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Cost Efficiency Analysis based on The DEA and StoNED Models: Case of Norwegian Electricity Distribution Companies

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***Abstract*—Our paper applies data envelopment analysis (DEA) and stochastic non-parametric envelopment of data (StoNED) to measure cost efficiency of electricity distribution companies. The data cover 123 Norwegian electricity distribution companies during 2004-2010, and the performance of these companies is compared across the two models with and without environmental variables, i.e., variables that account for local conditions that affect the companies' costs. The results indicate that the cost efficiency estimates with the StoNED approach are much higher than with the DEA method when we do not consider environmental variables. It shows that the choice of estimation methods is important with respect to the estimated impact of environmental variables on the performance. In addition, the inclusion of the environmental variables has considerable effect on the classification of companies with respect to local returns to scale.**

***Index Terms*—Cost efficiency; DEA; Environmental variables; Regulation; StoNED**

I. INTRODUCTION

In many countries, the deregulation of the electricity sector has divided the previously vertically integrated sector into separate businesses: generation, transmission and distribution. We only focus on the electricity distribution sector in this paper, i.e., a part of the business that is considered to be a natural monopoly.

Many countries have introduced incentive regulation in the electricity distribution sector in order to minimize costs. Ideally, electricity distribution companies should compare their observed costs with its competitors. In a setting with natural monopolies it is often difficult to find comparable companies and obtain an objective yardstick cost, and frontier estimation methods, for example, the classical non-parametric and parametric approach: data envelopment analysis (DEA) [4] and stochastic frontier analysis (SFA) [1] have been proposed to estimate the cost frontier function that represents the best practice benchmark. Reference [12] provides an extensive survey of different benchmarking methods used by regulators in the electricity sector worldwide.

Recently, a new frontier estimation approach called stochastic nonparametric envelopment of data (StoNED), combining the virtues of both SFA and DEA has been proposed by [14], [16]-[17] discusses how this approach has been applied to the Finnish electricity distribution regulation. Unlike SFA, StoNED has the advantage that the functional form of the production function or cost function does not need to be specified, except for general assumptions about monotonicity, homogeneity and concavity. On the other hand, the main relative advantage of StoNED to the nonparametric DEA approach is the better robustness to outliers, data errors, and other stochastic noise in the data. However, there is still no clear conclusion on which approach is most suitable in regulation. Hence, many regulators have applied two or all of these three approaches to investigate the performance of the electricity distribution sector [12].

Electricity distribution companies even in the same country do not work in similar conditions, and it makes the benchmarking regulation more complicated. The conditions, such as forest, snow and so on, depend on the geographic areas where the companies operate, and are very different, e.g., for urban and rural companies. Hence, many papers, e.g., [12], [19]-[20], pay attention to the operating conditions, which play a key role in the regulatory process. To make the regulation more effective, the operating conditions should be taken into account. We refer to these operating conditions as environmental variables.

In Norway, the deregulation of electricity market happened in 1991. The electricity network companies are regulated by the Norwegian Water Resources and Energy Directorate (NVE). Incentive regulation was introduced in 1997, and a yardstick regulation model has been used since 2007 [3]. Revenue caps for all network companies are based on a combination of actual cost and the optimal cost. Many papers [2]-[3], [7]-[8], [10], [12], [20], [22] have investigated the productivity and efficiency of Norwegian electricity distribution companies using DEA and/or SFA.

The purpose of this paper is to present a systematic comparison of the performance in different cost frontier estimation approaches. The environmental impact on the performance in different models is also examined. We focus on the DEA and StoNED models because the assumptions about the deviations from the frontier in DEA model only focus on inefficiency while the StoNED model captures two elements: inefficiency and noise. The estimated cost efficiency scores from the respective approaches without considering environmental variables are first compared. Then, we compare the cost efficiency estimates produced by the two models including environment variables in order to study the environmental impact on cost efficiency estimates. Finally, we analyze the local returns to scale of the companies. The rest of this paper is organized as follows: Section 2 introduces the DEA and StoNED models. Section 3 briefly describes the data used in this paper. Section 4 reports the empirical results based on the previous models and Section 5 concludes the paper.

II. Methodology

A frontier cost function defines the minimum cost at a given output level, input price and existing production technology. Technical and/or allocative inefficiency could result in failure of attaining the cost frontier. This section provides a specific description of the cost frontier models used in our paper.

A. DEA method

The DEA approach is an axiomatic, non-parametric approach to calculate the efficient or best-practice frontier of a sample [4]. The cost frontier in DEA is a deterministic function of the observed variables, but no specific functional form is imposed. DEA models can be input-oriented or output-oriented, and they can be specified as constant returns to scale (CRS) or variable returns to scale (VRS). We consider the input-oriented model to be appropriate for the electricity distribution sector, since the objective of an electricity distribution company is to produce an exogenously given level of desirable outputs at minimum cost. In this paper, the input-oriented DEA VRS model is applied. In order to estimate environmental impact on efficiency in a DEA model, environmental variables are treated as output cost drivers when we calculate efficiency scores. One advantage of this approach is that we can obtain information about the shape of the frontier, e.g., local returns to scale for the companies. Alternative approaches to incorporating environmental factors in DEA are discussed by [5] and [19].

B. StoNED assumptions

Referring to the model developed by [17] for the Energy Market Authority of Finland (EMV), the following cost frontier function is assumed:

$$x_i = C(\boldsymbol{y}_i)\cdot\exp(\boldsymbol{\delta}\mathbf{z}_i + \varepsilon_i) \textit{ where } \varepsilon_i = v_i + u_i, u_i \geq 0, \qquad (1)$$

where x_i is the total cost of firm i, C is the cost frontier function, $\boldsymbol{y}_i$ is the vector of the outputs of firm i, ε_i is the residual of firm i, u_i represents inefficiency, and v_i is a stochastic noise term. The coefficient vector $\boldsymbol{\delta}$ represents the environmental impact and $\mathbf{z}_i$ is the vector of environmental variables for firm *i*. The stochastic noise term v_i is assumed to follow a normal distribution $N\left(0,\sigma_v^2\right)$, while the inefficiency term u_i is assumed to follow a half-normal distribution with finite variance σ_u^2 and expected value given by $E\left(u_i\right) = \mu = \sigma_u\sqrt{2/\pi}$ [1]. Regarding the cost frontier function C, we do not assume a particular functional form, but it should satisfy continuity, monotonicity, convexity and variable returns to scale (VRS) constraints, similar to the classical DEA model [4].

C. StoNED estimation method

The purpose of stochastic nonparametric envelopment of data (StoNED) is to integrate a stochastic SFA-style noise term to the nonparametric DEA-style cost frontier, and to take the contextual variables, such as environmental variables, better into account ([14],[16]-[17]). The StoNED method consists of two stages:

Stage 1: Estimate the total cost by the convex nonparametric least squares (CNLS).

Stage 2: Estimate the variance parameters σ_u^2 and σ_v^2, the expected value of inefficiency μ, and the cost frontier function $\hat{C}^{StoNED}$.

Without loss of generality, the linear log transformation of the cost frontier function is used in the CNLS model. With respect to the functional form of the cost frontier function, [16]-[17] prove that CNLS regression provides a consistent estimator of the expected value of total cost when the semi-parametric cost linear function is applied. The CNLS estimator is obtained through the following quadratic programming (QP) model [17]:

$$\min_{\gamma,\boldsymbol{\beta}\ \varepsilon} \sum_{i=1}^{n} \varepsilon_i^2$$

Subject to:

$$\ln x_i = \ln\gamma_i + \boldsymbol{\delta}\mathbf{z}_i + \varepsilon_i, \quad \forall\, i = 1,\cdots,N$$

$$\gamma_i = \alpha_i + \boldsymbol{\beta}_i'\boldsymbol{y}_i \geq \alpha_h + \boldsymbol{\beta}_h'\boldsymbol{y}_i, \quad \forall i, h = 1,\cdots,N$$

$$\boldsymbol{\beta}_i \geq 0, \forall\, i = 1,\cdots,N, \qquad (2)$$

where γ_i is the CNLS estimator of the expected total cost of producing the output vector $\boldsymbol{y}_i$, $\boldsymbol{\beta}_i$ is the vector of the marginal cost of outputs for firm i, and α_i is the intercept of firm i. The estimated sign of α_i can be used to make inferences about local returns to scale. Model (2), where the value of α_i is unrestricted, is equivalent to assuming variable returns to scale, i.e., the assumption used in this paper. Reference [16] shows how to impose alternative assumptions about returns to scale by restricting the value of α_i. The first constraint of model (2) can be interpreted as the regression equation. The second and third constraints ensure convexity and monotonicity, respectively, of the resulting cost frontier function.

There are two methods to estimate the variance parameters based on the optimal solution $\hat{\varepsilon}_i$ of model (2) [16]. One is the pseudolikelihood estimation approach (PSL) [9] and the other alternative is the method of moments (MM) [1]. The latter method is applied in this paper. Under the maintained assumptions of half-normal inefficiency and normal noise, the estimators of the second and third central moments of the composite error distribution can be expressed as

$$\hat{M}_2 = \sum_{i=1}^{n}\left(\hat{\varepsilon}_i - \bar{\varepsilon}\right)^2 / n, \qquad (3)$$

$$\hat{M}_3 = \sum_{i=1}^{n} \left(\hat{\varepsilon}_i - \bar{\varepsilon}\right)^3 / n. \quad (4)$$

The estimators of σ_u and σ_v are obtained from the following equations:

$$\hat{\sigma}_u = \sqrt[3]{\frac{\hat{M}_3}{\left(\sqrt{2/\pi}\right)\left[4/\pi - 1\right]}}, \quad (5)$$

$$\hat{\sigma}_v = \sqrt[2]{\hat{M}_2 - \left[\left(\pi - 2\right)/\pi\right]\sigma_u^2}. \quad (6)$$

In equation (5), $\hat{M}_3$ only depends on the standard deviation of the inefficiency distribution. Given our distributional assumptions about u and v, we would expect $\hat{M}_3$ to be positive. However, as we discuss in Section 4, this is not always the case.

When environmental variables are not considered, the estimated cost frontier function is obtained as

$$\hat{C}\left(y_i\right) = \gamma_i \cdot \exp\left(-\hat{\sigma}_u \sqrt{2/\pi}\right). \quad (7)$$

According to [14], one can assume that environmental factors have effect on the efficiency or the frontier, and both assumptions are equally valid. In this paper, we choose to follow the latter approach, and the formula for estimating the cost frontier is therefore

$$\hat{C}\left(y_i\right) = \gamma_i \cdot \exp\left(-\hat{\sigma}_u \sqrt{\frac{2}{\pi}}\right) \cdot \boldsymbol{\delta}\mathbf{z}_i. \quad (8)$$

Furthermore, the cost efficiency score is defined as the ratio of the minimum cost to the observed cost and it is expressed as

$$CE_i = \hat{C}\left(\boldsymbol{y}_i\right) / x_i, \quad (9)$$

where CE_i and $\hat{C}\left(\boldsymbol{y}_i\right)$ are expressed as the cost efficiency score and estimated cost frontier of firm i, respectively.

III. Data

We have data for 123 Norwegian distribution companies from 2004 to 2010. The variables in our data set correspond to the variables used by the regulator in the benchmarking model that was implemented from 2007. The single input is total cost, which includes the four cost groups described in Table I.

TABLE I. Elements of the single input cost variable

Cost group	Unit of measurement
Capital costs	NOK
Operations and maintenance costs	NOK
Quality cost (value of lost load)	NOK
Cost of thermal power losses	NOK
Total cost	NOK

Table II lists the output variables. Customers are separated into regular customers and cottage customers, as the latter group usually consume less energy than the former, while the capacity requirements are similar. The last two output variables represent structural conditions that influence the required network size and thereby the cost level of the companies.

TABLE II. Output variables

Variable	Unit of measurement
Energy delivered	MWh
Customers (except cottage customers)	No. of customers
Cottage customers	No. of customers
High voltage lines	Kilometers
Network stations (transformers)	No. of stations

The environmental variables are listed in Table III. Their values are size-independent index measurements and need to be scaled in order to avoid the bias problems described by [6]. We use the length of the overhead high voltage network to scale the index variables for use in the DEA model, while unscaled variables are used in the StoNED model.

TABLE III. Environmental variables

Variable	Unit of measurement
Forest	Proportion (0–100) of area with high-growth forest
Snow	Average precipitation as snow (mm)
Coast	Average wind speed (m/s) / Average distance to coast (meters)

IV. Results

The presentation of results is divided into five broad parts: Firstly, we compare the estimated cost efficiency scores from the DEA and StoNED models without considering environmental variables. Secondly, we examine the impact from environmental variables in the two models. Then, we examine the correlation between the cost efficiency for the various approaches, and we compare classifications with respect to local returns to scale. Finally, we discuss the StoNED results in relation to assumptions about the inefficiency and noise term.

TABLE IV. Efficiency scores without env. variables

Year	Model	Min	Mean	Max	St.dev.
2004	DEA	0.57	0.82	1.00	0.12
	StoNED	0.68	0.96	1.36	0.13
2005	DEA	0.57	0.82	1.00	0.12
	StoNED	0.66	0.95	1.30	0.13
2006	DEA	0.55	0.81	1.00	0.12
	StoNED	0.63	0.94	1.34	0.12
2007	DEA	0.58	0.81	1.00	0.13
	StoNED	0.69	0.98	1.44	0.14
2008	DEA	0.60	0.81	1.00	0.13
	StoNED	0.76	0.98	1.58	0.13
2009	DEA	0.50	0.82	1.00	0.13
	StoNED	0.55	0.91	1.39	0.13
2010	DEA	0.54	0.82	1.00	0.12
	StoNED	0.60	0.92	1.39	0.13

A. *Efficiency analysis without environmental variables*

Table IV describes the efficiency estimates for each year, and Fig. 1 shows the average efficiency score for individual companies for the whole period 2004-2010. The most striking observation is that the StoNED efficiency estimates are higher than the DEA estimates, both in terms of the minimum, mean, and maximum for each year. The difference in efficiency score levels is important in a regulation context, since the regulator will use the estimated efficiency scores to set the companies' revenue caps [3].

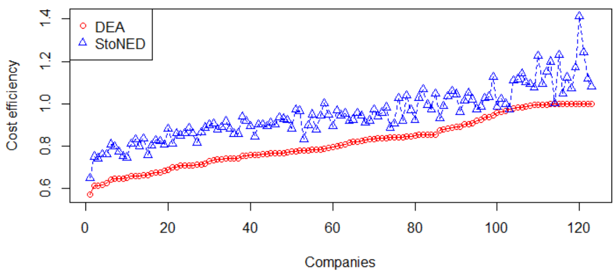

Figure 1. Average efficiency scores without env. variables for 2004-2010.

B. *Efficiency analysis with environmental variables*

We now add the environmental variables to the two estimation models. Table V and Fig. 2 show descriptive statistics for each year and company averages for the whole period, similar to Table IV and Fig. 1 above. Table V shows that for all years, the minimums and means estimated by the StoNED model are lower than the estimates from the DEA model, while the maximums from the StoNED model are higher than the maximums from the DEA model. Fig. 2 shows that most companies, but not all, receive a higher average efficiency scores with the StoNED model than with the DEA model.

TABLE V. EFFICIENCY SCORES WITH ENVIRONMENTAL VARIABLES

Year	Model	Min	Mean	Max	St.dev.
2004	DEA_EV	0.68	0.89	1.00	0.10
	StoNED_EV	0.59	0.85	1.14	0.11
2005	DEA_EV	0.61	0.89	1.00	0.11
	StoNED_EV	0.58	0.85	1.16	0.12
2006	DEA_EV	0.63	0.90	1.00	0.11
	StoNED_EV	0.54	0.82	1.10	0.11
2007	DEA_EV	0.63	0.88	1.00	0.12
	StoNED_EV	0.60	0.87	1.22	0.12
2008	DEA_EV	0.62	0.89	1.00	0.11
	StoNED_EV	0.65	0.88	1.39	0.13
2009	DEA_EV	0.60	0.89	1.00	0.11
	StoNED_EV	0.49	0.83	1.18	0.12
2010	DEA_EV	0.63	0.90	1.00	0.10
	StoNED_EV	0.53	0.84	1.21	0.12

To check the significance of environmental impact on the cost efficiency scores in the two models, Table VI reports p-values for t-tests comparing all the four approaches. All the p-values are lower than 0.05, which indicates that the average efficiency scores differ significantly. Specifically, we note that the effect of adding the environmental variables to the StoNED and the DEA models, respectively, has a significant effect on the efficiency results.

C. *Correlation analysis*

Table VII shows Pearson correlation coefficients and Spearman rank correlation coefficients between the results from the different model approaches. We see that DEA and StoNED yields highly correlated results when the environmental variables are not included. It is also interesting to note that the correlation between StoNED and StoNED_EV is considerably higher than between DEA and DEA_EV, indicating that the addition of the environmental factors has a more dramatic effect with DEA than with the StoNED approach.

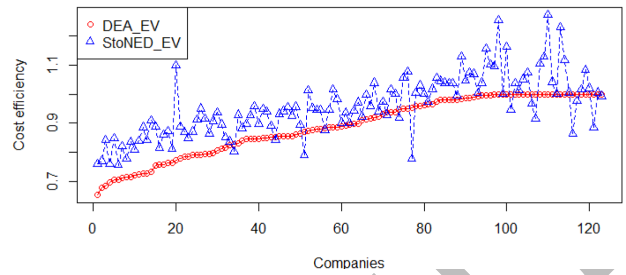

Figure 2. Average efficiency scores with env. variables for 2004-2010.

TABLE VI. STATISTICAL RESULTS (T-TEST)

Model	DEA	StoNED	DEA_EV	StoNED_EV
DEA	1			
StoNED	2.04E-07	1		
DEA_EV	2.20E-16	2.20E-16	1	
StoNED_EV	2.20E-16	2.20E-16	4.58E-07	1

TABLE VII. CORRELATION ANALYSIS OF COST EFFICIENCY SCORES

Model	Pearson correlation				Spearman rank correlation			
	DEA	StoNED	DEA_EV	StoNED_EV	DEA	StoNED	DEA_EV	StoNED_EV
DEA	1				1			
StoNED	0.90	1			0.94	1		
DEA_EV	0.68	0.61	1		0.67	0.64	1	
StoNED_EV	0.80	0.89	0.75	1	0.81	0.89	0.76	1

D. *Local returns to scale*

Fig. 3 shows the number of companies with increasing, and decreasing returns to scale, respectively, with the StoNED approach, with and without the environmental variables included. We see that the companies in the data set predominantly exhibit increasing returns to scale, i.e., they are smaller than the most productive size, and that the share of IRS companies in the data set increases over time. We also see that the inclusion of the environmental factors decreases the number of IRS companies in all years, i.e., the optimal company sizes are decreased. Fig. 4 shows similar results for the DEA approach, and we see the same tendencies here[1]. To investigate further the relationship between size and environmental variables, we show the correlations in Table VIII. The correlation is negative for snow and coast, and slightly positive for forest. The decrease in the optimal company size when environmental variables are included could be related to these negative correlations.

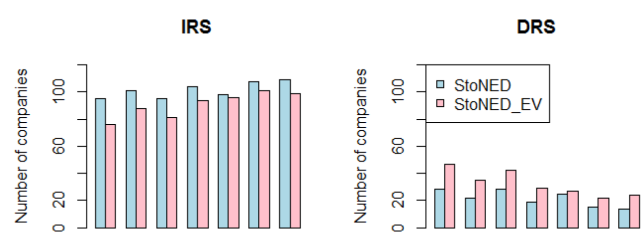

Figure 3. Distribution of returns to scale for the StoNED method

[1] Note that a few companies are classified as having constant returns to scale under DEA.

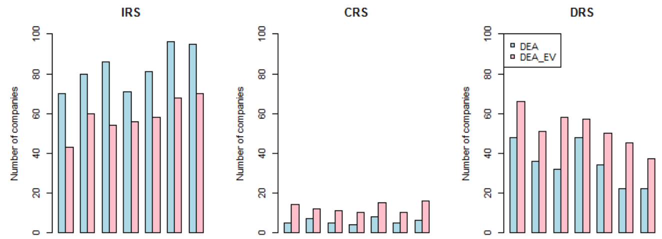

Figure 4. Distribution of returns to scale for the DEA method

TABLE VIII. CORRELATIONS BETWEEN SIZE (NO. OF CUSTOMERS) AND ENV.VARIABLES (2004-2010)

	Forest	Snow	Coast
Correlation	0.01	-0.13	-0.05

E. Assumption on the inefficiency and noise term

As discussed in Section 2, the StoNED model is applied under the assumptions of half-normal inefficiency and normal noise. This implies that the sum of the inefficiency and the noise term follows a positively skewed distribution. Table IX reports the estimated skewness for StoNED and StoNED_EV. For the StoNED model, the skewness in 2007 and 2008 is negative, and for StoNED_EV, the skewness is only positive in 2004 and 2010. The observed negative skewness estimates could be caused by small sample sizes [12]. In the cases where the estimated skewness was negative, we have set the value of M_3 to 1E-05 in the second-stage StoNED calculations. Note that the chosen value for M_3 will affect the cost efficiency scores for the companies in a proportional manner via equations (8), (9) and (10).

TABLE IX. ESTIMATED SKEWNESS (M_3)

Model	2004	2005	2006	2007	2008	2009	2010
StoNED	3.7E-05	8.8E-05	1.6E-04	-4.8E-04	-1.5E-03	4.9E-04	4.1E-04
StoNED_EV	8.2E-05	-2.4E-05	2.5E-04	-2.4E-04	-7.7E-04	3.3E-04	1.4E-04

V. CONCLUSION

In this paper, we have compared two frontier estimation techniques applied in the benchmark regulation of electricity distribution companies. The analysis has been divided into two parts, with and without environmental variables, respectively. The efficiency analysis without environmental variables shows that the cost efficiency scores from the StoNED model are higher, for all companies, than those in the DEA model. This may be important, e.g., for a regulator that uses the efficiency scores as input when setting revenue caps. When we include the environmental factors, we see the same tendency, but it is less strong. Furthermore, we have proved that the environmental variables have significant impact on cost efficiency estimates in the DEA and StoNED model, and that the effect is more dramatic under the former method. Both DEA and StoNED conclude that the companies in the data set are predominantly smaller than the optimal scale size, but we see that the optimal size is decreased when we include the environmental factors. We also observe that the distributional assumptions in StoNED are not necessarily reflected in the estimated results, and this may be due to small sample size.

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