Separation of uncontrollable factors and time shift effects from DEA scores

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Abstract

It has been pointed out that DEA scores may be influenced by several external environmental factors, which are uncontrollable for DMUs. It implies that the DEA efficiency score without data adjustment might be biased and impractical for measuring genuine management efficiency. Therefore it is essential to eliminate uncontrollable effects from DEA scores and evaluate "pure" managerial efficiency for DMUs.

In an effort to solve this problem, we employ a multi-stage data adjustment procedure using DEA and regression models, which is originally proposed by Fried *et al.* [1999] consisting of four stages. In this study, we further modify this procedure by introducing newly developed devices in each stage; Connected Slacks-Based Measure (CSBM) model at the first and fourth stages, the Tobit model with DMU dummies at the second stage, and a data tuning procedure at the third stage. Then we decompose the technical inefficiency into three factors, i.e. environmental effects, time shift effects and pure technical inefficiency. Lastly, we apply this procedure to the electric power utilities in Japan and the US and compare their pure technical efficiency and causes of inefficiency.

Keywords: data envelopment analysis, data adjustment, electric utilities, multi-stage model, decomposition

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1 Introduction

Data Envelopment Analysis (DEA) is a representative method to measure management efficiency of Decision Making Units (DMUs) such as economic entities, and plenty of researchers have applied it to empirical studies in various industries. Generally, DEA models measure relative efficiency scores of DMUs based on an efficiency frontier, which enables us to compare efficiency performance among DMUs. However, it has been pointed out that DEA scores may be influenced by external environmental factors, which are beyond the control of DMUs. It implies that the DEA efficiency score without data adjustment might be biased and impractical. Thus, we must eliminate these uncontrollable effects from DEA scores in order to evaluate “pure” managerial inefficiency of DMUs. In an effort to overcome this difficulty, several previous studies attempted to resolve it and proposed new methods.

This study follows the multi-stage data adjustment procedure developed by Fried *et al.* [1999], and further modifies the procedure using DEA and Tobit with DMU-specific dummies, which enables us to keep advantages of two different parametric models employed by previous studies, i.e. Stochastic Frontier Analysis (SFA) and Tobit models. In addition, Connected Slacks-Based Measure (CSBM) model (Avkiran, Tone and Tsutsui [2007]) and a new data tuning procedure (Tone and Tsutsui [2007b]) are also employed as components of the multi-stage procedure.

This study is organized as follows. In Section 2, we review previous studies on data adjustment for DEA scores, and then explain our multi-stage data adjustment procedure in the third section. Furthermore, we develop this procedure to time series analysis in Section 4. Then our procedure is applied to vertically integrated electric power companies in Japan and the US as an empirical study in Section 5. Section 6 concludes this study and mentions future extensions.

2 Literature review

In consideration of external environmental effects on DEA efficiency scores, several measures have been proposed by previous studies (see Fried *et al.* [1999]).

In the frontier separation approach (Charnes *et al.* [1981], Fizel and Nunnikhoven [1992]), DMUs are classified based on a categorical variable such as ownership structure or regional characteristics, and are evaluated by referring to a frontier for each category and a pooled frontier as well. The impact of the external environment explained by categorical data is measured by comparing efficiency scores between the categorical and the pooled frontiers. This approach however considers only one categorical variable as the external environmental effect, even though various factors may have an influence on DEA scores.

Banker and Morey [1986] introduced a DEA model that directly includes external fixed inputs and outputs as uncontrollable factors for DMUs. This model can deal with more than one feature of external environments and non-categorical data. In this model we need to define external variables as inputs or outputs in advance. However, we sometimes do not know whether the external environmental elements have an impact on efficiency scores positively or negatively. Thus, knowing the amount and direction of such external influences are other important subjects of our research.

Timmer [1971] proposed a basic idea of a two-stage model, and several empirical works employed this model, in which the DEA score is measured in the traditional way in the 1st stage and then used as the dependent variable of a regression analysis in the 2nd

stage (see Fizel and Nunnikhoven [1992], McCarty and Yaisawarng [1993], Bhattacharyya *et al.* [1997]). The external environmental variables are used as independent variables that explain the variations in the efficiency score. In this model, we need not specify the direction of external effects on efficiency in advance because the regression coefficients in the 2nd stage will inform us the direction by the sign of coefficients.

Fried *et al.* [1993] and Goto and Tsutsui [2003] also employed the two-stage model, but they used the slack of each component instead of the efficiency score as the dependent variable. Because efficiency score measured by a radial model neglects slacks, it might give misleading results if slacks have an important role in evaluating the managerial efficiency. The two-stage model using slacks as a dependent variable can consider the portion that the radial efficiency score does not consider, and thus, it brings us closer to an unbiased estimator.

In these previous studies, Tobit model was preferred to Ordinary Least Squares (OLS) as a regression because DEA efficiency scores are censored from above at one[2] and it provides unbiased estimator. Bhattacharyya *et al.* [1997] used SFA rather than OLS or Tobit. SFA is a representative method of efficiency measurement originally developed by three papers that were published nearly simultaneously; Aigner *et al.* [1977], Meeusen and van den Broeck [1977] and Battese and Corra [1977]. In SFA, the error term consists of two components; statistical noise that is assumed to be independent and identically distributed (i.i.d.), and an efficiency component based on a specific distributional assumption, e.g. a half normal distribution. Thus, the DEA

[2] Contrary to DEA efficiency scores, slacks are censored from below at zero.

efficiency score (dependent variable) can be decomposed into three components by SFA; environmental effects, statistical error, and managerial efficiency terms.

Although the two-stage model does consider and reveal the effects of external variables on efficiency scores or slacks, it cannot provide an integrated efficiency score after exclusion of these effects. Fried *et al.* [1999] proposed a multi-stage approach to obtain an integrated pure managerial efficiency score eliminating external effects and statistical error. In this model, in the same manner as the two-stage model, slacks of each input or output are measured by DEA in the 1st stage, and then they are used as dependent variables in the regression model in the 2nd stage. Independent variables are external environmental variables that are uncontrollable by management of DMUs and assumed to be influential on the slacks that represent inefficiency. Then, in the 3rd stage, the actual data are adjusted by the environmental effect term consists of environmental variables and their coefficients and the error term estimated in the previous stage. In the final stage, the DEA model is rerun using the adjusted data. Through this multi-stage procedure, we can obtain the adjusted efficiency score, which can be regarded as a measure of “pure” managerial efficiency.

Fried *et al.* [1999] pointed out that this multi-stage approach has four advantages; 1) the final result is an integrated index, 2) it is not necessary to specify the direction of external effects on efficiency in advance, 3) the direction of environmental effects can be tested, and 4) it does not neglect slacks latent in the radial model.

This multi-stage procedure was employed in several studies with further modifications. Drake *et al.* [2006] employed the SBM model in the 1st and 4th stages instead of a radial DEA model such as the CCR. In the case where a radial model is used in the 1st stage, we have to merge the radial and non-radial slacks for the 2nd stage. SBM is contrarily a non-radial model, and thus, we can directly and consistently obtain the slacks of each input and output. Hahn [2004] also used the SBM model and further applied the bootstrap method to the regression stage in order to overcome the inherent dependency of efficiency scores pointed out by Xue and Harker [1999].

Fried *et al.* [2002] and Liu and Tone [2006] used SFA as a regression model in the 2nd stage, while Fried *et al.* [1999], Drake *et al.* [2006] and Hahn [2004] used the Tobit model. SFA in the 2nd stage helps decompose slacks into three components; environmental effects, statistical noise and a managerial efficiency term. However, these studies do not take into account that slacks are non-negative variables censored from below at zero, while the efficiency term estimated in the SFA model is assumed to have a non-negative distribution.

In our study, we employ the Tobit model for the 2nd stage to obtain unbiased and consistent parameter estimates. Furthermore, we incorporate dummy variables for all DMUs in the Tobit model to capture the fixed effect of DMUs, which plays a similar role to the efficiency term of the SFA model. Thus, our approach can also decompose slacks into environmental effects, statistical noise and managerial efficiency terms in the same manner as SFA, where the managerial efficiency terms are expressed by dummy variables.

In addition, we applies Connected Slacks-Based Measure (CSBM) model (Avkiran, Tone and Tsutsui [2007]) in the 1st and 4th stages, which resolves shortcomings of traditional radial and non-radial DEA models such as CCR (Charnes, Cooper and Rhodes [1978]) and SBM (Tone [2001]). Furthermore, we introduce a new data tuning procedure in the 3rd stage, which re-adjusts the adjusted data obtained in the 2nd stage. The adjustment formulation of Fried *et al.* [1999, 2002] and Hahn [2004] might cause irrational DEA scores as Tone and Tsutsui [2007b] pointed out. Thus, this tuning procedure helps to obtain positive and feasible adjusted data.

3 Formulations of the multi-stage data adjustment procedure

This study separates uncontrollable factors from DEA efficiency scores using a multi-stage data adjustment procedure, in which several new methods are incorporated in each stage. Our procedure consists of four stages; 1) initial measurement of slacks by CSBM, 2) separation of uncontrollable factors using Tobit with DMU dummies, 3) adjustment of the observed data with a tuning procedure, and 4) re-running CSBM with tuned data.

3.1 Initial measurement of slacks by CSBM – 1st stage

In the 1st stage, we undertake DEA and obtain slacks for each input. In our study, we employ the input oriented Connected Slacks-Based Measure (CSBM-I) model, which links traditional CCR and SBM models in a unified framework and contributes to overcome shortcomings inherent in both approaches, i.e. taking into account the non-radial slacks in the radial models such as the CCR model, and moderating the extreme results of the non-radial SBM models (Avkiran, Tone and Tsutsui [2007]). The input oriented CSBM model under the Variable Returns-to-Scale (VRS) assumption is formulated as follows:

[CSBM-I-V]

$$
\begin{aligned}
\tau^* = \min_{\boldsymbol{\lambda}, \boldsymbol{s}^-, \boldsymbol{s}^+} \ & 1 - \overline{SR} \\
\text{s.t.} \ \ & \overline{SR} = \frac{1}{m}\sum_{i=1}^{m}\frac{s_i^-}{x_{io}}, \\
& \boldsymbol{x}_o \geq \boldsymbol{X\lambda} + \boldsymbol{s}^-, \\
& \boldsymbol{y}_o \leq \boldsymbol{Y\lambda} - \boldsymbol{s}^+, \\
& L \cdot \overline{SR} \leq SR_i \leq U \cdot \overline{SR}, \ \ (i = 1,\ldots,m) \\
& \boldsymbol{e\lambda} = 1, \\
& \boldsymbol{\lambda} \geq \boldsymbol{0},
\end{aligned} \tag{3.1}
$$

where $\boldsymbol{x_o}$ and $\boldsymbol{y_o}$ are the $m\times1$ input and $r\times1$ output vectors of DMU_o ($o = 1,\Lambda\ ,n$), respectively, and $\boldsymbol{X}$ and $\boldsymbol{Y}$ are $m\times n$ input and $r\times n$ output matrices, respectively. $\boldsymbol{\lambda}$ is a $n\times1$ vector to indicate the intensity of reference DMUs. $\boldsymbol{s}^-$ and $\boldsymbol{s}^+$ are $m\times1$ and $r\times1$ slack vectors for inputs and outputs. The ratio of a slack to an observed input x_{io} is named the Slack Ratio index ($SR_{io} = \frac{s_i^-}{x_{io}}$), i.e. input factor inefficiency index for x_{io}. $\overline{SR}$ is the average of the SR index ($\overline{SR} = \frac{1}{m}\sum_{i=1}^{m} SR_i$).

U and L are the upper and lower bounds of the SR index for all inputs, which avoid a sharp contrast of the SBM results. Depending on L and U, the deviations of SR indices from the average value $\overline{SR}$ are limited accordingly. If L=1 or U=1, then CSBM reduces to the CCR model, while if L = 0 and $U \geq m$, then CSBM becomes the SBM model.

In this study, we use SR_1 instead of $\overline{SR}$ for the SR restriction, and thus the upper and lower bounds can be respectively define for each input as

$$
L_i \leq \frac{SR_i}{SR_1} \leq U_i. \quad (i = 2,\mathrm{K}\ ,m) \tag{3.2}
$$

This can be rewritten as

$$\boldsymbol{B\varphi} = \begin{bmatrix} U_2 & -1 & 0 & 0 & \cdots & 0 \\ -L_2 & 1 & 0 & 0 & \cdots & 0 \\ U_3 & 0 & -1 & 0 & \cdots & 0 \\ -L_3 & 0 & 1 & 0 & \cdots & 0 \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ U_m & 0 & 0 & 0 & \cdots & -1 \\ -L_m & 0 & 0 & 0 & \cdots & 1 \end{bmatrix} \begin{bmatrix} SR_1 \\ SR_2 \\ \vdots \\ SR_m \end{bmatrix} \geq 0, \tag{3.3}$$

where $\boldsymbol{B}$ is a $2(m-1)\times m$ matrix that consists of U_i and $-L_i$ ($i = 2,\ldots,m$) on the 1st column, and 1, −1 and 0 on the remaining columns. $\boldsymbol{\varphi}$ is an $m\times 1$ vector of SR_i ($i = 1,\ldots,m$). In this case, if $L_i = 1$ and $U_i = 1$ ($i = 2,\ldots,m$), then CSBM reduces to the CCR model, while if $L_i = 0$ and $U_i = \infty$ ($i = 2,\ldots,m$), then CSBM becomes the SBM model.

For the choice of U and L, this study assumes that input factor inefficiency for input i denoted by SR_i is correlated in some degree with the factor productivity index such as $\frac{x_{io}}{y_o}$, and thus the ratio of slack ratio indices $\frac{SR_i}{SR_1}$ ($i = 2,\ldots,m$) is also correlated with the ratio of the factor productivity indices $\frac{x_{io}/y_o}{x_{1o}/y_o} = \frac{x_{io}}{x_{1o}}$. Based on this assumption, as the upper bound U and the lower bound L, we employed maximum and minimum value of $\frac{x_{io}}{x_{1o}}$ among DMUs, respectively, as follows:

$$L_i = \min_j\left(\frac{x_{ij}}{x_{1j}}\right), \quad U_i = \max_j\left(\frac{x_{ij}}{x_{1j}}\right). \quad (j = 1,\ldots,n, \quad i = 2,\ldots,m) \tag{3.4}$$

Figure 3.1 describes a simple image of equation (3.4) and a comparison of the projections onto the efficient frontier using respectively CCR, SBM and CSBM models.

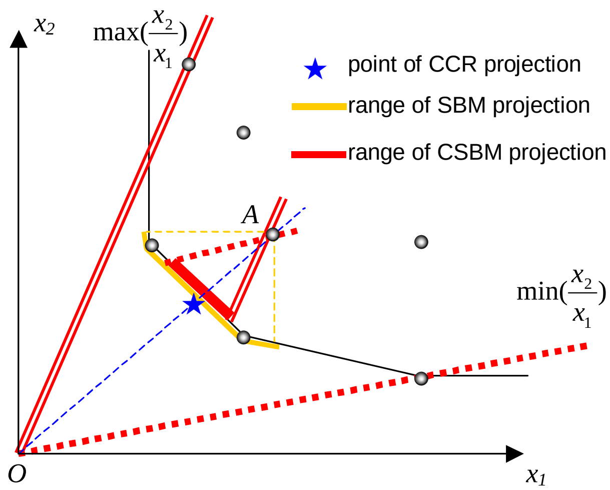


Figure 3.1: The simple image of CSBM restriction

Let $(\tau^*, \boldsymbol{\lambda}^*, \boldsymbol{s}_o^{-*}, \boldsymbol{s}_o^{+*})$ be an optimal solution for CSBM-I-V. Projection of DMU_o to the efficient frontier is then given by

$$[\text{CSBM} - \text{I} - \text{V projection}] \qquad \boldsymbol{x}_o^* = \boldsymbol{X}\boldsymbol{\lambda}^* = \boldsymbol{x}_o - \boldsymbol{s}_o^{-*}, \quad \boldsymbol{y}_o^* = \boldsymbol{Y}\boldsymbol{\lambda}^* = \boldsymbol{y}_o + \boldsymbol{s}_o^{+*}, \tag{3.5}$$

where $\boldsymbol{x}_o^*$ indicates the vector of technically efficient inputs for DMU_o for producing $\boldsymbol{y}_o^*$. Then technical efficient cost (C_o^{TE}) and technical efficiency index (TE) can be respectively defined as

$$[\text{Technical efficient cost}] \qquad C_o^{TE} = \sum_{i=1}^{m} w_{io} x_{io}^* \leq \sum_{i=1}^{m} w_{io} x_{io} = C_o, \tag{3.6}$$

$$[\text{Technical efficiency: } TE] \qquad TE_o = \frac{C_o^{TE}}{C_o} \geq 1 \tag{3.7}$$

where w_{io} is the input factor price of input i, and C_o is the observed cost of DMU_o.

3.2 Separation of uncontrollable factors using Tobit model with dummies – 2nd stage

The slack s_{io}^{-*} measured in the 1st stage is employed in the regression model as dependent variable S_j^i (= s_{ij}^{-*}) for input i of DMU_j (j=1,…,n) in the 2nd stage.

The Tobit model for the 2nd stage can be formulated as

[Ordinary Tobit model for input i]

$$S_j^{i*} = z_j^i \beta^i + v_j^i \quad (j=1,\dots,n) \tag{3.8}$$

where

$$S_j^i = S_j^{i*}, \qquad \text{if } S_j^{i*} > 0,$$
$$= 0, \qquad \text{otherwise.}$$

where z_j^i is a vector of environmental variables that is assumed to be influential on the slacks for input i of DMU_j. While S_j^i is observable and measured in DEA model as s_{ij}^{-*}, S_j^{i*} is the latent slack variable of input i for DMU_j. If $S_j^{i*} > 0$, S_j^i is defined as (3.8), and otherwise, S_j^i is observed as zero. In this model, a slack is defined as a non-negative variable censored from below at zero.

On the other hand, Fried *et al.* [2002] and Liu and Tone [2006] employed the SFA model as

[SFA model for input i]

$$S_j^i = z_j^i \beta^i + u_j^i + v_j^i . \quad (j=1,\dots,n) \tag{3.9}$$

This model can decompose the slack variable into three factors; environmental effects ($z_j^i \beta^i$), an efficiency component (u_j^i) based on a specific distributional assumption such as a half normal distribution, and statistical noise (v_j^i) assumed to be independent and identically distributed.

It is an advantage of SFA model to separate the efficiency component u_j^i from the residual. However, it does not take into consideration that slacks are non-negative variables censored from below at zero. Therefore, this study proposed compromised model as

[Tobit with DMU dummies for input *i*]

$$S_j^{i*} = z_j^i \beta^i + D(d_j;\delta) + v_j^i \quad (j=1,\ldots,n) \tag{3.10}$$

where

$$S_j^i = S_j^{i*}, \quad \text{if } S_j^{i*} > 0,$$
$$= 0, \quad \text{otherwise.}$$

This is the Tobit model where the slack variable is considered as non-negative censored variable. Furthermore, the dependent variable of (3.10) is decomposed into three factors same as SFA model, but the second component $D(d_j;\ \delta)$ is a DMU dummy term with a parameter vector δ and a dummy variable d_j for DMU_j. This term implies the fixed effects of DMUs and plays a similar role to the efficiency term u_j^i of the SFA model. Consequently, it can be said that our model keeps advantages of both SFA and ordinary Tobit models.

Through this regression stage, we can identify uncontrollable factors for DMUs such as the environmental effects ($z_j^i \hat{\beta}^{i*}$) and the statistical error ($\hat{v}_j^i$).

3.3 Adjustment of the observed data with a new tuning procedure – 3rd stage

To eliminate uncontrollable factors, we adjust the observed input data as

$$\begin{aligned} x_j^{ai} &= x_j^i - z_j^i \hat{\beta}^{i*} - \hat{v}_j^i \\ &= x_j^i - S_j^i + D(d_j;\delta), \quad (j = 1,\dots,n) \end{aligned} \tag{3.11}$$

where $\hat{\beta}^{i*}$ and $\hat{v}_j^i$ are estimated values in the 2nd stage. We notice that insignificant components of $\hat{\beta}^{i*}$ are replaced by zeros.

However, the adjusted value x_j^{ai} in (3.11) has a possibility to be negative. We re-run the SBM-based DEA model in the final stage, which does not accept negative value. Thus, adjusted data should be positive.

In order to obtain a non-negative adjusted value, Fried *et al.* [1996, 2002] and Harn [2004] employed a formula as

$$x_j^{ai} = x_j^i + \left[\max_j \left\{ z_j^i \hat{\beta}^{i*} \right\} - z_j^i \hat{\beta}^i \right] + \left[\max_j \left\{ \hat{v}_j^i \right\} - \hat{v}_j^i \right]. \tag{3.12}$$

This formula adjusts environmental effects to the common operating environment, i.e. the least favorable environment[3], and we can obtain non-negative adjusted value through (3.12).

However, (3.12) is equal to (3.11) added by $\max_j \left\{ z_j^i \hat{\beta}^{i*} \right\} + \max_j \left\{ \hat{v}_j^i \right\}$ that is the common value through all observations. As Tone and Tsutsui [2007b] pointed out, the new data generated by adding a certain value can result in irrational DEA scores. Therefore, we readjust input data using the tuning scheme proposed by Tone and Tsutsui [2007b] as

[3] In the case of most favorable environment, $x_j^{ai} = x_j^i + \left[z_j^i \hat{\beta}^i - \min_j \left\{ z_j^i \hat{\beta}^{i*} \right\} \right] + \left[\hat{v}_j^i - \min_j \left\{ \hat{v}_j^i \right\} \right]$ is utilized.

$$x_j^{Ai} = \frac{\max_j(x_j^i) - \min_j(x_j^i)}{\max_j(x_j^{ai}) - \min_j(x_j^{ai})}[x_j^{ai} - \min_j(x_j^{ai})] + \min_j(x_j^i). \quad (j = 1, \ldots n) \tag{3.13}$$

As Figure 3.2 explains, the readjusted data x_j^{Ai} remains in the range of the original observed data x_j^i, and has the same ranking with the adjusted data x_j^{ai}. These properties are appealing in eliminating ambiguity regarding the range of adjusted input values that influence the DEA scores significantly.

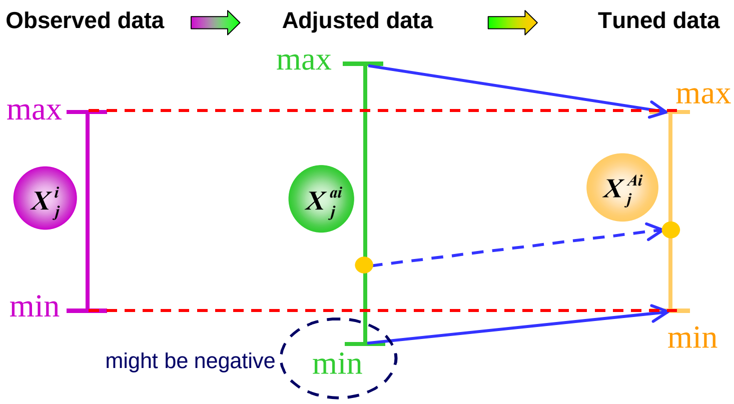


Figure 3.2: Tuning the adjusted data

3.4 Re-running CSBM model using the tuned data – 4th stage

After conducting the Tobit model with DMU dummies for all m slacks, adjusting and tuning input data, we re-run the CSBM model with readjusted data $\boldsymbol{x}_o^A$ (o = 1,…,n) and $\boldsymbol{X}^A = (\boldsymbol{x}_1^A, \ldots, \boldsymbol{x}_n^A)$ instead of $\boldsymbol{x}_o$ and $\boldsymbol{X}$ in (3.1). It can be said that the new efficiency score obtained at this stage reflects the pure managerial efficiency for each DMU.

4 Measuring time shift effect

In addition to cross sectional analysis, time series analysis, which captures the efficiency development over time, is an important research subject for dealing with panel data.

However, similarly to the cross sectional DEA efficiency scores we have mentioned in previous sections, the time shift effect measured by DEA also might be influenced by the external environmental effects. Thus, in this section, we attempt to detach the time shift effect from the environmental effects using our multi-stage procedure.

4.1 Time shift effect based on individual frontiers

For time series analysis, there are two approaches in DEA for measuring technical efficiency. One is to define the yearly efficiency frontiers, on which DMUs at the corresponding year are respectively evaluated, and the other is to evaluate DMUs by one pooled frontier for overall years.

If we define the efficiency frontier for each year, we can obtain not only a technical efficiency index (*TE*) for each year but also a frontier shift index (*FS*), which implies technical change in the industry. Figure 4.1 exhibits a simple example describing these two indices of a particular DMU operating at two different points in two different time periods. Assuming that DMU_o operates at point X^1 in period 1 and at X^2 in period 2, the technical efficiency of DMU_o in period 1 and 2 are, respectively, TE^1 and TE^2 (light gray lines), which are independently measured based on the frontiers 1 and 2 (f^1 and f^2), respectively.

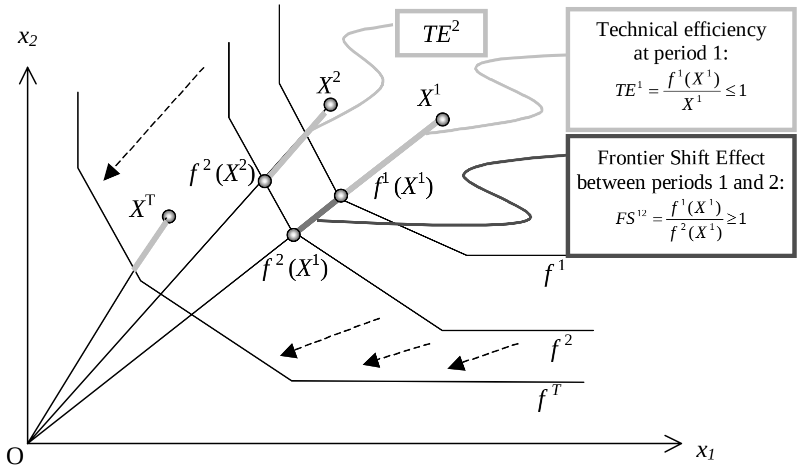


Figure 4.1: Technical efficiency and frontier shift effect

It should be noted that TE^1 and TE^2 are not consistently comparable, because they are independent. For the consistent time shift analysis, we have to measure technical efficiency on the same basis. If we take into account the frontier shift effect between these two periods (FS^{12}: dark gray line) adding to the TE^1 and TE^2,[4] we can compare the technical efficiency of DMU_o with respect to the single common frontier f^2.[5]

This method has an advantage for the time series analysis to capture technical efficiency of each period separated from the technical change (frontier shift) of the industry (Färe *et al*. [1989]). However, especially for unbalanced panel data, in which the numbers of DMUs across years are not identical, it might be difficult to obtain credible efficiency scores, because frontiers are measured by the different numbers of DMUs year by year[6]. In addition, as we noticed, the frontier shift FS^{12} in Figure 4.1 might be influenced by environmental factors similarly to the technical efficiency scores. Thus we should eliminate these factors to obtain practical indices helpful to

4 For instance, Malmquist index is a representative index that takes into account both technical efficiency score and frontier shift effect (Caves, Christensen and Diewert [1982]).

5 We can also consider frontier 1 as a basis. Färe *et al*. [1989] defined frontier shift index as the geometric mean of *FS* indices on the frontier 1 and 2 bases.

6 Especially in a period with less DMUs, the credibility goes down.

management. If we apply the multi-stage data adjustment procedure using DEA and Tobit with DMU dummies explained in Section 3, it must be too complicated to conduct Tobit models for both technical efficiency and frontier shift indices individually.

4.2 Time shift effect based on pooled frontier

On the other hand, we can also measure comparable technical efficiency scores based on the pooled frontier as described in Figure 4.2. In this case, we pool the whole data and define the overall efficiency frontier (f^{ALL}) for the full study period. This enables us to consistently measure efficiency scores on the same basis f^{ALL} and to treat the unbalanced panel data.

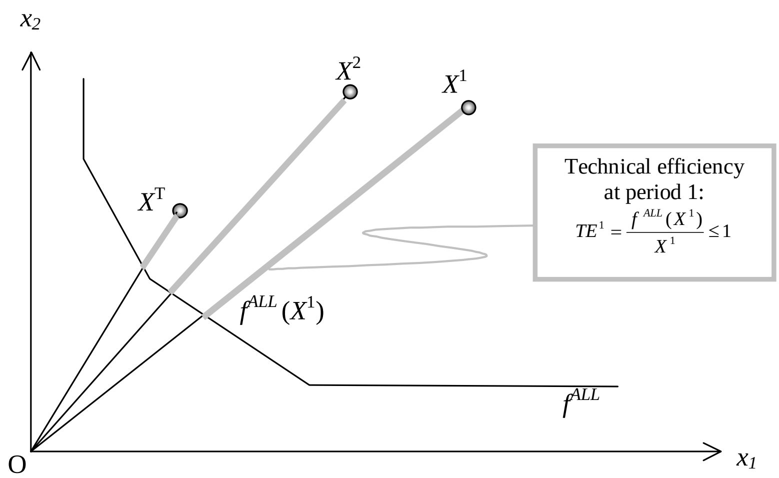


Figure 4.2: Technical efficiency on the pooled frontier

However, this cannot separate the time shift effect from the efficiency score. Thus, in our study, we attempt to separate the time shift effect from the DEA scores by the multi-stage data adjustment procedure in the same manner as the environmental effects. Using this procedure, we can obtain the environmental effects and the time shift effect together in a single Tobit model.

4.3 The 2nd stage regression model for time shift effect

For capturing the time shift effect, we add time trend variable (TT_j) to the Tobit with DMU dummies for input i in the 2nd stage as

$$S_j^{i*} = z_j^i \beta^i + TT_j \beta_{TT}^i + D(d_j;\delta) + v_j^i. \quad (j = 1,\ldots,n)^7 \tag{4.1}$$

Then we assume two different adjusted datasets using the estimated values at the 3rd stage as

$$x_j^{ai} = x_j^i - z_j^i \hat{\beta}^{i*} - TT_j \hat{\beta}_{TT}^{i*} - \hat{v}_j^i, \quad \text{(excluding time trend)} \tag{4.2}$$

$$x_j^{aTi} = x_j^i - z_j^i \hat{\beta}^{i*} - \hat{v}_j^i, \quad \text{(including time trend)} \tag{4.3}$$

where x_j^{ai} and x_j^{aTi} are the adjusted data excluding and including time shift effect, respectively, while x_j^i is the observed input data. Then we re-run two DEA models respectively using x_j^{Ai} and x_j^{ATi}, which are the tuned data of x_j^{ai} and x_j^{aTi} as explained in Section 3.3. Consequently, we can describe two different frontiers as Figure 4.3. If we assume a positive technical change, a frontier should shift toward the origin because of utilizing less inputs, thus a frontier including time trend (f^{in}) measured by x_j^{ATi} should be located closer to the origin than a frontier excluding time trend (f^{ex}) measured by x_j^{Ai}. We define the gap between the two frontiers indicates the technical change (TC) during the whole periods. Meanwhile, the deviation of adjusted data (X^A in the Figure 4.3) from the frontier f^{ex} indicates pure technical inefficiency.

[7] Since we treat the data as pooled, the number of observed DMUs in the whole periods is n.

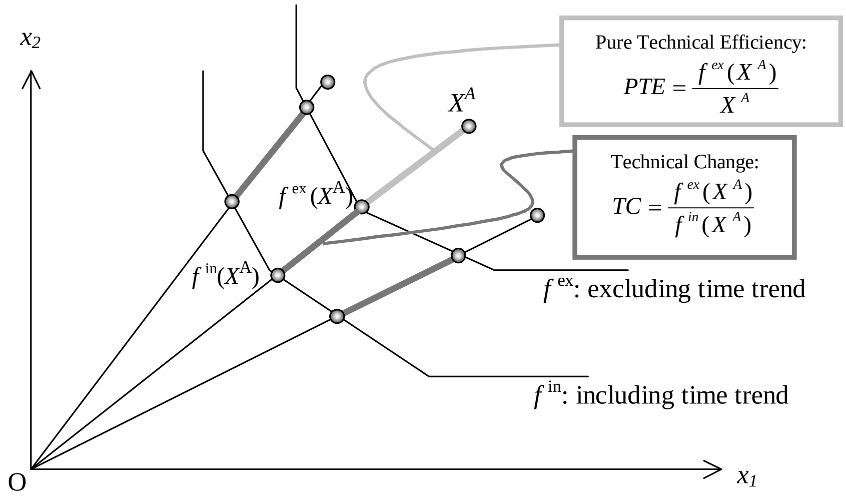


Figure 4.3: Time shift effect using the adjusted data

[Pure Technical Efficiency][8] $PTE = \frac{f^{ex}(X^A)}{X^A}$, (4.4)

[Technical Change][9] $$TC = \frac{TE \text{ on } f^{ex}}{TE \text{ on } f^{in}} = \frac{f^{ex}(X^A) / X^A}{f^{in}(X^A) / X^A} = \frac{f^{ex}(X^A)}{f^{in}(X^A)}. \quad (4.5)$$

However, if a negative technical change is observed, f^{in} will be located farther from the origin than f^{ex}. To avoid this case, we employed a "cumulative frontier", for which we measure the f^{in} using both x_j^{Ai} and x_j^{ATi}, while f^{ex} is measured only by x_j^{Ai}. This guarantees $TC \geq 1$ and gives a score unity to TC in the backward frontier shifts case.

As an extension of this model, we can also utilize time dummy variables (d_t) instead of TT_j in equation (4.1) in order to capture the frontier shift effect year by year. Using the estimated parameters, we obtain the adjusted data as

8 This is a case of radial model as Figure 4.3. In this study, we employed non-radial model, and thus we will redefine *PTE* in the non-radial case in Section 5.3.

9 Same as *PTE*, we will redefine *TC* for the non-radial model in Section 5.3.

$$x_{jt}^{Ai} = x_j^i - z_j^i \hat{\beta}^{i*} - d_t \hat{\delta}_t - \hat{v}_j^i \,. \tag{4.6}$$

It should be pointed out that using (4.6) we can generate $n \times T$ balanced panel data based on the estimated coefficients, thus it enables us to measure the consistent efficiency measure through the study period because the number of DMUs are same across years. In this study, we will also utilize this extensional model in Section 5.

5 Application to electric power companies in Japan and the US

5.1 Input and output variables for DEA models

In Japan, there are ten vertically integrated electric utilities; however, this study excluded one of them—Okinawa Electric Power Company —because Okinawa is very small and only services customers in the Okinawa islands. We selected US investor owned vertically integrated companies that were comparable to the Japanese companies with respect to the volume of electric power sales. After eliminating missing values and outliers by box plots, we obtained 407 unbalanced panel data from 1990 to 2001 with 56 companies (9 Japanese and 47 US).

The vertically integrated electric power companies consist of several divisions such as generation, transmission, distribution, retail sales and so forth. In this study the vertical structure of electric power companies is defined as described in Figure 5.1, and efficiency scores are measured by the network DEA model proposed by Tsutsui and Tone [2007], which takes into account the stream-lined vertical structure of companies.

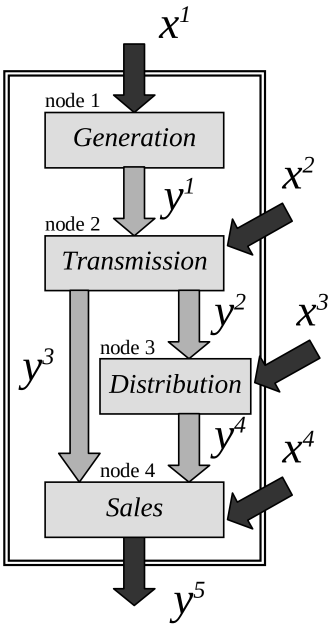


Figure 5.1: Structure of vertically integrated company

In the generation division (node 1), companies use capital, labor and fuel inputs (x^1). The capital input is the total nameplate capacity of electricity power plants measured in Mega Watts (MW), the labor input is the number of employees of this division, and fuel input is the consumed fuel at power plants. Since fuel consumption units differ amongst gas, coal, and petroleum, they were converted to British Thermal Units (BTU) in order to sum up the fossil fuel data. In contrast, the heat quantity from consumed nuclear fuel is difficult to measure. We thus performed backward calculations with the amount of nuclear power generation, assuming the thermal efficiency to be 0.32.

Using these three inputs, the generation division produces electric power (y^1), which is measured in Mega Watt hours (MWh). Then it becomes an intermediate input for the transmission division (node 2).

In the transmission division, we assumed three exogenous inputs (x^2) and one intermediate input (y^1). The capital input is the transmission line length (kilo meter: km) and the labor input is the number of employees in this division. Furthermore, we employed purchased power measured in MWh as an exogenous input. Electric power companies have two alternative power sources for supplying energy to customers; their own electric power plants and purchased power from other companies. The intermediate input (y^1) corresponds to the former source, and the third exogenous input corresponds to the latter one.

Electricity through transmission lines is sent to distribution lines. However distribution lines are used by only small customers such as residential. This study assumes that large customers such as industrial do not use distribution lines and are supplied electricity directly from transmission lines, while residential customers are supplied via distribution lines. Therefore, outputs of the transmission division are divided into two, i.e. electricity sent to small customers (y^2) and large customers (y^3).

The distribution division (node 3) uses capital and labor inputs (x^3) and the intermediate input from the transmission division (y^2). The capital input is the total capacity of transformers measured in Mega Volt Ampere (MVA), and the labor input is the number of employees in this division. The output of this division is also electricity to small customers (y^4) after eliminating the estimated distribution losses.

The sales division (node 4) provides electricity supply services to large and small customers. In our structure, this division uses a labor input as an exogenous input (x^4) and two intermediate inputs (y^3 and y^4), and produces the final output (y^5), which is the sum of y^3 and y^4. Table 5.1 shows input and output items for all four divisions.

Table 5.1: Dataset of all divisions

			Input and output factors	
Generation	x^1	G1	Capital Input	Nameplate Capacity (MW)
		G2	Labor Input	Number of Employess (#)
		G3	Fuel Input	Fuel Consumption (BTU)
	y^1		Output	Electric Power Generated (MWh)
Transmission			⇒ Intermediate Input	
	x^2	T1	Capital Input	Transmission Line Length (km)
		T2	Labor Input	Number of Employess (#)
		T3	Purchased Power	Purchased power (MWh)
	y^3		Output	Electric Power Transmitted to large customers(MWh)
	y^2		Output	Electric Power Transmitted to small customers(MWh)
Distribution			⇒ Intermediate Input	
	x^3	D1	Capital Input	Transformer Capacity (MVA)
		D2	Labor Input	Number of Employess (#)
	y^4		Output	Electric Power Distributed to small customers(MWh)
Sales			⇒ Intermediate Input	
	y^3		⇒ Intermediate Input	Electric Power Transmitted to large customers(MWh)
	x^4	S1	Labor Input	Number of Employess (#)
	y^5		Final Output	Total Electric Power Sales (MWh)

5.2 Environmental variables for the Tobit models

Furthermore, we used several environmental variables as explanatory variables of the Tobit models for data adjustment. In this study, we assumed that the composition of power source and characteristics of customer base were uncontrollable for electric utilities. Major power sources are fossil power fueled by oil, coal and gas, nuclear power, and hydraulic power. Generally the construction time of power plants is very long and it would be reasonable and proper to assume that the power composition is uncontrollable for utilities in the short-term, even if they can choose the energy mix in the long term. In our study, the characteristics of customer base, i.e. ratio of industrial, commercial, and residential customers, were also assumed to be uncontrollable, while it might be controllable in the long term, especially in the liberalized market. In addition, we employed time trend variable for capturing time shift effect explained in Section 4.

Table 5.2 explains those uncontrollable variables for each input item.

Table 5.2: Environmental variables

			Uncontrollable variables for input	
Generation	x1	G1:Capital Input	CR NR HR TT	Commercial Customer Ratio (%) Nuclear Power Ratio (%) Hydraulic Power Ratio (%) Time Trend
		G2:Labor Input	NR HR MW TT	Nuclear Power Ratio (%) Hydraulic Power Ratio (%) Nameplate Capacity (MW) Time Trend
		G3:Fuel Input	NR HR TT	Nuclear Power Ratio (%) Hydraulic Power Ratio (%) Time Trend
Transmission	x2	T1:Capital Input	-	-
		T2:Labor Input	DEN GR KM TT	Customer Density (#) Generation Power Ratio (%) Transmission Line Length (km) Time Trend
		T3:Purchased Power	-	-
Distribution	x3	D1:Capital Input	DEN TT	Customer Density (#) Time Trend
		D2:Labor Input	DEN MVA TT	Customer Density (#) Transfomer Capacity (MVA) Time Trend
Sales	x4	S1:Labor Input	DEN CUS LR TT	Customer Density (#) Total Number of Customers (#) Large Customer Ratio (%) Time Trend

As the uncontrollable variables for the generation capital input, we utilized commercial customer ratio (CR), nuclear power ratio (NR), hydraulic power ratio (HR), and time trend[10] (TT). Efficiency of capital utilization is strongly influenced by the load factor, i.e. low load factor causes inefficiency. Generally commercial customers have negative influence on load factor because their demands fluctuate more than those of industrial and residential customers. Therefore, we assume CR is positively influential on the slack. The sign of NR coefficient will be positive because of huge size of nuclear power plants, while HR will be negative. TT will explain the technical change of this input, e.g. if the coefficient of TT is negative, we can observe positive technical change.

For the generation labor input, we utilized NR, HR and TT as uncontrollable factors. We assume NR will have a positive impact on slacks because nuclear power plants need

[10] In this study, we utilized 0 to 11 as time trend variable for 1990 to 2001, respectively.

more employees than hydraulic ones, while HR will have a negative impact. In addition, we employed nameplate capacity (MW) in order to test the direction of the effect.

Fuel slack will depend on composition of power sources, i.e. HR must be negative because hydraulic power plant does not consume any explicit fuel and thus this study did not take account of it in the fuel data. On the other hand, NR might have a positive effect because of its huge heat quantity estimated from generated power.

For the slacks in the transmission division, we adjusted only the labor input, for which we utilized transmission line length (KM), customer density (DEN), generated power ratio to the total supplied electricity (GR), and TT as environmental explanatory variables. In the high-density area, labor productivity might be higher, thus it will have a negative impact on the slack. KM and GR were employed in order to test the direction of the effect. As we mentioned, a utility can procure electricity both from its own power plants and from other companies as purchased power. Thus, GR implies the ratio of self-sustaining. If we assume that high self-sustaining companies own more transmission assets, the GR would have a positive effect on the transmission labor slack.

In this study, we exempted the transmission capital and purchased power inputs from evaluation of their technical efficiency, thus making no adjustments. Concerning the capital input, the slack must be dependent on the service area, i.e. the transmission line length must be longer in the large service area than in the small area. However we could not obtain data on service area, and thus we regarded transmission line length as a given value in this study and did not evaluate its technical inefficiency. Also the slack of purchased power was not evaluated because it plays a role as adjuster in supplying energy. Generally, a large amount of input relative to outputs results in technical inefficiency of DMUs in the input-oriented model. However, in this case, it should be unpractical to evaluate DMUs as technical inefficient if they purchase large amount of electric power from other companies, because they might be efficient by reducing their own generation assets (capital input) instead of increase in the purchased power.

For the slack of the distribution capital and labor inputs, we employed DEN and TT. DEN might have a negative impact on these slacks because capital and labor productivities might be higher in a high-density area. In addition, we utilized transformer capacity (MVA) as an explanatory variable for the labor input slack. It is also assumed to have a negative impact because the work force required depends on the number of transformers rather than its capacity size, thus as MVA gets higher slack gets smaller.

In the sales division, the slack of labor input was regressed by DEN, the total number of customers (CUS), the large customer ratio (LR), and TT. Similarly to the distribution division, the labor productivity is supposed to be higher in the high-density area, so that it might have a negative impact on the slack. Concerning CUS, we assumed that the utilities with many customers would have an advantage, and the coefficient would be negative. LR was employed in order to test the direction of its effects. If LR is positive, it is concluded that utilities use more work force to serve large customers.

The Japanese dataset for this study was obtained from the “Handbook of Electric Power Industry” published by the Federation of Electric Power Companies (FEPC) in Japan, while the US dataset was constructed from the “FORM No.1” and “FORM No.423” published by the Federal Energy Regulatory Commission (FERC) and “Form EIA-860” published by Energy Information Administration (EIA).

5.3 Decomposition of technical efficiency index

As we pointed out earlier, DEA technical efficiency scores measured by equation (3.1) may be influenced by external environmental effects. If a DMU operates in a bad condition, its efficiency score might be worse than those of the others in a favorable condition. The multi-stage data adjusted model explained in Section 3 enables us to exclude the effect of unfavorable conditions from efficiency scores and to obtain “pure” technical efficiency scores. In this context, the gap between pure and non-pure efficiency scores implies the environmental effects.

However, the pure scores measured on the adjusted data are not guaranteed to be higher than those before adjustment for all DMUs. Thus, we added the restrictions of the SR indices to (3.1) as

$$SR_{io} = \frac{s_{io}^{-*}}{x_{io}} \geq \frac{s_{io}^{A-*}}{x_{io}^{A}} = SR_{io}^{A},\ (i=1,\ldots,m) \quad \text{for adjusted data excluding time shift} \qquad (5.1)$$

$$SR_{io} = \frac{s_{io}^{-*}}{x_{io}} \geq \frac{s_{io}^{AT-*}}{x_{io}^{AT}} = SR_{io}^{AT},\ (i=1,\ldots,m) \quad \text{for adjusted data including time shift} \qquad (5.2)$$

where superscript A and AT indicate the optimal value of the model on the adjusted data excluding and including time shift, respectively. These restrictions guarantee new DEA scores for all DMUs are higher than those pre-adjustment. Thus, the pure technical efficient input excluding time shift x_{io}^{A*} and including time shift x_{io}^{AT*} are respectively defined as

$$x_{io}^{A*} = x_{io}(1 - SR_{io}^{A}) \leq x_{io}, \qquad (5.3)$$

$$x_{io}^{AT*} = x_{io}(1 - SR_{io}^{AT}) \geq x_{io}(1 - SR_{io}) = x_{io}^{*}. \qquad (5.4)$$

In addition, pure technical efficient costs excluding and including time shift effect (C_o^A and C_o^{AT}) can be respectively expressed as

$$C_o^A = \sum_{i=1}^{m} w_{io} x_{io}^{A*} \le \sum_{i=1}^{m} w_{io} x_{io} = C_o \tag{5.5}$$

$$C_o^{AT} = \sum_{i=1}^{m} w_{io} x_{io}^{AT*} \ge \sum_{i=1}^{m} w_{io} x_{io}^{*} = C_o^{TE} \tag{5.6}$$

where w_{io}, C_o and C_o^{TE} are respectively the input factor price of input i, the observed cost and the technically efficient cost for DMU$_o$ defined in equation (3.6).

In this study, we assumed "cumulative frontier" for the frontier including time shift (f^{in}) to avoid the case of negative technical change as explained in Section 4.3. In particular, f^{in} was measured using both x_i^A and x_i^{AT}, while f^{ex} was measured only by x_i^A. This assumption leads to the inequality as

$$f^{ex}(x_{io}^A) \ge f^{in}(x_{io}^A), \tag{5.7}$$

where we define the projected values of x_{io}^A on f^{ex} and f^{in} respectively as

$$\text{[Projection on } f^{ex}\text{]:} \quad f^{ex}(x_{io}^A) = x_{io}^A - s_{io}^{A-*} = x_{io}^A(1 - SR_{io}^A), \tag{5.8}$$

$$\text{[Projection on } f^{in}\text{]:} \quad f^{in}(x_{io}^A) = x_{io}^A - s_{io}^{AT-*} = x_{io}^A(1 - SR_{io}^{AT}). \tag{5.9}$$

Then the relationships between x_{io}^{A*} and x_{io}^{AT*}, and C_o^A and C_o^{AT} are respectively,

$$x_{io}^{A*} = x_{io}(1 - SR_{io}^A) \ge x_{io}(1 - SR_{io}^{AT}) = x_{io}^{AT*}, \tag{5.10}$$

$$C_o^A = \sum_{i=1}^{m} w_{io} x_{io}^{A*} \ge \sum_{i=1}^{m} w_{io} x_{io}^{AT*} = C_o^{AT}. \tag{5.11}$$

Equations (5.5), (5.6) and (5.11) lead to the following inequalities:

$$C_o^{TE} \le C_o^{AT} \le C_o^{A} \le C_o \,. \tag{5.12}$$

Then we redefine[11] the *PTE* and *TC* using the ratios of these costs as

$$\text{[Pure Technical Efficiency: } PTE\text{]} \quad PTE_o = \frac{C_o^A}{C_o} \le 1 , \tag{5.13}$$

$$\text{[Technical Change: } TC\text{]} \quad TC_o = \frac{C_o^A}{C_o^{AT}} \ge 1 . \tag{5.14}$$

Furthermore, based on inequality (5.12), we define the differences of these various costs as:

$$\text{[Technical Inefficient cost]} \quad \overline{C}_o^{TI} = C_o - C_o^{TE} (\ge 0) , \tag{5.15}$$

$$\text{[Pure Technical Inefficient cost]} \quad \overline{C}_o^{PTI} = C_o - C_o^{A} (\ge 0) , \tag{5.16}$$

$$\text{[Technical Shift Effect]} \quad \overline{C}_o^{TSE} = C_o^A - C_o^{AT} (\ge 0) , \tag{5.17}$$

$$\text{[Environmental Effect]} \quad \overline{C}_o^{EE} = C_o^{AT} - C_o^{TE} (\ge 0) . \tag{5.18}$$

Thus, the actual cost C_o can be decomposed into technical efficient cost (C_o^{TE}) and technical inefficient cost ($\overline{C}_o^{TI}$), which can be further decomposed into three factors as

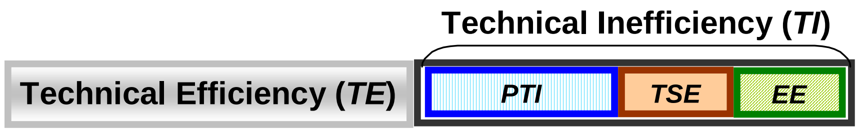
$$\begin{aligned} C_o &= C_o^{TE} + \overline{C}_o^{TI} \\ &= C_o^{TE} + \overline{C}_o^{PTI} + \overline{C}_o^{TSE} + \overline{C}_o^{EE} . \end{aligned} \tag{5.19}$$

[11] See Section 4.3, where we defined these indices for a radial model.

Then we can introduce the following additive form with Technical Efficiency index (*TE*), Pure Technical Inefficiency index (*PTI*), Time Shift Effect index (*TSE*) and Environmental Effect index (*EE*).

$$
\begin{aligned}
1 &= \frac{C_o^{TE}}{C_o} + \frac{\overline{C}_o^{PTI}}{C_o} + \frac{\overline{C}_o^{TSE}}{C_o} + \frac{\overline{C}_o^{EE}}{C_o} \\
&= TE + PTI + TSE + EE
\end{aligned}
\tag{5.20}
$$

Figure 5.2 depicts the decomposition of technical inefficiency (*TI*) into three factors.



PTI: Pure Technical Inefficiency, *TSE*: Time Shift Effect, *EE*: Environmental Effects

Figure 5.2: Decomposition of technical inefficiency (*TI*)

5.4 Empirical results

Figure 5.3 exhibits the results of technical efficiency (*TE*) on average for Japanese and the US electric power companies from 1990 to 2001. The average *TE* scores of both countries do not make much difference.

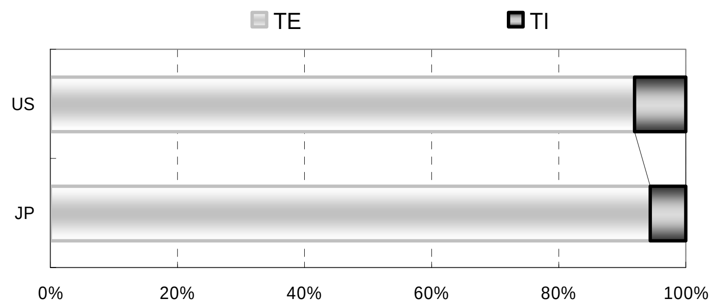


Figure 5.3: Comparison of technical efficiency (*TE*)

However, causes of technical inefficiency (*TI*) might be different between two countries. The decomposition procedure explained in Section 5.3 specifies the main cause of *TI*. Figure 5.4 focuses on the *TI*, i.e. the dark-gray portion of the bar graph on the right-hand side in Figure 5.3.

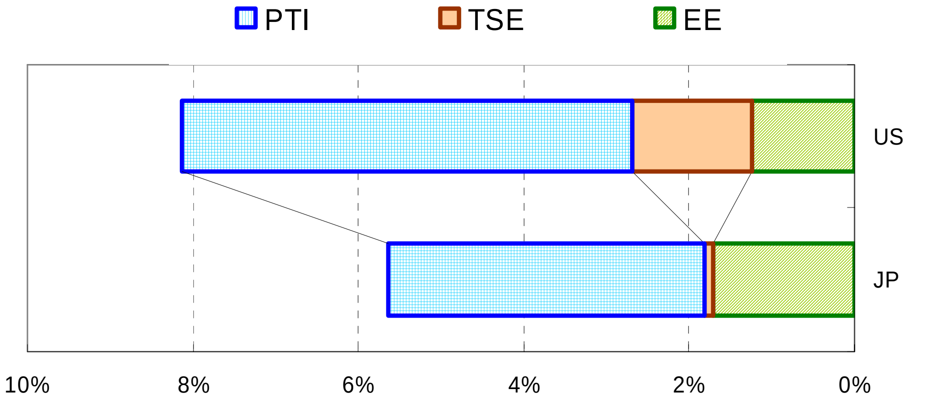


Figure 5.4: Decomposition of technical inefficiency (*TI*)

EE and *TSE* in Figure 5.4 were measured based on the results of Tobit model with DMU dummies as shown in Table 5.3.

Table 5.3: Result of Tobit model with DMU dummies

G1

	Coef.	t	
CR	0.321	(2.23)	**
NR	1.059	(4.49)	***
HR	0.098	(0.48)	
TT	-0.004	(-4.23)	***
Log likelihood		559.18	

T1

D1

	Coef.	t	
DEN	-0.406	(-8.92)	***
TT	-0.004	(-3.60)	***
Log likelihood		521.55	

G2

	Coef.	t	
NR	3.761	(2.70)	***
HR	0.050	(0.04)	
MW	0.110	(0.60)	
TT	-0.073	(-11.61)	***
Log likelihood		-92.96	

T2

	Coef.	t	
DEN	-0.098	(-1.64)	
GR	-0.143	(-1.83)	*
KM	0.015	(0.53)	
TT	-0.006	(-3.68)	***
Log likelihood		256.86	

D2

	Coef.	t	
DEN	-0.986	(-9.58)	***
MVA	-1.072	(-12.60)	***
TT	-0.013	(-4.06)	***
Log likelihood		254.07	

G3

	Coef.	t	
NR	0.501	(2.21)	**
HR	-0.511	(-2.59)	**
TT	-0.002	(-2.78)	***
Log likelihood		580.44	

T3

S1

	Coef.	t	
CUS	-0.754	(-5.94)	***
DEN	-0.373	(-2.53)	**
LR	-0.751	(-1.09)	
TT	-0.019	(-4.46)	***
Log likelihood		60.83	

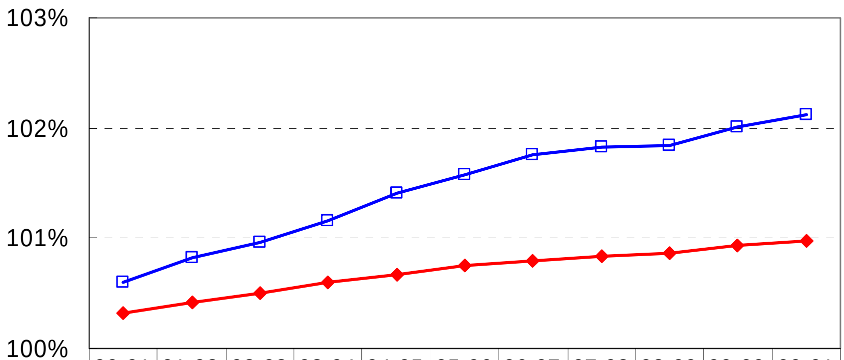
***: 1% significance level, **: 5% significance level, *: 10% significance level

In this case, Environmental Effects (*EE*) in Figure 5.4 account for 30% and 15% of *TI*

(1.7% and 1.2% of actual cost C_o) in Japan and the US, respectively. In addition, compared to the *TSE* of the US (18% of *TI* and 1.4% of C_o), little time shift effect is observed in Japan (2% of *TI* and 0.1% of C_o). It is pointed out that the technology of electric power industry is already saturated in Japan and drastic frontier shift could not be expected unless development and introduction of innovative technology, e.g. inexpensive decentralized power system. Several previous studies also observed little frontier shift in Japanese electric power industry, e.g. Tsutsui [2000] and Hattori [2002].

Both environmental and time shift effects are regarded as uncontrollable factors for DMUs in this study, and eliminated from DEA scores. In Japan, *EE* is larger than *TSE*, and vice versa in the US. As a result, the total effects of *EE* and *TSE* are nearly same between both countries, i.e. 32-3% of *TI*, and therefore pure technical inefficiency (*PTI*) scores also show insignificant difference as 3.8% and 5.4% of C_o, respectively.

While *TSE* in Figure 5.4 indicates the effect during the whole study period, Figure 5.5 describes the cumulative time shift effect year by year, which is captured by the time dummies defined in equation (4.6).



	90-91	91-92	92-93	93-94	94-95	95-96	96-97	97-98	98-99	99-00	00-01
JP	100.3	100.4	100.5	100.6	100.7	100.7	100.8	100.8	100.9	100.9	101.0
US	100.6	100.8	101.0	101.2	101.4	101.6	101.8	101.8	101.8	102.0	102.1

Figure 5.5: Cumulative frontier shift from 1990 to 2001

The result of Japan is relatively larger than that of Figure 5.4. However, in either case, the frontier shift is quite small.

6 Concluding remarks

This study introduced the modified multi-stage data adjustment procedure in order to detach environmental and time shift effects from DEA scores and obtain pure technical efficiency scores. Our procedure incorporated Tobit with DMU-specific dummies in 2^{nd} stage. This scheme keeps advantages of two different models employed by previous studies, i.e. SFA and Tobit models. In addition, we employed the CSBM model which resolved shortcomings of traditional radial and non-radial DEA models in the 1^{st} and 4^{th} stages, and also utilized the new data tuning procedure in the 3^{rd} stage, which enabled us to obtain positive and feasible adjusted data. Our procedure was applied to the electric power companies in Japan and the US as an empirical study, and decomposed technical inefficiency of both countries into environmental and time shift effects and pure technical inefficiency on cost basis.

This procedure can be also applied to the price efficiency, which is proposed by Tone and Tsutsui [2007a], and will be helpful to separate the external effects from DEA score and obtain the “pure” price inefficiency.

References

Aigner DJ, Lovell CAK and Schmidt P (1977) “Formulation and Estimation of Stochastic Frontier Production Function Models” *Journal of Econometrics*, 6(1), 21-37.

Avkiran NK, Tone K and Tsutsui M (2007) “Bridging radial and non-radial measures of efficiency in DEA” *GRIPS Research Report,* Series I-2006-0011.

Banker RD and Morey RC (1986) “Efficiency analysis for exogenously fixed inputs and outputs" *Operations Research*, 34(4), 513-521.

Battese GE and Corra GS (1977) "Estimation of a Production Frontier Model: with Application to the Pastoral Zone off Eastern Australia" *Australian Journal of Agricultural Economics*, 21(3), 169-179.

Bhattacharyya A, Lovell CAK and Sahay P (1997) "The impact of liberalization on the productive efficiency of indian commercial banks" *European Journal of Operational Research*, 98(2), 332-347.

Caves DW, Christensen LR and Diewert WE (1982) "The Economic Theory of Index Numbers and the Measurement of Input, Output and Productivity" *Econometrica*, 50, 1393-1414.

Charnes A, Cooper WW and Rhodes E (1978) "Measuring the Efficiency of Decision Making Units" *European Journal of Operational Research*, 2, 429-444.

Charnes A, Cooper WW and Rhodes E (1981) "Evaluating program and managerial efficiency: An application of data envelopment analysis to program follow through" *Management Science*, 27(6), 668-691.

Drake L, Hall MJ and Simper R (2006) "The impact of macroeconomic and regulatory factors on bank efficiency: A non-parametric analysis of Hong Kong's banking system" *Journal of Banking and Finance*, 30(5), 1443-1466.

EIA "Form EIA-860: Annual Electric Generator Report" Energy Information Administration, 1990-2001 (each year).

Färe R, Grosskopf S, Lindgren B and Roos P (1989) "Productivity Developments in Swedish Hospitals: A Malmquist Output Index Approach" *In:* Data Envelopment Analysis: Theory, Methodology and Applications, edited by Charnes A, Cooper WW, Lewin AY and Seiford LM (1994), Chap.13, Kluwer Academic Publishers.

FEPC "Handbook of Electric Power Industry" Federation of Electric Power Companies, 1990-2001 (each year). (in Japanese).

FERC "FORM No.1: Annual Report of Major Electric Utility" Federal Energy Regulatory Commission, 1990-2001 (each year).

FERC "FORM No.423: Cost and Quality of Fuels for Electric Plants" Federal Energy Regulatory Commission, 1990-2001 (each year).

Fizel JL and Nunnikhoven TS (1992) "Technical efficiency of for-profit and non-profit nursing homes" *Managerial and Decision Economics*, 13, 429-439.

Fried HO, Lovell CAK and Vanden Eeckaut P (1993) "Evaluating the performance of U.S. credit unions" *Journal of banking and finance*, 17(2-3), 251-265.

Fried HO, Schmidt SS and Yaisawarng S (1999) "Incorporating the operating environment into a nonparametric measure of technical efficiency" *Journal of Productivity Analysis*, 12, 249-267.

Fried HO, Lovell CAK, Schmidt SS and Yaisawarng S (2002) "Accounting for environmental effects and statistical noise in data envelopment analysis” *Journal of Productivity Analysis*, 17, 157–174.

Goto M and Tsutsui M (2003) “Efficiency analysis by Slack-Based Measures” *Journal of Public Utility Economics*, 55(2) 29-39. (in Japanese)

Harn FR (2004) “Measuring performance- a multiple-stage approach” *WIFO working papers*, No.228.

Hattori T (2002) “Relative performance of U.S. and Japanese electricity distribution: An application of stochastic frontier analysis” *Journal of Productivity Analysis*, 18, 269-284.

Liu J and Tone K (2007) “A multistage method to measure efficiency and its application to Japanese banking industry” *Socio-Economic Planning Sciences*, In Press.

McCarty TA and Yaisawarng S (1993) “Technical Efficiency in New Jersey School Districts” *In:* The Measurement of Productive Efficiency: Techniques and Applications, edited by Fried H, Lovell CAK and Schmidt SS (1993), 271-287, Oxford University Press.

Meeusen W and van den Broeck J (1977) “Efficiency Estimation from Cobb-Douglas Production Functions with Composed Error” *International Economic Review*, 18(2), 435-444.

Timmer CP (1971) “Using a probabilistic frontier production function to measure technical efficiency” *Journal of Political Economy*, 79(4), 776-794.

Tone K (2001) “A slacks-based measure of efficiency in data envelopment analysis” *European Journal of Operational Research*, 130, 498-509.

Tone K and Tsutsui M (2007a) “Decomposition of cost efficiency and its application to Japanese-US electric utility comparisons” *Socio-Economic Planning Sciences*, 41, 91-106.

Tone K and Tsutsui M (2007b) “Tuning SFA results for use in DEA” *GRIPS Research Report*, Series I-2006-0013.

Tsutsui M (2000) “Comparison of Intertemporal Technical Efficiency by Sector among Japanese and US Electric Utilities – the Application of Malmquist Index calculated by DEA” *CRIEPI REPORT*, Y99013. (in Japanese)

Tsutsui T and Tone K (2007) “Application of Network DEA Model to Vertically Integrated Electric Utilities” *GRIPS Discussion Paper*, 07-03.

Xue M and Harker PT (1999) “Overcoming the inherent dependency of DEA efficiency scores: A bootstrap approach” *Working paper*, Financial Institution Center, The Wharton School, University of Pennsylvania.