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THE PERFORMANCE OF UK AND JAPANESE ELECTRICITY DISTRIBUTION SYSTEMS 1985-1998: A COMPARATIVE EFFICIENCY ANALYSIS

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Abstract

This paper examines relative performance of electricity distribution systems in the UK and Japan between 1985 and 1998 using cost-based benchmarking with data envelopment analysis (DEA) and stochastic frontier analysis (SFA) methods. The results suggest that the productivity gain in the UK electricity distribution has been larger than in the Japanese sector. In particular, productivity growth accelerated during the last years when the UK utilities were operating under tightened revenue caps. The findings indicate that while both sectors exhibit efficiency improvements, the efficiency gap between the frontier firms and less efficient firms has widened. The findings also highlight the advantages of using multiple techniques in comparative analysis and in incentive regulation.

Key words: Technical efficiency, Efficiency analysis, Electricity distribution systems, Incentive regulation, International comparison.

JEL Classification: L94

1. Introduction

Electricity sector reforms are transforming the structure and operating environment of the industry across many different countries throughout the world. Although the main purpose of the reforms is to introduce competition and market mechanisms into electricity generation and supply, there is a growing interest in regulatory reforms to improve the efficiency of the natural monopoly activities of distribution and transmission networks. Moving away from traditional rate-of-return utility regulation, a number of electricity regulators in, for example the UK, Netherlands, Norway and Australia, have adopted price or revenue cap regulation based on the RPI-X formula, thereby promoting cost savings and lower prices for the end-users.[1]

UK has a rich experience of adopting the RPI-X type incentive-based regulation for an electricity network: both the charges for transportation of electricity over the national high voltage transmission network and over the lower voltage regional distribution networks have been regulated by this method for over a decade. The initial distribution price controls on the regional electricity distribution companies (RECs) were put in place by the government at the time of restructuring in 1990, and permitted price increases of up to 2.5% above the inflation rate (OFFER, 1994). These initial price caps were seen by many as generous to the companies.[2] In August 1994 OFFER announced reductions averaging 14% in final electricity prices to take effect in April 1995, requiring cuts in real terms of 11 to 17% in distribution charges in 1995/96, and further reductions in real terms of between 10 and 13% in 1996/97. Distribution charges were, thereafter, required to fall by 3% per year in real terms for the duration of the price control (until March 2000).[3]

Evaluation of the performance of UK RECs under RPI-X regulation and private ownership has been the subject of productivity and efficiency analysis. Several studies have undertaken panel data analysis focusing on a UK sample (e.g. Weyman-Jones, 1994, and Burns and Weyman-Jones, 1996). On the one hand, it is quite natural to restrict the sample to domestic utilities, as efficiency analysis requires comparability of firms. On the other hand, it has been recognized recently that international comparative analysis may be useful to evaluate the performance of national utilities within the larger context of international practice.

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[1] See Jamasb and Pollitt (2001a), Hall (2000), Comnes et al. (1995), Hill (1995), and Joskow and Schmalensee (1986) for reviews and comparisons of different incentive regulation models.

[2] The 1990-95 period saw large increases in the profitability and share prices of the RECs and the government announced a £1.25 billion windfall tax on the companies' profits (Inside Energy, 1997).

[3] The price controls were modified in 1998 to allow RECs make additional revenues (approximately £1 per customer) to facilitate competition in supply. The current price controls came into effect in 1 April 2000. OFGEM's (Office of Gas and Electricity Markets the successor to OFFER) price controls, the RECs face distribution price reductions averaging 3% per year for the five years to 30 March 2005, with an initial cut in allowed revenues by up to 23.4% (OFGEM, 1999). Controllable costs for the RECs are projected to fall by 2.3% per annum over the period 1998 to 2005. These consist mainly of operating charges net of NGC exit charges, rent and rates, and depreciation etc.

The addition of international comparators to a sample can improve the validity of the analysis, as utilities are benchmarked against a greater number of firms. Further, international comparisons enable us to measure efficiency relative to international best practice. The advantage of using international best practice is that the measured efficiencies are more likely to reflect technical possibilities. Thus far, there are a few cross-country studies of the performance of electric utilities that involve UK RECs. Pollitt (1995) reports a comparative study of 136 US and 9 UK distribution firms using 1990 data and finds that the relative performance of UK utilities is comparable to those of the US. The IPART (1999) benchmarking study is primarily focused on efficiency of Australian utilities but also includes UK companies in its analysis. Jamasb and Pollitt (2003) report a benchmarking study of 63 distribution utilities from 6 European countries based on the data for 1997/98. The study finds the performance of the UK firms does not significantly differ from the mean values in the various models. Yet, most of these studies use cross sectional data or short-panel data with no analysis of how the relative efficiency changes over time. Also, the comparison is limited to European and English-speaking countries.

One country that has not been compared with the UK is Japan. Although it is known that Japanese electricity prices are the highest among OECD countries, two recent studies found that the productive efficiency of Japanese utilities is, on average, not necessarily lower than the U.S. utilities. Goto and Tsutsui (1998) use DEA to measure technical and allocative efficiency of the vertically integrated utilities in the two countries, and Hattori (2002b) uses SFA to estimate technical efficiency of electricity distribution. It is noteworthy that these studies assume that input prices are given to the utilities, implying that the higher electricity prices in Japan can be explained by the higher input prices and, in particular, the cost of capital.

The electricity supply industry and its regulation in UK and Japan are somewhat similar in that there are a similar number of utilities. Utilities are in private ownership in both countries; the UK firms were privatised in 1990[4] but the Japanese electricity supply industry has been privately owned since 1951. The industry in Japan is dominated by 10 Electric Power Companies (EPCOs) responsible for generation, transmission, distribution, and supply of electricity to final customers.[5] There is no independent regulator in Japan but the Ministry of Economy, Trade, and Industry (METI) acts as regulator. Thus, in both UK and Japan, one regulator (OFGEM in UK and METI in Japan) regulates a similar number of utilities.

However, the structure of the industry differs between the two countries. In Japan, the electricity distribution function is undertaken in vertically integrated electric utilities

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[4] The UK electricity supply industry was in public ownership from 1948 to 1990. In England and Wales, the Central Electricity Generating Board (CEGB) was responsible for generation and transmission and sold electricity to twelve Area Boards under the terms of the Bulk Supply Tariff, based on its marginal costs. The Area Boards were responsible for distribution and supply of electricity to consumers. Shortly before privatisation in 1990, the Area Boards were replaced by 12 Regional Electricity Companies (RECs). Transmission became the responsibility of the National Grid Company (NGC), a company fully owned by the RECs.

[5] See Navarro (1996) for a historical overview of Japanese electricity industry. In this analysis we look at the largest firms excluding the very small Okinawa Electric Power Company.

while in the UK regional distribution companies perform this task. This difference may be overcome, at least partly, by carefully examining the dataset. Another difference between the two countries is the regulatory regime. The UK introduced price cap regulation at privatisation in order to control the distribution tariff while Japan relied on rate-of-return (ROR) regulation to control the final prices of electricity.[6] Although it would be difficult to separate the effect of a different regulatory regime from other country-specific factors, with a long panel data set to investigate changes in efficiency over time, it might be possible to isolate the effect of the regime.

This paper examines relative performance of electricity distribution in the UK and Japan between 1985 and 1998, applying the benchmarking techniques known as Data Envelopment Analysis (DEA) and Stochastic Frontier Analysis (SFA). The length of our panel data enables us to investigate the dynamics of efficiency. We focus on the development of mean efficiency levels over time in each country.

In the next section we discuss the model for electricity distribution. Specification of the relevant measures of output, input and environmental factors will be presented. Then in section 3, we briefly describe the two techniques for efficiency analyses in this paper: DEA and SFA. In section 4, we discuss the data issues. Section 5 presents the results. In the final section, we conclude by outlining the issues of international comparisons.

2. Model of Electricity Distribution

To model the technology of electricity distribution, we have to specify the relevant measures of inputs, outputs, and other (environmental) factors. The basic design features of electricity distribution systems and the technologies used in them are similar the world over, however, comparative efficiency studies have adopted different input and output variables.[7] This reflects the lack of consensus on how these utilities should be modeled. For example, a variable used as an input in one study can be used in others as output. The variety of variables used may also be explained, to some extent, by lack of data. This section discusses our choice of inputs, outputs and environmental factors for the present study.

Inputs

The preferred model in this study uses a single cost input in monetary terms. In the past, some studies have used operating and capital costs as inputs, while others have instead used physical measures of the main inputs. In order to account for all the resources, it is preferable, where possible, to represent inputs in monetary terms. Thus we chose to use monetary inputs with adjustments to increase accuracy. Of course, accurate measurements of costs can be difficult to obtain. The problem is compounded in

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[6] In 1996, the ROR regulation was slightly modified into a type of yardstick regulation. By setting the price in each supply territory partly by reference to the performance of the firms relative to that of other utilities, the new regulatory mechanism aimed at improving efficiency among utilities by encouraging competition among these. See Hattori (2002a) for an overview of the regulatory reform in Japanese electricity industry.

[7] See Jamasb and Pollitt, (2001c), for example.

international comparisons due to differences in accounting rules and the need to convert different currencies into a single unit. We will discuss this issue in detail in Section 4.

We have two candidates for the monetary inputs: regulators around the world evaluate the performance of regulated firms using either operating expenditure (OPEX) or total expenditure (TOTEX). TOTEX is the sum of operating and capital expenditures (CAPEX), as represented by gross addition of capital. Assuming that CAPEX (of our definition) is largely controllable for the utilities, and recognizing the possibility of substitution between OPEX and CAPEX, we primarily focus on the model with TOTEX as a single input with the model with OPEX used for comparison.

Outputs

It is quite difficult to define the output of electricity distribution services and to find the relevant measures. For the preferred model in this study, we take the "separate marketability of components" property, suggested by Neuberg (1987), as a necessary defining property of a vector of outputs. Within this view, for example, the maximum demand, though often used as an output variable, cannot be priced separately and is therefore not included in our model. Then, two possible measures can be regarded as separately priced and sold by the utilities: customers, and electricity units delivered in megawatt-hours (MWh). In both the UK and Japan, a two-part tariff is adopted for distribution/bundled price, and thus, with customers priced at fixed charge, electricity units delivered can still be viewed as separately priced and sold.

If these data are available for each customer segment, then, for example, electricity units delivered to residential customers and units delivered to other customers can also be viewed as separately priced. At the same time, increasing the number of outputs may lead to problems in calculating or estimating efficiency. A review of 20 efficiency studies of electricity distribution utilities showed that the most widely used output variables were units of energy delivered and number of customers (Jamasb and Pollitt, 2001b). Thus, based on the "separate marketability of components" property we adopt models that use total electricity units delivered and total number of customers as output variables.

Environmental factors (Non-discretionary inputs)

We have defined inputs and outputs in our preferred model, but obviously there are other factors, generally called environmental variables, that can influence the cost of electricity distribution. For example, for regulated electricity utilities, population density and climatic conditions are exogenous factors. Our models include environmental variables to control for the effect of factors that affect the performance of utilities that are beyond the control of management.

Although it might be desirable to take many factors into account, the difficulties of data collection cause us to limit the number of variables. Moreover, the methodologies for efficiency analyses may restrict the number of variables that can be used (see next section). In this study, we focus on two environmental factors: customer density and load factor. We expect that increasing customer density (the number of customers per network length) and load factor (the ratio of average units of energy delivered to the maximum demand) lead to higher technical efficiency, holding other things equal. There remain other factors that can potentially affect costs, such as service quality, that are not included in our model due to the lack of comparable data sets.

3. Method

There are several approaches to the measurement of the relative technical efficiency of firms in relation to an efficient frontier. These approaches can be placed into one of two broad categories of technique: programming (non-parametric) or statistical (parametric). Data Envelopment Analysis (DEA) is a linear programming approach, while Stochastic Frontier Analysis (SFA) is a statistical technique. While DEA has been used extensively in the regulation of the distribution price of electricity, we use both methods for methodology cross-checking of the results.

3.1. Data Envelopment Analysis (DEA)

DEA is a non-parametric method and uses piecewise linear programming to calculate a sample's (rather than estimate) efficient or best-practice frontier first developed in Farrell (1957) and Färe et al. (1985). The decision-making units (DMUs) or firms that make up the frontier envelop the less efficient firms. Firm i is compared to a linear combination of firms that produce at least as much of each output as the inefficient firm and minimum possible amount of inputs. Technical efficiency is calculated as a score on a scale of 0 to 1, with the frontier firms receiving a score of 1 (see Cooper et al., 2000 and Coelli et al. 1998).

DEA models can be input and output oriented, but an input-oriented specification is generally regarded as the appropriate form for electricity distribution utilities, as demand for distribution services is a derived demand that is beyond the control of utilities but has to be met.[8] In this case, technical efficiency measures the ability of a firm to minimise inputs to produce a given level of outputs.

DEA does not require specification of a function to represent the underlying technology. However, the efficiency scores tend to be sensitive to the choice of input and output variables. Further, as more variables are included in the models, the number of firms on the frontier increases.

We incorporate environmental or non-discretionary variables in our DEA models (see Cooper et al, 2000). The program used here follows the methodology in Banker and Morey (1986). The linear program calculating the efficiency score of the i-th firm in a sample of N firms in variable returns-to-scale (VRS) models takes the form specified in Equation (1) where θ is a scalar (equal to the efficiency score) and λ represents an $N\times 1$ vector of constants. Assuming that the firms use K inputs and M outputs, X and Y

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[8] Output-oriented models maximise output for a given amount of input factors. Conversely, input-oriented models minimise input factors required for a given level of output.

represent *K*×*N* input and *M*×*N* output matrices respectively. The input and output column vectors for the *i*-th firm are represented by x_i and y_i respectively. Mathematically, non-discretionary variables can be introduced through the additional sets of constraints (the second and the third constraint in (1)) where the subscripts *D* and *ND* refer to discretionary (environmental) and non-discretionary variables respectively. The fourth constraint (the fourth constraint in (1)) ensures that the firm is compared against other firms with similar size. In CRS models, this convexity constraint is dropped. The equation is solved once for each firm.

$$\begin{aligned} & \min_{\theta,\lambda} \theta \\ & s.t. \\ & -y_i + Y\lambda \geq 0 \\ & \theta x_{i,D} - X_D \lambda \geq 0 \\ & x_{i,ND} - X_{ND}\lambda \geq 0 \\ & N1'\lambda = 1 \\ & \lambda \geq 0 \end{aligned} \tag{1}$$

When non-discretionary variables are specified in DEA, the methodology ensures that the efficiency scores of inefficient firms are only calculated on the basis of reductions in their discretionary inputs, while controlling for non-discretionary variables since reductions in these are not feasible.

We described the DEA technique with cross section data. With panel data, we can simply calculate efficiency score in each year but this keeps us from identifying frontier shift due to technological change. The DEA techniques can be used to calculate Malmquist Index of productivity change over time (see for example Färe, 1989 and Coelli et al., 1998), assuming the underlying technology is CRS.

We use the Malmquist index as shown in (2) and described in Thanassoulis (2001). For example, $C\_EF_{T0}^{D1}$ represents the CRS DEA efficiency score for a decision-making unit measured relative to a technology in year 0 and the unit data for year 1. The left-hand-side ratio measures the efficiency of unit *j* using data set from period 1, (D1) with technology from year 0, (T0) to the efficiency of the unit with data and technology of year 0, (D0 and T0). The right-hand-side ratio measures the efficiency of unit *j* using data and technology from year 1, (D1 and T1) to efficiency of the unit with data of year 0, (D0) and technology of year 1, (T1). The Malmquist indices can be broken down into productivity catch-up and frontier shift components as in Equation (3). The catch-up factor is a measure of the extent to which a unit has moved close to the frontier while the frontier shift component reflects industry level technological change and innovation (see e.g. Thanassoulis, 2001, and Coelli et al., 1998).

$$MI_j = \left[\frac{C\_EF_{T0}^{D1} * C\_EF_{T1}^{D1}}{C\_EF_{T0}^{D0} * C\_EF_{T1}^{D0}} \right]^{1/2} \tag{2}$$

$$MI_j = \frac{C\_EF_{T1}^{D1}}{C\_EF_{T0}^{D0}} * \left[\frac{C\_EF_{T0}^{D1} * C\_EF_{T0}^{D0}}{C\_EF_{T1}^{D1} * C\_EF_{T1}^{D0}} \right]^{1/2} \tag{3}$$

The components of the Malmquist index as specified in Equations (2) and (3) can be calculated separately with DEA. The two technical efficiency components that are based on data and technology from the same period can be calculated using the basic DEA program described in Equation (1). The cross time efficiency based on year-0 technology and year-1 data can be calculated from Equation (4) using specification in Thanassoulis (2001).

$$\begin{aligned} & \min_{\omega,\lambda} \omega \\ & s.t. \\ & -y_i^1 + Y^0\lambda \geq 0 \\ & \omega x_{i,D}^1 - X_D^0\lambda \geq 0 \\ & x_{i,ND}^1 - X_{ND}^0\lambda \geq 0 \\ & \lambda \geq 0 \end{aligned} \tag{4}$$

The superscripts 1 and 0 for inputs *x* and outputs *y* of *i*-th unit indicate the relevant time period for data used for calculating efficiency. The superscripts for input matrix *X* and output matrix *Y* indicate the time period for technology used for calculating efficiency. This procedure can be modified in order to calculate relative efficiency for the remaining component of Equation (3) with year-1 technology and year-0 data.

3.2. Stochastic Frontier Analysis (SFA)

Stochastic Frontier Analysis is a parametric method used to estimate the efficient frontier and efficiency scores. This method requires specification of a distance function involving assumptions about the firms' production technologies and recognises the possibility of stochastic errors (see Coelli, et al., 1998). The statistical nature of the method allows for testing of hypotheses.

The SFA technique can be used to predict efficiency scores of models involving multiple outputs by estimating input distance functions (see Coelli and Perelman, 1999). Assuming that the electric utilities use single input *x* to produce *m* outputs y_m, $m = 1,\ldots M$, then, the stochastic frontier model for single input distance function in translog specification for *i*-th electric utility at time *t* will be as follows:

$$\begin{aligned} -\ln(x_{it}) = {} & \beta_0 + \gamma_{UK} D_{UK} + \sum_m \beta_m \ln y_{m,it} + \frac{1}{2}\sum_m\sum_k \beta_{mk} \ln y_{m,it} \ln y_{k,it} \\ & + \beta_t t + \sum_m \beta_{mt} \ln y_{m,it} t + \frac{1}{2}\beta_{tt} t^2 - u_{it} + v_{it}. \end{aligned} \tag{5}$$

where β and γ are unknown parameters, v is a random disturbance distributed as iid N(0, σ^2) and u is the (non-negative) technical inefficiency term. Time trend variable, t, is included to capture non-neutral technological change. A symmetric error term v accounts for statistical noise, thereby reducing reliance on measurements of a single efficient firm. However, it requires specification of a probability function for the distribution of the inefficiency term. It is usually assumed to be half-normal, $N^+(0, \sigma^2)$, or truncated normal, $N^+(\eta, \sigma^2)$, where the superscript '+' means that it takes only a non-negative value.

Note that the output elasticity must satisfy the monotonicity condition of the input distance function. The returns to scale are estimated as the inverse of the sum of output elasticity. The specification in Equation (5) allows variable returns to scale (VRS), but CRS can be imposed by the parameter restrictions, $\sum_m \beta_m = 1, \sum_k \beta_{mk} = 0, m = 1,\ldots,M$ and $\sum_m \beta_{mt} = 0$. Technological change is estimated by evaluating the partial derivative of the input distance function with respect to time trend variable.

Country dummy variable, D_{UK} is included to capture a systematic difference in technology between the two countries. Interpretation of this variable needs some caution. This variable captures the effect of systematic differences between UK and Japan. This allows possibility that a systematic difference in performance is accounted for by this dummy variable. If the coefficient on this variable turns out to be significant, then we are comparing the efficiency score relative to different frontier, which is not compatible with the DEA efficiency score comparison. Thus, we also estimate the stochastic distance function without the country dummy variable, with the assumption that there are no systematic differences in technology of the two countries.

It has been pointed out that the translog specification often fails to provide valid estimates due in part to the multicollinearity among the variables. In fact, our preliminary investigation revealed that the second order terms associated with time trend variable ($\ln y_1 \cdot t$, $\ln y_2 \cdot t$, and t^2) turned out to be insignificant. Thus we drop these variables but in order to test the difference in the rate of technological change between UK and Japan, we included the variable $D_{UK}*t$. Thus, our stochastic distance function is modified as follows:

$$
\begin{aligned}
-\ln(x_{it}) = {} & \beta_0 + \gamma_{UK} D_{UK} + \sum_m \beta_m \ln y_{m,it} + \frac{1}{2}\sum_m \sum_k \beta_{mk} \ln y_{m,it} \ln y_{k,it} \\
& + \beta_t t + \gamma_{UKt} D_{UK} t - u_{it} + v_{it}.
\end{aligned}
\tag{5'}
$$

To account for environmental influences in SFA, we use environmental variables directly to explain the variation of mean inefficiency, that is, we allow for environmental influence on mean inefficiency. In the efficiency effects model, reported in Battese and Coelli (1993, 1995), this is done by assuming a truncated-normal distribution for inefficiency and its mean to be specified as a linear function of environmental variables, z. Thus, the technical inefficiency is assumed to have distribution $N^+(\eta, \sigma^2)$, and its mean, η, is explained by a set of environmental variables. More specifically, η is specified as:

$$\eta_{it} = \delta_0 + \sum_{s=1}^{S} \delta_s z_{s,it} \tag{6}$$

With mean inefficiency as specified in (6), we estimate the input distance function with environmental variables included in the one-sided error term. The Maximum likelihood estimation procedure is described in Battese and Coelli (1993). The estimation procedure is automated in the computer program FRONTIER developed by Coelli (1996) to obtain the technology parameters, as well as $\sigma^2 = \sigma_u^2 + \sigma_v^2$ and $\gamma = \sigma_u^2 / \sigma^2$. Following Coelli, Perelman and Romano (1999) we obtain a predictor of technical efficiency of each utility as conditional expectation (conditional on $\varepsilon = u + v$) expressed as follows:

$$\begin{aligned} TE_{it} &= E[\exp(-u_{it} | \varepsilon_{it})] \\ &= \left\{ \exp\left[-\mu_{it} + \frac{1}{2}\sigma_*^2 \right] \right\} \cdot \left\{ \Phi\left[\frac{\mu_{it}}{\sigma_*} - \sigma_* \right] \Big/ \Phi\left[\frac{\mu_{it}}{\sigma_*} \right] \right\} \end{aligned} \tag{7}$$

where

$$\mu_{it} = (1-\gamma)\left[\delta_0 + \sum_{s=1}^{S} \delta_s z_{s,it} \right] - \gamma \varepsilon_{it} \tag{8}$$

$$\sigma_*^2 = \gamma(1-\gamma)\sigma^2 \tag{9}$$

The technical efficiency predicted can be said “gross measure,” as it involves the effect of the managerial environment.

We also compute the Malmquist Index by evaluating the changes in technical efficiency (ΔTE) and the technological changes (ΔTC, the partial derivative of the distance function (5) with respect to time) between the two consecutive periods. We follow the methodology outlined in Coelli, et al. (1998) in computing a parametric version of the Malmquist Index, which is comparable to equation (3).

$$MI_j \equiv \Delta TE \cdot \Delta TC = \frac{TE_{j,t+1}}{TE_{j,t}} \cdot \left\{ \left(1 + TC_{j,t}\right) \cdot \left(1 + TC_{j,t+1}\right) \right\}^{1/2} \tag{10}$$

4. Data Issues

The focus of this study is on relative performance of UK and Japanese electricity distribution systems between 1985/86 and 1997/98. Our dataset is balanced panel data of 21 utilities (12 UK RECs and 9 Japanese electric utilities) with a total number of observations of 273. It is critical to construct the dataset in order to make the UK-Japan comparison meaningful and this section describes how it is done.

Each REC owns and operates the distribution network in its service area. The distribution systems consist of overhead lines, cables, switchgear, transformers, control systems, and meters. The pre-privatisation (1985/6-1989/90) costs for the UK firms are based on the companies' annual reports, statistical reviews, and share offer prospectus. The post-privatisation costs for UK firms were obtained from OFGEM. The operating costs are exclusive of depreciation, exit charges to National Gird (transmission charges), and rates (local taxes) payable to authorities. Capital expenditures include network expansion and non-operational expenditures. The costs are also adjusted for estimated share of supply costs.[9] Supply businesses are engaged in the bulk purchase of electricity and its sale to customers. Compared to the supply business of, basically, billing and contract management,[10] the distribution business is highly capital-intensive.

As the Japanese utilities are vertically integrated, we need to estimate the costs of their distribution business that are equivalent to those of the UK RECs. We used accounting reports of the utilities showing the allocation of operating and capital costs into generation, transmission, transformation (substation), distribution, retail (including billing and metering), and general and administration. As power generation is not relevant for this study, we examined the other functions to obtain distribution costs that are comparable with those of the UK RECs.

Transmission, Transformation (Substation) and Distribution: Transmission and transformation cost for Japanese utilities include the high voltage electricity transmission that is not performed by RECs. Thus, we divide the transmission and transformation costs between high voltage transmission and low voltage regional transmission activities. We assume that at the voltage level 154kV or less, the Japanese transmission system is nearly equivalent to the RECs' regional transmission system that is at 132 kV and less. In order to calculate the appropriate share of costs, we multiply the length of transmission network by voltage level (km*kV). We then use the share of

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[9] Distribution and supply functions were uncoupled and the RECs could supply large customers outside their franchise area on the payment of an access charge for the use of another REC's network. Full supply competition for all customers was effective by 1999 with RECs' supply businesses and independent companies competing for business. In 1995, the government lifted the 'Golden Share' which had prevented mergers and acquisitions since privatisation. By March 1996, four RECs had been taken over and three others were the subject of take-over bids, including bids from the leading fossil fuel generating companies PowerGen and National Power (Green, 1996). Since then RECs have separated their distribution and supply businesses as required by OFGEM although this has been in the form of legal separation with ownership within the same group.

[10] Supply now also includes metering following some reallocation of functions between distribution in supply post 1997-98.

transmission with voltage 154kV or less in km*kV to obtain the cost of regional transmission. Distribution cost for Japanese utilities are all included.

Non-regulated Retail Activity: We also need to allocate the costs associated with retail into regulated and non-regulated activity. In the UK, during the period under examination, RECs were responsible for metering as a regulated activity but not for billing. Therefore, for the Japanese firms, we only use retail costs associated with metering but not billing.

General and Administration: Finally, we allocate the general and administration costs among different activities based on the share of labour costs in each activity.

The Japanese cost data for regional distribution is then, the sum of relevant part of transmission and transformation costs, distribution costs, metering part of retail costs, and a part of general and administration costs. In order to harmonise the costs over time and country, all costs are adjusted to 1997-98 price levels and then converted to Purchasing Power Parity (PPP) values using the $US-based rates for 1997/98.

Output data for the Japanese sector, such as units of energy distributed and the number of customers, and physical data, such as the length of transmission and distribution lines and the peak demand are taken from the Statistical Yearbook of Electric Utility Industry.

Table 1 shows the aggregate values of the input and output variables for the UK and Japanese distribution systems used in this study for 1985/86 and 1997/98. As shown in the table, the Japanese distribution network is considerably larger than the UK system. The UK sector shows significant reductions in the operating costs between 1985/6 and 1997/8. During the same period, the operating costs for the Japanese sector show a marked increase. Both sectors show large increases in capital expenditures as a result of growth in the main outputs.

5. Results

5.1. Efficiency Analysis Using DEA

Technical Efficiency Scores

We first present the pure technical efficiency scores calculated separately in each year for our preferred DEA models under the assumptions of CRS and VRS for the underlying technology. Table 2 shows arithmetic average of the efficiency scores for each country for the sub-periods 1985/86-1989/90, 1990/91-1994/95, and 1995/96-1997/98. The first sub-period represents the immediate pre-privatisation years in the UK while the second and third sub-periods correspond to the first and second distribution price controls in the UK. It should be noted that, in order to reduce reliance on the PPP exchange rates, the changes in the relative efficiency of the firms from the two countries are of more interest.

The relative performance of UK and Japanese distribution networks depends on the choice of assumptions about the underlying technology and input (Table 2). As expected, the efficiency scores from the VRS models are higher than those of the CRS models. In the TOTEX models, the mean scores for the UK firms are higher than those for the Japanese firms. However, in the OPEX models, the efficiency gap between the two countries is generally narrower and the picture is mixed.

In both models, with a few exceptions, the mean efficiency scores for the firms from both countries tend to decline over time. This result is somewhat unexpected and, in the light of cost savings in the UK firms in recent years, runs counter to intuition. However, a decline in average efficiency scores does not necessarily imply that productivity has declined. Rather, the likely reason is that while the whole sector has achieved some efficiency gains, the frontier firms have increased their efficiency lead over other firms. This observation is also in line with the large efficiency differences calculated by OFGEM for UK utilities. Nonetheless, this result poses a question as to the effectiveness of the UK incentive regulation model in closing the efficiency gap among the firms.

Table 2 also shows the results of a hypothesis test using analysis of variance tests of the differences in the sample means. We test the null hypothesis that the mean efficiencies in the UK and Japanese samples are equal in each of the three periods. The test statistic indicates that, for most sub-periods, the differences in efficiency scores between the two countries are statistically significant for the OPEX measures but not for the most recent TOTEX measures.

Malmquist Index

The Malmquist productivity index based on DEA (TOTEX-CRS) model and its decomposition into catch-up (technical efficiency change) effect and frontier shift (technological or innovation) effect are calculated for each year relative to the previous year and are shown in Figure 1. Index values higher than 1 indicate productivity improvement while values lower than 1 represent productivity regress. Although the Malmquist indices calculated could fluctuate from one year to the next, the length of the period under study allows us to examine the underlying long-term productivity trend. Table 3 shows the average (geometric) annual productivity change for the UK and Japan sectors (first columns) for the main sub-periods.

Overall, between 1985/86 and 1997/98, the average annual productivity improvement in the UK sector is 2.5% while the corresponding estimate for the Japanese sector is 0.7%. The indices suggest that the productivity of the UK RECs declined in the years prior to privatisation, while productivity in the Japanese sector improved during the second half of the same period (Figure 1a and Table 3).[11] In the second sub-period, the UK sector's productivity remains at the same level while the Japanese sector shows a slight decline. In the third sub-period, both sectors show improvement albeit the trend in the UK sector is considerably stronger.

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[11] Domah and Pollitt (2001) find that costs in the UK firms rise around this time reflecting the cost of organisational change. IPART (1999, p 80) finds similar Malmquist indices for the UK, 1990/91-1996/97.

A division of the productivity indices into a catch-up and a frontier shift component reveals a somewhat more mixed picture. As shown in Figure 1b and Table 3, the UK and sectors exhibits a weak tendency toward closing the efficiency gap in the second sub-period followed by a reversal in the third sub-period. The Japanese sector shows a narrowing efficiency gap in the first sub-period and strong regress during the second. Between 1985/86 and 1997/98, the average annual change in the catch-up factors for the UK and Japanese sectors are –0.4% and –0.8% respectively.

With regard to frontier shift, the UK RECs exhibit technological regress for the first sub-period while the Japanese firms show a positive boundary shift. Both sectors then show progress for the second and the third sub-periods (Figure 1c and Table 3). The average annual changes in technological change factors for the UK and Japanese sectors are 2.9% and 1.5% respectively. It is noteworthy that measured technological regress (or progress) does not necessarily represent loss (or gain) of technological knowledge. Rather, the frontier firms may have shifted their input-output mix because of changes in regulation, relative prices, or non-neutral technical change (see e.g. Førsund, 1993).

Table 3 also shows the hypothesis test using analysis of variance tests of the differences in the sample means. We test the null hypothesis that the mean productivity growth rates in the UK and Japanese samples are equal in each of the three sub-periods. The test statistic indicates that the differences in efficiency scores between the two countries are, except for the catch-up factor in the second sub-period, statistically insignificant for the most recent TOTEX measures.

5.2. Efficiency Analysis Using SFA

We now discuss the results from SFA. The estimated parameters are reported in Table 4a. We found that the hypothesis of CRS technology was rejected at the 5% level of significance and therefore we do not report here the results with CRS assumption. The average estimated returns to scale are, on average, 1.11 for the whole sample period. There is no temporal variation in returns to scale in both countries, but the UK electricity distribution system exhibit higher returns to scale (1.20) as compared to those of Japanese system (0.99). Note that the returns to scale here are based on the rate of change in input (TOTEX) when both outputs (units delivered and the number of customers) increase at the same rate. The estimated technological change shows statistically insignificant technological progress in both countries and no significant difference between them throughout the period under study. Assuming that the UK and Japanese firms employ common technology, using SFA, the results can be interpreted that UK firms became significantly more efficient relative to the Japanese firms.

The efficiency effect parameters (δ_1 and δ_2) indicate the effect of environmental variables (customer density and load factor) on the mean level of technical *inefficiency*, that is, negative parameter estimates indicate that inefficiency is systematically lower as the associated environmental variable increase. The result shows that an increase in customer density reduces inefficiency (that is, efficiency improving) but the effect of load factor is statistically insignificant.

The development of the Malmquist index and the predicted technical efficiency is shown in Figure 2(a) and Figure 2(b), respectively. Since we have only a small and constant rate of technological change and there is no significant difference in that between the two countries, the Malmquist index in Figure 2(a) does not look very much different from efficiency change in Figure 2(b). This may be because RTS is picking up technical progress relative to Malmquist that is based on CRS. Thus this result needs to be interpreted with some caution.

Note that the DEA and SFA results are not directly comparable due to the way in which panel data are handled, since the DEA scores are calculated independently for each year while the SFA model includes a time trend variable to capture the technological progress in electricity distribution that is assumed to be commonly available to all the utilities in each country. Moreover, in this case, the efficiency scores are predicted relative to different frontiers making cross-country comparison of efficiency scores incompatible with that from DEA. It is clear from the results, however, that the efficiency gain in the UK is larger than that in Japan in the last 3 years of our sample period during which the UK sector experienced rapid cost savings and end-user price reductions.

In order to make the efficiency comparison compatible with that of DEA, we impose the restriction that the UK and Japanese electricity distribution system employ the same technology and experience the same rate of technological change, so that the efficiency scores can be predicted relative to the same frontier. Then, in order to test the hypothesis that the UK electricity distribution is equally efficient as the Japanese electricity distribution in each of the three periods, we included country specific dummy variables to explain the mean inefficiency in the right hand side of equation (6). Specifically we used the following dummy variables:

UK1 = 1, for UK electricity distribution during the period 1985/86 through 1989/90
= 0, otherwise
UK2 = 1, for UK electricity distribution during the period 1990/91 through 1994/95
= 0, otherwise
UK3 = 1, for UK electricity distribution during the period 1995/96 through 1997/98
= 0, otherwise
JP2 = 1, for Japanese electricity distribution during the period 1990/91 through 1994/95
= 0, otherwise
JP3 = 1, for Japanese electricity distribution during the period 1995/96 through 1997/98
=0, otherwise

By including these dummy variables in equation (6), the efficiency effect of each period in each country can be estimated relative to the efficiency level of Japanese electricity distribution during the period 1985/86 through 1989/90. Table (4b) shows the parameter estimates of these efficiency effects as well as technology parameters of the distance function. An increase in the load factor has a statistically significant effect on reducing inefficiency. The parameter estimates of UK dummy variables (UK1, UK2 and UK3) are all statistically significantly different from zero and negative, which indicate that the UK electricity distribution are more efficient relative to the Japanese electricity distribution in the first period. Log-likelihood tests to examine the relative efficiency in each period (namely, $\delta_4=\delta_6$ and $\delta_5=\delta_7$) clearly rejects the hypothesis of equal efficiency between the two countries, indicating that in each period, UK electricity distribution systems are more efficient relative to the Japanese electricity distribution systems. These parameter estimates also suggest that the efficiency gap became narrower during the second period and then wider during the third period.

6. Conclusions

The results of our comparative efficiency analyses indicate that, during our sample period, the productivity gain in UK electricity distribution utilities has been larger than that of the Japanese electricity distribution. In particular, productivity growth accelerated during the last 3-year period of our sample when UK electricity distribution utilities were operating under tightened revenue caps. The DEA Malmquist index and its decomposition revealed that while there has been a technological progress in UK RECs, the efficiency gap between them may have widened. This finding is of interest to regulators who wish to introduce incentive regulation models using uniform efficiency improvement requirements for regulated utilities based on Total Factor Productivity.

The transition from single to cross-country regulatory comparisons poses rather rigorous requirements on data. It is difficult to determine beforehand whether a particular data set used with a certain technique may produce results that are “unreasonable” or counter-intuitive. A multi-technique approach can help in revealing possible peculiarities in data and assessing the results of individual methods for the purpose of comparisons. It is therefore important to incorporate different techniques in the study design.

Also, as suggested in Jamasb and Pollitt (2001c), due to the cyclical nature of some system investment requirements and maintenance costs and exogenous factors such as regulation, multi-year efficiency studies are preferred. Our findings confirm this concern. We observed that, in the short-run, there can be significant variations in the level of costs and, consequently, in relative efficiency measures in relation to preceding and subsequent years leading to uneven performance patterns.

The make-up of the sample used is important and should not be arbitrary. The countries included in the sample need be relatively comparable in order to yield most information on relative performance of domestic firms. For relatively efficient sectors such as those of the UK and Japan, it is important that the benchmarking samples include international best practice. One major step towards this task could be the inclusion of efficient US utilities.

An important area for future research is to incorporate additional dimensions of output such as measures of security and availability of supply in the analysis. The UK regulator has made considerable effort to address and include quality of supply in regulation of electricity utilities (see e.g. OFGEM, 2001). However, there is currently a lack of suitable data for international comparisons. With more data it may be possible to examine the effects of regulatory changes. Such cross-country comparisons can involve a large comparability problem. The data issues can only be resolved through long-term cooperation and coordinated effort among regulators.

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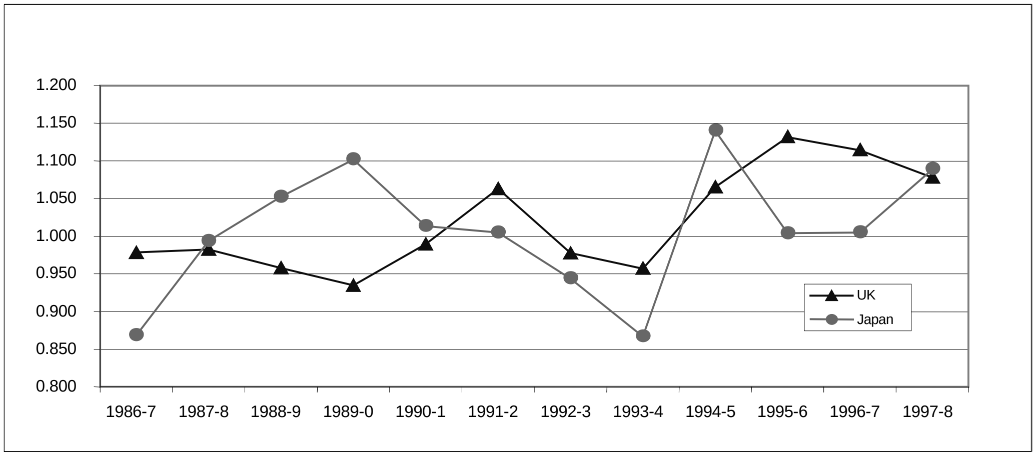
Table 1: Summary Statistics of UK and Japan Electricity Distribution

	1985/86		1997/98	
	UK	Japan	UK	Japan
Operating expenses (mill. $US PPP)	2,225	8,022	1,756	10,846
Capital expenditures (mill. $US PPP)	944	7,584	1,436	9,502
Units of energy delivered (GWh)				
• domestic	76,926	126,964	89,726	222,288
• others	132,290	368,754	172,905	539,296
Number of customers (000)	21,476	51,019	23,830	63,853
Length of network (km)	609,974	896,971	651,484	1,058,954
Maximum demand (MW)	44,301	106,946	49,392	165,918

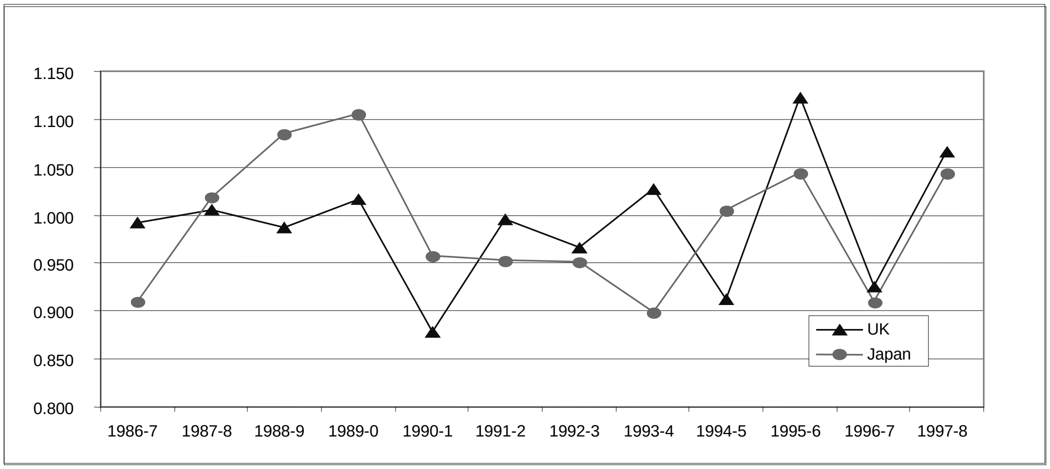
Table 2: DEA Efficiency scores for CRS and VRS

Input		TOTEX				OPEX			
Technology		CRS		VRS		CRS		VRS	
Country		JP	UK	JP	UK	JP	UK	JP	UK
Mean	1985/86-1989/90	0.796	0.919	0.808	0.984	0.838	0.898	0.850	0.978
	1990/91-1994/95	0.770	0.793	0.869	0.945	0.858	0.843	0.933	0.964
	1995/96-1997/98	0.719	0.811	0.833	0.910	0.692	0.683	0.865	0.856
Variance	1985/86-1989/90	0.010	0.047	0.046	0.002	0.03	0.01	0.028	0.0
	1990/91-1994/95	0.048	0.018	0.032	0.006	0.022	0.018	0.011	0.004
	1995/96-1997/98	0.066	0.027	0.045	0.014	0.074	0.039	0.035	0.028
P-value	1985/86-1989/90	0.000		0.000		0.000		0.000	
	1990/91-1994/95	0.000		0.000		0.196		0.000	
	1995/96-1997/98	0.007		0.001		0.039		0.244	

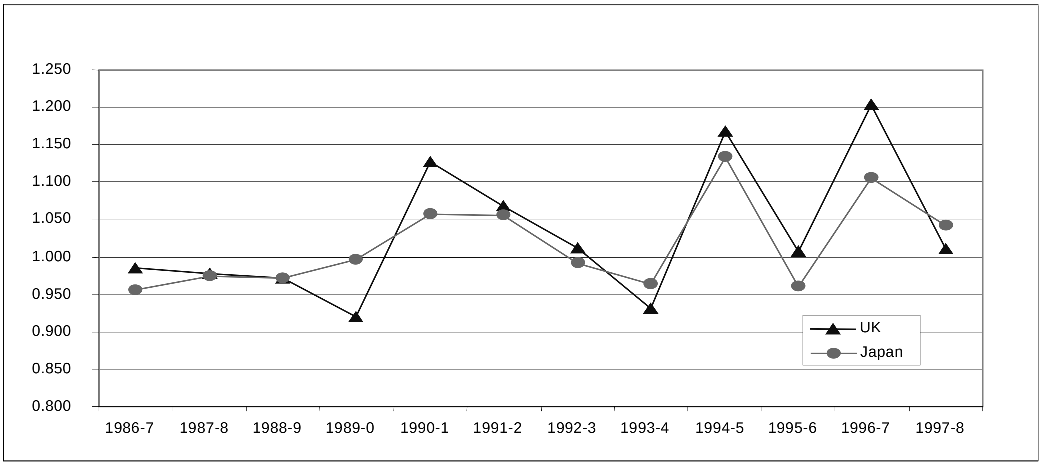
Figure 1: Malmquist productivity index and components - TOTEX Model



(a) Malmquist productivity index



(b) Catch up effect



(c) Frontier shift effect

Table 3: Average Malmquist productivity growth rate and decomposition – TOTEX-CRS model

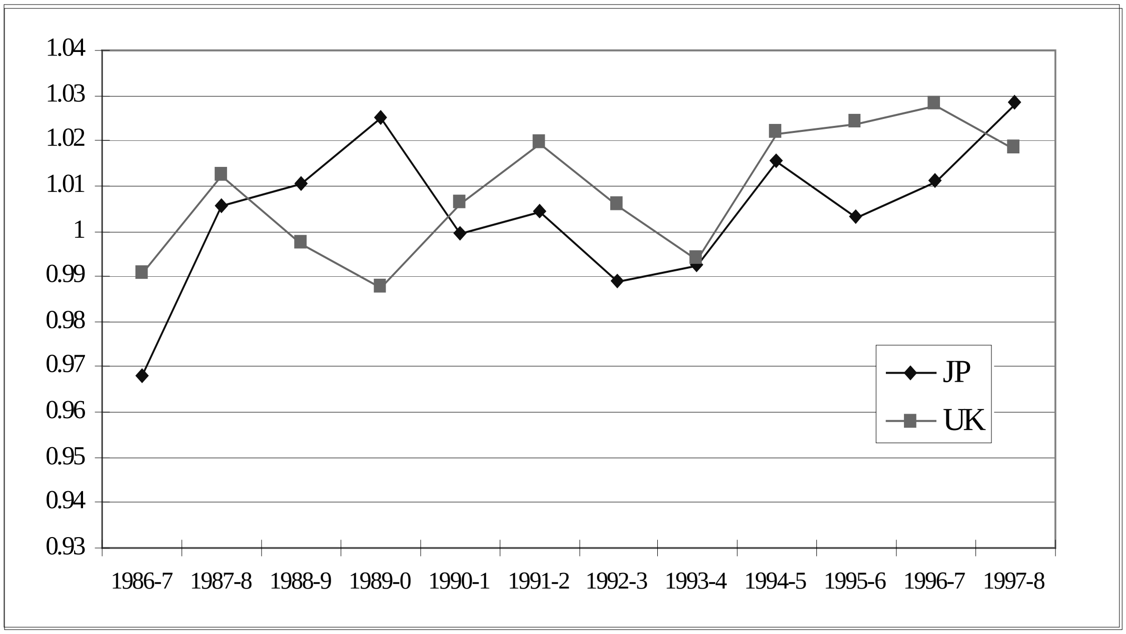
		UK	Japan	UK	Japan	UK	Japan
Mean		Malmquist		Catch-up		Frontier shift	
	1985/86 - 1989/90	-3.7%	0.0%	0.0%	2.7%	-3.7%	-2.6%
	1990/91 - 1994/95	0.9%	-1.0%	-4.6%	-4.7%	5.8%	3.9%
	1995/96 - 1997/98	10.8%	3.2%	3.5%	-0.2%	7.0%	3.4%
	1985/86-1997/98	2.5%	0.7%	-0.4%	-0.8%	2.9%	1.5%
t-Test:*							
	1985/86 - 1989/90	-3.65		-2.51**		-1.54	
	1990/91 - 1994/95	1.45		0.08		2.35	
	1995/96 - 1997/98	2.62		1.51		2.81	
	1985/86-1997/98	2.44		0.490		3.93	
P-value							
	1985/86 - 1989/90	0.001		0.015**		0.130	
	1990/91 - 1994/95	0.081		0.468		0.015	
	1995/96 - 1997/98	0.008		0.073		0.006	
	1985/86-1997/98	0.011		0.310		0.000	
Variance							
	1985/86 - 1989/90	0.0006	0.0004	0.0002	0.0009	0.0003	0.0006
	1990/91 - 1994/95	0.001	0.0008	0.001	0.0016	0.0002	0.0005
	1995/96 - 1997/98	0.005	0.003	0.003	0.003	0.001	0.0006
	1985/86-1997/98	0.00037	0.0002	0.0003	0.0004	0.000058	0.00007

* Two-sample means test assuming equal variances.
** Two-sample means test assuming unequal variances.

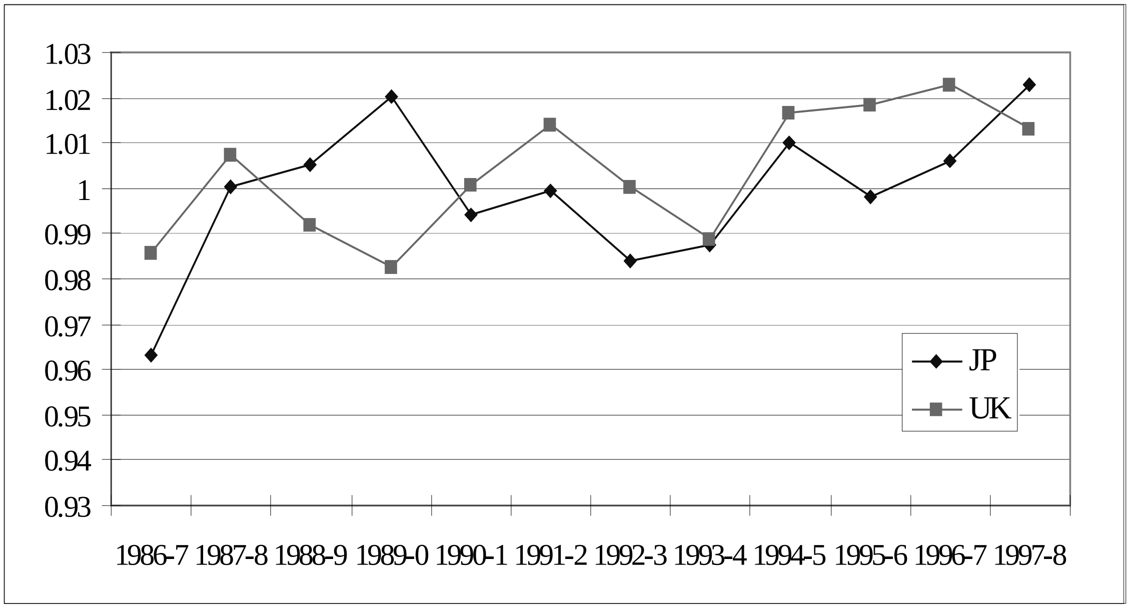
Table 4: Parameter estimates of input distance function

	(a) Separate frontier			(b) Common frontier		
Coefficient	Variable	Estimates	t-ratio	Variable	Estimates	t-ratio
β_0	(Constant)	-6.9285	-13.7172	(Constant)	-6.4219	-182.1285
β_1	ln y_1 (customer)	-0.5614	-6.3710	ln y_1 (customer)	-0.5073	-5.2928
β_2	ln y_2 (energy)	-0.4293	-4.8485	ln y_2 (energy)	-0.5089	-5.2338
β_{11}	$0.5*(\ln y_1)^2$	0.7701	2.1059	$0.5*(\ln y_1)^2$	0.7965	2.2583
β_{22}	$0.5*(\ln y_2)^2$	0.8637	2.5186	$0.5*(\ln y_2)^2$	0.8014	2.4101
β_{12}	$\ln y_1 * \ln y_2$	-1.7345	-2.4809	$\ln y_1 * \ln y_2$	-1.7176	-2.5514
β_τ	*t* (time trend)	0.0049	1.0347	*t* (time trend)	0.0094	3.1127
γ_{UK}	*UK-dummy*	0.7277	12.0830			
$\gamma_{UK\tau}$	*UK-dummy*t*	-0.0003	-0.0524			
δ_0	(Constant)	0.5912	1.0834	(Constant)	1.8235	5.5246
δ_1	z_1 (density)	-2.0868	-1.6079	z_1 (density)	-6.4500	-3.6338
δ_2	z_2 (load factor)	-0.4534	-1.1366	z_2 (load factor)	-1.3201	-2.8393
δ_3				z_3(UK1)	-1.1016	-6.2933
δ_4				z_4(UK2)	-0.6555	-11.0259
δ_5				z_5(UK3)	-1.1454	-6.8818
δ_6				z_6(JP2)	-0.0134	-0.3178
δ_7				z_7(JP3)	-0.0235	-0.4166
σ^2		0.0303	11.47		0.0272	9.16
γ		0.1616	0.2379		0.1560	1.5962
Log-likelihood		89.90			114.13	

Figure 2: Malmquist index and efficiency change of UK and Japanese electricity distribution systems



(a) Malmquist index



(b) Efficiency change