DOI: 10.20472/EFC.2025.027.003

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ENERGY EFFICIENCY AND ECONOMIC GROWTH IN NIGERIA: A LONG-RUN PERSPECTIVE

Abstract:

This study investigates the relationship between energy efficiency and economic growth in Nigeria using time series data from 1980 to 2023 and the Stochastic Frontier Analysis framework. Results reveal that Nigeria's energy demand is both price-elastic and income-elastic, indicating that changes in energy prices and income significantly influence consumption. Labour and capital act as substitutes for energy, while technological innovation boosts productivity but increases energy demand. The estimated average technical efficiency is relatively high at 95%, though marked by volatility and structural disparities across sectors. These findings highlight the critical role of policy consistency, reliable energy supply, and targeted investment in modern technologies to enhance efficiency and align Nigeria's growth with sustainable development goals.

Keywords:

Energy Efficiency, Economic Growth, Stochastic frontier analysis, Nigeria

JEL Classification: Q40, Q56, C32

 ISBN 978-80-7668-023-4, IISES

1. Introduction

Energy serves as a vital input across virtually all sectors of the economy. As economic activity expands, energy demand typically increases. Nonetheless, improvements in energy efficiency are essential, as they make it possible to produce more output with less energy, thereby progressively reducing the direct link between economic growth and energy consumption. (IEA, 2025). Huang et al. (2023) emphasized that improving energy efficiency can significantly minimize resource wastage, ease tensions arising from resource allocation, and promote sustainable socio-economic development. However, with the growing concerns over climate change, the interrelationship between energy, economic growth, and environmental sustainability has garnered increasing attention over the past two decades. Although, Shobande et al. (2023) emphasized the significance of renewable energy development in mitigating carbon emissions. Similarly, Wan (2022), revealed that clean energy contributes more substantially to green economic development compared to other energy sources. It is believed that, increasing energy efficiency can improve competitiveness at both the firm level by reducing costs, improving operations and increasing product value and at the country level, by reducing the amount of energy required to produce economic output. (IEA, 2025). Sound indicators of energy demand price and income elasticities in addition to sound indicators of energy efficiency is critical to designing and implementing effective energy policy instruments to promote an efficient and parsimonious utilization of energy. Energy efficiency policies play a significant role in achieving energy-policy goals such as reduction of energy bill, dealing with climate change, ensuring efficiency of supply and enhancing access to clean energy (IEA, 2016). Energy efficiency can be identified as an act of using less amount of energy to produce same number of outputs (Patterson, 1996). Energy efficiency has proven to have multiple benefits and co-benefits in different sectors across the economies. This can be validated with the findings of International Energy Agency (IEA) on the benefits and co-benefits of energy efficiency on the public budget, community health and well-being, the industrial sector and energy delivery such as reduced greenhouse gas emissions, making energy services affordable, reduction in spending on energy infrastructure, stabilizing energy poverty and hence supporting economic growth and development (IEA, 2014). However, energy efficiency is a contemporary element of limiting global warming to below 2^{o}C through emission reduction policy as stated in the Paris agreement (IEA, 2016).

Nigeria offers a strong context for exploring the link between energy efficiency and economic growth. In 2024, it remained one of Africa's largest economies, recording a GDP of about $477 billion. In the fourth quarter, the services sector dominated output, contributing approximately 57.38% of GDP, buoyed by trade, information and communication, financial services, and real estate. Agriculture held its position as the second-largest sector, accounting for around 25% of GDP, while industry contributed roughly 17%, driven by manufacturing, mining, and construction, though hampered by elevated production costs and exchange rate volatility. This sectoral composition underscores the central role of services in Nigeria's economy, with agriculture and industry maintaining significant yet comparatively smaller shares (CBN, 2024). Despite its strategic importance, the relationship between energy efficiency and economic growth remains underexplored in the Nigerian context using parametric frontier analysis.

Although research on the link between energy efficiency and economic growth is expanding, the majority of empirical investigations have been conducted in developed economies, where wealth, demographic stability, and continuous improvements in energy efficiency (EE) create conditions that differ significantly from those in developing nations. By contrast, relatively few studies have examined the context of developing countries (e.g., Hunt & Kipouros, 2023; Adom et al., 2021; Ohene-Asare et al., 2020). These countries are often marked by high poverty levels, rapid population growth, and limited access to modern energy. Such conditions restrict their ability to adopt advanced technologies or implement energy-saving measures. As noted by Simcock et al. (2017), in settings where poverty and income inequality are prevalent, the capacity to invest in EE is constrained, with the high initial costs of energy-efficient equipment posing a major barrier for low-income households. This imbalance in research focus is significant for Africa, where strong economic growth is essential to achieving Sustainable Development Goal 8 (SDG8), yet the continent continues to experience rising energy consumption, largely from non-renewable sources (Ohene-Asare et al., 2020). Moreover, the existing literature on the macroeconomic effects of energy efficiency (EE) in Africa remains limited, particularly in the post-SDGs era, leaving unanswered the question of whether improvements in EE generate positive synergies with economic growth in the region (Adom et al., 2021; Ohene-Asare et al., 2020). These gaps underscore the need for region-specific empirical studies that account for Africa's socio-economic realities, structural barriers, and post-SDGs policy context when assessing the economic impacts of EE.

Given that, this study aims to investigates the energy efficiency and economic growth nexus in Nigeria using time series data and modern econometric techniques. Unlike traditional methods that measure energy efficiency through energy intensity (energy consumption per unit of GDP), this research employs the frontier-based measure which integrates economic theory into the estimation of energy efficiency. Additionally, it addresses endogeneity concerns due to reverse causality between energy efficiency and economic growth, providing insights into policy formulation for sustainable economic growth and development.

2. Literature Review

2.1 Theoretical Framework

Empirical evidence on the growth effect of energy efficiency (EE) primarily addresses whether environmental protection measures, including EE improvements, hinder or enhance economic growth. Such insights are critical for policymakers, particularly in Africa, where energy policies must balance economic growth imperatives with environmental sustainability. Africa's growing energy demand, especially from non-renewable sources poses significant environmental challenges (Ohene-Asare et al., 2020). Consequently, EE measures are indispensable for achieving sustainable economic growth while mitigating environmental degradation. Moreover, understanding the growth effects of EE can enable policymakers to better evaluate the benefits and costs of adopting EE measures.

Theoretical foundations linking EE to economic growth are rooted in classical, neoclassical, endogenous growth, new endogenous growth, and catch-up theories of economic growth. These theories emphasize technological progress as a fundamental driver of output expansion and economic growth (Lakhera, 2016). Lipsey et al. (2005) concluded that general-purpose technologies, including those related to energy production, transmission, and utilization, account for a significant share of economic growth. Similarly, Ayres and Warr (2009) argue that technological advancements enhance input quality, reduce costs, and maximize output. Since energy is a critical input in the production process, technological innovation in energy systems can improve energy efficiency, lower energy costs, and reallocate resources to other productive inputs, thus driving economic growth.

However, conventional growth theories, such as the neoclassical and endogenous growth models, often downplay the role of EE as a significant driver of economic growth. According to this view, the cost of energy constitutes a minor share of total production costs, limiting the potential impact of EE improvements on overall economic growth (Sorrell, 2009). One explanation for this perspective is that traditional growth theories did not explicitly consider energy as an essential input in production. This view began to shift following the energy crises of the 1970s, which underscored the importance of energy inputs in economic systems (Adom et al., 2021).

Smulders and de Nooij (2003) developed a theoretical model linking energy conservation policies to economic growth. Their findings indicate that energy conservation policies may reduce per capita income. However, reductions in energy inputs when coupled with induced technical change can foster advancements in energy-related technologies, partially offsetting the costs of energy conservation measures. Despite this, induced technical innovation is unlikely to create the "win-win" scenario hypothesized by Porter and van der Linde (1995), who suggested that well-designed environmental policies, including EE measures, can simultaneously enhance productivity, competitiveness, profits, and economic growth.

In contrast to the conventional view, the ecological economics perspective highlights the significant role of high-quality energy inputs in driving economic growth over the past two decades (Compton, 2011). Ayres and Warr (2009) assert that improvements in EE have been among the primary drivers of economic growth since the Industrial Revolution. These perspectives align with the Porter and van der Linde (1995) hypothesis, suggesting that environmental policies fostering EE can drive innovation and sustainable growth.

While traditional growth theories often underestimate the role of EE, contemporary research and ecological economics perspectives underscore its critical importance. EE improvements not only contribute to cost reductions and productivity gains but also serve as a cornerstone for sustainable economic growth and development in an energy-intensive world.

2.2 Empirical Review

The relationship between energy efficiency (EE) and economic growth has attracted considerable attention in empirical literature, owing to its implications for sustainable development. This review synthesizes the existing empirical studies, focusing on the effects of EE on economic growth.

Empirical evidence from developed economies indicates a generally positive relationship between EE and economic growth. Rajbhandari and Zhang (2018) found that reducing energy intensity, which signifies improvements in EE, is positively associated with long-run economic growth in high-income countries. Bataille and Melton (2017) demonstrated that improvements in total EE contributed to a 2% increase in GDP in Canada. These findings align with the broader theoretical framework that technological advancements in energy production, transmission, and utilization enhance productivity, which in turn spurs economic growth (Ayres & Warr, 2009; Porter & van der Linde, 1995). In developed economies, there has been a noticeable decoupling of economic growth from environmental degradation, facilitated by technological innovation, sound policy frameworks, and significant investments in clean energy (Razzaq et al., 2021; Marques et al., 2019). These economies exemplify how EE improvements can simultaneously promote economic growth and environmental sustainability.

The evidence regarding the impact of EE on economic growth in developing economies presents a more complex and sometimes contradictory picture. Studies such as Dahmani et al. (2023), Akram et al. (2021) and Ohene-Asare et al. (2020) have reported positive effects of EE on economic growth, with the latter focusing on 46 African countries. Adom, et al., (2021), in their dynamic panel threshold regression analysis of 40 sub-Saharan African countries from 2000 to 2016, found that EE positively influences growth, but the benefits are more pronounced in low-inequality economies, suggesting that socio-economic conditions significantly moderate the EE–growth relationship. Zhang and Guo (2023) also, found that the action mechanism of energy efficiency can be either inhibited or amplified by various socio-economic factors, including the level of industrial structure, urbanization, and technological advancement. Consequently, examining the influence of energy efficiency improvements on green economic growth has become an urgent research priority. Similarly, Hunt and Kipouros (2023), using stochastic frontier analysis for 39 developing countries over 1989-2008, demonstrated that “true” EE varies significantly across countries and that relying solely on energy intensity as a proxy can mislead policy, particularly in contexts where structural and technological barriers limit genuine efficiency gains.

However, other studies, including Pan et al. (2019) and Mahmood and Kanwal (2017), found no significant impact of EE on economic growth in developing countries. Several factors contribute to these mixed findings. First, in developing economies, substantial energy inputs are required to meet developmental goals, which can make EE measures appear more like constraints than opportunities for growth. Dercon (2014) argues that environmentally friendly growth policies, such as EE improvements, may threaten rather than promote growth in these economies. Second, the rebound effect where energy cost savings from EE improvements lead to increased energy consumption and emissions has been identified as a major factor that can offset the gains from EE. Khazzoom (1980) critiqued the notion that EE improvements reduce pollution, pointing out that energy savings could lead to higher energy demand and thus increased emissions. This rebound effect is particularly evident in energy-intensive sectors such as food processing and manufacturing in developing economies (Fayiya et al., 2018; Conti et al., 2016). Lastly, in many developing economies such as Nigeria, high energy costs disproportionately burden the poor, which means that EE improvements can lead to significant cost savings that might free up resources for other productive activities. However, if these activities are energy-intensive, they could inadvertently lead to higher energy consumption and pollution, exacerbating the rebound effect (Adom & Adams, 2020).

A major challenge in the literature on EE and economic growth lies in the measurement of EE. Energy intensity, defined as energy consumption per unit of GDP, is the most commonly used proxy for EE such as (Ishola, 2025). However, this measure has been criticized for conflating the effects of technological progress with structural and environmental factors, such as changes in energy prices, population density, and economic structure (Adom et al., 2021; Hunt & Kipouros, 2023). Thus, interpreting lower energy intensity as an improvement in EE may not always reflect technological advancements. Alternative measures, such as total factor energy efficiency and thermodynamic efficiency, have been employed in some studies, offering more nuanced insights into the relationship between EE and economic growth. Nevertheless, these measures are often limited in their ability to provide precise estimates (Heun & Brockway, 2019; Pan et al., 2019).

A significant advancement in the literature is the application of stochastic frontier analysis (SFA) to estimate energy efficiency (EE), as Proposed by Filippini and Hunt (2015). Afolabi et. al (2025); Ohene-Asare et al. (2020); (Adom et al., 2021) extended this approach by using SFA to estimate total factor EE, yielding a more precise measure of efficiency. This methodology enables the decomposition of EE into transient and persistent components, effectively addressing endogeneity issues and offering more reliable estimates of the relationship between EE and economic growth.

3. Methodology

3.1 Data Sources and Variables Justification

This study adopts a Stochastic Frontier Analysis (SFA) framework to evaluate the relationship between energy efficiency and economic growth in Nigeria using annual time series data from 1980 to 2023. SFA is employed to measure energy efficiency as a deviation from an efficient energy demand frontier, accounting for inefficiencies and random noise. This section outlines the model specification, data sources, and estimation techniques. The data on GDP per capita, energy consumption, energy prices and capital were sourced from the World Bank's World Development indicators (WDI), while data on

 ISBN 978-80-7668-023-4, IISES

technological innovation was sourced from the Organization of Economic Corporation and Development (OECD). The Inclusion of capital (Gross fixed capital formation) and technological innovation into the energy efficiency model using SFA is essential in order to produce accurate and meaningful results. For instance, capital is a fundamental input in the production process, along with labor and energy, influencing the production frontier by accounting for output variations arising from differences in machinery, infrastructure, or fixed assets (some firms use capital-intensive technologies that reduce energy needs, while others rely on outdated equipment that consumes more energy). Hence, excluding capital may lead to omitted variable bias, where the model may incorrectly attributes output contribution of capital to energy input, thereby distorting the measurement of energy efficiency (Otsuka & Goto, 2015). Thus, without controlling for capital, these dynamics would be misrepresented. In the same vein, technological progress plays a critical role in improving energy efficiency over time.

New technologies often reduce the energy intensity required in the production process through process optimization or introduction of more efficient machinery. If technological progress is not included in the model through patent counts, it may be wrongly interpreted as improved efficiency. In time series data analysis, failing to account for innovation trends can conflate genuine efficiency improvements with systemic technological change. Including innovation variables helps isolate true operational inefficiency from advancements due to external progress (Shen & Lin, 2017). Therefore, controlling for both capital and technological innovation ensures that the inefficiency term in the SFA model accurately reflects real energy inefficiency and no other factors. This leads to a clearer, more policy-relevant understanding of how efficiently energy is used in production. Moreover, the determination of the sample is solely based on data accessibility, suitability, model specifications, and making key policy suggestions for the growth of Nigerian economy.

3.2 Data and Description of Dataset

The analysis uses annual time series data from 1981 to 2023, sourced from the following databases:

Variables	**Abbre viation**	**Description**	**Measurement**
GDP per capita	GDPP	GDP per capita is gross domestic product divided by midyear population sourced the World Development Indicators (WDI)	constant 2015 US$
Energy consumption	ENC	Total primary energy consumption from the International Energy Agency (IEA) and Energy Commission of Nigeria	Measured in kilogram of oil equivalent

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Capital	CAP	Gross fixed capital formation Sourced from the Central Bank of Nigeria (CBN) Statistical Bulletin	measured in local currency equivalent (NBillion).
Energy Prices	ENP	Real energy prices (oil, gas, or electricity prices) from the Nigerian Bureau of Statistics.	Measured in Local currency
Labour force	LAB	Labor force participation rate representing the proportion of the population ages 15-64 who supply labor for the production of goods and services during a specified period sourced from WDI	Measured as a % of total population (aged 15-64)
Technological Innovation	TEI	Technological Innovation is expressed as a percentage of all technologies, including those that are relevant to the environment Sourced from the OECD	expressed as a percentage of all technologies.

Source: Authors' Compilation

3.3 Model Specification

Following the approach introduced by Filippini and Hunt (2015), to explore the relationship between energy efficiency and economic growth, we specify an energy demand frontier model based on the stochastic frontier framework. The model assumes that energy consumption (E_t) depends on economic output (Y_t), energy prices (P_t), and other control variables, with inefficiency incorporated into the error term. The functional form is expressed as:

$$lnENC_t = \alpha + \beta_1 lnGDPP_t + \beta_2 lnENP_t + \beta_3 lnCAP_t + lnLAB + lnTEI + \varepsilon_t \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots . (1)$$

Where:

E_t: Total energy consumption (in BTUs or equivalent energy units).

Y_t: Real GDP (constant 2010 USD, proxy for economic output).

P_t: Real energy prices (deflated to 2010 USD).

K_t: Capital stock or other control variable proxies (e.g., labor or structural variables).

$\varepsilon_t = v_t + u_t$: Composite error term.

V_t: Symmetric random noise ($v_t \sim N(0, \sigma_v^2)$)

u_t: Non-negative inefficiency term $u_t \sim |N(0, \sigma_u^2)|$)

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3.4 Energy efficiency analysis

Measurement of energy efficiency indicators has become an essential component of energy strategy across the globe. Thus, in order to bypass the fundamental difficulties associated with defining and measuring energy efficiency along with the issues arising from the utilization of simple ratio indicators such as the energy intensity as a proxy of energy efficiency, some approaches have been proposed in the energy economics literature. Such approaches include non-Frontier approach, such as the Index Decomposition Analysis (IDA) and the Frontier Analysis. Figure 1 presents the approaches been used in the literature for the analysis of energy efficiency.

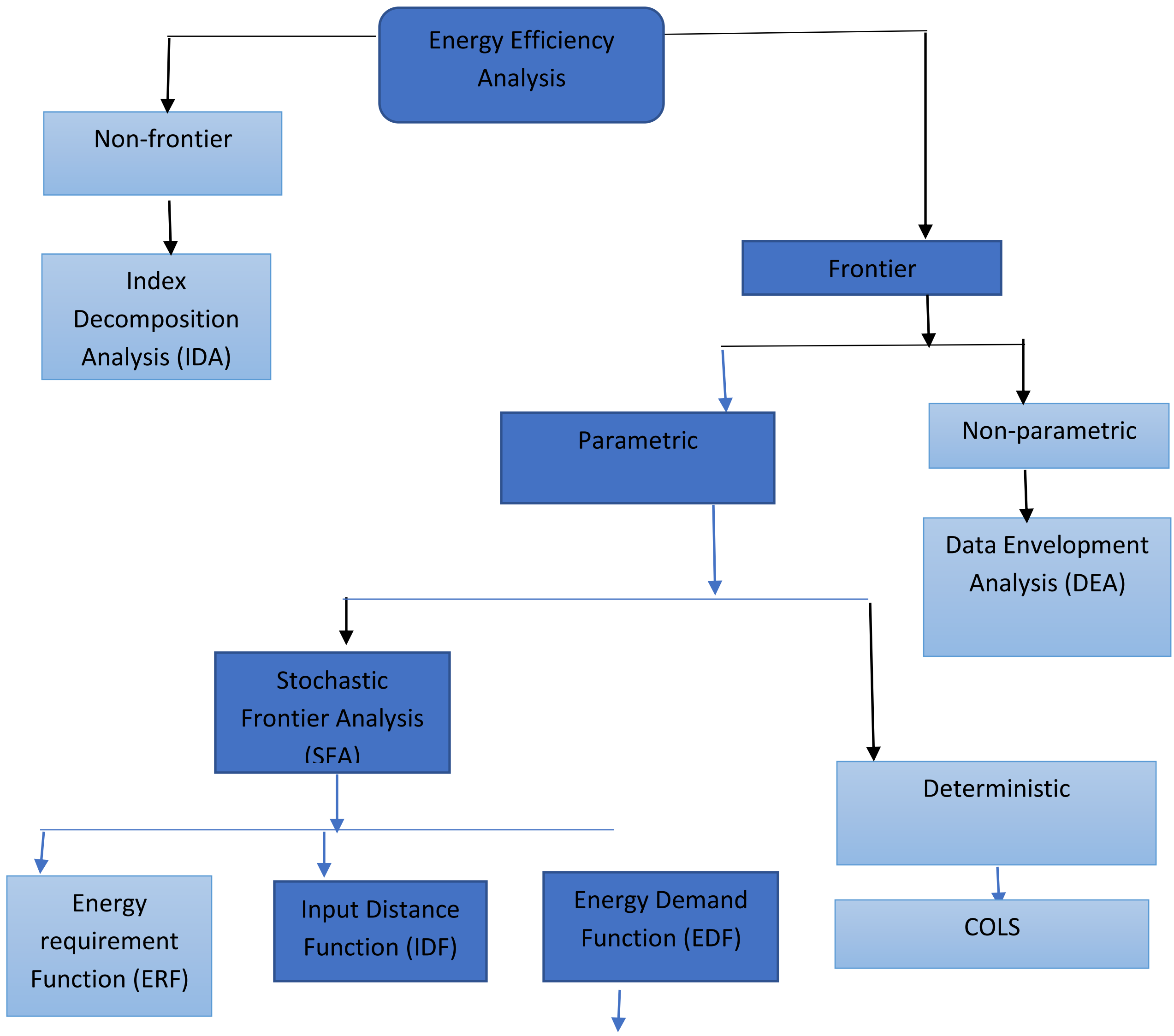

Figure 1: Energy Efficiency Approaches
Source: Authors' Compilation based on Filippini and Hunt (2015)

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IDA, initially proposed by Myers and Nakamura (1978) is a non-Frontier used to create energy efficiency indicators that disentangles energy intensity into changes in energy efficiency and none efficiency factors such as the structure of economy and fuel mix and is also widely used in both energy and environmental economics. Stochastic Frontier Analysis (SFA) was first developed by Aigner et al. (1977), and the concept gained more traction in Energy economic literature as the best tool to quantify the efficiency in the use of energy as an input in the process of production. It is essential to understand that demand for energy is a derived demand arising from the demand for energy services such as heating, cooling, lighting, motion etc. Hence, energy along with labour and capital are regarded as inputs in the production of several outputs.

Energy efficiency (EE_t) is derived from the inefficiency term (u_t) as follows:

$$EE_{it} = \exp(-u_{it}) \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots (2)$$

This efficiency score ranges between 0 and 1, where a value closer to 1 indicates higher energy efficiency, and lower values signify greater inefficiencies in energy utilization.

3.5 Estimation Procedure

The methodology involves the following steps:

3.5.1 Stationarity Testing

The stationarity of variables is tested using the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests. Non-stationary variables are transformed through first differencing or detrending. Co-integration analysis is employed if the variables are integrated of the same order.

3.5.2 Energy Demand Function

Filippini and Hunt (2015) empirically proved that energy intensity is very poor proxy for energy efficiency according to their measures, arguing that efficiency measurements from the estimation of an energy demand function is more appropriate measurement of energy efficiency. Though SFA has gained popularity in energy literature, its adoption to assess energy efficiency in developing countries like Nigeria are extremely scarce. Therefore, this study focuses on the frontier analysis to measure energy efficiency in Nigeria where it appears that non-frontier analysis is mostly used in the literature. Furthermore, the use of this approach allows for the estimation of the persistent and the transient energy efficiency simultaneously which is very crucial from policy perspective as different sources of inefficiency requires completely different strategies and instrument to be applied by policy makers to deal with (Hanley et al., 2009). Maximum Likelihood Estimation (MLE) is applied to estimate the parameters of the stochastic frontier model. The log-likelihood function combines the distributions of v_t and u_t, allowing decomposition of the error term.

Efficiency Analysis: The inefficiency term (u_t) is extracted to calculate energy efficiency scores for each year. Trends in efficiency are analyzed to assess improvements or deteriorations over time.

3.5.3 Diagnostic Tests and Robustness Checks

To ensure model reliability, the Likelihood Ratio Test will be employed to confirms the significance of the inefficiency term (u_t) in the model. Skewness test will also be used to verifies the asymmetry of the residuals to support the presence of inefficiency. Model Selection Criteria: Akaike Information Criterion (AIC) and Schwarz Bayesian Criterion (SBC) guide optimal lag length and model choice.

4. Results and Discussions

4.1 Summary Statistics

Table 2 presents the detailed summary statistics of the study variables. As displayed, ENP and GDPP are negatively skewed. Additionally, the mean and median values are approximately the same for GDPP, LAB, and TEI. However, the volatility in the variables as portrayed by the standard deviation is higher for GDPP and ENC, while the other variables are less volatile. The Jarque-Bera statistics indicated that all the variables are normally distributed except for ENP and CAP. Similarly, the results of the correlation matrix are presented in the lower part of Table 2, revealing that explanatory variables are weakly correlated.

Table 2: Descriptive Statistics

	ENC	ENP	CAP	GDPP	LAB	TEI
Mean	303.5558	-0.073931	12190.12	1967.899	82.99553	1.536987
Median	299.1560	0.241169	7266.445	1984.996	82.86500	1.156250
Maximum	376.0699	1.481544	65227.13	2585.734	84.30100	4.250000
Minimum	256.9182	-4.395345	285.5900	1390.469	81.74200	0.000000
Std. Dev.	31.22370	1.384459	1.623100	44.54054	0.962346	1.228050
Skewness	0.451956	-1.396996	2.073635	-0.057905	0.152179	0.665738
Kurtosis	2.293104	4.868534	6.551323	1.343520	1.350103	2.496611
Jarque-Bera	1.755679	15.06375	39.74899	3.676450	3.753058	2.701634
Probability	0.415680	0.000536	0.000000	0.159100	0.153121	0.259029

Correlation matrix

ENC	1.000000					
ENP	0.471032	1.000000				
CAP	0.480680	0.604760	1.000000			
GDPP	0.773433	0.783426	0.614196	1.000000		
LAB	-0.762400	-0.793842	-0.609061	-0.998319	1.000000	
TEI	0.221929	0.125400	0.427248	0.139407	-0.145582	1.000000

Source: Authors' computation

4.2. Results of unit root tests

Table 3 portrays the results of the ADF and PP unit root tests. From the outcome, all the variables were non-stationary at their level value except for ENC and TEI, but the remaining variables became stationary after differencing once.

Table 3 Results of unit root tests

Variables	ADF	PP	ADF	PP	Decision
lnENC	-1.687594	1.612711	-	--	
	(0.7387)	(0.7706)	-	-	I(0)
lnENP	-6.075810	-10.59101	-7.741259	-7.741259	
	(0.0001)	(0.0000)	(0.0000)	(0.0000)	I(1)
lnGDPP	-1.935397	-3.160097	-4.138828	-4.005799	
	(0.6166)	(0.1061)	(0.0115)	(0.0160)	I(1)
lnCAP	-1.754054	-2.257248	-4.257517	-4.269077	
	(0.7089)	(0.4470)	(0.0086)	(0.0083)	(I1)
LAB	0.085490	-0.239118	-5.169338	-5.209427	
	(0.9958)	(0.9893)	(0.0010)	(0.0009)	I(1)
TEI	-5.506018	-5.523060	-	-26.36250	
	(0.0003)	(0.0003)	-	(0.0000)	I(0)

Source: Authors' computation

4.3 Results of Frontier Production Functions

Table 4 Shows the estimation results of our preferred stochastic frontier energy demand models. The estimated OLS coefficients are only of significant value, but they provide a starting point for the Maximum Likelihood Estimation (MLE) process.

Table 4. Estimation Results of Frontier Production Functions

Variables	OLS	Maximum Likelihood Estimation (MLE) Results		
		Half-Normal	Exponential	Truncated Normal
LENP	-0.025806	-.0154494	-0.010511	-0.010898
	(0.6141)	(0.025)*	(0.0342)*	(0.2364)
LAB	-0.282040	-.0104162	-0.085903	-0.081539
	(0.7748)	(0.000)*	(0.0000)*	(0.0010)*
LCAP	-0.065913	-.0102667	-0.003714	-0.019782
	(0.4590)	(0.475)	(0.8439)	(0.5815)
LGDPP	-0.811046	0.4417898	0.017016	0.016343
	(0.8353)	(0.000)*	(0.0324)*	(0.8630)
TEI	0.014052	0018898	0.212806	0.237349
	(0.2633)	(0.799)	(0.0000)*	(0.0000)*
C	35.48479	.380114	-0.108920	-0.119459
	(0.7494)	(0.000)*	(0.0000)*	(0.0066)*
λ		2.478841		
$\sigma^2 V$		-7.017923		
$\sigma^2 U$		-5.202341		
R^2	0.6659			
F Value	8.304120	(0.000)		
Likelihood Ratio			64.368206	

Notes: Figures in parentheses indicate P-values.

Source: Authors' Computation

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The R^2 for the least square's method stands at 0.6659. This implies that the five inputs to the model satisfactorily explain approximately 67% of the variation in the model output. In addition, the F-statistic of 8.3 reveals that the relationship between mean squares due to the endogenous and exogenous factors is significant even at the 1% level. Generally, the model performs quite well as most of the coefficients have the expected sign and almost all are statistically significant at the 5% level. This indicates that the results in terms of the estimated coefficients tend to be robust across the three different specifications.

Regarding the energy demand frontier, the estimated coefficients can be interpreted as elasticities as most of the variables are in logarithmic form. The estimated magnitudes of both price (ENP) and income (GDPP) elasticities are quite reasonable from a theoretical point of view. The estimated frontier coefficients suggest that Nigeria's energy demand is price-elastic, with estimated elasticities of -.016, -0.011 and -0.011 for the three alternative inefficiency distributions of the MLEs, respectively. The results also suggest that Nigeria's energy demand is income-elastic, with an estimated elasticity of around 0.44 for the half-normal model but only about 0.017 for the exponential and 0.016 for the truncated models.

The negative coefficients of capital and labour obtained in all models suggests that energy consumption decreases with the increase in labour and capital inputs, suggesting that labour and capital may be acting as substitutes for energy. This further suggests that firms and households may be using more labor-intensive or capital-intensive technologies that reduce the need for energy, given the total amount of income. For technological innovation, it indicates a scale effect where technological progress boosts productivity and output, leading to higher energy demand to support increased output levels. Moreover, the likelihood ratio test statistic of 64.39 reveals a high degree of significance beyond the 1% level, leading to the rejection of the null hypothesis that the coefficients are equal to zero. The parameter λ (as calculated by $\sigma U/ \sigma V$) provides some insight into the relative variance of the two composite errors that make up the total variation in the structural disturbance term. The two variances of the two error components, indicate that the inefficiency component "u" varies more widely than the uncontrollable random exogenous component "v". This means that the productive inefficiency "u" makes a more important contribution to the variability of the total error in the frontier model.

4.4 Estimated Efficiency Scores

Descriptive statistics of estimated energy oriented technical efficiency, derived from the models used in the analysis are presented in Table 4.7. The estimated average technical efficiency of the preferred model is about 95% with a degree of variation around it, as shown by the standard deviation of 0.037.

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Table 4.7: Descriptive statistics of estimated efficiency scores

Variables	Mean	Std. Dev.	Min	Max
LENC	5.880706	0.3442979	5.548758	6.529624
LENP	-1.01e-08	1.245853	-4.395345	2.365777
LCAP	7.798543	2.072018	4.467572	11.32526
LAB	65.65477	34.18918	0	84.301
LGDPP	7.506597	0.234899	7.235563	7.857765
TEI	1.329767	1.211063	0	4.25
TE	0.9451638	0.037249	0.801266	.9906032

Source: Authors' Computation

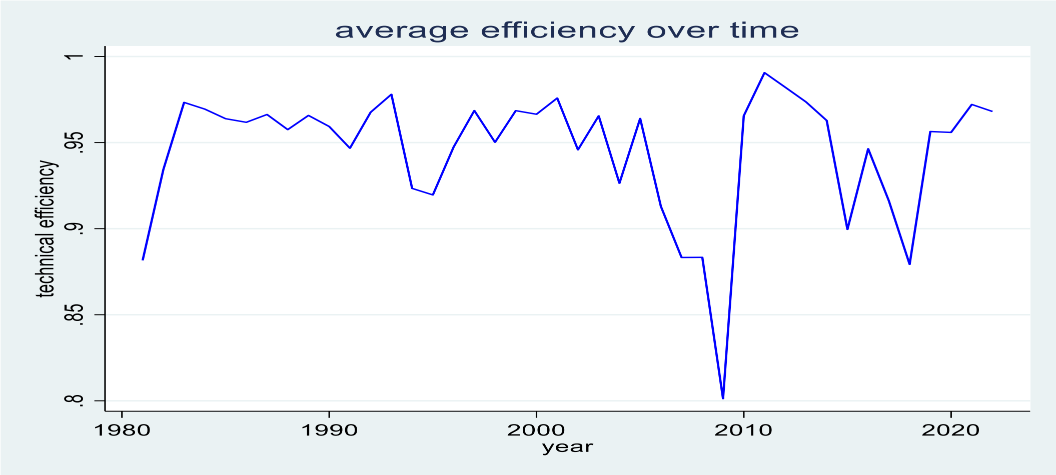

Figure 1. Average Energy Efficiency Scores Over Time

From figure 1 represents a volatile line plot of technical efficiency over time, indicating a significant fluctuation in how efficiently energy and other inputs are being converted into outputs across observed period. This volatility may be reflecting underlying instability in production process, inconsistent policy implementation, shifts in energy prices, or external shocks like economic crises or technological disruption. In Nigeria, this can be attributed to inconsistent energy supply particularly from the national grid, forcing industries and households to rely on inefficient backup sources like diesel generators, affecting overall efficiency. Another reason may be policy instability and poor energy regulation enforcement, leading to irregular investment in energy-saving technologies.

ISBN 978-80-7668-023-4, IISES

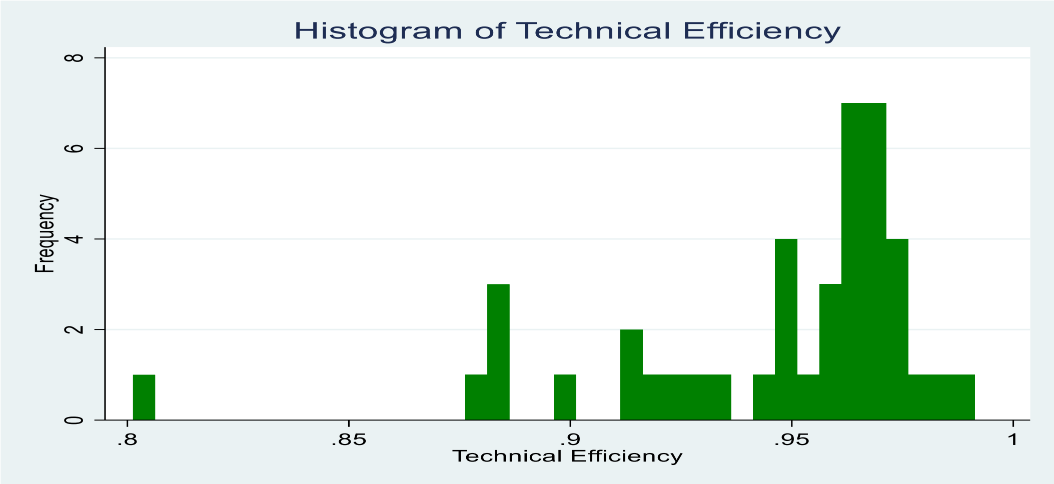

Figure 2. Histogram for Technical Efficiency Scores

Figure 2 presents a histogram of technical efficiency in Nigeria. The volatility reflects a widespread or uneven distribution of efficiency scores across firms, sectors, or regions, indicating significant disparities in how effectively resources are being utilized within the economy. This unevenness may result from structural differences across industries, where some sectors have access to modern technology and skilled labour, while others rely on outdated practices, and regional inequalities such as differences in infrastructure, electricity access, and institutional support.

5. Conclusions and Policy Recommendations

5.1 Conclusions

This study deployed Stochastic Frontier Analysis (SFA) to assess energy efficiency in Nigeria, to overcome the inadequacy of the traditional measures such as energy intensity for capturing true efficiency levels. Supporting the findings of Filippini and Hunt (2015), the analysis demonstrates that energy demand modeling through frontier techniques provides a more precise and policy-relevant measure of efficiency. The SFA approach used in this study allows for the separation of inefficiency into persistent and transient components, an important distinction for policy decisions as each requires different strategies. The findings from this study show that energy demand in Nigeria is both price-elastic and income-elastic, implying that changes in energy prices and income levels significantly influence the patterns of energy consumption in Nigeria. Additionally, the negative relationship between energy consumption and both labor and capital inputs suggest the substitutability of these inputs for energy, pointing to possibility for efficiency gains through labor- or capital-intensive technologies. Furthermore, the estimated average technical efficiency score is relatively high at 95%; however, the persistent year-to-year volatility and wide distribution of efficiency scores point to deeper structural issues such as inconsistent energy supply which forces reliance on inefficient diesel generators, policy instability, poor regulations enforcement, and unequal access to modern energy-saving technologies. The analysis attributes most these inefficiencies to endogenous rather than uncontrollable external factors, suggesting that a significant portion of energy inefficiency is addressable through well-crafted policies and regulatory interventions.

5.2 Policy Recommendations

Based on the findings of this analysis, several actionable policy recommendations are put forward. First, institutionalizing the use of frontier-based energy efficiency metrics by the government such as those derived from SFA is recommended for assessing energy efficiency at the national and sectoral levels, moving away from crude measures like energy intensity. Additionally, differentiating between persistent and transient inefficiencies by policy makers is essential, long-term structural issues such as poor infrastructure and outdated technologies requires investment in modernization, while short-term inefficiencies can be addressed through more flexible mechanisms, such as real-time monitoring and temporary pricing measures. Second, since energy demand is price-elastic, reforming energy pricing is crucial. Tariff structures should be adjusted to discourage wasteful consumption and encourage efficiency. Third, adoption of technologies that substitute labor or capital for energy should be supported by the policy makers through the provision of incentives such as tax breaks, subsidies, or low-interest loans. Improving the reliability of the national grid and expanding electricity access is necessary, especially in underserved regions along with strengthening the regulatory institutions and ensuring policy consistency over time will reduce the reliance on inefficient energy sources will help in building investor and stakeholder confidence, while supporting rigorous enforcement of energy efficiency standards.

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