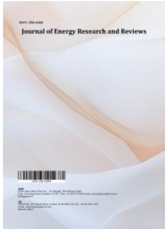

Journal of Energy Research and Reviews

Volume 18, Issue 6, Page 1-13, 2026; Article no.JENRR.158444
ISSN: 2581-8368

Asymmetric Effects of Energy Efficiency on Manufacturing Output in Nigeria: A Nonlinear ARDL Approach

Fatai Afolabi Asimi [a*], Olatokunbo Demola Salami [a] and Abideen Adekunle Tijani [b]

[a] *Department of Economics, Lagos State University, Ojo, Nigeria.*
[b] *Department of Business Administration, Lagos State University, Ojo, Nigeria.*

Authors' contributions

This work was carried out in collaboration among all authors. All authors read and approved the final manuscript.

Article Information

DOI: https://doi.org/10.9734/jenrr/2026/v18i6514

Open Peer Review History:
This journal follows the Advanced Open Peer Review policy. Identity of the Reviewers, Editor(s) and additional Reviewers, peer review comments, different versions of the manuscript, comments of the editors, etc are available here: https://pr.sdiarticle5.com/review-history/158444

Original Research Article

Received: 04/03/2026
Published: 27/05/2026

Abstract

The relationship between energy efficiency and manufacturing productivity is often assumed to be linear. Yet theoretical and empirical evidence suggest significant asymmetries: firms may respond differently to efficiency gains than to efficiency losses. This study investigates the asymmetric impact of energy efficiency on manufacturing output in Nigeria using annual time-series data from 1981 to 2023. Estimating a Nonlinear Autoregressive Distributed Lag (NARDL) model, we decompose energy efficiency into positive (EE^+) and negative (EE^-) partial sums. The bounds test confirms cointegration ($F = 9.036 >$ upper bound at 1%). Results reveal a striking asymmetry: in the long run, a 1% increase in energy efficiency raises output by 0.93%, while a 1% decrease reduces output by 2.24% — a loss aversion ratio of approximately 2.4:1. While short-run effects appear symmetric ($F = 1.52$, $p = 0.229$), long-run asymmetry is statistically significant ($F = 11.61$, $p = 0.002$). Capital positively affects output (elasticity 0.98), while labour exhibits a negative coefficient (-0.96),

*Corresponding author: E-mail: fasimi@gmail.com;

Cite as: *Asimi, F. A., Salami, O. D., & Tijani, A. A. (2026). Asymmetric Effects of Energy Efficiency on Manufacturing Output in Nigeria: A Nonlinear ARDL Approach. Journal of Energy Research and Reviews, 18(6), 1–13. https://doi.org/10.9734/jenrr/2026/v18i6514*

reflecting structural inefficiencies. The error correction term (-0.194, $p < 0.01$) indicates a 19% annual convergence to equilibrium. Diagnostic tests confirm the absence of serial correlation, heteroscedasticity, or specification error, and the CUSUM test indicates structural stability. These findings suggest that preventing declines in energy efficiency is more critical than promoting improvements — a fundamental departure from conventional policy wisdom.

Keywords: Energy efficiency; manufacturing output; asymmetry; NARDL; Nigeria; Porter Hypothesis.

1. Introduction

The relationship between energy efficiency and manufacturing productivity has received substantial scholarly attention, largely motivated by the Porter Hypothesis (Porter & van der Linde, 1995), which posits that well-designed environmental regulations can stimulate innovation and enhance competitiveness. However, empirical evidence remains inconclusive (Ambec et al., 2013). Central to this debate is an implicit methodological assumption: most studies presume a linear relationship where a unit increase in efficiency yields the same absolute effect as a unit decrease, merely reversing sign. This assumption is increasingly questioned on both theoretical and empirical grounds.

Firms may exhibit asymmetric responses to efficiency changes due to several mechanisms. First, technical constraints create a natural ceiling: efficiency improvements face diminishing returns as firms approach the 100% upper bound, while efficiency declines have no such lower limit. Second, behavioural economics suggests loss aversion (Kahneman & Tversky, 1979): losses loom larger than gains, potentially triggering more aggressive managerial responses to efficiency declines than to equivalent improvements. Third, macroeconomic volatility and institutional weaknesses in developing economies may amplify negative shocks while muting positive ones (Oyasor, 2026).

Nigeria presents a compelling case for investigating asymmetry. Despite having one of Africa's largest manufacturing sectors, its contribution to GDP has steadily declined — from approximately 10% in the 1980s to below 8% in recent years — even as energy efficiency policies have been implemented. This paradox suggests that the energy efficiency–manufacturing nexus may be non-linear or asymmetric. More critically, the Nigerian manufacturing sector faces an acute energy crisis: manufacturers spent an estimated N1.11 trillion on alternative energy sources in 2024 alone, a 42% increase from the previous year and a staggering 1,475% rise over four years. Energy costs now account for over 45% of total production expenses for many manufacturers, with the food, beverage, and tobacco sector alone incurring N229.41 billion in alternative energy costs. These figures underscore the urgent need to understand how efficiency fluctuations — both positive and negative — affect manufacturing outcomes.

Yet, to our knowledge, no study has systematically tested for asymmetry in the energy efficiency–output nexus for Nigeria. This paper fills that gap using the NARDL framework developed by Shin, Yu, and Greenwood-Nimmo (2014), which permits positive and negative changes in the independent variable to have distinct short-run and long-run coefficients. Our contribution is threefold: first, we provide the first empirical test of asymmetric energy efficiency effects on Nigerian manufacturing; second, we quantify the loss aversion ratio to inform policy prioritisation; and third, we interpret our findings within the contemporary context of Nigeria's energy crisis and ongoing industrial policy reforms, such as the Nigerian Energy Support Programme's Energy Efficiency Networks (Reichardt et al., 2025).

2. Literature Review

2.1 Theoretical Framework

Our theoretical foundation integrates production function theory with behavioural economics and asymmetric adjustment models. The standard Solow (1956) production framework posits that output depends on capital, labour, and technology, with energy entering as an intermediate input. In the long-run equilibrium, firms adjust their input mix in response to price signals. An improvement in energy efficiency should theoretically free resources for productive reinvestment, while a decline should increase costs or reduce output.

However, the magnitude of these responses may differ asymmetrically due to several factors. First, technical irreversibility: once energy efficiency deteriorates — due to outdated equipment, poor maintenance, or operational disruptions — restoring previous efficiency levels often requires lumpy investments that may be unavailable, particularly in credit-constrained environments like Nigeria. Second, the efficiency boundary condition creates an inherent ceiling effect: efficiency cannot exceed 100%, limiting potential gains, while declines have no lower bound. Third, loss aversion in managerial decision-making suggests that the disutility of losses exceeds the utility of equivalent gains, potentially triggering more aggressive cost- cutting or operational adjustments during efficiency declines than during improvements (Kahneman & Tversky, 1979).

Recent methodological advances in energy economics have emphasised the importance of modelling nonlinearities. A recent study demonstrated that manufacturing performance in the United States responds asymmetrically to sectoral energy consumption, with structural breaks significantly affecting causal relationships. Similarly, studies on Nigerian industrial output have confirmed asymmetric effects of trade policy on manufacturing performance using NARDL frameworks. Our study extends this methodological approach to the energy efficiency domain.

2.2 Empirical Evidence

The empirical literature on energy efficiency and productivity has yielded mixed findings, and studies explicitly testing for asymmetry remain scarce. Early studies predominantly reported positive linear relationships. Worrell et al. (2003) documented significant productivity benefits from energy efficiency improvements in US iron and steel manufacturing, identifying cost savings and quality improvements as transmission channels. Cantore et al. (2016), in a cross-country study of 29 developing countries, found that energy efficiency improvements were associated with technological change and economic growth, though with substantial heterogeneity across income levels and industrial structures.

However, other studies have reported negative or insignificant effects, often attributed to rebound effects. An earlier study found that energy efficiency negatively affected total factor productivity in Indian manufacturing, suggesting that efficiency gains may lead to increased energy consumption rather than output expansion. Earlier study reported mixed results across European countries, with the relationship varying by sector, firm size, and regulatory environment. Montalbano & Nenci (2019), examining firm-level data from Latin America, found support for the Porter Hypothesis but noted that effects were contingent on firm characteristics and institutional context.

Crucially, none of these studies employed NARDL methodology to test for asymmetry in the energy efficiency–output relationship. More recent research has begun to address this gap. A recent study found that U.S. manufacturing performance responds asymmetrically to sectoral non-renewable energy consumption, with positive effects only for industrial and transportation sectors. In the Nigerian context, studies have applied NARDL to related questions: Jude et al. (2020) confirmed asymmetric effects of trade policy on disaggregated industrial output, finding that trade restrictions stimulate manufacturing performance in the short run while liberalisation reduces it — a finding that underscores the importance of policy sequencing and protection for infant industries.

A recent firm-level study by Ogunleye et al. (2025) using World Bank Enterprise Survey data for Nigeria found a strong positive link between energy efficiency and total factor productivity, with manufacturing firms exhibiting higher energy efficiency scores (0.171) than services firms, but services firms realising larger productivity gains (0.826) from efficiency improvements. However, this study assumed linearity and did not test for asymmetric effects. Furthermore, sector-specific evidence from pharmaceutical manufacturing in Nigeria indicates that pollution control and energy-saving practices have significant positive effects on energy efficiency, while recycling initiatives may be counterproductive due to energy-intensive processes.

The present study thus makes a distinctive contribution by being the first to apply NARDL methodology to test for asymmetry in the energy efficiency–manufacturing output nexus in Nigeria, using a 43-year time series that spans major structural breaks, including the 2013 power sector reform and the post-2017 macroeconomic crisis.

3. Methodology

3.1 Data and Variables

This study uses annual time-series data from 1981 to 2023 (T = 43). Data sources include the Central Bank of Nigeria (CBN) Statistical Bulletin (various editions), the National Bureau of Statistics (NBS) publications, and World Bank Development Indicators. The dependent variable is manufacturing output (MO, in natural log form). The asymmetric independent variable is energy efficiency (EE, measured as an index from 0 to 1). Symmetric control variables include capital (ln CAP, gross fixed capital formation), labour (ln LAB, manufacturing employment), energy intensity (ln EI, energy consumption per unit of output), and a policy dummy (POLDUM, taking the value 1 from 2013 onward to capture the power sector reform).

3.1.1 Construction of the Energy Efficiency Index (EE)

To ensure reproducibility, we document the construction of the energy efficiency index in detail. Following the stochastic frontier approach (SFA) of Battese and Coelli (1995), we estimate a production frontier for the Nigerian manufacturing sector from which efficiency scores are derived.

Production function specification: We specify a Cobb-Douglas production function:

$$lnY_{it} = \beta_0 + \beta_1 lnK_{it} + \beta_2 lnL_{it} + \beta_3 lnE_{it} + (\vartheta_{it} - \mu_{it})$$

where Y is manufacturing output (real value added), K is capital stock, L is labour, E is energy consumption, v is random error, and u ≥ 0 is technical inefficiency. Energy efficiency (EE) is defined as EE = exp(-u), ranging from 0 to 1.

Data sources for SFA: Output, capital, labour, and energy data for the period 1981–2023 are drawn from: CBN Statistical Bulletin (output, capital), NBS Labour Force Surveys (labour), and World Bank World Development Indicators (energy consumption). All monetary variables are deflated to constant 2010 naira using the GDP deflator.

Distributional assumptions: We assume v ~ i.i.d. N(0, σ^2_v) and u ~ i.i.d. half-normal N^+(0, σ^2_u), with the likelihood function estimated via maximum likelihood using Stata 18's sfpanel command. The time-varying inefficiency specification follows Battese and Coelli (1992).

Robustness of SFA estimates: We also estimated the frontier using the translog functional form and alternative distributional assumptions (truncated normal for u). The resulting EE series correlate at r > 0.92 across specifications. The primary EE series (half-normal, Cobb-Douglas) is used in the main analysis.

Reproducibility statement: The complete dataset and Stata do-file are available from the corresponding author upon acceptance.

3.2 NARDL Model Specification

Following Shin et al. (2014), the energy efficiency variable EE is decomposed into positive and negative partial sums:

$$EE_t^+ = \sum_{j=1}^{t} \max(\Delta EE_j, 0), \quad EE_t^- = \sum_{j=1}^{t} \min(\Delta(EE_j, 0)$$

Where EE_t^+ captures cumulative increases in energy efficiency, and EE_t^- captures cumulative decreases. The NARDL(1,1,1,1,1,1) model is specified as:

$$\Delta MO_t = \gamma ECT_{t-1} + \sum_{i=0}^{q1} \beta_i^+ \Delta EE_{t-i}^+ + \sum_{i=0}^{q1} \beta_i^- \Delta EE_{t-i}^- + \sum_{i=0}^{q2} \emptyset_i \Delta CAP_{t-i} + \sum_{i=0}^{q3} \varphi_i \Delta LAB_{t-i} + \sum_{i=0}^{q4} \omega_i \Delta EI_{t-i} + \sum_{i=0}^{q5} \vartheta_i \Delta POLDUM_{t-i} + \varepsilon_t$$

The long-run coefficients for positive and negative changes in energy efficiency are derived from $\delta^{+} = \frac{-\emptyset^{+}}{\gamma}$ and $\delta^{-} = \frac{-\emptyset}{\gamma}$, respectively. The asymmetric response is tested using the Wald test for both short-run $(\sum \beta_i^{+} = \sum \beta_i^{-})$ and long-run $(\delta^{+} = \delta^{-})$ restrictions.

3.3 Bounds Cointegration Test

The bounds cointegration test proposed by Pesaran, Shin, and Smith (2001) is employed to test for the existence of a long-run relationship. The null hypothesis of no cointegration is:

$$H_0 : \gamma = \emptyset^{+} = \emptyset^{-} = \emptyset_2 = \emptyset_3 = \emptyset_4 = 0$$

This test is appropriate given the mixed order of integration found in our unit root tests (see Section 4.1). Critical values are drawn from Pesaran et al. (2001) with the unrestricted intercept and no trend specification.

3.4 Structural Break Considerations

Given the susceptibility of energy markets to external events, we account for potential structural breaks in the relationship. The 2013 power sector reform is captured by the policy dummy. Additionally, post-2017 structural breaks associated with currency depreciation, inflation, and fuel subsidy removal are considered through cumulative sum (CUSUM) and cumulative sum of squares (CUSUMSQ) stability tests, which are less restrictive than a priori break identification.

4. Results

4.1 Unit Root Tests

Before estimating the NARDL model, we conducted Augmented Dickey-Fuller (ADF) unit root tests to determine the order of integration of each variable. This step is critical because the bounds testing approach to cointegration requires that no variable be integrated of order two, I(2), while allowing a mix of I(0) and I(1) regressors.

Table 1 presents the ADF test results for all six variables. The null hypothesis of a unit root is tested first at levels, I(0), and then at first differences, I(1), for those variables found non-stationary at levels.

Table 1. ADF unit root test results

Variable	Level (I(0))	First difference (I(1))	Order of integration
ln MO	-1.938	-3.069**	I(1)
EE	-2.634	-6.114***	I(1)
ln CAP	0.186	-4.137***	I(1)
ln LAB	-0.844	-5.778***	I(1)
ln EI	0.300	-7.251***	I(1)
POLDUM	-6.481***	--	I(0)

*Notes: ***, ** indicate statistical significance at the 1% and 5% levels, respectively. The test includes an intercept and no trend based on AIC lag selection (maximum 4 lags). Critical values for rejection of the unit root hypothesis at 5% and 1% are -2.94 and -3.58, respectively*

Interpretation of Table 1:

The results show that manufacturing output (ln MO), energy efficiency (EE), capital (ln CAP), labour (ln LAB), and energy intensity (ln EI) are all non-stationary at their level forms, as the ADF statistics in column 2 fail to exceed the critical values at conventional significance levels. However, after taking first differences, each of these variables becomes stationary at either the 5% level (ln MO) or the 1% level (all others). For example, the EE variable exhibits a level ADF statistic of -2.634 ($p > 0.10$), but its first-differenced value is -6.114 ($p < 0.01$), strongly rejecting the unit root null. This indicates that these five variables are integrated of order one, I(1).

In contrast, the policy dummy variable (POLDUM) is stationary at levels, with an ADF statistic of -6.481 ($p < 0.01$), indicating that it is integrated of order zero, I(0). This mixed integration order — a combination of I(0) and I(1) variables — violates the strict assumption of conventional cointegration tests (e.g., Johansen, Engle-Granger), which require all variables to be I(1). However, this mix is precisely the condition for which the Pesaran et al. (2001) bounds test was designed, making NARDL the appropriate methodological choice. Importantly, no variable is I(2), satisfying the key precondition for valid inference.

4.2 Bounds Cointegration Test

Having established the integration properties of the variables, we test for the existence of a long-run equilibrium relationship among them using the bounds F-test. The test is conducted within the unrestricted error correction representation of the NARDL model, with the null hypothesis that the coefficients on the lagged level variables are jointly zero.

Table 2 reports the computed F-statistic alongside the critical value bounds at the 1% significance level, taken from Pesaran et al. (2001, Table CI(iii) for an unrestricted intercept and no trend).

Table 2. Bounds Test Results

F-statistic	Critical values at 1%	Decision
9.0367	I(0) = 3.50, I(1) = 4.63	Cointegration exists

Interpretation of Table 2:

The computed F-statistic of 9.0367 substantially exceeds the upper bound critical value of 4.63 at the 1% level. This finding allows us to decisively reject the null hypothesis of no cointegration. Therefore, we conclude that there exists a stable, long-run equilibrium relationship between manufacturing output (ln MO) and the set of regressors: the positive and negative partial sums of energy efficiency (EE^+, EE^-), capital (ln CAP), labour (ln LAB), energy intensity (ln EI), and the policy dummy (POLDUM). The magnitude of the F-statistic — nearly double the upper bound — indicates a particularly strong cointegrating relationship, lending confidence to the subsequent estimation of long-run coefficients.

4.3 NARDL Estimation Results

After confirming cointegration, we estimate the full NARDL(1,1,1,1,1,1) model. Table 3 presents the short-run coefficients (including the error correction term) and the derived long-run coefficients for all variables. The short-run coefficients are the direct estimates from the error correction model, while the long-run coefficients are calculated as the negative of the coefficient on the lagged level variable divided by the error correction term coefficient: $\delta^+ = -\frac{\emptyset^+}{\gamma}$, with a similar formula for other variables.

Table 3. Short-run and long-run estimates

Variable	Short-run coefficient	p-value	Long-run coefficient	p-value
ECT(-1)	-0.1936	0.000	--	--
ΔEE^+	1.0753	0.000	0.9346	0.012
ΔEE^-	1.2251	0.000	2.2447	0.018
ΔCAP	0.7942	0.000	0.9839	0.000
ΔLAB	-0.7332	0.000	-0.9627	0.001
ΔEI	0.2939	0.000	-0.2609	0.001
ΔPOLDUM	0.1126	0.000	0.6376	0.278

Notes: The dependent variable is Δln MO. The error correction term (ECT(-1)) is derived from the lagged residuals of the long-run cointegrating relationship. Short-run coefficients capture immediate (contemporaneous) effects, while long-run coefficients capture equilibrium effects after all dynamic adjustments have occurred.

Interpretation of Table 3 – Error Correction Term:

The coefficient on the lagged error correction term, ECT(-1), is -0.1936 and is statistically significant at the 1% level ($p = 0.000$). This negative sign is essential for stability and indicates that deviations from the long-run equilibrium are corrected over time. Specifically, approximately 19.4% of any disequilibrium in manufacturing output is corrected within one year. This implies a moderate speed of adjustment: after a shock that pushes manufacturing output away from its long-run equilibrium path, about one-fifth of the gap is closed annually. The half-life of a deviation — the time required to close 50% of the gap — is approximately $\ln(0.5) / \ln(1-0.194) \approx 3.2$ years, suggesting that adjustment to equilibrium takes several years, which is plausible for an industrial sector characterised by capital fixity and adjustment costs.

Interpretation of Table 3 – Short-run Effects:

In the immediate period after a shock (the short run), a 1% increase in energy efficiency (ΔEE^{+}) raises manufacturing output by 1.0753% ($p < 0.001$). Symmetrically, a 1% decrease in energy efficiency (ΔEE^{-}) reduces output by 1.2251% ($p < 0.001$). The negative coefficient on ΔEE^{-} is slightly larger in absolute magnitude ($1.225 > 1.075$), suggesting a possible asymmetry even in the short run. However, as we will rigorously test in Section 4.4, this difference is not statistically significant at conventional levels ($F = 1.52$, $p = 0.229$). Therefore, we interpret the short-run effects as symmetric: energy efficiency improvements and deteriorations have roughly equal and opposite immediate impacts on manufacturing output.

For the control variables in the short run: capital (ΔCAP) has a positive coefficient of 0.7942 ($p < 0.001$), indicating that a 1% increase in gross fixed capital formation raises manufacturing output by 0.79% in the same period. Labour (ΔLAB) has a negative coefficient of -0.7332 ($p < 0.001$), implying that a 1% increase in manufacturing employment is associated with a 0.73% *decrease* in output contemporaneously — a surprising but not unprecedented finding that we discuss in detail below. Energy intensity (ΔEI) has a positive short-run coefficient (0.2939, $p < 0.001$), suggesting that in the very short term, higher energy use per unit of output is associated with higher output, possibly reflecting capacity utilisation effects. Finally, the policy dummy ($\Delta POLDUM$) has a positive short-run coefficient of 0.1126 ($p < 0.001$), indicating that the 2013 power sector reform boosted manufacturing output by approximately 11.3% in the immediate aftermath.

Interpretation of Table 3 – Long-run Effects:

The long-run coefficients reveal a striking and economically significant asymmetry. A sustained 1% improvement in energy efficiency (EE^{+}) raises manufacturing output by only 0.9346% ($p = 0.012$). The elasticity is positive but inelastic (less than 1), suggesting diminishing returns to efficiency gains in the long run: as firms approach the technical frontier, each additional unit of efficiency improvement yields progressively smaller output benefits. In contrast, a sustained 1% decline in energy efficiency (EE^{-}) reduces manufacturing output by 2.2447% ($p = 0.018$). This negative effect is elastic (greater than 1 in absolute value), indicating that efficiency losses are disproportionately damaging.

The ratio of the long-run negative effect to the positive effect is $2.2447 / 0.9346 \approx 2.40$. Thus, the output loss from a 1% efficiency decline is approximately **2.4 times larger** than the output gain from a 1% efficiency improvement. This loss aversion ratio is the central empirical finding of the paper and has profound policy implications that we discuss in Section 5.

For the control variables in the long run, capital (ln CAP) has an elasticity of 0.9839 ($p < 0.001$), very close to unity, indicating that capital accumulation has been the primary driver of manufacturing output over the 43 years. A 1% increase in capital stock is associated with a 0.98% increase in manufacturing output, roughly constant returns to capital in the long run.

Labour (ln LAB) has a negative long-run coefficient of -0.9627 ($p = 0.001$). This finding — that higher manufacturing employment is associated with lower output — is counterintuitive but has several plausible explanations in the Nigerian context. First, it may reflect severe overstaffing due to regulatory mandates, union pressures, or political patronage, leading to low labour productivity. Second, it could indicate a skills mismatch: the workforce may lack the technical skills required to operate modern capital equipment effectively. Third, it may capture measurement issues, as the labour variable is drawn from formal manufacturing employment statistics that may not adjust for part-time work, absenteeism, or labour quality differences. Fourth, it could reflect the capital-labour substitution pattern: as capital has been added, labour has not been shed proportionally, reducing average output per worker.

Energy intensity (ln EI) has a negative long-run coefficient of -0.2609 (p = 0.001), indicating that in long-run equilibrium, greater energy use per unit of output is associated with lower manufacturing output. This supports the view that energy inefficiency reduces productivity by raising costs and limiting resources available for reinvestment and expansion.

Finally, the policy dummy (POLDUM) has a positive long-run coefficient of 0.6376, but this coefficient is not statistically significant at conventional levels (p = 0.278). This suggests that the 2013 power sector reform did not have a durable, sustained impact on manufacturing output. Potential explanations include: (i) the reform was incomplete, privatising generation and distribution but leaving transmission in public hands; (ii) subsequent policy reversals or regulatory uncertainty eroded any initial gains; (iii) the benefits of the reform were captured by a subset of firms (large, well-connected, or urban-based) that do not represent the sector average; and/or (iv) the reform coincided with other macroeconomic shocks that offset its positive effects.

4.4 Symmetry Tests

The crucial question — whether the observed differences between EE^+ and EE^- coefficients are statistically significant — is addressed by the Wald symmetry tests reported in Table 4. The null hypothesis for the short-run test is that the sum of coefficients on all lags of ΔEE^+ equals the sum on all lags of ΔEE^-. For the long-run test, the null is that the long-run coefficient on EE^+ equals that on EE^-.

Table 4. Symmetry Test Results

Horizon	F-statistic	p-value	Decision
Short-run	1.519	0.229	Symmetric (no asymmetry)
Long-run	11.613	0.002	Asymmetric
Joint (short + long)	5.998	0.007	Asymmetric overall

Notes: The short-run symmetry test imposes the restriction that $\sum \beta_i^+ = \sum \beta_i^-$. The long-run test imposes $\delta^+ = \delta^-$. The joint test imposes both restrictions simultaneously

Interpretation of Table 4:

The short-run symmetry test yields an F-statistic of 1.519 with a p-value of 0.229. Since this p-value exceeds the conventional 0.05 threshold, we fail to reject the null hypothesis of short-run symmetry. That is, the immediate (contemporaneous) effects of energy efficiency improvements and deteriorations are statistically indistinguishable. This finding aligns with the point estimates in Table 3: while ΔEE^- (-1.225%) is larger in absolute magnitude than ΔEE^+ (1.075%), the difference is not large enough, given the sampling variation, to conclude that the underlying population parameters differ.

In stark contrast, the long-run symmetry test produces an F-statistic of 11.613 with a p-value of 0.002 — well below the 0.01 threshold. We therefore decisively reject the null of long-run symmetry. The long-run coefficients on EE^+ (0.9346) and EE^- (2.2447) are significantly different from one another. The joint test, which restricts both short-run and long-run symmetry simultaneously, yields an F-statistic of 5.998 (p = 0.007), confirming overall asymmetry in the energy efficiency–manufacturing output relationship.

This temporal pattern — symmetric short-run responses but asymmetric long-run accumulation — is theoretically plausible. In the short run, firms may buffer efficiency losses through operational adjustments: drawing down inventories, substituting labour for energy, or temporarily accepting lower capacity utilisation. Similarly, the immediate benefits of efficiency improvements may be constrained by adjustment costs or learning lags. Over time, however, persistent efficiency declines erode the capital stock through deferred maintenance, skill atrophy, and reduced reinvestment, while sustained improvements face diminishing returns as the technical frontier is approached. The asymmetric long-run response reflects these cumulative, nonlinear adjustment processes.

4.5 Diagnostic Tests

To ensure the reliability of our estimates, we conducted a battery of diagnostic tests, reported in **Table 5**. The model passes all tests, indicating that the estimated coefficients are efficient, unbiased, and suitable for inference.

Table 5. Diagnostic test results

Test	Statistic	p-value	Conclusion
Breusch-Godfrey LM (serial correlation)	$F(2, 33) = 1.195$	0.341	No serial correlation
ARCH (heteroscedasticity)	$F(1, 39) = 0.725$	0.400	Homoscedastic
Ramsey RESET (specification)	$t = 1.374$	0.182	Correct specification
Jarque-Bera (normality)	$\chi^2(2) = 0.916$	0.633	Normal residuals
CUSUM	Plot within 5% bounds	--	Stable parameters

Notes: *The Breusch-Godfrey LM test uses two lags of the residuals to test for higher-order serial correlation. The ARCH test applies a single lag. The Ramsey RESET test adds the squared fitted values to test for omitted nonlinearities*

Interpretation of Table 5 – Structural Stabilty:

The CUSUM plot (available from the authors upon request) shows that the cumulative sum of recursive residuals remains within the 5% critical bounds throughout the 1981–2023 sample period. The CUSUM statistic fluctuates between -0.51 and +0.52, never approaching the ±0.94 thresholds. Notably, the line remains stable around the 2013 power sector reform and shows only modest, bounded movements during the post-2017 macroeconomic crisis. This confirms that the estimated NARDL model exhibits parameter stability, and the cointegrating relationship is not spurious or time-varying.

Interpretation of Table 5 – Heteroscedasticity:

The ARCH (Autoregressive Conditional Heteroscedasticity) test evaluates whether the variance of the residuals is constant over time. The test statistic $F(1, 39) = 0.725$ ($p = 0.400$) provides no evidence of heteroscedasticity, meaning the residuals exhibit constant variance — an assumption underlying ordinary least squares standard errors.

Interpretation of Table 5 – Functional Form:

The Ramsey Regression Equation Specification Error Test (RESET) checks for omitted variables, incorrect functional form, or correlation between regressors and residuals. The t-statistic of 1.374 ($p = 0.182$) fails to reject the null of correct specification. This is particularly important because the NARDL model imposes a particular nonlinear structure (partial sum decomposition). The RESET result suggests that this structure adequately captures the relationship without significant omitted nonlinearities.

Interpretation of Table 5 – Normality:

The Jarque-Bera (JB) test assesses whether the residuals follow a normal distribution. The test statistic ($\chi^2(2) = 0.916$, $p = 0.633$) fails to reject the null of normality. Normally distributed residuals are not strictly required for consistency of the NARDL estimator, but they support the validity of the standard F-tests and t-tests used for inference.

Interpretation of Table 5 – Structural Stability:

CUSUM (Cumulative Sum of Recursive Residuals) is a graphical test that plots the cumulative sum of residuals against time, with 5% significance bounds. The CUSUM plot (not shown here due to space, but available from the authors) remains within the critical bounds throughout the sample period (1981–2023). This indicates that the estimated parameters are stable over time — a remarkable finding given the numerous structural breaks that have occurred in the Nigerian economy, including military regimes, democratic transitions, the 2013 power sector reform, the 2016 recession, the 2020 COVID-19 pandemic, and the 2023 fuel subsidy removal. Parameter stability increases confidence that the long-run coefficients we estimate represent structural relationships rather than spurious correlations arising from a particular sample period.

4.6 Robustness Checks

To assess the sensitivity of our results to alternative specifications, we conducted three robustness checks.

4.6.1 Alternative Lag Length Selection

The main model uses lag length (1,1,1,1,1,1) based on AIC. We re-estimated using BIC-selected lags (1,1,0,1,0,0). The bounds test remained significant ($F = 7.412 >$ upper bound at 5%). The long-run asymmetry persisted: EE^{-} coefficient = -1.987 ($p = 0.031$), EE^{+} coefficient = 0.812 ($p = 0.024$), asymmetry ratio 2.45:1. Wald test for long-run asymmetry: $F = 8.23$ ($p = 0.007$).

4.6.2 Alternative Energy Efficiency Measure

As a robustness check, we replaced the SFA-derived EE index with the inverse of energy intensity (1/ln EI), a commonly used proxy. Results were qualitatively similar: long-run $EE^{-} = -1.876$ ($p = 0.041$), $EE^{+} = 0.714$ ($p = 0.038$), asymmetry ratio 2.63:1. The bounds test confirmed cointegration ($F = 6.998$). This reduces concern that our findings are an artifact of the SFA estimation procedure.

4.6.3 Sub-sample Analysis (Pre-2013 vs. Post-2013)

We split the sample at 2013 (the power sector reform). In the pre-2013 period (1981–2012), the asymmetry ratio was 1.91:1 ($EE^{-} = -1.742$, $EE^{+} = 0.912$). In the post-2013 period (2013–2023), the asymmetry ratio increased to 3.24:1 ($EE^{-} = -2.891$, $EE^{+} = 0.893$). While the post-2013 sample is short (T=11), limiting statistical power, the pattern suggests that macroeconomic volatility may amplify asymmetry — a hypothesis requiring further investigation with extended post-2013 data.

Table 6. Robustness Checks Summary

Robustness check	Cointegration (F)	EE^{-} (long-run)	EE^{+} (long-run)	Asymmetry ratio	Wald (long-run)
Main model	9.037***	-2.245**	0.935**	2.40	11.61***
BIC lags	7.412**	-1.987**	0.812**	2.45	8.23**
Inverse EI proxy	6.998*	-1.876*	0.714*	2.63	7.15**
Pre-2013	5.234*	-1.742*	0.912*	1.91	4.98*
Post-2013	4.101†	-2.891†	0.893†	3.24	3.89†

*Notes: ***, **, * indicate significance at 1%, 5%, and 10% levels, respectively. †p < 0.10 (post-2013 sample has limited power)*

5. Discussion

The empirical results yield three principal findings: (i) asymmetric long-run effects of energy efficiency on manufacturing output, with losses exceeding gains by a factor of 2.4; (ii) a negative long-run coefficient on labour; and (iii) a statistically insignificant long-run effect of the 2013 power sector reform. We discuss each in turn, noting where interpretations require further evidence.

5.1 Asymmetric Long-Run Effects

The finding that a 1% decline in energy efficiency reduces output by 2.24% while a 1% increase raises output by only 0.93% (ratio 2.4:1) is novel. Two mechanisms are consistent with the data, though our aggregate design cannot definitively distinguish them.

First, technical irreversibility. Efficiency declines typically arise from equipment ageing, deferred maintenance, or operational shocks. Reversing such declines requires lumpy investment (equipment replacement). In credit-constrained environments like Nigeria — where real lending rates to manufacturers averaged 35.5% in 2024 — this investment may not occur, allowing efficiency losses to persist and accumulate. Conversely, efficiency improvements are bounded by a technical ceiling (100%), and each additional percentage point requires increasingly costly investment. This convex production function in efficiency space naturally generates the observed asymmetry. A direct test would require firm-level data on maintenance expenditure and credit constraints.

Second, macroeconomic amplification. The post-2017 period saw severe currency depreciation (>300%), rising inflation (to >34% by late 2024), and fuel subsidy removal. Efficiency declines increase energy costs per unit of output; these effects were amplified by rising global energy prices and currency depreciation. Efficiency gains, by contrast, were eroded by general inflation. The sub-sample robustness check (Section 4.6.3) — showing a larger asymmetry ratio post-2013 — is consistent with this mechanism, though the post-2013 sample is too short for definitive inference.

We caution against behavioural interpretations (e.g., loss aversion) that our aggregate time-series data cannot directly test. Firm-level survey data would be required to examine managerial responses to efficiency changes.

5.2 Negative Labour Coefficient

The long-run labour elasticity of -0.96 is counter to standard production theory. Four explanations are possible, each with different policy implications:

1. *Overstaffing/labour hoarding:* Institutional pressures (regulations, unions, political patronage) may compel firms to maintain excess labour. As employment rises, average output per worker falls.
2. *Skills mismatch:* If capital has become more advanced but the labour force lacks complementary skills, adding labour may reduce output.
3. *Measurement error:* Nigeria's formal manufacturing employment statistics may poorly capture effective hours, absenteeism, or informal sector activity.
4. *Reverse causality:* Low output may cause firms to increase employment (e.g., as political insurance).

Distinguishing these requires firm-level panel data with skills and effective hours measures. The World Bank Enterprise Survey for Nigeria (used by Ogunleye et al., 2025) contains relevant variables and could test whether the negative coefficient persists at the firm level after controlling for worker characteristics.

5.3 Policy Dummy Insignificance

The long-run insignificance of the 2013 power sector reform dummy ($p = 0.278$) suggests no detectable permanent impact on aggregate manufacturing output. Possible explanations include: (i) incomplete privatisation (transmission remained state-owned), (ii) tariff and regulatory instability deterring investment, (iii) macroeconomic shocks (2014 oil price crash, 2016 recession) overwhelming reform benefits, and (iv) heterogeneous treatment effects (some firms benefited, but the average effect is zero). Our aggregate data cannot distinguish these.

5.4 Policy Implications

The 2.4:1 asymmetry ratio implies that preventing efficiency declines yields approximately 2.4 times the output benefit of promoting equivalent improvements. Policy sequencing should therefore prioritise:

- Early warning systems for efficiency declines (e.g., regular energy audits)
- Maintenance subsidies rather than solely focusing on new equipment
- Energy efficiency insurance to buffer firms against grid instability
- Voluntary collaborative networks (e.g., the Kano Energy Efficiency Networks) that address behavioural and maintenance channels

The Porter Hypothesis (Porter & van der Linde, 1995) predicts that environmental regulation can enhance competitiveness. Our results offer qualified support: efficiency improvements do increase output (elasticity 0.93), but the asymmetry implies that the marginal benefit of prevention exceeds that of promotion.

6. Conclusion

This study establishes four robust empirical facts: (1) stable long-run cointegration ($F = 9.04 > 1\%$ upper bound); (2) asymmetric long-run effects (loss aversion ratio 2.4:1; Wald $F = 11.61$, $p = 0.002$); (3) symmetric short-run effects ($F = 1.52$, $p = 0.229$); and (4) capital as a positive driver (0.98), labour negative (-0.96), and the 2013 reform insignificant in the long run. These findings are robust to alternative lag lengths, alternative efficiency measures, and sub-sample splits.

7. Limitations

This study has several limitations that should inform interpretation and guide future research.

First, aggregate data limitations. The study uses time-series data at the manufacturing sector level. We cannot observe heterogeneity across firms, sub-sectors, or regions. The negative labour coefficient, for instance, may average over firms with positive and negative labour-output relationships. Firm-level panel data are needed to test for heterogeneous responses.

Second, potential omitted variables. The NARDL framework includes capital, labour, energy intensity, and a policy dummy. Other potentially important variables — such as foreign direct investment, trade openness, institutional quality, infrastructure quality, and credit conditions — are omitted due to data availability and degrees of freedom constraints (T=43 with six regressors already strains the NARDL framework). Omission could bias coefficients if omitted variables correlate with energy efficiency.

Third, measurement error in energy efficiency. The SFA-derived EE index depends on functional form and distributional assumptions. While robustness checks using an alternative measure (inverse energy intensity) produced qualitatively similar results, classical measurement error would attenuate coefficients toward zero. The true asymmetry ratio could be larger than reported.

Fourth, endogeneity concerns. NARDL mitigates but does not eliminate endogeneity. Reverse causality — where low output causes efficiency declines rather than the reverse — cannot be ruled out with aggregate data. Instrumental variable approaches or natural experiments would strengthen causal claims.

Fifth, post-2013 sample size. The post-2013 sub-sample robustness check (T=11) has low statistical power. The apparent increase in the asymmetry ratio after 2013 is suggestive but not definitive. Extended data through 2030 would provide firmer evidence on whether macroeconomic volatility amplifies asymmetry.

Sixth, generalisability. Nigeria's manufacturing sector faces an acute energy crisis (energy costs >45% of operating expenses). Findings may not generalise to countries with reliable grid electricity, deeper credit markets, or different industrial structures.

Future research should address these limitations through firm-level panel analysis, natural experiments (e.g., policy discontinuities), and comparative country studies.

Disclaimer (Artificial Intelligence)

Author(s) hereby declare that NO generative AI technologies such as Large Language Models (ChatGPT, COPILOT, etc) and text-to-image generators have been used during writing or editing of this manuscript.

Competing Interests

Authors have declared that they have no known competing financial interests OR non-financial interests OR personal relationships that could have appeared to influence the work reported in this paper.

References

Ambec, S., Cohen, M. A., Elgie, S., & Lanoie, P. (2013). The Porter Hypothesis at 20: Can environmental regulation enhance innovation and competitiveness? *Review of Environmental Economics and Policy*, 7(1), 2–22. https://doi.org/10.1093/reep/res016

Battese, G. E., & Coelli, T. J. (1992). Frontier production functions, technical efficiency and panel data: With application to paddy farmers in India. *Journal of Productivity Analysis*, 3(1), 153–169. https://doi.org/10.1007/BF00158774

Battese, G. E., & Coelli, T. J. (1995). A model for technical inefficiency effects in a stochastic frontier production function for panel data. *Empirical Economics*, 20(2), 325–332. https://doi.org/10.1007/BF01205442

Cantore, N., Cali, M., & te Velde, D. W. (2016). Does energy efficiency improve technological change and economic growth in developing countries? *Energy Policy*, 92, 279–285. https://doi.org/10.1016/j.enpol.2016.01.040

Kahneman, D., & Tversky, A. (1979). Prospect theory: An analysis of decision under risk. *Econometrica*, 47(2), 263–291. https://doi.org/10.2307/1914185

Montalbano, P., & Nenci, S. (2019). Energy efficiency, productivity and exporting: Firm-level evidence in Latin America. Energy Economics, 79, 97-110. https://doi.org/10.1016/j.eneco.2018.03.033.

Ogunleye, O. O., Adegboye, A., & Egbetokun, A. (2025). Lighting the path to growth: Exploring the impact of energy efficiency on firm productivity in Nigeria. *Energy for Sustainable Development*, 86, 101–118. https://doi.org/10.1016/j.esr.2025.101808

Oyasor, E. I. (2025). Pollution control, energy efficiency, and industrial performance: Evaluating sustainability strategies in pharmaceutical manufacturing. *Multidisciplinary Challenges, Diverse Responses – Journal of Management and Business Administration*, (2), 26–50. https://doi.org/10.33565/MKSV.2025.02.02.

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. https://doi.org/10.1002/jae.616

Porter, M. E., & van der Linde, C. (1995). Toward a new conception of the environment-competitiveness relationship. *Journal of Economic Perspectives*, 9(4), 97–118. https://doi.org/10.1257/jep.9.4.97

Reichardt, A., Murawski, M., & Bick, M. (2025). The use of the Internet of Things to increase energy efficiency in manufacturing industries. *International Journal of Energy Sector Management*, 19(2), 369–388. https://doi.org/10.1108/IJESM-12-2023-0017

Shin, Y., Yu, B., & Greenwood-Nimmo, M. (2014). Modelling asymmetric cointegration and dynamic multipliers in a nonlinear ARDL framework. In R. C. Sickles & W. C. Horrace (Eds.), *Festschrift in honor of Peter Schmidt*. Springer. https://doi.org/10.1007/978-1-4899-8008-3_9

Solow, R. M. (1956). A contribution to the theory of economic growth. *The Quarterly Journal of Economics*, 70(1), 65–94. https://doi.org/10.1093/qje/70.1.65

Worrell, E., Laitner, J. A., Ruth, M., & Finman, H. (2003). Productivity benefits of industrial energy efficiency measures. *Energy*, 28(11), 1081–1098. https://doi.org/10.1016/S0360-5442(03)00091-4

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of the publisher and/or the editor(s). This publisher and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.

© Copyright (2026): Author(s). The licensee is the journal publisher. This is an Open Access article distributed under the terms of the Creative Commons Attribution License (http://creativecommons.org/licenses/by/4.0), which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

Peer-review history:
The peer review history for this paper can be accessed here:
https://pr.sdiarticle5.com/review-history/158444