability of some mining operations into question. This translated into greater price sensitivity, with the price elasticity coefficient turning negative for a short period of time. Notwithstanding this noticeable change, the variation in the elasticity coefficient was within a very narrow margin. There is no evidence of any significant variation in the price elasticity estimate over time. As a result there is no material difference between the OLS average and the Kalman filter estimate. This is consistent with the findings of Morrison & Pike (1977: 774). Both the OLS regression model and the Kalman filter technique indicate that price was not a significant determinant of electricity consumption at any point during the period under review. This is not really surprising, given the capital intensive nature of mining activity in South Africa. Once the production plant has been constructed and mining operations commence, it is very difficult for mines to alter their electricity consumption in response to a variable cost like electricity costs. They do not have the agility to change their production process in the short term. Therefore, price sensitivity in the mining sector is a long term consideration. The mining houses may consider the electricity price trajectory when setting up new plants or extending their current operations, but they are unlikely to scale down on consumption solely on the back of higher prices in the short to medium term. In addition, even if a decision to shut down operations were to be made, it would take at least several months to implement. A decision to shut down operations is usually an elaborate process. There are several regulatory and legal processes that have to be followed. All this takes time. Thus a reaction to a higher electricity price may not be swift and immediate.

Chapter 5
Conclusion and Policy Implication

5.1 Conclusion

This study is motivated by the recent high increases in electricity prices and the seemingly related declining level of electricity sales in the mining sector. The historically low level of electricity prices in South Africa has caused economic researchers and policy makers to pay less attention to the sensitivity of electricity consumption by large power users to changes in prices. In a few studies where the subject was investigated, researchers found a relatively benign response owing to a low price level. In the past decade or so, electricity prices increased at a substantial rate. The findings of a low price elasticity emanating from a period of low prices cannot be extrapolated into a new era of high prices. Due to this reason, a literature gap exists in South Africa particular with respect to the demand response to high electricity prices by large power users like the mining sector. This study is geared towards filling this gap.

The objectives of this study are to estimate the price and income elasticities of electricity demand in the South African mining sector. This study also examines the break points events that may have contributed to the evolution of the elasticity coefficients over time. In pursuit of these objectives this study explores the literature in this area exhaustively, identifying gaps and making an effort to fill those gaps. The study also provides recommendations to policy makers with respect to the demand sensitivity to price changes.

The findings of the study suggest that electricity prices have on average not played a significant role in determining electricity consumption in the mining sector. Electricity consumption in the mining sector has by and large remained very price in-elastic, notwithstanding the recent price increases. This partly reflects the nature of the mining industry itself, and is also partly because electricity prices come from a historically low base. For most mining operations, there is limited scope to reduce electricity consumption in a significant manner. This is because the production process (i.e. plant and machinery) is already set up, therefore it is a sunk cost. Any attempts to change this structure may require substantial amounts of investments and a significant down time. It follows that, notwithstanding the cost implications of higher electricity costs, continuing with operations as normal may be the optimal option available to the mines. This will remain the dominant strategy until the cost of investing in a more efficient mining process is lower than the cost of higher electricity costs. It is only when a significant change in the opportunity cost occurs that a profit maximising mine would find it necessary to change their production processes. Until then it may seem like the mines are not responsive to electricity price changes. However, higher electricity prices have undoubtedly put pressure on the profit lines of mining operations. Should the mines close in large numbers due to higher electricity costs, this would be reflected as reduction in electricity sales and potentially a step change in the price elasticity coefficient. Therefore, given the nature of the mining business, changes in the price elasticity coefficient are likely to be miniscule until a significant step change occurs. Similarly, the income elasticity of electricity demand was found to be very in-elastic. However, mining production has consistently remained a significant determinant of electricity consumption throughout the period under review.

Furthermore, the results indicate that both price and output elasticity coefficients were time-varying, although the variation was more pronounced for income elasticity than for price. This time variation indicates a change in the parameters' respective levels of significance in explaining electricity consumption during the period under review. The Kalman filter technique is particularly useful in estimating elasticity coefficients, given the existence of parameter instability. The impact of key break point events like the 2009 global financial crisis can be observed in elasticity estimates that are produced by the model. In fact, there is sufficient evidence to suggest that prices played a more critical role in explaining electricity consumption during the period immediately after the crisis. However, as the economy and commodity prices recovered electricity prices became a less significant determinant of electricity consumption in the sector. Nevertheless, the variation in the price elasticity coefficient has remained within a relatively narrow band. It is important to note that these findings do not negate the negative financial impact that higher electricity prices may have on marginal mining operations. In addition to other cost pressures, higher electricity prices may push some marginal mining operations into a non-viable financial position.

The income elasticity of electricity demand in the mining sector has gradually declined during this period. This means that changes in output are having a smaller impact on electricity consumed in the sector. It is important to bear in mind that the mining sector has been subjected to a radical energy-efficiency and electricity conservation drive as part of Eskom's Demand Side Management (DSM) programme. As part of these programmes, the mines were given financial incentives to invest in more energy efficient equipment and processes. This intervention could be partly responsible for the gradual decline in income elasticity. It could also be argued that the cumulative price increases over time have encouraged mining companies to use electricity in a more efficient way as a means of reducing their production costs. The increasing price serves as an incentive to consumers to use electricity more sparingly. The gradually declining income elasticity coefficient could be reflective of the results of these initiatives. It should be noted, however, that the income elasticity coefficient has remained generally flat since 2013. This suggests that the scope for further efficiency gains in the sector is limited, notwithstanding a significant increase in the electricity price during this period.

5.2 Policy Implications

These results could be of great value to electricity price policy makers and macro-economic planners in the country. The results suggest that for the mining sector as a whole, output and price elasticity levels are very low. In theory, it could be argued that there is still some scope for further price increases without materially constraining demand. However, such a position can only be sustained if a further analysis on the profitability of the mining operations has been undertaken. In the case of the mining sector, a lack of response is largely due to an inability to respond and not an unwillingness to do so.

Nevertheless, it is important to note that the price elasticity coefficient has become slightly more sensitive. After reaching a plateau for a while during the latter parts of the study period, the price elasticity coefficient could make a step change in the near future. It is evident that the cumulative impact of the electricity price increases since 2006 has made the sector slightly more price-sensitive over the course of time. As further price increases come into effect, the sector could undergo a step change in the price elasticity coefficient. Therefore, any further price increases must take these constraints into account.

The declining level of electricity consumption in the mining sector creates a unique dilemma for policy makers. This is more concerning given the evidence of support for the feedback hypothesis that has been found in South Africa. The bidirectional nature of the causality between electricity consumption and economic output suggest that any demand response which is negative for electricity consumption could have negative repercussions for economic growth as well. It follows that if the price elasticity level goes through a step change subsequent price increases could have a negative impact on electricity consumption, thereby resulting in negative developmental and social consequences.

The electricity price policy should take these developments into account. Notwithstanding these concerns, the movement towards cost–reflective pricing cannot be avoided. This should be done in tandem with ensuring that Eskom as a dominant player in the energy sector becomes more efficient. Policy makers should make a clear commitment to long-term cost-reflective pricing. This price path should converge towards the long-run marginal cost of supplying electricity. If the electricity sector is to attract the levels of investment it requires in order to alleviate supply constraints, there must be an assurance that electricity prices will reflect the long-term marginal cost of production. Such a policy position would ensure that investment in the sector could yield a fair return. This would attract new entrants to the electricity industry value chain, thereby diluting Eskom's monopoly position in the sector. It could also result in an improved security of aggregate electricity supply.

Similarly, investors in the mining sector would benefit from such a price–signal. The mining sector is characterised by long lead projects with huge capital outlays and high energy intensity. A long-term price signal would be crucial for investors to evaluate the feasibility of the various projects that they may consider. Electricity price increases must be smooth and fairly predictable, so that the long-term planning and capital investment that is required to sustain both the mining and the electricity sectors can be achieved in a less volatile environment. This kind of price stability could contribute immensely to both regulatory stability in the energy sector and operational sustainability in the mining sector.

5.3 Areas for Further Research

It is crucial to consider the impact of distributed demand (DGs) on the price elasticity coefficient for large power users like the mines. These customers have both the means and the incentive to consider electricity self-generation options in the future. As the technology for self-generation becomes cheaper and more proliferated, large customers will find it increasingly attractive to have their own electricity generation plants. If a significant number of large power users opt to have DGs to either replace or complement electricity supplied from the national grid, this could have a material impact on the price elasticity coefficient. As discussed in the literature review, in jurisdictions where these options have been considered and implemented, their availability result in a marked increase in price sensitivity. Furthermore, this kind of large scale demand transformation may result in negative revenue implications for the utility.

It is also crucial to consider what the impact of higher electricity prices has been on the profit margins of the mining sector. As articulated earlier, the finding that price is not a significant determinant of electricity demand does not mean that higher prices do not have negative consequences for the sector. Mining is a long term business. If electricity prices become too high, they may serve as a hindrance to long term investment and growth in the sector. Worse still, they could result in some mining operations being abandoned on account of them becoming non-profitable. The findings of such a research would indicate to policy makers whether or not there is still scope for further price increases without placing the financial viability of the sector in jeopardy. Furthermore, it could better inform policy makers about whether or not to introduce targeted electricity price relief programmes for the sector. Policy makers may also want to establish whether or not any further demand shifting could be unlocked through tailor made TOU assistance packages.

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