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Modified Wald Test Approach into Causality between Electricity and Manufacturing Sector in Nigeria

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Abstract: *Nigeria has experienced years of epileptic power supply. This has a dimensional effect on different sectors of the economy. In the modern production system where production is mainly machine-driven, electricity is seen as a primary factor in the production function. Poor electricity is therefore assumes to lead to malfunction in sectors that only perform well with electricity. The Nigerian manufacturing sector has turned moribund over years. This has been attributed to the gross under supply of electricity in the country.*
Most of the literatures on the effect of electricity in Nigeria were concentrated on its relationship with the overall economic growth, neglecting its effect on the various sectors of the economy. This study therefore investigates the causal relationship between electricity and the manufacturing sector output in Nigeria using annual data from 1971 to 2010. The study adopts the Modified Wald (MWALD) test approach to causality, developed by Toda and Yamamoto, and Forecast Error Variance Decomposition (FEVD). Our findings from MWALD test reveal a bi-directional causality with a strong causality from electricity to manufacturing sector. Electricity was found to be positive and significant at 5% in causing manufacturing while manufacturing sector was only significant at 10%. The policy implication of these findings is that for the manufacturing sector to be resuscitated and thrive, stable and reliable electricity supply must be the focus. This is necessary for the mitigation of the current unemployment crisis in the country.
Keywords*: Electricity, Manufacturing, Factors of production, Modified Wald Test, Causality*

I. Introduction

Manufacturing is the life force for sustainable economic growth, is a catalyst for economic transformation from a raw materials to an active and productive economy (Okonjo-Iweala & Osafo-kwaako, 2007).Economic growth sustainability is imperative for development and this is realizable only when a sound manufacturing sector is in place. An economy without sound manufacturing sector could only be a supplier of raw materials and a consumer of finished goods which is detrimental to growth and development. In a modern economy where industrialization is taking pace and mass production is needed for domestic consumption and exports, the traditionally known factors of production namely, land, labour and capital only, cannot serve this demand.

Therefore, manufacturing sector needs some basic infrastructural facilities for efficient performance as well as high productivity. Adenikinju (2003) expresses these infrastructures as necessary structural and physical factors in an organization. Part of these infrastructures is electricity supply. Electricity is considered as primary and explicit factor input in modern manufacturing process. Though classical economists considered energy as an intermediate input in production, facilitating factors of production, (Alam, 2006) argues that it serves as factor input in certain production circumstances.Beaudreau (1998) sees electricity as a speed stimulator in efficiency and productivity. More consumption of electricity by the manufacturing sector translates into increase in efficiency and productivity in the sector. A country could be able to export significantly if its industries have efficient supply of electricity, (Riker, 2011). It is discernible therefore that a country that wants to industrialized must take stable electricity supply as a priority. The more industrialized a nation is the more electricity it required.

Inadequate and erratic power supply is the obvious factor that militate the growth of the manufacturing sector in Nigeria. This has made the cost of production unbearable to many firms, hence add to their incapability to compete their foreign counterparts, (Yakubu, Manu & Bala, 2015). The high cost of production has also cost the shutting down of firms intermittently. With this perceived dependency of the manufacturing sector on electricity, numerous literatures on the effect of electricity in Nigeria only concentrated on its impact on the overall economy. Yakubu et al. (2015)observed that this could lead to fallacy of decomposition because economic growth is a function of the performance of different sectors which certainly differ in their need for electricity[1]. In the midst of this perceived literature gap, the Nigerian manufacturing sector continue to recordyears of malfunctioning and debilitating experience which many attribute to the general electricity problem in the country.

In the wake of this lingering electricity problem in the country and its pronounced effect on the core heart of the economy, there is acute need to unravel the relationship between manufacturing sector's output and electricity supply in Nigeria. Does electricity actually causes manufacturing output? How significant and to what extent is the causality? To provide details for policy direction, this study attempts to investigate this relationship.

II. Literature Review

2.1.1 *Electricity and Economic Growth*

Numerous literatures have explored the relationship between electricity and economic growth with little attention on the sectoral effect. Overwhelming literatures support causal relationship between electricity and economic growth across the globe. In a comprehensive study of over one hundred countries of the world, Ferguson, Wilkinson & Hill (2000) reveal strong correlation between the amount of electricity use and GDP per capita at general level. These countries represent over 90% of the world economy.This relationship was found to be stronger in rich countries than in poor countries. The rich countries are industrialized nation, hence the imperativeness of electricity for the growth of industries. Akinlo (2008) in a study of 11 sub-Saharan African countries including Nigeria between 1980 to 2003 reveals the existence of cointegration between the use of energy and economic growth in seven of the countries, bi-directional causality in three countries and unidirectional from GDP to energy consumption in two countries. Neither long run relationship nor causality between the energy consumption and economic growth was identified in Nigeria. However, in a later study with an improved sample period between 1980 to 2006, long run relationship and unidirectional causality from electricity consumption to GDP per capita was found in Nigeria, (Akinlo, 2009). A similar study was also conducted in China with the same techniques and sample size used by Akinlo (2009),Yuan, Zhao, Yu, & Hu (2007) found the same results revealed byAkinlo (2009).

Enang (2010) found the existence of long run relationship between economic development, electricity supply and industrialization in Nigeria from 1970 to 2008. Electricity in particular was found to be significant in determining growth at 5%.Bi-directional causality was further revealed between GDP per capita and electricity supply.Odularu & Okonkwo (2009) reveal the existence of cointegration between economic growth proxied by GDP per capita, labour stock, capital stock and use of energy in Nigeria. The study decomposes energy into coal, crude oil and electricity and found the current period of all the three constituent of energy to be positive determinants of economic growth. This indicates that electricity, both independently and in a composed energy form, influences economic growth.

This relationship was also investigated in Malaysia by Tang (2008). Using Autoregressive Distributed Lag (ARDL) and Modified Wald (MWALD) test for granger causality over a quarterly data from 1972 to 2003, the results reveals no long run relationship while bidirectional causality was identified between the variables – electricity consumption and economic growth. However, a later study by Chandran, Sharma, & Madhavan (2010) in Malaysia over annual time series data between the period of 1971 to 2003, shows that long run relationship exists between electricity consumption and economic growth.

Kouakou (2011) employs ARDL bounds testing techniques and studies electricity consumption, industrial output and economic growth in Cote d' Ivoire over the period of 1971 to 2008. The study reveals the existence of cointegration between the variables. A test of granger causality identified short run bi-directional causality between economic growth and electricity consumption while causality only runs from electricity consumption to growth in the long run. Shahbaz & Lean (2012) undertook a related study in Pakistan on electricity consumption and economic growth from 1972 to 2009. Employing similar analytical techniques used by Kouakou (2011), the variables were found to relate in the long run with electricity consumption having positive impact on growth. The causality result shows the existence of feedback causality between the variables. Pakistan and Cote d' Ivoire therefore share the same scenario which supports the link between electricity and economic growth. Squalli (2007) investigates the link between electricity consumption and economic growth in the Organization of Petroleum Exporting Countries (OPEC) from 1980 to 2003. Using the ARDL bounds testing technique, long run relationship was found to exist between the variables in all the countries – including Nigeria. Employing the MWALD test for causality, feedback or unidirectional causality was revealed in all the countries with exception of Algeria, Iraq and Libya. Though the author relates the result in Algeria, Iraq and Libya to mismanagement, the results question the earlier identified long run relationship between the variables in those

[1]Some sectors of the economy require more energy – electricity – than others. Example, the manufacturing sector requires more energy than agricultural sector; thus, looking at the effects of electricity on the economy as whole lacks policy design direction that leads to sectoral distribution and maximization of electricity.

countries. According to Engle & Granger (1987), if cointegration exists between variables, there must be at least one causality. The causal relationship in Nigeria shows unidirectional causality from electricity consumption to economic growth, this supports the finding of Akinlo (2009).

Similarly, group of countries study was undertaken by Wolde-Rufael (2006) in seventeen African countries within the period of 1971 and 2001. The author also uses ARDL and MWALD and reveals long run relationship in nine countries and causality in twelve countries. This result shows that African scenario also exhibit relationship between electricity and economic growth, though the relationship might not be strong as obtainable in developed countries. – see Ferguson et al. (2000). Welle-Strand, Ball, Hval, & Vlaicu (2012) studied the effect of power sector on economic growth and development, using panel data approach in seventy seven countries – combined developed and developing countries, within the period of 1980 to 2005. The study uses Solow growth model by including electricity, explicitly, as an independent variable. Estimating the model without electricity gave 57% power of the explanatory variables while the inclusion of electricity extended it to 76% - indicating the contribution of electricity to growth in the countries at 19%. The study further revealed positive coefficient for electricity at 0.47, thus, a 10% increase in electricity supply leads to 4.7% positive change in growth. Though the study might suffer from heterogeneity problem, the number of countries involve presents global picture of the linkage between electricity and economic growth as well as corroborating Ferguson et al. (2000).

The South American countries also do not evade the pervasive relationship between electricity and economic growth. Yoo & Kwak (2010) studied seven countries of this region over annual data from 1975 to 2006, the causality test of Granger (1969) reveals causality from electricity consumption to economic growth in five of the countries – Argentina, Brazil, Chile, Columbia and Ecuador. Bidirectional causality was identified in Venezuela while no causality link was established in Peru. The result for Peru probably needs to be subjected to a more rigorous study, considering its high growth and prudency in managing resources compared to Ecuador. However, the region generally displays correlation between electricity consumption and economic growth.

In a study on the effect of industrial energy consumption on the economic growth of Shanghai from 1952 to 1999; Wolde-Rufael (2004) employs the MWALD test of granger causality and reveal that industrial energy consumption in general form and in its disaggregated – coal, coke and electricity – causes economic growth in Shanghai. In a similar study by the same author, Wolde-Rufael (2010), found nuclear energy to be positive and significant in promoting economic growth in India. India is one of the countries in the World that possess nuclear energy; this facilitates the country's electricity supply and hence economic growth. The study uses ARDL approach, MWALD test of granger causality and Forecast Error Variance Decomposition (FEVD) and found long run relationship between economic growth and nuclear energy as well as unidirectional causality from nuclear energy to economic growth.Paul & Bhattacharya (2004) use the Johansen-Juselius and Engle and Granger approach to cointegration in India between the period of 1950 to 1996 and found bi-directional causality in both approaches. Lee (2005) studies group of eighteen developing countries from 1975 to 2001, using Fully-Modified ordinary least square method, the result shows long run relationship between the variables. Similarly in Canada, a study by Ghali & El-Sakka (2004). With the use of Vector Error Correction Method (VECM), they establish bi-directional relationship between output and energy.

Yuan et al. (2008) studies the effect of energy consumption on economic growth in China at both aggregate and disaggregate level, from 1963 to 2005, and reveals long run relationship between aggregate and disaggregate form of energy and level of output. Long run causality was also identified from electricity and oil to GDP. Hence, the fast growing economy of China is dependent on electricity. Apergis & Payne (2009) reveals cointegration between energy consumption and real GDP over the period 1991 to 2005 among commonwealth states. Energy displays positive and significant coefficient in influencing GDP.

2.1.2 *Electricity and Manufacturing Sector*

In this regard,Soytas & Sari (2007) studies the effect of energy on the production of Turkish manufacturing industry within the period of 1968 to 2002. Long run relationship as well as unidirectional causality from electricity consumption to manufacturing output was identified.(Yakubu et al., 2015) studied long run relationship between electricity supply and manufacturing output in Nigeria from 1971 to 2010. Cointegration was identified and electricity was found to be positive and significant in determining manufacturing output in the long run.

Beaudreau (1995) investigates the effect of electric power on the United States (US) manufacturing sector and reveals strong positive effect of electricity on manufacturing output. Using the neoclassical production model and estimated the shares of factor inputs including electric power between the periods of 1950 to 1984, the study found that decline in manufacturing output and productivity results from decline in electric power supply. Similarly, the same author, Beaudreau (2005), later studies the effect of electricity on the manufacturing of Japan (1965-1988), Germany (1963 – 1988) and United States (1950 -1984). Adopting the same methodology in his previous study, he reveals positive coefficients for electricity in all the countries.

Specifically, the coefficient of electricity for United States, Germany and Japan manufacturing are 0.53, 0.75 and 0.61 respectively. This indicates that a 10% increase in electricity use leads to 5.3%, 7.5% and 6.1% increase in manufacturing output for US, Germany and Japan respectively. This reveals that electricity is a necessary and primary factor input in manufacturing. However, the study is on developed countries' manufacturing that are already industrialized, this might not be the case in the poor countries as reveals by Ferguson et al. (2000). Adenikinju (1998) in a study of panel data analysis among 667 firms over the period of 1988 to 1990 found that the contribution of energy consumption (electricity) to the growth of manufacturing firms in Nigeria is not significant. However, the firms displayed mixed coefficient signs, but on the overall, the manufacturing sector coefficient is positive. This shows that positive relationship exists between electricity and the sector's growth.

The array of literatures reviewed sufficiently support the existence of relationship between electricity and economic growth. Generally, most of the literatures found positive relationship as well as the existence of causal relationship between electricity consumption and economic growth; specifically, unidirectional causality with electricity causing growth appears to be more emphatic. However, the interest of this study is to investigate the link between electricity and manufacturing sector in Nigeria, which is a core component of an economy. There seems to be a literature vacuum in the relationship between electricity and the constituents of the overall economy, particularly in Nigerian context. In view of this, this study will add to the existing limited literatures.

III. Methodology

The study uses annual time series data from 1971 to 2010. It employs Cobb Douglas production function and explicitly included electricity as an independent variable. Data on gross fixed capital formation and labour force from 1971 to 2005 were adopted from Odularu & Okonkwo (2009), while from 2006 to 2010 were from the National Bureau of statistics, (NBS, 2011)[2]. Data on manufacturing output and electricity supply were sourced from Central Bank of Nigeria Statistical Bulletin (2010)[3] and World Bank's World Development Indicators[4] Data respectively.To achieve the objective of the study, we employ the Vector Autoregressive (VAR) Model, and adopt Toda & Yamamoto (1995) and Dolado & Lütkepohl (1996) Modified Wald (MWALD) test and Forecast Error Variance Decomposition (FEVD), used in explaining and interpreting Vector Autoregressive model pioneered by Sims (1980), once determined, (Lütketpohl, 2005).

3.1.1 Toda and Yamamoto (1995) Modified Wald (MWALD) Test

The Modified Wald test is an improved granger causality test developed by Toda and Yamamoto (1995). Causality is one the methods employed in the interpretation of Vector Autoregression (VAR) model which originated from the work of Sargent and Sims (1977) and pioneered by Sims (1980). The VAR system shows the correlations among variables and analyzes the dynamic relationship between the variables, (Yakubu, 2015). The popular granger causality test of Granger (1969) has been widely adopted in the interpretation and analysis of the VAR model and remains the easier method in explaining VAR under suitable conditions. The idea around granger causality is, an effect cannot precede a cause, hence, if a variable or sets of variables, x, y, z affect(s) a particular variable, q, then the former is/are believed to help in the prediction of the latter (Lütkepohl, 2005). Therefore, granger causality test uses the Wald test of zero restrictions hypothesis (F-statistics) to assess the significance of the lagged values of x, y, z on q, once the VAR model is determine and estimated.

However, the estimation of VAR model requires all variables to be integrated at first difference, I (1), and if cointegrated, Vector Error Correction Model or level VAR is estimated; if otherwise, first difference VAR is estimated. The basis of the Wald test statistics, the conventional asymptotic theory, is detected to be non-standard if VAR model is estimated at level with variables that are either integrated at first difference or cointegrated. Thus, the Wald test of zero restrictions hypothesis on the lagged variables of granger causality becomes unreliable and misleading when is done in the framework of level VAR estimation (Sims, Stock, & Watson, 1990), (Toda & Phillips, 1993) and (Toda & Yamamoto, 1995).

Another problem with the traditional granger causality test is the uncertainty associated with the integration order and cointegration of the variables. The unit root tests such as the Augmented-Fuller test (Dickey & Fuller, 1979), Kwiatkowski, Phillips, Schmidt and Shin test (Kwiatkowski, Phillips, Sshmidt, & Shin, 1992) and Phillips-Perron test (Phillips & Perron, 1988) are found to lack power, hence no uniformly better unit root test (Sj, 2008) and (Toda & Yamamoto, 1995). The same uncertainty also relates to the VAR associated cointegration test, Johansen & Juselius (1990, 1992) and Johansen (1995) cointegration test. Simulation evidence reveals that it is sensitive to specification errors in finite sample which made it unreliable particularly when using economic time series (Reimers, 1992; Sj, 2008). These problems relating to the

[2] www.nigerianstat.gov.ng
[3] www.cbn.gov.ng
[4] www.worldbank.org

traditional granger causality test and the fact that research interest often is not concern about integration and cointegration of variables, but causal effects among the variables through restrictions test on the lagged coefficients of the regressors in the model, led to the development of the MWALD test for granger causality by Toda & Yamamoto (1995), which is robust to the integration and cointegration properties of time series, in order to circumvent the pre-test biases.

In conducting the MWALD test for granger causality, though avoids unit roots pre-testing biases, it however requires the determination of the maximum possible order of the integration of the underlying variables (d_{max}). The variables could be a mixture of I (0), I (1) and I (2), in such situation, $d_{max} = 2$. The determination of the optimal lag length (k) for the VAR model is very important because greater or less than the true lag leads to inefficient and biased estimates. It therefore leads to accepting the null hypothesis when it should be rejected or rejecting when it should not (Wolde-Rufael, 2010; Yakubu, 2015). Once d_{max} and k are appropriately identified, a level VAR model of order ($k + d_{max}$) is estimated and zero restrictions test is conducted on lagged coefficients of the regressors up to lag k. This process ensures that the Wald test statistics has an asymptotically chi-square (x^2) distribution whose critical values can be used to draw a valid inference and conclusion (Toda & Yamamoto, 1995).

In view of the obviation of the integration and cointegration properties of the granger causality Wald test by the MWALD tests, we choose `to use the Toda & Yamamoto (1995)'s MWALD test for the zero restrictions test on the coefficients of the lagged values of our regressors on the dependent variable.

3.1.2 Forecast Error Variance Decomposition (FEVD)

Forecast Error Variance Decomposition (FEVD) is an innovation accounting technique central to the analysis a VAR framework pioneered by Sims (1980). It reveals information concerning the percentage contribution of each variable to the other variable in a VAR model through the error variance in forecasting a variable, attributable to innovations or shocks in other variables (Lütkepohl, 2005). FEVD therefore determines the percentage of forecast error variance of any variable in the VAR system explained by innovations in its self and each of the explanatory variables over a given horizon. The higher the percentage of the variance explained by shocks in a variable, the higher is its explanatory power in the model. The FEVD is computed using cholesky factorization introduced by Sims (1980)

Innovations or shocks in the variables may be contemporaneous thereby leading to identification problem in determining whose variable innovation is responsible for the variation; this can be avoided if the error terms have low contemporaneous correlation. However, Sims (1980) suggests ordering of the variables to start with the most exogenous and end with the most endogenous. This process require conducting correlation matrix among the variables, if the off-diagonal elements are generally low, ordering will only have marginal effect on the FEVD. If otherwise, the ordering begins with variables with lower correlation to variables with higher correlation (Duasa, 2007). This study complements the MWALD test with FEVD for robustness and reliability of outcomes. Additionally, FEVD gives insight into the possible relationship between the variables in a given time horizon into the future.

3.1.3 Model Specification

The study followsYakubu et al. (2015),Beaudreau, (1995, 2005), Wolde-Rufael (2004, 2006, 2009, 2010), Akinlo (2008, 2009) and Enang (2010, 2011), in adopting the neoclassical Cobb Douglas production function to establish the relationship between electricity supply and manufacturing output in Nigeria. The Cobb & Douglas (1928) production function expresses the technical relationship between given level of output and a given quantity of physical inputs. A variation in output is a resultant effect of variation in the physical inputs. The production function has only two factor inputs in production, but with the emergence of empirical evidence identifying energy or electricity as an independent and primary factor inputs in production process, there is departure from the neoclassical thinking of production function to that which includes energy as an independent factor of production (Alam, 2006). Hence our model for manufacturing sector's output in equation 1 constitutes an explicit inclusion of electricity supply as primary and independent factor of production.

$$M = f(E^{\gamma} K^{\theta} L^{\sigma}) \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots (1)$$

Where;
M = Manufacturing sectors output
E = Electricity supply
K = Gross fixed capital formation
L = Labour force
f = Function

γ, θ and σ are the respective contributions of E, K and L to manufacturing sector's output. Labour and capital are treated as controlled or additional variable to avoid the possible biased findings as a result of exclusion of relevant variables (Wolde-Rufael, 2010).

The production function in equation (1) is an exponential function, therefore there is need to log the data in order to linearly express the equation. The estimation of time series properties can best be done through VAR model expressed in log – linear form with time trend or intercept (Pesaran, Shin, & Smith, 2001). Thus, taking the log of equation (1) and transforming it to econometric regression model to be estimated, we have equation 2.

$$lnM_t = \alpha + \gamma lnE_t + \theta lnK_t + \sigma lnL_t + \mu_t \dots\dots\dots\dots\dots\dots\dots\dots\dots (2)$$

Where;
lnM_t = Natural log of manufacturing output at time t
lnE_t = Natural log of electricity supply at time t
lnK_t = Natural log of capital at time t
lnL_t = Natural log of labour at time t
μ_t = Error term or residual term
$\gamma, \theta and \sigma$ are the respective coefficients of $lnE_t, lnK_t and lnL_t$

3.1.4 VAR Models for MWALD

MWALD test for granger causality requires estimation of a level VAR of lag (k+dm), where k is the optimal lag and dm is the possible maximum order of integration of the process; and we test the zero restriction hypotheses on each of the coefficient of the regressors in each of the level VAR models up to lag k. To explore the dynamic causality among our variables, we made each variable as a dependent in a VAR model and we conduct the zero restriction tests on each of the coefficient of a regressor and jointly on coefficients of the regressors in a particular VAR model, up to lag k. If the chi-square (X^2) is significant we reject the null hypothesis of no causality in favour of the alternative, otherwise, we fail to reject the null. Equation 2, 3, 4 and 5 are the level VAR (k+dm) to be estimated with $lnM_t, lnE_t, lnK_t and lnL_t$ as dependent variable respectively.

$$lnM_t = \alpha_1 + \sum_{i=1}^{k+dm} \pi_{1i}\, lnM_{t-i} + \sum_{i=1}^{k+dm} \delta_{1i}\, lnE_{t-i} + \sum_{i=1}^{k+dm} \theta_{1i}\, lnK_{t-i} + \sum_{i=1}^{k+dm} \varphi_{1i}\, lnL_{t-i} + \mu_{1t} \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots (2)$$

$H_0: \delta_{1i} = 0, \theta_{1i} = 0, \varphi_{1i} = 0\ and \delta_{1i} = \theta_{1i} = \varphi_{1i} = 0$
$H_1: \delta_{1i} \neq 0, \theta_{1i} \neq 0, \varphi_{1i} \neq 0\ and \delta_{1i} \neq \theta_{1i} \neq \varphi_{1i} \neq 0$
Where;
H_0 is null hypothesis (No causality)
H_1 is alternative hypothesis (causality exists)
i = 1………..k
$\delta_{1i}, \theta_{1i} and \varphi_{1i}$ are the respective coefficients of the regressors, $lnE_t, lnK_t and lnL_t$, whose causality to be tested when lnM_t is the dependent variable. $\alpha_1 and \mu_t$ are the intercept and the residual term, (k + dm) is the VAR optimal lag, k, augmented by the possible maximum order of the process integration, dm. The concepts definitions apply to the remaining equations of our VAR models when other variables are made dependent.

$$lnE_t = \alpha_2 + \sum_{i=1}^{k+dm} \pi_{2i}\, lnE_{t-i} + \sum_{i=1}^{k+dm} \delta_{2i}\, lnM_{t-i} + \sum_{i=1}^{k+dm} \theta_{2i}\, lnK_{t-i} + \sum_{i=1}^{k+dm} \varphi_{2i}\, lnL_{t-i} + \mu_{2t} \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots. (3)$$

$H_0: \delta_{2i} = 0, \theta_{2i} = 0, \varphi_{2i} = 0\ and \delta_{2i} = \theta_{2i} = \varphi_{2i} = 0$
$H_1: \delta_{2i} \neq 0, \theta_{2i} \neq 0, \varphi_{2i} \neq 0\ and \delta_{2i} \neq \theta_{2i} \neq \varphi_{2i} \neq 0$
Where;
H_0 is null hypothesis (No causality)
H_1 is alternative hypothesis (causality exists)
i = 1………..k

$$lnK_t = \alpha_3 + \sum_{i=1}^{k+dm} \pi_{3i}\, lnK_{t-i} + \sum_{i=1}^{k+dm} \delta_{3i}\, lnM_{t-i} + \sum_{i=1}^{k+dm} \theta_{3i}\, lnE_{t-i} + \sum_{i=1}^{k+dm} \varphi_{3i}\, lnL_{t-i} + \mu_{3t} \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots (4)$$

$H_0: \delta_{3i} = 0, \theta_{3i} = 0, \varphi_{3i} = 0 \; and \delta_{3i} = \theta_{3i} = \varphi_{3i} = 0$
$H_1: \delta_{3i} \neq 0, \theta_{3i} \neq 0, \varphi_{3i} \neq 0 \; and \delta_{3i} \neq \theta_{3i} \neq \varphi_{3i} \neq 0$
Where;
H_0 is null hypothesis (No causality)
H_1 is alternative hypothesis (causality exists)
i = 1………..k

$$lnL_t = \alpha_4 + \sum_{i=1}^{k+dm} \pi_{4i}\, lnL_{t-i} + \sum_{i=1}^{k+dm} \delta_{4i}\, lnM_{t-i} + \sum_{i=1}^{k+dm} \theta_{4i}\, lnE_{t-i} + \sum_{i=1}^{k+dm} \varphi_{4i}\, lnK_{t-i} + \mu_{4t} \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots .. (5)$$

$H_0: \delta_{4i} = 0, \theta_{4i} = 0, \varphi_{4i} = 0 \; and \delta_{4i} = \theta_{4i} = \varphi_{4i} = 0$
$H_1: \delta_{4i} \neq 0, \theta_{4i} \neq 0, \varphi_{4i} \neq 0 \; and \delta_{4i} \neq \theta_{4i} \neq \varphi_{4i} \neq 0$
Where;
H_0 is null hypothesis (No causality)
H_1 is alternative hypothesis (causality exists)
i = 1………..k

All equations in this study are estimated with deterministic (time) trend. The properties of time series variables are well estimated, if the variables are transformed into log and the VAR model captures the intercept and time trend (Pesaran et al., 2001). Hence, all our equations shall be estimated to capture the deterministic trend (intercept and time) in order to reveal the best approximations for our variables.

IV. Empirical Results and Analysis

4.1.1 Stationarity Tests

Though MWALD was designed to obviate the unit roots pre testing problem, however, there is need to determine the maximum order of integration of the variables. The MWALD test for granger causality by Toda & Yamamoto (1995) requires the knowledge of the possible maximum order of integration of the process which augment the optimal lag of the VAR model for the estimation of the level VAR. However, none of the available unit roots tests is completely better in detecting the integration order, hence, the need to employ more than one test for cross checking (Sj, 2008). Therefore, this study employs the Augmented Dickey – Fuller (ADF) test of Dickey & Fuller (1979), Phillips – Perron (PP) test of Phillips & Perron, (1988) and Kwiatkowski, Phillips, Schmidt and Shin (KPSS) test of Kwiatkowski et al. (1992), to test for the stationarity of the variables in order to have a robust stationarity result. Table 4.1, 4.2 and 4.3 show the results of ADF, PP and KPSS respectively.

Table 4.1 Augmented Dickey-Fuller (ADF)

Series	Constant	Constant and Trend
lnM_t	-3.175791**	-2.408883
lnE_t	-2.751961*	-2.339312
lnK_t	-1.782007	-2.045613
lnL_t	-0.258493	-1.357550
ΔlnM_t	-4.212591***	-4.835494***
ΔlnE_t	-4.224029***	-5.025062***
ΔlnK_t	-4.742761***	-4.673089***
ΔlnL_t	-4.282347***	-4.538711***

Note: The critical values for constant (and trend) at 1%, 5% and 10% level of significance are -3.621023 (-4.226815), -2.943427 (-3.536601) and -2.610263 (-3.200320) respectively. ***, ** and * denote significance at 1%, 5% and 10% respectively. ADF test the null hypothesis of 'not stationary' against the alternative of 'stationary'.

Table 4.2: Phillips – Perron (PP)

Series	Constant	Constant and Trend
lnM	-3.175791**	-2.408883
lnE	-2.751961*	-2.339312
lnK	-1.782007	-2.045613

lnL	-0.258493	-1.357550
ΔlnM	-5.063211***	-5.488163***
ΔlnE	-6.827195***	-7.710005***
ΔlnK	-4.686198***	-4.623233***
ΔlnL	-6.111701***	-6.304617***

Note: Just like the ADF, the PP unit root test has the null hypothesis of 'not stationary' against the alternative, which is 'stationary'. *, ** and *** indicate the level of significance at 10%, 5% and 1% respectively. The respective critical values at 1%, 5% and 10% are -4.219126, -3.533083, -3.198312 (with trend), and -3.615588, -2.941145, -2.609066 (constant).

Table 4.3 Kwiatkowski-Phillips-Schmidt-Shin (KPSS)

Series	Constant	Constant and Trend
lnM	2.844059***	0.737269***
lnE	3.491888***	0.783962***
lnK	1.273816***	0.358249***
lnL	1.862787***	0.581365***
ΔlnM	0.452229*	0.111150
ΔlnE	0.520949**	0.083076
ΔlnK	0.052949	0.053603
ΔlnL	0.226970	0.054104

Note: In contrast to ADF and PP, KPSS unit root test has the null hypothesis of 'stationarity' against the alternative, 'not stationary'. Critical values for constant (with trend) are 0.739000 (0.216000), 0.463000 (0.146000) and 0.347000 (0.119000) at 1%, 5% and 10% respectively. ***, ** and * represent 1%, 5% and 10% level of significance respectively.

All of the unit roots tests confirmed all our process to be overwhelmingly integrated at first difference and at 1% level of significance. The virtual similarity in the three tests made robust our conclusion that all our variables are I(1).

4.1.2 Modified Wald (MWALD) Test for Granger Causality

The conduct of MWALD requires the determination of optimal lag which is presented in table 4.4. We use AIC - (Akaike, 1974), SBC - (Schwarz, 1978) and (Hannan & Quinn, 1979) to determine the optimal lag for the VAR system. AIC minimizes its value at lag 2 while SBC and HQC do at lag 1. Though Wolde-Rufael (2010) suggests increase in the VAR optimal lag to improve the VAR models if they deviate from the true models in terms of the satisfying the classical assumptions, in the case of our VAR system it worsen the diagnostic tests. Two out of the three criteria suggesting 1 as the optimal lag, the study chooses its optimal lag for the VAR models to be 1.

Table 4.4: VAR Lag Order Selection Criteria

Lag	AIC	SBC	HQC
0	2.266	2.441	2.328
1^{g}	-6.148	**-5.277***	**-5.841***
2	**-6.290***	-4.723	-5.738
3	-5.964	-3.700	-5.166

Note: * indicates optimal lag order selected by the respective criterion. AIC: Akaike Information Criterion, SBC: Schwarz Bayesian Criterion and HQC: Hannan – Quinn Criterion. ^{g} indicates the VAR optimal lag

Table 4.5 presents the diagnostic tests of our models (equation 2, 3, 4 and 5) with the augmented lag (k+dm). We checked for autocorrelation, heteroscedasticity, misspecification and normality. All the equations are relatively better except for equation 5 that only passed autocorrelation test. However, to confirm that the residuals of the whole VAR system are serially independent (no autocorrelation), we undertook langrange multiplier test of residual correlation up to 5 lags. The result shown in table 4.6 reveals that from lag 1 to 5, the VAR system is free from autocorrelation; hence our VAR models do not show serious deviation from the classical linear regression model assumptions. We therefore estimated the equations.

Table 4.5: Diagnostic Tests for the VAR Equations

Dep. Var.	LM[X^2]	ARCH	RR	JB
lnM_t	2.677	0.005	1.307	75.09^{***}
	(0.262)	(0.944)	(0.202)	(0.000)
lnE_t	0.966	0.008	2.022^{*}	0.606
	(0.617)	(0.931)	(0.053)	(0.738)
lnK_t	3.255	0.870	0.553	0.681
	(0.196)	(0.351)	(0.585)	(0.711)
lnL_t	2.524	8.335^{***}	2.947^{***}	98.271^{***}
	(0.283)	(0.004)	(0.007)	(0.000)

Note: Figures in parenthesis are the probability values of the respective tests. * and *** denote 10% and 1% level of significance respectively. LM: Langrange Multiplier Test of Residual Correlation, ARCH: Autoregressive Conditional Heteroscedasticity Test of Residuals, Ramsey's RESET: Misspecification Test based on square of fitted values, JB: Jarque – Bera Test of Normality Based on Skewness and Kurtosis of Residuals

Table 4.6: VAR Residual Serial Order Correlation LM Tests

Lags	LM – STAT	Probability
1	13.33387	0.6482
2	13.17734	0.6597
3	11.76326	0.7601
4	10.70692	0.8272
5	14.54017	0.5585

LM: Langrange Multiplier Test of Residual Correlation

Table 4.7 presents the MWALD test for equation 2 where manufacturing is the dependent variable. The result rejects the null hypothesis that electricity supply does not cause manufacturing output at 5% significance level. The positive sum of lagged coefficient of electricity indicates that, not only electricity is significant but positive significance in causing manufacturing.

Table 4.7: MWALD Test of Granger Causality for Equation 2

Dependent Variable: lnM_t		
Null Hypothesis	X^2 [MWALD]	Σ Lagged Independent Coefficient(s)
lnE_t ₵ lnM_t	$5.936 (0.015)^{**}$	Σ Lagged lnE_t Coefficient = 1.082
lnK_t ₵ lnM_t	0.208 (0.649)	Σ Lagged lnK_t Coefficient = -0.080
lnL_t ₵ lnM_t	1.433 (0.231)	Σ Lagged lnL_t Coefficient = 2.597
All ₵ lnM_t	$7.176 (0.067)^{*}$	Σ Lagged of all Independent Variable coefficients = 3.599

Note: ₵ signifies the null hypothesis 'does not cause' X^2 and Σ represent chi-square statistics and 'summation of' respectively. 'All' denotes combine causality from all the regressors while * and ** show significance at 10% and 5% level respectively.

Though no causality from capital and labour to manufacturing; the combination of all the regressors positively and significantly causes manufacturing output. This implies that in the process of manufacturing, electricity, capital and labour are required but electricity is more required and important to manufacturing industry in Nigeria. Similarly, table 4.8 reveals that manufacturing is positively significant in causing electricity supply, though at a lower significance (10%), while neither labour nor capital or the combination of all the regressors in equation 3 is found to cause manufacturing output.

The sum of lagged coefficient of manufacturing causing electricity (0.153), however positive, is comparatively far less than the sum of lagged coefficient of electricity causing manufacturing (1.082). The causal relationship between electricity and manufacturing is bi-directional, but detailing into their level of significance and sum of lagged coefficients, electricity becomes more a causal factor to manufacturing than manufacturing to electricity.

Table 4.8: MWALD Test of Granger Causality for Equation 3

Dependent Variable: lnE_t		
Null Hypothesis	X^2 [MWALD]	Σ Lagged Independent Coefficient(s)
$lnM_t \not\subset lnE_t$	3.229 (0.072)*	Σ Lagged lnM_t Coefficient = 0.153
$lnK_t \not\subset lnE_t$	0.090 (0.765)	Σ Lagged lnK_t Coefficient = 0.026
$lnL_t \not\subset lnE_t$	0.342 (0.559)	Σ Lagged lnL_t Coefficient = -0.619
All $\not\subset lnE_t$	3.826 (0.281)	Σ Lagged of all Independent Variable coefficients = -0.440

Note: ⊄ signifies the null hypothesis 'does not cause' X^2 and Σ represent chi-square statistics and 'summation of' respectively. 'All' denotes combine causality from all the regressors while * shows significance at 10% level.

The MWALD test for equation 4 shown in table 4.9, reveal positive and significant causality from electricity to capital at 1% level. In equation 3, there is no causality from capital to electricity, thus, the causal relationship between capital and electricity is unidirectional, running from electricity to capital. The implication of this is electricity supply facilitates the use capital in manufacturing process, therefore if capital intensive production is needed for growth in the sector, electricity supply must be improved. The combination of the variables is also found to be positive and significant in causing capital at 1% level.

Table 4.9: MWALD Test of Granger Causality for Equation 4

Dependent Variable: lnK_t		
Null Hypothesis	X^2 [MWALD]	Σ Lagged Independent Coefficient(s)
$lnM_t \not\subset lnK_t$	0.861 (0.353)	Σ Lagged lnM_t Coefficient = 0.153
$lnE_t \not\subset lnK_t$	6.634 (0.010)***	Σ Lagged lnE_t Coefficient = 1.081
$lnL_t \not\subset lnK_t$	4.276 (0.039)**	Σ Lagged lnL_t Coefficient = 4.240
All $\not\subset lnK_t$	11.995 (0.007)***	Σ Lagged of all Independent Variable coefficients = 5.474

Note: ⊄ signifies the null hypothesis 'does not cause' X^2 and Σ represent chi-square statistics and 'summation of' respectively. 'All' denotes combine causality from all the regressors while ** and *** show significance at 5% and 1% level respectively.

The causality test for equation 5 in table 4.10shows no causality from any of the regressors to labour (dependent variable), however, labour positively and significantly causes capital at 5% level in equation 4. Hence, unidirectional causality from labour to capital; this implies increase in labour will require more capital.

Table 4.10: MWALD Test of Granger Causality for Equation 5

Dependent Variable: lnL_t		
Null Hypothesis	X^2 [MWALD]	Σ Lagged Independent Coefficient(s)
$lnM_t \not\subset lnL_t$	0.024 (0.878)	Σ Lagged lnM_t Coefficient = -0.002
$lnE_t \not\subset lnL_t$	1.528 (0.217)	Σ Lagged lnE_t Coefficient = -0.048
$lnK_t \not\subset lnL_t$	0.007 (0.932)	Σ Lagged lnK_t Coefficient = -0.001
All $\not\subset lnL_t$	1.988 (0.575)	Σ Lagged of all Independent Variable coefficients = -0.052

Note: ⊄ signifies the null hypothesis 'does not cause' X^2 and Σ represent chi-square statistics and 'summation of' respectively. 'All' denotes combine causality from all the regressors.

4.1.3 Forecast Error Variance Decomposition (FEVD)

Before conducting the FEVD, to avoid the possible problem of contemporaneous residual shocks, we undertook the residual correlation matrix among our variables to identify the level of correlation and order them as suggested by (Sims, 1980), starting with the most exogenous and end with the most endogenous, (Duasa, 2007)

Table 4.11 shows that variables lnE and InK are more correlated with 0.45, followed by lnL and lnK with 0.21. The remaining correlations are low, less than 0.2, hence cannot affect the result (Duasa, 2007). Variables with higher correlation are more endogenous, hence, the ordering of our variables in the FEVD is: lnM, lnL, lnK and lnE.

Table 4.11: Residual Correlation Matrix

	lnM	lnE	lnK	lnL
lnM	1			
lnE	0.04	1		
lnK	0.12	0.45	1	
lnL	0.07	0.01	0.21	1

We employed the cholesky factorization in the E-Views software and forecast the variables relationship up to 15 years into the future in order to provide a reasonable term policy insight. Table 4.12 reveals the 15 years forecast of the manufacturing output. In forecasting a variable, shocks in the residual of the forecasted variable contribute more to the variance than the shocks in other variables (Alami, 2001). Table 4.12 shows that shock in manufacturing output contribute more to its variance, from 100% in first year down to 47.5% in the last year of the forecast. It followed by electricity which contributes ranges from 11% in the second year up to 31% in the last 5years of the forecast. These followed by capital and then labour whose contributions decline from 5% at the early period to 4% at the half to the last period. The contribution of capital, like electricity, is an increasing contribution ranging from 7% in the fourth year to 17% in the 15th year. FEVD of lnM shows that more time into the future, electricity supply increasingly becomes a major determinant, among other variables apart from the manufacturing itself, in deciding the manufacturing sector's output.

Table 4.12: Variance Decomposition of lnM

% of Variance in ForecastinglnM Attributable to Innovation in: lnM, lnLlnK, lnE

Period	SE	lnM	lnL	lnK	lnE
1	0.223	100.000	0.000	0.000	0.000
2	0.301	85.362	1.533	1.854	11.252
3	0.357	66.175	5.462	4.984	23.380
4	0.385	59.672	5.886	7.465	26.975
5	0.409	56.144	5.389	10.489	27.978
6	0.432	53.085	4.923	13.269	28.722
7	0.448	50.706	4.639	15.057	29.598
8	0.458	49.209	4.467	16.049	30.276
9	0.464	48.387	4.361	16.589	30.662
10	0.467	47.948	4.307	16.875	30.870
11	0.469	47.710	4.283	17.010	30.998
12	0.470	47.580	4.274	17.062	31.084
13	0.471	47.512	4.272	17.075	31.141
14	0.471	47.477	4.274	17.074	31.175
15	0.471	47.459	4.276	17.069	31.196

Note: SE refers to the total variance error in forecasting lnM. Other columns represent the percentage of the variance attributable to shocks in the residual of the respective variables.

The result also reveals that capital becomes increasingly important in manufacturing as shocks in electricity become more influential in manufacturing. Interestingly, the relationship observed among these variables within the sample period also manifest into the future. In the forecast of lnL shown in table 4.13, it is obvious that apart from shocks in itself, none of the other variables contributes reasonably to its forecasting error variance. This futuristic relationship is apparently what was observed within the study's sample period as revealed by equation 5 for MWALD test respectively. The error variance in forecasting lnL is generally minimal and it contributes more that 70% to 80% of the variance, hence, shocks in the residuals of other variables do not have much effect on labour force.

Table 4.13: Variance Decomposition of lnL

% of Variance in ForecastinglnL Attributable to Innovation in: lnM, lnLlnK, lnE

Period	SE	lnM	lnL	lnK	lnE

1	0.020	1.454	98.546	0.000	0.000
2	0.021	1.236	92.622	1.750	4.392
3	0.023	1.277	90.983	3.467	4.273
4	0.024	1.176	87.513	7.342	3.969
5	0.024	1.120	84.515	10.603	3.762
6	0.025	1.341	82.529	12.489	3.640
7	0.025	2.026	81.192	13.092	3.691
8	0.025	2.955	79.937	13.045	4.063
9	0.025	3.893	78.576	12.823	4.708
10	0.025	4.746	77.100	12.666	5.486
11	0.026	5.476	75.580	12.656	6.288
12	0.026	6.051	74.141	12.770	7.039
13	0.026	6.468	72.901	12.945	7.687
14	0.026	6.752	71.916	13.126	8.206
15	0.027	6.942	71.179	13.281	8.598

Note: SE refers to the total variance error in forecasting lnL. Other columns represent the percentage of the variance attributable to shocks in the residual of the respective variables.

In table 4.14, shock in the residual of lnK contributes a larger percentage of its error variance which ranges from more than 70% at the last half of the forecast period. However, electricity has shown comparative influence on the variance percentage of 14% in the last 5 years of the forecast, followed by manufacturing which is around 10% in the same period. This shows that in future, like the period within the sample, electricity will be more influential on capital, followed by manufacturing. Thus, increase in electricity supply facilitates the use of capital by the manufacturing sector.

Table 4.14: Variance Decomposition of lnK

% of Variance in ForecastinglnK Attributable to Innovation in: lnM, lnLlnK, lnE					
Period	SE	lnM	lnL	lnK	lnE
1	0.211	0.561	3.351	96.088	0.000
2	0.347	4.274	2.050	85.220	8.456
3	0.381	3.813	2.083	83.948	10.156
4	0.390	4.760	2.025	82.934	10.281
5	0.396	6.834	2.072	80.951	10.142
6	0.402	8.179	2.411	78.582	10.828
7	0.408	8.956	2.673	76.664	11.707
8	0.414	9.532	2.765	75.251	12.452
9	0.419	9.959	2.776	74.180	13.085
10	0.424	10.206	2.762	73.415	13.617
11	0.427	10.317	2.741	72.928	14.014
12	0.429	10.362	2.721	72.645	14.272
13	0.430	10.383	2.707	72.484	14.427
14	0.431	10.394	2.699	72.390	14.517
15	0.431	10.400	2.697	72.334	14.569

Note: SE refers to the total variance error in forecasting lnK. Other columns represent the percentage of the variance attributable to shocks in the residual of the respective variables.

Table 4.15 presents the reverse of table 4.12, similar to equation 2 and 3 of MWALD test. It shows that compared to capital and labour, manufacturing contributes more of the error variance in forecasting lnE, it contributes more 20% from the 7th to the last year of the forecast. However, in table 4.12, the influence of electricity on manufacturing is more than that of manufacturing on electricity in the future. In the 7th year of the forecast, electricity contributes 29% of the manufacturing error variance and more than 30% in remaining years. The futuristic relationship between manufacturing and electricity is similar to what was obtained in the study's sample period; hence, there is consistency in this relationship which is favourable for policy implication.

Table 4.15: Variance Decomposition of lnE

% of Variance in ForecastinglnE Attributable to Innovation in: lnM, lnLlnK, lnE					
Period	SE	lnM	lnL	lnK	lnE
1	0.109	0.943	1.923	23.853	73.281

2	0.125	9.617	3.746	22.469	64.168
3	0.140	16.214	5.328	20.328	58.130
4	0.150	18.124	4.802	19.206	57.867
5	0.156	18.816	4.528	18.388	58.268
6	0.160	19.477	4.424	17.887	58.211
7	0.163	20.215	4.322	17.579	57.884
8	0.166	20.836	4.195	17.394	57.576
9	0.169	21.245	4.077	17.295	57.382
10	0.171	21.507	3.984	17.259	57.250
11	0.173	21.691	3.912	17.263	57.133
12	0.174	21.825	3.856	17.290	57.028
13	0.175	21.918	3.813	17.325	56.944
14	0.176	21.980	3.781	17.357	56.882
15	0.176	22.020	3.756	17.385	56.839

Note: SE refers to the total variance error in forecasting lnE. Other columns represent the percentage of the variance attributable to shocks in the residual of the respective variables.

Generally, the results from the Forecast Error Variance Decomposition (FEVD) show that the relationship that existed among our variables in the past will persist into the future for at least 15 years when the variables are given shocks. Improvement in electricity will therefore galvanize manufacturing activities and vise versa. If adequate measures are not taken to improve the electricity supply in the country, the situation in the manufacturing sector will get worsen and the visionary policies of the country that relate to production, employment and growth will be undermined and unachievable.

V. Conclusion

From the existing literatures, the necessity of electricity in promoting economic growth across the globe is undisputable. Though most of the literatures reviewed in this study relate to the relationship between electricity supply and economic growth, overwhelmingly, the literatures support positive relationship between electricity supply and economic growth. However, economic growth in toto reflects the summation of the performance of different sectors of the economy such as primary sector which involves the production of raw materials (example, agriculture), secondary sector which transforms raw materials into finished or intermediate goods (example, manufacturing) and tertiary sector which involves services, example banking and trading. The intensity for the need of electricity for effective performance by these different sectors differs. Hence the relevance of identifying the relationship between electricity supplies and different sectors of the economy for proper policy, particularly in the midst of shortage supply of electricity in the whole system.

The major findings of the study were in accordance with the apriori expectation based on the reviewed literatures. In the modern manufacturing process where heavy machines that require electricity are used, supply of electricity is expected to facilitate and increase the level of productivity. The MWALD test of granger causality shows that there exists bi-directional causality between electricity and manufacturing output. Electricity positively and significantly causes manufacturing at 5% level while manufacturing does at 10%. The positive sum of lagged coefficients of electricity is 1.082 and for manufacturing is 0.153. To depict the futuristic relationship, the Forecast Error Variance Decomposition (FEVD) of 15 years into the future shows that electricity supply influence on manufacturing ranges 11.252% in the second year to 31.196% in last year of the forecast, while the influence of manufacturing on electricity supply range between 0.943% to 22.020% in first and last year of the forecast respectively. Though both electricity and manufacturing influences each other in the future, the influence of electricity supply is comparatively greater, showing similar relationship that existed within the sample period.

Based on the outcome of this study, we empirically confirmed the existence of bi-directional causality between electricity and manufacturing sector in Nigeria. It shows interdependency between the manufacturing and electricity supply, with overwhelming dependency of manufacturing on electricity supply within the sample period andat least 15 years into the future. The study therefore identifies the long history of inadequate and unstable electricity supply in the country as one the major causes of the debilitating nature of the manufacturing sector. The growth of the Nigerian manufacturing industry is heavily anchored on adequate and stable electricity supply; because manufacturing output proves to be very responsive to changes in electricity supply. For the Nigerian manufacturing sector to serve as a catalyst for the transformation of the Nigerian economy, adequate and stable electricity supply must be a priority.

References

[1]. Adenikinju, A. F. (1998). Productivity growth and energy consumption in the Nigerian manufacturing sector: a panel data analysis. Energy Policy, 26(3), 199–205. http://doi.org/10.1016/S0301-4215(97)00098-0
[2]. Adenikinju, A. F. (2003). Electric infrastructure failures in Nigeria: a survey-based analysis of the costs and adjustment responses. Energy Policy, 31(14), 1519–1530. http://doi.org/10.1016/S0301-4215(02)00208-2
[3]. Akaike, H. A. I. (1974). A New Look at the Statistical Model Identification. IEEE TRANSACTIONS ON AUTOMATIC CONTROL, AC-19(6), 716–721.
[4]. Akinlo, A. E. (2008). Energy consumption and economic growth : Evidence from 11 Sub-Sahara African countries. Energy Economics, 30, 2391–2400. http://doi.org/10.1016/j.eneco.2008.01.008
[5]. Akinlo, A. E. (2009). Electricity consumption and economic growth in Nigeria: Evidence from cointegration and co-feature analysis. Journal of Policy Modeling, 31(5), 681–693. http://doi.org/10.1016/j.jpolmod.2009.03.004
[6]. Alam, M. S. (2006). Economic Growth with Energy. Munich Personal RePEc Archive (MPRA), (1260), 1–25.
[7]. Alami, T. H. (2001). Variance decomposition analysis of the demand for foreign money in Egypt. Journal of Economic Studies, 28(2), 122–135. http://doi.org/10.1108/EUM0000000005427
[8]. Apergis, N., & Payne, J. E. (2009). Energy consumption and economic growth: Evidence from the Commonwealth of Independent States. Energy Economics, 31(5), 641–647. http://doi.org/10.1016/j.eneco.2009.01.011
[9]. Beaudreau, B. C. (1995). The impact of electric power on productivity A study of US manufacturing 1950-84. Butterworth Heinemann, Energy Economics, 17(3), 231–236.
[10]. Beaudreau, B. C. (1998). ENERGY AND ORGANIZATION, Growth and Distribution Reexamined. Contribution and Economic History, No. 193, Greenwood Press, London.
[11]. Beaudreau, B. C. (2005a). Engineering and economic growth. Structural Change and Economic Dynamics, 16(2), 211–220. http://doi.org/10.1016/j.strueco.2004.05.001
[12]. Beaudreau, B. C. (2005b). Engineering and economic growth ☆. Structural Change and Economic Dynamics, 16(December 2001), 211–220. http://doi.org/10.1016/j.strueco.2004.05.001
[13]. Chandran, V. G. R., Sharma, S., & Madhavan, K. (2010). Electricity consumption–growth nexus: The case of Malaysia. Energy Policy, 38(1), 606–612. http://doi.org/10.1016/j.enpol.2009.10.013
[14]. Cobb, C. W., & Douglas, P. H. (1928). A Theory of Production. American Economic Association, 18(1), 139–165.
[15]. Dickey, D. A., & Fuller, W. A. (1979). Distribution of the Estimators for Autoregressive Time Series With a Unit Root. Journal of the American Statistical Association, 74(366), 427–431.
[16]. Dolado, J. J., & Lütkepohl, H. (1996). Making wald tests work for cointegrated VAR systems. Econometric Reviews, 15(4), 369–386. http://doi.org/10.1080/07474939608800362
[17]. Duasa, J. (2007). Determinants of Malaysian Trade Balance: An ARDL Bound Testing Approach. Global Economic Review, 36(1), 89–102. http://doi.org/10.1080/12265080701217405
[18]. Enang, B. (2010). Industrial Development , Electricity Crisis and Economic Performance in Nigeria. European Journal of Economics, Finance and Administrative Sciiences, 18(18), 106 – 121.
[19]. Enang, B. (2011). Energy Crises , Stabilization Policies and Economic Performance in Nigeria : An Empirical Investigation. Interdisciplinary Journal of Research in Business, 1(9), 27–37.
[20]. Engle, R. F., & Granger, C. W. J. (1987). Co-Integration and Error Correction : Representation , Estimation , and Testing. Econometrica, 55(2), 251–276.
[21]. Ferguson, R., Wilkinson, W., & Hill, R. (2000). Electricity use and economic development. Energy Policy, 28(13), 923–934. http://doi.org/10.1016/S0301-4215(00)00081-1
[22]. Ghali, K. H., & El-Sakka, M. I. T. (2004). Energy use and output growth in Canada : a multivariate cointegration analysis. Energy Economics, 26, 225–238. http://doi.org/10.1016/S0140-9883
[23]. Granger, C. . . . . (1969). Investigating Causal Relations by Econometric Models and Cross-spectral Methods. Econometrica, 37(3), 424–438.
[24]. Hannan, E. J., & Quinn, B. G. (1979). The Determination of the Order of an Autoregression. Journal of the Royal Statistical Society , Soc. B, 41(2), 190–195.
[25]. Johansen, S. (1995). LIKELIHOOD-BASED INFERENCE IN COINTEGRATED VECTOR by Søren Johansen. Econometric Theory, 14, 517–524.
[26]. Johansen, S., & Juselius, K. (1990). MAXIMUM LIKELIHOOD ESTIMATION AND INFERENCE ON COINTEGRATION - WITH. Oxford Bulletin of Economics and Statistics, 2(52), 169 – 209.
[27]. Johansen, S., & Juselius, K. (1992). Testing structural hypotheses in a multivariate cointegration analysis of the PPP and the UIP for UK. Journal of Econometrics, 53(1-3), 211–244. http://doi.org/10.1016/0304-4076(92)90086-7
[28]. Kouakou, A. K. (2011). Economic growth and electricity consumption in Cote d'Ivoire: Evidence from time series analysis. Energy Policy, 39(6), 3638–3644. http://doi.org/10.1016/j.enpol.2011.03.069
[29]. Kwiatkowski, D., Phillips, P. C. B., Sshmidt, P., & Shin, Y. (1992). Testing the null hypothesis of stationarity against the alternative of a unit root How sure are we that economic time series have a unit root ?*. Journal of Econometrics, 54, 159–178.
[30]. Lee, C. (2005). Energy consumption and GDP in developing countries : A cointegrated panel analysis. Energy Economics, 27, 415–427. http://doi.org/10.1016/j.eneco.2005.03.003
[31]. Lütkepohl, H. (2005). New introduction to multiple time series analysis.Medical care (Vol. 31). Springler Berlin Heideberg, New York.
[32]. Odularu, G., & Okonkwo, C. (2009). Does energy consumption contribute to economic performance in Nigeria. East-West Journal of Economics and Business, XII(2), 43 – 79.
[33]. Okonjo-Iweala, N., & Osafo-kwaako, P. (2007). Nigeria ' s Economic Reforms Progress and Challenges Ngozi Okonjo-Iweala N igeria ' s E conomic R eforms : The Brooking Institution, 1775 Massachusetts Ave, NW Washington, DC 20036.
[34]. Paul, S., & Bhattacharya, R. N. (2004). Causality between energy consumption and economic growth in India: a note on conflicting results. Energy Economics, 26(6), 977–983. http://doi.org/10.1016/j.eneco.2004.07.002
[35]. Pesaran, M. H., Shin, Y., & Smith, R. J. (2001). Bounds testing approaches to the analysis of level relationships. Journal of Applied Econometrics, 16(3), 289–326. http://doi.org/10.1002/jae.616
[36]. Phillips, P. C. B., & Perron, P. (1988). Testing for a Unit Root in Time Series Regression. Biometrika, 75(2), 335. http://doi.org/10.2307/2336182
[37]. Reimers, H. (1992). Comparisons of tests for multivariate cointegration. Statistical Papers, 359, 335–359.
[38]. Riker, D. (2011). Electricity Efficiency and U.S. Manufacturing Exports. The Electricity Journal, Elsevier, 25(1), 84 – 92.
[39]. Sargent, J. T., & Sims, A. C. (1977). Business Cycle Modelling Without Pretending to Have Too Much A Priori Economic Theory.

Seminar Paper on New Business Cycle Research.
[40]. Schwarz, G. (1978). Estimating the Dimension of a Model. JSTOR, 6(2), 461–464.
[41]. Shahbaz, M., & Lean, H. H. (2012). The dynamics of electricity consumption and economic growth: A revisit study of their causality in Pakistan. Energy, 39(1), 146–153. http://doi.org/10.1016/j.energy.2012.01.048
[42]. Sims, C. A. (1980). COMPARISON OF INTERWAR AND POSTWAR CYCLES : Monetarism Reconsidered, (1430).
[43]. Sims, C. A., Stock, J. H., & Watson, M. W. (1990). Inference in Linear Time Series Models with some Unit Roots. Econometrica, 58(1), 113–144.
[44]. Sj, B. (2008). Testing for Unit Roots and Cointegration Testing for Unit Roots and Cointegration, (2).
[45]. Soytas, U., & Sari, R. (2007). The relationship between energy and production: Evidence from Turkish manufacturing industry. Energy Economics, 29(6), 1151–1165. http://doi.org/10.1016/j.eneco.2006.05.019
[46]. Squalli, J. (2007). Electricity consumption and economic growth: Bounds and causality analyses of OPEC members. Energy Economics, 29(6), 1192–1205. http://doi.org/10.1016/j.eneco.2006.10.001
[47]. Tang, C. F. (2008). A re-examination of the relationship between electricity consumption and economic growth in Malaysia. Energy Policy, 36(8), 3077–3085. http://doi.org/10.1016/j.enpol.2008.04.026
[48]. Toda, H. Y., & Phillips, P. C. B. (1993). The spurious effect of unit roots on vector autoregressions An analytical study. Journal of Econometrics, 59, 229–255.
[49]. Toda, H. Y., & Yamamoto, T. (1995). Statistical Inference in Vector Autoregression with Possible Integrated Processes. Journal of Econometrics, 66, 225–250.
[50]. Welle-Strand, A., Ball, G., Hval, M. V., & Vlaicu, M. (2012). Electrifying solutions: Can power sector aid boost economic growth and development? Energy for Sustainable Development, 16(1), 26–34. http://doi.org/10.1016/j.esd.2011.11.001
[51]. Wolde-Rufael, Y. (2004). Disaggregated industrial energy consumption and GDP: the case of Shanghai, 1952–1999. Energy Economics, 26(1), 69–75. http://doi.org/10.1016/S0140-9883(03)00032-X
[52]. Wolde-Rufael, Y. (2006). Electricity consumption and economic growth: a time series experience for 17 African countries. Energy Policy, 34(10), 1106–1114. http://doi.org/10.1016/j.enpol.2004.10.008
[53]. Wolde-rufael, Y. (2009). Energy consumption and economic growth : The experience of African countries revisited. Energy Economics, 31(2), 217–224. http://doi.org/10.1016/j.eneco.2008.11.005
[54]. Wolde-Rufael, Y. (2010). Bounds test approach to cointegration and causality between nuclear energy consumption and economic growth in India. Energy Policy, 38(1), 52–58. http://doi.org/10.1016/j.enpol.2009.08.053
[55]. Wolde-rufael, Y. (2010). Bounds test approach to cointegration and causality between nuclear energy consumption and economic growth in India. Energy Policy, 38(1), 52–58. http://doi.org/10.1016/j.enpol.2009.08.053
[56]. Yakubu, Y. (2015). Banking Consolidation and Economic Growth in Nigeria: Dynamic Chain Transmission Evidence. IOSR Journal Of Humanities And Social Science Ver. IV, 20(5), 27–33. http://doi.org/10.9790/0837-20542733
[57]. Yakubu, Y., Manu, S. B., Bala, U., Campus, B., State, B., & Ehsan, S. D. (2015). Electricity Supply and Manufacturing Output in Nigeria : Autoregressive Distributed Lag (ARDL) Bound Testing Approach. Journal of Economics and Sustainable Development, 6(17), 7–20.
[58]. Yoo, S.-H., & Kwak, S.-Y. (2010). Electricity consumption and economic growth in seven South American countries. Energy Policy, 38(1), 181–188. http://doi.org/10.1016/j.enpol.2009.09.003
[59]. Yuan, J., Zhao, C., Yu, S., & Hu, Z. (2007). Electricity consumption and economic growth in China: Cointegration and co-feature analysis. Energy Economics, 29(6), 1179–1191. http://doi.org/10.1016/j.eneco.2006.09.005
[60]. Yuan, J.-H., Kang, J.-G., Zhao, C.-H., & Hu, Z.-G. (2008). Energy consumption and economic growth: Evidence from China at both aggregated and disaggregated levels. Energy Economics, 30(6), 3077–3094. http://doi.org/10.1016/j.eneco.2008.03.007