Trends and Determinants of Energy Efficiency in Nigeria's Manufacturing Sector: A Stochastic Frontier Analysis (1981–2023)

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ABSTRACT

Energy efficiency is a cornerstone of industrial competitiveness and sustainable development, yet its empirical measurement in sub-Saharan Africa's manufacturing sectors remains limited. This study estimates energy efficiency levels and their determinants in Nigeria's manufacturing sector using annual time-series data from 1981 to 2023. Employing an input-oriented Stochastic Frontier Analysis (SFA), we find that the sector operates at an average energy efficiency of 82.2%, indicating a moderate but improvable performance. The trend reveals three distinct phases: improvement from 1985–1995 (efficiency reaching 100% in several years), relative stability from 1996–2015, and a notable decline after 2017, falling to 54.7% by 2023. Manufacturing output and labour input have significant positive effects on energy intensity (coefficients: 2.284 and 2.134, respectively; $p < 0.01$), indicating that they increase energy use per unit of output. Capital investment and the 2013 power-sector restructuring dummy significantly reduce energy intensity (coefficients: -1.213 and -1.669, respectively; $p < 0.01$). The generalized likelihood ratio test (167.13, critical value 6.63) confirms the presence of inefficiency, justifying SFA over OLS. The lambda parameter (4.54×10^7) indicates that inefficiency dominates random error. These findings suggest that sustained capital investment in energy-efficient technologies and consistent policy implementation are essential to reverse the post-2017 decline.

Keywords: Energy efficiency, Stochastic Frontier Analysis, manufacturing sector, energy intensity, Nigeria, power sector reform

INTRODUCTION

Energy efficiency is widely recognized as a low-cost strategy for reducing energy consumption, mitigating environmental degradation, and enhancing industrial productivity (IEA, 2014; UN, 2015). For developing countries like Nigeria, where energy supply is unreliable and demand is growing rapidly, improving energy efficiency is not merely an environmental imperative but an economic necessity (Sambo, 2008; Oyedepo, 2012).

Nigeria's manufacturing sector is the second-largest consumer of refined petroleum products and the largest consumer of electricity among economic sectors (NBS, 2018). Yet its contribution to GDP has declined from 11.75% in 2011 to 7.61% in 2024 (NBS, 2024). This paradox – rising energy consumption alongside falling output – raises fundamental questions about the sector's energy efficiency.

Despite policy initiatives such as the National Energy Efficiency Action Plan (NEEAP, 2016) and the dissolution of the Power Holding Company of Nigeria (PHCN) in 2013, empirical evidence on energy efficiency levels and their determinants remains scarce. Previous studies have focused on telecommunications (Fayemi et al., 2019), cross-country African samples (Atoyebi, 2023), or the technical efficiency of quoted firms (Tijani, 2022) rather than sector-wide energy efficiency.

This study addresses three gaps. First, it provides the first sector-wide energy efficiency scores for Nigeria's manufacturing sector over 43 years using SFA. Second, it quantifies the contributions of capital, labour, output, and policy reform to energy intensity. Third, it identifies the recent decline in efficiency (post-2017) as a policy concern requiring urgent attention.

LITERATURE REVIEW

Conceptual Framework

Energy efficiency is the ratio of useful output to energy input (IEA, 2016). In production economics, it is measured either by single-factor indicators (e.g., energy intensity = energy/output) or by total-factor methods that account for multiple inputs (Lin & Long, 2015). Single-factor measures are easy to compute but ignore substitution possibilities among inputs (Lundgren et al., 2016). Total-factor measures, such as those derived from SFA or Data Envelopment Analysis (DEA), are theoretically superior because they recognize that output depends jointly on capital, labor, and energy.

Empirical Evidence

International studies using SFA to estimate energy efficiency include Boyd and Lee (2019) for US manufacturing, Lundgren et al. (2016) for Sweden, and Lin and Long (2015) for China's chemical industry. These studies generally find that capital investment and technological change improve energy efficiency, while output growth increases energy intensity unless accompanied by efficiency gains.

In Nigeria, Ogundari and Awokuse (2018) used DEA to measure technical efficiency but did not focus on energy specifically. Adenikinju and Alaba (2010) examined productivity-energy linkages using firm-level data but did not produce time-series efficiency scores. No study has applied SFA to estimate energy efficiency trends in Nigeria's manufacturing sector at the aggregate level over an extended period.

Theoretical Underpinning

This study is anchored in the neoclassical production theory (Solow, 1957) and the energy efficiency gap theory (Jaffe & Stavins, 1994). The former provides the basis for modelling output as a function of capital, labour, and energy. The latter explains why firms may underinvest in energy-efficient technologies due to market failures, information asymmetries, and split incentives.

METHODOLOGY

Data and Variables

The study uses annual time-series data from 1981 to 2023 (T=43). Sources include the Central Bank of Nigeria (CBN) Statistical Bulletin (various editions), National Bureau of Statistics (NBS) publications, and World Bank Development Indicators.

The dependent variable is energy intensity (EI), measured as the total cost of energy divided by manufacturing output (NBS, 2014). Independent variables are:

- Manufacturing output (MO): total annual sales/value of output (₦ million)
- Capital input (CAP): total value of machinery and equipment (₦ million)
- Labour input (LAB): total wages paid to employees (₦ million)
- Policy dummy (POLDUM): 0 before 2013, 1 after 2013, capturing the dissolution of PHCN and privatisation of generation and distribution companies.

All variables except POLDUM are transformed using natural logs to normalise distributions and interpret coefficients as elasticities.

Stochastic Frontier Model

Following Aigner, Lovell, and Schmidt (1977) and Lin and Long (2015), the stochastic frontier model is specified as:

$$lnEI_t = \beta_0 + \beta_1 lnMO_t + \beta_2 lnCAP_t + \beta_3 lnLAB_t + \beta_4 POLDUM_t + \vartheta_t + \mu_t$$

Where $\vartheta_t \sim N(0, \sigma_\vartheta^2)$ is random error, and $\mu_t \sim N^+(0, \sigma_u^2)$ is one-sided inefficiency term. The energy efficiency score for each year is calculated as $EE_t = \exp(-u_t)$.

The presence of inefficiency is tested using the generalised likelihood ratio test (GLRT) for the null hypothesis $H_0 : \sigma_u^2 = 0$. The model is estimated using maximum likelihood in STATA 17.

RESULTS

Summary Statistics

Table 1 presents summary statistics. Before log transformation, variables exhibit non-normality (Jarque-Bera p<0.01 for all). After log transformation, skewness and kurtosis approach normality, and p-values become non-significant, validating the log-linear specification.

Table 1: Summary Statistics (Log-transformed variables, T=43)

Variable	**Mean**	**Std. Dev.**	**Skewness**	**Kurtosis**	**Jarque-Bera (p-value)**
ln EI	3.340	0.250	-0.018	2.195	0.559
ln MO	6.946	1.807	0.407	3.124	0.545
ln CAP	5.786	1.807	0.407	3.124	0.545
ln LAB	15.922	0.250	0.061	1.794	0.268
POLDUM	0.023	0.152	6.326	41.024	0.000

Source: Author’s computation

SFA Estimation Results

Table 2 reports the SFA estimates alongside OLS for comparison.

Table 2: SFA and OLS Estimation Results

Variable	SFA Coefficient (p-value)	OLS Coefficient (p-value)
Constant	-39.165 (0.000)	-16.105 (0.038)
ln MO	2.284 (0.000)	1.634 (0.000)
ln CAP	-1.213 (0.000)	-0.424 (0.241)
ln LAB	2.134 (0.000)	0.641 (0.182)
POLDUM	-1.669 (0.000)	-1.299 (0.000)
σ_v	1.58×10^{-8}	–
σ_u	0.7162	–
λ	4.54×10^{7}	–
Log-likelihood	-16.854	-100.421
GLRT	167.13 (critical 6.63 at 1%)	–

Note: p-values in parentheses. GLRT = Generalized Likelihood Ratio Test.

The GLRT statistic (167.13) far exceeds the 1% critical value (6.63), rejecting the null of no inefficiency. The lambda value (σ_u/σ_v = 4.54×10^{7}) indicates that inefficiency dominates random error, confirming SFA as the appropriate model.

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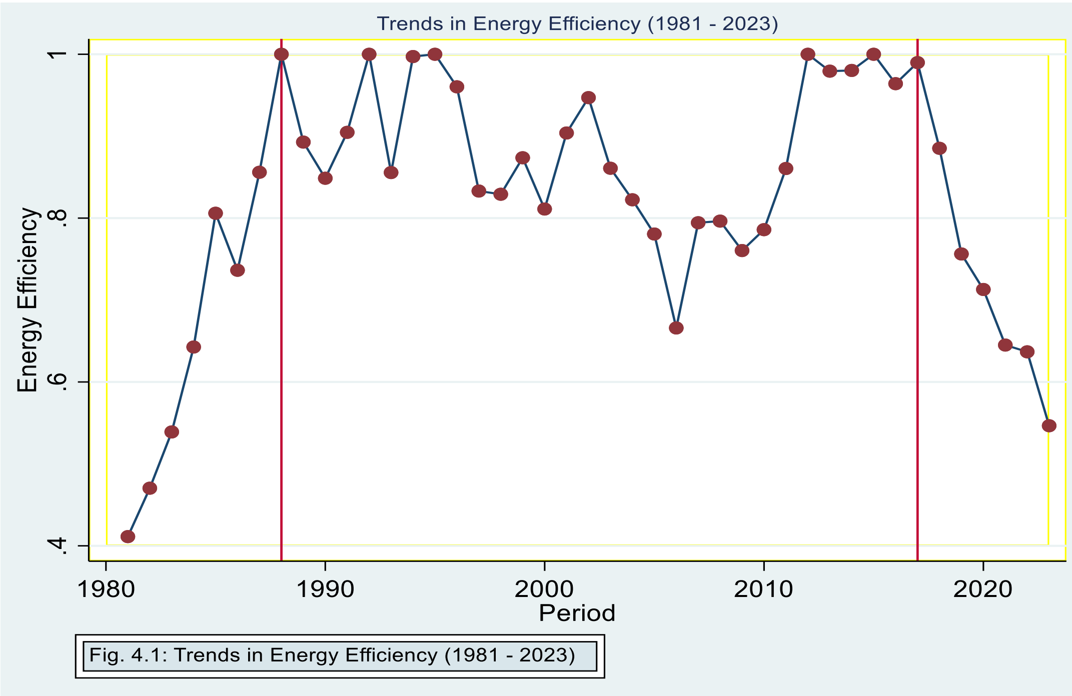
The coefficients show that a 1% increase in manufacturing output raises energy intensity by 2.28%, while a 1% increase in capital reduces energy intensity by 1.21%. Labour increases energy intensity by 2.13%. The policy dummy reduces energy intensity by 1.67 units (semi-elasticity), indicating that the 2013 power sector reform had a significant efficiency-enhancing effect.

Energy Efficiency Trends

Table 3: Summary of Energy Efficiency Scores (N=43)

Statistic	Value
Mean	0.822
Std. Dev.	0.151
Minimum (1981)	0.411
Maximum (various years)	1.000
2023 value	0.547

Figure 1: Energy Efficiency Trend (1981–2023)



The trend reveals:

- 1981–1984: Low but improving efficiency (0.411 → 0.643)
- 1985–1995: High efficiency, multiple years at 1.000 (full efficiency)
- 996–2015: Fluctuating but generally above 0.80
- 2016–2023: Steady decline from 0.964 (2016) to 0.547 (2023)

The post-2017 decline coincides with macroeconomic instability, foreign exchange shortages, and rising energy costs following subsidy reforms.

DISCUSSION

The average energy efficiency of 82.2% implies that the Nigerian manufacturing sector could reduce energy consumption by approximately 17.8% without reducing output, simply by adopting best practices already present within the sector. This “efficiency gap” is consistent with Jaffe and Stavins (1994) and suggests market

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failures such as information asymmetries, credit constraints, and split incentives between landlords and tenants.

The positive effect of manufacturing output on energy intensity (elasticity >1) indicates that output growth has historically been energy-intensive. This is typical of developing economies where industrial structure is skewed towards energy-heavy sub-sectors like cement, chemicals, and metal processing (Lin & Long, 2015).

The negative effect of capital on energy intensity supports the neoclassical view that capital deepening promotes efficiency. Each 1% increase in capital stock reduces energy intensity by 1.21%, likely through the adoption of modern, energy-efficient machinery. This finding aligns with Boyd and Lee (2019) for US manufacturing and Lundgren et al. (2016) for Sweden.

The positive effect of labour on energy intensity is concerning. It suggests that labour-intensive production methods are associated with higher energy waste, possibly due to lack of training, poor maintenance practices, or the use of outdated equipment. This calls for investment in human capital and energy management systems.

The significant negative coefficient of the policy dummy confirms that institutional reform matters. The 2013 dissolution of PHCN and privatisation of generation and distribution companies improved energy efficiency in the short to medium term. However, the post-2017 decline suggests that initial gains were not sustained, possibly due to inadequate regulatory oversight, tariff inconsistencies, or infrastructure decay.

The recent decline (2017–2023) is alarming. Factors may include: (i) depreciation of the naira making imported energy-efficient equipment unaffordable; (ii) increased reliance on diesel generators due to grid collapse; (iii) COVID-19 disruptions; and (iv) the removal of fuel subsidies in 2023, which temporarily distorted input choices before adjustments.

CONCLUSION AND RECOMMENDATIONS

This study provides the first long-term SFA-based estimates of energy efficiency for Nigeria's manufacturing sector. The key findings are:

1. Average energy efficiency is 82.2%, implying a 17.8% reduction potential.

2. Efficiency improved from 1985–1995 but has declined sharply since 2017.

3. Capital investment and the 2013 power sector reform improve efficiency.

4. Labour-intensive production and output growth increase energy intensity.

Policy recommendations:

- **Reverse the post-2017 decline:** Implement a National Manufacturing Energy Efficiency Fund to provide low-interest loans for retrofitting.
- **Target labour inefficiency:** Mandate energy audits and training programmes for factory workers.
- **Sustain policy reforms:** Complete the privatisation of distribution companies and enforce performance benchmarks.
- **Monitor efficiency annually:** Establish a manufacturing energy efficiency dashboard using real-time data from the Manufacturers Association of Nigeria (MAN).

Limitations and future research:

The study used aggregate, sector-wide data for the entire Nigerian manufacturing industry. This approach, while necessary for a macro-level view, conceals the differences among various manufacturing sub-sectors (e.g., textiles, food processing, cement). The factors influencing energy efficiency and productivity effects likely differ greatly across these sub-sectors due to their unique technological and operational features. Therefore, the results reflect the sector average and may not be directly applicable to specific industries.

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