INTERNATIONAL BENCHMARKING AND REGULATION OF EUROPEAN ELECTRICITY DISTRIBUTION UTILITIES

FINAL REPORT

PREPARED FOR:

THE COUNCIL OF EUROPEAN ENERGY REGULATORS (CEER) -

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Tooraj Jamasb

Department of Applied Economics, University of Cambridge

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

Michael Pollitt

Judge Institute of Management, University of Cambridge

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

EXECUTIVE SUMMARY

Aim

The present study is commissioned by the Benchmarking Working Group of the Council of European Energy Regulators (CEER) to conduct and report on the benchmarking of European electricity distribution utilities. The purpose of the study is to examine the scope for and identify the main issues in the use of international benchmarking of electricity utilities for the regulation and price controls. The analytical parts of the study use data provided by the Group. The main aim is to arrive at more general findings through these results.

Terms of Reference

- to conduct an empirical cross-country benchmarking of selected electricity utilities using data collected for the purpose of the study,
- to employ alternative frontier-oriented benchmarking methods and model specifications,
- to compare benchmarking results,
- to discuss regulatory implications, and
- to identify issues for next steps and further development of the approach.

Methods

The study employs the 3 most widely adopted frontier-based benchmarking methods:

- the non-parametric method Data Envelopment Analysis (DEA),
- the deterministic-parametric method Corrected Ordinary Least Square (COLS), and
- the stochastic method Stochastic Frontier Analysis (SFA).

Data

The analytical parts of the study are based on the data from 63 electricity transmission / distribution utilities in Italy, Netherlands, Norway, Portugal, Spain, and United Kingdom. The data used in the study is provided by the participating regulators.

Empirical Results

- The methods used show large efficiency differences amongst the utilities. The DEA results show country mean efficiency scores from 50 to 68%.
- Small/medium firms tend to dominate the frontiers and there is an indication of lack of large comparators for variable returns-to-scale DEA models, as the scores increase significantly with these models.

- The scores from the initial DEA model with outputs (energy delivered, number of customers, and network length) shows a low correlation of 0.29 with the DEA-2 model that uses network length as the physical measure of capital stock, and assumes T&D losses and number of transformers as non-discretionary variables.

- The mean efficiency scores from constant returns-to-scale DEA models are considerably lower than the scores from COLS and SFA. The latter methods produced comparable scores. The loglinear model with COLS and SFA methods show a correlation of 0.96. The translog model with COLS and SFA methods show a correlation of 0.90.

Recommendations for Next Steps

- discuss benchmarking models and functional forms (e.g. CRS versus VRS models or assigning weights to inputs and outputs) suitable for regulation of electricity distribution and transmission utilities,

- agree 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),

- agree detailed specification of each variable especially capital,

- agree long-term commitment and procedures for data collection, common templates, and submission dead-lines for data standardisation,

- collect time-series data for several years - recent and future years on an annual basis,

- data should also sufficiently represent different size groups of utilities,

- conduct an in-depth examination of similarities and differences between the inefficient firms and their peers, and

- explore co-operation with other bodies involved in international utilities data such as the US Federal Energy Regulatory Commission (FERC), Australian energy regulators, and Comisión de Integración Eléctrica Regional (CIER) in Latin America.

1. Introduction

Power sector reforms are transforming the structure and operating environment of the electricity industries across many countries. The central aim of the reforms has been to introduce competition and market-oriented measures in the generation and supply activities of the sector. Increasingly, power sector reforms also attempt to improve the efficiency of the natural monopoly segments of the industry, namely, electricity distribution and transmission through regulatory reforms. This study is primarily concerned with this latter aspect of the reforms.

Regulatory reform of distribution and transmission utilities generally involves moving away from traditional rate of return regulation towards incentive-based regulation. A number of incentive-based regulation models have been proposed in the literature.[1] These models are generally not attributed to theoretical advances in regulatory economics, rather, they reflect dissatisfaction with incentive signals and performance of rate of return regulation and the need for alternative approaches.

In practice, many regulators have adopted some form of price and revenue cap regulation models based on the RPI-X formula. However, a crucial issue is how the utilities' efficiency requirements or X-factors are to be set. There are different approaches to the setting of X-factors.[2] An increasingly favoured approach is through relative efficiency analysis and benchmarking of utilities. To this end, countries such as the Netherlands, United Kingdom,

[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] See for example Jamasb and Pollitt (2001) and DTe (1999) for reviews of alternative approaches.

and Norway have used utility benchmarking in the national context as part of the process of setting X-factors.

The aim of benchmarking is to reveal performance variations amongst the regulated utilities. Benchmarking is used for identifying the most efficient firms in the sector and for measuring the relative performance of less efficient firms. Individual X-factors are then assigned based on their relative efficiency. Generally, the greater the inefficiency of a firm, the higher the efficiency requirement assigned to it. The purpose of individual X-factors is to provide firms with an incentive to close the efficiency gaps between them.

However, most countries have limited number of utilities, a situation that does not satisfy the data requirements of some analytical benchmarking techniques. Also, due to merger and acquisition activities within the sector, the existing domestic information base is subject to change or reduction. In addition, as a result of electricity market liberalisation and privatisation, power sectors tend to become interconnected, and ownership and operation of utilities grow increasingly international.

As a result, regulators can use cross-country relative efficiency analysis in order to evaluate performance of their utilities within the larger context of international practice. However, whilst international utility benchmarking has clear advantages, in order to enhance the reliability of the approach, 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 issues arising in international benchmarking.

1.2 Terms of reference

The present study is commissioned to undertake a cross-country analysis of the relative efficiencies of electricity distribution utilities. The aim of the study is to examine the potential for, and the main issues involved in international benchmarking for the purpose of the regulation of electric utilities. The terms of reference for the study are to:

- conduct an empirical frontier-oriented analysis and benchmarking using the data collected for the purpose of the study.

- employ alternative frontier methods and model specifications,

- compare the benchmarking results,

- discuss the regulatory implications, and

- identify issues for further development of the approach.

1.3 Organisation of the Study

The next section presents the benchmarking methods used in this study. Section 3 is an overview of previous benchmarking studies of electricity utilities. Section 4 discusses the main issues in international benchmarking. Sections 5 and 6 review the data used in the study and discuss the preferred models. Section 7 presents the results of the benchmarking. The final section discusses the results and regulatory implications of international benchmarking and offers recommendations for further steps.

2. Frontier-Oriented Benchmarking Methods

As discussed in Section 1, there are several different approaches to measuring the relative efficiency of firms in relation to an efficient frontier or best practice of a sample of firms based on programming or statistical techniques. This section outlines the main features of Data Envelopment Analysis (DEA), Corrected Ordinary Least Square (COLS), and Stochastic Frontier Analysis (SFA) methods used in this study.[3]

2.1 Data Envelopment Analysis (DEA)

DEA is a non-parametric method that uses piecewise linear programming to calculate (rather than estimate) the efficient or best-practice frontier of a sample of firms. The firms that make up the frontier envelop the less efficient firms. The efficiency scores of the firms are calculated on a scale of 0 to 1, with the frontier firms receiving a score of 1. DEA can be used to calculate the allocative and technical efficiency of the firms and the latter measure can be decomposed into scale, congestion, and pure technical inefficiency.

DEA models can be specified as input and output oriented and each of these can be further specified as constant returns to scale (CRS) or variable returns to scale (VRS) models. Output-oriented models maximise output for a given amount of input factors while input-oriented models minimise the input factors required for a given level of output. Input-oriented models are generally more appropriate for electricity distribution utilities, as demand

[3] This section is largely based on Pollitt (1995) and DTe (1999).

for their output is a derived demand which is beyond the control of utilities and can be taken as given.

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 costs per unit of output respectively and the line PP shows the relative price of the two inputs. 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 efficiency of firm R relative to the frontier are 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.

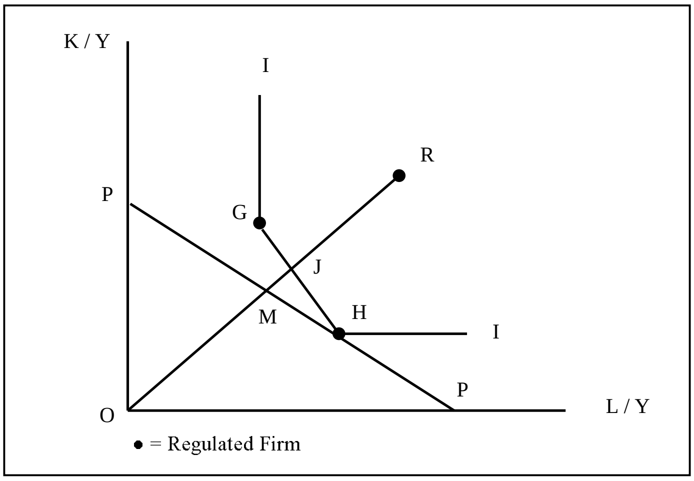

Figure 1: Data envelopment analysis

Another crucial stage in DEA is the choice of appropriate input and output variables. The choice of variables should, as far as possible, reflect the main aspects of resource-use in the activity concerned. DEA can also be used to account for other factors that can be specific to the operating environment of some firms (environmental variables).

An advantage of DEA is that inefficient firms are compared to actual firms rather than to 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 model, the number of firms on the efficient frontier increases. Therefore, it is important to examine the sensitivity of the efficiency scores and changes in the rank order of firms to variations in model specification.

2.2 Corrected Ordinary Least Square (COLS)

An alternative frontier method 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. Similar to DEA, the method estimates the efficiency scores of 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 from that of the other errors.

Figure 2 illustrate a COLS model with one cost input C and one output Y. The cost equation $C_{OLS}=\alpha+f_1(Y)$ is estimated using OLS regression and then shifted by CA to $C_{COLS}=(\alpha\text{-}CA)+f_1(Y)$ on which the most efficient firm A lies. The efficiency score for an inefficient firm such as B is then calculated as EF/BF.

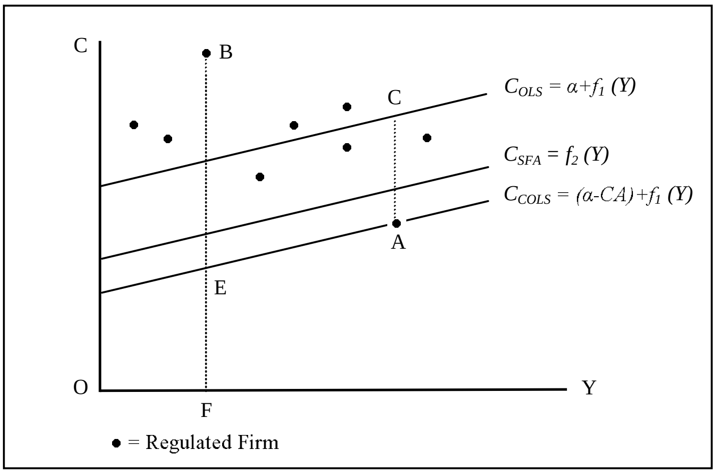

Figure 2: COLS and SFA

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.

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. This reduces reliance on measurements of a single efficient firm.

However, accounting for stochastic errors requires specification of a probability function for 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 efficiency scores are usually higher than those estimated by COLS. Figure 2 illustrates (approximately) the estimated cost equation $C_{SFA}=f_2(Y)$ using SFA for the same sample of firms. Another drawback of the method is that even if there are no errors in efficiency measurements, some inefficiency may be wrongly regarded as noise.

3. Previous Benchmarking Studies

A number of studies have addressed different efficiency and related aspects of the electricity industry. However, the focus of many of these is on the economies of scale and density or the relationship between ownership type and efficiency (Kumbhakar and Hjalmarsson, 1998). The scope of many of the studies is limited to a single country while a few have a cross-country focus. This section outlines a selected number of relevant empirical studies of relative efficiency of electricity (mostly distribution) utilities. Table 1 summarises the main features of a larger number of efficiency studies of the electricity sector.

3.1 International Studies

3.1.1 Pardina and Rossi (2000)

In another international benchmarking study Pardina and Rossi (2000) examine the performance development of 36 distribution utilities from 10 Latin American countries between 1994 and 1997. The study applies the SFA method using a loglinear function, with the number of customers as dependent variable. The data used for the study are obtained from reports by Secretaría General de la Comisión de Integración Eléctrica Regional (CIER).

The single-output model specification is based on Neuberg (1977) which rejects the notion that distribution utilities are multi-product firms as their suggested outputs can not be priced or sold separately. Thus, assuming a price equal to average annual revenue per customer, the energy delivered is no longer a separate product. The independent variables used in the study are shown in Table 1.

Table 1: Variables used in Pardina and Rossi (2000)	
Independent variables	**Dependent variable**
Network length	Number of customers
Number of employees	
Service area (sq. km)	
Transformer capacity (MVa)	
Residential sales/total sales (%)	
Number of units (MWh)	
Time trend variable	
Time trend variable*reform variable (dummy)	

In addition to physical data, the initial model also includes a time trend variable in order to account for technical change and a dummy variable to reflect whether the electricity sectors in which the utility operates has been reformed. The study does not find evidence of catching up among the utilities during the period. The findings also suggest better performance amongst the utilities operating in countries that have implemented power sector reforms. The study also finds that utilities operating in countries which have reformed their electricity sectors have increased their capital share, whilst those operating in countries without such reforms have increased their labour share.

3.1.2 IPART (1999)

The IPART study is an international benchmarking sponsored by the New South Wales (NSW) regulator in Australia. It examines the relative technical efficiency of 6 electricity distribution utilities in NSW using a sample of 219 utilities from Australia, England and Wales, New Zealand, and US from 1995 to 1998. The sources of data used for the study include solicited information and regulatory returns submitted by the utilities. The input and output variables of the DEA production function are given in Table 2.

Table 2: Input, output, and environmental variables in IPART study		
Inputs	**Outputs**	**Environmental Variables**
Total O&M expenditure (1997/98 $AUS)	Total energy delivered (GWh)	Customer density (customers/sq. kilometres)
Rout length (km)	Total customers (number)	Network mix (overhead wires/total wires)
Nameplate transformer capacity (MVa)	Peak demand (MW)	Customer mix (residential/total customers)

The efficiency scores are calculated using a CRS model based on the argument that distribution utilities have no control over the scale of their operation. Operating expenses are converted from national currencies into a single monetary unit using Producer Purchasing Power Parities. A second-stage (Tobit) regression analysis is then used in order to adjust the efficiency scores for the effect of environmental variables. The study estimates that the NSW utilities are, after adjustment of efficiency scores for the effect of environmental factors, between 13 and 41% less efficient than the frontier firms.

3.1.3 Lawrence, Houghton, and George (1997)

Benchmarking studies generally target individual sectors in one or more countries. Lawrence, Houghton, and George (1997) report a notable exception in the form of an international multi-industry benchmarking by the Australian Bureau of Industry Economics.

The project was carried out between 1991 and 1996 and examined relative efficiency of eight Australian infrastructure industries, including the electricity sector, using price, service quality, labour productivity, and capital productivity as indicators. The size of the sample of firms for different indicators varies from 19 to 41. On the whole, the Australian electricity sector appears to be closing some aspects of performance gap with the international comparators.

3.1.4 Pollitt (1995)

This study examines the effects of public versus private ownership on performance through an international comparison of electricity generation, transmission, and distribution utilities. The study of the distribution utilities includes a sample of 145 US and UK utilities and uses DEA and an average cost function. The sources of data for the US utilities are the US Energy Information Administration, Electric World *Directory of Electric Utilities*, and the American Public Power Association. Data for the UK utilities are based on company accounts and annual statistical reviews. Input and output variables used with the DEA are shown in Table 3.

Table 3: Inputs and outputs in Pollitt (1995)

Inputs	Outputs
Number of employees	Number of customers
Transformers (MVA)	Residential sales (mKWh)
Circuit (km)	Non-residential sales (mKWh)
	Service area (sq. km)
	Maximum demand (Mw)

The study separates distribution utilities into small, medium, large samples in order to increase the likelihood that utilities are compared with similar firms. Purchasing Power Parity rates are used to covert the operation and maintenance costs and wages into a single monetary unit. The results do not find strong evidence suggesting that ownership affects performance of utilities. The study also suggests that RECs in the UK prior to their privatisation were not less efficient than US distribution utilities.

3.2 Single-Country Studies

3.2.1 DTe (2000)

This study was commissioned by the Dutch electricity regulator (DTe) to examine possible benchmarking models to be used in conjunction with price control of regional network companies for the 2000-2003 period. The study reports the results of 7 DEA-CRS models used in benchmarking of 18 utilities using data from 1999 and 2000. The choice of CRS models is based on the assumption that utilities can control their scale through ownership changes. Table 4 shows the input and output variables used in the models.

Table 4: Models and variables in DTe (2000)

Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Input							
Controllable OPEX and Controllable revenues (OPEX + annualised standardised capital costs)	X	X	X	X	X	X	X
Outputs							
Units distributed	X	X	X	X	X	X	X
No. of customers	X	X	X	X	X	X	
Peak demand (LV)		X	X		X	X	X
Peak demand (HV)			X			X	X
Network length				X	X	X	X
Number of transformers				X	X	X	X
No. of small customers							X
No. of large customers							X

The first set of models use controllable operating expenditures as input with different combinations of output variables. The preferred model in the study is Model 7 which, splits the number of customers according to consumption level and includes transmission specific variables. The efficiency scores of Model 7 range from 0.41 to 1. The efficiency scores of Model 7 place nine utilities on the efficient frontier. The study also calculates the efficiency scores of a set of models using total controllable revenues (operating expenditures plus annualised standardised capital cost) as the input variable with the same outputs shown in Table 4. The efficiency scores of the new Model 7 range from 0.60 to 1 while the number of frontier firms is reduced to six.

The preliminary X-factors over 3 years and before frontier shift assigned to utilities range from -8% to +2%. A negative X-factor implies a reduction in the regulated revenues while a positive X-factor allows for revenue increase. The X-factors are not entirely based on the benchmarking results and take into account factors such as the ability of the firm to improve performance. In addition to the X-factors, the frontier shift is estimated at 2% per year.

3.2.2 Førsund and Kittelsen (1998)

Førsund and Kittelsen (1998) use DEA and Malmquist indices to measure productivity development among Norwegian distribution utilities. The study uses pre-reform data from 1983 and 1989 for 150 utilities. The data source is the official electricity statistics of Statistics Norway. The DEA model used is CRS. Table 5 shows the input and output variables of the model.

Table 5: Inputs and outputs in Førsund and Kittelsen (1998)	
Inputs	**Outputs**
Capital (000 kroner)	Total energy delivered (MWh)
Materials (000 kroner)	Number of customers
Labour (hours)	Customer density (distance index)
Energy loss (MWh)	

Outputs show that average energy delivered from 1983 to 1988 has increased by 40% while the averages of the other two outputs have increased at about half that rate. The results show that the utilities have achieved an annual productivity growth of 2%. However, the calculated productivity gain is mostly attributed to a shift in frontier technology and smaller utilities exhibit lower productivity growth than larger firms.

3.2.3 Burns and Weyman-Jones (1996)

In another study of distribution utilities in England and Wales, Burns and Weyman-Jones (1996) measure cost efficiency of the 12 Regional Electricity Companies (RECs) between 1980/81 and 1992/93. The data used is based on the accounts and regulatory reports of the utilities. The method of analysis is SFA with translog cost function and panel data. The dependent and independent variables of the cost function are shown in Table 6.

Table 6: Variables in Burns and Weyman-Jones (1996)	
Independent variables	**Dependent variable**
Number of customers	Operating costs
Total units sold	
Maximum demand	
Service area	
Customers/service area	
Network size	
Industrial units/total units	
User cost of capital (in manufacturing)	
User cost of labour (in manufacturing)	

The average efficiency scores of the utilities for the 1981-1993 period ranges from 0.88 to 0.98. However, when moving from panel data to cross section data the rank order of most utilities change. The study identifies the number of customers and maximum demand as the main determinants of operating costs of distribution utilities. The results also show that there has been a small but significant improvement in cost-efficiency among the utilities in the years following their privatisation. The study also shows that there is evidence of some economies of scale.

3.2.4 Hougaard (1994)

Hougaard (1994) in a study of 82 Danish distribution utilities in 1991 finds significant potential for efficiency improvement among these. The study uses DEA with CRS and VRS types of four different model specifications by altering the combination of input and output variables (Table 7). The source of data used for the study is official electricity statistics.

Table 7: Models and variables in Hougaard (1994)

Variables	Model 1	Model 2	Model 3	Model 4
Inputs				
Operating expenses	X			
Operating expenses – wage bill			X	X
Capital – book value	X	X	X	X
Employees			X	X
T&D Losses	X	X	X	X
Outputs				
Total energy supplies	X	X	X	X
No. of customers	X	X	X	X
Network length		X		X

The results for CRS models are relatively close to those of the VRS models indicating that there is not a significant correlation between utility size and efficiency. The study also finds evidence that less efficient utilities have higher prices for their household end-users. In addition, the study shows that while the calculated efficiency scores are sensitive to model specifications used, the rank orders across the models is rather robust.

3.2.5 Weyman-Jones (1991)

The study reports an efficiency study of the 12 Area Electricity Boards (AEBs) in England and Wales prior to privatisation in 1986/87. The study uses the DEA method to calculate technical efficiency using data from Electricity Consumers' Council and Electricity Council. The two DEA models used in the study have two inputs and three outputs which only differ with regard to the measure of capital. Table 8 shows the input and output variables used in the models.

Table 8: Input and output variables in Weyman-Jones (1991)

Variables	Model 1	Model 2
Inputs		
Capital (asset value)	X	
Capital (network length)		X
Number of employees	X	X
Outputs		
Units sold to domestic users	X	X
Units sold to commercial users	X	X
Units sold to industrial users	X	X

Model 1 uses the asset values as a capital input while in Model 2 the length of the networks is used as proxy for capital. The study finds a wide divergence among the AEBs. The calculated efficiency scores ranging from 0.82 in Model 1 and 0.79 in Model 2 to 1.

However, the models and data exhibit some limits in revealing the efficiency differences among the AEBs. The calculated scores of Models 1 and 2 indicate that 8 and 5 of the AEBs are on the efficient frontier.

3.3 Lessons from Previous Studies

Table 9 shows that benchmarking studies of distribution utilities have adopted different methods. These studies have also used a wide range of input and output variables, despite the fact that the technologies and characteristics of the utilities are relatively similar. Also, a variable used in one study as an input can be used in others as an output.

This shows that there is not a firm consensus as to how the basic functions of the utilities can be modelled. The variety of the variables used may, to some extent, be explained by the lack of data. However, the inputs and outputs used in these studies can give an indication of which of variables are more widely chosen. Table 10 gives an overview of the frequency with which different input and output variables are used in the studies outlined in Table 9.

As shown in the table, the most frequently used inputs are operating costs, number of employees, transformer capacity, and network length whilst the most widely used outputs are units of energy delivered, number of customers, and the size of service area. Although some studies have used operating and capital costs as input variables, in many cases the physical measures of inputs are used. From a regulatory point of view, it is often preferable to use monetary values of input variables. However, accurate measures of operating and, in particular, capital costs are often difficult to obtain. The problem is compounded in international comparison due to differences in accounting principles and the need to convert different currencies into a single monetary unit.

Table 9: Single and cross-country benchmarking studies[4]

Author	Data	Inputs	Outputs	Method
DTe (2000)	18 Dutch regional network utilities	• OPEX • OPEX+annualised standardised capital costs	• units sold • no. of customers • no. of small customers • no. of large customers • network size • no. of transformers • network density	DEA
Grifell-Tatje and Lovell (2000)	9 Spanish dist. utilities 1995	• LV lines (km) • MV lines (km) • HV lines (km) • transf. cap.–HV to MV/LV • transf. cap.–MV to LV	• no of LV custom. • no. of MV/HV custom. • area • units distributed • service reliability	linear programming
Pardina and Rossi (2000)	36 Latin American distr. Utilities 1994-97	• units sold • no. of employees • service area • transf. Capacity • network size • resid./tot. sales (%)	• no. of customers	SFA
IPART (1999)	219 Australian, New Zealand, UK, US dist. utilities 1995-98	• OPEX • network size • transform. cap.	• electricity delivered • no. of custom. • peak demand (MW)	Malmquist and Tornqvist indexes
Whiteman (1999)	7 Australian and 32 other utilities 1994/95	• no. of full-time employees • hydro power cap. • thermal power cap.	• electricity generated (GWh)	DEA SFA
Filippini (1998)	39 Swiss municipal dist. utilities 1988-91	• Labour • load factor • purchased power	• units delivered • load factor • service area • no. of custom.	cost function
Førsund and Kittelsen (1998)	150 Norwegian distr. utilities 1983-89	• labour • losses • capital • materials	• distance index (density) • no. of custom. • energy supplied	DEA Malmquist
Goto and Tsutsui (1998)	9 Japanese and 14 US utilities 1983 –93	• generation cap. • fuel (kCal) • labour • power purchases	• residential sales (GWh) • non-residential sales (GWh)	DEA
Meibodi (1998)	26 LDCs, 30 Iranian plants and dist utilities (1995)	• no. of employees • labour • network size • transform. cap. • generating cap. • fuel efficiency	• sales – resid. custom. • sales - ind. custom. • no. of resid. custom. • no. of ind. custom.	• SFA • DEA
Zhang and Bartels (1998)	32 Australian power authorities 51 New Zealand power boards, 173 dist. in Sweden	• no of employees • total km of dist. lines • total transform. cap.	• total no. of customers served	•DEA •Monte Carlo simulation
Lawrence, Houghton, and George (1997)	International comparison of 8 Australian industries – incl. power sector 1991-96	-	-	eff. indicators – price, quality., labour, capital
Yunos and Hawdon (1997)	27 LDCs (1987), Malaysia, Thailand, and UK (1975-90)	• installed cap. • labour • losses • generation cap. factor (%)	• gross electricity production (GWh)	DEA cross-section and time-series
Bagdadioglu, Price, and Weyman-Jones (1996)	76 Turkish retail distribution organisations 1991	• labour • transf. cap. • network size • general expenses • network losses	• no. of customers • units supplied • max demand • service area	DEA
Burns and Weyman-Jones (1996)	UK RECs 1980/1 to 1992/93	• max. demand • no of custom. • custom. dispersion • service area • units sold • network • transf. cap. • ind. demand • user CAPEX and labour cost • OPEX	• OPEX	SFA - cross-sectional and panel data

4 Distribution utilities in the above studies may include both the distribution and supply functions.

Table 9 (ctd…): Single and cross-country benchmarking studies

Author	Data	Inputs	Outputs	Method
Claggett, Hollas, and Stansell (1995)	74 municipals and 45 co-operatives of Tennessee Valley Authority 1985-89	• cost per KWh • price per KWh • losses • wages by departments • revenue less OPEX • resid. custom./network length • network size	• electricity distributed (KWh)	• profit function • Cobb-Douglas
Pollitt (1995)	129 US transmission firms 136 US and 9 UK distribution firms 1990	Transm: • labour • length*voltage • transf. cap. Dist: • labour • transf. cap. • network size	Transm.:• electricity input • max. demand • network size Dist.: • no of custom. • sales (resid.) • sales (non-resid.) • service area	• DEA and OLS
Whiteman (1995)	85 electricity systems in LDCs	• labour • thermal power • hydropower • nuclear power • other generation	• electricity output (GWh)	DEA
Berry (1994)	US rural co-operatives and private utilities 1988	• capital • labour • fuel • bulk power purchased	power sold to: • other utilities • indust. custom. • resid. / commercial custom.	translog cost functions
Burns and Weyman-Jones (1994)	UK RECs in England 1973-93	• no of full time employees • network size • transf. capacity • customer density • share of industrial energy)	• no of custom. • units to domestic custom. • units to commercial users • units to ind. users • max. demand	• non-parametric programming • Malmquist index
Claggett (1994)	157 TVA distributors 1982-89 (108 municipals and 49 co-operatives)	• no. of full-time and full-time equivalent employees • book value of the dist. system, • purchased electricity	• energy delivered and sold retail • no. of custom.<50 KWh • no. of custom. >50kWh • dist. load factor • service area	translog cost function
Hougaard (1994)	82 Danish distr. utilities 1991	• no. of employees • wages • OPEX • losses • capital value	• network size • electricity supplied • no. of custom.	DEA
Giles and Wyatt (1993)	60 electricity authorities in New Zealand 1986/87	• labour • network size • transf. cap. • electricity purchased	• units sold	translog cost model ML estimation
Hjalmarsson and Veiderplass (1992)	289 Swedish distribution utilities 1970-86	• labour (hrs) • LV lines • HV lines • transf. cap.	• LV units delivered • HV units delivered • no. of LV customers • no. of HV customers	DEA
Klein, Schmidt, and Yaiswarng (1992)	US coal-burning plants 1975-87	• fuel (BTUs) • labour • installed cap.	• annual net generation • net one-hour peak demand	• DEA • Malmquist Index
Miliotis (1992)	45 dist. Districts of the Greek Public Power Corporation (PPC)	• network size • transf. cap. • general expenses • admin. labour (hrs) • techn. labour (hrs)	• no. of custom. • energy supplied • network size • transf. cap. • dummies for urban centres • service area	DEA
Weyman-Jones (1991)	12 UK Area Boards 1986/87	• no. of employees • capital value • network size	retail sales to: • domestic • commercial • ind. customers	DEA
Twada and Katayama (1990)	9 Japanese power companies (generation) 1965-82	• capital • labour • fuel consumption	• annual output from steam power generation by fossil fuelled generators (kW)	production function
Charnes et al. (1989)	75 Texas electric co-operatives	• OPEX • maintenance • custom. account cost • admin. costs • network/custom. • wages • outage • % system unload • losses • plant size • inventories	• net margin • units sold • revenue from sale	• DEA • regression and ratios

Table 10: Frequency of the use of main variables used in 20 benchmarking studies of distribution utilities in Table 1

Input	Output
• units sold (2)	• units sold (12) • residential sale (6) • non-residential sale (6)
• no. of customers	• no. of customers (11) • no. resid. cust. (5) • no. non-resid. cust. (5)
• network size (11) • LV lines (2) • MV lines • HV lines (2)	• network size (4)
• transformer capacity (11) • MV cap. • HV cap.	• transformer capacity • no. of transformers
• service area (2)	• service area (6)
• maximum demand	• maximum demand (4)
• purchased power (2)	• power sold to other utilities
• losses (4)	
• labour/wages (15) • admin. labour • technical labour	
Cost measures: • OPEX (7) • OPEX+annualised standard capital costs • admin. and account costs (2) • maintenance costs • capital (5) • CAPEX user cost+labour costs • materials	
Miscellaneous: • customer dispersion (2) • ind. demand • share of industrial energy • network size/customers • % system unload • residential/total sales • outage • no. residential customers/network size • inventories • line length*voltage	
	Miscellaneous: • service reliability • load factor • net margin • revenues • distance index • network density • categorical variable for urban areas

4. International Benchmarking: Benefits and Problems

Electricity markets are increasingly international through interconnections and take-overs. The number of actors operating in different regulatory jurisdictions is increasing. It is also possible that utilities may use efficiency studies when taking strategic decisions such as those with regard to mergers and acquisitions. In keeping with these market developments, from a regulatory point of view it is advantageous to be able to assess the efficiency of the domestic utilities in an international context. The main advantages of international efficiency comparisons are:

- the benchmarking methods discussed above require relatively large samples and the number of utilities in some countries is not sufficient for national studies. Regulators in these countries can use international benchmarking to increase the sample size.

- in some countries, following merger activities, the number of comparators and consequently potential sources of information to regulators is likely to be shrinking.

- addition of international comparators to a sample can improve the validity of the analysis as firms are more likely to be benchmarked against comparable firms.

- international comparisons enable the regulators to measure the relative efficiency of the utilities relative to international best practice. An important advantage of international best practice frontiers is that they are likely to be rather stable over time and only reflect general efficiency and technological progress.

Whilst international benchmarking has a number of advantages, in order to increase the reliability and accuracy of the relative efficiencies, there are some issues that need to be addressed. We discuss some of these issues in the following subsections.

4.1 Environmental Variables

An important concern associated with the use of international comparisons is the extent to which possible differences across countries may reduce the validity of the outcome. Factors that are beyond the control of the utility are generally referred to as environmental variables. Underlying electricity distribution and transmission technologies are largely similar across the countries. However, geographical factors such as topological and climatic conditions, as well as demographic characteristics of service areas, can vary considerably.

For example, while the low winter temperatures in Norway can result in higher system maintenance costs, large service areas and low customer density in countries such as Italy, Portugal, and Spain may provide some economies of scale. One approach to account for the effect of environmental variables is to use the results of regression analysis to adjust the estimated efficiency scores.

In addition, the regulatory framework in which the utilities operate can affect aspects of the utilities' performance such as decisions on operating and capital costs. However, while the regulatory environment is beyond the utility’s control, it is not exogenous to the regulators. For example, regulators can decide whether to use price or revenue cap models or adopt specific incentives to improve the quality of supply. On the other hand, given sufficient data, international benchmarking can be used to determine the effect of different regulatory models on performance of utilities.

4.2 Comparability of Costs

The main objective of benchmarking for the purpose of regulation is to assess the cost efficiency of regulated utilities. It is therefore important that, to the extent possible, the operating and capital cost inputs used in the benchmarking exercise are represented in monetary terms rather than in physical inputs. However, the use of monetary values of costs in international benchmarking poses several issues.

4.2.1 Quality of Data

The reliability and quality of data can vary considerably across countries. Comparative regulation models that are based on setting individual X-factors and benchmarking require more accurate and reliable data than under traditional models. As a result of power sector reforms, regulators are increasingly aware of data quality and adopt standardised reporting formats and audit requirements.

4.2.2 Accounting principles

In addition to data quality, accounting rules vary across (and indeed within) the countries, e.g., the distinction between operating and capital costs and the treatment of asset depreciation. And in studies where separate analysis of operating and capital expenditures is desirable, these differences in accounting rules become more important. Therefore, in order to increase the accuracy of the cost data, the main cost classes may need to refer to a uniform definition and be adjusted accordingly. In addition, operating costs may include social security contributions, taxes, or other components beyond the utilities control and, therefore, should be excluded from the analysis.

4.2.3 Conversion of monetary units

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

As currency exchange rates often differ from PPPs, the choice of conversion method affects the relative cost levels. The extent of this effect, however, depends on the countries comprising the sample. The significance of the monetary conversion factor may vary depending on the type of cost inputs. For example, with regards to operating costs, PPPs are the appropriate measure as these costs are largely affected by domestic price levels and are incurred in local currencies.

On the other hand, capital costs generally include large amounts of material and equipment purchase which are usually traded in the international markets and settled in foreign currencies. A plausible way to examine the robustness of the results is through sensitivity analysis of the conversion factors.

5. Data

5.1 General

One aim of this study has been to evaluate a range of variables in order to identify the preferred model specifications. An initial examination of the collected data set showed a need for some adjustments. In relative efficiency analysis it is important to maintain a reasonable degree of comparability among the units in the sample.

The data on pure transmission utilities confirmed the well-known fact that these generally exhibit considerably lower numbers of customers and lower losses than the distribution utilities. The presence of pure transmission utilities in the sample could distort the results for the distribution utilities, which comprise the main body of firms and information studied here. These were, therefore, separated from distribution and transmission/distribution utilities. As the number of pure transmission utilities was found to be too low for a separate type of analysis, these are not included in the present study. Analysis of relative efficiency of transmission utilities need to include data from the US and other countries.

Also, review of the data showed that for some variables complete information was not available. For the purpose of efficiency comparison it is necessary to have reliable data for all the variables used in model specification and the decision-making units included in the analysis. This presented us with a trade-off between the number of countries and the variables that could be included in the study. It was seen as important to include all the participating countries in the study. We, therefore, selected variables where data from all six countries was available, then excluded individual utilities for which the required data was not available.[5]

Table 11 shows the number of utilities included in the study from each country. Table 12 shows the input and output variables that were retained for evaluation. Summary statistics of the variables are shown in Table 13. Definitions of the input and output variables are given in Appendix A.

Table 11: Number of utilities

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

Table 12: Input and output variables retained for the study

Input Variables	**Output Variables**
• Controllable operating costs • Capital costs	• Energy delivered (GWh) • No. of customers - Residential - Non-residential • Length of network (km) - overhead cables - underground cables
	Environmental Variables
	• Transmission/distribution losses (GWh) • No. of transformers

[5] This procedure excluded two firms.

Table 13: Statistics over variables in the preferred models

Variables	Min	Max	Mean
Operating expenditures (mill. $PPP)	1.1	3430.6	160.07
Capital costs (mill.)	0.21	1785.75	83.99
Total costs (mill.)	1.72	5216.38	244.06
Units 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

5.2 Cost data

This study uses the monetary values of inputs in specifying cost-based frontier analysis models. In this respect, this approach is out of line with some of the previous studies where physical units are used as inputs. This is particularly advantageous from a regulatory point of view as monetary values can reflect all controllable operating and capital inputs in a standard unit to measure the cost efficiency of utilities.

The task of standardisation of cost data was carried out by the participating regulators based on the guidelines outlined in Appendix 1. This section adjusts the cost data to a common reference year and subsequent conversion into a single monetary unit.

The cost data collected for this study refers to different time periods. Table 14 shows the years for which data from participating countries was available. Therefore, in order to establish a common time reference data was adjusted to mid-1999 levels using the OECD statistics on quarterly Consumer Price Index (CPI) changes OECD (1999). This adjustment resulted only in minor changes to the reported costs. Table 14 shows the percentage change resulting from the adjustment for the reference year for each country.

Table 14: Reference years for the data set and CPI change to mid-1999
Source: (OECD 1999)

Country	Data Reference Year	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%

The capital expenditures data reflect new investments in the reference year and exclude stock of existing capital and depreciation. The main shortcoming of using annual capital expenditures is that these may not reflect the value of capital stocks. The problem can be more profound when the scope of the study is limited to one year due to the cyclical nature of investments in distribution and transmission utilities.

An alternative approach would have been 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 the difficulties involved in accounting for factors such as inflation, assets depreciation, and currency fluctuations for several countries over many years would not increase the accuracy of measurement.

The costs were then converted into a single monetary unit using the PPPs of the currencies against the US dollar. The choice of the reference currency is an arbitrary one and any currency can be used without affecting the relative cost differences among the utilities. Table 15 shows the US dollar based PPPs for the relevant currencies in 1999.

Table 15: PPPs and Euro conversion rates (1999)
Source: EUROSTAT

Country	Purchasing Power Parity (1999) $PPP1=	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

5.3 Technical data

As noted in the previous section, cost definitions may be harmonised and monetary values can be converted into a single unit for currency differences. Technical standards and functional divisions of electricity transmission and distribution networks also vary across the countries. This can affect the capital stock levels and operating expenditures of utilities and so influence the results of international efficiency comparisons.

In particular, voltage levels of cut-off points between the transmission and distribution functions of networks differ across countries and, it is difficult to determine their direction and their cost implications. However, given sufficient data, it is possible to correct 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).

Table 16 shows the differences in the voltage levels of the transmission and distribution networks of the countries studied here. As shown in the table, the maximum voltage levels range from 22 kV or less for the Norwegian distribution utilities to 132 kV or less for the RECs in the Great Britain.

Table 16: 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 D: 0-22 kV (regional networks 30-132 kV)	T: 45, 66, 132, 220, 300, 420 kV D: 0.22, 0.4, 11, 22, (132) kV
Portugal	T: >110 kV D: ≤110 kV	T: VHV>110 kV D: 45<HV≤110 kV 1 kV<MV≤45 kV LV≤1 kV
Netherlands	T: 220/380 D: 110/150 kV and <50 kV	T: EHV 220/380 kV D: HV 110/150 kV (9 companies) IV 25-50 kV MV 10-20 kV LV<10 kV
Great Britain	T: E&W>275 kV Scotland>132 kV D: E&W ≤132 kV Scotland≤132 kV	D: EHV≥22 kV (≥66 kV at substations) 22 kV>HV>1000 V LV<1000 V
Italy	T: ≥220 kV (EHV) and portions of 120-220 kV (HV) grid D: <220 kV	D: portions of 120-220 kV grid, 10, 15, 20 kV (MV), and 380 V (LV)
Spain	T: ≥220 kV D: <220 kV	T: EHV 400 kV, HV 220 kV D: 36 kV≤HV<220 kV 1 kV≤MV<36 kV LV<1 kV

6. Preferred models

This study uses the more commonly used frontier-oriented methods DEA, COLS, and SFA for benchmarking the utilities. The input and output variables can be used in various combinations and model specifications. At the same time, for the purpose of comparability of different methods and models, it is desirable that, the models include similar variables. It was decided to report on four DEA-CRS models and two DEA-VRS models.

In addition, the loglinear and translog specification types of the initial model are calculated using both COLS and SFA-DF methods. It should be noted that a loglinear model specification assumes constant elasticity of substitution amongst the output variables. The translog specification is a generalised form of loglinear and is therefore more flexible and allows for variations in elasticity of substitution among the output factors. 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 Perleman (1996)).

The data available for this study provide the framework within which the main features of the distribution utilities' operation can be defined for performance analysis. In DEA the number of frontier firms tends to increase as variables are added 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 differences in their performance of the firms.

The initial model (DEA-1) comprises total units of electricity delivered, number of customers and network length as the output variables. These variables are commonly regarded as important cost drivers and are used in efficiency studies of electricity distribution and transmission utilities. The same variable are also used by OFGEM to derive a composite measure of output (number of customers 50%, units distributed 25%, and network length 25%) in COLS analysis of the operating costs of the distribution utilities in England and Wales (see OFGEM, 1999).

The 'units of electricity delivered' is an important indicator of the scale of operation of the firms. The 'number of customers' reflects the spread of the volume among the connection points as an important aspect of the scope of the activity. The number of connection points is generally regarded as a major cost driver. This variable also captures the important difference between regional transmission and distribution utilities, both of which are included in the sample. The 'size of the network' reflects the geographical dispersion of output that is another aspect of the scope of operation. Inclusion of this variable increases the possibility that firms with similar service areas, in terms of size and type (such as urban and rural), are compared with each other so making the comparison more valid.

The total costs (operating and capital expenditures) of the utilities were used as the input variable. Subsequent model runs showed that the efficiency scores obtained after 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 obtained when the output variable network length was divided into overhead and underground cables. We then split the total costs variable into separate operating and capital costs and the efficiency scores' correlation with the initial model remained high. We therefore retain the initial model as one of the preferred models.

In DEA-2 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 (e.g. IPART 1999). The model, however, 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-2v model is a VRS version of DEA-2 model in which all variables are treated as discretionary.

In the remaining models we retain the same output and input variables as in the initial DEA-1 model. The model specification for the loglinear and translog models used with COLS and SFA methods are shown in Equations 1 and 2 respectively.

Loglinear model specification:

$$LogTOTEX = \beta_0 + \beta_U \, LogUNIT + \beta_C \, LogCUST + \beta_N \, LogNETW - \mu \quad (1)$$

Translog model specification:

$$
\begin{aligned}
&LogTOTEX = \\
&\beta_0 + \beta_U \, LogUNIT + \beta_C \, LogCUST + \beta_N \, LogNETW + \\
&\beta_{UU} (LogUNIT)^2 + \beta_{CC} (LogCUST)^2 + \beta_{NN} (LogNETW)^2 + \\
&\beta_{UC} \, LogUNIT * LogCUST + \beta_{UN} \, LogUNIT * LogNETW + \\
&\beta_{CN} \, LogCUST * LogNETW - \mu
\end{aligned}
\qquad (2)
$$

where:

TOTEX *total expenditures*

UNIT *total number of units of electricity delivered*

CUST *total number of customers*

NETW *network length*

μ half-normal non-negative random variable associated with technical inefficiency (in SFA a normal random error term ν is also added to the models).

An overview of the preferred models for this study, the methods used, and the input and output variables are given in Table 17.

Table 17: 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 (Eur)	
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

7. Results

This section presents the main results of the selected models for this study outlined in Table 17. The results from the base model DEA-1 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.

7.1 DEA-1 model

As noted previously, DEA-1 model is input-oriented which means that it calculates the required cost savings for a given level of output. The model is also constant return to scales, which assumes that all the utilities are operating at the optimum scale. The benchmarking summary results for the model are shown in Table 18.

The utilities from Italy, Netherlands, Norway, Portugal, Spain, and UK are denoted with I, D, N, P, S, and U respectively. The distribution/transmission utilities are denoted with TD. The third columns in the table show calculated efficiency scores. The fourth columns show the peer firms against which the less efficient utilities have been benchmarked and lambda values for these which is a measure of the intensity of the peer are shown in parentheses. For example, utility U1 has an efficiency score of 60.5% indicating it is 39.5% less efficient than the frontier. The frontier firms which are peers for the utility are N18(TD) and D18. The intensity of the influence of the peer firms on utility U1’s score is 4.08 and 30.9 respectively. For the efficient firms on the frontier, this column indicates the number of times that the frontier firm has been a peer for inefficient firms.

As shown in the table, the three firms N11, N18(TD), and D18 have efficiency scores of 100% and appear on the frontier. Two of the firms on the frontier are Norwegian utilities and the third firm is a Dutch utility. The Norwegian utilities with an asset base of 40% or higher in regional and national transmission activities are denoted TD. The Norwegian utility N18(TD) on the frontier is almost entirely a regional distribution utility. This might have reduced comparability of this utility with a large number of the firms in the sample. However, a closer examination of the results in Table 18 shows that the influence of this utility as a peer in benchmarking of other utilities has been rather less than the other two firms on the frontier.

The variation in efficiency scores is considerable and ranges from 26% to 100%. Table 19 shows the minimum, maximum, and mean of the efficiency scores for the sample as well as the individual countries. The mean of the efficiency score for all the firms in the sample is 61%.

The Dutch utilities include the highest (100%) and lowest (26%) scores. However, this is predominantly due to the observed inefficiency of utility D4. When this firm's score is disregarded the range of the scores for the Dutch utilities closely matches those of Norwegian utilities.

For the UK utilities, the range of the scores is smaller and span from 34.6% to 65.8%. The score range is even smaller for the Spanish utilities, that is from 44.9% to 65.9% and the Portuguese (53.4%) and Italian (49.5%) utilities also lie within this range. Despite the variations in the ranges, the differences in the mean values of the efficiency scores for the countries are smaller.

Table 18: Efficiency scores for DEA-1 model

	Utility	Score	Peers (lambda)		Utility	Score	Peers (lambda)
1	U1	60.5%	25 (4.076) 57 (30.901)	40	D1(TD)	62.7%	25 (5.465) 57 (23.577)
2	U2	50.4%	25 (3.476) 32 (0.500) 57 (21.500)	41	D2	57.0%	25 (0.067) 32 (0.007) 57 (1.144)
3	U3	43.2%	32 (1.397) 57 (20.119)	42	D3(TD)	65.0%	25 (0.648) 32 (0.966) 57 (1.567)
4	U4	50.4%	25 (2.746) 32 (0.384) 57 (12.569)	43	D4	26.0%	25 (0.036) 32 (0.108) 57 (0.453)
5	U5	58.1%	25 (3.034) 32 (0.627) 57 (21.227)	44	D5	53.5%	25 (0.036) 32 (0.023) 57 (0.841)
6	U6	49.5%	25 (2.411) 32 (0.012) 57 (13.355)	45	D6(TD)	50.2%	25 (2.381) 32 (1.220)
7	U7	34.6%	25 (2.460) 32 (0.323) 57 (21.045)	46	D7(TD)	67.5%	25 (2.267) 32 (0.602) 57 (8.226)
8	U8	65.8%	25 (0.692) 32 (0.398) 57 (21.031)	47	D8(TD)	88.6%	25 (5.336) 57 (6.165)
9	U9	58.5%	25 (3.125) 32 (0.631) 57 (25.211)	48	D9	54.7%	25 (0.017) 57 (0.449)
10	U10	35.1%	25 (2.057) 32 (0.229) 57 (8.855)	49	D10	95.7%	25 (0.036) 57 (0.274)
11	U11	54.7%	25 (3.322) 57 (11.664)	50	D11	65.8%	25 (0.137) 57 (0.419)
12	U12	50.8%	25 (2.143) 32 (0.590) 57 (19.904)	51	D12(TD)	60.9%	25 (0.210) 32 (0.389) 57 (10.571)
13	U13	51.7%	25 (4.340) 57 (16.350)	52	D13(TD)	49.3%	25 (0.024) 32 (0.073) 57 (4.949)
14	U14	42.2%	25 (4.605) 57 (4.146)	53	D14	67.5%	57 (0.385)
15	N1(TD)	61.4%	25 (0.813) 32 (1.381) 57 (2.650)	54	D15	42.6%	57 (0.117)
16	N2(TD)	51.8%	25 (1.208) 32 (0.935) 57 (0.664)	55	D16	94.8%	25 (0.030) 57 (0.188)
17	N3	67.5%	25 (0.864) 32 (0.039) 57 (0.440)	56	D17	49.3%	32 (0.018) 57 (0.460)
18	N4	59.2%	25 (0.594) 32 (0.207) 57 (0.528)	57	D18	**100%**	52
19	N5	72.5%	25 (1.638)	58	S1(TD)	49.6%	25 (16.212) 57 (88.487)
20	N6	59.9%	25 (0.339) 32 (0.316) 57 (0.552)	59	S2(TD)	65.9%	25 (1.023) 32 (0.274) 57 (4.576)
21	N7	53.4%	25 (1.112) 32 (0.137) 57 (0.023)	60	S3(TD)	44.9%	25 (7.651) 57 (79.550)
22	N8	66.1%	25 (0.923) 32 (0.184) 57 (0.092)	61	S4(TD)	51.9%	25 (6.464) 57 (27.343)
23	N9	65.6%	25 (0.359) 32 (0.266) 57 (0.376)	62	P1	53.4%	25 (11.738) 57 (47.476)
24	N10	60.5%	25 (0.517) 32 (1.142) 57 (0.266)	63	T1	49.5%	25 (71.020) 57 (255.683)
25	N11	**100%**	56				
26	N12(TD)	59.6%	25 (0.403) 32 (0.915) 57 (0.314)				
27	N13	81.1%	25 (1.132)				
28	N14	46.1%	25 (0.875)				
29	N15	69.3%	25 (0.698) 57 (0.003)				
30	N16(TD)	49.3%	25 (0.006) 32 (1.433)				
31	N17(TD)	80.7%	25 (0.004) 32 (1.265)				
32	N18(TD)	**100%**	38				
33	N19(TD)	50.6%	25 (0.003) 32 (1.030)				
34	N20(TD)	88.1%	25 (0.037) 32 (0.693)				
35	N21	89.8%	25 (0.340) 32 (0.004) 57 (0.109)				
36	N22(TD)	71.7%	25 (0.743) 57 (0.067)				
37	N23(TD)	54.5%	25 (0.109) 32 (0.331) 57 (0.221)				
38	N24	85.6%	25 (0.296) 32 (0.046) 57 (0.196)				
39	N25	48.2%	25 (0.175) 32 (0.126) 57 (0.212)				

Table 19: Summary statistics for efficiency scores – DEA1 model

	Min	Max	Mean
Sample	26.0%	100.0%	61.0%
Italy	49.5%	49.5%	49.5%
Norway	46.1%	100.0%	67.7%
UK	34.6%	65.8%	50.4%
Portugal	53.4%	53.4%	53.4%
Spain	44.9%	65.9%	53.1%
Netherlands	26.0%	100.0%	63.9%

7.2 Alternative DEA models

As discussed in Section 6, in addition to the initial DEA-1 model, a few selected DEA models were also calculated in order to examine the effect of changes in variables, model specifications and methods on the resulting efficiency scores and rankings (see Table 17). The resulting efficiency scores from the models are summarised in Table 20, the summary statistics of the scores are shown in Table 21, the simple and rank correlation of the efficiency scores are then given in Tables 22 and 23 respectively.

As shown in Table 20, in the variable return to scale model DEA1v the number of utilities on the frontier increases, from 3 firms in DEA1, to 15 firms. Also, the mean efficiency score increases from 61% in DEA1 to 79% in DEA1v. The validity of the results of VRS models depends on the extent to which the cost efficiency of distribution utilities can be thought to be affected by the scale of operation, and whether different size categories are sufficiently represented in the sample. The first issue can not be settled with certainty. However, it is more plausible that lack of comparable firms may put some inefficient firms on the frontier and therefore produce misleading results.

One concern with having a large number of frontier firms is loss of information as their relative inefficiencies of these cannot be revealed. In addition, the efficiency scores of less efficient firms also tend to increase. Therefore it is important that VRS models include a sufficient number of comparators in all size categories.

An examination of the DEA-1v scores reveals that it moves some large and fairly inefficient firms (in DEA-1 model) to the frontier. This magnitude of change in the scores is hard to justify. Also, as pointed out previously, utilities sizes in our sample cover a wide range. Within this background we have reason to question the validity of the regulatory usefulness of the VRS model for the largest firms with the given data.

In DEA-2, the use of controllable operating expenditures as the input variable and inclusion of non-discretionary variables (network length and T&D losses) has a mixed effect on the efficiency scores. The scores for some firms show considerable increase while the scores for others decrease significantly. The efficient frontier is dominated by 6 firms, two of which (N18 and D18) were also on the frontier in DEA-1 model. The mean and minimum efficiency scores are 54% and 20% respectively, both lower than in DEA-1 model (Table 21). It should be noted that the efficiency scores in DEA-2 refer to a potential for savings in the operating expenditures as opposed to total expenditures in DEA-1. In addition, the efficiency scores show very high correlation with the scores from DEA-1.

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

As mentioned previously, an important issue in international benchmarking is the choice of method for converting currencies into a single monetary unit. The DEA1-EUR model is intended to illustrate the impact of currency conversion method (PPPs vs. Euro exchange rates) on the benchmarking. As shown in Table 20, the impact of using the Euro conversion rates on the efficiency scores is rather small. The efficiency scores and their rank orders in DEA-1 and DEA1-EUR show very high correlations. The composition of the efficient frontier of the DEA-1EUR model is rather stable and the three efficient firms in the DEA-1 model remain on the frontier. Also, the minimum and mean scores for the sample amount to 27% and 63% respectively.

The DEA1-OPEX 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 efficiency scores as utilities with relatively higher capital expenditures may show higher scores than in this model. As shown in Table 20, in relation to the DEA-1 model, the efficiency scores of some utilities in DEA1-OPEX increase and the scores of others decrease. Minimum and mean efficiency scores in DEA1-OPEX are higher than in the DEA-1 model with 28% and 65% respectively. At the same time, the simple and rank correlations of the scores between the DEA-1 and DEA1-OPEX models are not particularly high and amount to 67% and 66% respectively (Table 22).

7.3 COLS Models

Models COLS1 (LL) and COLS1 (TL) models use loglinear and translog functional forms of the input and output variables of the initial DEA model as specified in Equations (1) and (2). As mentioned 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 22 shows the estimated parameters and t-values for the four regression-based models. However, 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.

As shown in Table 20, as expected, the calculated efficiency scores of the COLS models are higher than DEA1. However, the extent of increase in the scores is rather substantial. The mean efficiency scores of COLS (LL) and COLS (TL) models are 79 and 81% respectively relative to 61% in DEA1. The higher scores in the COLS (TL) model can be attributed to the flexibility of translog functional forms.

7.4 SFA Models

Similarly, the SFA (LL) and SFA (TL) 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 (LL) and SFA (TL) models are 81 and 86% respectively.

Tables 23 and 24 shows 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. The efficiency scores for the DEA1 model show, despite some significant changes in the scores of some firms, a relatively high correlation (0.82) with those of the DEA2 model. The DEA1 model's efficiency scores also show a high correlation (0.84) with those of COLS1 (TL). This is despite the weak significance of the estimated parameters with translog specification.

The correlation of the DEA1 scores with other regression-based models is relatively weak. However, we find stronger correlation among the scores of these models. For example, the COLS1 (LL) and SFA1 (LL) have a correlation factor of 0.96 which indicates a 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 COLS1 (TL) and SFA1 (TL) 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 20: Efficiency scores for alternative models

	DEA1	DEA1v	DEA2	DEA2v	COLS1 (LL)	COLS1 (TL)	SFA1 (LL)	SFA1 (TL)	DEA1 EUR	DEA1 OPEX
U1	60.5%	100%	70.46%	100%	81.3%	85.6%	86.6%	94.8%	57.24%	70.4%
U2	50.4%	85.2%	49.34%	94.13%	77.2%	79.9%	81.8%	88.3%	48.34%	51.2%
U3	43.2%	76.8%	79.07%	100%	71.8%	73.8%	73.6%	86.9%	39.55%	50.1%
U4	50.4%	77.5%	48.30%	75.93%	76.9%	78.9%	81.2%	85.0%	48.90%	53.5%
U5	58.1%	98.3%	56.19%	100%	82.3%	84.8%	86.9%	94.1%	55.48%	56.9%
U6	49.5%	70.3%	40.88%	85.66%	74.7%	77.4%	78.9%	82.8%	47.58%	43.4%
U7	34.6%	55.4%	51.84%	97.80%	64.8%	67.0%	68.7%	74.1%	32.74%	50.7%
U8	65.8%	100%	87.63%	100%	84.9%	87.5%	88.6%	97.9%	60.70%	76.5%
U9	58.5%	100%	87.35%	100%	82.5%	85.2%	87.2%	95.4%	55.55%	86.2%
U10	35.1%	48.4%	38.08%	82.74%	65.0%	66.5%	68.6%	70.6%	34.13%	42.8%
U11	54.7%	72.6%	59.08%	84.39%	75.5%	79.9%	80.4%	83.1%	53.27%	71.4%
U12	50.8%	83.0%	66.05%	96.75%	77.2%	79.4%	81.3%	88.1%	48.04%	63.8%
U13	51.7%	76.4%	51.28%	77.80%	75.0%	79.3%	80.1%	84.0%	50.30%	60.3%
U14	42.2%	49.2%	34.41%	52.20%	61.9%	70.6%	67.5%	68.1%	43.92%	68.7%
N1	61.4%	100%	42.17%	79.62%	94.9%	89.4%	96.0%	99.2%	54.72%	48.9%
N2	51.8%	71.0%	43.70%	63.47%	86.8%	79.3%	89.7%	86.0%	49.73%	75.0%
N3	67.5%	70.7%	30.06%	37.38%	83.7%	82.4%	87.6%	85.4%	64.53%	61.3%
N4	59.2%	62.3%	41.22%	45.14%	84.4%	79.0%	86.9%	83.8%	55.54%	69.2%
N5	72.5%	88.4%	23.85%	29.40%	78.9%	83.1%	84.7%	84.5%	72.45%	80.6%
N6	59.9%	62.4%	41.07%	46.20%	89.4%	81.4%	90.3%	88.1%	54.92%	56.5%
N7	53.4%	60.0%	28.68%	31.39%	77.1%	74.0%	81.3%	78.1%	53.29%	75.1%
N8	66.1%	69.0%	36.22%	38.89%	86.4%	81.1%	90.4%	86.3%	65.42%	86.8%
N9	65.6%	65.6%	49.48%	54.83%	92.3%	83.1%	93.4%	90.1%	61.38%	76.0%
N10	60.5%	83.4%	56.60%	100%	100%	86.4%	97.9%	97.0%	58.72%	82.8%
N11	**100%**	100%	35.09%	38.70%	96.3%	95.4%	98.3%	99.9%	100%	100%
N12	59.6%	68.3%	50.05%	58.34%	98.9%	85.5%	97.3%	95.9%	57.18%	70.3%
N13	81.1%	86.4%	21.48%	25.65%	76.8%	81.9%	82.6%	85.0%	81.09%	90.0%
N14	46.1%	46.6%	24.41%	26.91%	67.0%	66.1%	71.2%	70.0%	46.05%	76.4%
N15	69.3%	71.5%	28.58%	35.57%	76.0%	78.3%	80.6%	82.0%	69.27%	90.1%
N16	49.3%	100%	48.10%	100%	67.0%	70.1%	65.2%	73.3%	49.32%	48.2%
N17	80.7%	100%	83.77%	100%	72.8%	89.1%	71.6%	91.6%	80.71%	83.9%
N18	**100%**	100%	100%	100%	79.5%	92.1%	77.6%	97.8%	100%	93.9%
N19	50.6%	52.4%	100%	100%	56.9%	71.4%	56.3%	75.2%	50.55%	100%
N20	88.1%	94.8%	100%	100%	98.9%	81.5%	95.0%	94.7%	88.09%	75.2%
N21	89.8%	92.4%	42.47%	44.81%	91.2%	88.0%	94.2%	94.4%	87.06%	96.2%
N22	71.7%	71.9%	24.88%	27.42%	80.2%	80.9%	84.7%	84.5%	70.88%	69.5%
N23	54.5%	55.1%	44.54%	51.94%	92.9%	81.1%	90.9%	90.5%	50.49%	53.9%
N24	85.6%	86.6%	43.87%	45.87%	93.4%	88.0%	95.3%	94.3%	81.04%	81.8%
N25	48.2%	48.9%	31.77%	39.38%	78.8%	70.8%	79.3%	77.2%	44.75%	47.4%
D1(TD)	62.7%	100%	46.13%	100%	82.0%	87.1%	87.7%	93.8%	66.72%	52.3%
D2	57.0%	61.0%	100%	100%	73.8%	77.8%	74.3%	78.5%	58.31%	60.6%
D3(TD)	65.0%	83.5%	53.15%	100%	96.9%	89.8%	97.0%	98.7%	73.18%	61.8%
D4	26.0%	26.3%	41.71%	62.02%	58.8%	58.0%	58.0%	61.0%	27.31%	39.1%
D5	53.5%	53.7%	95.97%	98.86%	72.4%	76.3%	72.4%	77.1%	54.62%	85.0%
D6(TD)	50.2%	95.4%	20.08%	98.13%	75.9%	74.8%	81.1%	78.6%	62.57%	58.8%
D7(TD)	67.5%	100%	50.95%	95.80%	88.7%	89.6%	93.0%	96.1%	73.20%	59.6%
D8(TD)	88.6%	100%	46.75%	96.82%	89.7%	99.2%	96.1%	98.2%	100%	83.1%
D9	54.7%	56.2%	61.78%	85.01%	66.3%	74.9%	66.2%	73.7%	55.46%	54.2%
D10	95.7%	99.1%	100%	100%	87.5%	95.2%	86.9%	96.2%	99.57%	100%
D11	65.8%	66.5%	66.57%	75.08%	70.9%	78.3%	72.7%	78.0%	70.87%	86.3%

D12(TD)	60.9%	92.3%	57.07%	97.26%	81.8%	83.8%	84.3%	91.4%	61.70%	49.0%
D13(TD)	49.3%	72.8%	55.70%	100%	71.6%	74.6%	73.1%	78.1%	49.51%	46.8%
D14	67.5%	74.2%	100%	100%	67.7%	92.1%	63.6%	86.2%	67.54%	42.8%
D15	42.6%	91.6%	52.86%	100%	53.8%	69.0%	52.3%	66.9%	42.58%	35.2%
D16	94.8%	100%	75.16%	100%	87.7%	94.8%	86.7%	97.0%	99.48%	77.9%
D17	49.3%	52.4%	83.26%	91.80%	67.5%	75.8%	65.5%	75.6%	49.56%	43.0%
D18	**100%**	100%	100%	100%	92.2%	100%	91.6%	99.9%	100%	84.7%
S1(TD)	49.6%	100%	29.63%	98.52%	70.5%	79.5%	77.4%	88.0%	61.94%	32.0%
S2(TD)	65.9%	88.5%	41.25%	65.44%	85.8%	86.2%	88.9%	90.8%	83.89%	45.7%
S3(TD)	44.9%	96.1%	28.96%	100%	68.1%	74.6%	73.9%	84.3%	54.93%	27.7%
S4(TD)	51.9%	86.1%	33.17%	85.55%	69.6%	77.7%	75.5%	80.3%	65.39%	33.2%
P1	53.4%	97.9%	32.30%	88.14%	66.3%	78.7%	73.0%	79.3%	83.23%	38.2%
T1	49.5%	100%	35.01%	100%	71.3%	85.8%	80.2%	98.9%	57.06%	43.0%

Table 21: Summary statistics of efficiency scores

	DEA1	**DEA1v**	**DEA2**	**DEA2v**	**COLS1 (LL)**	**COLS1 (TL)**	**SFA1 (LL)**	**SFA1 (TL)**	**DEA1 EUR**	**DEA1 OPEX**
Mean score	0.613	0.793	0.54	0.78	0.789	0.811	0.813	0.861	0.63	0.65
Std. Error	0.021	0.024	0.03	0.03	0.014	0.011	0.014	0.012	0.02	0.02
Min. score	0.260	0.263	0.20	0.26	0.538	0.580	0.523	0.610	0.27	0.28

Table 22: Estimated variable parameters and statistics for the COLS and SFA models (t statistics in parenthesis)

	COLS1 (LL)	**COLS1 (TL)**	**SFA1 (LL)**	**SFA1 (TL)**
UNIT	0.662 (9.55)	0.231 (0.402)	0.603 (12.4)	0.308 (0.665)
CUST	0.214 (.5.90)	1.517 (4)	0.188 (7.79)	0.856 (1.084)
NETW	0.180 (1.99)	-1.096 (-1.94)	0.299 (5.54)	-0.486 (-0.488)
$(UNIT)^2$	-	0.395 (1.53)	-	0.319 (0.753)
$(CUST)^2$	-	0.141 (2.79)	-	0.129 (0.929)
$(NETW)^2$	-	0.578 (2.01)	-	0.456 (0.708)
UNIT*CUST	-	-0.068 (-0.421)	-	0.12 (0.409)
UNIT*NETW	-	-0.637 (-1.3)	-	-0.575 (-0.645)
CUST*NETW	-	-0.384 (-1.87)	-	-0.388 (-0.655)

Table 23: Efficiency score correlations

	DEA1	DEA1v	DEA2	DEA2v	COLS1 (LL)	COLS1 (TL)	SFA1 (LL)	SFA1 (TL)	DEA1-Eur	DEA1-OPEX
DEA1	1.00									
DEA1v	0.54	1.00								
DEA2	0.29	0.11	1.00							
DEA2v	-0.09	0.41	0.62	1.00						
COLS1 (LL)	0.63	0.37	0.03	-0.17	1.00					
COLS1 (TL)	0.84	0.69	0.30	0.15	0.71	1.00				
SFA1 (LL)	0.57	0.42	-0.13	-0.22	0.96	0.70	1.00			
SFA1 (TL)	0.69	0.71	0.23	0.18	0.81	0.90	0.82	1.00		
DEA1-Eur	0.94	0.61	0.20	0	0.52	0.81	0.50	0.63	1.00	
DEA1-OPEX	0.67	0.10	0.29	-0.27	0.42	0.43	0.38	0.35	0.53	1.00

Table 24: Rank order correlations

	DEA1	DEA1v	DEA2	DEA2v	COLS1 (LL)	COLS1 (TL)	SFA1 (LL)	SFA1 (TL)	DEA1-Eur	DEA1-OPEX
DEA1	1.00									
DEA1v	0.47	1.00								
DEA2	0.19	0.14	1000							
DEA2v	-0.06	0.49	0.69	1.00						
COLS1 (LL)	0.69	0.34	0.08	-0.12	1.00					
COLS1 (TL)	0.84	0.66	0.27	0.19	0.75	1.00				
SFA1 (LL)	0.63	0.37	-0.06	-0.17	0.97	0.72	1.00			
SFA1 (TL)	0.68	0.70	0.26	0.27	0.80	0.92	0.79	1.00		
DEA1-Eur	0.99	0.58	0.07	0.05	0.52	0.77	0.52	0.62	1.00	
DEA1-OPEX	0.66	0.10	0.23	-0.15	0.45	0.42	0.40	0.34	0.49	1.00

8. Discussion of results and regulatory implications

In price and revenue cap incentive regulation based on the RPI-X model the X-factors have significant financial consequences for the regulated utilities. International benchmarking is a potentially effective approach for setting the X-factors based on relative efficiency of utilities. However, as discussed in the previous sections, the choice of benchmarking methods, models, and variables can affect the efficiency scores as well as the rank order of firms.

In addition, the benchmarking method and process can have (long-term) implications for the utilities as well as for the regulators. Utilities adapt to their regulatory framework and benchmarking by highlighting certain variables improves their performance measured in terms of those variables. For the regulator, benchmarking involves decisions about data requirements, collection procedures, reporting formats and quality, as well as regulatory governance issues such as commitment and transparency. Therefore, the use of cross-country benchmarking for regulatory purposes and to derive the X-factors requires careful consideration of a number of issues.

Barriers to Implementation of International Benchmarking

An advantage of DEA is that inefficient firms are compared with real and identifiable frontier firms. As shown in our results, in CRS models, the frontier firms may be considerably different from many of the less efficient firms. A frontier dominated by very large or small firms may reduce the validity and relevance of the results for other size categories. A practical implication of such comparisons is that a frontier dominated by small firms may provide other firms with incentives for uneconomic scale reductions.

Also, our results from the DEA-VRS models confirmed the theoretical concern that a lack of similar comparators may place inefficient utilities on the frontier. In addition, our results also indicate that data sets containing utilities with a wide range of sizes may reduce the accuracy of applying translog model specifications in COLS and SFA methods. It is therefore important that the data, to the extent possible, include a sufficient number of firms for different size categories or panel data. Alternatively, given a sufficiently large data set, the sample can be divided up into sub-samples based on the size of the firms.

Another strength of DEA is that it accommodates the use of models with multiple inputs and outputs. However, in models where a single measure of total costs is used as input, this advantage of DEA relative to other benchmarking methods becomes redundant. As noted, the use of total costs implicitly assumes a trade-off between operating and capital costs.

Power sector reforms often involve separation of the distribution and supply functions of the utilities. This also has bearings on the model specification and data requirements of benchmarking distribution activity. The functional separation will transform the role of the distribution function into provision of: (i) sufficient capacity capable of carrying the maximum demand for electricity supply, (ii) reliable and quality delivery, (iii) to a given number of customers, who are (iv) in a designated service area. Therefore, it is important to incorporate capacity-related variables such as the maximum demand and transformer capacity that reflect the nature of the role of these firms more accurately.

In international benchmarking the cost data need to be converted into a common unit. Therefore, issues such as inflation and currency conversion need to be addressed. In particular, it is important to consider to what extent the use of PPP relative exchange rates is appropriate. As PPP adjusts the costs for price differences across the countries, a conversion based on PPP may be more appropriate for operating costs as such costs are often incurred in local currencies and have a common year-end. To the extent that material and equipment acquired internationally, market exchange rates may be more appropriate for conversion of capital costs. Sensitivity analysis for individual countries can show the extent of responsiveness of the scores to conversion methods and factors. At the same time, to the extent that inefficient firms are compared with frontier firms from the same country, they are not affected by the cost conversion method.

The international benchmarking samples should, as far as possible, include utilities representing the best world practice. Inclusion of efficient US utilities can help in achieving this objective by increasing the possibility that utilities are compared against the best attainable efficiency. Inclusion of the world best practice also provides a stable reference frontier which, in the long-run, only shifts with technological progress.

Regulatory Benefits of International Benchmarking

International benchmarking enables the regulators to use analytical techniques that require samples that are larger than the number of local utilities. These techniques can allow the regulators to acquire better knowledge of the relative efficiency of utilities in their respective countries, those in other countries, and the best international practice. In particular, multi-period international benchmarking can reveal the efficiency-improvement path over time in relation to other countries or international best practice.

The effect of different combinations of variables on the efficiency scores of a country's utilities can shed light on possible distinctive features that separates them from utilities in other countries.

International benchmarking may also be used to study the optimum scale of utilities. This could, in particular, be useful to countries with few utilities that intend to reform or privatise the power sector and are seeking an optimal structure for the sector in terms of number and size. Also, international comparisons may also be used to examine the effect of different regulatory frameworks such as revenue/price cap or rate of return regulation on efficiency improvement.

Regulatory Implications

The above subsections outlined the main barriers to, and benefits of using international benchmarking in regulation. However, it is also important to view international benchmarking in a broader context and beyond the choice of appropriate data, methods, models, and variables. In closing we briefly introduce some of these issues.

Regulators need to ensure that the adopted benchmarking approach will not lead to strategic behaviour amongst the utilities. For example, DEA-VRS models may provide incentive for mergers and de-mergers intended to improve the utilities' scores and rankings but which do not result in real efficiency gains.

Particular attention should be given to the quality of service. Benchmarking increases the focus of the utilities on the variables that are included in the regulator's models. Quality of supply can be incentivised by explicit inclusion of relevant variables in the models. Alternatively, in cost efficiency benchmarking models, reward and penalty schemes targeting quality of supply can be designed to indirectly affect the level of utilities' costs used as input variables.

For the purpose of setting the X-factors, the reliability and benefits of benchmarking are greatly enhanced with continuity and consistency. This in turn requires long-term co-operation and commitment on the part of the participants. International comparisons can create other interdependencies among the contributing regulators. As utilities from one country may be compared with those from other countries, a high degree of "trust" among the regulators for each other's data quality and timely delivery of data is needed. Therefore, annual collection of data on a consistent basis may be required.

Also, the timing of rate reviews varies across the countries. International benchmarking inevitably leads to some dissemination of data. As a result, some regulators may find the timing of rate reviews in other countries as untimely and disrupting. International benchmarking may therefore not be suitable for countries with closed rate setting practices.

Another consequence of international benchmarking can be that a given set of data shared by different regulators may be used with different methods and model specifications. Although many regulators are independent and enjoy full discretion with regard to the choice of methods, models, and data, widely different uses of similar data may be questioned.

In the absence of theoretical solutions to some of the methodological issues in benchmarking it is important that the benchmarking process, as well as the adopted methods and variables, enjoy high levels of acceptability among the main players in the industry. This can, for example, be achieved through consultations and hearings. However, it is also conceivable that as a result of international comparisons, benchmarking practices in different countries can gradually become more similar as it may become difficult to impose different X-factors to equally efficient utilities that converge on a common frontier but operate in different countries.

Recommendations for Next Steps

The results of the study reveal some variations in minimum scores, mean scores, and rank orders of utilities obtained from different methods and models. However, this does not imply exclusion of any specific method used here. Although some preferred methods and models may emerge from a benchmarking exercise, cross-checking with different approaches can help to detect possible data problems and to increase confidence in the results.

The data set on which our analysis is based has helped in identifying several areas for further work to strengthen the usefulness of analytical techniques and enhance the quality of results in international benchmarking.

- discuss benchmarking models and functional forms (eg. CRS versus VRS models or assigning weights to inputs and outputs) suitable for regulation of electricity distribution and transmission utilities,

- agree a minimum set of input, output, and environmental variables for data collection (some potentially useful additional variables include maximum demand, transformer capacity, service area, quality of service, and voltage-based physical and monetary breakdown of assets),

- agree detailed specification of each variable, especially capital,

- agree long-term commitment and procedures for data collection, common templates, and submission dead-lines for data standardisation,

- collect time-series data for several years - recent years and future on annual basis,

- ensure data sufficiently represents different size groups of utilities,

- conduct in-depth examination of similarities and differences between the inefficient firms and their peers, and

- explore co-operation with other bodies involved in international utilities data such as the US Federal Energy Regulatory Commission (FERC), Australian energy regulators, and Comisión de Integración Eléctrica Regional (CIER) in Latin America.

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