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Assessing the Technical Efficiency of Electricity Distribution Companies in Nigeria: The Bootstrapped Data Envelopment Analysis (BDEA) Approach

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Abstract
The privatization and support of government for the Nigerian Electricity Distribution Companies (DisCos), were aimed at improving their performance in terms of availability and reliability of electricity supply. This, however, appears to be unrealistic, raising doubts on the technical efficiency of the sector. It is on the basis of this, therefore, that this study assessed the technical efficiency (TE) of Nigerian DisCos and their drivers. Data on the 11 DisCos were obtained from 2014-2021 and analysed by applying the bootstrap technique to the Data Envelopment Analysis (DEA) in order to resolve the stochastic challenge associated with the previous studies, which might be bias hence giving misleading results. The analysis was done in two stages. At stage one, the TE scores were obtained under both constant and variable returns to scale technology assumptions while at stage two, the impact of the environmental factors were measured on TE scores using truncated regression method. The results showed that, on average, DisCos are both technically and scale inefficient. Among others, the second stage result showed that customer metering has significantly negative impact on DisCos' efficiency while DisCos located in the north are about 4.9% more likely to be inefficient compared to their southern counterparts. However, customer density and subsidy were insignificant. As a consequence, the following recommendations are made: that massive investments be made in technology to automate processes and reduce the operational costs, hence boost technical efficiency. Also, that government halts its subsidy payment pending its proper impact assessment.

Keywords: Bootstrapping, Electricity Distribution Companies, Technical Efficiency, Truncated Regression
JEL Classification Codes: C44, L94, L25, C34

1. Introduction

Within the last four decades, the Technical Efficiency (TE) of electricity industry has been accorded priority globally, mainly through restructuring and privatization (Jamasb, 2006). In order to improve the sector's efficiency and ease off government fiscal burden, liberalization has been seen as a sure path. In 2005, Nigeria began the process of liberalization by enacting the Electricity Power Sector Reform Act [EPSRA], (2005) which eventually led to the unbundling of the sector into eleven distribution firms and their eventual privatization in November, 2013. Given the ever-increasing demand for power on the basis of population growth, urbanization and increase in power demand for industrial purposes, there seems to be a disparity between the demand and supply of electricity in the country. This deficiency has been blamed on the inefficiency of Electricity Distribution Companies (DisCos), which is occasioned by huge distributional losses. For instance, Onyishi and Ofualagba (2021) found that, only 41.7% of electricity received by Enugu Electricity Distribution Company (EEDC) from generation companies (GenCos) was eventually distributed to its franchise states in July, 2020. Besides, not all energies delivered to customers are equally billed and not all billed are collected. As an example, in the first quarter of 2021 out of 7,879.8gigawatt hour (GWh) of electricity received by all DisCos, only 6,049.2 GWh, representing about 77% were billed and out of the total billed amount of N277.5 billion, only N181.0 billion representing 65% was collected as revenues (Association of Nigerian Electricity Distributors [ANED], 2021). this makes DisCos' operational efficiency doubtful.

Different studies across climes such as those of (Rahmawati, Wahyudi, & Sakti, 2023; Lee, Wilson, Simshauser, & Majiwa, 2021) in Indonesia and Australia respectively have found that most electricity distribution firms are inefficient. In Nigeria, however, though performance measurements of DisCos have been carried out as evidenced from the study of (Onyishi & Ofualagba, 2021), very scanty studies such as Olayemi, Mukhtar, Bernard, Duru, and Alpha (2022) and Olanrele (2024), which used the deterministic DEA approach to measure technical efficiency of DisCos; an approach that ignores basic fundamental statistical assumptions such as normality. Although the Stochastic Frontier Analysis (SFA) resolves the statistical weaknesses associated with the deterministic DEA, its inability to simultaneously incorporate multiple inputs and multiple outputs into its analysis as DEA does, renders it of less preference compared to the DEA method.

Although there are two approaches to resolving the DEA statistical challenge, the stochastic Data envelopment Analysis (SDEA) and the statistical/econometric approach (Olesen & Petersen, 2016), the statistical approach which mimics the Data Generating Process (DGP) of the original dataset through bootstrapping is applied. This is because, it addresses both relative and statistical issues unlike the former, which only addresses statistical challenge. According to Simar and Wilson (1998, 2000, 2002 & 2007), bootstrapping helps to address the DGP of the variables which is a failure of the classical DEA. An untreated noise in a model may result into wrong results, wrong recommendations and hence, the accompanying economic consequences.

The Nigerian electricity sector has been bedevilled with myriad of challenges requiring robust solutions. The initial attempts by Olanrele (2024) and Olayemi *et al.* (2022) to address the sector's efficiency issue have come with some reservations for their inability to account for statistical shocks in their analyses. The outcomes of these works could therefore produce a misleading result, which if implemented may further worsen the already desperate energy situation in the country. It is on this ground, therefore, that this study applied a two-stage DEA model and the Simar and Wilson (2002) bootstrapping technique to address the relative and statistical concerns of the previous studies and also accounted for the DisCos' efficiency drivers at the stage two analysis. Literature is reviewed in section 2. In section 3, methodology is presented while section 4 embodies analyses of the data and their results. Section 5 contains conclusion and recommendations.

2. Literature Review

2.1 Conceptual Review

2.1.1 Concept of Technical Efficiency (TE)

According to Chang, Chang, Das, and Li (2004), TE is a uniform constriction of all inputs while holding output and technology constant (input-orientation) or a proportionate expansion of all outputs at the same level of inputs and technology (output-orientation). The score is usually arrived at using the Constant Returns to Scale (CRS) technology. Pure Technical Efficiency (PTE) is TE devoid of the scale of operations, that is, efficiency purely due to the managerial expertise of the company's management (Ohene-Asare, 2020d). This is arrived at using the Variable Returns to Scale (VRS) technology.

2.1.2 Concept of Electricity Distribution Companies

These constitute the downstream sector of the electricity industry. They step down high voltage energy usually from 33 kilovolt (kv) to either 11kv or 0.415kv—a form appropriate for different customer groupings. There are eleven of them in Nigeria covering between 3-5 states except Eko and Ikeja electricity distribution firms which are both franchised within Lagos state. Table 1 is the list of DisCos, geographical location and size.

Table 1: Electricity Distribution Companies in Nigeria

S/N	DisCos	Location	Size in Square Km
1	Abuja Electricity Distribution Company (AEDC)	North	709,207
2	Jos Electricity Distribution Company (JEDC)		
3	Kaduna Electricity Distribution Company (KAEDCO)		
4	Kano Electricity Distribution Company (KEDCO)		
5	Yola Electricity Distribution Company (YEDC)		
6	Benin Electricity Distribution Company (BEDC)	South	217,010
7	Eko Electricity Distribution Company (EKDC)		
8	Enugu Electricity Distribution Company (EEDC)		
9	Ibadan Electricity Distribution Company (IBEDC)		
10	Ikeja Electricity Distribution Company (IKEDC)		
11	Porthacourt Electricity Distribution Company (PHEDC)		

Source: Adopted from Olayemi *et al*. (2022)

Decision Making Units (DMUs): These are synonymous with firms or units, departments, sections or branches of a firm such as hospitals, schools, farms etc. that are being assessed for efficiency (Ohene-Asare, 2020b). They are similar in their operational activities as they use identical inputs to produce similar outputs (Charnes, Cooper, & Rhodes, 1978).

Bootstrapping: The Classical DEA attributes all deviations from optimality to inefficiency. The real-life situation is actually dotted with uncertainties, uncertainty from the frontier estimation or from sampling errors. The neglect of these fundamental issues may result in computational inaccuracies. It is, therefore, imperative to correct the biases in DEA estimates by creating confidence intervals using bootstrapping technique. Bootstrapping is, therefore, a self-starting process that uses computer simulation to re-sample a single data set from a thousand times in order to replicate the original Data Generating Process (DGP) thereby eliminating the associated data biases (Simar & Wilson, 2000). Ohene-Asare (2020a) posited that efficiency that has been adjusted for bias produces a better performance.

Environmental Variables: These do not constitute inputs or outputs but play into firm's efficiency. Those identified and used in this study include tariff shortfall, customer density, customer metering and location.

2.2 Theoretical Review

The following theories are considered to be pertinent to the topic of study, hence they are briefly discussed:

2.2.1 Stochastic Production Frontier Theory

This theory was independently developed by (Aigner, Lovell, & Schmidt, 1977; Meeusen, & van den Broeck, 1977) who held an opposite opinion to the neoclassicists who held that efficiency was natural to production (Kokkinou, 2010). They asserted that the divergence could be attributed to unanticipated external shocks or stochastic noise and inefficiency, which must be extricated to attain true optimality/efficiency. The criticisms of this approach include strict normality assumption of the stochastic noise, half normality of the technical inefficiency and inability to account for multiple inputs and outputs concurrently making it less suitable for DMUs with several inputs and outputs such as DisCos.

2.2.2 Extreme Point Theory of Linear Programming Optimization

This theory belongs to the linear programming or linear optimization theories pioneered by George Bernard Dantzig (Birge, 2021). It asserts that, the feasible point of a Linear Programming Problem (LPP) occurs at the vertex of the convex set or at the convex combination of two vertexes. Since optimization is all about minimizing input and or maximizing output, the efficient solutions are always found at the vertexes or the linear combinations of the vertexes of the production frontier, be it convex or concave. The DEA approach falls within this extreme point theorem given that it uses frontier extremes to arrive at optimality. Following Olayemi *et al.* (2022), this study is therefore situated within the framework of the extreme point theorem, which also accommodates concurrent estimation with multiple inputs and multiple outputs.

2.3 Empirical Review

Rahmawati *et al.* (2023) measured the efficiency of thirty-three Indonesian electricity distribution firms between 2010 and 2019 using the classical and bootstrapped DEA approach. The findings showed that, no firm was technically efficient during the period. Besides, the result of Classical DEA was exaggerated over the bootstrapped TE scores justifying the need for stochastic view of the DEA. In a related study, Zhang, Nisar, and Mu (2022) applied similar method to measure the TE of fish polyculture in two Indian regions. One hundred and sixty farmers, eighty from each region were sampled and the result showed that the bootstrapped TE had lower scores than the classical approach attesting to bias in the classical approach.

Also, Lee *et al*. (2021) investigated the TE and their sources in 14 electricity distribution companies in Australia between 2009 and 2019 using BDEA technique and truncated regression at stage two. Operating expenditures, network capacity in mega volt amp (MVA) and distribution line length in kilometre (Km) constituted input variables. Electricity delivered in gigawatt hour (GWh) was used as output while three environmental variables customer number, supply reliability and age of poles were also used. Based on the outcomes, most DMUs were inefficient within the time frame. Reliability became a significant source of efficiency based on the second stage analysis result. The double-bootstrapping technique makes this work sturdy as it resolves the relative efficiency score problem. Among other things, they suggested placing priority on steady electricity supply and replacement of aging poles by the firm to enhance their competition.

Bobde and Tanaka (2018) studied the efficiency and their sources in thirteen Indian electricity distribution firms between 2005 and 2012 using bootstrapped DEA method and based on input-orientation at stage one and at the second stage the environmental factors were regressed on the bootstrapped scores. The findings showed that customer structure and population density positively and significantly accounted for the firms' technical efficiency. Also, public utilities tended to be more efficient than their private counterparts. Lastly, subsidy payment was found to constitute a disincentive to efficiency. This work is robust to the effect that it accounted for statistical noise. They suggested a further evaluation of the disparity between public and private electricity firms' technical efficiencies and the reason for inverse relationship between subsidy payment and technical efficiency in subsequent studies.

In Sweden, Bergqvist (2018) estimated the TE of 150 grid firms using bootstrapped DEA between 2015 and 2016. Drivers of TE were also investigated. The findings among others showed that proportion of underground cables to the total route length, customer density, large geographical differences, and small-scale production correlated with firms' TE. He advised a regulatory incentive to power distribution firms in order to raise the ratio of underground cables to the total cable route length since it enhances their technical efficiency.

Xie, Gao, Chen, and Xi (2018) adopted the meta-frontier and bootstrapping techniques to assess 31 grid companies from 2004 to 2013 in China. Tobit regression model was used to assess TE drivers. The results affirmed the superiority of meta-frontier technique, as it provided better efficiency scores. Additionally, technological advancement and customer density were found to have accounted for the steady TE scores. They however, recommended a linkage between China's grid planning and economic forecasts. Besides, additional investments in grid construction and technical upgrade by grid companies, especially those in less developed areas was also recommended to enhance their efficiency.

Locally, Onyishi and Ofualagba (2021) in their study used power optimization approach to estimate EEDC's operational efficiency in distributing the allocated power from the national grid to their customers in July 2020. The outcome showed that 41.7% of allotted power was eventually delivered to their customers while the rest constituted technical loss. They recommended an accelerated investment by EEDC including embedded generation so as to stabilize power supply in the region.

Olayemi *et al.* (2022) measured the TE and their derivers among Nigerian DisCos using deterministic DEA approach and censored regression for first and second stage respectively. Data from 2014 to 2021 were collected on inputs, outputs and environmental variables. Though about 44% of the firms across time were efficient based on VRS technology, on average, none was efficient across the years. At the second level analysis, DisCos in the north were about 9.1% more inefficient than those in the south while customer metering exerted inverse relationship with TE. The major drawback of this study is its inability to account for relative and stochastic shocks of the TE scores. Among other things, they suggested a re-evaluation of government subsidy support on electricity to guarantee its effectiveness. Besides, government tackling the socio-economic challenges of the citizenry, especially those in the north was also advised.

Similarly, Olanrele (2024) estimated the TE of the eleven DisCos using data from 2015 to 2022. By using a single output, energy received as a proxy for electricity supply and network losses and aggregate technical commercial and collection losses (ATC&C) as input variables. The outcome showed that no DisCo was efficient. His result revealed that DisCos' performance worsened post-COVID-19 outbreak. Three observable weaknesses in this paper are: (i) the approach did not account for random shock (ii) the input variables used, network losses and ATC&C are not truly inputs and its inability to test the appropriate technology CRS or VRS. She, however, suggested a revisit of the privatization exercise to have a clearer path on investment commitment to the sector's infrastructure by DisCos, especially those with worst performance. Besides, she emphasized strict regulatory compliance enforced by the Nigerian Electricity Regulatory Commission.

From the reviewed literature, to the best of our knowledge, no known work in the context of Nigerian DisCos has accounted for the stochastic noise, true efficiency score (not relative), which are sources of bias. The bootstrapping technique, which addresses the data generating process (DGP) and provides confidence interval within the DEA methodology, is, therefore, deployed to resolve the stated issues following Lee *et al*. (2021).

3. Methodology

3.1 Source of Data

Data on capital, labour units and operating revenues of DisCos were obtained from their annual statements of accounts, 2014-2021. Number of metered customers and energy billed, a proxy for Energy delivered to end users were extracted from electricity report of the National Bureau of Statistics, June 2022. Energy received for 2014 was computed from Multi-Year Tariff Order (MYTO) 2015 of the Nigerian Electricity Regulatory Commission (NERC) based on the energy allocation formula. Energy received between 2015 and 2018 were extracted from Minor Review (MR) NERC (2022); those between 2019 and 2021 came from NERC (2023). Customer density was computed as the quotient of DisCo's area in square kilometre (Sqkm) to customer population. DisCos' size was obtained from various sources such as States and DisCos' websites. Electricity price deflator for the period, 2014-2021 was obtained from the Central Bank of Nigeria [CBN], (2022). Statistical Bulletin to convert the financial variables to their 2018 real values.

3.2 First Stage Estimation Technique

The classical DEA method by Charnes, Cooper, and Rhodes (1978) also known as CCR, and the Banker, Charnes, and Cooper (1984) also called BCC are respectively based on CRS and VRS technologies were used for the estimation, and the most appropriate is selected based on Simar and Wilson (2002) bootstrapping model. The models are as follow:

Charnes, Cooper and Rhodes (CCR) model which is stated based on input-orientation since demand for electricity is said to be out of DisCos' control (Lee *et al.*, 2021), and on CRS assumption is expressed as follows:

Minimize TE or PTE (where model is VRS)

$$\theta^* = \min_{\lambda_j \theta} \theta \tag{1}$$

Subject to (The Constraints):

$$\sum_{j=1}^{n} \lambda_j x_{ij} \leq \theta x_{i0}; \quad i = 1, \dots, m \tag{2}$$

$$\sum_{j=1}^{n} \lambda_j y_{rj} \geq y_{r0}; \quad r = 1, \dots, s \tag{3}$$

$$\lambda_j \geq 0; \quad j = 1, \dots, n \tag{4}$$

$$\sum_{j=1}^{n} \lambda_j = 1\ (VRS) \tag{5}$$

Where; θ^* is TE index of the target $DisCo_0$ based on input-orientation. If $\theta^* = 1$, $DisCo_0$ is efficient because it is operating on the efficiency boundary, but where $\theta^* < 1$, $DisCo_0$ is inefficient, that is operating within the frontier; $i\ and\ r$ represent inputs and outputs respectively; λ_j is the weights attached to inputs and outputs; x_{ij} equals the units of inputs, i, the jth DisCo used, and y_{rj} represents the quantity of output, r, the jth DisCo produced. x_{i0} and y_{r0} are the ith input and the rth output of DisCo under consideration. m and s are the last input and output variables respectively while n represents the last DisCo.

Banker, Charnes and Cooper **(**BCC) came up with the VRS technology approach in 1984 by assuming that all firms cannot be operating at optimal scale at all times. Hence, the identity, $\left(\sum_{j=1}^{n} \lambda_j\right)$=1 accords significance to the firms' operational size in efficiency assessment and the only distinguishing factor between the two approaches. Both models, were estimated and most suitable returns to scale technology based on Simar and Wilson (2002) test. The efficiency score from BCC estimation is also known as PTE scores (true scores devoid of managerial expertise). Scale efficiency score is the ratio of CRS scores to that of VRS, that is, $({\theta^*}_{(CRS)}/{\theta^*}_{(VRS)})$. It estimates every DisCo's closeness to its optimal scale size.

3.2.1 DEA Returns to Scale Test

Returns to scale test is key to DEA estimation because the output is sensitive to technology type (Dyson *et al*., 2001). Different methods are used in determining the nature of technology via DEA. The Simar and Wilson (2002) bootstrapping technique has become handy as it addresses the DGP in the DEA procedure. The hypothesis:

$$H_o: T\ is\ CRS \tag{6}$$

$H_1: T\ is\ VRS$; T =Technology

Simar and Wilson (2002) bootstrapping techniques for obtaining test statistics include: Mean of ratio ($\hat{s}_1$) and ratio of mean ($\hat{s}_2$):

$$\hat{S}_1 = n^{-1} \sum_{j=1}^{n} \left[\frac{\hat{\theta}_j^{CRS}(x,y)}{\hat{\theta}_j^{VRS}(x,y)}\right] \tag{7}$$

$$\hat{S}_2 = \left[\frac{\Sigma_{j=1}^{n} \hat{\theta}_j^{CRS}(x,y)}{\Sigma_{j=1}^{n} \hat{\theta}_j^{VRS}(x,y)}\right] \tag{8}$$

Where: $\hat{\theta}_j^{CRS}(x,y)$ and $\hat{\theta}_j^{VRS}(x,y)$ are respectively TE scores CRS and VRS. For inference, the p-value is required, but $\hat{S}$ distribution is unknown, hence bootstrapping, seems more suitable to obtain the critical values. Where the t-statistic is less than the critical value at 5% p-value, H_o, that is technology is CRS is rejected and if not, H_o is not rejected, that is, technology is VRS.

3.2.2 Bias Correction, the Bootstrapping Process

The efficiency scores of the classical DEA are bias because the model does not address random errors and correlation among TE scores. This is because the scores are relational to the frontier. Besides, it does not also provide confidence interval, hence, the emergence of the bootstrapping technique (Simar & Wilson 1998). The aim of the bootstrapping technique, therefore, is to simulate the DGP with repeated sampling to approximate the original data set.

Bootstrapping approximates the sampling distribution (mean and standard deviation) of the true unknown score ($\hat{\theta}_j(x,y)$) by the estimated ones ($\theta_j(x,y)$) by repeating the DGP and testing the reliability of the data set to arrive at bootstrap estimate ($\theta_j^*(x,y)$). From the original sample, the variance between estimated score and the real unknown one can be equated to the divergence between bootstrapped estimate and originally estimated score. By adapting Ohene-Asare, Turkson, and Afful-Dadzie (2017), this process is thus illustrated:

$$\left(\theta_j(x,y) - \hat{\theta}_j(x,y)\right) \mid s \approx \left(\theta_j^*(x,y) - \theta_j(x,y)\right) \mid s^* \qquad (9)$$

After obtaining the bootstrap estimates, $\theta_b^*(x,y), b = 1, \dots, B$ is gotten for a specific firm $\boldsymbol{j}$ the bootstrap bias estimate of original estimator $\theta_j(x,y)$ can be assessed thus:

$$\widehat{Bias}\,(\theta_j(x,y)) = \mathrm{B}^{-1} \Sigma_{b=1}^{B} \theta_j^*(x,y) - (\theta_j(x,y)\,) \qquad (10)$$

From equation 10, the bias-corrected estimator of the true score can be obtained as thus:

$$\begin{aligned} \theta_j^*(x,y) &= \theta_j(x,y) - \widehat{Bias}\,(\theta_j(x,y)) \\ &= (\theta_j(x,y)) - \mathrm{B}^{-1} \Sigma_{b=1}^{B} \theta_j^*(x,y) + \theta_j(x,y) \qquad (11) \\ &= 2(\theta_j(x,y)) - \mathrm{B}^{-1} \Sigma_{b=1}^{B} \theta_j^*(x,y) \end{aligned}$$

B represents the number of times bootstrap is replicated. This is expected to be large. Simar and Wilson (2007) suggested it to be as many as 2,000 times although not sacrosanct. The process allows for testing of hypothesis via confidence intervals Ohene-Asare (2020c), which the conventional DEA could not achieve. This work, however, used 3,000 replications.

3.2.3 Input Variables

Real capital $\boldsymbol{x_1}$, this is the deflated value of the companies' total assets and liabilities measured in Nigerian Naira. It is a widely used variable in related papers including Lin and Zhang (2017). Number of employees $\boldsymbol{x_2}$, depicts the total units of labour factor employed. Sánchez-Ortiz, García-Valderrama, Vanessa, and Giner-Manso (2020) used it; it is a significant input factor. Energy Received $\boldsymbol{x_3}$, represents the unit of energy received by DisCo from GenCos through the transmission lines in megawatt hour (MWh). This variable was used by Lin and Zhang (2017)

3.2.4 Output Variables

Energy delivered $\boldsymbol{y_1}$ equals to the proportion of energy received by DisCos that is delivered to end users; it is their key output variable used also by Bobde and Tanaka (2018). In this study, however, energy billed is used as a proxy for energy delivered to customers as a result of data inadequacy. Real operating revenues $\mathbf{y_2}$ constitutes the total revenues from supplying electricity to end users. Sánchez-Ortiz *et al.* (2020) employed it too. Number of customers $\boldsymbol{y_3}$, is also popular output variable (Lee *et al.*, 2021).

3.3 Second Stage Estimation Technique

3.3.1 Truncated Regression

At this stage, the environmental factors can be regressed on the TE scores. Other factors which play into the efficiency scores but cannot be considered direct inputs or outputs are incorporated at stage two (Fried, Lovell, & Eeckaut, 1993). Given that DEA model produces efficiency score which is truncated at 1, that is, it has an upper bound of 1, in the case of bootstrapping, the truncated regression method is preferable to the popular censored regression method used by (Xie *et al.*, 2018) whose result may be indeterminate as evidenced in Bergqvist (2018) due to the fact that biased corrected scores may be greater than 0 but less than 1 ($0<\hat{\theta}_b<1$) because, according to Bobde and Tanaka (2018) θ through a classical DEA approach is biased upwardly, hence the bias must be netted out. The work of Ohene-Asare (2017) reflected this outcome. Following Bergqvist (2018) and Lee *et al*. (2021), this work, therefore, employed the truncated regression method at this stage as follows:

$$\theta_{bi} = \pi + Z_i\Omega + \varepsilon_i \quad i = 1, \cdots, n \qquad (8)$$

Where: θ_{bi} is the bootstrapped TE scores; $\varepsilon_i \sim N(0, \delta_\varepsilon^2)$ is the random component, π is the intercept; Ω equals slope of Z variables whereas Z_i is the vector of the environmental variables.

3.3.2 Measurement of Environmental Variables

Factors which do not constitute inputs or outputs but indirectly affect technical efficiency employed in this study include:

Tariff shortfall z_1, which is the difference between the cost of producing 1 kwh of energy and what is allowed to be charged. This variance is paid as subsidy by government to the Market Operators (MO) for DisCos. The variable is found in Sánchez-Ortiz *et al.* (2020).

Customer density z_2, is the ratio of DisCo's customer population to its land area in square kilometres, that is, number of customers to a square kilometre of land. It is expected to be positively correlated with TE. Xie *et al*. (2018) employed it.

Customer Metering z_3, is expected to enhance efficiency given that it allows for energy accountability. Coincidentally, literature does not have a single work that has considered metering as environmental variable, perhaps, it is a non-issue in most societies unlike Nigeria.

Location z_4 refers to the geographical location of a DisCo, that is, north or south. This is imperative because of differential in socio-economic factors between the two regions. If a DisCo resides in the north, it takes a dummy of, 1 and if south, 0; Bergqvist (2018) employed it in his study.

4. Results and Discussion

4.1 Descriptive Statistics

Table 2 presents the inputs, real capital, labour and energy received and the outputs number of customers, real operating revenues and energy delivered in estimating the TE of DisCos.

Table 2: Descriptive Statistics of the Input and Output Variables

	Variables	Real Capital (N'M)	Labour No.	Energy Received MWh	Customer No.	Real Ope. Rev (N'M)	Energy Delivered MWh
Pooled	Mean	148,657	2,149	2,738,899	819,472	76,582	2,015,912
	Min	22,765	779	901,744	348,014	10,296	419,848
	Max	828,771	3,494	5,890,988	2,136,857	448,216	4,158,700
	N	78	78	78	78	78	78
Grouping by Location	Mean (N)	129,628	2,276	2,271,708	640,284	63,189	1,587,472
	nN	33	33	33	33	33	33
	Mean (S)	162,612	2,055	3,081,505	950,877	86,403	2,330,101
	nS	45	45	45	45	45	45
	t-Stat	-1.02	-4.64**	-3.64**	-3.71**	-1.28	-4.40**

*p<0.10; **p<0.05; t-stat.=Welch two sample t-test

Source: Estimation by the Author with R 4.3.0 software

From the Table 2, the average of real capital is about N148 billion and the maximum peaking at about N829 billion for Ibadan Electricity Distribution Company (IBEDC) while the minimum is about N23 billion for Yola Electricity Distribution Company (YEDC). The other two input variables, labour employed and energy received also vary significantly as shown in the same Table 2, suggesting that DisCos vary in sizes. On the output variables too, on average, the real average of the operating revenues stood at about ₦76.6 billion while the highest and the lowest respectively are ₦448.2 billion for EEDC and about ₦10.3 billion for Jos Electricity Distribution Company (JEDC). Customer number and amount of energy in MWh delivered to the Customers also suggests reasonable variation in the DisCos sizes.

As a comparison, however, input and output variables of DisCos located in the north have lower means compared to their southern counterparts besides employees' count. On average, the population of DisCos customers in the north (640,284) is just about two-third of their southern colleagues (950,877). The means of the variables in the two categories excluding capital and operating revenues are statistically different on the basis of Welch 2-sample t-test and probability level of 5%. showing that there is size variation among DisCos.

4.2 Correlation Analysis

Ohene-Asare (2020c) posited that within inputs and within outputs correlations should be low to avoid multicollinearity. On the other hand, input-output correlation should be positive in order to avoid spurious estimation. Table 3 presents the correlation relationships.

Table 3: Correlation Relationships Among Variables

		Input			Output			Environmental			
		RCapital	Labour	Energy Rcd	CustNo.	ROpRev	Energy Devd	RTfSf	Loc	Cden	Cus M
Input	RCapital	1									
	Labour	0.33**	1								
	EnergyRcd	0.18	0.49**	1							
Output	CustNo.	0.52**	0.45**	0.57**	1						
	ROpRev	0.59**	0.41*	0.33**	0.54**	1					
	EnergyDevd	0.26**	0.54**	0.88**	0.53**	0.44**	1				
Environ-mental	RTfSf	0.62**	0.33	0.43**	0.49**	0.58**	0.42**	1			
	Loc	-0.11	0.15**	-0.39**	-0.37**	-0.14	-0.45**	-0.18	1		
	Cden	0.04	0.25**	0.55**	0.07	0.21**	0.69**	0.22*	-0.43**	1	
	CusM	0.39**	0.41**	0.78**	0.86**	0.53**	0.69**	0.41**	-0.51**	0.24**	1

*p<0.10; **p<0.05; t-stat.=Welch two sample t-test
Source: Estimation by the Author with R 4.3.0 software

On a priori, it is expected that the input variables maintain low correlation (Ohene-Asare, 2020c). This is actually so as seen in Table 3, as correlations among inputs are all lower than average with the least being 18% while the highest is 49%. The correlation among the output variables also hovers around average with minimum being 44% and maximum also standing at 54%. Input-output correlation agrees with a priori expectation of positive and high correlation, since employment of inputs should not lead to the reduction of output. Energy received and energy delivered, however, produced the highest correlation relationship of 88%. On the principle of separability, it is expected that environmental variables (Z) maintain low correlation with input and with output factors at the first stage. Despite the fact that variables such as number of metered customer (CusM) and energy received (EnergyRcd) still maintain correlation coefficient as high as 78%, the bootstrapping techniques addresses it as it reduces to the barest minimum the impact of sampling error, outliers and other biases between the frontier and efficiency scores (Ohene-Asare, 2020c). This work, therefore, incorporates the bootstrapping technique to account for the statistical variances.

4.3 Returns to Scale Technology Test

Whether technology is CRS or VRS is key to the efficiency of DMUs, and as such, Table 4 presents the returns to scale test.

Table 4: Returns to Scale Result

		$\hat{S}_1$	$\hat{S}_2$	Conclusion
H_o: $T\ is\ CRS$				
Test statistic		0.9934**	0.9555**	
Critical:	5%	0.9945	0.9931	Reject H_o at 5%

*p<0.10; **p<0.05; t-stat.=Welch two sample t-test
Source: Estimation by the Author with R 4.3.0 software

Table 4 shows that test statistic at 5% level of significance is less than the critical value, it can, therefore, be concluded that the technology under which DisCos operate is VRS while also estimating CRS as a means of comparing the two technologies.

4.4 Estimation: First Stage DEA Efficiency Result

The bias-corrected TE, PTE and Scale Efficiency (SE) scores by DisCos and across the period 2014-2021 are respectively presented in Tables 5, 6 and 7. The bootstrapped scores, which represent the true scores of individual DisCos, accounts for biases such as the dependence on the frontier, measurement errors and other statistical anomalies associated with the conventional DEA approach. Across DisCos and across times, it is apparent from Tables 5 and 6 that, no DisCo is efficient both under CRS or VRS, though emphasis is on VRS.

Table 5: Bias -Corrected TE Scores (CRS) 2014-2021

	2014	2015	2016	2017	2018	2019	2020	2021	Mean	Counts
AEDC	0.772	0.883	0.885	0.879	0.839	0.869	0.709	0.768	0.825	0
BEDC	0.906	0.921	0.907	0.804	0.936	0.954	NA	NA	0.905	0
EKEDC	0.944	0.955	0.911	0.899	0.958	0.949	0.954	0.948	0.940	0
EEDC	0.809	0.859	0.803	0.801	0.852	0.863	0.905	0.909	0.850	0
IBEDC	0.921	0.920	0.945	0.906	0.954	0.927	0.921	NA	0.928	0
IKEDC	0.948	0.921	0.813	0.786	0.836	0.950	0.950	0.954	0.895	0
JEDC	0.668	0.863	0.820	0.863	0.789	NA	NA	NA	0.801	0
KAEDCO	0.752	0.910	0.859	0.740	0.748	0.875	0.673	0.848	0.800	0
KEDCO	0.945	0.834	0.889	0.835	0.836	0.871	0.850	0.852	0.864	0
PHEDC	0.927	0.915	0.935	0.786	0.812	0.830	0.825	0.943	0.872	0
YEDC	NA	NA	NA	NA	0.805	0.753	0.600	0.791	0.737	0
Mean	0.859	0.898	0.877	0.830	0.851	0.884	0.821	0.877		
Counts	0	0	0	0	0	0	0	0		

*p<0.10; **p<0.05; t-stat.=Welch two sample t-test
Source: Estimation by the Author with R 4.3.0 software

The mean scores across DisCos under CRS shows that, no DisCo is efficient within the period, given all the scores across DisCos and time are less than 1. Given that the technology of DisCos is VRS, the discussion is therefore based on Table 6.

Table 6: Bias -Corrected PTE Scores (VRS) 2014-2021

	2014	2015	2016	2017	2018	2019	2020	2021	Mean	Counts
AEDC	0.860	0.940	0.889	0.881	0.854	0.897	0.723	0.779	0.853	0
BEDC	0.941	0.966	0.959	0.858	0.947	0.963	NA	NA	0.939	0
EKEDC	0.942	0.960	0.933	0.920	0.955	0.953	0.961	0.953	0.947	0
EEDC	0.829	0.865	0.830	0.854	0.925	0.916	0.943	0.943	0.888	0
IBEDC	0.942	0.942	0.956	0.928	0.940	0.943	0.966	NA	0.945	0
IKEDC	0.942	0.945	0.840	0.809	0.841	0.954	0.941	0.941	0.902	0
JEDC	0.919	0.959	0.974	0.941	0.942	NA	NA	NA	0.947	0
KAEDCO	0.770	0.919	0.919	0.815	0.808	0.939	0.739	0.900	0.851	0
KEDCO	0.947	0.978	0.974	0.917	0.927	0.973	0.932	0.920	0.946	0
PHEDC	0.945	0.942	0.952	0.860	0.881	0.901	0.899	0.954	0.917	0
YEDC	NA	NA	NA	NA	0.942	0.967	0.943	0.942	0.948	0
Mean	0.904	0.942	0.923	0.878	0.906	0.940	0.894	0.917		
Counts	0	0	0	0	0	0	0	0		

Source: Computation by Author using R 4.3.0 Benchmarking Package.

By assuming the appropriate technology (VRS) which test results upheld for the industry, the bias-corrected score (PTE) as displayed in Table 6, shows that no DisCo across the years is efficient as none had the unity score (1). If JEDC and YEDC are excluded since they have missing data for (2019-2021) and (2014-2017) respectively, EKEDC still topped the mean score with about 95%, that is, it had about 5% input slacks over the years. By the same token, Kaduna Electricity Distribution Company (KAEDCO) had the lowest efficiency score of about 85% showing that about 15% of its inputs was not justified for the output it turned out over the same period.

The industry's year-in-year-out performance also shows that 2015 still happened to be the best for DisCos with efficiency score of about 94%, that is, about 6% of the industry's resources for that year was actually a waste, because that output equivalent could be achieved with just 94% of inputs they jointly committed. While the efficiency level was down to about 90% in 2020 (period of Covid-19), the performance in 2017 was actually lower with the efficiency score of about 88% showing that about 12% of the resources used could be saved. The bootstrap results showed that the scores are statistically significant within the confidence interval of 95%.

Table 7: Scale Efficiency Result, 2014-2021 (Bootstrapped)

	2014	2015	2016	2017	2018	2019	2020	2021	Mean	Counts
AEDC	0.897	0.939	0.995	0.997	0.983	0.969	0.979	0.986	0.968	0
BEDC	0.963	0.953	0.945	0.937	0.988	0.991	NA	NA	0.960	0
EKEDC	1.003	0.994	0.977	0.977	1.003	0.996	0.993	0.995	0.992	2
EEDC	0.975	0.993	0.967	0.939	0.921	0.942	0.960	0.963	0.958	0
IBEDC	0.978	0.976	0.988	0.977	1.014	0.983	0.968	NA	0.984	1
IKEDC	1.006	0.974	0.967	0.972	0.994	0.996	1.009	1.014	0.992	3
JEDC	0.727	0.900	0.842	0.917	0.838	NA	NA	NA	0.845	0
KAEDCO	0.976	0.990	0.935	0.908	0.925	0.932	0.910	0.942	0.940	0
KEDCO	0.998	0.852	0.913	0.911	0.902	0.896	0.912	0.927	0.914	0
PHEDC	0.981	0.972	0.982	0.914	0.921	0.921	0.918	0.989	0.950	0
YEDC	NA	NA	NA	NA	0.855	0.779	0.636	0.839	0.777	0
Mean	0.950	0.954	0.951	0.945	0.940	0.940	0.921	0.957		
Counts	2	0	0	0	2	0	1	1		

Source: Computed with R 4.3.0 Benchmarking Package.

Table 7 presents the SE for each DisCo across the years. The table shows that EKEDC (2014 and 2018). IKEDC (2014, 2020 and 2021) and IBEDC (2018) were optimal in their scale of operations while others were not given their SE scores being less than 1 across all the years. On average, no DisCo was scale efficient in the eight-year period, neither was the industry, on average, scale efficient. By implication, this means that none of the DisCos is steadily scale efficient, hence, it is imperative to optimise operational size based on the need of the moment.

4.5 Illustrating the Movement along the Frontier and Radial Projection

Table 8: Illustrating what to do to be Efficient

AEDC 2014	Actual inputs used (A)		PTE Score (B)	Input required to be efficient C=(A*B)	Inputs that could be saved D=(A-C)
RCapital (000'N) x_1	62,068,991	X	0.860	=53,379,332.8	8,689,658
Labour (No.) x_2	2,249	X	0.860	=1,934	315
EnergyRcd (MWh) x_3	4,516,424	X	0.860	=3,884,125.6	632,299

Source: Computed by the author.

Table 8 explains how AEDC which was inefficient in 2014 can adjust its input combination along the frontier and also be radially projected onto the frontier to become efficient. Inefficiency score of 0.860, that is a cut back of its input by about 14.0% to be technically efficient. To do this, it had to reduce each of its inputs by the reciprocal of the efficiency score (1-0.860 = 14.0%) for that year, 2014. As shown in Table 8, x_1 (RCapital) needed to be cut back by about ₦8.7 billion to about ₦53.4 billion. Labour (x_2) also needed to go down by 315 staff to retain a work force of 1,934 people. To also have optimal amount of received energy (x_3), it could reject about 632,300 MWh to remain at about 3.8 million MWh of energy. This will eliminate the mix inefficiency and radially project AEDC to the efficiency boundary.

4.6 Determinants of Efficiency: The Truncated Regression Result

Table 9: Efficiency Determinants: Truncated Regression Output

Var.	Mode1		Model 2	
	bTE		bPTE	
	Parameters.	t	Parameters.	t
Const	0.8610**	2.9543	1.4809***	5.981
LRTfSf	-0.0121	-1.0661	-0.0033	-0.341
Cden	0	1.0656	0	-0.3396
LCusm	0.0247	1.6863	-0.0370**	-2.9718
Loc	-0.0520**	-2.6015	-0.0486**	-2.8631
Sigma	0.0612***	11.6634	0.0520***	11.5645
Log-Likelihood	93.48		104.95	
DisCos	11		11	
Observation	68		68	

LRTfSf= log of real tariff shortfall; Cden= customer density; LCusm=log of customer Metering while Loc =location of DisCo, either North South. ***p<0.001; **p<0.01; *p<0.05

Source: Estimation by the Author with R 4.3.0 software

Table 9 presents the result of truncated regression to determine the impact of heterogenous variables such as tariff shortfall or subsidy, customer density, customer metering and geographical location of DisCos on their bootstrapped efficiency (bTE & bPTE) scores. Tariff shortfall has negative relationship with bTE in model 1 and 2, though not statistically significant making the impact on efficiency to be unclear. In both model 1 and 2 the coefficients of customer density are insignificant making it unclear what the impact of customer density is. Metering of customer on a priori is expected to be directly related with TE because customers are assumed to fully account for the energy they consume. However, this result shows otherwise, that is, an inverse relationship between metered customer and TE. At p-value less than 5%, the coefficient of 0.037, shows that, if metering goes up by 1%, DisCos' efficiency drops by about 3.7%. The result of Table 9 also shows that, DisCos in the North are about 4.9% more likely to be technically inefficient compared to those in the south based on -0.0486 coefficient and probability value, which is less than 5%.

4.7 Discussion of Results

Table 2 shows that, on average, there are 640,284 DisCos customers in the north as against 950,877 in the south, that is, two-third of their southern colleagues. This is appalling given the high population concentration in the north in comparison to the south. This outcome may be instructive for revenue collection for DisCos in the north, that they have the burden of huge energy consumers who are not their customers but are illegally connected to their networks. While the result showed that all DisCos across times were inefficient, 2017 and 2020 were worst hit. In 2017, about 12% of DisCos' total recourses could have been saved but were wasted. This may be due to the inability of DisCos' managements to do proper resources optimization. In addition to that, the partial global economic shutdown occasioned by the outbreak of Covid-19 might have also contributed to the low efficiency score in 2020, where about 10% of committed inputs were a waste because, on humanitarian ground, while majority of non-essential staff were on break, salaries were still being paid. Also, energy supply was also still being delivered to customers who could not be accessed for revenue collections.

Tariff shortfall/subsidy has inverse but statistically insignificant relationship with technical efficiency making its impact unclear on technical efficiency. This though agrees with Olayemi *et al.* (2022) but at variance with that of Sánchez-Ortiz *et al.* (2020) who found an inverse but significant relationship between TE and tariff shortfall/subsidy. The reason for this may not be far-fetched from mismanagement of national resources, given the level of corruption in government. In both model 1 and 2 the coefficients of customer density are insignificant making its impact obscure on TE. This, however, negates a priori expectation because customer concentration is expected to have positive impact on TE. This outcome agrees with those of Xie *et al.* (2018).

A negatively significant relationship between technical efficiency and customer metering was unexpected. This result may be as a consequence of customers getting metered to be free from estimated billing and probably thereafter engage in energy theft. The dearth of smart meters which could remotely detect and communicate tampering to DisCos' servers may be a major culprit in this situation. DisCos in the north are found to be about 4.9% more likely to be technically inefficient compared to those in the south This finding agrees with Olayemi *et al*. (2022) who had similar result with higher coefficient of 9.1% perhaps due to the inability of the model to account for statistical errors. This outcome is not surprising given the level of socio-economic challenges such as poverty and insecurity bedevilling the region. This finding also agrees with that of Bergqvist (2018) who had the similar result in a different clime.

5. Conclusion and Recommendations

This study assessed the technical efficiency of Nigerian DisCos and their drivers from 2014-2021, while accounting for the stochastic problem associated with the classical DEA approach. The outcome shows that no DisCo was efficient over the entire period, implying that, if this situation is not reversed, there is no likelihood of the country coming out of power crisis very soon. The outcome also reveals that DisCos, which are located in the north have more tendency to be technically inefficient than those in the south. In addition, the metering activity has also been counter-productive for DisCos, while government bailouts in terms of subsidy have not also made the desired impact.

As a consequence of the stated findings, the following recommendations are made:

(i) that government terminates the contract with DisCos that have clearly shown lack of capacity in order to allow firms that genuinely have technical and financial wherewithal to turnaround the sector's fortunes take over;

(ii) that massive investments in technology by DisCos, especially acquisition of smart meters that can interface with DisCos' servers and reduce revenue leakages through energy theft. This will also reduce operational cost as idle resources are significantly eliminated;

(iii) continuous training of staff, especially the management staff on resources management to enable them optimize their resources and eliminate waste occasioned by inappropriate resources combination.

(iv) that government suspends payment on subsidy in order to further evaluate its impact pending, (a) when government through the regulatory body NERC, embarks on an independent audit of DisCos' customers records and subsidy payment claims to ascertain the true position of things and (b) a proper customer enumeration and asset mapping to arrive at the true position of assets and the DisCos' customer base, while the firms for enumeration be selected through a competitive bidding process supervised by NERC to guarantee process integrity.

References

Aigner, D., Lovell, C. A. K., & Schmidt, P. (1977). Formulation and estimation of stochastic frontier production function models. *Journal of Econometrics*, *6*(1), 21–37.

Association of Nigerian Electricity Distributors (2021). Analysis of the commercial KPIs for ANED´s members Q2/2021. Retrieved from http://www.anedng.com/wp-content/uploads/2022/01/2021Q2.pdf

Banker, R. D., Charnes, A., & Cooper, W. W. (1984). Some models for estimating technical and scale inefficiencies in data envelopment analysis. *Management Science*, *30*, 1078-1092.

Bergqvist, M. (2018). Efficiency in Swedish power grids: A two-stage double bootstrap DEA approach for estimating the effects from environmental variables (Master's thesis, Umea University, Umea, Sweden). Retrieved from https://www.semanticscholar.org/paper/Efficiency-in-Swedish-Power-Grids-%3A-A-Two-Stage-DEA-Bergqvist/dee3216deb5bb178a86203569109c83d967c26aa

Birge, J. (2021). George Bernard Dantzig: The pioneer of linear optimization. Retrieved from https://mbrjournal.com/2021/01/26/george-bernard-dantzig-the-pioneer-of-linear-optimization/

Bobde, S. M., & Tanaka, M. (2018). Efficiency evaluation of electricity distribution utilities in India: A two-stage DEA with bootstrap estimation. *Journal of Operational Research Society*, *69*(9), 1423-1434.

Central Bank of Nigeria (2022). Annual Statistical Bulletins. Retrieved from https://www.cbn.gov.ng/documents/statbulletin.asp

Chang, H., Chang, W., Das, S., & Li, S. (2004). Health care regulation and the operating efficiency of hospitals: Evidence from Taiwan. *Journal of Accounting and Public Policy*, *23*, 483–510.

Charnes, A., Cooper, W. W., & Rhodes, E. (1978). Measuring the efficiency of decision-making units. *European Journal of Operational Research 3*, 429-444.

Dyson, R. G., Allen, R., Camanho, A. S., Podinovski, V. V., Sarrico, C. S., & Shale, E. A. (2001). Pitfalls and protocols in DEA. *European Journal of Operational Research*, *132*, 245-259.

Electric Power Sector Reform Act 2005. Retrieved from https://rea.gov.ng/wp-content/uploads/2017/09/Electric-Power-Sector-Reform-Act-2005.pdf

Fried, H. O., Lovell, C. A. K., & Eeckaut, P. V. (1993). Evaluating the performance of U.S. credit unions. *Journal of Banking and Finance, 17*(2/3), 251–265.

Jamasb, T. (2006). Between the state and market: Electricity sector reform in developing countries. *Utility Policy, 14*(1), 14–30.

Kokkinou, A. (2010). A note on theory of productive efficiency and stochastic frontier models. *European Research Studies*, *XIII*(4), 109-118.

Lee, B. L., Wilson C., Simshauser, P., & Majiwa, E. (2021). Deregulation, efficiency and policy determination: An analysis of Australia's electricity distribution sector. *Energy Economics*, *98*, 1-11.

Lin, B., & Zhang, G. (2017). Energy efficiency of Chinese service sector and its regional differences. *Journal of Cleaner Production*, *168*, 614-625.

Meeusen, W., & Van den Broeck, J. (1977). Efficiency estimation from Cobb-Douglas production functions with composed error. *International Economic Review, 18*(2), 435-444.

Multi-Year Tariff Order (2015). Retrieved from https://nerc.gov.ng/wp-content/uploads/2015/12/MYTO%202015%20PH%20DisCo%20Tariff%20Order.pdf

National Bureau of Statistics (2022). June Electricity Report. Retrieved from https://nigerianstat.gov.ng/elibrary/read/1241342

Nigerian Electricity Regulatory Commission (2022). Orders. Retrieved from https://nerc.gov.ng/resource-category/orders/?doc_term=myto+2015&ins=1#nerc-documents

Nigerian Electricity Regulatory Commission (2023). NESI key operational & financial data for 2019 – 2021. Retrieved from https://www.nerc.gov.ng/index.php/component/remository/func-startdown/864/?Itemid=591

Ohene-Asare, K. (2020a, December 20). Bootstrap for nonparametric test of returns to scale technology [Video file]. https://www.youtube.com/watch?v=qMlMtyfSyHU&list=PLDoDpzf4kevDs7juiNdejGDTN8HZN90Sy&index=30

Ohene-Asare, K. (2020b, December 20). Efficiency and productivity for researchers, data envelopment analysis [Video file]. Retrieved from https://www.youtube.com/watch?v=_DigSe_KIdk&list=PLDoDpzf4kevDs7juiNdejGDTN8HZN90Sy&index=11

Ohene-Asare, K. (2020c, December 20). Second stage DEA regression motivation, correlation, isotonicity [Video file]. Retrieved from https://www.youtube.com/watch?v=iU9WM4_plX0&t=5s

Ohene-Asare, K. (2020d, December 20). Efficiency & Productivity, Data Envelopment Analysis [Video file]. Retrieved from. https://www.youtube.com/watch?v=AF0L5e9gG2o&list=PLDoDpzf4kevDs7juiNdejGDTN8HZN90Sy&index=2

Ohene-Asare, K., Turkson, C., & Afful-Dadzie, A. (2017). Multinational operation, ownership and efficiency differences in the international oil industry. *Energy Economics, 68*, 303-312.

Olanrele, I. (2024). Efficiency performance of electricity distribution companies in Nigeria. *African Journal of Economic Review, 12*(1), 188-202.

Olayemi, J. S. Mukhtar, M., Bernard. O. A., Duru, M., & Alpha, Y. (2022). Assessing the technical efficiency of electricity distribution companies in Nigeria –The deterministic DEA Approach. *Journal of Economics and Policy Analysis, 7*(1), 44-64.

Olesen, O. B., & Petersen, N. C. (2016). Stochastic data envelopment analysis—A review. *European Journal of Operational* Research, *251*(1), 2-21.

Onyishi, D. U., & Ofualagba, G. (2021). Analysis of the electricity distribution supply in eastern Nigeria: Current challenges and possible solutions. *Journal of Electrical Engineering, Electronics, Control and Computer Science, 7*(25), 1-8.

Rahmawati, A., Wahyudi, S. T., & Sakti, R. K. (2023). Measuring the effectiveness of electricity distribution in Indonesian provinces using DEA bootstrap. *Journal of Indonesian Applied Economics, 11*(1), 75-89.

Sánchez-Ortiz, J., García-Valderrama, T., Vanessa, R., & Giner-Manso, Y. (2020). The effects of environmental regulation on the efficiency of distribution electricity companies in Spain. *Energy & Environment, 31* (1). DOI:10.1177/0958305X17745791

Simar, L., & Wilson, P. (2002). Non-parametric tests of returns to scale. *European Journal of Operational Research, 139*, 115-132.

Simar, L., & Wilson, P. W. (1998). Sensitivity analysis of efficiency scores: how to bootstrap in nonparametric frontier models. *Manage Sci, 44*, 49-61.

Simar, L., & Wilson, P. W. (2000). Statistical inference in nonparametric frontier models: The state of the art. *Journal of Productivity Analysis, 13*(1), 49–78.

Simar, L., & Wilson, P. W. (2007). Estimation and inference in two-stage, semi-parametric models of production processes. *Journal of Econometrics*, *136*, (1), 31–64.

Xie, B. C., Gao, J., Chen, Y. F., & Deng, N. Q. (2018). Measuring the efficiency of grid companies in China: A bootstrapping non-parametric meta-frontier approach. *Journal of Cleaner Production, 174*, 1381-1391.

Zhang, H., Nisar, U., & Mu, Y. (2022). Evaluation of technical efficiency in exotic carp polyculture in Northern India: Conventional DEA vs. bootstrapping methods. *Fishes*, *7*(4), 168.