*DAE Working Paper, No. 0115, Department of Applied Economics, University of Cambridge*

# International Utility Benchmarking & Regulation:

# An Application to European Electricity Distribution Companies

*Tooraj Jamasb*[*]

*Department of Applied Economics, University of Cambridge*

*Sidgwick Avenue, Cambridge CB3 9DE, UK*

*Phone: +44-1223-335271   Fax: +44-1223-335299*

*email: tooraj.jamasb@econ.cam.ac.uk*

*Michael Pollitt*

*Judge Institute of Management, University of Cambridge*

*Trumpington Street, Cambridge CB2 1AG, UK*

*Phone:+44-1223-339615    Fax: +44-1223-339701*

*email: m.pollitt@jims.cam.ac.uk*

**Revised June 2002**

[*] Corresponding author. The authors wish to thank David Newbery and Cemil Altin for their detailed comments.

This work was financed by OFGEM and ESRC project No. R00023 8563. The usual disclaimer applies.

*DAE Working Paper, No. 0115, Department of Applied Economics, University of Cambridge*


**Abstract**

Due to a shortage of data and increased international mergers, national energy regulators are looking to international benchmarking analyses for help in setting price controls within incentive regulation. We present an international benchmarking study of 63 regional electricity distribution utilities in 6 European countries that aims to illustrate the methodological and data issues encountered in the use of international benchmarking for utility regulation. The study examines the effect of the choice of benchmarking methods using DEA, COLS and SFA models. We discuss what problems of international benchmarking are highlighted by the study and how they can be overcome.


Keywords: benchmarking, incentive regulation, performance analysis

JEL Classification: L94

## 1. Introduction

Electricity sector reforms are transforming the structure and operating environment of the electricity industries across many countries. The central aims of these reforms are to introduce market-oriented measures in electricity generation and supply, and improve the efficiency of the natural monopoly activities of distribution and transmission through regulatory reforms. This paper is concerned with this latter aspect of the reforms.

Recent regulatory reforms have tended to move away from traditional rate-of-return regulation towards incentive-based regulation models.[1] A number of regulators have adopted price and revenue cap regulation based on the RPI-X formula. A central issue is how the efficiency requirements or X-factors are to be set. A widely favoured approach is through benchmarking of utilities based on their relative efficiency. Countries such as The Netherlands, United Kingdom, and Norway have adopted benchmarking as part of the process of setting the X-factors. Benchmarking identifies the most efficient firms in the sector and measures the relative performance of less efficient firms against these. Individual X-factors are then assigned to utilities based on their relative inefficiency. Generally, the more inefficient a utility is, the higher is the X-factor assigned to that firm. The aim is to provide the firms with an incentive to close their efficiency gap with the frontier firms.

However, the number of utilities in many countries is limited and does not lend itself to the data requirements of some of the widely used benchmarking techniques. Also, due to electricity market liberalisation and privatisation policies, power markets and ownership of the utilities are becoming increasingly international, and mergers and acquisitions tend to reduce the domestic information base. Regulators can use cross-country benchmarking in order to evaluate the performance of national utilities within the larger context of international practice. The addition of international comparators to a sample can improve the validity of the analysis as utilities are more likely to be benchmarked against similar firms. Further, international comparisons enable the regulators to measure efficiency of the utilities relative to international best practice. The advantage of using international best practice is that the measured efficiencies are more likely to reflect technical possibilities rather than the degree of comprehensiveness of the sample used.

While international utility benchmarking has clear advantages, the methodological and practical aspects, as well as possible implications of this approach, need careful consideration. Empirical studies can be a useful instrument to identify and shed light on some of the main issues arising in international benchmarking. There are a number of single-country and a few cross-country studies of relative efficiency of electricity distribution utilities. However, most of these either do not have an explicit regulatory focus or use physical measures of inputs as proxies for the operating and capital costs.

Benchmarking with the use of physical quantities of inputs measures the potential for efficiency improvements in terms of reductions in physical units. However, the primary aim of regulators when using benchmarking is to promote cost savings in the utilities that result in lower prices for the end-users. Relative performance measured in terms of units of physical inputs bears an indirect relationship with cost savings potential as the basis for setting X-factors.

It should be noted that this study uses an empirical analysis of selected electricity distribution utilities to highlight and discuss the main issues in international benchmarking and the results have not been intended for direct use in an actual regulatory process. In this paper we examine some methodological and applied aspects of cost-based international benchmarking in electric utility regulation. We apply the widely used benchmarking techniques of Data Envelopment Analysis (DEA), Corrected Ordinary Least Square (COLS), and Stochastic Frontier Analysis (SFA) to an international sample of utilities and compare the results. We then examine the significance of the choice of method for currency conversion for the DEA results. We also compare the DEA results with a model specification that uses measures of physical units as a proxy for capital costs. We finally outline the regulatory implications of international benchmarking and draw some conclusions.

## 2. Benchmarking Techniques[2]

There are several different approaches to the measurement of the relative efficiency of firms in relation to an efficient frontier of a sample. These approaches can be placed into two broad categories of programming (non-parametric) or statistical (parametric) techniques. Data Envelopment Analysis (DEA) is a programming approach, while Corrected Ordinary Least Squares (COLS) and Stochastic Frontier Analysis (SFA) are statistical techniques. We use these three techniques in this study and discuss them in this section.

### 2.1 Data Envelopment Analysis (DEA)

DEA is a non-parametric method and uses piecewise linear programming to calculate (rather than estimate) the efficient or best-practice frontier of a sample (see Farrell 1957; Färe et al. 1985). The decision-making units (DMUs) or firms that make up the frontier envelop the less efficient firms. The efficiency of the firms is calculated in terms of scores on a scale of 0 to 1, with the frontier firms receiving a score of 1. DEA can calculate the allocative and technical efficiency of the firms. The latter can be decomposed into scale, congestion, and pure technical inefficiency.

DEA models can be input and output oriented and can be specified as constant returns to scale (CRS) or variable returns to scale (VRS). Output-oriented models maximise output for a given amount of input factors. Conversely, input-oriented models minimise input factors required for a given level of output. An input-oriented specification is generally regarded as the appropriate from for electricity distribution utilities, as demand for distribution services is a derived demand beyond the control of utilities that has to be met.

The linear program calculating the efficiency score of the i-th firm in a sample of N firms in CRS models takes the form specified in Equation (1) where $\theta$ is a scalar (equal to the efficiency score) and $\lambda$ represents an $N\times1$ vector of constants. Assuming that the firms use E inputs and M outputs, X and Y represent $E\times N$ input and $M\times N$ output matrices respectively. The input and output column vectors for the i-th firm are represented by $x_i$ and $y_i$ respectively. The equation is solved once for each firm. In VRS models a convexity constraint $\Sigma\lambda=1$ is added. This additional constraint ensures that the firm is compared against other firms with similar size.

$$
\begin{aligned}
&\min_{\theta,\lambda} \theta, \\
&s.t. \\
&-y_i + Y\lambda \geq 0, \\
&\theta x_i - X\lambda \geq 0, \\
&\lambda \geq 0
\end{aligned}
\tag{1}
$$

In equation (1) firm i is compared to a linear combination of sample firms which produce at least as much of each output as it does and the minimum possible amount of inputs. Figure 1 illustrates the main features of an input-oriented model with constant returns to scale. The figure shows three firms (G, H, R) that use two inputs (capital K, labour L) for a given output Y. The vertical and horizontal axis represent the capital and labour input per unit of output respectively and the line PP shows the relative price of the two inputs.

**[Figure 1 here]**

Firms G and H produce the given output with less inputs and form the efficient frontier that envelops the less efficient firm R. The technical and allocative efficiencies of firm R relative to the frontier can be calculated from OJ/OR and OM/OJ ratios respectively. Technical efficiency measures the ability of a firm to minimise inputs to produce a given level of outputs. Allocative efficiency reflects the ability of the firm to optimise the use of inputs given the price of the inputs. The overall efficiency of firm R is measured from OM/OR.

A central step in DEA is the choice of appropriate input and output variables. The variables should, as far as possible, reflect the main aspects of resource-use in the activity concerned. DEA can also account for factors that are beyond the control of the firms and can affect their performance (environmental variables).

An advantage of DEA is that inefficient firms are compared to actual firms rather than some statistical measure. In addition, DEA does not require specification of a cost or production function. However, the efficiency scores tend to be sensitive to the choice of input and output variables. Also, the method does not allow for stochastic factors and measurement errors. Further, as more variables are included in the models, the number of firms on the frontier increases. Therefore, it is important to examine the sensitivity of the efficiency scores and rank order of the firms to model specification.

## 2.2 Corrected Ordinary Least Squares (COLS)

An alternative frontier-oriented approach to measure relative efficiency of firms is to use statistical methods to ‘estimate’ the best practice frontier and efficiency scores. COLS is one such method based on regression analysis (Richmond, 1974). Similar to DEA, the method estimates the efficiency scores of the firms on a 0 to 1 scale. The regression equation is estimated using the OLS technique and then shifted to the efficient frontier by adding the absolute value of the largest negative estimated error to that of the other errors (for a cost function).

The COLS method requires specification of a cost or production function and therefore involves assumptions about technological properties of the firms' production process. A drawback of the method is that the estimated parameters may not make engineering sense. In addition, the method makes no allowance for stochastic errors and relies heavily on the position of the single most efficient firm. Similar to DEA, COLS assumes that all deviations from the frontier are due to inefficiency.

The COLS technique can be used to calculate efficiency scores of models involving multiple inputs and outputs by estimating distance functions. Following Coelli and Perleman (1999) and Coelli, Rap et al. (1998), Equation (2) show a translog input distance function.[3] $D_{Ii}$ is the input-oriented distance for the i-th firm in a sample of N firms with K inputs and M outputs and where $\alpha$, $\beta$, and $\delta$ are unknown parameters. The function is homogeneous of degree +1 in inputs. Inputs and outputs are denoted x and y respectively and $x^*_k=x_k/x_K$. Equation (2) can rewritten as in (3) where TL is the translog function in (2) and "–Ln($D_{Ii}$)" is an unobservable term interpreted as the random error term $\mu_i$.

$$Ln( D_{Ii} / x_{K_i} ) = \alpha_0 + \sum_{m=1}^{M} \alpha_m Lny_{mi} + \frac{1}{2}\sum_{m=1}^{M}\sum_{n=1}^{M}\alpha_{mn} Lny_{mi} Lny_{ni} + \sum_{k=1}^{K-1}\beta_k Lnx_{ki}^{*}$$
$$+ \frac{1}{2}\sum_{k=1}^{K-1}\sum_{1=1}^{K-1}\beta_{kl} Lnx_{ki}^{*} Lnx_{ki}^{*} + \sum_{k=1}^{K-1}\sum_{m=1}^{M}\delta_{km} Lnx_{ki}^{*} Lny_{mi}, \quad (2)$$
$$i = 1,2,...,N$$

$$- Ln( x_{Ki} ) = TL( x_i / x_{Ki}, y_i, \alpha, \beta, \delta ) - Ln( D_{Ii} ),$$
$$i = 1,2,....,N, \quad (3)$$

The function in Equation (3) is estimated using the Ordinary Least Square (OLS) technique. The estimated constant term of the function is then adjusted by subtracting the value of the largest positive residual from those of all units. This transformation ensures that the function passes through the most efficient unit and bounds the other units. The distance measures for the inefficient units are then calculated as the exponential of their corrected residuals.

## 2.3 Stochastic Frontier Analysis (SFA)

SFA is another parametric method used to estimate the efficient frontier and efficiency scores. The statistical nature of the method allows for inclusion of stochastic errors in the analysis and testing of hypotheses. Similar to COLS, this method requires specification of a cost or production function involving assumptions about the firms' production technologies. Estimation of efficiency scores in SFA is similar to that of COLS. In addition, SFA recognises the possibility of stochastic errors (see Coelli, Rap et al., 1998).

The notation of an input-oriented distance function for multiple input and output models is similar to that described for COLS. However, when applying SFA a symmetric error term $\nu$ is added to the random error term $\mu$ to account for noise. SFA reduces reliance on measurements of a single efficient firm. However, accounting for stochastic errors requires specification of a probability function for the distribution of the errors and distribution of inefficiencies (e.g. half normal). As for the result of stochastic factors and their effect on the position of the most efficient firm, the estimated scores are higher than those estimated by COLS. Figure 2 illustrates a COLS model with a single cost input C and one output Y.

**[Figure 2 here]**

The cost equation $C_{OLS}=\alpha+f_1(Y)$ is estimated using OLS regression and then shifted by CA to $C_{COLS}=(\alpha-CA)+f_1(Y)$ on which the most efficient firm A lies. The efficiency score for an inefficient firm B is calculated as EF/BF. The figure also shows the estimated cost equation $C_{SFA}=f_2(Y)$ using SFA. A firm, such as A, which lies below the stochastic frontier might be regarded as 100% efficient, i.e. the difference between its actual costs and its expected costs on the frontier are effected by a negative cost shock. A drawback of the method is that even if there are no errors in efficiency measurements, some inefficiency may be wrongly regarded as noise.

## 3. Data

The benchmarking study reported here is based on data on 63 electricity distribution and regional transmission utilities in Italy, Netherlands, Norway, Portugal, Spain, and United Kingdom. The data used in the study is collected by the regulators in the relevant countries for the purpose of an international benchmarking exercise. Table 1 shows the number of utilities included in the study from each country. As shown in the table, the number of utilities varies across the countries and in most of these it is not large enough for identifying broad-based production possibilities using benchmarking techniques.[4] Table 2 shows the variables and summary statistics of data used.

**[Table 1 here]**

**[Table 2 here]**

## 3.1 Cost data

As mentioned previously, this study uses monetary values of the input variables and differs from many of the previous studies where inputs are expressed in physical units. This is particularly advantageous from a regulatory point of view, as monetary values of the inputs can reflect all operating and capital inputs and measure the relative cost efficiency of utilities. In addition, expression of different inputs in a single measure recognises the possible trade-offs among these. This section presents adjustment of the cost data to a common reference year and their subsequent conversion into a single monetary unit.

### 3.1.1 Harmonisation and adjustment of costs

The task of standardisation of cost data for this study has was carried out by the participating regulators. The controllable operating costs used in the benchmarking of the utilities were derived from company law accounts adjusted for: (i) cost of sales, (ii) transmission system exit charge, (iii) income or federal taxes paid to local governments, (iv) licence fees, (v) depreciation and amortisation of tangible fixed assets, and (vi) federal and state employers taxes.

The capital expenditures data used in this study represent new investments in one year and exclude capital stocks and depreciation. A shortcoming of using annual capital expenditures is that these may not reflect the value of capital stocks. The problem can, due to the cyclical nature of investments in distribution utilities, be more profound when the scope of analysis is limited to one year as unusually large (small) investments by a utility in that year may under (over) estimate its efficiency. The choice of annual capital expenditures has largely been dictated by availability of comparable data across different countries.

As noted previously, the main focus of this study is on methodological issues of international benchmarking. An alternative approach would be to use the value of the capital stocks and work out the rental cost of the capital. However, capital stocks have long economic lives and difficulties involved in accounting for factors such as inflation, assets depreciation, and currency fluctuations over many years for several countries would reduce the accuracy of measurements.

The cost data collected for this study refer to different years. Table 3 shows the years for which data from participating countries was available. In order to establish a common time reference for the cost data these were adjusted to mid-1999 levels using the OECD statistics on quarterly Consumer Price Index (CPI) changes. The adjustments resulted in minor changes to cost data. Table 3 shows the percentage change to cost data to bring these to the level of the reference year.

**[Table 3 here]**

### 3.1.2 Currency conversions

An important step in cross-country comparisons is how to convert the cost data expressed in national currencies into a single monetary unit. A commonly used approach is to convert the costs using the Purchasing Power Parities (PPPs) of currencies. The PPPs equalise the differences in the price levels in different countries and measure the purchasing power of the currencies in relation to a certain basket of goods. The conventional exchange rates, however, do not account for these differences.

As the currency exchange rates often differ from the PPPs, the choice of conversion method affects the relative costs to be compared. The extent of this effect depends on the countries that comprise the sample. The significance of the conversion method may vary with the type of cost inputs. For example, with regards to operating costs, the PPPs may appear as the appropriate measure as they are largely incurred in local currencies and affected by domestic price levels. Capital costs include purchase of large amounts of materials and equipment traded in the international markets and settled in foreign currencies.

The operating and capital costs used in this study were converted into a single monetary unit using the PPPs of the currencies against the US dollar. The choice of the reference currency for the PPPs is, however, arbitrary and the conversion can use the PPPs against any currency without affecting relative cost differences among the utilities. Table 4 shows US dollar based PPPs for the relevant currencies in 1999.

**[Table 4 here]**

### 3.2 Technical data

As noted in the previous section, cost data definitions can be harmonised and different currencies can be converted into a single unit for currency differences. Another factor that complicates international efficiency comparisons is that technical standards and definitions of transmission and distribution systems vary across the countries. These differences can have implications for the level of capital stock and operating expenditures of utilities and influence the benchmarking results. In particular, the voltage levels of the cut-off points between the transmission and distribution functions of networks differ across the countries. At the same time, it is difficult to determine the direction and extent of cost implications of these differences for the utilities.

However, given sufficient data, it is possible to attempt to account for technical differences by using categorical variables representing different voltage levels or, given the data, separation of sub-functions (e.g. low or high voltage) of utilities. Table 5 shows the differences in the voltage levels of the transmission and distribution networks across the countries. The maximum voltage level of distribution utilities in this study range from 22 and 132 kV for the Norwegian distribution and regional transmission utilities to 132 kV for the RECs in England and Wales.

**[Table 5 here]**

### 3.3 Preferred models

This study uses the frontier-oriented benchmarking techniques DEA, COLS, and SFA described in the previous section. The data available for this study give the framework within which important features of the operation of distribution utilities can be modelled. The data on electricity distribution utilities can be used in various combinations and model specifications. For comparison of the results of different techniques, it is desirable that the models include similar variables. In this paper we report the results form ten models, six DEA, two COLS, and two SFA models. An overview of the preferred models for this study, the methods used, and the input and output variables are given in Table 6.

**[Table 6 here]**

In DEA the number of frontier firms tends to increase with addition of variables to the models. In particular, when the sample size is not large, this results in loss of information. There is therefore a trade-off between capturing the main aspects of the utilities' operation and revealing the performance variations among the firms. Our base model DEA-1CRS comprises the total units of electricity delivered, number of customers, and network length as the outputs. These variables are among the most important cost drivers and are frequently used in efficiency studies of electricity distribution and transmission utilities. A summary of the inputs and outputs used in 20 benchmarking studies of electricity distribution utilities outlined in Jamasb and Pollitt (2001) shows that our outputs are among the most frequently used variables (Table 7).

**[Table 7 here]**

Some authors such as Neuberg (1977) have suggested that only traded outputs can be regarded as outputs. However, inclusion of the 'number of customers' reflects the spread of demand among the connection points that is generally regarded as a major cost driver. This variable also captures the important differences in average consumption levels as well as between the regional transmission and distribution utilities both of which types are included in the sample. Also, the ‘size of the network’ reflects the geographical dispersion of the output and the scope of operation. These variables are used by OFGEM to derive a composite measure of output (number of customers 50%, units distributed 25%, and network length 25%) in a COLS-type analysis of the operating costs of the distribution utilities in England and Wales (see OFGEM, 1999).

The total costs of the utilities were used as the only input variable. Subsequent model runs showed that the efficiency scores obtained when splitting the number of customers into residential and non-residential users, have a high correlation with those from the initial model. A similar result was also obtained when output variable network length was divided into overhead and underground cables. We then split the total costs into separate operating and capital cost variables and the efficiency scores' correlation with the initial model remained high. We therefore retain the initial model as one of preferred models. DEA-1VRS is a VRS specification of the base model.

In DEA-2CRS model we use the controllable operating expenditures together with T&D losses and network length (as proxy for capital stocks) as input variables. These variables are often used as inputs in DEA models of distribution utilities. The model specifies the network length and T&D losses as non-discretionary variables. This means that the distance of variable to the frontier does not affect the efficiency scores of the firms. This specification assumes that these technical characteristics of the network lie outside management control and can be regard as given. This assumption is suitable for this study as the T&D of some of the utilities in the sample are derived from standard rates rather than their actual losses.

The DEA-2VRS model is the VRS version of DEA-2CRS and all input variables are by definition discretionary. DEA-1E model uses a similar specification as DEA-1CRS while total expenditures are converted into Euro (1999-rates). DEA-1OP uses operating expenditures as the only input while output variables are similar to DEA-1CRS.

In addition, the loglinear and translog specifications of the initial DEA model (DEA-1CRS) are calculated using COLS, and SFA techniques. The specification of loglinear and translog models used with COLS and SFA methods are shown in Equations 4 and 5 respectively.

Loglinear model specification:

$$-LnTOTEX = \beta_0 + \beta_U LnUNIT + \beta_C LnCUST + \beta_N LnNETW + v \tag{4}$$

Translog model specification:

$$\begin{aligned}
&-LnTOTEX = \\
&\beta_0 + \beta_U\, LnUNIT + \beta_C\, LnCUST + \beta_N\, LnNETW + \\
&\beta_{UU}\,(LnUNIT)^2 + \beta_{CC}\,(LnCUST)^2 + \beta_{NN}\,(LnNETW)^2 + \\
&\beta_{UC}\, LnUNIT * LnCUST + \beta_{UN}\, LnUNIT * LnNETW + \\
&\beta_{CN}\, LnCUST * LnNETW + v
\end{aligned} \tag{5}$$

*where:*

| | | | |
|---|---|---|---|
| *TOTEX* | *total expenditures* | *UNIT* | *units of electricity delivered* |
| *CUST* | *total number of customers* | *NETW* | *network length* |
| $v$ | *error term (in SFA models)* | | |

It should be noted that loglinear specification assumes constant elasticity of substitution among output variables. Translog specification is a generalised form of loglinear that is more flexible and allows for variations in elasticity of substitution among inputs. However, due to this flexibility, translog models they may not always produce statistically significant results for all samples. In particular, parameter values may be meaningless when the scale of the firms included in the sample covers a rather wide range (see for example Coelli, Rap and Battese, 1998, pp.52-53, and Coelli and Perelman, 1996, p.19).

## 4. Results

This section presents the results of the selected models outlined in Table 6. The results from the base model DEA-1CRS are discussed in some detail. The results from the other models are then presented in less detail as these can be regarded as derivatives of the base model. The efficiency scores of the utilities with different models and summary statistics of the efficiency scores are shown in are summarised in Tables 8 and 9 respectively.[5] Tables 10 and 11 show the simple and rank correlation of the efficiency scores respectively for the eight selected models. A high correlation among the scores reflects high consistency of the rankings when the variables, model specifications, or methods used change.

### 4.1 DEA models

As shown in the table, in the DEA-1CRS model, three utilities have efficiency scores of 100% and dominate the frontier. Utility F32 on the frontier is almost entirely a regional distribution utility, as this may have reduced comparability of the utility with some of the firms in the sample.[6] The results show a considerable variation in efficiency scores ranging from 26% to 100%.[7] The mean of the efficiency score for all the firms in the sample is 61%. Table 12 shows the minimum, maximum, and mean of the efficiency scores for the sample as well as the individual countries. As shown in the table, the mean values of the efficiency scores for the countries are comparable.

In the DEA-1VRS model the number of frontier firms increases from three to 15 and the mean efficiency score increases from 61% to 79% in DEA-1VRS. The validity of results of VRS models depends on the extent to which cost efficiency of distribution utilities is affected by their scale of operation and whether various size categories are sufficiently represented in the sample as lack of comparable firms may place inefficient firms on the frontier. One concern with having a large number of frontier firms is that of loss of information as inefficiencies of these will not be revealed. In addition, in VRS models, the efficiency scores of firms tend to increase. Therefore, it is important that VRS models include sufficient number of comparators in all size categories. The DEA-1VRS scores reveal that some large and fairly inefficient firms in DEA-1CRS move to the frontier. The magnitude of change in some of scores indicates that while the size of the utilities in our sample cover a wide range, some of these lack suitable comparators. Within this background we have reason to treat the VRS scores of our data with caution.

In DEA-2CRS, the use of controllable operating expenditures as input and inclusion of non-discretionary variables (network length and T&D losses) has a mixed effect on efficiency scores. The scores for some utilities show considerable increase while for others they decrease significantly. The efficient frontier is dominated by six firms, two of which (F32 and F57) were also on the frontier in DEA-1CRS. The mean and minimum scores are 54% and 20% respectively and lower than in DEA-1CRS. In addition, the efficiency scores show low correlation with the scores from DEA-1CRS.

In DEA-2VRS, there are 21 frontier firms while the mean and minimum efficiency scores (78% and 26%) are very similar to those of DEA-1VRS. However, the scores show low correlation with those of the DEA-1VRS model. The results from DEA-2CRS and DEA-2VRS underline the importance of the choice of model type and economising the number of variables in order to limit loss of information on relative inefficiencies of the frontier firms.

DEA-1E examines the effect of the choice of monetary conversion method on scores. As shown in Table 8, replacing the PPP conversion rate with Euro exchange rates has a limited effect on the efficiency scores. The minimum and mean scores for the sample amount to 27% and 63% respectively. The scores and rank orders in DEA-1CRS and DEA-1E show high correlations. The composition of the efficient frontier is rather stable and the three efficient firms in DEA-1CRS model also remain on the DEA-1E frontier.

The DEA1-OP model uses the controllable operating expenditures as the only input variable. This specification allows examination of the effect of exclusion of capital expenditures on the scores as utilities with high capital expenditures may score low. As shown in Table 8, in relation to DEA-1CRS model, the scores of some utilities in the DEA1-OP increase while the scores of others decrease. The minimum and mean efficiency scores in DEA1-OP are higher than in the DEA-1CRS model with 28% and 65% respectively. At the same, the simple and rank correlations of the scores between the DEA-1CRS and DEA1-OP models are 67% and 66% respectively.

### 4.2 COLS Models

Models COLS-1LL and COLS-1TL models use loglinear and translog functional forms of the input and output variables of the initial DEA-1CRS model as specified in Equations (4) and (5). As mentioned in previously, when the operating scale of firms covers a wide range, the translog functional forms may not produce statistically significant results. This is also the case here. Table 13 shows the estimated parameters and t-values for the four regression-based models. However, as the occurrence of the problem can be caused by the composition of the data rather than the choice of model specification, for the purpose of comparison, we report the results of the translog models used with COLS and SFA methods.

Table 8 shows the calculated efficiency scores of the COLS models. The mean efficiency scores of COLS-1LL and COLS1-TL models are 60 and 63% respectively relative to 61% in DEA-1CRS (Table 9). Higher scores calculated in the COLS-1TL model can be attributed to the flexibility of translog functional forms.

### 4.3 SFA Models

The SFA-1LL and SFA-1TL models use the same loglinear and translog variable specifications as the COLS method. As SFA allows for statistical noise in the data, the calculated SFA scores are somewhat higher than those of the COLS method. The mean efficiency scores of SFA-1LL and SFA-1TL models are 62% and 72% respectively.

The summary statistics in Table 13 show the relative importance of statistical noise with assumed normal distribution and inefficiency in estimation of the stochastic frontier. The sigma square $\sigma^2$ is the sum of variances of statistical noise $\sigma_v^2$ and inefficiency $\sigma_\mu^2$. The relative importance of inefficiency is measured by gamma as $\gamma = \sigma_\mu^2 / (\sigma_\mu^2 + \sigma_v^2)$.[8] The value of gamma (99.9%) for SFA-1LL and SFA-1TL models suggest that noise has nearly no influence in the estimated function. These very high values of $\gamma$ need be treated with caution as others have previously reported similar unusually high values that cannot be readily explained (see for example Coelli and Perleman, 1996).

To summarise the results, the efficiency scores for the DEA-1CRS model show significant changes in some scores and a relatively low correlation (0.29) with those of the DEA-2CRS model (see Tables 8 and 10). The DEA-1CRS model's efficiency scores also show a high correlation (0.84) with those of COLS-1TL. This is despite the weak significance of the estimated parameters with translog specification. The correlation of the DEA-2CRS scores with regression-based models is relatively weak. However, we find stronger correlation among the scores of the regression-based models.

For example, the COLS-1LL and SFA-1LL models exhibit a correlation factor of 0.98, which indicates a rather high degree of consistency of the scores across the two methods with translog specification. We also find a high correlation factor between the scores of the COLS-1TL and SFA-1TL models. This shows that with consistent specification forms, the SFA and COLS methods produce very comparable efficiency scores. Indeed, model specification form appears to be more important for consistency or high correlation among the scores than the moving from COLS to SFA method.

**[Table 8 here]**

**[Table 9 here]**

**[Table 10 here]**

**[Table 11 here]**

**[Table 12 here]**

**[Table 13 here]**

## 5. Conclusions and Regulatory Implications

The X-factors in price and revenue cap regulation models have significant financial consequences for the regulated utilities. As we discussed, international benchmarking is potentially an effective approach to setting the X-factors. However, our results show that the choice of benchmarking techniques, model specifications, and choice of variables can affect the efficiency scores as well as the rank order of firms.

Our results show a strong correlation between the non-parametric base model DEA-1CRS and the parametric COLS and SFA models. However, we found that the mean and minimum efficiency scores in DEA-1CRS model are significantly lower than the other two models. We also found that the DEA-1CRS efficiency scores are significantly lower than those of DEA-1VRS and the VRS model exhibits a somewhat weaker correlation with the latter model than with COLS and SFA models. Although CRS scores are generally lower than those of VRS models, as we pointed out, this is also partly due to lack of suitably comparable firms for some of the larger utilities in the sample.

From a regulatory point of view, substantial variations in the scores and rankings from different methods is not reassuring. In addition, a one-to-one translation of efficiency scores to X-factors is not justified. A practical approach in the absence of consensus on the most appropriate technique, model specification, and variables is to combine the results from different models. Coelli and Perleman (1999) suggest the use of geometric means of the scores of preferred methods for each data point as this tends to reduce the possible bias in individual models.

Our results also showed that the choice of cost conversion method (PPP vs. Euro exchange rates) has a rather limited effect on the results. We however, found a considerable difference in the results when using network length as proxy for capital stocks instead of capital expenditures in a given year. Although it is preferable to also account for depreciation and weighted average capital costs, the magnitude of variations observed here signifies the importance of how capital costs are represented in the models. This suggests a need for more data and investigation into the appropriate measures of capital and capital costs in the models.

*Issues to be Addressed*

Utilities adapt to their regulatory framework. Benchmarking, by highlighting certain variables, improves performance measured in terms of those variables, possibly at the expense of other variables such as quality. Also, for the regulator, benchmarking involves decisions about data requirements, collection procedures, reporting formats, and quality of supply as well as regulatory governance issues such as commitment and transparency. Therefore, the use of cross-country benchmarking for regulatory purpose and to derive the X-factors requires careful consideration of these issues.

Consistency of data - The reliability of and benefits from benchmarking are greatly enhanced by continuity and consistency. This requires continuing co-operation and commitment for collection and exchange of data between countries. Achieving co-ordination among the regulators may be serious problem. This may because some types of information may be readily available in some countries but difficult to obtain in others - for instance some countries collect much better data on system losses than others. Also the quality of the auditing process for company supplied data may vary between countries.

Timing of rate reviews - The timing of price reviews varies across the countries and international benchmarking inevitably leads to some dissemination of data and results. Regulators may find the timing of rate reviews in other countries is disruptive.  International benchmarking may therefore not be suitable for closed rate setting practices.

Pressure to converge - A consequence of international benchmarking may be that a given set of data shared by different regulators may be used with different methods and model specifications. Although many regulators enjoy full discretion with regard to the choice of methods, models, and data, widely different uses of similar data may be questioned and even met with legal challenges. International benchmarking is likely to lead to pressure for convergence in use of methods and models. It is therefore conceivable that the benchmarking practices in different countries can gradually converge, as it may be difficult to impose different X-factors to equally efficient utilities that operate in different countries.

*Recommendations for Best Practice*

If regulators were to decide it is worth co-ordinating further international benchmarking exercises we would recommend the following. Regulators need to agree upon long-term commitment and procedures for data collection, common templates, and submission deadlines for data standardisation. It is important to identify and define a minimum set of input, output, and environmental variables for data collection. Some potentially useful additional variables are maximum demand, transformer capacity, service area, quality of service, and voltage-based physical and monetary breakdown of assets. The sample should also sufficiently represent different size groups and types of utilities.

In addition, in order to reduce the effect of measurement errors and data shocks; the data should be in the form of time-series for the recent past and then collected annually for future years. Regulators should also discuss benchmarking models and functional forms such as CRS versus VRS models or consider assigning different weights to inputs and outputs suitable for regulation of electricity distribution and transmission utilities. The benchmarking results can also be followed up by in-depth examination of the extent of similarities and differences between the inefficient firms and their peers. Finally, exchange of data and experience can be facilitated by co-operation with bodies involved in international utilities data such as the US Federal Energy Regulatory Commission (FERC), Secretaría General de la Comisión de Integración Eléctrica Regional (CIER) in Latin America, and the Australian energy regulators.

**End Notes**

[1] See Hall (2000), Comnes et al. (1995), Hill (1995), and Joskow and Schmalensee (1986) for reviews and comparisons of different incentive regulation models.

[2] This section draws mainly on Jamasb and Pollitt (2001).

[3] See above references for detailed descriptions and various steps involved in the technique.

[4] There are over 200 distribution utilities in Norway. The firms used in this study represent the largest 25 utilities.

[5] For calculations of DEA, COLS, and SFA models computer programmes EMS, Excel, and Frontier4.1 were used respectively.

[6] However, a closer examination of the results showed that the degree of the influence of the firm on scores of other utilities has been rather less than the other two frontier firms.

[7] The wide range in the scores may partly be due to extraordinary levels of operating or capital costs in the observation year. In practice, in order to increase confidence in extreme scores, such costs for the utilities concerned in the reference year can be compared with those of other years.

[8] See Coelli (1996) for a further description of these measures.

## References


Coelli, T., 1996. A guide to FRONTIER Version 4.1: A computer program for stochastic frontier production and cost function estimation, Centre for Efficiency and Productivity Analysis, University of New England.

Coelli, T., Perleman, S., 1996. Efficiency measurement, multiple-output technologies and distance functions: with application to European railways, CREPP, Faculty of Economics, University of Liege.

Coelli, T., Perleman, S., 1999. A comparison of parametric and non-parametric distance functions: With application to European railways, European Journal of Operational Research 117, 326-339.

Coelli, T., Rap, D. S. P., Battese, G. E., 1998. An Introduction to Efficiency and Productivity Analysis. Kluwer Academic Publishers, London.

Comnes, G. A., Stoft, S., Greene, N., Hill, L. J., 1995. Performance-based ratemaking for electric utilities: Review of plans and analysis of economic and resource planning issues, Volume I. Oak Ridge, Ten. Oak Ridge National Laboratory and University of California, Berkeley.

DTe, 1999. Price Cap Regulation in the Electricity Sector. Hague. Netherlands Electricity Regulatory Service.

Färe, R., Grabowski, R., Grosskopf, S., 1985. The Measurement of Efficiency of Production. Kluwer Academic Publishers, Boston.

Farrell, M. J., 1957. The measurement of productive efficiency. Journal of Royal Statistical Society Series A, 120, 253-281.

Hall, G. L. 2000. Electricity pricing and regulatory practice in a competitive environment - Workshop Paper No. 2: Analysis of alternative ratemaking methodologies. Manila. Prepared by Hagler Bailly Services, Inc. for Asian Development Bank and the Philippines Energy Regulatory Board and Department of Energy.

Hill, L., 1995. A primer on incentive tegulation for electric utilities. Oak Ridge National Laboratory.

Jamasb, T., Pollitt, M., 2000. Benchmarking and regulation: International electricity experience. Utilities Policy, Vol. 9, No. 3, 107-130.

Joskow, P. J., Schmalensee, R., 1986. Incentive regulation for electric utilities. Yale Journal on Regulation Vol. 4 (1), 1-49.

Neuberg, L., 1977. Two issues in municipal ownership of electric power distribution systems. Bell Journal of Economics 8.

OECD, 1999. Main Economic Indicators. Paris. Organisation for Economic Cooperation and Development (OECD).

OFGEM, 1999. Reviews of Public Electricity Suppliers 1998 to 2000: Distribution Price Control Review: Update. October 1999. London. Office of Gas and Electricity Markets.

Pollitt, M., 1995. Ownership and Performance in Electric Utilities. Oxford Ubiversity Press, Oxford-New York.

Richmond, J., 1974. Estimating the efficiency of production. International Economic Review 15 (2 June), 515-521.

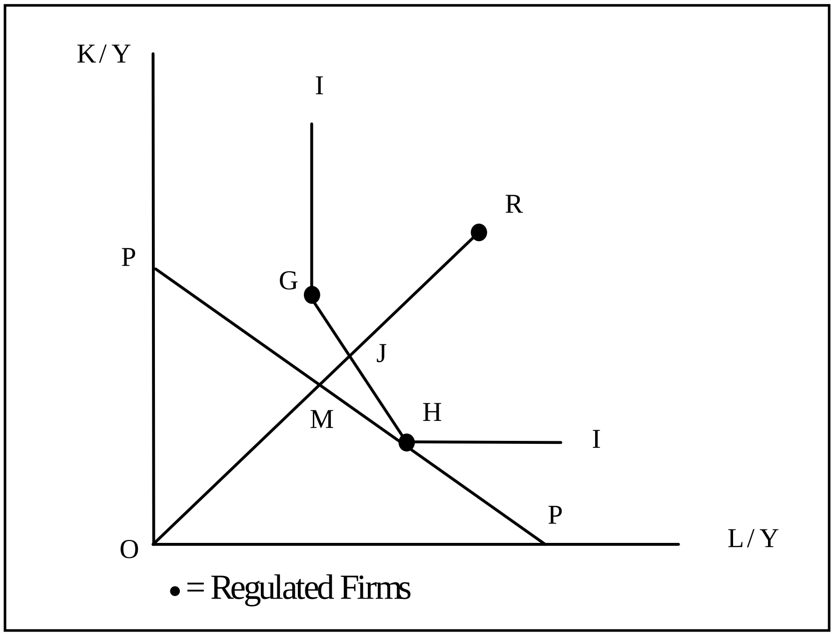


**Figure 1: Data envelopment analysis**

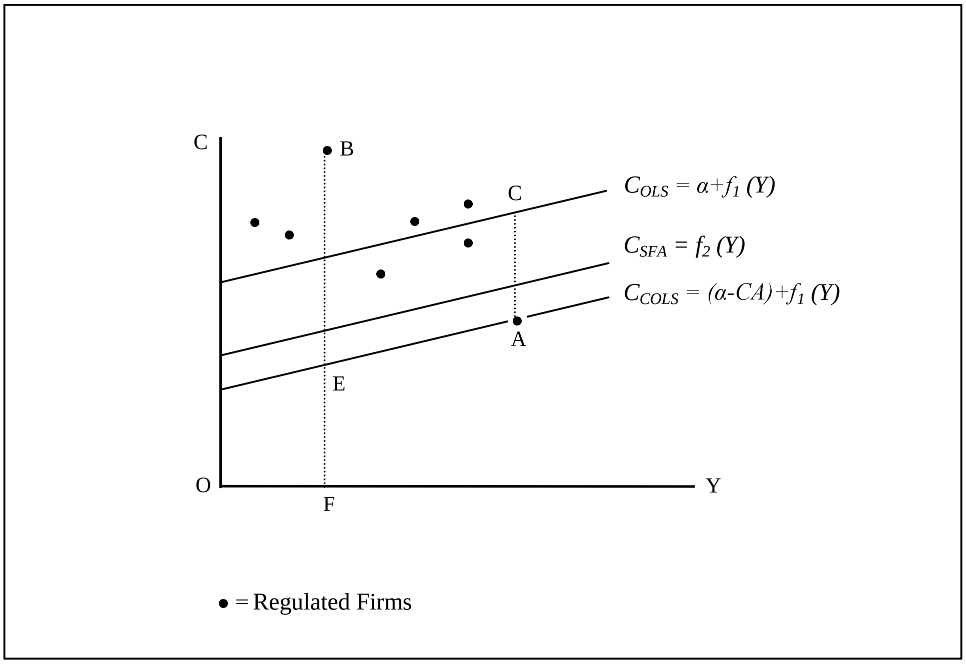


**Figure 2: COLS and SFA**

**Table 1:**

**Number of utilities in the sample**

| Country | No. |
|---|---|
| Italy | 1 |
| Netherlands | 18 |
| Norway | 25 |
| Portugal | 1 |
| Spain | 4 |
| UK | 14 |
| Total | 63 |

**Table 2:**

**Summary statistics over variables**

| Variables | Min | Max | Mean |
|---|---|---|---|
| Operating costs (mill €) | 1.1 | 3430.6 | 160.07 |
| Capital expenditures (mill €) | 0.21 | 1785.75 | 83.99 |
| Total costs (mill. €) | 1.72 | 5216.38 | 244.06 |
| Units of energy delivered (GWh) | 70.123 | 226010 | 13944.11 |
| Number of customers (000) | 0.03 | 28906.55 | 1430.44 |
| • residential | 0.00 | 22553.04 | 1260.29 |
| • non-residential | 0.02 | 6353.51 | 170.16 |
| Length of network (km) | 180 | 1038145 | 47247.91 |
| • overhead cables | 0 | 732505 | 27969.84 |
| • underground cables | 0 | 305640 | 19278.03 |
| Distribution / transmission losses (GWh) | 4.37 | 10651 | 850.12 |
| Number of transformers | 59 | 343833 | 20654.03 |

**Table 3:**

**Reference years for the data and CPI change to mid-1999**

**Source: OECD (1999)**

| Country | Reference year for data | CPI Change (reference year to mid-1999) |
|---|---|---|
| Italy | 1997 | 3.0.% |
| Norway | 1998 | 2.2% |
| UK | 1997/98 | 4.1% |
| Portugal | 1999 | 0.0% |
| Spain | 1998 | 2.3% |
| Netherlands | 1999 | 0.0% |

**Table 4:**

**PPPs and Euro conversion rates (1999)**

**Source: EUROSTAT**

| Country | Purchasing Power Parity (1999) 1 PPP= | Euro Conversion Rate (1999) 1 Euro= |
|---|---|---|
| Italy | 1668 | 1936.3 |
| Norway | 9.6 | 8.31 |
| UK | 0.673 | 0.659 |
| Portugal | 127 | 200.48 |
| Spain | 130 | 166.39 |
| Netherlands | 2.04 | 2.20 |

**Table 5:**

**Voltage boundaries between and within T&D networks**

**Source: CEER survey returns**

| | **Voltage boundaries between T & D** | **Voltage boundaries within T & D** |
|---|---|---|
| Norway | T: 30-420 kV<br>D: 0-22 kV<br>(regional networks 30-132 kV) | T: 45, 66, 132, 220, 300, 420 kV<br>D: 0.22, 0.4, 11, 22, (132) kV |
| Portugal | T: >110 kV<br>D: ≤110 kV | T: VHV>110 kV<br>D: 45<HV≤110 kV<br>1 kV<MV≤45 kV<br>LV≤1 kV |
| Netherlands | T: 220-380 kV<br>D: 110-150 kV (regional distribution) and <50 kV | T: EHV 220-380 kV<br>D: HV 110-150 kV<br>IV 25-50 kV MV 10-20 kV<br>LV<10 kV |
| Great Britain | T: E&W≥275 kV<br>Scotland≥ 132 kV<br>D: E&W <132 kV<br>Scotland<132 kV | D: EHV≥22 kV<br>(≥66 kV at substations)<br>22 kV>HV>1000 V<br>LV<1000 V |
| Italy | T: ≥220 kV (EHV) and portions of 120-220 kV (HV) grid<br>D: <220 kV | D: portions of 120-220 kV grid, 10, 15, 20 kV (MV), and 380 V (LV) |
| Spain | T: ≥220 kV<br>D: <220 kV | T: EHV 400 kV, HV 220 kV<br>D: 36 kV≤HV<220 kV<br>1 kV≤MV<36 kV LV<1 kV |

**Table 6:**

**Overview of methods, models, and variables**

| | **Model 1** | **Model 2** | **Model 3** | **Model 4** | **Model 5** | **Model 6** | **Model 7** | **Model 8** | **Model 9** | **Model 10** |
|---|---|---|---|---|---|---|---|---|---|---|
| | DEA-1 CRS | DEA-1VRS | DEA-2CRS | DEA-2VRS | COLS-1LL | COLS-2TL | SFA-1LL | SFA-2TL | DEA-1E | DEA-1OP |
| **Inputs** | | | | | | | | | | |
| OPEX (PPP) | | | X | X | | | | | | X |
| TOTEX (PPP) | X | X | | | X | X | X | X | X (Euro) | |
| Network length | | | | X | | | | | | |
| T&D losses | | | | X | | | | | | |
| **Non-discretionary inputs** | | | | | | | | | | |
| Network length | | | X | | | | | | | |
| T&D losses | | | X | | | | | | | |
| **Outputs** | | | | | | | | | | |
| Units delivered | X | X | X | X | X | X | X | X | X | X |
| No. of customers | X | X | X | X | X | X | X | X | X | X |
| Network length | X | X | | | X | X | X | X | X | X |

**Table 7:**

**Frequency of the use of main input and output variables used in 20 Benchmarking studies of electricity distribution utilities.**

| Input | Output |
|---|---|
| • units sold (2) | • units sold (12)<br>• residential sale (6)<br>• non-residential sale (6) |
| • no. of customers | • no. of customers (11)<br>• no. residential customers (5)<br>• no. non-residential customers (5) |
| • network size (11)<br>• LV lines (2)<br>• MV lines<br>• HV lines (2) | • network size (4) |
| • transformer capacity (11)<br>• MV transformer capacity<br>• HV transformer capacity | • transformer capacity<br>• no. of transformers |
| • service area (2) | • service area (6) |
| • maximum demand | • maximum demand (4) |
| • purchased power (2) | • power sold to other utilities |
| • transmission/distribution losses (4) | |
| • labour/wages (15)<br>• administrative labour<br>• technical labour | |
| Cost measures:<br>• OPEX (7)<br>• OPEX+annualised standard capital costs | |

| | |
|---|---|
| • administrative/accounting costs (2)<br>• maintenance costs<br>• capital (5)<br>• CAPEX user cost+labour costs<br>• materials | |
| Miscellaneous:<br>• industrial demand<br>• customer dispersion (2)<br>• share of industrial energy<br>• network size/customers<br>• % system unload<br>• residential/total sales<br>• outage<br>• no. residential customers/network size<br>• inventories<br>• line length*voltage | Miscellaneous:<br>• service reliability<br>• load factor<br>• net margin<br>• revenues<br>• distance index<br>• network density<br>• categorical variable for urban areas |

**Table 8:**

**Efficiency scores for alternative models**

| | DEA-1CRS | DEA-1VRS | DEA-2CRS | DEA-2VRS | COLS-1LL | COLS-1TL | SFA-1 LL | SFA-2 TL | DEA-1E | DEA-1OP |
|---|---|---|---|---|---|---|---|---|---|---|
| F1 | 60.5% | 100% | 70.5% | 100.0% | 62.1% | 69.9% | 68.3% | 86.2% | 57.2% | 70.4% |
| F2 | 50.4% | 85.2% | 49.3% | 94.1% | 55.1% | 59.6% | 60.0% | 73.1% | 48.3% | 51.2% |
| F3 | 43.2% | 76.8% | 79.1% | 100.0% | 46.7% | 49.7% | 47.7% | 71.2% | 39.6% | 50.1% |
| F4 | 50.4% | 77.5% | 48.3% | 75.9% | 54.6% | 57.9% | 59.1% | 67.1% | 48.9% | 53.5% |
| F5 | 58.1% | 98.3% | 56.2% | 100.0% | 63.8% | 68.5% | 69.2% | 84.6% | 55.5% | 56.9% |
| F6 | 49.5% | 70.3% | 40.9% | 85.7% | 51.0% | 55.4% | 55.3% | 63.1% | 47.6% | 43.4% |
| F7 | 34.6% | 55.4% | 51.8% | 97.8% | 36.8% | 39.8% | 39.9% | 48.7% | 32.7% | 50.7% |
| F8 | 65.8% | 100% | 87.6% | 100.0% | 68.5% | 73.6% | 73.0% | 92.5% | 60.7% | 76.5% |
| F9 | 58.5% | 100% | 87.4% | 100.0% | 64.1% | 69.2% | 69.7% | 87.3% | 55.6% | 86.2% |
| F10 | 35.1% | 48.4% | 38.1% | 82.7% | 37.1% | 39.1% | 39.9% | 43.7% | 34.1% | 42.8% |
| F11 | 54.7% | 72.6% | 59.1% | 84.4% | 52.3% | 59.7% | 57.7% | 64.0% | 53.3% | 71.4% |
| F12 | 50.8% | 83.0% | 66.1% | 96.8% | 55.1% | 58.8% | 59.4% | 72.7% | 48.0% | 63.8% |
| F13 | 51.7% | 76.4% | 51.3% | 77.8% | 51.5% | 58.6% | 57.0% | 65.5% | 50.3% | 60.3% |
| F14 | 42.2% | 49.2% | 34.4% | 52.2% | 33.2% | 44.9% | 37.9% | 41.8% | 43.9% | 68.7% |
| F15 | 61.4% | 100% | 42.2% | 79.6% | 88.7% | 77.2% | 89.8% | 95.6% | 54.7% | 48.9% |
| F16 | 51.8% | 71.0% | 43.7% | 63.5% | 72.1% | 58.6% | 74.9% | 68.2% | 49.7% | 75.0% |
| F17 | 67.5% | 70.7% | 30.1% | 37.4% | 66.5% | 64.0% | 71.3% | 67.9% | 64.5% | 61.3% |
| F18 | 59.2% | 62.3% | 41.2% | 45.1% | 67.7% | 58.1% | 70.4% | 64.4% | 55.5% | 69.2% |
| F19 | 72.5% | 88.4% | 23.9% | 29.4% | 57.9% | 65.4% | 64.8% | 68.2% | 72.5% | 80.6% |
| F20 | 59.9% | 62.4% | 41.1% | 46.2% | 77.3% | 62.3% | 77.6% | 72.1% | 54.9% | 56.5% |
| F21 | 53.4% | 60.0% | 28.7% | 31.4% | 54.9% | 50.0% | 59.3% | 55.1% | 53.3% | 75.1% |
| F22 | 66.1% | 69.0% | 36.2% | 38.9% | 71.4% | 61.7% | 76.2% | 69.0% | 65.4% | 86.8% |
| F23 | 65.6% | 65.6% | 49.5% | 54.8% | 83.1% | 65.2% | 84.0% | 75.7% | 61.4% | 76.0% |
| F24 | 60.5% | 83.4% | 56.6% | 100.0% | 100.0% | 71.5% | 98.3% | 90.6% | 58.7% | 82.8% |
| F25 | 100% | 100% | 35.1% | 38.7% | 91.6% | 89.8% | 100.0% | 98.2% | 100.0% | 100% |
| F26 | 59.6% | 68.3% | 50.1% | 58.3% | 97.5% | 69.8% | 95.3% | 88.3% | 57.2% | 70.3% |
| F27 | 81.1% | 86.4% | 21.5% | 25.7% | 54.4% | 63.1% | 61.1% | 69.8% | 81.1% | 90.0% |

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| F28 | 46.1% | 46.6% | 24.4% | 26.9% | 39.7% | 38.6% | 43.4% | 43.4% | 46.1% | 76.4% |
| F29 | 69.3% | 71.5% | 28.6% | 35.6% | 53.2% | 56.9% | 58.4% | 63.4% | 69.3% | 90.1% |
| F30 | 49.3% | 100% | 48.1% | 100.0% | 39.8% | 44.2% | 34.8% | 52.4% | 49.3% | 48.2% |
| F31 | 80.7% | 100% | 83.8% | 100.0% | 48.2% | 76.6% | 42.7% | 86.4% | 80.7% | 83.9% |
| F32 | 100% | 100% | 100.0% | 100.0% | 59.0% | 82.8% | 51.8% | 98.9% | 100.0% | 93.9% |
| F33 | 50.6% | 52.4% | 100.0% | 100.0% | 27.3% | 46.1% | 24.2% | 53.9% | 50.6% | 100% |
| F34 | 88.1% | 94.8% | 100.0% | 100.0% | 97.4% | 62.5% | 86.5% | 88.0% | 88.1% | 75.2% |
| F35 | 89.8% | 92.4% | 42.5% | 44.8% | 81.0% | 74.6% | 85.6% | 85.9% | 87.1% | 96.2% |
| F36 | 71.7% | 71.9% | 24.9% | 27.4% | 60.2% | 61.3% | 65.6% | 67.2% | 70.9% | 69.5% |
| F37 | 54.5% | 55.1% | 44.5% | 51.9% | 84.5% | 61.8% | 79.8% | 78.0% | 50.5% | 53.9% |
| F38 | 85.6% | 86.6% | 43.9% | 45.9% | 85.5% | 74.6% | 88.7% | 84.9% | 81.0% | 81.8% |
| F39 | 48.2% | 48.9% | 31.8% | 39.4% | 57.8% | 45.1% | 57.6% | 53.2% | 44.8% | 47.4% |
| F40 | 62.7% | 100% | 46.1% | 100.0% | 63.3% | 72.8% | 70.4% | 84.6% | 66.7% | 52.3% |
| F41 | 57.0% | 61.0% | 100.0% | 100.0% | 49.7% | 56.1% | 50.0% | 56.9% | 58.3% | 60.6% |
| F42 | 65.0% | 83.5% | 53.2% | 100.0% | 93.1% | 78.1% | 93.8% | 94.2% | 73.2% | 61.8% |
| F43 | 26.0% | 26.3% | 41.7% | 62.0% | 29.4% | 28.5% | 28.2% | 32.0% | 27.3% | 39.1% |
| F44 | 53.5% | 53.7% | 96.0% | 98.9% | 47.5% | 53.6% | 47.1% | 55.1% | 54.6% | 85.0% |
| F45 | 50.2% | 95.4% | 20.1% | 98.1% | 53.0% | 51.2% | 57.4% | 56.8% | 62.6% | 58.8% |
| F46 | 67.5% | 100% | 51.0% | 95.8% | 75.9% | 77.7% | 81.5% | 88.7% | 73.2% | 59.6% |
| F47 | 88.6% | 100% | 46.8% | 96.8% | 77.8% | 98.2% | 88.2% | 96.0% | 100.0% | 83.1% |
| F48 | 54.7% | 56.2% | 61.8% | 85.0% | 38.8% | 51.5% | 38.5% | 50.8% | 55.5% | 54.2% |
| F49 | 95.7% | 99.1% | 100.0% | 100.0% | 73.6% | 89.3% | 73.1% | 93.0% | 99.6% | 100% |
| F50 | 65.8% | 66.5% | 66.6% | 75.1% | 45.4% | 56.9% | 47.2% | 57.3% | 70.9% | 86.3% |
| F51 | 60.9% | 92.3% | 57.1% | 97.3% | 62.9% | 66.6% | 65.5% | 79.2% | 61.7% | 49.0% |
| F52 | 49.3% | 72.8% | 55.7% | 100.0% | 46.3% | 50.9% | 47.5% | 55.5% | 49.5% | 46.8% |
| F53 | 67.5% | 74.2% | 100.0% | 100.0% | 40.7% | 82.6% | 36.2% | 80.0% | 67.5% | 42.8% |
| F54 | 42.6% | 91.6% | 52.9% | 100.0% | 24.0% | 42.6% | 22.7% | 43.3% | 42.6% | 35.2% |
| F55 | 94.8% | 100% | 75.2% | 100.0% | 73.8% | 88.5% | 72.8% | 95.3% | 99.5% | 77.9% |
| F56 | 49.3% | 52.4% | 83.3% | 91.8% | 40.5% | 52.9% | 38.0% | 54.6% | 49.6% | 43.0% |
| F57 | 100% | 100% | 100.0% | 100.0% | 82.9% | 100.0% | 82.1% | 99.7% | 100.0% | 84.7% |
| F58 | 49.6% | 100% | 29.4% | 94.7% | 44.7% | 59.0% | 51.6% | 73.8% | 61.9% | 32.0% |
| F59 | 65.9% | 88.5% | 40.7% | 67.7% | 70.3% | 71.0% | 74.1% | 77.8% | 83.9% | 45.7% |
| F60 | 44.9% | 96.1% | 29.0% | 100.0% | 41.2% | 50.9% | 46.7% | 66.1% | 54.9% | 27.7% |
| F61 | 51.9% | 86.1% | 33.2% | 78.1% | 43.5% | 55.9% | 49.3% | 59.6% | 65.4% | 33.2% |
| F62 | 53.4% | 97.9% | 32.3% | 88.6% | 38.8% | 57.5% | 45.3% | 58.9% | 83.2% | 38.2% |
| F63 | 49.5% | 100% | 35.0% | 100.0% | 45.9% | 70.4% | 55.2% | 99.2% | 57.1% | 43.0% |

**Table 9:**

**Summary statistics of efficiency scores**

| | DEA-1CRS | DEA-1VRS | DEA-2CRS | DEA-2VRS | COLS-1LL | COLS-1TL | SFA-1 LL | SFA-2 TL | DEA-1E | DEA-1OP |
|---|---|---|---|---|---|---|---|---|---|---|
| **Mean score** | 0.613 | 0.793 | 0.539 | 0.777 | 0.595 | 0.627 | 0.619 | 0.716 | 0.626 | 0.648 |
| **Std. Error** | 0.021 | 0.024 | 0.030 | 0.033 | 0.024 | 0.018 | 0.024 | 0.022 | 0.022 | 0.024 |
| **Min. score** | 0.260 | 0.263 | 0.201 | 0.257 | 0.240 | 0.285 | 0.227 | 0.320 | 0.273 | 0.277 |

**Table 10:**

**Efficiency score correlations**

| | DEA-1CRS | DEA-1VRS | DEA-2CRS | DEA-2VRS | COLS-1LL | COLS-1TL | SFA-1LL | SFA-2TL | DEA-1E | DEA-1OP |
|---|---|---|---|---|---|---|---|---|---|---|
| **DEA-1CRS** | 1.00 | | | | | | | | | |
| **DEA-1VRS** | 0.54 | 1.00 | | | | | | | | |
| **DEA-2CRS** | 0.29 | 0.11 | 1.00 | | | | | | | |
| **DEA-2VRS** | -0.09 | 0.41 | 0.62 | 1.00 | | | | | | |
| **COLS-1LL** | 0.61 | 0.35 | 0.04 | -0.16 | 1.00 | | | | | |
| **COLS-1TL** | 0.84 | 0.67 | 0.31 | 0.17 | 0.68 | 1.00 | | | | |
| **SFA-1LL** | 0.59 | 0.39 | -0.09 | -0.21 | 0.98 | 0.69 | 1.00 | | | |
| **SFA-1TL** | 0.73 | 0.73 | 0.29 | 0.23 | 0.75 | 0.92 | 0.75 | 1.00 | | |
| **DEA-1E** | 0.94 | 0.61 | 0.20 | 0.00 | 0.51 | 0.82 | 0.50 | 0.67 | 1.00 | |
| **DEA-1OP** | 0.67 | 0.10 | 0.29 | -0.27 | 0.41 | 0.44 | 0.40 | 0.36 | 0.53 | 1.00 |

**Table 11:**

**Rank order correlations**

| | DEA-1CRS | DEA-1VRS | DEA-2CRS | DEA-2VRS | COLS-1LL | COLS-1TL | SFA-1LL | SFA-2TL | DEA-1E | DEA-1OP |
|---|---|---|---|---|---|---|---|---|---|---|
| **DEA-1CRS** | 1.00 | | | | | | | | | |
| **DEA-1VRS** | 0.47 | 1.00 | | | | | | | | |
| **DEA-2CRS** | 0.19 | 0.14 | 1.00 | | | | | | | |
| **DEA-2VRS** | -0.06 | 0.49 | 0.69 | 1.00 | | | | | | |
| **COLS-1LL** | 0.69 | 0.34 | 0.08 | -0.12 | 1.00 | | | | | |
| **COLS-1TL** | 0.84 | 0.66 | 0.27 | 0.19 | 0.75 | 1.00 | | | | |
| **SFA-1LL** | 0.63 | 0.37 | -0.06 | -0.17 | 0.97 | 0.72 | 1.00 | | | |
| **SFA-1TL** | 0.68 | 0.70 | 0.26 | 0.27 | 0.80 | 0.92 | 0.79 | 1.00 | | |
| **DEA-1E** | 0.99 | 0.58 | 0.07 | 0.05 | 0.52 | 0.77 | 0.52 | 0.62 | 1.00 | |
| **DEA-1OP** | 0.66 | 0.10 | 0.23 | -0.15 | 0.45 | 0.42 | 0.40 | 0.34 | 0.49 | 1.00 |

**Table 12:**

**Summary statistics for efficiency scores – DEA-1CRS model**

| | Min | Max | Mean |
|---|---|---|---|
| Sample | 26.0% | 100.0% | 61.0% |
| Country 1 | - | - | 49.5% |
| Country 2 | - | - | 67.7% |
| Country 3 | - | - | 50.4% |
| Country 4 | - | - | 53.4% |
| Country 5 | - | - | 53.1% |
| Country 6 | - | - | 63.9% |

**Table 13:**

**Estimated variable parameters and statistics for the COLS and SFA models (t statistics in parenthesis)**

| | **COLS-1LL** | **COLS-1TL** | **SFA-1LL** | **SFA-1TL** |
|---|---|---|---|---|
| Intercept | -4.498 (-15.65) | -0.407 (-0.36) | -5.33 (-20.5) | -1.53 (-1.08) |
| UNIT | 0.662 (9.55) | 0.23 (0.40) | 0.602 (11.27) | 0.287 (0.547) |
| CUST | 0.214 (5.90) | 1.52 (4.01) | 0.202 (7.79) | 1.02 (2.15) |
| NETW | 0.180 (1.99) | -1.1 (-1.95) | 0.274 (4.80) | -0.718 (-1.56) |
| $(UNIT)^2$ | - | 0.17 (1.54) | - | 0.176 (1.32) |
| $(CUST)^2$ | - | 6.14 (2.8) | - | 6.06 (3.27) |
| $(NETW)^2$ | - | 0.251 (2.02) | - | 0.456 (0.708) |
| UNIT*CUST | - | -2.95 (-0.42) | - | 5.4 (1.2) |
| UNIT*NETW | - | -0.277 (-1.3) | - | -0.318 (-1.35) |
| CUST*NETW | - | -0.168 (-1.88) | - | -0.192 (-2.46) |
| $R^2$ | 0.97 | 0.98 | - | - |
| Log likelihood | -18.8 | 1.03 | -14.78 | 4.24 |
| $\sigma^2$ | - | - | 0.208 (2.86) | 0.134 (4.73) |
| $\gamma$ | - | - | 0.999 (98869) | 0.999 (1139.7) |