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Efficiency Gap in Nigerian Power Generation: Operational Improvement or Capacity Expansion? (2017–2024)

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Abstract

Nigeria's electricity supply has persistently lagged behind demand despite sector reform since the Electric Power Sector Reform (EPSR) Act of 2005. This study evaluates the operational efficiency of twenty-four grid-connected electricity generation companies (GenCos) over 2017–2024 using output-oriented Data Envelopment Analysis (DEA). The CCR model of Charnes, Cooper and Rhodes, which imposes constant returns to scale (CRS), and the BCC model of Banker, Charnes and Cooper, which allows variable returns to scale (VRS), are estimated with installed and available capacity as inputs and electricity generated as the output, using a pooled panel of 190 firm-year observations. Returns-to-scale regimes are classified through the CCR–BCC–Non-Increasing Returns to Scale (NIRS) decomposition. Mean CCR efficiency was 0.710, implying a potential output gain of 40.8 per cent through better use of existing assets. Mean scale efficiency of 0.985 and a CRS share of 64.7 per cent confirm that most GenCos already operate near their optimal production scale. A fractional logistic regression finds positive but statistically insignificant average marginal effects for private management (AME = 0.063) and hydroelectric fuel type (AME = 0.072); neither reaches conventional significance given the modest sample of 24 firms. Location and plant age show no material association with efficiency. Nigeria's generation problem is primarily operational: improvements in plant availability, maintenance, and fuel procurement offer a more direct path to greater output than further capacity expansion.

Keywords: *data envelopment analysis; electricity generation; operational efficiency; fractional logistic regression.*

1. Introduction

Nigeria's electricity sector is among the most consequential economic bottlenecks the country faces. As Africa's most populous country and one of the continent's largest economies, with substantial natural gas and hydropower resources, Nigeria has endured persistent electricity shortages for decades. Nameplate installed generation capacity nominally exceeded 13,000 megawatts (MW) by the mid-2020s, yet effective dispatch rarely surpassed 5,000 MW on most days, leaving over 200 million people either unserved or reliant on diesel and petrol generators (Adoghe et al., 2023). The divergence between installed capacity and what actually reaches consumers is the defining diagnostic of the sector's problem and the starting point of this study.

The EPSR Act of 2005 unbundled the former vertically integrated national utility, established the Nigerian Electricity Regulatory Commission (NERC) as an independent regulator, and opened generation and distribution to private ownership. Privatisation of the generation companies was completed in November 2013, with the expectation that private management would translate into improved plant reliability, better maintenance, and more effective fuel procurement. More than a decade on, persistent equipment outages, chronic gas-supply disruptions, and deferred maintenance continue to depress output well below what installed assets could produce (Usman et al., 2015; Obasi & Nwambo, 2026). The gap between potential and realised output motivates this study.

DEA provides an empirical basis for diagnosing that gap. By constructing an efficiency frontier from observed best practice; without imposing a production function, that is, it benchmarks each GenCo against its peers rather than against engineering standards or sector averages (Charnes et al., 1978; Coelli et al., 2005). The CCR–BCC decomposition of Banker et al. (1984) separates total technical efficiency into a managerial component and a scale component, and the NIRS model assigns each observation to an Increasing Returns to Scale (IRS), CRS, or Decreasing Returns to Scale (DRS) regime. Whether Nigeria's generation shortfall originates in operational management, inappropriate plant scale, or some combination of both is an empirical question with fundamentally different policy implications depending on the answer.

This study applies output-oriented CCR, BCC, and NIRS DEA to a pooled panel of 190 firm-year observations from twenty-four grid-connected GenCos over 2017–2024. A fractional logistic regression of efficiency scores on ownership type, fuel type, geographic location, and plant age supplements the frontier analysis. The study contributes on three fronts: it provides updated GenCo-level efficiency evidence from post-privatisation panel data extending to 2024; it derives a formal returns-to-scale classification using the CCR–BCC–NIRS decomposition; and it estimates the second stage using the Papke and Wooldridge (1996) quasi-maximum likelihood procedure appropriate for bounded response variables, with installed capacity excluded from the contextual covariates to avoid the circularity documented by Ruggiero (1998).

2. Literature Review

2.1 Theoretical Foundations

The measurement of productive efficiency begins with Farrell (1957), who formalised the distinction between technical efficiency; producing the maximum output attainable from a given set of inputs, and allocative efficiency, which reflects a firm's ability to combine inputs and outputs in optimal proportions given their market prices, and proposed estimating a production frontier from observed firm data. Charnes et al. (1978) operationalised Farrell's concept as a linear programme, the CCR model, which evaluates each Decision-Making Unit (DMU) against all possible peer combinations without requiring a specified production function. Banker et al. (1984) extended the CCR model by relaxing the constant-returns assumption through a convexity restriction on the intensity weights, yielding the BCC model. The CCR score conflates two sources of inefficiency: poor operational management and the effect of operating at a non-optimal production scale. The BCC model separates these by benchmarking each firm only against peers of similar size, so its score reflects pure managerial efficiency alone. Scale efficiency, which is the ratio of the CCR score to the BCC score, isolates the scale component: a value close to unity confirms that most inefficiency stems from management rather than plant size. The NIRS model then establishes the direction of any scale inefficiency, determining whether a firm would benefit from expanding toward its optimal scale (increasing returns to scale) or contracting toward it (decreasing returns to scale), following the three-way classification procedure of Coelli et al. (2005, pp. 171–174).

The orientation of the DEA model reflects the operational context. Output-oriented DEA asks how much output could be expanded proportionally, holding inputs constant (Färe et al., 1994), which corresponds to the managerial decision problem in electricity generation where installed capacity cannot be adjusted quickly. The implied potential output gain is $(1/\theta - 1) \times 100$ per cent — the proportional increase in output required to reach the frontier. This differs from $(1 - \theta) \times 100$ per cent, which measures the shortfall as a fraction of frontier output, and from the input-oriented analogue that asks how far inputs could be reduced while holding current output fixed. These are answers to different managerial questions.

For the second-stage regression, the bounded nature of DEA efficiency scores creates a specification problem that Ordinary Least Squares (OLS) does not address. Scores are constrained to the unit interval, and several observations in any sample will typically reach the upper bound of unity. OLS assumes an unbounded, normally distributed response; applying it to efficiency scores produces inconsistent estimates when ceiling observations are non-trivial and may generate predicted values outside the feasible range. Papke and Wooldridge (1996) developed a quasi-maximum likelihood estimator (QMLE) for fractional response variables, which uses a Bernoulli log-likelihood function paired with a non-linear link function to keep predicted efficiency scores strictly within the bounded [0,1] interval, while consistently accommodating boundary observations of fully efficient firms without requiring arbitrary data truncation or ad-hoc transformations. Ramalho et al. (2010) showed explicitly that fractional regression models outperform Tobit and OLS in second-stage DEA efficiency analysis: they produce better-specified likelihoods, handle boundary values naturally, and remain consistent under a broad range of distributional assumptions. The present study follows their recommendation.

Simar and Wilson (2007) showed that OLS and Tobit regression on DEA scores produce inconsistent estimates because the scores are serially correlated by construction; they proposed a double-bootstrap truncated regression to correct this. The Papke–Wooldridge QMLE does not require distributional assumptions, making it more robust to the serial-correlation concern than Tobit, though the Simar–Wilson bootstrap remains the most statistically rigorous option for future work. A further concern is the circularity identified by Ruggiero (1998): including in the second stage any variable already used as a DEA input conflates the production and efficiency relationships. Installed capacity, which could have proxied firm size, is an input in Stage 1 of this study and is therefore excluded from Stage 2; the returns-to-scale classification captures the scale dimension independently.

2.2 DEA Applied to Power Generation

DEA has become the dominant method for efficiency analysis in the electricity sector, providing a robust non-parametric framework for utility benchmarking (Mardani et al., 2017). Across the global literature, managerial capability, maintenance quality, and fuel reliability consistently explain more of the cross-firm variation in efficiency than production scale—a pattern the Nigerian evidence in this study corroborates.

In a global systematic review of DEA energy-efficiency literature spanning Europe, Asia, the Americas, and Africa, Mardani et al. (2017) confirmed that static frontier models remain a premier framework for utility performance evaluation. While individual empirical studies of comparable developing and transitioning economies frequently observe power generation efficiency scores ranging between 0.60 and 0.85, this established baseline range provides a vital benchmark against which the static Nigerian results in this study can be interpreted.

At a cross-country level, Zhang et al. (2008), in an econometric assessment of electricity sector reforms across 36 developing and transitional economies over 1985–2003, found that privatisation alone did not produce observable gains in economic performance; improvements emerged only when ownership change was accompanied by the concurrent introduction of competition or effective independent regulation. That finding bears directly on Nigeria, where the 2013 privatisation was partial—covering former Power Holding Company of Nigeria (PHCN)-owned generation assets while plants built under the National Integrated Power Project (NIPP) remained in federal ownership through the Niger Delta Power Holding Company (NDPHC), and the competitive wholesale market envisaged by the EPSR Act has not fully emerged. Sarpong et al. (2022) examined energy efficiency across nine West African countries using a static Slacks-Based Measure (SBM-DEA) framework, finding Nigeria above the West African regional benchmark, and identifying socioeconomic factors such as Gross National Income, population, and urbanization rather than investment levels as the dominant drivers of cross-country efficiency differences.

In country-specific assessments, Kumar and Managi (2010), in a DEA-Malmquist study of Indian thermal plants, decomposed productivity change and found that 40% of gains came from technical change, while capacity expansion without efficiency improvement led to stranded assets. They further demonstrated the importance of using Available Capacity to control for outages and deratings. In the Chinese context, Chai, Fan, and Han (2020) used a 3-stage DEA model and showed that energy efficiency influences market status, and that the composition of Installed Capacity—particularly clean vs coal—significantly affects efficiency scores. However, similar to the Nigerian context, China also battled with low capacity availability.

2.3 The Nigerian Electricity Sector

Usman et al. (2015) examined the institutional implications of the EPSR Act and concluded that its intended market outcomes were severely constrained by infrastructure deficits, inadequate domestic gas supply, and weak contract enforcement—the identical operational barriers still impeding GenCo performance and grid stability a decade later.

Ogbonna and Chituru (2018) applied Data Envelopment Analysis (DEA) to six Nigerian GenCos from 2012-2016 and found an average technical efficiency of 62%, attributing inefficiency to poor utilization of available capacity due to gas supply constraints, grid limitations, and maintenance issues rather than insufficient installed capacity. They used Available Capacity as an input to provide a realistic benchmark for the Nigerian context where plant availability factors remained low. Adoghe et al. (2023) documented the persistent gap between installed capacity and effective dispatch, attributing it to deferred maintenance, equipment deterioration, and gas-supply volatility. Obasi and Nwambo (2026) estimated a correlation of $r = 0.97$ between gas offtake and electricity output at Egbin 1 Power Plant, Nigeria's largest gas-fired station with an installed capacity of 1,320 MW, over a thirty-month period. That figure places fuel-supply disruption among the statistically dominant constraints on Nigerian generation performance.

The closest empirical precedent for this study is Olayemi et al. (2022), who applied a two-stage deterministic DEA approach using the Benchmarking package in R (Bogetoft & Otto, 2011) to evaluate eleven Nigerian distribution companies (DisCos) over 2014–2021. However, while their framework utilized an input-oriented specification to measure a DisCo's ability to minimize resources for an externally determined demand, this study provides a vital methodological counterpart by deploying an output-oriented framework to isolate maximum generation by GenCos. Additionally, their second-stage regressions focused heavily on regional environmental constraints—uncovering a 9.1% efficiency penalty for northern DisCos, whereas this study focuses on ownership and fuel type. The 0.366-point spread in GenCo efficiency reported here closely mirrors their distributional finding for DisCos, suggesting the operational management problem extends across both segments of the electricity supply industry.

2.4 Research Gap

No published study applies the static CCR–BCC–NIRS decomposition to Nigerian GenCos using post-2015 panel data. No study links static GenCo efficiency to firm characteristics in a properly specified second-stage fractional regression that observes Ruggiero's (1998) circularity constraint. And none tracks how this static efficiency distribution evolved from the gas crises of 2017–2018 through the Coronavirus (COVID-19) disruption of 2020 and up to the macroeconomic recovery through 2024. This study addresses all three.

3. Methodology

3.1 Research Design

The study uses output-oriented DEA. Throughout this paper, CCR and BCC are model identifiers derived from their authors' surnames — Charnes, Cooper and Rhodes (1978) and Banker, Charnes and Cooper (1984) respectively; they are not abbreviations of the returns-to-scale assumptions those models impose. The terms CRS (constant returns to scale), VRS (variable returns to scale), DRS (decreasing returns to scale), and IRS (increasing returns to scale) are reserved exclusively for classifying the returns-to-scale regime of each firm-year observation. Three models are estimated sequentially: CCR, which imposes CRS; BCC, which allows VRS through a convexity restriction on the intensity weights; and NIRS, which enables the full three-way CRS/DRS/IRS classification. Scale efficiency is derived from the CCR/BCC ratio. A fractional logistic regression of firm-year efficiency scores on plant-type and ownership characteristics supplements the frontier analysis.

3.2 Data and Sample

The study was originally designed to span the full post-privatisation decade (2015–2025). Because consistent NERC operational records for 2015 and 2016 are not publicly available, the panel begins in 2017. Labour, capital inputs and revenue outputs, which would have enriched the production specification, were likewise unavailable for the full period and are therefore excluded while Installed Capacity (MW) and Available Capacity (MW) were employed as inputs following (Kumar & Managi, 2010; Ogbonna & Chituru, 2018; Chai et al., 2020). The estimation sample is a balanced panel of 24 GenCos observed annually from 2017 to 2024, comprising 192 firm-year records prior to cleaning. Two observations were dropped: Omotosho 1 in 2017 (missing production data) and Alaoji 1 in 2024 (zero generation, which violates the strict positivity requirement of output-oriented DEA). The final estimation sample contains 190 firm-year observations.

One vintage issue warrants clarification. The NERC covariate file reports a commissioning year of 2021 for Afam 1, corresponding to the Afam III Fast Power unit operated by Transcorp. The production records used here (2017–2024) instead represent the consolidated Afam IV and V units, commissioned in 1982 and 2002 respectively. Because the panel reflects these earlier assets, 1982 is adopted as the reference commissioning year, implying plant ages of 35–42 years across the panel.

Generation data were obtained from NERC annual reports. Figures for 2017–2020 were extracted from NERC (2022) and reported in megawatt-hours (MWh), whereas figures for 2021–2024 were drawn from NERC (2025) and reported in gigawatt-hours (GWh). For comparability, GWh values were converted to MWh (GWh × 1,000). A unit-of-measurement discrepancy was identified in Table A.6 of NERC (2022), *Plant Share of Total Electricity Output, 2017–2020*, where output is labelled in MW rather than MWh. Treating the entries as MW and converting them to MWh would inflate 2017–2020 generation by several orders of magnitude relative to the 2021–2024 series in Table D.5 of NERC (2025). The values were therefore retained as MWh, which preserves cross-year consistency and aligns with reported system-level output for Nigeria.

Data on Average Available Capacity were published only for 2024. For the remaining years, values were imputed using the NERC (2025) identity:

Average Available Capacity (MW) = Plant Availability Factor × Installed Capacity (MW).

The imputation was benchmarked against the 2024 published series; deviations were negligible, with most plants matching exactly. Finally, all generating plants were renamed in 2024; the current nomenclature is used throughout, as listed in Appendix A, Table A.1. All results are reproducible from the dataset. Table 1 defines the production variables.

Table 1: Definition and Measurement of Study Variables

Variable	Description	Role	Unit
Installed Capacity	Maximum rated generation capacity of each GenCo	Input	MW
Available Capacity	Capacity operationally deployable after maintenance and technical outages	Input	MW
Electricity Generated	Actual electricity produced and delivered annually	Output	MWh

Note. All data sourced from NERC operational records. Author's tabulation.

3.3 Ownership Classification

Each GenCo is assigned to one of two management categories; Private (= 1) or Public (= 0), based on the operational management arrangements in effect during the study period, not on legal asset ownership.

Private (= 1) covers: GenCos fully transferred to private operators under the November 2013 privatisation, including, Delta 1 (Transcorp Power), Egbin 1 (Sahara Group/KEPCO), Omotosho 1 (Pacific Energy), Geregu 1 (Transcorp), Afam 1 and Afam 2 (Transcorp), Okpai 1 (Agip/NAOC), Sapele Steam 1 (Eurafric/CMEC), Trans Amadi 1 (Trans-Amadi Power), and GenCos under long-term concession by private companies, such as, Kainji 1 and Jebba 1 (Mainstream Energy Solutions) and Shiroro 1 (North-South Power Company Limited). Concession operators bear day-to-day operational and commercial responsibility, making their incentive structure functionally equivalent to full private management.

Public (= 0) covers: GenCos owned and operated by the federal NDPHC including Omoku 1, Rivers 1, Ihovbor 1, Ihovbor 2, Geregu 2, Odukpani, Omotosho 2, Sapele 2, Olorunsogo 2, and Alaoji 1; Olorunsogo 1, whose privatisation under post-PHCN successor arrangements did not complete within the study period; and Ibom Power 1, owned by the Akwa Ibom State Government. The public category encompasses both federal and state government management.

3.4 DEA Model Specification

For n = 190 DMUs, each using m = 2 inputs to produce s = 1 output, the output-oriented CCR model for DMU_0 solves:

$$max_{\Phi,\lambda}\ \Phi \quad (1)$$

$$subject\ to{:}\ X\lambda \leq x_0,\ Y\lambda \geq \Phi y_0,\ \lambda \geq 0 \quad (2)$$

where X is the (n × m) input matrix, Y the (n × s) output matrix, x_0 and y_0 are the observed inputs and output of the reference DMU, λ is the (n × 1) intensity vector, and Φ is the output-expansion factor. The efficiency score is expressed as $\theta_{CCR} = 1/\Phi \in (0, 1]$; unity places the GenCo on the efficient frontier, while values below unity indicate that output could be expanded proportionally by the factor Φ (or equivalently, $1/\theta_{CCR}$) while inputs remain constant.

To accommodate Variable Returns to Scale, the BCC model incorporates the convexity restriction:

$$\textstyle\sum_{j=1}^{n} \lambda_j = 1 \quad (3)$$

This constraint separates managerial efficiency from scale effects, allowing firms operating at non-optimal scales to be distinguished from those exhibiting operational inefficiency. Scale efficiency is then:

$$SE = \frac{\theta_{CCR}}{\theta_{BCC}} \in (0, 1] \quad (4)$$

Values of SE approaching unity indicate that a GenCo operates close to its most productive scale size. When both θ_{CCR} and θ_{BCC} equal unity, the firm is both managerially and scale-efficient.

3.5 Returns-to-Scale Classification

The direction of scale inefficiency is established by comparing BCC and NIRS model scores following Coelli et al. (2005, pp. 171–174), with numerical precision threshold $\varepsilon = 10^{-4}$: (a) CRS if $\theta_{BCC} \approx \theta_{NIRS}$ and SE ≈ 1, implying, the GenCo is at its most productive scale size; (b) DRS if $\theta_{BCC} \approx \theta_{NIRS}$ and SE < 1 – ε, that is, GenCo operating beyond optimal scale; and (c) IRS if $\theta_{BCC} > \theta_{NIRS} + \varepsilon$, meaning GenCo is operating below optimal scale. All three models, CCR, BCC, and NIRS are estimated using the Benchmarking package in R with the NIRS specification set to RTS = 'drs'.

3.6 Ranking Criterion: CCR Rather than BCC

GenCos are ranked by mean CCR efficiency rather than BCC efficiency because CCR reflects total technical efficiency; managerial performance and scale effects combined, and it is the appropriate measure for regulatory benchmarking and investment prioritisation where long-run capital decisions remain within the firm's control (Coelli et al., 2005). The potential output gain is derived from θ_{CCR}: $(1/\theta_{CCR} - 1) \times 100$ gives the proportional expansion in output needed to reach the frontier. It differs from $(1 - \theta_{CCR}) \times 100$, which measures the shortfall relative to frontier output, and from the input-oriented measure that asks how far inputs could be reduced while holding current output fixed.

3.7 Second-Stage Fractional Logistic Regression

To evaluate the determinants of operational efficiency while avoiding the misspecification pitfalls of OLS and Tobit models, a fractional logistic regression framework is estimated using the Quasi-Maximum Likelihood (QML) procedure of Papke and Wooldridge (1996). The empirical model is specified as:

$$E[\theta_{it} \mid X_{it}] = \Lambda(\alpha + \beta_1 Private_i + \beta_2 Hydro_i + \beta_3 North_i + \beta_4 PlantAge_{it} + \Sigma\gamma_t YearDummy_t) \quad (5)$$

where $\Lambda(v) = \frac{\exp(v)}{1+\exp(v)}$ is the cumulative logistic function that constrains the fitted values to the unit interval (0,1]. The dependent variable θ_{it} is the CCR efficiency score for firm *i* in year *t*. While multi-stage DEA often favours the BCC score, this study utilizes the CCR score because the empirical mean scale efficiency of 0.95, based on the preliminary diagnostic result on the dataset, confirms that scale inefficiencies are negligible (1.5%), rendering the frontiers statistically convergent. The covariates for this stage include, $Private_i = 1$ if the GenCo is under private or concession management; $Hydro_i = 1$ for hydroelectric plants; $North_i = 1$ for North Central zone GenCos; $PlantAge_{it} = Year_t - \text{Commissioning Year}_i$ is the year-varying plant age in years.

Year fixed effects ($YearDummy_t$, t = 2018, …, 2024) are binary indicators equal to 1 in year *t* and 0 otherwise, with 2017 as the omitted base. They simultaneously absorb any common annual shock affecting all GenCos, such as, changes in national gas-supply conditions, macroeconomic disruptions, foreign-exchange constraints on maintenance inputs, and sector-wide regulatory events. Their inclusion ensures that the coefficients on Private, Hydro, North, and Plant Age reflect cross-firm variation in management and technology rather than temporal trends common to the whole industry.

Fractional logistic regression (Papke & Wooldridge, 1996) is adopted because DEA efficiency scores are bounded in [0,1] and several observations reach the upper boundary of unity. OLS does not account for this structure and may generate predicted values outside the feasible range. The Papke–Wooldridge quasi-maximum likelihood estimator uses the Bernoulli log-likelihood with the logistic link, handling boundary observations without truncation and remaining consistent under a broad range of distributional assumptions. Ramalho et al. (2010) demonstrated formally that fractional regression is better specified than Tobit or OLS for DEA second-stage analysis, producing more reliable inference on efficiency determinants. Installed capacity is excluded from the right-hand side because it is a DEA input in Stage 1; including it again in the second stage would create an econometric circularity that conflates the frontier production relationship with the efficiency distribution relationship (Ruggiero, 1998). Results are reported as Average Marginal Effects (AME = mean of $\Lambda(X\hat{\beta})[1 - \Lambda(X\hat{\beta})] \times \hat{\beta}$ across all observations), which translate log-odds coefficients into marginal changes in the efficiency score that are directly comparable across covariates. Standard errors are clustered at the firm level (G = 24 firms) following Cameron and Miller (2015), using the delta method applied to the cluster-robust variance-covariance matrix. With 24 clusters, the cluster-robust estimator operates near the lower bound recommended for reliable inference (conventionally $G \geq 30$), a small-sample degrees-of-freedom adjustment $\frac{G}{G-1}$ is structurally enforced to preserve the conservative precision of the hypothesis tests and prevent the over-rejection of the null hypothesis results. Table 2 defines the contextual covariates.

Table 2: Second-Stage Contextual Covariates

Variable	Definition	Level	Type
Private	= 1 if under private or concession management; = 0 otherwise	Firm	Binary
Hydro	= 1 if hydroelectric; = 0 if thermal (gas-fired or steam)	Firm	Binary
North	= 1 if located in North Central Nigeria; = 0 if southern zone	Firm	Binary
Plant Age	Year of observation minus commissioning year; increases annually	Firm-year	Years

Note. All firm-level dummies are time-invariant across the study period. Plant Age is the sole time-varying covariate, increasing by one year per annual observation. Author's tabulation.

4. Results and Discussion

4.1 Descriptive Statistics

Table 3 reports descriptive statistics for the three production variables, computed from the full 192-record dataset before the exclusion of the two anomalous observations. The most striking feature is the gap between average installed capacity (530 MW) and average available capacity (237 MW) — less than half of nameplate capacity was operationally deployable on average. This ratio, calculated before any formal efficiency analysis, is a direct measure of how far the existing asset stock falls short of deployment. The coefficient of variation (SD ÷ Mean × 100) quantifies relative dispersion across variables. Electricity Generated carries the highest relative dispersion at approximately 85.6% (1,202,735 ÷ 1,405,746 × 100), followed by Available Capacity at 80.8% (191.2 ÷ 236.7 × 100), and Installed Capacity the most uniform at 49.4% (262.1 ÷ 530.4 × 100). The wide dispersion in Available Capacity and Electricity Generated reflects substantial differences in maintenance standards, equipment condition, and gas-supply access across GenCos (Obasi & Nwambo, 2026). The zero minima for both Available Capacity and Electricity Generated are genuine observations, not missing values: they record plant-years in which a GenCo had no capacity available for dispatch or produced no electricity, conditions that occurred during the gas crises of 2017–2018. Replacing them with the next positive value would misrepresent the operational record.

Table 3: Descriptive Statistics of Study Variables

Variable	Mean	SD	Min	Max
Installed Capacity (MW)	530.4	262.1	100.0	1,320.0
Available Capacity (MW)	236.7	191.2	0.0	987.2
Electricity Generated (MWh)	1,405,746	1,202,735	0.0	5,626,000

Note. N = 192 for Installed and Available Capacity; N = 191 for Electricity Generated (one missing raw record). Statistics are from the full dataset before exclusion of two anomalous observations (Section 3.2). Author's computation from NERC data.

4.2 Overall Technical Efficiency

Table 4 summarises the distribution of DEA efficiency scores across the 190 estimation observations. Mean CCR efficiency of 0.710 means that the average GenCo produced approximately 71 per cent of the electricity achievable had it operated on the best-practice frontier with the same inputs. The appropriate measure of improvement potential in an output-oriented framework is $(1/\theta_{CCR} - 1) \times 100$. For $\theta_{CCR} = 0.710$, this gives $(1/0.710 - 1) \times 100 = 40.8$ per cent; the proportional increase in output attainable by reaching the frontier while holding installed and available capacity constant. This differs from $(1 - 0.710) \times 100 = 29.0$ per cent, which measures how far current output falls short of the frontier as a fraction of that frontier. In input-oriented DEA, 29.0 per cent would represent the proportional reduction in inputs achievable while holding current output constant— a different question and a different number.

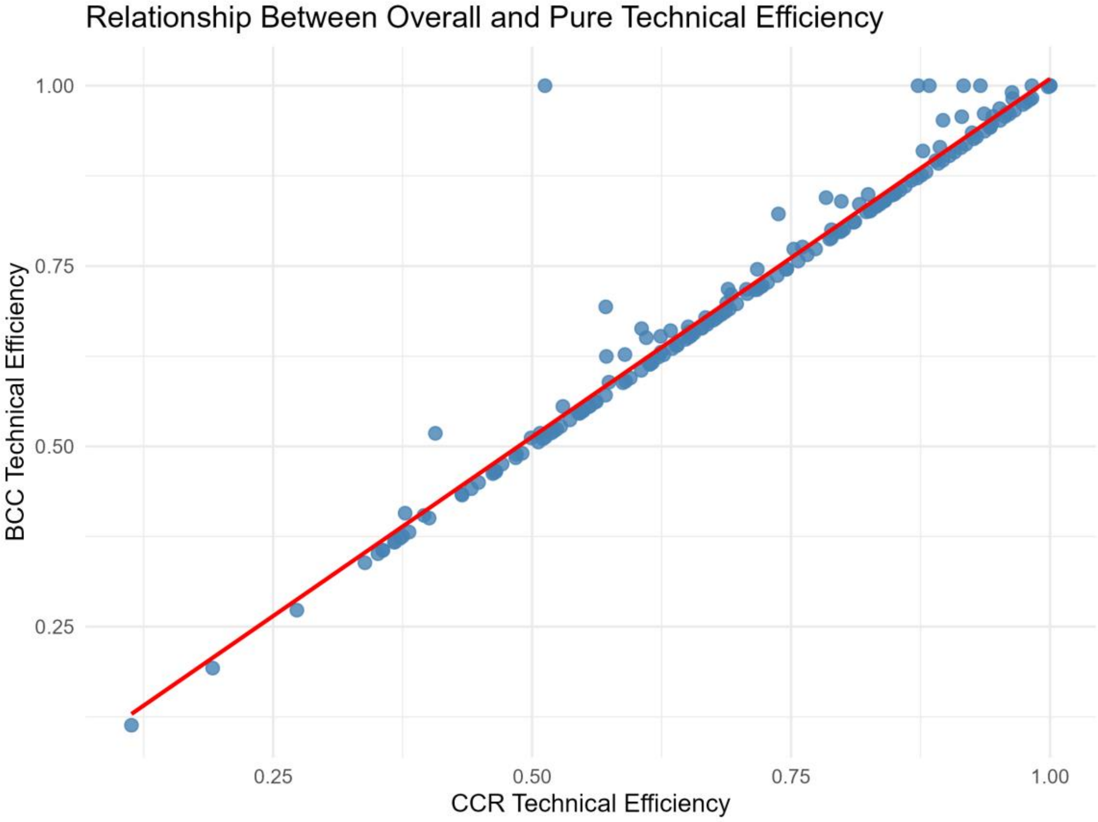
The gap between mean CCR (0.710) and mean BCC (0.722) is 1.2 percentage points, the share of the shortfall attributable to scale inefficiency. Mean scale efficiency of 0.985 confirms that most GenCos are already close to their most productive scale size. Figure 3 illustrates the observation-level relationship between θ_{CCR} and θ_{BCC}: the large majority of firm-year points cluster tightly along the 45-degree reference line, and departures are confined to a small group of larger plants. The shortfall is predominantly managerial and operational, not structural.

***Table 4**: Summary of DEA Efficiency Scores*

Statistic	CCR	BCC	Scale Efficiency
Mean	0.710	0.722	0.985
Median	0.711	0.718	1.000
Minimum	0.113	0.113	0.512
Maximum	1.000	1.000	1.000
Standard Deviation	0.197	0.200	0.045

Note. N = 190 firm-year observations (2017–2024), after exclusion of two anomalous records. Estimated using the Benchmarking package in R 4.6.1. Author's computation.

Figure 3: Relationship Between Overall (CCR) and Pure (BCC) Technical Efficiency Scores



Note. Each point represents one firm-year observation. The reference line is the 45-degree locus of equal CCR and BCC scores. Clustering along this line confirms that scale inefficiency is not the dominant source of the performance gap.

4.3 Returns-to-Scale Classification

Table 5 reports the three-way returns-to-scale classification using the CCR–BCC–NIRS decomposition. Of the 190 observations, 123 (64.7%) exhibit CRS, 44 (23.2%) DRS, and 23 (12.1%) IRS. That nearly two-thirds of firm-year observations fall in the CRS regime confirms that inappropriate plant scale accounts for a minority of observed inefficiency. DRS observations cluster among the larger plants. Kainji 1, Delta 1, Egbin 1, Afam 2, and Shiroro 1 are all predominantly classified as DRS, having expanded beyond their most productive scale. IRS observations, prevalent in 2017–2019 (four to five per year), largely disappear by 2022, consistent with the efficiency improvements documented in Section 4.5. The policy implication is direct: adding generation capacity will not close the efficiency gap unless the operational deficiencies holding firms below the frontier are addressed concurrently.

***Table 5**: Distribution of Firm-Year Observations by Returns-to-Scale Regime*

Category	Classification Criterion	N	Share (%)	Interpretation
CRS	θBCC ≈ θNIRS, SE ≈ 1	123	64.7	At or near optimal scale
DRS	θBCC ≈ θNIRS, SE < 1	44	23.2	Operating beyond optimal scale
IRS	θBCC > θNIRS	23	12.1	Operating below optimal scale

Note. Classification follows Coelli et al. (2005, pp. 171–174). The NIRS model is estimated with RTS = 'drs' in the Benchmarking package, implementing the restriction $\Sigma j \lambda j \leq 1$. Numerical precision threshold $\varepsilon = 10^{-4}$. Author's computation.

4.4 Firm-Level Benchmarking

Table 6 ranks the 24 GenCos by mean CCR efficiency over the study period, with fuel type, ownership, geographic zone, and mean plant age shown alongside. CCR is used as the ranking criterion because it captures total technical efficiency, which are the, managerial and scale components combined, making it the comprehensive measure appropriate for regulatory benchmarking (Section 3.6).

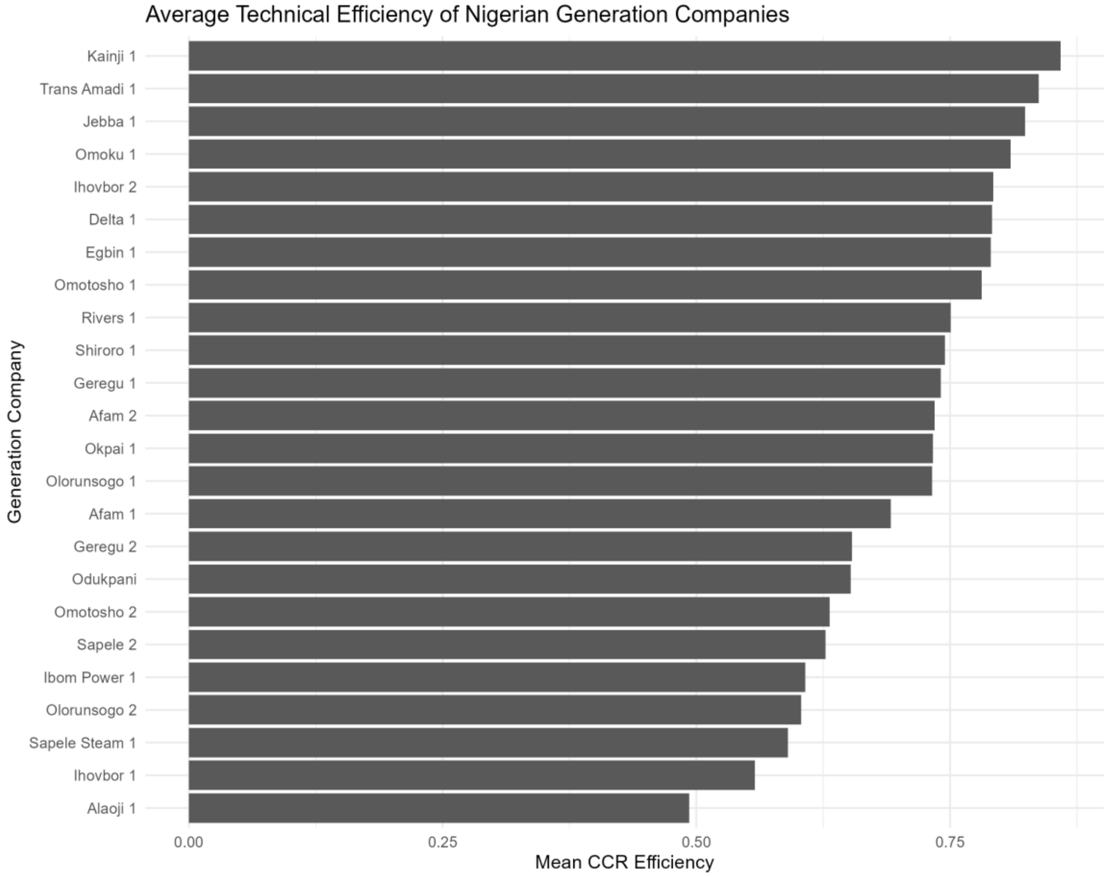
The efficiency distribution runs from 0.493 (Alaoji 1) to 0.859 (Kainji 1), a spread of 0.366 points within a common national regulatory environment. On average, bottom-quartile firms operate at about 60 per cent of the efficiency level of their top-quartile peers. Because scale efficiency exceeds 0.98 for all but a handful of firms, the spread reflects operational and managerial differences rather than differences in production scale. Kainji 1 and Jebba 1, both hydroelectric stations under long-term private concession, rank first and third. Their positions reflect two reinforcing advantages: the fuel-supply certainty of hydroelectric generation, which insulates them from the gas disruptions constraining thermal peers, and their operation under private concession arrangements, the ownership category that the regression in Section 4.6 associates with the largest positive average marginal effect (AME = 0.063), though that estimate is statistically insignificant. Trans Amadi 1, a gas-fired plant under private management, ranks second at a mean CCR of 0.837, demonstrating that thermal plants can sustain top-tier performance when management secures reliable fuel. Egbin 1 ranks seventh (0.790), consistent with Obasi and Nwambo's (2026) finding that its output closely tracks gas offtake. At the bottom, Alaoji 1, Ihovbor 1, and Sapele Steam 1 all average below 0.60, with scale efficiency above 0.98 in every case ($\theta_{CCR} \approx \theta_{BCC}$), rules out plant size explanation.

Table 6: Average DEA Efficiency Scores, Returns-to-Scale Classification, and Firm Characteristics (2017–2024)

Rank	Company	Mean CCR	Mean BCC	Scale Eff.	Dom. RTS	Fuel	Ownership	Zone	Avg Age
1	Kainji 1	0.859	0.879	0.976	DRS	Hydro	Private	North	53
2	Trans Amadi 1	0.837	0.839	0.998	CRS	Thermal	Private	South	20
3	Jebba 1	0.824	0.833	0.987	CRS	Hydro	Private	North	36
4	Omoku 1	0.810	0.829	0.978	CRS	Thermal	Public	South	16
5	Ihovbor 2	0.793	0.794	0.998	CRS	Thermal	Public	South	8
6	Delta 1	0.791	0.817	0.967	DRS	Thermal	Private	South	55
7	Egbin 1	0.790	0.844	0.935	DRS	Thermal	Private	South	36
8	Omotosho 1	0.781	0.782	0.999	CRS	Thermal	Private	South	16
9	Rivers 1	0.751	0.815	0.936	CRS	Thermal	Public	South	12
10	Shiroro 1	0.745	0.757	0.983	DRS	Hydro	Private	North	31
11	Geregu 1	0.741	0.751	0.989	CRS	Thermal	Private	North	14
12	Afam 2	0.735	0.744	0.980	DRS	Thermal	Private	South	39
13	Okpai 1	0.733	0.734	0.998	CRS	Thermal	Private	South	16
14	Olorunsogo 1	0.733	0.733	0.999	CRS	Thermal	Public	South	14
15	Afam 1	0.692	0.692	1.000	CRS	Thermal	Private	South	39
16	Geregu 2	0.654	0.654	0.999	CRS	Thermal	Public	North	8
17	Odukpani	0.652	0.656	0.993	CRS	Thermal	Public	South	7
18	Omotosho 2	0.631	0.640	0.986	CRS	Thermal	Public	South	8
19	Sapele 2	0.627	0.641	0.973	CRS	Thermal	Public	South	9
20	Ibom Power 1	0.607	0.608	0.999	CRS	Thermal	Public	South	12
21	Olorunsogo 2	0.603	0.603	0.999	CRS	Thermal	Public	South	9
22	Sapele Steam 1	0.590	0.595	0.992	CRS	Thermal	Private	South	43
23	Ihovbor 1	0.558	0.558	1.000	CRS	Thermal	Public	South	8
24	Alaoji 1	0.493	0.510	0.983	CRS	Thermal	Public	South	5

Note. Ranked by mean CCR efficiency. Dom. RTS = dominant RTS regime (modal classification). Fuel: Thermal = gas-fired or steam. Ownership: Private includes firms under full private management and long-term concession (Kainji 1, Jebba 1, Shiroro 1); Public includes NDPHC-operated plants, Olorunsogo 1, and Ibom Power 1 (state government). Zone: North = North Central Nigeria. Avg Age = mean plant age in years across all observation years, computed as mean (Year – Commissioning Year); averages for Omotosho 1 and Alaoji 1 are based on 7 observations (one excluded year each). Afam 1 commissioning year = 1982 (Afam IV reference unit; see Section 3.2). Author's computation.

Figure 1: Average Technical Efficiency of Nigerian GenCos, 2017–2024



Note. Mean CCR efficiency scores, ranked from highest to lowest. Bars represent study-period averages for each GenCo.

4.5 Annual Efficiency Trends

Table 7 and Figure 2 track sector-wide efficiency from 2017 to 2024 alongside the annual distribution of returns-to-scale regimes.

The sector recorded its lowest performance in 2017–2018. Mean CCR fell from 0.529 to 0.505, with no GenCo reaching the CCR frontier in either year. Notably, one firm achieved full BCC efficiency in 2017, indicating that its management was using available plant as effectively as any peer, even though a scale constraint held its overall CCR score below unity. IRS observations of four to five in both years confirm that several smaller plants had not yet reached their minimum efficient scale, adding a scale-related layer of underperformance to an already operationally weak period. The gas crises driven by pipeline vandalism and upstream pricing disputes are the primary explanation for these results.

A sustained recovery followed from 2019 to 2021. Mean CCR rose from 0.618 to 0.775, CRS observations climbed from 13 to 16, and the first CCR-frontier GenCo appeared in 2020. Three firms reached the BCC frontier by 2021. Greater gas-supply stability and growing operational experience among private managers are the most plausible drivers, consistent with Sarpong et al.'s (2022) finding that, Nigerian energy efficiency remained above the West African regional benchmark across this period.

The period 2022–2023 was the strongest in the panel. Mean CCR reached 0.861 in 2022 and peaked at 0.912 in 2023, when four CCR-frontier GenCos and five BCC-frontier GenCos were recorded. IRS observations dropped to zero in both years, indicating that plants previously constrained by insufficient scale had resolved that disadvantage. The 2024 retreat to 0.821 warrants monitoring: foreign-exchange constraints on imported spare parts after the naira devaluations of 2023, combined with renewed gas-supply instability, are the most plausible contributors.

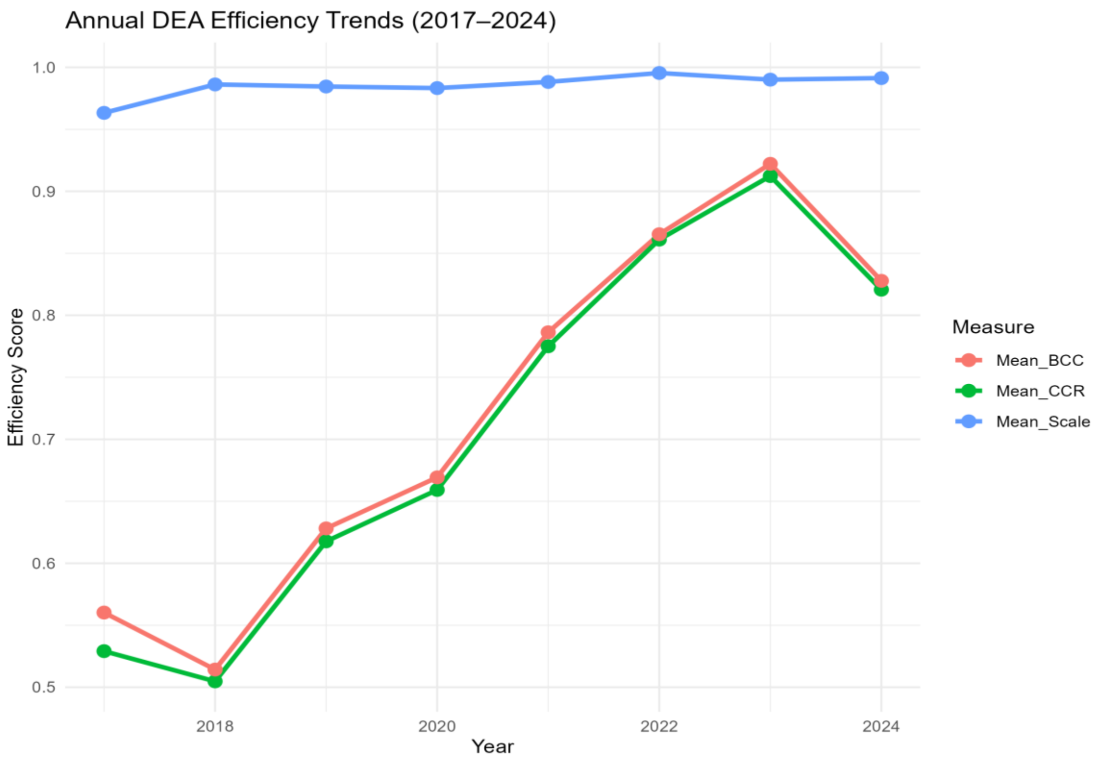
Scale efficiency varied narrowly between 0.963 and 0.995 throughout the eight years. Because this metric barely moved while mean CCR efficiency swung from 0.505 to 0.912 and back to 0.821, the observed changes reflect shifts in operational and managerial effectiveness rather than any change in the scale composition of the industry.

***Table** 7: Annual Average DEA Efficiency Scores and Returns-to-Scale Distribution (2017–2024)*

Year	Mean CCR	Mean BCC	Mean Scale	N	CRS	DRS	IRS	CCR Frontier	BCC Frontier
2017	0.529	0.560	0.963	23	12	7	4	0	1
2018	0.505	0.514	0.986	24	12	7	5	0	0
2019	0.618	0.628	0.985	24	13	6	5	0	0
2020	0.659	0.669	0.983	24	17	3	4	1	1
2021	0.775	0.786	0.988	24	16	4	4	1	3
2022	0.861	0.865	0.995	24	20	4	0	4	5
2023	0.912	0.922	0.990	24	18	6	0	3	5
2024	0.821	0.828	0.991	23	15	7	1	2	2

Note. CCR Frontier and BCC Frontier: number of GenCos scoring exactly 1.000. N = 23 in 2017 (Omotosho 1 excluded for missing values) and N = 23 in 2024 (Alaoji 1 excluded for zero output); N = 24 in all other years. CRS, DRS, IRS counts sum to N for each year. Author's DEA estimation.

***Figure 2**: Annual Trend in Mean CCR, BCC, and Scale Efficiency (2017–2024)*



Note. Mean efficiency scores computed across all GenCos for each year of the study period.

4.6 Contextual Regression: Determinants of Efficiency

Table 8 reports Average Marginal Effects from the fractional logistic regression with standard errors clustered at the firm level (G = 24). The cluster-robust estimator with 24 groups operates near the lower bound for reliable inference, conventionally placed at G ≥ 30 (Cameron & Miller, 2015). All results should be read accordingly.

No firm characteristic reaches conventional significance thresholds. Private management shows a positive AME of 0.063 (clustered SE = 0.043, p = 0.139) and hydroelectric fuel type a positive AME of 0.072 (clustered SE = 0.052, p = 0.167). Both point in the expected direction, but neither is distinguishable from zero. Geographic location and plant age are also insignificant ($p > 0.70$ in both cases).

The universal insignificance should not be read as evidence that ownership, fuel type, location, and plant age are irrelevant to efficiency. It reflects a structural data constraint. The effective sample size for identifying cross-firm differences in time-invariant covariates is the number of firms, not the number of observations: with 24 GenCos, of which only three are hydroelectric and twelve are private-managed, the regression does not have enough independent cross-sectional variation to resolve effects of this magnitude. Clustering forces the standard errors to reflect this reality honestly. In addition, the North-Hydro correlation of 0.74 means their individual contributions cannot be separated even in principle with the current sample. Variance Inflation Factors (VIFs) are all below 4 (Private = 2.65, Hydro = 2.78, North = 2.42, PlantAge = 3.03), confirming that multicollinearity is present but not at a level that inflates variances severely.

What the second stage does establish is the boundary of what this dataset can answer. The DEA findings carry the paper's contribution independently of the contextual regression: the 40.8 per cent output gap, the returns-to-scale distribution, the firm rankings, and the eight-year efficiency trend are robust findings that require no regression confirmation. The year fixed effects, all significant from 2019 onwards, confirm the temporal pattern already visible in Table 7. The McFadden pseudo-R^2 of 0.138 reflects a reasonable fit for this estimator class (Ramalho et al., 2010). Identifying the firm-level drivers of efficiency differences with statistical rigour would require either a cross-country panel of GenCos that provides more cross-sectional variation or a within-firm design that exploits changes in ownership and fuel mix over time. The Malmquist Productivity Index extension identified as future work would support the latter by generating time-varying efficiency measures linkable to time-varying covariates.

***Table 8**: Second-Stage Fractional Logistic Regression: Average Marginal Effects*

Variable	**AME**	**Robust SE**	**z-Statistic**	**p-Value**	**VIFs**
Private (= 1 if privately or concession-managed)	0.063	0.043	1.478	0.139	2.65
Hydro (= 1 if hydroelectric plant)	0.072	0.052	1.382	0.167	2.78
North (= 1 if North Central Nigeria)	0.002	0.023	0.066	0.947	2.42
Plant Age (years, time-varying)	0.001	0.002	0.367	0.714	3.03
Year fixed effects (2018–2024)	—	—	—	Included	
Observations	190				
McFadden pseudo-R^2	0.138				

Note. Dependent variable: firm-year CCR efficiency score, bounded in [0,1]. Fractional logistic regression estimated by quasi-maximum likelihood following Papke and Wooldridge (1996). Average Marginal Effects (AME = mean of $\Lambda(X\hat{\beta})[1-\Lambda(X\hat{\beta})] \times \hat{\beta}$ across all 190 observations) reported; raw log-odds coefficients available on request. Standard errors clustered at firm level (G = 24). With 24 clusters, the cluster-robust estimator is near its reliability lower bound (Cameron & Miller, 2015); inference is approximate. VIFs: Private = 2.65, Hydro = 2.78, North = 2.42, Plant Age = 3.03; all below 10. Correlation (North, Hydro) = 0.74. Installed capacity excluded per Ruggiero (1998). McFadden pseudo-R^2 = 0.138. Year FE for 2018 not significant ($p = 0.450$); for 2019–2024 all significant ($p \leq 0.006$).

5. Conclusion and Policy Implications

Four results emerge with policy consequence. Mean CCR efficiency of 0.710 implies a potential output gain of approximately 40.8 per cent through better operational use of existing assets; this is derived as $(1/\theta - 1) \times 100$ and explained in full in Section 4.2. Mean scale efficiency of 0.985 and a CRS share of 64.7 per cent establish that inappropriate plant scale accounts for a minority of the shortfall. The 0.366-point spread in mean efficiency among firms within a common regulatory environment confirms that operational and managerial differences drive the gap. The contextual regression is inconclusive: no firm characteristic reaches statistical significance once standard errors are clustered at the firm level with G = 24 firms. Private management (AME = 0.063) and hydroelectric fuel type (AME = 0.072) both show positive marginal effects consistent with prior expectations, but the confidence intervals are too wide to distinguish these effects from zero. This reflects the structural constraint that time-invariant firm characteristics can only be identified from 24 independent cross-sectional units, not from 190 pooled observations.

The policy implications are concrete. NERC should incorporate efficiency benchmarking into its regulatory toolkit, publishing CCR and BCC scores alongside existing capacity utilisation statistics; transparency of this kind creates measurable performance accountability and has supported efficiency improvements in regulated utility sectors internationally. The gap between average installed capacity (530 MW) and average available capacity (237 MW) is 293 MW per plant on average. That shortfall represents capacity that is nominally installed but cannot be dispatched, pointing to plant availability rather than technology as the binding operational constraint. Preventive maintenance and rehabilitation programmes targeted at the lowest-ranked GenCos could close a substantial part of that gap without new investment. Gas-supply security is a necessary structural condition for sustained efficiency gains: the 2017–2018 efficiency collapse and Obasi and Nwambo's (2026) plant-level evidence of r = 0.97 between gas offtake and output at Egbin 1 both confirm this, requiring coordination between the gas and electricity sectors beyond what individual plant managers can achieve.

Given the inconclusive contextual regression, no evidence-based claim about the efficiency effects of completing the privatisation programme can be made from these data. The directional evidence is consistent with private management being beneficial, but a credible causal estimate would require quasi-experimental identification, such as difference-in-differences around the 2013 event, which is beyond the scope of this study.

Four limitations define the scope of the findings. The pooled DEA approach assumes a common production frontier across all eight years; annual DEA runs combined with the Malmquist Productivity Index would separate efficiency changes from frontier shifts. The three-variable production specification omits fuel cost, maintenance expenditure, plant technology vintage, and environmental outputs. The fractional logistic regression should be supplemented with the Simar and Wilson (2007) double-bootstrap truncated regression for fully rigorous inference on efficiency determinants. Finally, the study covers only the generation stage; whether efficiency gains there translate into electricity reaching consumers depends on transmission and distribution performance outside this study's scope.

Conflict of Interest

The author declares that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper. No grant from any funding agencies in the public, commercial, or not-for-profit sectors.

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Appendix A

***Table A.1**: Updated Nomenclature of Nigerian Power Plants*

S/N	Old Name	New Name
1	Shiroro	Shiroro_1
2	Kainji	Kainji_1
3	Jebba	Jebba_1
4	Dadin-Kowa	Dadin-Kowa_1
5	Zungeru	Zungeru_1
6	Egbin ST (1-6)	Egbin_1
7	Sapele Steam	Sapele Steam_1
8	Delta	Delta_1

9	Geregu	Geregu_1
10	Omotosho	Omotosho_1
11	Olorunsogo	Olorunsogo_1
12	Afam IV-V	Afam_1
13	Sapele NIPP	Sapele_2
14	Alaoji NIPP	Alaoji_1
15	Geregu NIPP	Geregu_2
16	Olorunsogo NIPP	Olorunsogo_2
17	Omotosho NIPP	Omotosho_2
18	Ihovbor NIPP	Ihovbor_1
19	Gbarain NIPP	Gbarain_1
20	Okpai	Okpai_1
21	Afam VI	Afam_2
22	AES	AES_1
23	Omoku	Omoku_1
24	Azura IPP	Ihovbor_2
25	Ibom Power	Ibom Power_1
26	Trans Amadi	Trans Amadi_1
27	Rivers IPP	Rivers_1
28	Odukpani	Odukpani_1
29	Paras Energy	Ikeja_1
30	Taopex Energy	Igbafo_1

Note. All generating plants were renamed by NERC in 2024. This study adopts the current nomenclature throughout (NERC, 2025). Only 24 plants with complete data for the scope formed the scope of the research