Cambridge Working Papers in Economics CWPE 0423

UNIVERSITY OF
CAMBRIDGE
Department of Applied Economics

Comparing Brazil and USA Electricity Distribution Performance: What was the Impact of Privatisation?

Raffaella L. Mota

The Cambridge-MIT Institute

*Massachusetts Institute of Technology
Center for Energy and
Environmental Policy Research*

CMI Working Paper 39

Cambridge Working Papers in Economics

UNIVERSITY OF
CAMBRIDGE
Department of
Applied Economics

Not to be quoted without permission

The
Cambridge-MIT
Institute

Massachusetts Institute of Technology
Center for Energy and
Environmental Policy Research

CMI Working Paper

Comparing Brazil and U.S.A. Electricity Distribution Performance: What Was the Impact of Privatisation?

Raffaella Lisbôa Mota*
CNPq
Churchill College, University of Cambridge

April 7, 2004

Abstract

Beginning in 1995 a large proportion of the Brazilian electricity distribution sector went through privatisation and restructuring, whereas privately-owned U.S. utilities did not suffer similar ownership change process. This paper is an empirical assessment of the efficiency of the Brazilian distribution sector relative to its U.S. counterpart in 1994 and 2000. Two techniques are applied: Data Envelopment Analysis (DEA), including the computation of Malmquist indices of productivity growth, and Stochastic Frontier Analysis (SFA). For the models that use operating costs as input, we find a positive but not statistically significant impact of Brazilian privatisation on technical efficiency. For the models that use total costs, the impact is significantly negative. Although this should be taken with caution, the negative impact can be the result of an investment surge after privatisation or of an increased rate of substitution of capital for labour in the Brazilian distribution sector. These results suggest that capital costs should not be excluded from the benchmarking. The findings also highlight the importance of establishing standard measures of capital costs for international benchmarking and incentive based regulation.

Keywords: benchmarking, international comparison, technical efficiency, Data Envelopment Analysis, Stochastic Frontier Analysis, Malmquist Productivity Index, electricity distribution systems

JEL Classification: L94

*Raffaella Lisbôa Mota is at Churchill College, University of Cambridge. The author is thankful to Michael G. Pollitt and Tooraj Jamasb for very helpful comments and suggestions. Financial support of CNPq (Conselho Nacional de Pesquisa e Desenvolvimento) is gratefully acknowledged.

1 Introduction

> "*The nerve of the regulator will depend heavily on the quality of the ongoing benchmarking studies. The regulator must have confidence that the method properly accounts for all inputs and outputs, and that any environmental differences between firms have been properly accounted for in the analyses. Otherwise, there is a danger that an unlucky firm will be sent broke because a particular variable was ignored, or a lucky firm will scoop regularly excessive profits.*" (Coelli 2000, p. 10)

Until recently either public ownership or heavily-regulated private ownership characterised the electricity supply industry (ESI) in most countries. Since the late 1980s liberalising reforms have featured in the agenda of an increasing number of developed, developing, and transition countries. Although the driving forces behind reforms in developed and developing countries differ considerably, the primary goals of reform in the electricity sector were to promote lower costs through efficiency improvements and to ensure reliable electricity supply to customers.[1]

Liberalising reforms in the ESI usually include sector reform (corporatisation, restructuring and/or privatisation) and regulatory reform. These changes are often accompanied by the introduction of competition into generation, and the gradual liberalisation of the supply market.

The main elements of regulatory reform are the establishment of an independent regulator, the adoption of incentive regulation, and the gradual deregulation of the potentially competitive segments of the industry. In the current reform process the emphasis has shifted from traditional cost-of-service regulation to incentive based regulation. The latter should be able to avoid the Averch-Johnson (overcapitalisation) effect, typical of cost-of-service regulation, and to give signals conducive to operating and investment efficiency.[2] As pointed in Jamasb and Pollitt (2001), irrespective of the specific incentive scheme adopted, a common feature of incentive based regulation is the use of benchmarking. In particular, in the case of revenue or price cap (RPI-X formula), benchmarking can help decide the X factor – a crucial step on the tariff review process.[3]

[1] Besides efficiency objectives, macroeconomic factors dictated the pace and sequence of reforms in developing countries. For instance, privatisation was expected not only to improve the finances of the sector, but also to increase revenues for the Treasury, and to help reducing and restructuring public debt. At the same time, the burden of investment for capacity expansion – which has greater significance in countries growing fast and where a large share of the population still does not have access to electricity services – or quality improvement was expected to be transferred to the private sector.

[2] See Averch and Johnson (1962).

[3] A brief description of price-cap regulation is as follows. The regulator sets price increases

International benchmarking is a very useful tool for incentive based regulation. It can provide a larger sample of comparable companies, and allows comparisons with international best practices. Besides, when the number of national companies is not sufficient for benchmarking techniques, including international comparable companies in the sample can be a *sine qua non*. International benchmarking can also help to identify the dynamics of the sector, i.e., how successful national sector and regulatory reforms have been in terms of relative performance over time, and what problems need to be addressed. In Australia, for instance, international benchmarking has played a key role for improving performance.[4]

In this paper we benchmark a representative sample of privatised Brazilian distribution companies against comparable U.S. investor-owned utilities. The time frame of our analysis, 1994-2000, allows us to capture the effects of Brazilian privatisation and restructuring, as the U.S. sample remained stable in terms of ownership structure. Given the larger number of companies in the American electricity sector, the data requirements of the most common benchmarking techniques are satisfied with the inclusion of U.S. investor-owned utilities in the sample. Furthermore, Brazil and the U.S.A. are comparable countries in terms of area. Since the area of service is an important factor affecting operating and capital costs of distribution companies, this common feature increases the comparability between the two samples.

We benchmark 14 recently privatised Brazilian distribution companies against a sample of 72 investor-owned American electric utilities. Two techniques are applied: Data Envelopment Analysis (DEA) and Stochastic Frontier Analysis (SFA), and we cross-check our findings. In addition, we use DEA to compute Malmquist indices of productivity growth.

This paper is structured as follows. Section 2 provides the background for our empirical analysis, summarising the current state of reforms in the ESIs of Brazil and the U.S.A.. In Section 3 we review the benchmarking literature, discussing the techniques and models used in academic studies and in studies sponsored by regulators. Section 4 discusses the techniques of efficiency measurement that are used in this study – DEA and SFA. In Section 5 we present the datasets and justify our choice of models. Section 6 presents our findings and compares the results of the two methodologies. Finally, Section 7 summarises our conclusions

---

that may be permitted over a fixed number of years (usually five or four years). Prices increases are usually set equal to the rate of increase in the consumer index (RPI or CPI, for instance) minus a productivity factor (the X factor). The value of X can be based upon previous rates of productivity growth in the industry or upon some form of benchmarking. The regulator can also choose to set different X factors for different firms in the industry (Coelli, 2000, p. 2). A number of key papers that appeared on the 1989 Autumn issue of The Rand Journal of Economics (Symposium on Price-cap Regulation) discuss theoretical and applied issues raised by price caps.

[4] See on this topic Lawrence et al. (1997).

and policy recommendations.

2 Background

2.1 Brazil

Until the recent reform of the electricity sector the Brazilian ESI was characterised by the overwhelming participation of the public sector. Approximately 50% of generation and transmission was concentrated at federal utilities (mostly under the control of the *holding* Eletrobrás), and the remaining half was owned by the states. Most of the distribution was carried out by state-owned companies. Usually each state had one distribution company with a monopoly over distribution and supply; however, there were states with more than one distribution company.

Electricity sector reform in Brazil followed the international trend towards market mechanisms, competition wherever possible, and a new approach to utility regulation. The ESI was formally unbundled into four businesses – generation, transmission, distribution and supply –, which were required to be accounted for separately. All network of voltage less than 230 kV was considered distribution asset and could be kept by the distribution companies. Distribution companies were granted authorisation to continue to supply customers in their concession areas, and were allowed to keep their own generation up to the limit of 30% of their captive markets. The reform also established a gradual transition to a competitive environment in both generation and supply.

Beginning in 1995, privatisation of distribution companies in Brazil attracted a great deal of interest, and today over 60% of the distribution market is privately-owned. In contrast, privatisation of the large federal generation companies faced more serious difficulties, and generation remains mostly publicly-owned.

An independent regulatory agency, the National Agency for Electric Energy (ANEEL, in Portuguese), was instituted in 1996. ANEEL is in charge of both economic and technical regulation, but can delegate its monitoring activities to state-level regulatory agencies.

The reform replaced the regime of guaranteed rate-of-return for price cap regulation, but, in order to promote privatisation, the X factor was initially set to zero until the first tariff review. With the exception of one distribution company (Escelsa, which had already suffered two tariff reviews), the first tariff reviews are taking place in 2003 and 2004. The documents of the current tariff review process indicate that ANEEL is adopting benchmarking techniques to calculate the X factor. However, as in other South American countries the regulator favours benchmarking against a model or theoretical firm. This benchmarking approach overcomes the problem of finding comparable companies in the Brazilian national market, but the construction of a theoretical firm is highly controversial. What we propose in this paper is an alternative route to overcome the limitations of the national market: international benchmarking.

In 2001 Brazil faced its worst electricity supply crisis in fifty years. This was caused by underinvestment in generation and transmission, and severe drought conditions. Electricity consumption had to be rationed and, as a consequence, distribution companies (after years of profits since privatisation) suffered financial losses and threatened law suits against generation companies. The crisis made obvious the difficulties in the transition to a market-oriented model when there is shortage of supply. The new left-wing government is currently undertaking a review of the ESI model, but in the meantime the transition has come to a halt.

In summary, the main changes Brazilian distribution companies suffered in the period from 1994-2000 were privatisation, some restructuring (especially to comply with the 30% limit of own generation), and very limited competition in the supply market. Therefore, we expect the incentives to improve performance to come mainly from shareholders pressure and incentive regulation.

2.2 United States

In contrast to the Brazilian electricity sector, private participation has always been important in the U.S.A.. Although there are over 2,000 electric utilities owned by states, municipalities, public power districts, irrigation districts or other state organisations, investor-owned utilities account for most of generation and sales. There are more than 200 investor-owned electric utilities, which are often very large and vertically-integrated. These utilities operate as local monopolies and are subject to both federal and state regulation. In addition to public utilities and investor-owned utilities, there are rural electricity cooperatives and a few federal projects.

Historically most regulatory authority has been vested in each state, which explains the differences in regulatory arrangements and investment decisions within the country. However, for the past two decades the federal level has gained importance for two reasons. First, the Public Utility Regulatory Policy Act (PURPA) of 1978 stimulated the development of a non-utility power sector by requiring utilities to purchase power from cogenerators and renewable energy producers. Second, the Energy Policy Act of 1992 authorised the Federal Energy Regulatory Commission (FERC) to order utilities to provide transmission services for local distribution systems and other wholesale purchasers. Although the legislation reflected a move towards introducing competition at the wholesale level, the basic model of regulated vertically-integrated monopolies remained mostly unchanged, and the first comprehensive reform programmes were only implemented by 1998 (Joskow, 2003).

High prices were the main drivers of reforms at the state-level. In states such as California, Michigan, New York, Connecticut and Massachusetts previous investment decisions created a significant gap between the price of generation services embedded in the regulated bundled price, and the unbundled price of wholesale generation plus transmission and distribution charges. The first state reform programmes aimed to deregulate the sector, and to extend competition to the supply market, allowing customers to choose their suppliers. Pressures from competition as well as from new incentive based regulation (which gradually replaced the traditional rate-of-return regulation) were expected to drive costs down. Some states have also made restructuring compulsory. California, for instance, required the incumbent utilities to substantially unbundle their distribution activities from their generation and transmission activities. In addition, transmission system operation had to be transferred to an independent system operator.

Since 2000, however, the pace of state reforms has slowed down, with a number of states delaying or even cancelling their programmes. The transition to competitive wholesale and supply markets has therefore been less smooth than initially anticipated. The California 2000-2001 crisis illustrates how important it is to get the market design right, especially in a context of supply shortage – but California was only one of the many challenges.[5] The financial problems of Enron and many merchant generating and trading companies, volatile wholesale prices, and rising final prices in some states have shed doubt on the way reforms have been implemented (Joskow, 2003). The level of confidence in the reliability of electricity services seemed to reach an all-time low in August 2003, when the lights went out for hours in the Eastern states.

Given the problems encountered so far, some states have recently opted for a more gradual approach to ESI reform. Early reformers, however, who have already committed much to the process, are pushing forward with reforms. The results of their programmes will be important to convince other states to join the process. At the federal level, the FERC remains committed to introducing competition in the wholesale market (now through the Standard Market Design), but it also has to negotiate the terms of implementation with each of the states.

With respect to price regulation, rate-of-return has predominated in the U.S. electricity sector. As pointed out in Irastorza (2003), benchmarking in its simpler forms (e.g., direct comparison of a specific utility's price with an average retail price) has also been around in the U.S. for decades. It has been used as a mechanism to measure performance and provide incentives in rate-of-return regulation.

[5] See Joskow (2001) and Besant-Jones and Tenembaum (2001) for an assessment of the California electricity crisis.

3 Empirical Benchmarking Studies

Benchmarking is the process of comparing actual performance against a reference (benchmark) performance. There are a number of ways to classify the benchmarking literature. According to the Dutch electricity regulator, two main approaches have been used by regulators: cost linked benchmarking and unlinked benchmarking (DTe, 1999). The first approach links the setting of X to the inefficiency of each individual firm measured relatively to the chosen benchmark. The behaviour of individual firms is not directly used in the unlinked approach. One example is the price regulation of U.S. telecommunications, where X was set equal to the average rate of productivity growth of the telecoms sector. In a survey of the international benchmarking and regulation electricity experience, Jamasb and Pollitt (2001a) favour a classification based on whether the benchmarks are derived from the best (frontier) practice or the average performance. Alternatively, some authors (e.g. Sarafidis, 2002) identify two approaches to estimating relative efficiency across firms: the parametric (or statistical) approach and the non-parametric approach.[6]

In our overview of the benchmarking electricity literature, we divide the studies into two broad categories: academic studies and studies conducted by the regulator.[7] The objectives and the rigorousness of the two types of study are different. The regulator is more immediately concerned with price setting; therefore, the process of translating benchmarking results into specific incentive targets may receive relatively more attention. While academic studies have to stand the scrutiny of specialised journals, regulatory analyses are often used to support decisions that might be challenged by judiciary courts. In terms of the techniques used, academic studies tend to use frontier benchmarking which can be more or less directly translated into cost linked regulation. In contrast, regulatory studies are more diverse in the type of method used. In the Chilean electricity regulation, for instance, benchmarking has been based on the model (theoretical) firm. It will be clear from the text or from our summary tables what specific methods have been adopted by each study and whether international benchmarking has been used.

---

[6] A slightly modified version of the parametric/ non-parametric classification adds a third type of benchmarking technique: the process approach. Process approaches are bottom-up techniques to assess efficiency. They can be based on reviews of company practices and plans or on engineering data. See CEPA (2003).

[7] With respect to electricity transmission and distribution, Domah (2002a) observes that there are two related strands in the efficiency literature: one concerned with the existence of economies of scale and one focused on the impact of ownership on efficiency.

3.1 Academic Studies

Table 1 summarises a few relevant academic benchmarking studies. These studies have traditionally concentrated on electricity generation or vertically-integrated utilities, but more recently the interest on distribution has increased. Most of these studies use frontier methodologies and focus on developed countries.

Table 1 here

Grifell-Tatjé and Lovell (2003) use DEA to benchmark the performance of nine Spanish electricity distributors against the performance of an ideal network. The study finds that the actual distribution network operates at a higher cost than its ideal counterpart, but most of the difference comes from lower input prices.

Both Kittelsen (1999) and Førsund and Kittelsen (1998) use Malmquist DEA to study productivity changes in the Norwegian distribution market. The first study reports some mean productivity change in the period from 1983-1989, but no significant catching-up effects. The second estimates that most of the productivity change in the same period was due to frontier shifts. Because geography is such an important cost driving factor in Norway, both studies attempt to capture this aspect of the distribution business. The models used are similar, but Førsund and Kittelsen (1998) use a more comprehensive measure of the geographic aspect – the distance index, which encompasses not only physical distance but also topographical characteristics. Kittelsen (1999), on the other hand, uses network length. Hjalmarsson and Veiderpass (1992a) also use Malmquist DEA, but it is used to examine the productivity growth of 289 distribution utilities in Sweden during the period from 1970-1986. The study measures a substantial productivity growth in Sweden and concludes that this was mostly due to economies of density. There are no clear catching-up effects as the distance between the average and the frontier decreased slightly during the first subperiod (1970-1978), but increased during the second subperiod (1978-1986). Type of ownership or economic organisation do not seem to be correlated with productivity change.

Bagdadioglu et al. (1996) study the efficiency of the Turkish electricity distribution market using a DEA model. The study attempts to investigate the relationship between ownership and efficiency, but only a very limited number of privately-owned companies are included. Some support (although not econometric) is found for the hypothesis that governments offer to sell the most efficient companies first. The study suggests that it is as likely to be efficiency which leads to privatisation as the other way round. Similar DEA models are used in Resende (2002) to measure the performance of 24 Brazilian distribution utilities. The focus is not so much in ownership effects but in providing guidance for a yardstick competition framework. Resende's sample is more heterogenous than the one used in the previous study; as a consequence, the dispersion of efficiency scores is greater, with some companies substantially below the frontier. Also in contrast with Bagdadioglu et al. (1996), scale inefficiencies are more important sources of overall inefficiency. In a similar type of study and one of the first studies to focus only on distribution, Weyman-Jones (1991) uses DEA to compare the efficiency of 12 electricity distribution utilities in England & Wales, and finds only five companies operating on the efficiency frontier.

Both Kittelsen (1993) and Hjalmarsson and Veiderpass (1992b) use various DEA models to examine the efficiency of electricity distributors using cross-section samples. Kittelsen (1993) develops a methodology to help determine the appropriate model specification for a sample of 172 Norwegian distribution utilities. Model specificiation is a relevant issue since increasing the number of variables in DEA models might improve the representation of the underlying technology, but could be detrimental to consumers. As observed in the study, including a large number of irrelevant variables could lead to too many companies on the frontier.[8] The study finds that Norwegian distribution utilities exhibit extensive technical inefficiency and scale inefficiency is not important. Hjalmarsson and Veiderpass (1992b) analyse the efficiency of 285 Swedish electricity distribution companies, emphasising the relationship between efficiency and ownership, as well as between efficiency and type of service area. On average, efficiency scores are low in Sweden distribution and the authors attribute this to the lack of competition. Although urban distribution is found to be slightly more efficient than rural distribution, the study fails to detect any significant efficiency effects of ownership, economic organisation or service area.

Hattori (2001), Pardina and Rossi (2000) and Burns and Weyman-Jones (1996) estimate the efficiency of electricity distribution utilities using SFA. Hattori (2001) uses translog input distance functions to compare the electricity distribution performance of 12 U.S. and 9 Japanese utilities during the period 1982-1997. Results show that Japanese utilities are, on average, more efficient than their U.S. counterparts, but the respective frontiers are close to each other. Pardina and Rossi (2000) estimate a stochastic production function for a sample of 36 distribution utilities from ten South American countries. The study aims to analyse technical change in the electricity distribution sector in South America, and to test for performance effects of electricity reforms. The study fails to detect any catching-up effects, and only finds partial evidence of correlation between reforms and performance. Burns and Weyman-Jones (1996) develop a cost frontier model and estimate it for 12 electricity distribution companies in England & Wales. The study attempts to identify the main cost drivers of

[8] "There is some advantage in keeping the number of inputs (m) and outputs (s) small relative to the number of firms (n). As the ration m+s/n rises, the ability of programmes (...) to discriminate amongst firms falls significantly, since it becomes more likely that any given firm will find some set of output and input weights which will make it appear efficient." (Weyman-Jones, 1991, p. 119)

electricity distribution, to assess the efficiency of the companies, and to test for possible privatisation effects on efficiency. The estimation results suggests that the main cost drivers are the number of customers and simultaneous maximum demand. The study also finds evidence of economies of scale and small, but significant, privatisation effects. However, the authors suggest that these effects of privatisation are as likely due to changes in accounting policies as any real effect.

Instead of estimating stochastic cost frontiers, Scully (1998), Giles and Wyatt (1993) and Filippini (1998) estimate deterministic cost models. The first two studies focus on the New Zealand distribution sector, while the last examines the efficiency of Swiss Municipal distribution utilities. Scully (1998) uses a panel dataset covering the period from 1982-1994, aiming to assess the impact of privatisation on efficiency and on consumer welfare. Giles and Wyatt's (1993) paper consists of an econometric study of economies of scale, and uses cross-section data for 1986-1987. Scully (1998) relates the estimated cost reductions not so much to privatisation *per se,* but to the economy-wide reforms started in 1988. Results also show that reforms benefitted consumers, especially commercial, rural and industrial customers. In addition, the study detects the existence of economies of scale throughout the observed range of output. Giles and Wyatt (1993) confirm the existence of significant economies of scales, and suggests a reduction in the number of companies in the New Zealand distribution market. Filippini (1998) assesses economies of scale and density and the desirability of competition in the Swiss electricity distribution sector. The sample consists of 39 Swiss Municipal distribution utilities over the period 1988-1991. The results suggest the existence of economies of scale for small and medium-sized utilities, and the existence of economies of density for most output levels. Similar to what was observed for New Zealand, some merging is likely to reduce costs.

Some studies use more than one benchmarking methodology. This has the advantage of allowing to cross-check results and to study the sensitivity of results to model and methodology specification.[9] Jamasb and Pollitt (2001b) use various DEA, SFA and COLS (corrected ordinary least squares) models in a benchmarking study of 63 distribution utilities in six European countries. Different from most previous studies, Jamasb and Pollitt (2001b) use monetary values for the input variables instead of physical values. The authors argue that this is advantageous from the regulatory point of view as all operating and capital inputs can be included. It also allows the expression of inputs and outputs in a single measure, making explicit the possible trade-off among these. The results show that the choice of models and methods can affect efficiency scores and ranking, but the choice of cost conversion methods (PPP or Euro exchange rates) does not significantly alter results.

[9]For instance, it is possible to compare means, standard deviations, score and ranking correlations across different models or techniques.

Pollitt (1995) uses both DEA and OLS (Ordinary Least Squares) to investigate the relationship between ownership and performance. The benchmarking exercise uses data of 136 U.S. and 9 UK utilities engaged in distribution.[10] The results of statistical tests on the DEA efficiency measures indicate that the null hypothesis of no difference in productive efficiency between publicly-owned and privately-owned utilities cannot be rejected. In addition, OLS regression results corroborate this finding.

3.2 Regulatory Studies

The ESI has traditionally been subject to price regulation. After liberalisation, regulation has concentrated on the natural monopoly businesses – transmission and distribution – while generation and supply (or retailing) have been gradually opened to market competition. Regulators have also moved towards incentive based regulation as a mechanism to encourage efficiency and curb market power. Benchmarking provides regulators with an objective assessment of the performance of the regulated utility or industry. Considering that the first liberalising reforms started in the late 1980s, regulators have accumulated experience in benchmarking and incentive based regulation. Table 2 is an updated summary of this experience and shows a variety of methods and models that have been used in electricity distribution benchmarking.[11]

Table 2 here

Our brief overview of benchmarking studies conducted by the regulator shows that regulators have tended towards cost linked regulation and frontier methods, although different techniques have been tried. The UK regulator adopted a COLS model with OPEX (operating expenditure) as the dependent variable and a composite output variable (consisting of number of customers, units delivered and network length) as the independent variable (Ofgem, 1999). A recent study prepared for the UK regulator as a background assessment for the next price review planned for 2005 suggests the use of a combination of DEA and COLS (CEPA, 2003). Due to the limited sample size, SFA is not an option in this case, but the study hints that it might be possible to use SFA if panel data is available in the future. Ideally TOTEX (total expenditure) should be used instead of OPEX, but the difficulties in measuring capital expenditure might prevent TOTEX from being used. The study also suggests that the com-

[10] Pollitt (1995) studies separately the performance of the various businesses in the electricity supply industry: generation, transmission and distribution. For the purposes of our brief survey, we will concentrate on distribution.

[11] Jamasb and Pollitt (2001a) conduct a survey of electricity regulation and the state of benchmarking in 18 OECD and 4 non-OECD countries. International benchmarking surveys with this scope are still unusual in the literature – it is easier to find surveys of the experience of individual countries (e.g. Rudnick and Raineri, 1997) or of a group of countries with some degree of market integration (e.g. Kinnunen, 2002).

posite variable previously used by the regulator could be simplified, considering that number of customers is highly correlated with units delivered.

The Dutch regulator opted for the use of a number of DEA models (DTe, 1999 and Frontier Economics, 2000) to estimate efficiency in the electricity distribution sector. The models use either OPEX or TOTEX as the input variable. TOTEX is defined as OPEX plus annualised standardised capital costs. With respect to outputs, different specifications are estimated taking into account the volume of electricity distributed, number of customers, and network configuration. Although a central model has to be chosen, the comparison between different models allows not only to check the sensitivity of the results to model specification, but also to study the source of inefficiency, i.e. whether inefficient companies are inefficient on operating expenditure, capital or both.

In Norway, where there are over 200 network electricity utilities, there is a special concern for standardising procedures, including company reporting. The Norwegian regulator has also adopted DEA since 1997, when it established revenue caps for each company (Grasto, 1997; Langset, 2000; Kinnunen, 2002). The efficiency requirement for each company consists of two terms: a general correction term and an individual correction term. The general correction term is common to all utilities and is based on a DEA study (Førsund and Kittelsen, 1998) that uses as inputs labour (hours), electricity losses, and costs of materials and capital. As outputs it uses a distance index, number of customers and electricity delivered. The individual correction term is based on another DEA study which includes network length and length of sea cables as inputs.

The regulator in New South Wales, Australia, does not favour a single benchmarking technique, but uses an array of methods: DEA, SFA, TFP (total factor productivity), and process and organisational benchmarking (IPART, 1999 and UMS Group, 1999). Benchmarking is used as an aid in determining the efficient level of operating and maintenance expenditure, and there is no direct relationship between benchmarking results and the X factor. For inputs the DEA model uses network length, transformer capacity and OPEX, and for outputs it uses units delivered, peak demand and number of customers. One feature of the New South Wales benchmarking is the extensive use of an international database. In a study for the regulator conducted by London Economics the sample includes 219 firms from Australia, New Zealand, England & Wales, and the U.S.A.. Another benchmarking study, this time conducted by the UMS Group, uses 35 firms world-wide. Given the very limited number (only six) of distribution utilities, international (and interstate) benchmarking is a requirement for most of the techniques used.

Although frontier methods are becoming increasingly common, alternative techniques have been applied. In South America regulators, in an attempt to overcome their credibility problems, have favoured the model (or theoretical) firm approach.[12] Chile, having started its electricity reform in the early 1980s, introduced the concept of value added of distribution (VAD), which is the value required to remunerate the distribution business. This remuneration should allow an efficient (or theoretical) distribution utility to recover its operating and maintenance costs and to achieve a pre-determined rate-of-return on investment. The actual distribution utility benchmarks its costs against the costs of the model firm, which are used to compute the VAD (yardstick competition).

The benchmarking process might vary across countries but Argentina, Peru, Colombia and more recently Brazil have followed the guidelines of Chile's model firm approach.[13] In Chile the VAD is based on the costs of an efficient firm established using the weighted average of estimates made by the National Energy Commission and by consultants hired by the distribution utility. The discrepancies in these estimates, and the difficulty in establishing a credible model firm, have led to conflicts and lengthy judicial processes (Rudnick and Raineri, 1997).[14] In Argentina the distributor's cost is estimated based on the average incremental cost of the distribution network and on operating and maintenance costs. The incremental cost is calculated on the basis of a least cost investment plan for an efficient firm, given the expected demand growth rate. In Colombia actual costs are benchmarked against the computed costs of an efficiently-run similar distribution system. In Peru, after VAD calculation, the regulator computes the internal rate of return, which must be between 8% and 16%. In Brazil the model firm approach is only used to determine the efficient operating costs – the remuneration on investment is the result of a separate individual analysis (ANEEL, 2003 and ANEEL, 2002).

[12] Fischer and Serra (2000) point out that this attempt to limit regulatory discretion resulted in overprotection of companies. First-generation South American reformers "(...) ended up with a weak regulator that lacks relevant information or the means of obtaining it, is starved for funds, is subject to strong pressures from electric utility lobbies, and does not have the tools to enforce regulations." Fischer and Serra (2000, p. 193).

[13] Fischer and Serra (2000) argue that, although the VAD may or may not include commercialisation services, price regulation in Latin American countries shares some principles, such as the self-financing of companies, the pursuit of efficiency and the transfer of efficiency gains to consumers. However, there are important differences between countries, especially with respect to service quality regulations and types of subsidy used. See Fischer and Serra (2000, p. 181).

[14] The empirical study of Di Tella and Dyck (2002) finds that distribution companies have behaved strategically under price cap regulation in Chile. This is suggested by the estimated U-shaped pattern of costs as a proportion of revenues, with the strongest cost reductions early on in the regulatory periods. This is further confirmed by the incorporation of stock market information into the empirical framework. High cost reports (i.e., cost reports that are higher than the constructed expected costs) depress the firm's stock returns in ordinary years, but increase them during review years. The authors suggest that although under price cap regulation efficiency gains have been large in the Chilean distribution sector, there has been slack in the system for appropriation of these gains by producers behaving strategically.

3.3 Summary

From our review of the benchmarking literature we observe that there is not a general consensus on the specific model or benchmarking technique chosen, but frontier techniques are the most widely used in electricity distribution. The choice of method depends partly on the data available. Issues of data standardisation and currency conversion have prevented a greater use of international benchmarking. However, if improved data is made available the use of an international sample might overcome the problems of applying statistical techniques in markets with a limited number of companies. Recent studies have attempted to cross-check the results by the use of different methods and input, output and environmental variables.

From the point of view of the regulator, models that use monetary values to represent inputs and outputs are clearly preferred. However, total costs are a function not only of input, output and environmental variables, but also of input prices. It is possible to simplify the total cost function by assuming that all firms in all periods face the same input prices, but this is not so straightforward when the time series is long or when there is an international sample of firms. In this case, it would be required to deflate nominal costs by an input price index, ideally one which uses firm-specific share weights. We would be implicitly assuming allocative efficiency and separability between the input price vector and the output-environmental variables vector. In addition, if a general PPP is all that is available to deflate costs – what is often the case – significant discrepancies might occur.[15]

Although regulators recognise that a measure of total costs would be desirable to represent the regulated utility's input, a number of benchmarking studies have chosen to work with operating costs due to difficulties in measuring capital costs.[16] As pointed out in Coelli (2000), this approach dilutes the impact of incentive based regulation, because it restricts possible cost savings to operating costs whereas capital costs are usually larger in electricity distribution.

Finally, despite the fact that issues of information asymmetry mean that constructing a credible model firm is problematic (and has been challenged by courts), regulators in some developing countries – perhaps with the intent of overcoming their perceived lack of credibility – have adopted the model firm approach.

[15] The comments on the consequences of dropping input prices from the analysis draw substantially on the interesting discussion conducted in Coelli (2000).

[16] The usual procedure is to treat operating costs and capital costs separately, and only impose productivity improvements based on the operating performance. In order to remunerate the capital, the regulator sets a fair rate of return on capital.

4 The Measurement of Efficiency

In this paper we use two benchmarking techniques: Data Envelopment Analysis (DEA) and Stochastic Frontier Analysis (SFA). This follows the trend in the empirical literature towards frontier methods. In addition, the use of both parametric and non-parametric approaches should grant some interesting comparisons.[17]

4.1 Data Envelopment Analysis

DEA is a non-parametric method that uses mathematical linear programming to construct the efficiency frontier (or best practice) and to compute efficiency measures relative to the frontier. The framework was first proposed by Farrell (1957), but it is usually accepted that Charnes, Cooper and Rhodes (1978) made the technique operational.

In general terms, the DEA method consists of a series of maximisation problems. Each firm (or decision making unit) maximises the ratio of weighted ouputs to inputs, subject to the constraint that all output-input ratios should be less than or equal to one. The basic problem (that should be solved for each firm) can be expressed as:

$$max_{u,v}\,(u'y_i/v'x_i) \qquad (1)$$
$$s.t.\,(u'y_i/v'x_i) \leq 1, j = 1, 2, ..., N$$
$$u, v \geq 0,$$

where u is a Mx1 vector of output weights and v is a Kx1 vector of input weights, x_i is a column vector of the inputs used by firm i and y_i is a column vector of the outputs used by firm i.[18]

We can derive an *envelopment* formulation (for the constant returns to scale case) for this problem as:

$$min_{\theta,\lambda}\theta \qquad (2)$$
$$s.t. - y_i + Y\lambda \geq 0,$$
$$\theta x_i - X\lambda \geq 0,$$
$$\lambda \geq 0,$$

where θ is a scalar, λ is a Nx1 vector of constants, Y is the MxN matrix of outputs and X is the KxN matrix of inputs. θ is the technical efficiency score – it gives how much we should multiply the input vector of firm i in order to achieve technical efficiency. This formulation satisfies $\theta \leq 1$, with firms on the frontier receiving a score of 1. The efficiency scores are computed in (2) by comparing each firm to a linear combination of sample firms which produce at least as much of each output with the minimum combination of inputs. This

[17] For comparisons of alternative approaches see Lovell and Schmidt (1988), Sarafidis (2002) or CEPA (2003).

[18] We draw the formulation and the terminology from Coelli et al. (1998).

process is illustrated in Figure 1 for an input orientation and constant returns to scale, for two inputs and one output.

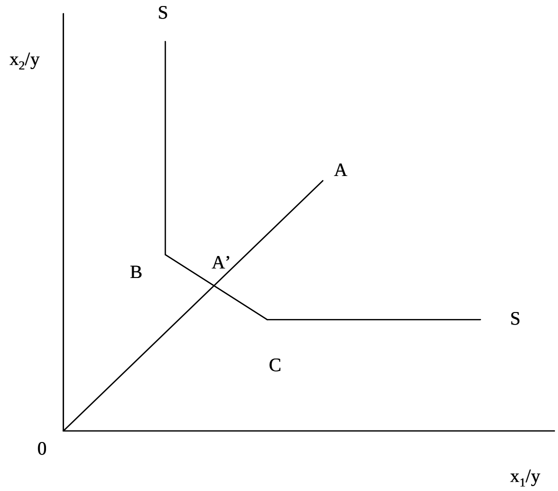

Figure 1

DEA constructs a piece-wise linear frontier from the best practice firms in the sample. All firms inside the constructed frontier are considered inefficient. In Figure 1 firms B and C define the frontier, while firm A is inefficient. Firm's A measure of technical efficiency is given by 0A'/0A.

DEA can also account for the influence on efficiency of factors beyond the control of the manager. These factors are usually named *environmental variables.* In electricity distribution there are a number of factors that affect costs but are not under the control of the management: customer density, the size of the service area, system configuration, climatic, topographic and geographic conditions. There are different methods to accommodate environmental variables (Coelli, 1998, pp. 166-171) – one possibility is to include them as non-discretionary variables, either as inputs or outputs. We can rewrite equation (2) (for the variable returns to scale case) to include both discretionary and non-discretionary inputs (denoted as X^D and X^{ND}, respectively) as:

$$min_{\theta,\lambda}\theta \qquad (3)$$
$$s.t. - y_i + Y\lambda \geq 0,$$
$$\theta x_i^D - X^D\lambda \geq 0,$$
$$x_i^{ND} - X^{ND}\lambda \geq 0,$$
$$N1'\lambda = 1,$$
$$\lambda \geq 0,$$

where $N1$ is an Nx1 vector of ones.

In the above formulation the linear programme for the computation of θ will only seek radial contraction in the discretionary inputs, holding the non-discretionary inputs fixed.

DEA models can be specified as constant returns to scale (CRS) or variable returns to scale (VRS). As we can see by comparing (2) and (3), the CRS problem can be modified to accommodate VRS by adding one constraint: $N1'\lambda = 1$. This constraint ensures that only firms of similar size are compared. Assuming CRS when not all firms are operating at the optimal scale will pollute the technical efficiency measures by including in θ scale effects. In the context of electricity distribution there is no consensus as to what specification should be preferable. On the one hand, it seems unrealistic to compare firms of such different scales (as it is the case in the electricity distribution business) and therefore VRS should be assumed. On the other hand, it can be argued that distribution utilities can control scale through mergers or demergers and thus CRS is more appropriate. One possibility could be to run both CRS and VRS models, and to cross-check the results.

The models specified in (2) and (3) are both input-oriented, but DEA can also be output-oriented. An input-oriented efficiency measure is calculated by minimising input quantities for a given level of output, while an output-oriented efficiency measure is calculated by maximising output quantities for a fixed amount of input. As stressed in Coelli (1998, pp. 158-159), the two measures provide the same value under CRS, but are unequal when VRS is assumed. More importantly, although the efficiency measures may differ, both will estimate exactly the same frontier and therefore identify the same set of efficient firms. Considering that distribution utilities take their output levels as given (i.e. they must meet demand), input orientation is usually preferred.

DEA requires the choice of input and output variables, and efficiency scores might be sensitive to model specification. When selecting the variables a trade-off between including as many variables as necessary to represent the business concerned and keeping the number of variables small relative to the number of firms (see note 6) should be carefully considered.

DEA has a number of desirable features. First, it is a non-parametric method and therefore does not require the specification of a functional form. Second, inefficient firms are compared to actual firms rather than a statistically constructed frontier. Third, relative to parametric methods, DEA can be implemented in a smaller dataset; however, it is recommended to keep the number of variables under control in order not to get an unreasonable number of companies on the frontier. Finally, DEA is flexible enough to allow for the use of physical and monetary values alike as input or output variables, what can be very useful in the context of electricity distribution. However, there are also disadvantages of the method. A major drawback is that it does not allow for stochastic factors or measurement errors. This implies that all deviations from the best practice frontier are accounted for as inefficiency. In addition, as previously observed, the selection of input and output variables is a central aspect of DEA and results might be highly sensitive to model specification. Another problem is the possible influence of outliers on the frontier and consequently on the efficiency scores. Only a careful examination of the results might help spotting outliers, as they will go undetected by the DEA method. Finally, DEA constructs the frontier from the most efficient companies within the sample. Therefore, if the sample is too small or not representative of the industry, the computed frontier will not reflect the most efficient practice.

Following the computation of efficiency scores, a natural progression on efficiency measurement is to assess productivity growth. If panel data is available, DEA can be used to calculate a Malmquist index for measuring total factor productivity change over time. A Malmquist index of productivity growth is defined as the geometric average between two Malmquist indices – one that uses as benchmark the earlier period technology (period t) and one that uses as benchmark the later period technology (period t+1). The input-oriented Malmquist index of productivity growth between periods t and $t+1$ can be written as:

$$m_i\left(x_t, y_t, x_{t+1}, y_{t+1}\right) = \left[\frac{D_i^t(x_{t+1}, y_{t+1})}{D_i^t(x_t, y_t)} \times \frac{D_i^{t+1}(x_{t+1}, y_{t+1})}{D_i^{t+1}(x_t, y_t)}\right]^{1/2}, \qquad (4)$$

where $D_i^{t+1}(x_t, y_t)$ represents the input distance function of the production point (x_t, y_t) to the frontier, considering technology from period $t+1$. The first ratio of the right-hand side term measures the efficiency of the production point (x_{t+1}, y_{t+1}) to the efficiency of the production point (x_t, y_t), using period t technology. The second ratio measures the efficiency of the production point (x_{t+1}, y_{t+1}) to the efficiency of the production point (x_t, y_t), using period $t+1$ technology.

The distance functions can be calculated using four separate DEA linear programmes. The distance functions which use data and technology from the same time period can be computed from programmes such as (2). The distance functions which use production points and technologies from different time periods require a programme such as:

$$min_{\phi,\lambda}\phi \qquad (5)$$
$$s.t. - y_{it+1} + Y_t\lambda \geq 0,$$
$$\phi x_{it+1} - X_t\lambda \geq 0,$$
$$\lambda \geq 0,$$

where the first subscripts of y and x indicate the firm, while the second subscripts indicate the data time period. The subscripts of the matrices X and Y indicate the time period of the technology. Therefore (5) can be used to calculate $D_i^t\left(x_{t+1}, y_{t+1}\right)$.

The use of a Malmquist index of productivity growth is useful for benchmarking and this is reflected in the growing empirical literature. It introduces some dynamics into the efficiency analysis and allows to check for convergence. In addition, the Malmquist index can be further decomposed into a catching-up component (movement towards the frontier) and a technical change component (movement of the frontier). Another advantage of the Malmquist index which differentiates it from other productivity indices is that it does not require price information. In this study we will use a Malmquist productivity index to shed some light on the impact of privatisation.

4.2 Stochastic Frontier Analysis

Stochastic Frontier Analysis (SFA) is a parametric approach that uses statistical techniques to estimate a frontier and to estimate efficiency relative to the frontier. Differently from the deterministic statistical frontier approach, SFA allows the frontier to be stochastic (Lovell and Schmidt, 1988, p.20). The technique was first proposed by two papers, published nearly simultaneously – Meeusen and van den Broeck (1977) and Aigner, Lovell and Schmidt (1977) –, and has been extended by Schmidt and Lovell (1979), Jondrow et al. (1982), Cornwell, Schmidt and Sickles (1990), Kumbhakar (1990), and Battese and Coelli (1992, 1995), among others.

To illustrate the approach, we will consider the problem of estimating a parametric Cobb-Douglas production function, using data of a sample of N firms: [19]

$$ln(y_i) = x_i\beta - u_i,\ i = 1, 2..., N, \qquad (6)$$

where $ln(y_i)$ is the logarithm of the output for the ith firm; x_i is a $(K+1)$-row vector, whose first element is "1" and the remaining elements are the logarithms of the K input quantities used by firm i; β is a $(K+1)$-column vector of the parameters to be estimated; and u_i is a non-negative ramdom variable that represents technical inefficiency. Equation (6) expresses the deterministic frontier model. The model is deterministic because the production frontier is bounded above by the non-stochastic quantity, $exp(x_i\beta)$.

The original SFA models added another error component to the production function, to provide:

$$ln(y_i) = x_i\beta + v_i - u_i,\ i = 1, 2..., N, \qquad (7)$$

where the random error v_i is intended to capture measurement error and other random factors. It is usually assumed that $v_i's$ are independently and identically distributed (i.i.d.) normal variables with mean zero and variance σ_v^2, and are independent of the $u_i's$, which have exponential, half-normal or truncated normal i.i.d. distribution.[20] The technical efficiency of firm i is defined as:

$$TE_i = exp(-u_i) \qquad (8)$$

[19] As we did for DEA we draw the formulation and terminology from Coelli et al. (1998).

[20] How important are distributional assumptions to the estimation of efficiency? There is empirical evidence of the sensitivity of mean efficiencies to the distribution of v, but it is not so clear whether distributional assumptions are relevant to the ranking of individuals by their efficiency scores. See Kumbhakar and Lovell (2000), p. 90.

Now the model is no longer deterministic because the production frontier is bounded above by a stochastic quantity, $exp(x_i\beta + v_i)$. β and $u_i's$ can be estimated by maximum likelihood methods or by corrected ordinary least squares (COLS). Given that the maximum likelihood estimator is asymptotically more efficient than the COLS estimator, and that for finite samples there are situations in which the maximum likelihood estimator is found to be better than the COLS estimator, we will use maximum likelihood estimation in this paper.[21]

The greatest strength of SFA is the introduction of a stochastic error representing measurement errors or noise, and the attempt to separate this component from inefficiency effects. This contrasts with DEA, which attributes all deviations from the frontier to inefficiency. Therefore, whenever data is expected to be substantially influenced by measurement error or by random shocks, SFA should probably be preferred. In addition, SFA allows the estimation of standard errors and tests of hypothesis regarding the existence of inefficiency, the functional form of the frontier and the significance of explanatory factors on the shape of the frontier. SFA permits the inclusion of environmental variables (this can be done by modelling inefficiency effects as a function of these variables), and can accommodate both CRS and VRS specifications.[22] However, the procedure of separating the error component from inefficiency effects can be problematic. In the presence of outliers, SFA can fail to differentiate between companies' different performance and may find little inefficiency in the sample. A way to tackle this problem would be to submit the sample to a preliminary data analysis to identify the likely outliers and then to exclude them from the sample. SFA has other drawbacks: in order to select an appropriate functional form to be estimated, behavioural assumptions are required and need to be justified; SFA also requires the specification of the distribution of the inefficiency term; finally, the estimation requires a reasonable sample size.

We introduced the SFA framework using a production function as an example. However, as pointed out in Coelli and Perelman (1999), a production technology may be represented in many ways. In addition to the production function, it is possible to use SFA to estimate cost, profit, revenue and input or output distance functions. As previously presented in the context of DEA, the input distance function is defined by considering how much inputs can be contracted whereas outputs are held fixed.

We chose to estimate input distance functions motivated by various reasons. First, input distance functions can accommodate multiple outputs. Since our DEA models involve multiple outputs and we want to keep as much as possible comparability between the results of the two methods, input distance functions

[21] On the finite sample properties of COLS and maximum likelihood estimators for stochastic frontier functions, see Coelli (1995).

[22] We detail our procedure to model inefficiency effects at the end of this section, when we present the specifications for our SFA.

are the obvious choice. Second, input distance functions do not require price information. Third, input distance functions do not require behavioural assumptions, such as profit maximisation or cost minimisation, which would be difficult to justify in the context of the Brazilian electricity distribution sector in 1994.[23]

Two sets of functional specifications are used in this study – one for cross-section data and one for panel data. Coelli and Perelman (1999, p. 329) observe that the translog functional form for distance funtions may be preferred to the popular Cobb-Douglas form because of the latter's restrictive elasticity of substitution and scale properties. In order to derive our functional specifications we start with a general translog input distance function:[24]

$$lnD_i(x,y) = \beta_0 + \sum_{m=1}^{M} \beta_m lny_{mi} + \frac{1}{2}\sum_{m=1}^{M}\sum_{n=1}^{M} \beta_{mn} lny_{mi} lny_{ni} + \sum_{k=1}^{K} \alpha_k lnx_{ki} + \frac{1}{2}\sum_{k=1}^{K}\sum_{l=1}^{K} \alpha_{kl} lnx_{ki} lnx_{li} + \sum_{k=1}^{K}\sum_{m=1}^{M} \delta_{km} lnx_{ki} lny_{mi}, \qquad i = 1, ..., N, \qquad (9)$$

where x_{ki} denotes one of the K inputs for the ith firm, y_{mi} is one of the M outputs of the ith firm, $\beta' s$, $\alpha' s$ and $\delta' s$ are unknown parameters. Because the distance function as well as inputs and outputs refer to the same time period, we can omit the time subscript.

Assuming that the restrictions required for homogeneity of the distance function are satisfied, we arbitrarily choose one of the inputs, such as the Kth input, to obtain:

$$lnD_i(x/x_K, y) = \beta_0 + \sum_{m=1}^{M} \beta_m lny_{mi} + \frac{1}{2}\sum_{m=1}^{M}\sum_{n=1}^{M} \beta_{mn} lny_{mi} lny_{ni} + \sum_{k=1}^{K-1} \alpha_k lnx^*_{ki} + \frac{1}{2}\sum_{k=1}^{K-1}\sum_{l=1}^{K-1} \alpha_{kl} lnx^*_{ki} lnx^*_{li} + \sum_{k=1}^{K-1}\sum_{m=1}^{M} \delta_{km} lnx^*_{ki} lny_{mi}, \qquad (10)$$

where $x^* = x/x_K$.

We can express the previous equation as:

$$lnD_i(x/x_K, y) = TL(x/x_K, y, \alpha, \beta, \delta) \qquad (11)$$

Using homogeneity:

$$lnD_i(x/x_K, y) = ln(D_i(x,y)/x_K) = lnD_i(x,y) - lnx_K \qquad (12)$$

Hence

$$-ln(x_K) = TL(x/x_K, y, \alpha, \beta, \delta) - lnD_i(x,y) \qquad (13)$$

[23] Coelli (2000) adds another reason to prefer input distance functions over cost or production functions. "(...) the production function may suffer from simultaneous equations bias problems because the independent variables (inputs) are endogenous, while the dependent variable (output) is exogenous. However, in an input distance function the independent variables (outputs and input ratios) are exogenous, while the dependent variable (an input) is endogenous." Coelli (2000, p. 8)

[24] With respect to the terminology and derivations we draw on Coelli and Perelman (1999).

Observe that the term $lnD_i(x, y)$ can be interpreted as the unobservable technical inefficiency effect, u_i. Furthermore, in the context of SFA we must add a random error to account for measurement error and other stochastic factors. The final (VRS) expression for the single-input multiple-output translog model for the ith firm is as follows:

$$-ln(x_i) = \beta_0 + \sum_{m=1}^{M} \beta_m lny_{mi} + \frac{1}{2} \sum_{m=1}^{M} \sum_{n=1}^{M} \beta_{mn} lny_{mi} lny_{ni} + v_i - u_i, \qquad (14)$$

where x_i is the single (scalar) input for firm i, y_{mi} is one of the M outputs of the ith firm, $\beta's$ are unknown parameters to be estimated, v_i denotes a random disturbance term with i.i.d. $N(0, \sigma_v^2)$ distribution and u_i represents the (non-negative) technical inefficiency term, which can have half-normal, $N^+(0, \sigma_u^2)$, or truncated normal distribution, $N^+(\mu, \sigma_u^2)$, depending on whether inefficiency effects are explicitly modelled. We only model inefficiency effects when environmental variables are included; in this case, the mean efficiency, μ_i, is a function of these variables:

$$\mu_i = \delta_0 + \sum_{k=1}^{K} \delta_k z_{ki}, \qquad (15)$$

where $\delta's$ are unknown scalar parameters to be estimated, and $z's$ are the environmental variables.

We estimate each model (see the next section for our choice of models) for each available year (1994 and 2000) using the translog specification. Because of possible problems of multicollinearity among variables in the translog specification, we also estimate a loglinear function, which is as follows:

$$-ln(x_i) = \beta_0 + \sum_{m=1}^{M} \beta_m lny_{mi} + v_i - u_i \qquad (16)$$

In order to take full advantage or our time series and to investigate the dynamics of the industries, we also estimate panel data models. The derivation of the panel data specification is analagous to the cross-section case and we will not reproduce it. The panel data specification is as follows :

$$-ln(x_{it}) = \beta_0 + \gamma_{BR} D_{BR} + \gamma_{BRt} D_{BR} t + \sum_{m=1}^{M} \beta_m lny_{mit} + \frac{1}{2} \sum_{m=1}^{M} \sum_{n=1}^{M} \beta_{mn} lny_{mit} lny_{nit} +$$
$$\beta_t t + \sum_{m=1}^{M} \beta_{mt} lny_{mit} t + \frac{1}{2} \beta_{tt} t^2 + v_{it} - u_{it}, \qquad (17)$$

where $\gamma's$ are unknown parameters, D_{BR} is a country dummy that takes the value of 1 when the firm is from Brazil and 0 when the firm is from the U.S.A., and t is the time trend. The distance function now includes a country dummy variable, D_{BR}, to test for systematic differences in technology between Brazil and the U.S.A., a time trend, and an interaction between the country dummy and the time trend, to test for systematic differences in the rate of technological changes between the two countries. As before, we also estimate a loglinear version of the translog specification. In order to simplify the exposition for the panel data case, instead of estimating the parameters for all selected models, we concentrate on only two models – which nevertheless include all selected variables.

5 Data and Choice of Models

5.1 Choice of Models

The variables and models selected should reflect as much as possible the basic functions of the industry concerned. However, our review of the benchmarking literature showed that there is no consensus on how these functions should be translated into input or output variables. Our choice of variables was partly based on the most frequently used variables in academic benchmarking studies. Table 3 shows the frequency of the use of variables in selected academic benchmarking studies of distribution utilities.[25]

[25] Jamasb and Pollitt's (2001a) survey of the benchmarking literature reports numbers that are close to the ones we report here. Both their survey and ours identify as the most frequently used inputs network length, transformer capacity and labour. Both identify number of customers and units delivered as the most frequently used output variables. However, since we did not include regulatory studies in our frequency number, cost measures are reported as more frequently used in Jamasb and Pollit (2001a).

Inputs	Outputs
• *network length:*	• *number of customers:*
LV lines (km) (3)	LV customers (#) (3)
MV lines (km) (1)	HV customers (#) (2)
HV lines (km) (3)	M/ HV customers (#) (1)
total network length (9)	residential customers (#) (1)
• *transformer capacity:*	industrial customers (#) (1)
substation transformer capacity	total customers (#) (9)
HV/MV and MV/MV (MVA) (1)	• *units sold:*
substation trasformer capacity MV/LV	LV electricity sales (MWh) (2)
(MVA) (1)	HV electricity sales (MWh) (2)
(distribution) transformer capacity	residential electricity sales (MWh) (4)
(MVA) (9)	non-residential electricity sales (MWh) (2)
• *labour:*	industrial sales (MWh) (3)
employees (#) (6)	non-industrial sales (MWh) (1)
labour/ manpower (hours) (6)	commercial sales (MWh) (1)
	total electricity sales (MWh) (6)
service area (km^2) (1)	
customer density (# customers/ km^2)	service area (km^2) (3)
(1)	service reliability (sales/ losses (%)) (1)
industrial sales/ total sales (1)	total network length (km) (1)
losses (5)	line length 1-24 kV (km) (1)
maximum demand (1)	distance index (1)
transformers (1)	maximum demand (MW) (2)
total electricity sales (MWh) (2)	
residential sales to total sales ratio (1)	
OPEX ($) (1)	
TOTEX ($) (1)	
goods and services ($) (2)	
materials ($) (1)	
capital ($) (3)	
general expenses ($) (1)	
Environmental variables:	
network length (km) (1)	
losses (MWh) (1)	
load factor (average demand/ peak demand) (1)	
customer density (# customers/ # transformers) (1)	
consumption density (sales/ customer) (1)	
distance index (1)	

Note: Grifell-Tatjé and Lovell (2003), Resende (2002), Jamasb and Pollitt (2001b), Hattori (2001), Pardina and Rossi (2000), Kittelsen (1999), Førsund and Kittelsen (1998), Meibodi (1998), Burns and Weyman-Jones (1996), Bagdadioglu et al. (1996), Pollitt (1995), Kittelsen (1993), Hjalmarsson and Veiderpass (1992a, 1992b), and Weyman-Jones (1991) are the studies included here. We only included the academic studies on electricity distribution that explicitly classify the variables used into input, output or environmental variables. See Table 1 for more details on all academic studies reviewed.

Table 3: Frequency of The Use of Variables in Selected Studies

From a regulatory point of view, when selecting input and output variables it is important to consider the factors that affect the level of costs. Because the regulator is mainly concerned with assessing utilities in terms of cost efficiency, regulatory studies usually use monetary measures as inputs rather than physical values. Operating expenditures, capital expenditures and total expenditures are the preferred measures in benchmarking studies conducted by the regulator (See Table 2). The expression of different inputs in the same measure (monetary value) allows to assess different input configurations without an *ad-hoc* preference for any specific one. We use either operating expenditures (OPEX) or total expenditures (TOTEX) as input variables.[26] [27] Table 4 outlines the model specifications used in this study.

	Model 1	**Model 2**	**Model 3**
Inputs	OPEX	OPEX	OPEX
Outputs	total units (MWh) customers (#)	total units (MWh) customers (#) network length (km)	total units (MWh) customers (#)
Environmental variables			peak demand (MW) customer density residential ratio

	Model 4	**Model 5**	**Model 6**
Inputs	OPEX	TOTEX	TOTEX
Outputs	total units (MWh) customers (#) network length (km)	total units (MWh) customers (#)	total units (MWh) customers (#)
Environmental variables	peak demand (MW) customer density residential ratio		peak demand (MW) customer density residential ratio

Note: customer density is the number of customers per km of network, and residential is the ratio of number of residential customers to total number of customers.

Table 4: Preferred Models

Ideally we would like to have included a greater number of environmental factors, some of which were suggested in Subsection 4.1. Lack of available data prevented us from including more environmental variables. However, the selected variables incorporate two important factors that affect costs but are beyond management control: customer density and system configuration. We have experimented with several versions of these six models, but found highly correlated results.[28]

[26] As observed in a study prepared for the Dutch regulator: "(...) companies that are found to be inefficient on operating expenditure might simply be choosing to operate with a high labour, low capital structure. An operating expenditure-only benchmark might unfairly identify such company as inefficient (since it would be compared to companies that might choose to operate with a low labour, high capital structure)" (Frontier Economics, 2000, p. 6). Only a monetary measure of total costs as input allows to consider all possible trade-offs between different inputs.

[27] We define our measures of OPEX and TOTEX when we present our data in the next subsection.

[28] In particular, we checked the impact of using the break-up of customer numbers and sales

5.2 Data

This benchmarking study is based on data for 72 U.S. investor-owned utilities and 14 Brazilian distribution companies. Until 1994 all companies in the Brazilian sample were publicly-owned. The first privatisation took place in 1995 and by 1998 all companies in our sample had been privatised. Because our data refers to 1994 and 2000, we are able to incorporate into the analysis the change in ownership in the Brazilian distribution sector. Our panel is unbalanced and, as a consequence, the number of companies used varies across models. However, we kept a minimum of 81 companies, including at least 10 Brazilian distribution utilities in each model. The U.S. investor-owned utilities in our database account for approximately 28% of national sales to ultimate customers, and are spread over 40 states. The companies in the Brazilian sample are spread over nine states and four regions (out of a total of five), and correspond to approximately 54% of the national distribution market.[29]

U.S. data was gathered from two sources: the FERC (Federal Energy Regulatory Commission) Form No. 1 database and various editions of the Platts Directory of Electric Power Producers and Distributors.[30] The cost and sales data for Brazilian companies is based on annual reports, and most of the required technical data was collected during fieldwork. For some of the Brazilian companies that went through extensive restructuring before privatisation, more detailed information on assets break-up was required. This was provided by a number of policy documents on state-level electricity reforms and were supplemented by fieldwork. In order to harmonise the monetary values over time and country, these were converted into 1995 prices and then the values in Brazilian currency (Real) were converted into U.S. dollars using the purchasing power parity (PPP) factor for 1995.

Table 5 presents the descriptive statistics of the U.S. and Brazilian companies for 2000. We can observe some clear differences between the two samples. The U.S. companies are on average bigger than their Brazilian counterparts in terms of units delivered and peak demand, but the Brazilian distribution companies have to meet the demand of larger numbers of customers. This is due to a much higher consumption per customer in the U.S. market – the MWh consumption per customer is about five times larger in the U.S. sample than in the Brazilian sample. In order to supply on average a larger number of customers, Brazilian companies have to establish a larger distribution network. These facts are reflected on the expenditure per MWh, which is larger for the Brazilian sample, and on the expenditure per customer and per km of network,

into types of customers (e.g. residential, commercial, industrial, resale and other), but it was not significant.

[29] The market shares were computed for 2000. Sources: ANEEL (2001) and EIA (2001).

[30] The FERC data can be downloaded from the FERC website (http://rimsweb2.ferc.fed.us/form1viewer/).

which are, as expected, larger for the U.S. sample.

	U.S.A.			BRAZIL		
	total	mean	coefficient of variation	total	mean	coefficient of variation
Number of companies	72			14		
OPEX (mi US$ PPP 1995)	6,814.95	94.65	90.3 %	2,590.41	185.03	83.5 %
TOTEX (mi US$ PPP 1995)	15,338.65	213.04	93.8 %	4,646.51	331.89	87.4 %
Units delivered (GWh)	1,338,998	18,597	79.6 %	170,345	12,167	86.0 %
residential	325,171	4,516	83.2 %	46,182	3,299	99.8 %
non-resid.	1,013,827	14,081	82.4 %	124,164	8,869	85.4 %
Number of customers	35,902,262	498,643	82.9 %	25,089,484	1,792,106	68.8 %
Number resid. customers	31,438,684	436,648	84.6 %	21,939,461	1,567,104	71.6 %
Number non-resid. customers	4,463,578	61,994	76.4 %	3,150,023	225,002	55.5 %
residential ratio (number resid. customers/ total number customers)	-	0.87	3.6 %	-	0.86	5.7 %
Network length (km)	1,757,399	24,408	78.9 %	816,875	58,348	56.8 %
Peak demand (MW)	213,707	2,968	83.2 %	29,733	2,124	84.2 %
customer density (customer/ km of network)	-	24	74.0 %	-	32	43.1 %
OPEX/ MWh (US$/MWh)	-	6	58.68 %	-	16	29.19%
OPEX/ customer (US$/ customer)	-	198	27.79 %	-	98	20.23 %
OPEX/ km (US$/ km)	-	4,839	84.19 %	-	3,185	55.55%
TOTEX/ MWh (US$/ MWh)	-	13	51.76 %	-	29	37.40 %
TOTEX/ customer (US$/ customer)	-	426	30.52 %	-	174	27.96 %
TOTEX/ km (US$/ km)	-	10,569	81.05 %	-	5,751	59.80 %

Table 5: Summary Statistics of U.S.A. and Brazil Electricity Distribution (2000)

5.2.1 Cost Data

Because the only input variables we use are OPEX and TOTEX , it is important to ensure that they represent the costs of the same activities in the two samples and that they exclude the costs of all other non-distribution/ supply related businesses. Our OPEX should reflect only the operating costs of the distribution and supply businesses and therefore should exclude depreciation, transmission charges, purchases of electricity and taxes. For the U.S. dataset, OPEX consists of total operation and maintenance (O&M) distribution costs, customer service and informational expenses, customer accounts expenses, sales expenses, and adjusted administrative and general expenses. The administrative and general expenses were adjusted to reflect only the distribution and supply businesses. This was done by applying a correction factor to the total O&M administrative expenses. This correction factor was given by the ratio of wages and salaries paid in the distribution and supply related activities to total wages and salaries. Each account was directly taken from the FERC Form No. 1 files and includes the cost of labour, materials used and expenses incurred on each specific activity. For the Brazilian dataset, OPEX consists of labour, material and third party service contracts expenses, as reported in the income statement. For the financial year 1994 Brazilian companies were not required to report their accounts discriminated by business, and we had to adjust their income statements to exclude costs relative to generation, transmission and other businesses. This was done at the level of each individual account on the income statement.

Total expenditure consists of OPEX and capital expenditure (CAPEX). In contrast to OPEX, finding an appropriate measure for CAPEX is not so straightforward, especially for cross-country comparisons. The CAPEX measure used in this study is the distribution/ supply share of total revenues, net of total OPEX:[31]

$$CAPEX_{dist} = s_{dist.} \times (Revenue - OPEX_{total}), \qquad (18)$$

where $CAPEX_{dist}$ is the capital expenditure allocated for the distribution business, s_{dist} is the distribution share of total capital expenditure, $Revenue$ is the total sales revenue (including sales for resale) and $OPEX_{total}$ is the total operating expenditure of the company (including purchase power costs and transmission charges payments). s_{dist} is given by the share of distribution assets over total assets, where distribution assets include adjusted administrative assets (adjusted as before).

This measure has an obvious drawback – the comparison will be spurious if the rates of return on capital are significantly different. However, the feasible alternatives to our measure are not without problems. For instance, new annual investments, as used in Jamasb and Pollitt (2001b), are subject to cyclical fluctuations and for this reason might not reflect the value of capital stocks. Physical measures of the capital stock are the most widely used alternatives (See Section 3). As observed elsewhere (See Note 26), the use of monetary measures allows more flexibility in terms of input configuration and capital-labour mix. An interesting alternative, suggested by Jamasb and Pollitt (2001b), is to use the value of capital stocks and to work out the rental cost of the capital. This, however, requires compatible and accurate measures of capital value that may

[31] This measure relates to the concept of revenue efficiency. A revenue indirect measure of technical efficiency provides a measure of efficiency of input usage in the generation of at least a certain revenue level at given output prices. See formal definitions at Färe et al. (1994), pp. 128-152.

be difficult to obtain for cross-country analyses. Regulators have attempted to design standard measures that are a better approximation to capital costs – the Chilean regulator with its New Replacement Value of installations, the Dutch regulator with its standardised capital costs, and the UK regulator with its standard efficient investment costs. Unfortunately, even when this information is published, there is the issue of international data compatibility.

For both U.S. and Brazilian datasets capital expenditure was calculated as in (18), with only one difference – since 1994 assets are not discriminated by business for Brazilian companies, we used the s_{dist} calculated for 2000. However, for the Brazilian companies that went through extensive restructuring this procedure would not be reasonable and we resorted to individual company adjustments.

5.2.2 Technical Data

In contrast to accounting data, which has to be published in a standard format and is expressed in monetary values, technical data is less uniform and different variables are usually expressed in different units. International benchmarking complicates matters even more as definitions may vary and distribution systems are different. Considering our choice of variables, two technical variables had to be studied carefully: distribution network length and peak demand. Unfortunately network length is not reported by voltage and we had to resort to the way companies define their distribution network, given the limits established by the regulator. In Brazil network of voltage less than 230 kV was allowed to remain in the distribution utilities, which then classified their network in two categories: subtransmission and distribution network. In this study we only include the network classified as distribution network. A problem we found is that the cut-off voltage level between these two categories varies across companies reflecting different system configurations. However, we established during our fieldwork that in Brazil distribution network ranges from 220/ 127 V or 380/220 V to 13.8, 23.1 or 34.5 kV. For the U.S. dataset, although we only have the totals, the most common distribution voltages are 5, 15, 25 and 35 kV. Therefore, although the correspondence is not perfect, we believe that the values for the two datasets represent a similar range of network voltages.

With respect to peak demand, two slightly different definitions are used. Brazilian distribution utilities usually report peak load demand, while U.S. utilities report maximum simultaneous demand. Peak load demand is the maximum load during a specified period of time, and maximum simultaneous demand is the system's maximum load for an integrated period of time (usually 60-minute integration). The values produced can be different, but as the difference is not significant we use the values as reported by the companies to represent the same variable, which we denominate as 'peak demand'.

6 Results and Analysis

This section presents the findings of our efficiency analysis for the models outlined in Table 4.

6.1 Data Envelopment Analysis Models

We first present the technical efficiency scores using DEA and later introduce the results of a productivity analysis using Malmquist indices. Table 6 shows the average efficiency scores and the respective coefficients of variation for each country for two years, 1994 and 2000. The first year should reflect the scenario of the Brazilian distribution sector just before privatisation and the last year should capture post-privatisation performance.

Studying first efficiency over time, we find that for all models that use OPEX as input (models 1 to 4) there is an increase in technical efficiency scores from 1994 to 2000, for both the U.S. and Brazil. For the same models we also detect that the coefficient of variation for the Brazilian sample is substantially reduced from 1994 to 2000. This means that the efficiency gap among Brazilian companies has been closing-in since privatisation. The same is not always true for the U.S. sample. For the models that use TOTEX as input (models 5 and 6) the picture is different, with a decrease in average scores in the period for model 5. For model 6 there is a small increase in the scores from 1994 to 2000. These results indicate that there has been a consistent improvement in operating performance over time in both U.S. and Brazil distribution sectors, but the picture is more ambiguous when we include capital expenditure in the input measure and examine overall performance. This might suggest some substitution of capital for labour in the period, which demands substantial upfront investment. Besides, from our data analysis we observed that in 1994 capital expenditures (as expressed in equation (18)) were very small in Brazil (even negative for some companies), suggesting that the level of investment was extremely low just before privatisation. With privatisation the financial constraint is reduced and capital expenditures are at a much higher level in 2000.

Model		Model 1				Model 2				Model 3			
Technology		CRS		VRS		CRS		VRS		CRS		VRS	
Country		BR	US	BR	US	BR	US	BR	US	BR	US	BR	US
Mean	1994	0.544	0.412	0.710	0.531	0.576	0.443	0.722	0.567	0.691	0.616	0.796	0.701
	2000	0.763	0.545	0.822	0.622	0.797	0.606	0.848	0.665	0.794	0.708	0.899	0.790
Coefficient	1994	38.78	30.05	32.32	35.99	37.08	32.68	28.22	36.44	25.21	32.62	20.90	30.27
variation	2000	20.32	32.35	17.58	32.06	19.05	32.96	15.59	31.14	18.48	29.40	14.44	26.35
P-value	1994	0.002		0.003		0.008		0.018		0.261		0.177	
	2000	0.000		0.001		0.002		0.004		0.214		0.112	

Model		Model 4				Model 5				Model 6			
Technology		CRS		VRS		CRS		VRS		CRS		VRS	
Country		BR	US	BR	US	BR	US	BR	US	BR	US	BR	US
Mean	1994	0.693	0.616	0.796	0.701	0.711	0.410	0.857	0.508	0.773	0.596	0.895	0.692
	2000	0.807	0.714	0.907	0.794	0.362	0.304	0.702	0.467	0.882	0.616	0.954	0.718
Coefficient	1994	25.11	32.63	20.90	30.23	28.00	34.94	17.34	40.40	24.15	37.73	17.30	32.09
variation	2000	19.11	29.13	13.68	26.04	52.75	47.80	41.26	52.13	16.08	38.37	10.95	31.91
P-value	1994	0.255		0.179		0.000		0.000		0.020		0.006	
	2000	0.175		0.098		0.202		0.002		0.001		0.002	

Note: for model 1 the whole sample was used (86 companies); for model 2 CERJ and Light were excluded from the sample (84 companies); for models 3 and 4 CERJ, Light, AES Sul and RGE were excluded from the sample (82 companies); for model 5 Tampa was excluded from the sample (85 companies); for model 6 Tampa, CERJ, Light, AES Sul and RGE were excluded from the sample (81 companies).

Table 6: DEA Results

Comparing Brazilian and U.S. average efficiency scores, we observe that for all models and for all years Brazil performs better. In order to test how significant is this difference, we perform a hypothesis test of the difference in the sample means. Table 6 shows the two-tailed p-values of the test. The null hypothesis states that there is no difference in means, and if the p-value is larger than the significance level we cannot reject it. In three of the six models (models 1, 2 and 6) the test rejects the null at a 5% significance level, which means that Brazilian companies are significantly more efficient than U.S. investor-owned utilities. In model 5 the evidence is ambiguous, while for models 3 and 4 we cannot reject the null. Therefore, we cannot conclude that the Brazilian sample statistically significantly outperforms its U.S. counterpart irrespective of model.

In order to have a better grasp of these results, we further study the relationship between model specification and efficiency scores. First, concentrating on the OPEX models, we observe that in the models where there are no environmental variables (models 1 and 2) Brazilian companies are significantly more efficient than U.S. utilities. This is due to the fact that while Brazilian companies are less efficient than U.S. companies in terms of OPEX per MWh distributed, they are much more efficient in terms of OPEX per number of customers and OPEX per km of network. However, if we include environmental variables in the models (models 3 and 4) the difference in scores, although still favourable for Brazilian companies, is not statistically significant. This stems from the fact that in these models the difference between the two systems is at least partially incorporated. In particular, in models 3 and 4 customer density, which is on average much lower in the U.S. sample, is considered beyond management control. Second, studying the results of the TOTEX models, Brazilian companies are statistically more efficient on average than their U.S. counterparts for all specifications, with the exception of the model 5 CRS specification for the year 2000. The main driver of better results for Brazilian companies is their significantly lower TOTEX per customer.

6.1.1 Malmquist DEA Index Results

Here we discuss productivity change over time using a Malmquist index. As pointed out in Coelli et al. (1998, p. 224), a Malmquist index may not correctly measure productivity change if VRS is assumed. Therefore, we will impose CRS technology for the computation of Malmquist indices. Table 7 presents the main results.

1994-2000	Model 1		Model 2		Model 3		Model 4		Model 5		Model 6	
	BR	US	BR	US	BR	US	BR	US	BR	US	BR	US
Mean	1.435	1.386	1.416	1.381	1.412	1.319	1.406	1.318	0.697	1.327	0.798	1.238
Coeff. variation	22.16%	23.35%	23.29%	24.47%	19.07%	24.74%	20.07%	24.66%	36.45%	27.27%	22.73%	27.24%
Productivity change	43.45%	38.61%	41.60%	38.08%	41.24%	31.86%	40.57%	31.78%	-30.3%	32.69%	-20.2%	23.81%
Average annual productivity change	5.29%	4.77%	5.10%	4.72%	5.06%	4.03%	4.98%	4.02%	-5.03%	4.12%	-3.17%	3.10%
P-value	0.609		0.738		0.388		0.419		0.000		0.003	

Table 7: Malmquist DEA Index Results – CRS Technology

We start by examining the mean values of the Malmquist index for Brazilian and U.S. companies. Numbers greater than one indicate productivity growth. Focusing first on the OPEX models, we observe that the computed indices show a substantial productivity growth from 1994 to 2000. Average productivity changes range from 31.78% to 43.45%, which translated into annual averages is 4% and 5.3%, respectively. There are especially large values for individual productivity growth rates, with companies reaching as high as a 206.7% productivity improvement – however, there are also companies that experience productivity regress. Comparing Brazilian and U.S. performance, the direction of changes in Malmquist indices is the same for both samples, but the magnitude of productivity growth is on average higher for Brazilian companies. Nevertheless, the difference in productivity growth between Brazilian and U.S. companies over the whole period is not statistically significant, as indicated by the computed p-values. This result indicates that the impact of privatisation on operating performance relative to the U.S. benchmark is positive, but not statistically significant.

Examining the results of the TOTEX models, we detect a difference in the direction of change in Malmquist indices between Brazilian and U.S. companies. U.S. companies experience productivity growth, whereas Brazilian companies suffer, on average, productivity regress. This difference in performance is reflected in the computed p-values, and we now reject the null hypothesis of no difference in sample means. This, taken together with our previous analysis of DEA results, suggests that although Brazilian companies start at a higher efficiency level, the difference in performance is reduced over time. This result should be considered with caution. First, the increase in investment when not accompanied by a proportional increase in outputs reduces the index. However, as we observed before, the level of investment in Brazilian distribution utilities was extremely low before privatisation. Investment levels before privatisation were considered insufficient to ensure the expansion of rural electrification and the continuous improvement in quality. Therefore, the investment recovery after privatisation, although negatively reflected on Malmquist DEA indices, is a positive impact of privatisation. Over time we expect that the impact of this investment surge on efficiency will be at least partially reflected in the indices. Second, significant redundancy programmes that took place after privatisation indicate that Brazilian companies experienced a higher rate of substitution of capital for labour in the period. Given the importance of sunk capital costs in the ESI and of redundancy programmes costs, both which immediately inflate current expenditures, we also expect the efficiency effects of this process to become visible over time. Finally, due to the lack of suitable data our analysis does not incorporate quality of service. As a consequence, the improvements in quality fostered by investment are not included, what probably underestimates the benefits of privatisation.

6.2 Stochastic Frontier Analysis Models

We present and discuss results from two sets of models: the ones that use only cross-section data, and the ones that use panel data.

6.2.1 Cross-Section Models

In order to keep comparability between our cross-section SFA models and the DEA models, we use the same specification of input, output and environmental variables, but now within the input distance function framework described in Subsection 4.2. Therefore, we estimate our six models using both loglinear (LL) and translog (TL) specifications, for both 1994 and 2000. The maximum likelihood estimates are presented in Tables 8 and 9. We also include ordinary least squares (OLS) estimates in order to test for the existence of technical inefficiency.[32]

Studying the coefficient estimates associated with the outputs, we observe that there is a great variation in significance across models, with LL models exhibiting three β coefficients significant at 5%. Because the exclusive analysis of t-ratios can be deceptive, we use the Likelihood Ratio test to decide on the most appropriate model specification.[33] The results of the Likelihood Ratio tests for model specification are reproduced at the bottom of each table. For 2000 data the TL specification is preferred, but for 1994 data there is no clear preferrence.

[32] We do not report the results rejected by the FRONTIER programme, which is the software used in the estimation. FRONTIER generates a warning whenever the maximum likelihood function value is less than that obtained using OLS.

[33] The likelihood ratio is defined as:
$\varphi = \frac{\hat{L}_R}{\hat{L}_U}$, where $\hat{L}_R$ and $\hat{L}_U$ are the likelihood functions evaluated at the constrained and uncontrained maximum likelihood estimates, respectively. The distribution of $\lambda \equiv -2ln\varphi$ is chi-squared, with degrees of freedom equal to the number of restrictions imposed. According to the Likelihood Ratio Test, the null hypothesis is rejected if the calculated value exceeds the appropriate critical value from the chi-squared tables.

1994	Model 1		Model 2			Model 3			Model 4			Model 5		Model 6		
	OLS	LL	OLS	LL	TL	OLS	LL	TL	OLS	LL	TL	OLS	LL	OLS	LL	TL
Intercept β_0	-5.24** (0.534)	-5.01** (0.609)	-15.49 (9.883)	-4.8** (0.615)	-13.19 (10.02)	-17.44** (7.590)	-5.10** (0.877)	-16.80** (8.108)	-5.40** (0.532)	-5.01** (0.801)	-12.65** (1.00)	-4.47** (0.596)	-4.21** (0.717)	-8.19 (7.826)	-2.91** (1.358)	-9.21 (7.667)
β_1	-0.26** (0.048)	-0.27** (4.849)	0.08 (1.350)	-0.2** (0.050)	-0.22 (1.387)	0.61 (1.123)	-0.22** (0.055)	0.61 (1.139)	-0.22** (0.050)	-0.22** (0.055)	-0.03 (0.567)	-0.67** (0.054)	-0.68** (0.054)	-1.30 (1.157)	-0.67** (0.082)	-1.18 (1.058)
β_2	-0.68** (0.472)	-0.68** (0.046)	-0.42 (1.418)	-0.69** (0.067)	-0.55 (1.352)	0.11 (0.764)	-0.73** (0.047)	0.08 (0.727)	-0.73** (0.065)	-0.78** (0.083)	-0.88 (0.845)	-0.27 ** (0.053)	-0.27** (0.051)	1.01 (0.787)	-0.38** (0.060)	1.14 (0.739)
β_3			1.18 (1.315)	0.03 (0.054)	1.44 (1.351)	0.15 (0.112)		0.149 (0.123)	-0.00 (0.052)	0.05 (0.071)	1.53* (0.842)			0.49** (0.115)		0.5** (0.113)
β_4			0.18 (0.127)		0.20 (0.123)	0.23* (0.118)		0.23* (0.125)			0.19** (0.092)			0.55** (0.121)		0.57** (0.122)
β_5			-0.01 (0.272)		-0.05 (0.275)	-0.24** (0.097)		-0.24** (0.103)			0.61 (0.248)			-0.54** (0.100)		-0.57** (0.097)
β_6			-0.04 (0.117)		-0.04 (0.111)						-0.05 (0.083)					
β_7			-0.11 (0.140)		-0.08 (0.148)						-0.12 (0.131)					
β_8			-0.17 (0.109)		-0.21* (0.120)						-0.16 (0.099)					
β_9			0.16 (0.181)		0.18 (0.175)						0.12 (0.147)					
Intercept δ_0							-9.23 (22.18)	-4.52 (11.68)		-5.30 (11.52)	-1.13 (2.642)				0.35 (0.296)	-3.54 (3.377)
δ_1 (peak)							-0.00 (0.000)	-0.00 (0.000)		-0.00 (0.000)	-0.00 (0.000)				-0.00 (0.000)	-0.00 (0.000)
δ_2 (customer density)							-0.00 (0.017)	0.01 (0.021)		-0.01 (0.019)	-0.01 (0.011)				-0.00 (0.002)	-0.00 (0.002)
δ_3 (resid. ratio)							9.93 (23.14)	5.04 (12.36)		5.99 (12.14)	1.99 (3.055)				-0.03 (0.056)	4.39 (3.687)
σ^2	0.089	0.119* (6.474)	0.08	0.14** (0.057)	0.12** (0.054)	0.07	0.28 (0.519)	0.23 (0.354)	0.08	0.21 (0.283)	0.15* (0.077)	0.11	0.14* (0.085)	0.08	0.15** (0.044)	0.12** (0.06)
γ		0.436 (0.577)		0.56 (0.377)	0.59 (0.391)		0.85** (0.855)	0.83** (0.267)		0.83** (0.215)	0.77** (0.18)		0.40 (0.649)		0.59** (0.232)	0.58** (0.263)
LLF	-16.719	-16.663	-10.330	-16.629	-10.177	-6.334	-8.746	-4.544	-10.722	-8.448	-2.665	-25.671	-25.624	-8.573	-20.830	-6.644
λ				12.91			8.40			11.57					28.37	
χ^2 critical (5%)				12.59			7.81			12.59					7.81	
Decision: LL or TL?		LL		TL			TL			LL			LL		TL	
λ	0.11		0.31			3.58			4.55			0.09		3.86		
χ^2 critical (5%)	3.84		3.84			11.07			11.07			3.84		11.07		
Decision: OLS or ML?	OLS		OLS			OLS			OLS			OLS		OLS		

Notes: ** significant at 5%; * significant at 10%; standard errors in parentheses;
the TL column corresponds to maximum likelihood estimates for the TL specification;
the LL cdumn corresponds to maximum likelihood estimates for the LL specification; ML stands for maximum likelihood estimation.

Table 8: SFA Models – 1994 Cross-section Data

2000	Model 1			Model 2			Model 3			Model 4			Model 5		Model 6		
	OLS	LL	TL	OLS	LL	TL	OLS	LL	TL	OLS	LL	TL	OLS	OLS	OLS	LL	TL
Intercept β_0	-0.94	-5.30**	0.51	1.78	-5.22**	1.98	0.69	-6.09**	5.89*	4.44	-6.11**	4.73**	-5.42**	-3.97	-1.24	-6.02**	-3.78
	(7.387)	(0.458)	(6.872)	(9.329)	(0.480)	(7.712)	(7.360)	(0.564)	(2.949)	(9.194)	(0.614)	(0.996)	(0.633)	(9.031)	(8.241)	(0.737)	(4.02)
β_1	-1.95*	-0.23**	-2.23*	-2.32*	-0.23**	-1.69	-2.02*	-0.18**	-3.12**	-2.49*	-0.18**	-2.52**	-0.34**	-1.61	-1.58	-0.25**	-
	(1.138)	(0.037)	(1.121)	(1.326)	(0.038)	(1.063)	(1.142)	(0.039)	(0.568)	(1.300)	(0.039)	(0.703)	(0.056)	(1.390)	(1.277)	(0.057)	1.576**
																	(0.693)
β_2	0.72	-0.68**	0.90	-0.16	-0.71**	-1.54	0.54	-0.67**	1.12**	-0.53	-0.53**	-0.53	-0.603**	0.72	0.22	-0.66**	-0.675
	(0.749)	(0.036)	(0.735)	(1.530)	(0.065)	(1.58)	(0.775)	(0.042)	(0.359)	(1.503)	(0.088)	(0.831)	(0.053)	(0.913)	(0.866)	(0.049)	(0.806)
β_3	0.39**		0.39**	1.21	0.05	1.951	0.40**		0.45**	1.42	-0.18	1.43		0.48**	0.46**		0.343**
	(0.116)		(0.116)	(1.580)	(0.063)	(1.475)	(0.117)		(0.082)	(1.548)	(0.108)	(0.906)		(0.142)	(0.130)		(0.116)
β_4	0.31**		0.28**	0.42**		0.35**	0.32**		0.25**	0.43**		0.38		0.5**	0.49**		0.38**
	(0.104)		(0.109)	(0.130)		(0.149)	(0.105)		(0.106)	(0.128)		(0.494)		(0.127)	(0.118)		(0.129)
β_5	-0.34**		-0.33**	0.31		0.33	-0.34**		-0.32**	0.4		0.18		-0.49**	-0.46**		-0.31**
	(0.091)		(0.093)	(0.305)		(0.577)	(0.091)		(0.085)	(0.303)		(0.8)		(0.112)	(0.102)		(0.116)
β_6				-0.03		-0.57				0.00		-0.11					
				(0.174)		(0.28)				(0.170)		(0.551)					
β_7				-0.30**		-0.23				-0.31**		-0.3					
				(0.135)		(0.155)				(0.133)		(0.578)					
β_8				-0.07		-0.10*				-0.06		0.01					
				(0.119)		(0.554)				(0.120)		(0.275)					
β_9				0.02		0.02				-0.04		-0.04					
				(0.224)		(0.382)				(0.222)		(0.677)					
Intercept δ_0								-0.83	-1.28		-1.45	0.05				-1.37	-5.37**
								(1.380)	(0.979)		(1.579)	(0.991)				(5.885)	(2.01)
δ_1 (peak)								0.00	0.00		0.00	0.00				-0.00	-0.00**
								(0.000)	(0.000)		(0.000)	(0.000)				(0.004)	(0.000)
δ_2 (customer density)								0.00	-0.00		0.01*	-0.00				0.00	0.00
								(0.002)	(0.005)		(0.004)	(0.025)				(0.002)	(0.003)
δ_3 (resid. ratio)								1.25	1.18		1.83	0.05				0.02	5.911**
								(1.565)	(1.152)		(1.765)	(0.994)				(0.054)	(2.146)
σ^2	0.07	0.16**	0.14**	0.07	0.17**	0.20**	0.07	0.10**	0.10**	0.07	0.11**	0.13	0.124	0.10	0.08	0.29	0.08**
		(0.045)	(0.037)		(0.046)	(0.025)		(0.031)	(0.027)		(0.032)	(0.109)				(0.741)	(0.017)
γ		0.84**	0.83**		0.85**	1.00**		0.93**	1.00**		0.96**	1.00**				0.77	0.15
		(0.119)	(0.120)		(0.116)	(0.000)		(0.077)	(0.002)		(0.051)	(0.081)				(0.586)	(0.277)
LLF	-4.376	-9.605	-2.639	-4.546	-9.924	2.536	-3.101	-6.767	2.237	-2.334	-5.629	4.200	-30.536	-21.180	-11.991	-19.922	-6.657
λ		13.93			14.78			18.01			19.66					26.53	
χ^2 critical (5%)		7.81			12.59			7.81			12.59					7.81	
Decision: LL or TL?		TL			TL			TL			TL			n.a.		TL	
λ	3.474			14.163			10.677			13.068			18.712		10.669		
χ^2 critical (5%)	3.84			3.84			11.07			11.07			7.81		11.07		
Decision: OLS or ML?	OLS			ML			OLS			ML			OLS loglinear or OLS translog? translog		OLS		

Notes: ** significant at 5%; * significant at 10%; standard errors in parentheses;
the TL column corresponds to maximum likelihood estimates for the TL specification;
the LL column corresponds to maximum likelihood estimates for the LL specification; ML stands for maximum likelihood estimation

Table 9: SFA Models – 2000 Cross-section Data

Once the model specification is chosen, we consider the question of whether there is technical inefficiency in the sample. We first focus on the estimated values of γ, which show how much of the total residual variation is due to the inefficiency effect. For seventeen out of twenty estimations γ is greater than 0.5, and for fourteen estimations it is significantly greater than 0.5.[34] In the models in which environmental variables are included as factors influencing technical efficiency (models 3, 4 and 6), the estimated coefficients of these variables (δ) are often close to zero and not significant. This, taken together with the results on γ, imply that although the individual coefficients of the environmental variables are not particularly significant, their significance as a group of coefficients might be relevant. However, we cannot be certain of the existence of a technical inefficiency effect before testing maximum likelihood estimates against the corresponding OLS estimates, which do not include a technical inefficiency error term. These Likelihood Ratio tests are reproduced at the bottom of the tables, just below the specification tests. With two exceptions (models 2 and 4 for 2000 data), the tests fail to reject the restricted model. Therefore, the results of our cross-section analysis imply that a model that accounts for technical inefficiency (at least in the way we modelled technical inefficiency here) is not warranted and an OLS specification should be preferred. Unfortunately this indicates that all error can be considered pure noise, preventing a more meaningful benchmarking exercise in this context.

Table 10 presents a summary of the technical efficiency scores derived from SFA. For most models Brazilian companies perform slightly better than the U.S. companies (with the exception of model 6 for 1994 data), but the p-values show that the differences are not statistically significant (with the exception of model 5 for 1994 data).

Model		Model 1		Model 2		Model 3		Model 4		Model 5		Model 6	
Country		BR	US	BR	US	BR	US	BR	US	BR	US	BR	US
Mean	1994	0.848	0.840	0.820	0.818	0.855	0.838	0.835	0.803	0.864	0.827	0.840	0.859
	2000	0.818	0.770	0.720	0.701	0.743	0.660	0.778	0.685	n.a.	n.a.	0.890	0.866
Coefficient	1994	6.36	6.25	10.03	8.95	5.91	11.72	11.06	14.12	3.75	6.38	14.32	10.59
variation	2000	10.23	15.89	26.78	25.18	16.19	25.64	18.13	25.34	n.a.	n.a.	13.03	14.14
P-value	1994	0.603		0.932		0.597		0.393		0.013		0.572	
	2000	0.161		0.722		0.138		0.111		n.a.		0.551	

Note: All results for VRS specification.

Table 10: SFA Technical Efficiency Scores – Cross-section Data

Comparing the Results of the Two Methodologies. As we have pointed out in our discussion of methods for efficiency measurement, all methods have weaknesses and for this reason efficiency estimates should be interpreted with caution. Therefore some sensitivity analysis is advisable. The comparison of efficiency scores generated by different methods can help identifying what drives inefficiency. In this paper, efficiency scores generated from DEA and SFA using

[34] $\gamma = \frac{\sigma_u^2}{\sigma_v^2+\sigma_u^2}$

the same specification of inputs, outputs and environmental variables allow for a comparison between the performance of the Brazilian and the U.S. electricity distribution sectors. In Table 11 the mean technical efficiency scores for Brazil, U.S. and for the whole sample are presented.

		Brazil		U.S.A.		All Sample		Significant Difference?	
		DEA	SFA	DEA	SFA	DEA	SFA	DEA	SFA
1994	Model 1	0.710	0.848	0.531	0.840	0.560	0.841	Yes	No
	Model 2	0.722	0.820	0.567	0.818	0.589	0.818	Yes	No
	Model 3	0.796	0.855	0.701	0.838	0.712	0.840	No	No
	Model 4	0.796	0.835	0.701	0.803	0.713	0.807	No	No
	Model 5	0.857	0.864	0.508	0.827	0.566	0.833	Yes	Yes
	Model 6	0.895	0.840	0.692	0.859	0.717	0.856	Yes	No
2000	Model 1	0.822	0.818	0.622	0.770	0.655	0.778	Yes	No
	Model 2	0.848	0.720	0.665	0.701	0.691	0.703	Yes	No
	Model 3	0.899	0.743	0.790	0.660	0.804	0.670	No	No
	Model 4	0.907	0.778	0.794	0.685	0.808	0.697	No	No
	Model 5	0.702	n.a.	0.467	n.a.	0.506	n.a.	Yes	n.a.
	Model 6	0.954	0.890	0.718	0.866	0.747	0.869	Yes	No

Notes: All models use VRS technology; significance at 5%.

Table 11: Mean Efficiency Scores: DEA x SFA – Cross-section Data

We expected the means of the SFA estimated efficiency scores to be larger than the computed DEA scores, and the opposite to be true with respect to the variance of the efficiency scores.[35] The estimated SFA scores are larger (for the whole sample) than DEA scores for models 1, 2 and 5 and, because the variance (for the whole sample) is smaller, the difference between Brazilian and U.S. scores is statistically significant for DEA, but may not be always significant for SFA. That is, for both methods Brazilian companies outperform their U.S. counterparts in models 1, 2 and 5 – but the difference in performance only remains significant in SFA for model 5 (1994 data).

We singled out models 3, 4 and 6 because they include environmental variables. The way environmental variables are modelled differs between methods and, as a consequence, the cross-method comparison is not so straightforward. In our DEA models the environmental variables are introduced as non-discretionary variables. Therefore the linear programme holds them fixed while seeks contraction in the other variables. In contrast, in SFA these variables are modelled as regressors of the mean of the technical inefficiency effect distribution. However, the results of the models that include environmental variables show some robustness to the method chosen, with DEA and SFA conclusions for models 3 and 4 in agreement over the significance of the difference between Brazil and U.S. mean efficiency scores.

[35] This is because DEA includes the residuals in the efficiency measure, when some of them should have been attributed to measurement error or statistical noise. In addition, SFA might not always be able to separate error from inefficiency effects, leading to an upward bias in the scores. A more detailed discussion of these issues can be found in Sarafidis (2002), pp. 16-17.

Finally, we focus on how efficiency scores and rank order correlate across different methods. Tables 12 and 13 present the relevant efficiency score and rank order correlations, respectively.[36] As we expected, the higher correlations occur in the models that do not include environmental variables. For models 3, 4 and 6 SFA and DEA efficiency scores are not so well correlated. The treatment given to environmental variables appears to be more relevant than method choice *per se* for consistency among the scores. From the point of view of the regulator, this sensitivity to model specification is not reassuring. A way to tackle this problem would be to follow the benchmarking study by a more detailed analysis on how environmental variables affect efficiency (including an individual comparison between the inefficient firms and their peers).

	DEA-1		DEA-2		DEA-3		DEA-4		DEA-5		DEA-6	
year	1994	2000	1994	2000	1994	2000	1994	2000	1994	2000	1994	2000
SFA-1	0.583**	0.709**										
SFA-2			0.567**	0.678**								
SFA-3					0.460**	0.504**						
SFA-4							0.398**	0.495**				
SFA-5									0.704**	n.a.		
SFA-6											0.386**	-0.195

Notes: All models use VRS technology; ** significant at 1%; correlations computed using SPSS statistical package (Pearson correlation coefficient)

Table 12: Efficiency Score Correlations

	DEA-1		DEA-2		DEA-3		DEA-4		DEA-5		DEA-6	
year	1994	2000	1994	2000	1994	2000	1994	2000	1994	2000	1994	2000
SFA-1	0.698**	0.737**										
SFA-2			0.643**	0.660**								
SFA-3					0.466**	0.463**						
SFA-4							0.430**	0.453**				
SFA-5									0.795**	n.a.		
SFA-6											0.439**	-0.153

Notes: All models use VRS technology; ** significant at 1%; correlations computed using SPSS statistical package (Spearman's rank correlation).

Table 13: Rank Order Correlations

6.2.2 Panel Data Models

In order to take full advantage of the time series data available and, more importantly, to capture the impact of privatisation, we now estimate panel data models. As pointed out in Coelli et al. (1998, p. 202), panel data has some advantages over cross-section data in the estimation of stochastic frontiers. First,

[36] The correlation across different models is not attempted here because the samples actually used differ slightly from model to model (but remain inaltered across different methods for the same model specification).

the availability of a greater number of observations generally implies better estimates. Second, panel data allows the simultaneous investigation of both technological change and technical efficiency change over time. The technical inefficiency effects, as before, are represented by one of the error terms, whereas technological change is now defined in the parametrisation of the model by the inclusion of a time trend.

We concentrate on the panel data versions of models 4 and 6, which include all our variables of interest. In addition to the time trend, we introduce a country dummy, which captures a possible systematic difference in technology between the Brazil and the U.S.A.. Because we wanted to check the possibility of a difference in the rate of technological change between the two countries, we also include an interaction between the time trend and the country dummy. The specifications used allow VRS. The estimated parameters and relevant tests are reported in Table 14. As in the previous analysis, we will first compare the TL with the LL specification, and then test the preferred specification against the corresponding OLS model.

First we discuss the results of the models that use OPEX as input. We observe that eleven out of sixteen coefficients are statistically significant at the 5% level of confidence (one additional coefficient is significant at the 10% level), what means the TL specification appears to have a very good fit.[37] However, two unusual estimates suggest further analysis into specification. First, the estimated γ is not statistically different from one, which suggests that there are no measurement or random errors in the function. Second, the value of the maximum likelihood function is very small. This is reflected in the result of the Likelihood Ratio test, which cannot reject the null of LL specification. The LL seems to have a good fit, with four out of six estimates statistically significant at the 5% level of confidence. The estimated technological change is statistically significant showing progress in both countries. The country dummy is significant, what suggests a systematic difference in technology between the two countries. The δ coefficients are statistically insignificant, but γ is significant and estimated as 83%, suggesting potential for incentive regulation. Following we ask whether there is technical inefficiency in the industry by performing a Likelihood Ratio test. Once again we cannot reject the null and the model can be better estimated by a deterministic frontier. The OLS estimation shows that the number of customers, the time trend and the country dummy have statistically significant coefficients.[38]

We now look at the results of the models that use TOTEX as input. For

[37] We also estimated the same model including an interaction variable (time * D_{BR}), but, as it was not significant, we dropped it from the OPEX models analysis.

[38] The fact that the sales coefficient is not significant, whereas number of customers coefficient is, suggests a multicollinearity among the variables, as number of customers and total sales tend to be highly correlated.

the TL specification, five out of ten coefficients are statistically significant at the 5% level of confidence (one additional coefficient is significant at the 10% level), what means that again we have a model with a good fit. However, the value of the maximum likelihood function is extremely small, and as before, the estimated γ is not statistically different from one. We perform a Likelihood Ratio test, using the LL specification as the null hypothesis, and the null cannot be rejected. The LL model estimates show a very good fit, with five out of six coefficients statistically significant at 5%. Total sales is the only variable which does not have a significant coefficient, but that might be the result of multicollinearity with number of customers. In this specification the interaction variable (time * D_{BR}) is significant, suggesting that there is a significant difference in the rate of technological change between the two countries. The signals of the coefficients suggest that Brazil performs systematically better than the U.S.A., but the rate of technological change has been faster for the U.S.A.. Because the γ and δ coefficients are statistically insignificant and small, we test for the existence of technical inefficiency effects. The computed value of our likelihood ratio is very close to the critical chi-squared value, so we cannot rule out any of the two specifications.

Dependent variable	- OPEX			- TOTEX		
Specification	TRANSLOG	LOGLINEAR	OLS	TRANSLOG	LOGLINEAR	OLS
Intercept β_0	4.08** (1.01)	-6.20** (0.51)	-6.34** (0.37)	23.27** (1.00)	-6.86** (0.47)	-6.21** (0.35)
β_1 (ln sales)	-1.84** (0.77)	-0.02 (0.06)	-0.02 (0.06)	-1.76* (0.99)	-0.03 (0.06)	-3.07 (0.06)
β_2 (ln customers)	0.79 (0.83)	-0.93** (0.08)	-0.92** (0.07)	1.11 (0.99)	-0.91** (0.07)	-0.97** (0.06)
β_3 (ln length)	0.33 (1.00)	0.01 (0.06)	-0.00 (0.04)			
β_4 (0.5*(ln sales)^2)	2.01** (0.51)			0.44 (0.86)		
β_5 (0.5*(ln customers)^2)	4.09** (1.23)			0.50 (0.94)		
β_6 (0.5*(ln length)^2)	-0.39 (0.28)					
β_7 (ln sales * ln customers)	-2.99** (0.74)			-0.56 (0.60)		
β_8 (ln sales * ln length)	0.86** (0.30)					
β_9 (ln customers * ln length)	-0.73 (0.54)					
β_{10} (time trend)	-11.23** (1.29)	0.24** (0.04)	0.26** (0.04)	63.83** (1.00)	0.16** (0.05)	0.16** (0.05)
β_{11} (ln sales * time)	-0.69* (0.37)					
β_{12} (ln customers * time)	1.34** (0.44)					
β_{13} (ln length * time)	-0.87** (0.27)					
β_{14} (0.5 * time^2)	9.53** (1.60)			-2.42** (0.72)		
β_{15} (BR dummy)	-2.10** (0.81)	0.47** (0.13)	0.48** (0.13)	-2.39** (0.84)	1.92** (0.42)	2.01** (0.23)
β_{16} (time*BR dummy)				15.74** (1.00)	-0.61** (0.29)	-0.62** (0.13)
Intercept δ_0	-115.40** (1.09)	-2.77 (5.27)		-0.25 (1.00)	-0.05 (11.34)	
δ_1 (peak)	0.00 (0.00)	0.00 (0.00)		-0.04 (1.00)	0.00 (0.00)	
δ_2 (customer density)	0.06 (0.06)	-0.00 (0.01)		-0.05 (1.00)	0.00 (0.00)	
δ_3 (resid. ratio)	-99.54 (1.02)	2.91 (5.25)		-0.11** (0.00)	0.06 (11.971)	
σ^2	604.95** (1.48)	0.18 (0.16)	0.07	16.997** (1.00)	0.07* (0.04)	0.07
γ	1.00** (0.00)	0.83** (0.14)		1.00** (0.00)	0.16 (1.47)	
LLF	-275.79	-11.01	-14.35	-717.51	-8.38	-13.91
λ	-529.56			-1.418.26		
χ^2 critical (5%)	18.31			9.49		
Decision	TL OR LL? Accept LL			TL or LL? Accept LL		
λ		6.68			11.06	
χ^2 critical (5%)		11.07			11.07	
Decision		LL or OLS? Accept OLS			No clear result	

Notes: ** significant at 5%; * significant at 10%; standard errors in parentheses; for the OPEX models CERJ, Light, AES Sul and RGE were excluded from the sample (82 companies), for the TOTEX models Tampa was excluded as well (81 companies).

Table 14: SFA Results – Panel Data

Finally we consider the efficiency scores generated by SFA using panel data. The SFA estimation allows for a comparison of efficiency scores between Brazilian and U.S. companies (Table 15). For the specification that uses OPEX as input Brazilian and U.S. mean efficiency scores over the whole period are equal up to the third decimal place. For the TOTEX specification, Brazil performs only slightly better, but the difference is not statistically significant, as shown by the computed p-value.

Model	OPEX		TOTEX	
Country	BR	US	BR	US
Mean	0.805	0.805	0.907	0.906
Coefficient variation	14.68	13.08	9.43	7.86
P-value	0.980		0.915	

Note: Both panel data models estimated using LL specification.

Table 15: SFA Technical Efficiency Scores – Panel Data

7 Conclusion

Following we summarise our main conclusions:

1) efficiency scores

- the analysis of efficiency scores shows that Brazilian companies outperform their U.S. counterparts for almost all model specifications and for both 1994 and 2000 – this result is robust to method chosen (DEA, cross-section or panel data SFA);
- however, this difference in performance is not statistically significant for all panel data and almost all SFA cross-section models, and for the DEA models that use environmental variables and OPEX as input;
- the significantly superior performance of Brazil in DEA models that do not include environmental variables and in DEA models that use TOTEX as input is due to the proportionally higher number of customers supplied by Brazilian companies – they are more efficient in terms of OPEX per customer and also in TOTEX per customer;
- given that customer density is a variable beyond management control, we consider the models with environmental variables more relevant to the analysis and therefore conclude that the difference in performance is not statistically significant for OPEX models.

2) impact of privatisation on efficiency

- the Malmquist index analysis shows that the impact of privatisation is mostly positive but not statistically significant for OPEX models, but negative and statistically significant for TOTEX models – this suggests the importance of including capital costs in the benchmarking.;
- the results of TOTEX models should be taken with caution due to the difficulties in obtaining perfectly compatible measures of CAPEX;

- the results of TOTEX models can be partly explained by the low level of investment in Brazilian companies before privatisation – with privatisation, the financial constraint is reduced and investment picks up; we cannot overemphasise the importance of financing infractructure investment in developing countries such as Brazil – by transferring the investment burden to the private sector privatisation can help to avoid further deterioration of the public finances and at the same time ensure the expansion of capacity (in particular, rural electrification) and quality improvement;

- the results of TOTEX models can also be partly explained by a faster rate of substitution of capital for labour in Brazil – this seems to be the case taking into account the magnitude of redundancy programmes after privatisation;

- we expect the effects of the investment surge and the input substitution process on efficiency to become visible in the future, especially once the redundancy payments and the sunk costs are absorbed;

- our panel data SFA indicates that there is a systematic technological difference between the two countries, and that this difference is favourable for Brazilian companies for both OPEX and TOTEX models; however, technological change has been growing faster for U.S. companies for the TOTEX model (this confirms the negative impact of privatisation on performance for TOTEX models suggested by the Malmquist index analysis).

3) other issues

- we do not account for quality of service – it is clear that international benchmarking should accommodate in some way the differences in quality standards across countries, as pointed out in Coelli (2000, p. 11), but the lack of appropriate data prevents us from doing it;

- the correspondence between physical variables is not perfect, as shown by the differences in voltage levels, although all care was taken to make the datasets compatible;

- the findings highlight the importance of establishing standard measures of capital costs for international benchmarking and incentive based regulation – as observed in Jamasb and Pollitt (2001a), regulators have only begun the effort of standardising data within and across countries.

Paper	Data	Cross-country?	Inputs and outputs	Method	Main results
Grifell-Tatjé and Lovell (2003)	9 Spanish distr. utilities 1996	No	*Inputs:* - LV lines (km) - MV lines (km) - HV lines (km) - substation transformer capacity HV/ MV and MV/ MV (MVA) - substation transformer capacity MV/ LV (MVA) *Outputs:* - LV customers (#) - M/ HV customers (#) - service area (km^2) - elect. distributed (GWh) - service reliability (= L and MV elect. distributed (MWh)/ L and MV electricity lost (MWh))	DEA	The actual distr. network operates at a higher cost than the ideal network's cost. Most of this reduction comes from lower price inputs, but some cost savings are due to better network design. However, the consultancy's network is not as cost efficient as the actual network.
Delmas and Tokat (2003)	177 investor-owned U.S. electric utilities 1998-2001	No	*Inputs:* - labour cost - plant value - production expenses - transmission expenses - distribution expenses - sales, administrative and general expenses - electricity purchases *Outputs:* - LV sales (MWh) - HV sales (MWh) - sales for resale (MWh)	DEA and Tobit regression	Deregulation had a negative impact on efficiency in the short term. In addition, firms that are vertically integrated or that rely on the market for the supply of their electricity are more efficient than hybrid utilities.
Domah (2002b)	16 (vertically-integrated) generators from small islands and 121 U.S. investor-owned utilities with generation capacity 1993-2000	Yes	Model 1 *Inputs:* - employees (#) - capacity (MW) - fuel *Output:* - units generated (MWh) Model 2 *Inputs:* - employees (#) - capacity (MW) - fuel *Output:* - units generated (MWh) *Environmental variables:* - per capita electricity consumption - customers served (#) - capacity utilisation - island dummy - connection dummy	Malmquist DEA; SFA	There are no significant differences in the production structure between islands and non-islands utilities, nor there is any evidence suggesting that islands are less technically efficient.

Table 1: Academic Benchmarking Studies

Paper	Data	Cross-country?	Inputs and outputs	Method	Main results
Resende (2002)	24 Brazilian distr. utilities 1997	No	Model 1 *Inputs:* - employees (#) - transformers' capacity (MVA) - network extension (km) *Outputs:* - service area (km^2) - customers (#) - industrial sales (MWh) - non-industrial sales (MWh) Model 2 *Inputs:* - employees (#) - transformers' capacity (MVA) - network extension (km) *Outputs:* - service area (km^2) - industrial sales (MWh) - non-industrial sales (MWh)	DEA	Some firms displayed especially poor performance. The author suggests the use of yardstick competition schemes as a feasible efficiency-inducement mechanism for Brazilian electricity distribution.
Jamasb and Pollitt (2001b)	63 distr. utilities from 6 European countries 1997, 1998 or 1999 (reference year varies across countries)	Yes, 6 European countries	Various models are tried. The following are inputs and outputs used in the different models: *Inputs:* - OPEX - TOTEX - network length - T&D losses *Non-discretionary inputs:* - network length - T&D losses *Outputs:* - units delivered - customers (#) - network length	COLS; DEA; SFA	The choice of models and methods can affect efficiency scores as well as the rank order of firms. The authors recommend the improvement and standardisation of data as well as more co-operation between regulators.
Hattori (2001)	21 investor-owned (vertically-integrated utilities from U.S. and Japan (12 from the U.S. and 9 from Japan), but the focus is on distribution 1982-1997	Yes, U.S. and Japan	*Inputs:* - employees (#) - transformer capacity (MVA) *Outputs:* - residential sales (GWh) - non-res. sales (GWh) *Environmental variables:* - load factor (avg. demand/ peak demand) - customer density (# cust./ # transformers) - consumption density (sales/ customer)	SFA	Japanese utilities are on average more efficient than their U.S. counterparts. There is a consistent decline in U.S. performance after 1993. Considering only the frontiers, U.S. and Japan frontiers are very close to each other.

Table 1 (Cont.)

Paper	Data	Cross-country?	Inputs and outputs	Method	Main results
Pardina and Rossi (2000)	Company-level data of 36 utilities from 10 South American countries (period 1994-1997, but not all years are available for each company).	Yes, 10 South American countries.	*"Inputs"*: - distribution network length (km) - employees (#) in the distribution sector - service area (km^2) - transformer capacity (kVA) - residential sales to total sales ratio - total sales (MWh) Obs.: The authors argue that these factors cannot be considered inputs (because there are no input prices), so they introduce them in the model as specific characteristics of the firms. *Regressors*: - all "inputs" - a time trend - an interaction variable between time and a dummy variable (which takes a value of 1 when a firm belongs to a country that has already reformed its ESI) *Output*: - customers (#)	SFA	The results fail to find catching-up effects in the period 1994-1997. In addition, there is only partial evidence of correlation between reforms and performance. Only when more interaction variables are included the coefficients are significant.
Arocena and Waddams-Price (1999)	33 Spanish generators (19 privately-owned and 14 publicly-owned) 1984-1997	No.	*Inputs:* - capacity (MW) - employees (#) - fuel (therms million) *Outputs:* - net power produced (MWh) - SO_2 emmissions (tons) - NO_x emmissions (tons) - particulates emmissions (tons)	Graphyp. Malmquist Index	Publicly-owned generators are more efficient under cost-of-service regulation. Privately-owned generators respond to incentive based regulation by increasing efficiency. The public sector produces higher leverls of pollutants per unit.
Plane (1999)	Annual company-level data on production, installed capacity, length of distribution network, number of permanent employees, number of customers, etc., for the period 1959-1995.	No, case study for the Côte d'Ivorie Electricity Company (CIE).	*Inputs (regressors):* - installed generating capacity (MW) - permanent employees (#) - ratio of consumers to the length of the distribution network (# consumers/ km) - institutional change (privatisation dummy) *Output:* - gross production (GWh)	SFA	The six technical efficiency measures of the post-privatisation period (1990-95) are significantly higher than the six previous ones (1984-89). However, over the six post-privatisation years technical efficiency has been irregular, with a decline in 1990-93 and then an upturn with a final level remaining below its highest level in 1971.

Table 1 (Cont.)

Paper	Data	Cross-country?	Inputs and outputs	Method	Main results
Whiteman (1999).	39 electricity suppliers, including 7 Australian suppliers, covering the period 1994 to 1995.	Although it is a case study for Australia, uses companies of various countries as benchmarks for Australian utilities.	*Inputs:* - hydro capacity (MW) - thermal capacity (MW) - full time employees (#) *Output*: - electricity generated (GWh)	DEA; SFA	For Australia as a whole the DEA estimate of x-inefficiency is 17%, and the corresponding SFA estimate is 30%. Microeconomic reform of the electricity sector would raise real GDP by 0.22% in the long run. However, the study suggests that the outcome will depend critically on the result of the trade-off of the benefits between wages and employment growth.
Hattori (1999)	Company-level panel data on 9 Japanese electric utilities over the period 1982-1997 (the focus is on fossil fuel generation).	No, it is a case study for Japan	*Estimation of a translog cost function.* *Regressors:* - net electricity generation by fossil fuel plants (MWh) - total fuel used (BTU) - employees (#) - capital	Deterministic frontier (cost function)	There is no evidence of an impact of the 1995 regulatory reforms on technical and allocative efficiency.
Kittelsen (1999).	Norwegian electricity distribution utilities	No, case study for Norway	*Inputs:* - labour - energy loss - transformers - lines - goods and services *Outputs:* - energy delivered - customers (#) - line length 1-24 kV	Malmquist DEA	The study estimates Malmquist change of 1.9% p.a. in the period 1983-1989.
Førsund and Kittelsen (1998).	157 Norwegian distribution utilities in 1983 and 170 utilities in 1989	No, it is a case study of Norway.	*Inputs*: - labour (hours) - energy loss (MWh) - materials (1000 NoK) - capital (1000 NoK) *Outputs*: - distance index (based on the population's average travelling time to the municipal centres) - customers (#) - energy delivered (MWh)	Malmquist DEA	Total productivity change has been positive for those utilities that appear in both years and that is mostly the result of frontier shifts. A significant share of units representing 78% of total electricity deliveries has experienced a positive change due to frontier shift. Some units had a substantial improvement (245% in total productivity for one specific unit) due to the reduction of losses.

Table 1 (Cont.)

Paper	Data	Cross-country?	Inputs and outputs	Method	Main results
Meibodi (1998)	Data on the ESI of 26 developing countries; data on 30 Iranian power plants for the period 1990-1995; data on 30 Iranian distribution companies for 1995.	Yes, 26 developing countries.	Model for the cross-country comparison: *Inputs:* - capital (MW) - labour (which is dropped for the DEA calculation) - fuel *Output:* - electricity production (GWh) Model for the generation analysis *Inputs:* - installed capacity (MW) - energy (Btu) *Output:* - electricity production (MWh) Model for the distribution analysis *Inputs:* - network size (km) - transformer capacity (MVA) - employees (#) in distribution *Outputs:* - electricity sales to residential customers (GWh) - electricity sales to industrial customers (GWh) - residential customers (#) - industrial customers (#)	Malmquist DEA; SFA.	Results suggest that public ownership of electricity production might have an adverse effect on technical efficiency. However, there are other relevant factors in explaining efficiency changes, such as the size of the plant. The study also indicates that there is room for significant cost reductions: by 23% for the ESI of developing countries, by 27.3% for Iranian power plants, and by 19% for Iranian distribution companies.
Scully (1998)	Company-level panel data on New Zealand electricity distribution companies over the period 1982-1994 (total of 704 observations)	No, case study for New Zealand	*Estimation of a translog (total) cost function.* *Regressors:* - employees (#) - installed maximum capacity (KMW) - electricity generated or purchased (MWh) - network length (km) - distribution substations (#) - annual load factor - % MWh of electricity self-generated - % domestic customers - % commercial customers - % farm customers - dummy for municipal control - dummy for merger between two municipal companies - dummy for merger between a municipal company and an electrical power board - dummy for merger between two continuous electrical power boards - dummy for market-driven companies or council-owned firms whose assets are managed by an external team - dummy for the years 1992-1994 (years of freer labour market)	Deterministic frontier (cost function)	The study identifies significant cost reductions due to the reforms that were begun in 1988. Cost has declined over time, independent of merger, privatisation, and system characteristics. The conclusion is that the cost reductions reflect at least partly the effect of economy-wide reforms. In addition, reforms benefitted customers.
Filippini (1998)	Company-level panel data on 39 Swiss municipal electricity distribution utilities over the period 1988-1991.	No, case study for Switzerland	*Estimation of a translog (total) cost function.* *Regressors:* - electricity delivered (kWh) - load factor - service area (km^2) - customers (#)	Deterministic frontier (cost function)	The results suggest the existence of economies of scale and density in electricity distribution. There is evidence that Swiss distribution utilities operate at an inappropriately low scale and density level, what suggests that consolidation of small utilities is likely to reduce costs.

Table 1 (Cont.)

Paper	Data	Cross-country?	Inputs and outputs	Method	Main results
Yunos and Hawdon (1997)	Data on 27 electricity producers from various developing countries for 1987; time series data on the Malaysia's National Electricity Board (NEB), the electricity board of Thailand (EGAT) and the electricity board of England & Wales (CEGB) from 1975 to 1990.	Yes, 27 developing countries as well as England & Wales	Model 1 *Inputs:* - installed capacity (MW) - labour - total system losses (%) - public generation capacity factor (%) *Output:* - gross electricity produced (GWh) Model 2 *Inputs:* - installed capacity (MW) - labour - electricity losses (%) - thermal efficiency (%) *Output*: - electricity generated (GWh)	Malmquist DEA	Malaysia's NEB ranked 18th out of the 27 developing countries in the sample. With respect to the comparisons against EGAT and CEGB, NEB was on average relatively less efficient in electricity generation, mainly due to its high excess capacity and low thermal efficiency. There was no productivity growth of NEB from 1975 to 1990.
Lawrence et al. (1997)	Price, quality and physical data of Australian and international infrastructure firms (one year of data is available for each infrastructure service).	Yes, Australian firms are benchmarked against international companies.	For electricity, the indicators used are: - price (cents/ kWh) - GWh per employee - average customer outage time (min per customer) - capacity factor (%) - reserve plant margin (%)	Direct comparison with the Australian and the world best performances. A normalisation allows comparisons between different industries.	In respect to prices, Australia has moved closer to the world best practice in electricity. Electricity reliability has also improved in recent years. In addition, Australia has closed the performance gap in respect to capital productivity, although excess capacity is still a problem in some states' electricity systems.
Burns and Weyman-Jones (1996)	Company-level data of 12 regional electricity distribution companies of England & Wales. 1980-1993 (total of 156 observations)	England & Wales	*Exogenous factors (can be viewed as multiple outputs, fixed inputs, or operating characteristics exogenous to the firm):* - electricity delivered (kWh) - maximum demand (MW) - customer density (= #customers/ km^2) - network length (km) - transformer capacity - industrial kWh as a proportion of total *Output:* - customers (#) *Regressors:* - exogenous factors - output - price of capital - price of labour - privatisation dummies *Dependent variable:* - total distribution costs	SFA	The study finds a significant positive effect on efficiency in the years following privatisation. Irrespective of the type of model estimated, the results show that there are significant economies of scale in electricity distribution.

Table 1 (Cont.)

Paper	Data	Cross-country?	Inputs and outputs	Method	Main results
Bagdadioglu et al. (1996)	Company-level physical and financial data of 70 retail distribution organisations (66 publicly-operated, 2 privately-operated, and 2 were the distribution activities of the 2 private generators) for 1991.	No, it is a study of the Turkish distribution market.	*Inputs:* - manpower - transformer capacity (MVA) - network size (km) - general expenses ($) - network losses (MWh) *Outputs:* - customers (#) - electricity supplied (MWh) - maximum demand (MW) - service area (km^2)	DEA	At the 5% significance level, the study rejects the null hypothesis that there is no significant difference in efficiency scores between public and private distribution organisations. However, the authors warn caution in considering this result, especially given that the number of private organisations is very small. The 4 privately operated distribution organisations exhibit unit technical and scale efficiency scores, while their publicly operatedcounterparts show more diverse results.
Pollitt (1995)	Company-level cross-section data of 129 U.S. electric utilities engaged in transmission, and 136 U.S. and 9 UK utilities engaged in distribution for 1990.	Yes, U.S. and UK	For transmission *Inputs:* - employees (#) - length (km) * voltage (kV) - transformer capacity (MVA) *Outputs:* - electricity input - maximum system demand - network length (km) For distribution *Inputs:* - employees (#) - transformer capacity (MVA) - network length (km) *Outputs:* - customers (#) - residential sales (mkWh) - non-res. sales (mkWh) - service area (km^2) - maximum demand (MW)	DEA and OLS	It is not possible to reject the null hypothesis that publicly-owned and privately-owned electricity transmission and distribution systems exhibit no significant difference in technical or cost efficiency. The distribution study shows that UK utilities did not exhibit a substantialy different performance on the DEA scores from their U.S. counterparts.
Whiteman (1995)	Country-level cross-section physical data of 85 developing countries electricity systems for 1988.	Yes, 85 developing countries	*Inputs:* - labour - thermal generating capacity (MW) - hydro generating capacity (MW) - nuclear generating capacity (MW) - other generating capacity (MW) *Output:* - electricity production (GWh)	DEA	The study identifies the best-practice countries and the countries which fall below the 100% score. It also examines in more detail the sources of inefficiency of Bangladesh, Benin, Burundi, Ethiopia, Mozambique and Myanmar.
Berry (1994)	Company-level cross-section data of 169 U.S. utilities for 1988 (83 vertically-integrated investor-owned utilities, 37 generation and transmission cooperatives, and 49 distribution cooperatives).	No, it is a case study for the U.S.	*Estimation of a translog cost function.* *Regressors:* - wholesale electricity delivered (10^6 MWh) - industrial electricity delivered (10^6 MWh) - LV electricity delivered (10^6 MWh)	Deterministic frontier (cost function)	Estimated costs of rural electricity cooperatives are much higher than those incurred by investor owned utilities. Generation and transmission cooperatives are the least efficient of the three types of utility examined.

Table 1 (Cont.)

Paper	Data	Cross-country?	Inputs and outputs	Method	Main results
Giles and Wyatt (1993)	Company-level cross-section data of 60 New Zealand distribution companies for the 1986-1987 financial year.	No, it is a case study for New Zealand	*Estimation of a translog cost function.* *Regressors:* - employees (#) - network length (km) - transformer capacity (kVA) - type of distribution company dummy - location dummy - load factor - density (measured either by # customers/ km^2 service area or by # customers/ km distribution line) - urban/ rural dummy	Deterministic frontier (cost function)	There is evidence of significant economies of scale, and these economies are not exhausted at the current structure of the market. If the number of companies is reduced from 60 to 40 the total industry cost will be reduced by 8%.
Kittelsen (1993)	Company-level cross-section physical and financial data of 172 Norwegian electricity distribution utilities for 1989.	No, case study of Norway	Model 1 *Inputs:* - labour (hours) - energy loss - capital - goods and services *Output:* - energy delivered Model 2 *Inputs:* - labour (hours) - energy loss - capital - goods and services *Outputs:* - energy delivered - number of customers Model 3 *Inputs:* - labour (hours) - energy loss - capital - goods and services *Outputs:* - energy delivered - number of customers *Environmental variable:* - distance index	DEA	Norwegian distribution utilities exhibit extensive technical inefficiency, with average technical efficiency estimates in the order of 80%. Scale inefficiency is a less important problem.
Hjalmarsson and Veiderpass (1992a)	Company-level physical data of 289 Swedish retail electricity distribution companies for the period 1970-1986.	No, case study for Sweden.	*Inputs:* - hours worked - low voltage power lines (km) - high voltage power lines (km) - total transformer capacity (kVA) *Outputs:* - low voltage electricity delivered (MWh) - high voltage electricity delivered (MWh) - low voltage customers (#) - high voltage customers (#)	Malmquist DEA	Productivity growth has been substantial in Sweeden, and it can be largely attributed to economies of density. Type of ownership or economic organisation do not seem to be correlated with productivity change.

Table 1 (Cont.)

Paper	Data	Cross-country?	Inputs and outputs	Method	Main results
Weyman-Jones (1991)	Company-level cross-section physical and financial data of 12 electricity distribution utilities of England & Wales for 1986-1987.	Case study for England & Wales	*Inputs:* - capital (either measured as the total value of the utility's assets or as km of circuit) - employees (#) *Outputs:* - sales to domestic customers - sales to commercial customers - sales to industrial customers	DEA	Results show great variance among England & Wales distribution utilities, with only five operating on the technically efficient frontier.
Färe et al. (1985)	Company-level cross-section data of 123 private and 30 public U.S. electric utilities for 1970.	No, it is a case study for the U.S.	*Inputs:* - labour (full time equivalent employees) - fuel (BTUs) - installed generating capacity *Output:* - electricity production (mi kWh)	DEA	Mean efficiency values of four of the six efficiency measures are slightly higher for publicly-owned utilities. The two types of utilities are not statistically significantly different in terms of overall allocative and overall technical efficiency. However, publicly-owned utilities are significantly better in terms of purely technical efficiency, but worse in terms of congestion and scale efficiency.
Färe et al. (1983)	Company-level physical data of coal-fired steam generating plants of privately-owned firms subject to regulation by the Illinois authority. The data covers the 1975-1979 period.	No, it is a case study for a state (Illinois) of the U.S.	*Inputs:* - employees (#) - fuel (10^{10} BTUs) - installed generating capacity (MW) *Output:* - net electricity production (mi kWh)	DEA	Only 4 of the 86 observations were overall technically efficient. No plant operated at overall efficiency over the entire time period. The study cannot find evidence of increasing efficiency over time.

Table 1 (Cont.)

Country	Year of the document publication	Retention Period	Benchmarking / regulation method	Sample	Inputs	Outputs	Notes
Great Britain	December 1999	April 2000/ March 2005	top down modelling: COLS regression analysis of OPEX; efficiency analysis/ revenue cap	14 PES (Public Electricity Suppliers)	OPEX	Composite variable (number of customers, units distributed (MWh), line length (miles)).	The level of efficient OPEX was assumed to remain constant in real terms (frontier), but those companies not on the frontier were placed on a path to reduce costs.
Great Britain	July 2003	April 2005/ March 2010	Still to decide on the most appropriate approach to top down modelling of OPEX: COLS regression analysis, stochastic frontier analysis or DEA/ revenue cap	14 individuals DNOs (Distribution Network Operators) / 8 company groups	OPEX	units distributed (MWh), number of customers, line length (miles).	This document represents only the second stage of the review – initial consultation stage.
Netherlands	August 2000	2001/ 2003	DEA / revenue cap	18 T&D utilities	OPEX or total controllable costs	Model 1: units (MWh), number customers Model 2: units (MWh), number customers, peak demand (LV) **Model 3**: units (MWh), number customers, peak demand (LV), peak demand (HV) Model 4: units (MWh), number customers, network lenght, number transformers Model 5: units (MWh), number customers, network lenght, number transformers, peak demand (LV) **Model 6**: units (MWh), number customers, network lenght, number transformers, peak demand (LV), peak demand (HV) **Model 7**: units (MWh), number small customers, number large customers, network lenght, number transformers, peak demand (LV), high demand (HV) In bold: preferred models. Model 7: central model.	Argues that the inclusion of network length and number of customers allows to account implicitly for density and dispersion of customers. Assumes CRS (considered more appropriate for benchmarking network companies, as the regulator intends to capture scale across different dimension; besides, scale is a factor that the companies can control through changes in ownership). Compares the score of each company under the central model – with total controllable costs as an input and with OPEX as an input – to check whether inefficiency comes from operating inefficiency, capital or both.

Table 2: Benchmarking and Incentive Regulation

Country	Year of the document publication	Retention Period	Benchmarking / regulation method	Sample	Inputs	Outputs	Notes
Norway	various sources	1997/ 2001: 5 year period, first started on 1st January, 1997 (therefore, distribution utilities have been subject to individual efficiency correction from 1998)	DEA / revenue cap (the regulator sets income frames for each 5 year period – i.e. there is an upper and lower limit for the revenue for each individual utility)	ca. 200 distribution utilities	(1) For the general correction term: labour (h), energy loss (MWh), materials (in monetary value), and capital (in monetary value). See Førsund and Kittelsen (1998). (2) For the individual correction term: personal work years (amount), losses (MWh), capital (monetary value).	(1) For the general correction term: distance index, number of customers, units distributed (MWh). (2) For the individual correction term: number of customers, units distributed (MWh), line length (km), length of sea cables (km).	The efficiency requirement correction consists of two terms: a general term and an individual term. The general correction term is the same for every utility, and the individual correction term is determined for each utility (Kinnunen). For the next regulation period (2002/2006) quality is taken into account in the benchmarking process (Kinnunen).
Australia – New South Wales	February 1999	5 year period: July 1999/ 2004	DEA, stochastic frontier approach, total factor productivity / revenue cap	The London Economics (DEA) study draws on a database of 219 firms from Australia, New Zealand, England & Wales, and the U.S. However, 23 firms were removing from the database. Total actually used: 196 firms.	network lenght, transformer capacity, OPEX	units distributed, peak demand, number of customers	For IPART (Independent Pricing and Regulatory Tribunal of New South Wales) there is no direct relationship between benchmarking and the X factor. The information gained from benchmarking is considered an important (although not the only) input to the estimation of efficient costs. Financial modelling is then used to develop a profile of annual revenue requirement over the review period. (IPART, 1999, p. 3) The London Economics study used two approaches to account for environmental variables: specifying operating enviromental factor in the DEA model itself, and using a 2nd-stage statistical analysis to adjust the efficiency scores.

Table 2 (Cont.)

Country	Year of the document publication	Retention Period	Benchmarking / regulation method	Sample	Inputs	Outputs	Notes
Chile	various sources	4 year period: (1) 1988/ 1991 (most distribution utilities still state-owned) (2) 1992/ 1995 (distribution utilities totally privatised) (3) 1996/ 1999	model (theoretical) firm / yardstick regulation	(2) 30 distribution utilities (1) 39 distribution utilities	CAPEX, losses, administration and customer related costs	VAD (value added of distribution)	Distribution tariffs are based on the VAD, which consists of infrastructure and equipment costs, losses, and operating expenses. The components are calculated for each specific distribution zone. The estimated VAD for model firms of each zone are then applied for comparable real distribution utilities (Rudnick and Raineri, 1997).
Brazil	February 2003	4-5 year period, in most cases starting in 2003	operating costs computed from model (theoretical) firm; investments in distribution network based on Alboury (IDB) methodology/ price cap	One model firm for each of the 64 Brazilian distribution companies.	O&M costs, customer related costs, and administration costs.	OPEX	The methodology benchmarks each distribution company against its respective model firm in order to determine its efficient operating costs. In order to construct the theoretical firm, a bottom-up approach is adopted: the cost of each specific process or activity is determined. This allows the calculation of O&M costs, customer related costs, and administration costs. The remaining expenditure items are not based on the model firm.

Table 2 (Cont.)

References

[1] Aigner, D. J., C. A. K. Lovell and P. Schmidt (1977), 'Formulation and Estimation of Stochastic Frontier Production Function Models', Journal of Econometrics, vol. 6, no. 1, pp. 21-37.

[2] ANEEL (Agência Nacional de Energia Elétrica) (2003), 'Revisão Tarifária Periódica da Concessionária de Distribuição de Energia Elétrica Companhia Energética de Minas Gerais CEMIG', Audiência Pública AP 007/2003, Nota Técnica no. 040/2003 - SRE/ANEEL, February 2003, Brasília.

[3] ANEEL (Agência Nacional de Energia Elétrica) (2002), 'Metodologia e Critérios Gerais Para Definição da Base de Remuneração de Ativos Para Fins de Revisão Tarifária Periódica das Concessionárias de Distribuição de Energia Elétrica', Nota Técnica no. 148/2002/ SRE/ SFF/ ANEEL.

[4] ANEEL (Agência Nacional de Energia Elétrica) (2001), 'Mercado de Distribuição Brasil 2000: Concessionárias de Energia Elétrica', *mimeo*.

[5] Arocena, Pablo and Catherine Waddam-Price (1999), 'Generating Efficiency: Economic and Environmental Regulation of Public and Private Electricity Generators in Spain', *mimeo*, July 1999.

[6] Averch, H. and L. L. Johnson (1962), 'Behaviour of the Firm Under Regulatory Constraint', American Economic Review, vol. 52, pp. 1052-1069.

[7] Bagdadioglu, Necmiddin, Catherine M. Waddams-Price and Thomas G. Weyman-Jones (1996), 'Efficiency and Ownership in Electricity Distribution: A Non-Parametric Model of The Turkish Experience', Energy Economics 18, pp. 1-23.

[8] Battese, G. E. and T. J. Coelli (1995), 'A Model for Technical Inefficiency Effects in a Stochast Frontier Production Function for Panel Data', Empirical Economics 20, pp. 325-332.

[9] Battese, G. E. and T. J. Coelli (1992), 'Frontier Procution Functions, Technical Efficiency and Panel Data: With Application to Paddy Farmers in India', Journal of Productivity Analysis, vol. 3, no. 1/2, pp. 153-169.

[10] Berry, Dan Michael (1994), 'Private Ownership Form and Productive Efficiency: Electric Cooperatives Versus Investor-Owned Utilities', Journal of Regulatory Economics 6, pp. 399-420.

[11] Besant-Jones, John and Bernard Tenembaum (2001), 'The California Power Crisis: Lessons for Developing Countries', The Energy and Mining Sector Board, The World Bank, Washington, D. C., 28 pp.

[12] Burns, Philip and Weyman-Jones, Thomas (1996), 'Cost Functions and Cost Efficiency in Electricity Distribution: A Stochastic Frontier Approach', Bulletin of Economic Research, vol. 48, no. 1, pp. 41-64.

[13] CEPA (Cambridge Economic Policy Associates) (2003), 'Background to Work on Assessing Efficiency for the 2005 Distribution Price Control Review', prepared for Ofgem, September 2003.

[14] Charnes, A., W. W. Cooper and E. Rhodes (1978), 'Measuring the Efficiency of Decision Making Units', European Journal of Operational Research, Vol. 2, no. 5, pp. 429-444.

[15] Coelli, Tim (2000), 'Some Scattered Thoughts on Performance Measurement for Regulation of a Natural Monopoly Network Industry', Centre for Efficiency and Productivity Analysis, August 2000, Armidale, Australia, *mimeo.*

[16] Coelli, Tim (1995), 'Estimatores and Hypothesis Tests for a Stochastic Frontier Function: A Monte Carlo Analysis', Journal of Porductivity Analysis 6, pp. 247-268.

[17] Coelli, Tim and Sergio Perelman (1999), 'A Comparison of Parametric and Non-Parametric Distance Functions: With Application to European Railways', European Journal of Operational Research, no. 117, pp. 326-339.

[18] Coelli, Tim, D. S. Prasada and George E. Battese (1998), 'An Introduction to Efficiency and Productivity Analysis', Kluwer Academic Publishers, Boston/ Dordrecht/ London.

[19] Cornwell, C., P. Schmidt, and R. C. Sickles (1990), 'Production Frontiers With Cross-Sectional and Time-Series Variation in Efficiency Levels', Journal of Econometrics, vol. 46, no. 1/2, pp. 185-200.

[20] Comisión de Tarifas de Energía (2001), 'Informe de Situación de Las Tarifas Eléctricas 1993-2000', February 2001.

[21] Delmas, Magali and Yesim Tokat (2003), 'Deregulation Process, Governance and Efficiency: The U.S. Electric Utility Sector', Energy Policy and Economics no. 4, University of California Energy's Institute (UCEI), Berkeley, California.

[22] Di Tella, Rafael and Alexander Dyck (2002), 'Cost Reductions, Cost Padding and Stock Returns: The Chilean Experience with Price-cap Regulation', *mimeo.*

[23] Domah, Preetum (2002a), 'The Economics of Reform of the Electricity Supply Industry: The Case of Small Islands', PhD dissertation, University of Cambridge, Cambridge, UK.

[24] Domah, Preetum (2002b), 'Technical Efficiency in Electricity Generation – The Impact of Smallness and Isolation of Islands Economics', Department of Applied Economics Working Paper no. 0232, University of Cambridge, Cambridge, UK.

[25] DTe (The Netherlands Electricity Regulatory Service) (1999), 'Price Cap Regulation in The Electricity Sector – Information and Consultation Document', July 1999, Hague, the Netherlands.

[26] EIA (Energy Information Administration) (2001), 'Electric Power Annual 2000', Vol. 1, August, Office of Coal, Nuclear, Electric and Alternate Fuels, U.S. Department of Energy, Washington.

[27] Färe, R., S. Grosskopf and C. A. Knox Lovell (1994), 'Production Frontiers', Cambridge University Press, Cambridge, UK, 296 pp.

[28] Färe, R., S. Grosskopf and J. Logan (1985), 'The Relative Performance of Publicly-Owned and Privately-Owned Electric Utilities', Journal of Public Economics, 26, pp. 86-106.

[29] Färe, R., S. Grosskopf and J. Logan (1983), 'The Relative Efficiency of Illinois Electric Utilities', Resources and Energy 5, pp. 349-367.

[30] Farrell, M. J. (1957), 'The Measurement of Productive Efficiency', Journal of the Royal Statistical Society Series A-General,Vol. 120, no. 3, pp. 253-290.

[31] Filippini, Massimo (1998), 'Are Municipal Electricity Distribution Utilities Natural Monopolies?', Annals of Public and Cooperative Economics, vol. 69, no. 2, pp. 157-174.

[32] Fischer, Ronaldo and Pablo Serra (2000), 'Regulating The Electricity Sector in Latin America', Economia, Fall 2000.

[33] Førsund, Finn R. and Sverre A. C. Kittelsen (1998), 'Productivity Development of Norwegian Electricity Distribution Utilities', Resource and Energy Economics 20, pp. 207-224.

[34] Frontier Economics (2000), 'The Efficiency of The Dutch Network and Supply Companies', final report prepared for Dte, August 2000, London.

[35] Giles, David E. A. and Nicolas S. Wyatt (1993), 'Economics of Scale in The New Zealand Electricity Distribution Industry', in Phillips, Peter C. B. (1993) (ed.), 'Models, Methods and Applications of Econometrics', pp. 370-382.

[36] Grasto, Ketil (1997), 'Norwegian Water Resources and Energy Administration: Incentive-based Regulation of Electricity Monopolies in Norway – Background, Principles and Directives, Implementation and Control System', NVE (Norges Vassdrags-og Energiverk), Oslo, Norway.

[37] Grifell-Tatjé, E. and C. A. K. Lovell (2003), 'The Managers Versus The Consultants', The Scandinavian Journal of Economics, vol. 105, no. 1, pp. 119-138.

[38] Hattori, Toru (2001), 'Relative Performance of U.S. and Japanese Electricity Distribution: An Application of Stochastic Frontier Analysis', Central Research Institute of Electric Power Industry Working Paper no. Y01914, October 2001, Japan.

[39] Hattori, Toru (1999), 'Parametric Tests of Cost Efficiency for Japanese Electric Utilities', draft prepared for the 6th European Workshop on Efficiency and Productivity Analysis, Copenhagen, 31.10.1999.

[40] Hjalmarsson, Lennart and Ann Veiderpass (1992), 'Productivity in Swedish Electricity Retail Distribution', Scandinavian Journal of Economics 94, Supplement, pp. 193-205.

[41] Hjalmarsson, Lennart and Ann Veiderpass (1992), 'Efficiency and Ownership in Swedish Electricity Retail Distribution', The Journal of Productivity Analysis 3, pp. 7-23.

[42] Hosek, James R. (ed.) (1989), 'Symposium on Price-cap Regulation', The Rand Journal of Economics, vol. 20, no. 3, Autumn, pp. 369-472.

[43] IPART (Independent Pricing and Regulatory Tribunal of New South Wales) (1999), 'Efficiency and Benchmarking of New South Wales Electricity Distributors', Discussion Paper DP-33, February 1999, Sidney, Australia.

[44] Irastorza, Veronica (2003), 'Benchmarking for Distribution Utilities: A Problematic Approach to Defining Efficiency', The Electricity Journal, vol. 16, no. 10, December.

[45] Jamasb, Tooraj and Michael G. Pollitt (2001a), 'Benchmarking and Regulation: International Electricity Experience', Utilities Policy 9, pp. 107-130.

[46] Jamasb, Tooraj and Michael G. Pollitt (2003), 'International Benchmarking and Yardstick Regulation: An Application to European Electricity Utilities', Energy Policy vol. 31, no. 15.

[47] Jondrow, J., C. A. K. Lovell, I. S. Materov, and P. Schmidt (1982), 'On The Estimation of Technical Inefficiency in The Stochastic Frontier Production Function Model', Journal of Econometrics, vol. 19, no. 2/3, pp. 233-238.

[48] Joskow, Paul L. (2003), 'The Difficult Transition to Competitive Electricity Markets in The U.S.', paper prepared for the Conference 'Electricity Deregulation: Where from Here?' at the Bush Presidential Conference Center, Texas A&M University, Texas, April 4th.

[49] Joskow, Paul L. (2001), 'California's Electricity Crisis', Oxford Review of Economic Policy, vol. 17, no. 3.

[50] Kinnunen, Kaisa (2002), 'Electricity Network Regulation – Pratical Implementation in The Nordic Countries', *mimeo*, Bremen Energie Institut, Denmark.

[51] Kittelsen, Sverre A. C. (1999), 'Using DEA to Regulate Norwegian Electricity Distribution Utilities', Presentation at the 6th European Workshop on Efficiency and Productivity Analysis, Copenhagen, 29.10.1999.

[52] Kittelsen, Sverre A. C. (1993), 'Stepwise DEA: Choosing Variables for Measuring Technical Efficiency in Norwegian Electricity Distribution', Memorandum 6/1993, Ragnar Frisch Centre for Economic Research, University of Oslo, Oslo, Norway.

[53] Kumbhakar, S. C. (1990), 'Production Frontiers, Panel Data, and Time-Varying Technical Efficiency', Journal of Econometrics, vole. 46, no. 1/2, pp.201-212.

[54] Kumbhakar, S. C. and C. A. K. Lovell (2000), 'Stochastic Frontier Analysis', Cambridge University Press, Cambridge, UK, 333 pp.

[55] Langset, Tore (2000), 'Efficiency Analysis in Regulation of Electricity Monopolies', *mimeo*, NVE (Norges Vassdrags-og Energiverk), Oslo, Norway.

[56] Lawrence, Denis, John Houghton and Anna George (1997), 'International Comparisons of Australia's Infrastructure Performance', Journal of Productivity Analysis 8, pp. 361-378.

[57] Legisa, Juan (2000), 'The Argentine Electric Power Pricing System', Paper presented at the National Conference on Regulation in 'Infrastructure Services: Progress and Way Forward', New Delhi, 14th November 2000.

[58] Lovell, C. A. Knox and Peter Schmidt (1988), 'A Comparison of Alternative Approaches to The Measurement of Productive Efficiency', in Dogramaci, A. and R. Fare (1998), 'Applications of Modern Production Theory: Efficiency and Productivity', Boston, pp. 3-32.

[59] Meeusen, W. and J. van den Broeck (1977), 'Efficiency Estimation from Cobb-Douglas Production Functions with Composed Error', International Economic Review, vol. 18, no. 2, pp. 435-444.

[60] Meibodi, Ali Emami 91998), 'Efficiency Considerations in The Electricity Supply Industry: The Case of Iran', Surrey Energy Economics Discussion Paper Series no. 95, University of Surrey, UK.

[61] Ofgem (Office of Gas and Electricity Markets) (1999), ' Reviews of Public Electricity Suppliers 1998 to 2000: Distribution Price Control Review – Final Proposals', December 1999, London.

[62] Pardina, Martín Rodríguez and Martín Rossi (2000), 'Technical Change and Catching-Up: The Electricity Distribution Sector in South America', Centro de Estudios Económicos de la Regulación Working Paper no. 11, Departamento de Economía y Finanzas, Universidad Argentina de la Empresa, November 2000.

[63] Plane, Patrick (1999), 'Privatization, Technical Efficiency and Welfare Consequences: The Case of the Côte d'Ivorie Electricity Company (CIE)', World Development vol. 27, no. 2, pp. 343-360.

[64] Pollitt, Michael G. (1995), 'Ownership and Performance in Electric Utilities, Oxford University Press, Oxford.

[65] Resende, Marcelo (2002), 'Relative Efficiency Measurement and Prospects for Yardstick Competition in Brazilian Electricity Distribution', Energy Policy 30, pp. 637-647.

[66] Rudnick, Hugh and Ricardo Raineri (1997), 'Chilean Distribution Tariffs: Incentive Regulation', in Morande, F. G. and R. Raineri (eds.), '(De)Regulation and Competition: The Electric Industry in Chile', ILADES/ Georgetown University, Santiago.

[67] Sarafidis, Vasilis (2002), 'An Assessment of Comparative Efficiency Measurement Techniques', Europe Economics Occasional Paper 2, London.

[68] Schmidt, P. and C. A. K. Lovell (1979), 'Estimating Stochastic Production and Cost Frontiers When Technical and Allocative Inefficiency Are Correlated', Journal of Econometrics, vol. 13, no. 1, pp. 83-100.

[69] Scully, Gerald B. (1998), 'Reform and Efficiency Gains in The New Zealand Electrical Supply Industry', Journal of Productivity Analysis 11, pp. 133-147.

[70] UMS Group (1999), 'Summary Report of 1998 Distribution Benchmarking', IPART Research Paper no. 14, February 1999, Sidney, Australia.

[71] Weyman-Jones, Thomas G. (1991), 'Productivity Effiency in a Regulated Industry', Energy Economics, April, pp. 116-122.

[72] Whiteman, John (1999), 'The Potential Benefits of Hilmer and Related Reforms: Electricity Supply', The Australian Economic Review, vol. 32, no. 1, pp. 17-30.

[73] Whiteman, John L. (1995), 'Benchmarking Developing Countries Electricity Systems Using DEA', Asia-Pacific Economic Review, vol. 1, no. 3, pp. 71-78.

[74] Yunos, Jamaluddin Mohd and David Hawdon (1997), 'The Efficiency of The National Electricity Board in Malaysia: An Intercountry Comparison Using DEA', Energy Economics 19, pp. 255-269.