Assessing the Technical Efficiency of Electricity Distribution Companies in Nigeria –The Deterministic DEA Approach

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Abstract

Technical efficiency (TE) is key to the productivity and profitability of firms, there is, however, a dearth of empirical assessment of the TE of the Nigerian electricity distribution companies (DisCos), raising questions about their perceived dismal performance over time. From this standpoint, therefore, it is the aim of this study to assess the TE of Nigerian DisCos using the deterministic data envelopment analysis (DEA) approach and to identify the drivers, which is significant to tackling efficiency deviations. In doing this, panel data of the eleven DisCos from 2014-2021 were used. A two-stage deterministic DEA analysis was carried out; in the first stage, the benchmarking package of R software was used to obtain the TE and the pure technical efficiency (PTE). In the second stage, the censored and truncated regression methods were used to estimate the impact of the environmental variables on TE and PTE scores. The result showed that out of 78 decision-making units (DMUs), 21 (27%) were efficient under the constant returns to scale (CRS) assumption while 34 (44%) under variable returns to scale (VRS) were also efficient. The second stage result also showed that DisCos in the north have about a 9.1% likelihood of being more inefficient than those in the south while customer metering has a negative impact on TE. Besides, subsidy and customer density did not have any significant impact on TE. The study, therefore, makes the following recommendations: a merger among DisCos that have smaller size since the industry exhibited scale inefficiency most of the time to enjoy economies of scale; that government focuses on reducing the socio-economic problems of Nigerians especially poverty and insecurity to boost the people's economic power thereby enabling them to settle their bills. It is also, recommended that government suspends the payment of subsidies on electricity to allow such funds to be used for the provision of infrastructure.

Key Words: DisCos, Technical Efficiency, Returns to Scale, Privatization and Two-stage DEA

Introduction

A firm is technically efficient if it can make the most output of a fixed amount of input factors or can use the least input resources to attain a fixed amount of output. Resources optimization is key to the profitability of the business. Profitability and efficiency issues led to the unbundling and privatization of the Electricity Distribution Companies (DisCos) in Nigeria in 2014 given its hitherto public ownership status, which was adjudged inefficient. Since the sector's unbundling into eleven DisCos (as contained in Appendix I) and privatized, a lot of efficiency indices were expected to have changed 8 years down the line. However, the industry's outputs in terms of power availability and reliability seem to be at variance with the general expectations giving rise to the question of the optimality of the production process.

At privatization, customer metering, Aggregate Technical, Commercial and Collection (ATC&C) loss reduction and adequate, reliable and affordable electricity to customers were the DisCos' Key Performance Indicators (KPIs) within five years of operations (Adebulu, 2015). About eight years into the exercise, the sector's statistics are staggering. According to the Nigerian Electricity Regulatory Commission (NERC) (2021), as of the end of 2019, the industry ATC&C loss stood at about 45% against the Multi-Year Tariff Order (MYTO) reduction target of 27.97% and by 2020, the loss rate further increased to 50.57% against the target of 22.11%. The surge may be attributed to the impact of the coronavirus (COVID-19) pandemic of 2019. By the same NERC report, at the close of 2019, about 40% of industry customers were metered but by the end of 2020, the rate had declined to about 37.4% showing more customers were acquired than metered. On energy off-take, in 2017, the total off-take from the grid by all DisCos excluding Yola Electricity Distribution Company (YEDC) whose ownership alternated between private and public due to insurgency, was 24,616 GWh and by 2020 it grew by about 14.56% to about 28,000 GWh (Association of Nigerian Electricity Distributors (ANED) quarterly reports, 2017-2020). With these statistics, investigating the Technical Efficiency (TE) of Nigerian DisCos becomes imperative.

Two major approaches are used to measure the TE of firms—parametric such as Stochastic Frontier Analysis (SFA) and non-parametric such as Data Envelopment Analysis (DEA). Within the last four decades, the DEA, which is deterministic (i.e., attributes all deviations from optimality to inefficiency) has gained more recognition in terms of usage owing to its simplicity and nonrequirement of statistical assumptions such as normality, non-correlation etc. compared with the parametric approach, SFA which has to fulfil all the assumptions. Though the pioneer of the DEA approach, Charnes, Cooper, and Rhodes (1978) also called CCR developed the model under the assumption that firms operate under Constant Returns to Scale (CRS), the combined work of Banker, Charnes and Cooper (BCC) in 1984, however, saw to its modification as it allows DMUs the attributes of Variable Returns to Scale (VRS) which seems to be more realistic.

This methodology is very popular in Asia with works such as Sudhir and Madoko (2018), Lin and Zhang (2017); in America Pérez-Reyes & Tovar (2021), Leme et al. (2014); and in Europe Sa´nchez-Ortiz et al. (2018), its adoption in measuring efficiency is still minimal in Africa, especially in Nigeria. To our knowledge, few related studies in the Nigerian power sector such as Samuel (2021) and Onyishi and Ofualagba (2021) are different from the approach used in this study in the following ways: (i) none borders on resource optimization (ii) none used the panel data of the eleven DisCos at a go and (iii) none has used the non-parametric DEA method or its variants in DisCos' TE assessment.

Badunenko and Tauchmann (2019) observed that knowing the TE status of firms is not as instructive as ascertaining their drivers, hence, its imperativeness. If DisCos' TE and their drivers are not determined, for proper attention, the current dismal state of electricity may persist and ultimately lead to the collapse of the industry. Given that no known study has empirically assessed the TE of Nigerian DisCos via the DEA approach, this study fills the gap by using the deterministic two-stage DEA method under both CRS and VRS assumptions to respectively assess and investigate the TE and their drivers with a focus on DisCos' geographical location; this is due to the differences in socio-cultural and economic factors between the north and the south of the country. The outcome of this research is undoubtedly significant to the government whose responsibility is to ensure power availability and reliability; the electricity industry which has to cut costs to maximise profit and researchers who will find it useful being a novel work in the Nigerian power sector. The rest of the paper is organized as follows: Section two provides the literature review— conceptual, theoretical and empirical literature; Section three outlines the methodology employed; Section four presents the results of data analyses while Section five presents the conclusion and policy recommendations.

Literature Review
Conceptual Review

Technical Efficiency (TE) also known as operational efficiency (Zhao et al., 2018) or global efficiency (Guerrini, 2013) is measured by the lowest input combination for a given level of output or the expansion of outputs at the same level of input consumption (Guerrini, 2013). According to (Farrell 1957 and Chang et al 2004) TE involves a proportional reduction in all inputs while maintaining the same level of output and technology (input-orientation) or a proportional increase in all outputs while holding the inputs and technology constant (output-orientation). A proportional reduction in all inputs and expansion in all outputs (non-orientation) simultaneously is also a possibility (Ohene-Asare, 2020a).

Technical efficiency can be decomposed into three, mixed (in)efficiency, pure technical efficiency (PTE) and scale efficiency (SE) (Ohene-Asare, 2020a). Mix (in)efficiency is a result of the right/wrong composition of inputs or outputs (Ohene-Asare, 2020a). PTE arises purely as a result of management skills; it is devoid of the firm's scale of operation. Scale efficiency on the other hand measures the effectiveness of the decision to operate at a certain production scale (Guerrini, 2013). This work, therefore worked within the frame of Guerrini, 2013 definition of TE since the DEA methodology used in this work allows some firms to be weakly efficient, that is, efficiency in the presence of input slacks.

Theoretical Review

Different theories are used to explain firms' efficiency beginning from the classical input-output approach of the theory of production, which enables efficiency to be measured as output-input quotient. In this case, efficiency is attained at the point of tangency between the isoquant and the isocost. Although it is also applicable in the case of multi-plant firms, where multiple inputs and outputs are involved, there is still the need to pre-specify the model. Another theory that has been used in explaining the efficiency of firms is the stochastic production frontier theory which attributes deviation from production optimality to two factors, namely: (i) statistical noise or irregular components, which are unobserved factors and measurement errors. (ii) inefficiency, which has to do with the managerial skill of the management. These two sources of deviation from optimality can therefore be separated via stochastic frontier measurement. The limitation of this approach is that it does not have an explanation for handling multiple inputs and multiple outputs simultaneously. The extreme point theorem which is the basis for Farell methodology, which also metamorphosed into the DEA method of efficiency measurement allows multiple analyses of variables simultaneously. The feasible or optimal solution of a linear programming problem (LPP) is established at the extreme points of the convex set or the convex combination of two extremes or corner points, which is akin to the piece-wise frontier of the DEA methodology on which relative efficiency or optimality of DMUs are measured. Of these theories, the extreme point theorem which allows firms' efficiency to be measured against the frontier and at the same time allows as many variables as are required to be factored into estimation, becomes ideal. This work is therefore, situated within the framework of extreme point theorem where on a scatterplot, firms that fall on the frontier—either at the extreme points or the convex combination of any two extreme points are considered relatively efficient whereas those that are off the frontier are measured relative to those on the frontier.

Empirical Literature

Measuring efficiency magnitude, especially at the early stage of DEA application was what most authors focused on. In their work, Çelen & Yalçın (2012) assessed the TE of twenty-one regulated electricity distribution firms in Turkey from 2002 to 2009 Fuzzy Analytic Hierarchy Process (FAHP) and Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) and DEA methods based on input orientation and CRS and VRS assumptions. The result showed that above 50% of the utility firms were efficient. Authors such as Vaninsky (2006) did similar works earlier.

Badunenko & Tauchmann (2019) posited that efficiency drivers are more instructive than their score size, hence, authors such as Pérez-Reyes & Tovar (2021) estimated the efficiency of fourteen Peruvian electricity distribution firms from 1996 to 2014 and the influence of certain firm-specific environmental variables such as reforms on their efficiencies. The first stage estimation was done under the VRS assumption using input-orientation. Two-stage DEA was used and the result showed that reform incentives significantly drive TE of Peruvian firms. In Ukraine, the same approach was used by Goncharuk et al (2020) who found that a continuous rise in tariffs did not enhance efficiency in most of the regions. Similarly, Sa´nchez-Ortiz et al (2018) studied the efficiency of five key electricity distribution firms in Spain from 2006 to 2015 using the multi-period efficiency technique of DEA with input orientation under CRS assumption. The result among others showed that tariff shortfalls and overcapacity had adverse effects on their TE. Zhao et al (2018) did similar works and had similar findings.

Given that the sources of non-homogeneity of production technology differ significantly based on factors such as location, economic situation, customer spread, resource endowment etc., O'Donnell et al. (2008) suggested a global or meta-frontier approach to addressing the effect of technological heterogeneity among distribution firms based on their varied environmental factors. In line with this, Xie, et al. (2017) used the DEA meta-frontier estimation technique to measure the TE of China's 31 grid firms between 2004 and 2013. In the second stage, the Tobit regression model was used to determine the influences of certain policies and non-homogenous factors on efficiency scores. The results showed that the grouping approach (meta-frontier), provided a better efficiency score. Among others, customer density had a positive impact on TE while clean power proportion had a negative impact. Lin & Zhang (2017) did similar works.

Undoubtedly, several works have been done on electricity and performance in Nigeria such as Samuel (2021) who assessed the impact of NERC on the performance of IBEDC and IKEDC using explanatory mixed method. By generalizing the result for all DisCos, his finding shows that NERC did not provide an appropriate regulatory environment for DisCos to thrive. Similarly, Idowu et al (2019) assessed the impact of privatization on IBEDC and IKEDC performance by administering a questionnaire to 881 participants. (IBEDC, 499 and IKEDC, 382) based on these indices: electricity supply, load shedding, pricing, metering, response to customers, and coverage area. The findings revealed that the privatization of IBEDC and IKEDC had no significant impact on their performance. Onyishi and Ofualagba (2021) assessed the operational efficiency of EEDC in distributing energy allocated to its franchise states in July 2020. Electricity Distribution Analysis on EEDC was conducted in July 2020 using Power Optimization Software. They found that EEDC distributed only 41.7% of the energy received to its franchise states.

From the review so far, efforts have been made from measuring efficiency magnitude only Çelen & Yalçın (2012) to the inclusion of environmental variables to identifying efficiency drivers Pérez-Reyes & Tovar (2021). Based on firms' possibility of heterogeneous technology, meta-frontier analysis was also introduced to measure firms' TE relative to the appropriate local frontier with studies such as Xie, et al. (2017). In the Nigerian context, however, no known work has been done on TE on the eleven Discos using the DEA approach. Performance measurements were done based on selected DisCos such as those of Samuel (2021) and Onyishi and Ofualagba (2021). None of these studies considered TE, that is, input-output optimization. This study, therefore, filled this gap by employing the two-stage DEA to assess DisCos' TE and also ascertain the efficiency drivers. The meta-frontier approach could not be used because of the inability to stratify Nigerian DisCos based on technology and the wants of reliable data.

Methodology

Sources of Data

Data from 2014-2021 were sourced from the Nigerian Electricity Regulatory Commission (NERC) website, their publications and statutory reports. The annual implicit price deflator for electricity from 2014-2021 was extracted from the Central Bank of Nigeria (CBN) Statistical Bulletin and used to deflate the financial variables using 2018 as the base year. Gupta (n.d.) posited that though subjective, the base year should not be very far from the current year and should not be characterised by serious or notable economic activity to avoid misleading results. 2018 was the eve of the COVID-19 pandemic, which shut down the global economy. The most stable year from 2014 to just before the pandemic was, therefore, 2018, hence its choice as the base year. Several metered customers were obtained from the National Bureau of Statistics (NBS) June 2022 Electricity Report.

Efficiency Estimation Technique: The First Stage DEA Deterministic Model

Estimation of the technical efficiency of DisCos is based on the novel DEA work of Charnes, Cooper, and Rhodes (1978) also known as the CCR model. The CCR model assumes CRS technology to attain TE. In reality, certain firms or DMUs may be operating at either optimal, below or above scale size, hence, the CRS assumption might not always hold and as, such, relaxing the CRS paves the way for the estimation of PTE which, is efficiency devoid of scale factor via VRS assumption as postulated by BCC in 1984. Scale Efficiency (SE) scores are, therefore, derivatives of the quotient of efficiency scores (θ) under CRS and that of VRS, that is, $(\theta_{CRS}/\theta_{VRS})$. The twain models are thus, specified:

DEA Model (CCR)

CCR in 1978, formulated their deterministic model under the assumption that all firms are optimal in operational size, hence, they operate under constant returns to scale (CRS, TE). Generally, the electricity demand is a derived demand, which is external to the control of electricity distribution companies (Pollit, 2003 as cited in Lee et al, 2021), hence, in an optimization attempt, minimizing input resources to meet the externally determined demand for electricity seems plausible.

Following Lee et al. (2021), Pérez-Reyes and Tovar (2021), and Sanchez-Ortiz et al. (2018), therefore, the input-oriented CCR linear programming model used in this study, is thus stated:

Minimize TE

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

Subject to:

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

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

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

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

DEA Model (BCC)

BCC in 1984, formulated the DEA model under the assumption that firms can operate under VRS as a departure from the rigid assumption of CCR. The sum of weights $\left(\sum_{j=1}^{n} \lambda_j\right)$ equals unity (1) means that the size of firms matters in efficiency measurement. This is the only constraint that differentiates the CCR model from the BCC model. i stands for inputs; r denotes output; λ_j is the weight assigned to both outputs and inputs; x_{ij} denotes the number of inputs, i, consumed by the jth DisCo, and y_{rj} denotes the volume of output, r, produced by the jth DisCo. x_{i0} and y_{r0} are the ith input and the rth output of DMU_0 (i.e., DMU/firm being evaluated). θ^* equals the input-oriented TE score of DMU_0. If $\theta^* = 1$, then the current level of input cannot be decreased proportionately, and that means DMU_0 is efficient or operating on the boundary but if $\theta^* < 1$, DMU_0 is dominated by the frontier and therefore inefficient. The quotient of the CRS efficiency score to that of VRS gives the SE score, which measures how near a firm is to the optimal scale of operation. This work intends to estimate both CCR and BCC models compare both results and then select the most appropriate technology based on returns to scale test results.

Test of Returns to Scale in DEA Space

Ascertaining the return-to-scale technology of production is key since the DEA result is sensitive to the nature of the technology involved (Dyson, et al, 2001). Authors such as Chang et al (2004) used a statistical test approach, however, Simar & Wilson (2011) suggested a bootstrapping approach to determine the technology set of production—CRS or VRS because of its ability to address the data generating process in the DEA procedure. The hypothesis is given as:

$$\boldsymbol{H_o}: T\ is\ \ CRS \tag{2}$$

$$\boldsymbol{H_1}: T\ is\ VRS; \qquad T = \text{Technology}$$

The nonparametric method of measuring returns to scale efficiency (S) was earlier put forward by Simar and Wilson (2002) using the bootstrapping approach, which guarantees test statistics. He proposed the use of two formulae: Mean of ratio $(\hat{s}_1)$ and the ratio of mean $(\hat{s}_2)$, which are respectively stated thus:

$$\hat{S}_1 = n^{-1} \sum_{j=1}^{n} \left[\frac{\hat{\theta}_j^{CRS}(x,y)}{\hat{\theta}_j^{VRS}(x,y)} \right] \tag{3}$$

$$\hat{S}_2 = \left[\frac{\Sigma_{j=1}^{n} \hat{\theta}_j^{CRS}(x,y)}{\Sigma_{j=1}^{n} \hat{\theta}_j^{VRS}(x,y)} \right] \tag{4}$$

Simar and Wilson (2011) came up with another test of the mean of ratios $(\hat{S}_3)$ of the form:

$$\hat{S}_3 = n^{-1} \sum_{j=1}^{n} \left[\frac{\hat{\theta}_j^{CRS}(x,y)}{\hat{\theta}_j^{VRS}(x,y)} - 1 \right] \geq 0 \tag{5}$$

$\hat{\theta}_j^{CRS}(x, y)$ equals the TE index under CRS and $\hat{\theta}_j^{VRS}(x, y)$ equals the TE index under VRS technology. If $\hat{\theta}_j^{CRS}(x, y) = \hat{\theta}_j^{VRS}(x, y)$ for every DMU ($j = 1,2, \ldots, n$), then H_0 holds and $\hat{S}$= 1, that is, CRS otherwise $\hat{S}$< 1, that is, VRS. As a result, H_0 will be rejected when $\hat{s}$ is less than 1. To make inferences from the identities, the p-values must be estimated but the distribution of $\hat{S}$ is not known; bootstrapping is, therefore, used to appropriate the critical values (Lee et al, 2021 and Ohene-Asare et al, 2017) used this method.

Variable Definition

Real capital, **(₦)** $\boldsymbol{x_1}$, equals the total equity and liabilities of the firms. Authors such as Sudhir & Madoko, 2018 used it. The number of employees $\boldsymbol{x_2}$ also constitutes an input variable in the literature and it comprises all categories of staff (Pérez-Reyes & Tovar 2021 and Goncharuk et al., 2020) have used this.

Energy Received (MWh) x_3, which is the amount of energy delivered to DisCos by generating companies (GenCos) in megawatt-hours (MWh) per year. Authors including (Lin & Zhang, 2017) have used it also.

Energy delivered (MWh) y_1, is the amount of high voltage electrical energy that is stepped down and made available to customers by DisCos. Several works including (Pérez-Reyes & Tovar, 2021) have used it in previous studies. It is, however, proxied by energy billed due to data unavailability. Real operating revenues $\mathbf{y_2}$ is the revenues earned from the delivery of energy to customers Goncharuk et al. (2020) used it also. The number of customers y_3, and energy delivered are the most widely used output variables in the literature (Leme et al., 2014),

The Second Stage Model - The Censored Regression

Efficiency scores range from 0-1, hence some sort of censoring happens. That is, values of the explained variable $\hat{\theta}_{it}$ are bounded between 0 and 1. Precisely, if we have all the information on the predictor but on just a subsample of the dependent variable, then censoring arises. In radial efficiency analysis, if a firm is efficient, it assumes a score of 1, otherwise, 0<$\hat{\theta}_{it}$ <1. To investigate the drivers of TE, the censored/tobit regression becomes appropriate. Xie, et al. (2017 used this method. In comparison with the truncated regression which, is also popular in this type of estimation as deployed by (Lee et al., 2021). The merit of censored regression is that it includes the censored observations of the dependent variable 0 and 1 in the regression estimates while the truncated approach drops out both the lower, 0 and the upper, 1, which could result in some biases. Both models are, however, used for comparison's sake while the decision is based on the censored regression. The censored model is thus stated following Çelen (2013). The estimated efficiency score can be defined by some environmental variables Z_{it} and unobserved variable $\hat{\theta}^*{}_{it}$ which are both dependent on the environmental variables and can be described thus:

$$\hat{\theta}^*{}_{it} = Z'_{it}\beta + \varepsilon_{i\,t} \quad i = 1, \cdots, n \qquad (6)$$

Where $\varepsilon_{it} \sim N(0, \delta^2)$, $Z_{it} = (r * 1)$ vector of independent variables, and β = $(r * 1)$ vector of the parameters for estimation. By using this unobserved variable, the observed efficiency score $\hat{\theta}_{it}$ can be defined in such a way as to allow censoring from both ends, 0 to the left and 1 to the right.

$$\hat{\theta}_{it} = \begin{cases} \hat{\theta}^*{}_{it} & \text{if } 0 < \hat{\theta}^*{}_{it} < 1 \\ 0 & \text{for other values of } \hat{\theta}^*{}_{it} \end{cases} \quad (7)$$

Environmental Variables Measurement

Tariff shortfall z_1 is the difference between allowed and cost-reflective tariffs. It represents the subsidy paid by the government for DisCos to Market Operators (MO) to cover the tariff shortfall. DisCos do not have control over it. Ortiz et al (2018) used the variable in their work. Customer density z_2, is the number of customers per square kilometre. This is expected to contribute positively to efficiency because, the shorter the field of coverage, the lower the investment required in terms of infrastructure provision Lee et al. (2021) used it. Customer Metering z_3 enables customers' energy consumption to be accurately measured Measurement is usually in Kilowatt hour (KWh). It is expected that the more customers are metered, the more energy is accounted for and the more efficient the firms are, ceteris paribus. Location z_4 refers to whether DisCo is located in the north or south (as contained in Appendix I). This variable proxies for economic power, cultural difference and insecurity. The reason is that the North has a higher poverty and insecurity burden than the South. This variable is represented by a dummy, 0 for south and 1 for north. Bergqvist (2018) used this variable in his work.

Presentation and Analysis of Results

The Descriptive Statistics

Table 1 presents the descriptive statistics for the input and output variables used in the first stage of analysis. The first panel is the pooled variables, while the second panel segregates the DisCos into north and south to account for the possibility of significant differences in the means of the variables based on location.

Table 1. 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**

*Source: Author's computation from research data using R 4.3.0 software. *p<0.10; **p<0.05; t-stat.=Welch two sample t-test; N=north; S=south*

From Table 1, across all the variables, inputs (real capital, labour and energy received in MWh) and outputs (customer number, real operational revenues and energy delivered to customers in MWh), it can be seen that DisCos vary in size, while some are large others are small; this is particularly shown by the maximum and minimum figures of each of the variables used. In comparison, southern DisCos have higher means than those in the north except for labour. The variables for both groupings except capital have means that are statistically different based on Welch's two-sample t-test and p-value less than 5%.

Correlation Analysis

Input-input and output-output correlations should be high to avoid multicollinearity (Ohene-Asare, 2020b) and as such, the correlation/isotonicity test among the variables is thus presented.

Table 2. Correlation Matrix Among Input and Output Variables

	Variables	Inputs			Outputs		
		RCapital	Labour	EnergyRcd	CustNo.	ROpRev	EnergyDevd
Inputs	RCapital	1.00					
	Labour	0.33 **	1.00				
	EnergyRcd	0.18	0.49**	1.00			
Outputs	CustNo.	0.52 **	0.45**	0.57 **	1.00		
	ROpRev	0.59 **	0.41**	0.33 **	0.54 **	1.00	
	EnergyDevd	0.26**	0.54**	0.88 **	0.53 **	0.44 **	1.00

*Source: Author's computation from research data using R 4.3.0 software. *p<0.10; **p<0.05; t-stat.=Welch two sample t-test*

Table 2 is the correlation matrix among the variables, among the inputs, among the outputs and between inputs and outputs. To avoid running into statistical problems such as multicollinearity low correlation among inputs and outputs are expected. The result showed that except between energy received and real capital, correlation among the inputs is generally low with the minimum being about 18% between real capital (Rcapital) and energy received and the highest 49% being between energy received and labour. The correlations among the output variables are also low and hence can be accommodated. Correlation between inputs and outputs are all positively and statistically significant ranging from the least which, is between energy delivered to customers and the real capital at 26% and the highest correlation between energy received by DisCos and energy delivered to the customers. This, therefore paves the way for further analysis.

Test of Returns to Scale

A vital assumption of the DEA efficiency assessment is the nature of technology/returns to scale. Given that not many works have statistically determined the exact nature of the global returns to scale, it, therefore, becomes imperative in this research.

Table 3. Returns to Scale Result

		$\hat{S}_1$	$\hat{S}_2$	$\hat{S}_3$	Conclusion
$\boldsymbol{H_o}$: $T\ is\ CRS$					
Test statistic		0.9939647**	0.9555317**	-0.006188244**	
Critical:	5%	0.9944953	0.9930728	-0.005568126	Reject $\boldsymbol{H_o}$ at 5%
	1%	0.9912656	0.9853484	-0.008504764	Do not Reject $\boldsymbol{H_o}$ at 1%

*Source: Author's computation from research data using R 4.3.0 software. ***p<0.01; **p<0.05*

Following the assumption of the null hypothesis (*Ho*) that the technology is CRS, the estimates of all three-test statistics as shown in Table 3 are less than the critical values at the 5% level although not at 1%. It is, therefore, concluded that DisCos exhibit VRS in their operations. That is, Nigerian DisCos vary in size. VRS and CRS are both used to compare TE and PTE.

Estimation: First Stage DEA Efficiency Result

From Table 4 TE (CRS), no DisCo was efficient for eight consecutive years. The TE (VRS) of Table 5 which, is the technology underlining the industry as presented in Table 3, IBEDC and EKEDC still topped the list by efficiency counts. AEDC and KAEDCO, however, have zero TE counts across the years and technology as displayed in Tables 4 and 5. Table 6 presents the results of the scale efficiency across all DisCos and periods. It suggests that no DisCo is consistently operating at optimal scale size, hence the need to adjust the scale of operations appropriately.

Table 4 Technical Efficiency Scores (CRS) /TE 2014-2021

	2014	2015	2016	2017	2018	2019	2020	2021	Mean	Counts
AEDC	0.817	0.923	0.905	0.900	0.861	0.913	0.733	0.803	0.857	0
BEDC	1.000	0.972	0.935	0.833	0.970	1.000	NA	NA	0.950	2
EKEDC	1.000	1.000	0.944	0.937	1.000	0.993	0.995	1.000	0.984	4
EEDC	0.855	0.887	0.837	0.828	0.896	0.904	1.000	1.000	0.901	2
IBEDC	1.000	1.000	1.000	0.948	1.000	1.000	0.968	NA	0.988	5
IKEDC	1.000	0.961	0.836	0.806	0.864	1.000	0.985	1.000	0.931	3
JEDC	0.698	0.890	0.842	0.906	0.815	NA	NA	NA	0.830	0
KAEDCO	0.788	0.945	0.883	0.758	0.761	0.895	0.692	0.870	0.824	0
KEDCO	1.000	0.854	0.904	0.854	0.860	0.894	0.875	0.880	0.890	1
PHEDC	1.000	1.000	1.000	0.828	0.851	0.863	0.849	1.000	0.924	4
YEDC	NA	NA	NA	NA	0.849	0.782	0.631	0.825	0.772	0
Mean	0.916	0.943	0.909	0.860	0.884	0.924	0.859	0.922		
Counts	6	3	2	0	2	3	1	4		

Table 5 Technical Efficiency Scores (VRS) /PTE 2014-2021

	2014	2015	2016	2017	2018	2019	2020	2021	Mean	Counts
AEDC	0.886	0.971	0.907	0.902	0.870	0.928	0.740	0.804	0.876	0
BEDC	1.000	1.000	0.980	0.877	0.973	1.000	NA	NA	0.972	3
EKEDC	1.000	1.000	0.955	0.948	1.000	1.000	1.000	1.000	0.988	6
EEDC	0.856	0.889	0.856	0.871	0.952	0.944	1.000	1.000	0.921	2
IBEDC	1.000	1.000	1.000	0.956	1.000	1.000	1.000	NA	0.994	6
IKEDC	1.000	1.000	0.854	0.822	0.864	1.000	1.000	1.000	0.942	5
JEDC	0.948	0.990	1.000	1.000	0.970	NA	NA	NA	0.981	2
KAEDCO	0.794	0.947	0.936	0.828	0.821	0.954	0.752	0.915	0.869	0
KEDCO	1.000	1.000	1.000	0.932	0.941	0.986	0.950	0.940	0.969	3
PHEDC	1.000	1.000	1.000	0.884	0.908	0.923	0.915	1.000	0.954	4
YEDC	NA	NA	NA	NA	1.000	1.000	0.974	1.000	0.994	3
Mean	0.948	0.980	0.949	0.902	0.936	0.974	0.926	0.957		
Count	6	6	4	1	3	5	4	5		

Table 6 Scale Efficiency Scores (Input orientation)2014-2021

	2014	2015	2016	2017	2018	2019	2020	2021	Mean	Counts
AEDC	0.922	0.951	0.998	0.999	0.990	0.984	0.991	0.999	0.979	0
BEDC	1.000	0.972	0.954	0.949	0.997	1.000	NA	NA	0.980	2
EKEDC	1.000	1.000	0.988	0.988	1.000	0.993	0.995	1.000	0.996	4
EEDC	0.999	0.998	0.978	0.951	0.942	0.958	1.000	1.000	0.978	2
IBEDC	1.000	1.000	1.000	0.991	1.000	1.000	0.968	NA	0.994	5
IKEDC	1.000	0.961	0.978	0.981	1.000	1.000	0.985	1.000	0.988	4
JEDC	0.737	0.899	0.842	0.906	0.841	NA	NA	NA	0.845	0
KAEDCO	0.992	0.998	0.943	0.916	0.927	0.937	0.920	0.951	0.948	0
KEDCO	1.000	0.854	0.904	0.917	0.914	0.907	0.921	0.936	0.919	1
PHEDC	1.000	1.000	1.000	0.937	0.938	0.934	0.927	1.000	0.967	4
YEDC	NA	NA	NA	NA	0.849	0.782	0.648	0.825	0.776	0
Mean	0.965	0.963	0.959	0.953	0.945	0.950	0.928	0.964		
Count	6	3	2	0	3	3	1	4		

Source: Author's computation R software.; TE=Technical efficiency; PTE= Pure Technical Efficiency and SE =Scale Efficiency; NA= Not available

Illustrating the Slack and Radial Movement

As an illustration, Table 7 shows what AEDC needed to have done to achieve TE in 2014. Given that it was inefficient in the year with the PTE score of 0.886, it needed to reduce all its inputs by (1-0.886) 11.4% to become technically efficient. As illustrated in Table 7, it had to reduce x1 (RCapital) by about ₦7.1 billion to about ₦55.1 billion. It also had to reduce units of labour (x2) by 256 workers to maintain a workforce of 1,993 and reduce energy uptake of (X3) by about 515 thousand MWh to 4 million MWh. This will both eliminate slacks in resources used and radially project it to the efficiency frontier.

Table 7. Illustration of How to be Efficient

AEDC 2014	Actual inputs used	PTE Score		Input required to be efficient	Inputs that could be saved
RCapital (000'N) X1	62,068,991	X	0.886	=54,992,307	7,076,684
Labour (No.) X2	2,249	X	0.886	=1,993	256
EnergyRcd (MWh) X3	4,516,424	X	0.886	=4,001,492	514,932

Source: Author's computation

Estimation: Second Stage DEA Result

Correlation Analysis

According to the Gauss Markov regression assumption, to have a valid result, explanatory variables are not expected to be collinear, that is, their covariance should equal zero Cov (X_i, X_j) =0 (Gujarati & Porter, 2009). Table 8 shows that all the variables have correlation coefficients less than average, hence appropriate for further estimation.

Table 8. Correlation Matrix of the Environmental Variables

	RTfSf	Cden	CusM	Loc
RTfSf	1.00			
Cden	0.22*	1.00		
CusM	0.41**	0.24*	1.00	
Loc (dummy)	NA	NA	NA	NA

*Source: Author's computation from research data using R 4.3.0 software. *p<0.10; **p<0.05*

Determinants of Efficiency: The Censored Regression Result

Following Xie, et al. (2017), censored regression is used to explain the impact of the environmental variables on the estimated efficiency scores TE (CRS) and PTE (VRS). The TE and PTE scores obtained from the first stage analysis from 2014 and 2021 are used as the dependent variables while the environmental variables served as the explanatory variables. Since the test of return to scale shows that DisCos exhibit VRS and the chosen regression model is censored regression, the interpretation of the result of Table 9, is, therefore, based on the duo.

Table 9. Efficiency Determinants: Censored and Truncated Regression Results

Var.	Censored Regression (Model 1)				Truncated Regression (Model 2)			
	TE		PTE		TE		PTE	
	Coef.	T	Coef.	T	Coef.	t	Coef.	t
Const.	0.844*	2.07	1.791***	3.72	0.873**	2.71	1.550***	5.44
LRTfSf	-0.011	-0.68	-0.003	-0.17	-0.011	-0.90	-0.003	-0.28
Cden	0.000	0.38	0.000	0.35	0.000	0.49	-0.000	-0.07
LCusm	0.029	1.45	-0.056**	-2.39	0.026	1.60	-0.030**	-2.79
Loc	-0.092***	-3.32	-0.091**	-2.90	-0.074***	-3.33	-0.061**	-3.12
DisCos	11		11		11		11	
Observation	68		68		68		68	

*Source: Author's Computation from Research data using R 4.3.0 software. LRTfSf= log of real tariff shortfall; Cden= customer density; LCusm=log of customer number while Loc =location of DisCo, either in the North or in the South. ***p<0.001; **p<0.01; *p<0.05*

LRTfSf is the logged value of the real tariff shortfall (subsidy), though negatively related to PTE, in model 1, it is not statistically significant showing that the government paying subsidy on electricity does not have any bearing with the TE of DisCos. This finding departs from that of Ortiz et al (2018) who established a negative relationship between tariff shortfall and TE. This result may be because the subsidy is not paid directly to DisCos but to the (MO) to settle arrears to the Nigerian Electricity Supply Industry (NESI), hence they could not determine how best such funds could be deployed. Customer density (Cden) is also not significant as a determinant of DisCos' TE given that the p-value is greater than 5%. The result is unexpected given the disparity between the customer density of DisCos in the north and those of the south with a ratio of 6:232 respectively. This result, however, agrees with those of Xie, et al. (2017) and Celen (2013) but not with that of (Lee et al., 2021).

On a priori, a positive and significant relationship between TE and metering was expected, However, the coefficient of -0.056 shows that metering of customers results in about a 5.6% decline in the TE of DisCos. Metering is expected to enable customers to account for energy consumption while DisCos account for energy delivered. The result may be due to energy theft by some metered customers since most installed meters are not smart enough to allow detection of fraud/tampering. The geographical location (Loc) of the DisCos complied with the a priori expectation. With a coefficient of -0.091, if a DisCo is located in the north, it has about a 9.1% likelihood of being inefficient. The following reasons may support this finding: (i) Based on the 2022 NBS report there is a higher poverty rate in the north than in the south which, will impede DisCos revenues from their operations and hence, their performance, (ii) insecurity which also prevents effective daily operations in the franchise areas. To the north, throughout this work, states like Zamfara, Katsina, Kaduna, Plateau, Benue, Niger, Borno, Yobe Adamawa etc. have had their fair share of insecurity thwarting DisCos operations. This result agrees with (Bergqvist, 2018).

Conclusion and Recommendation

This work assessed the TE of the Nigerian DisCos post-privatization. Panel data from 2014-2021 concerning the 11 DisCos in Nigeria were used. A two-stage DEA analysis was carried out. In the first stage, TE, PTE and SE scores were obtained. In the second stage, the censored and truncated regressions methods were used to estimate the efficiency drivers (TE and PTE). Out of 78 DMUs, 21 (27%) were efficient under CRS assumption while 34 (44%) were efficient when VRS was assumed. The eight-year efficiency score (PTE) placed IBEDC and EKEDC on top of the efficiency score while KAEDCO and AEDC became the least efficient. Of all the DMUs, only 34 (44%) were efficient while the remaining 44 (56%) were not. The second stage result also shows that geographical location has a statistically significant effect on the efficiency of DisCos; DisCos in the north are 9.1% more likely to be inefficient than those in the south. Government subsidy is not significant in influencing the TE of DisCos. Customer metering was negatively significant, against a priori expectation.

Based on these outcomes, the following recommendations are made: DisCos are not scale efficient and could change their scale of operation by way of merging (firms that have smaller asset values such as JEDC and YEDC, which also have proximity could merge into one to allow for economies of scale); that inefficient DMUs should copy from their efficient peers. DisCos, especially those in the north need to embark on community reorientation on the need for customers to offset their bills and the significance of productive use of power to relieve their bills' burdens. The government on their part can embark on poverty alleviation through agriculture to enhance the people's income and hence enable them to meet their socio-economic needs. Being economically engaged will also take them off crimes hence, DisCos will be free to diligently carry out their tasks without security threats while viable investors are also attracted. Since government subsidy does not have a significant impact on the TE of the firms, such policy should be discarded and the funds directed to more productive areas such as the provision of infrastructure. Since customer metering has not contributed to DisCos' TE, the government should prohibit the installation of meters that are not smart to reduce energy tampering and theft. This work did not take into account the relative nature of the efficiency scores, since they are measured against the frontier, it will be good for future research to consider bootstrapping to obtain the true efficiency scores.

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Appendix

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	Port Harcourt Electricity Distribution Company (PHEDC)		

Source: NERC (nerc.gov.ng) adapted