# Resource Use Efficiency of US Electricity Generating Plants During the $SO_2$ Trading Regime: A Distance Function Approach

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**Abstract:** Resource use efficiency is considered as the product of technical and environmental efficiencies. Three methods are used to calculate the resource use efficiency: stochastic frontier analysis, parametric and non-parametric linear programming. The geometric means of three methods for technical efficiency, environmental efficiency and resource use efficiency are 0.737, 0.335 and 0.248, respectively. The regression analyses of performance across plants shows units in phase I of the $SO_2$ trading program suggest that the market for $SO_2$ allowances, *per se*, may not be minimizing compliance cost. It is found that a decrease in $SO_2$ emission rate not only increases environmental efficiency but also leads to an increase in resource use efficiency. This finding concurs with the hypothesis that enhancement in the environmental performance of a firm leads to an increase in its overall efficiency of resource use as well.

**Key Words:** Technical Efficiency, Environmental Efficiency, Resource-Use Efficiency, Distance Functions, $SO_2$ Allowance Program.

**JEL Classification**: L94, Q40

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# I. Introduction

To achieve competitiveness, firms should use marketable inputs (conventional resources) as efficiently as possible, and to be an environment-friendly they should use the environmental resources efficiently. Porter and van der Linde (1995) visualize pollution as inefficiency in production process. They are of the view that enhancement in environmental performance of a firm leads to increase in the resource use productivity of the firm. This raises the question whether firms use conventional and natural resources efficiently, or whether technical and environmental efficiencies are compatible. Reinhard (1999) has defined resource use efficiency (RE) as the product of technical and environmental efficiencies of production units. Technical efficiency (TE) measures how far is a firm from the best practicing of its colleague in terms of the usage of conventional inputs. Environmental efficiency (EE) evaluates a firm in terms of the optimality of output-mix, i.e. it compares the good to bad output ratio of a firm with the firm that is producing the highest quantity of good output for a given level of bad outputs.

The measurement of environmental performance of firms has recently received increasing attention. To account for more inputs and outputs, Färe et al. (1989) has developed a vector of environmental performance measure. They evaluate producer performance in terms of the ability to obtain an equi-proportionate increase in desirable output and reduction in undesirable output. The ratio of the efficiency scores under strong and weak disposability[1] of bad outputs determines the environmental performance indicator. They use a nonparametric mathematical programming technique known as Data Envelopment Analysis (DEA) to construct their best-practice frontier.

Some studies (e.g., Tyteca, 1997; and Reinhard et al., 1999) define EE as the ratio of minimum feasible to observed use of an environmentally detrimental input, conditional on observed levels of the desirable output and conventional inputs. Their definition implies TE and not necessarily a small amount of bad output per unit of good output, and thus the EE score differs for the firms who are operating on the same technically efficient frontier. Therefore, we follow Färe et al. (2000) in constructing the index of EE. They use an index number approach for constructing the index of EE using distance functions in a multi-output case. This index is equivalent to the ratio of good to bad output in a single good and a single bad output scenario. It satisfies all of the desirable properties of index numbers.

There are various methods for computation of efficiency scores, but three are of particular interest: parametric linear programming (PLP) (e.g., Forsund and Hjalmarsson, 1987; Fare et al., 1993; Murty and Kumar, 2002); data envelopment analysis, (DEA) (e.g., Färe et al., 1989; Khanna et al. 2002); and econometric methods (e.g., Hetemaki, 1996; Kumar and Rao, 2003). There are two essential differences between the econometric approach and mathematical programming methods. The econometric approach is stochastic, and so attempts to distinguish the effects of noise from the effects of inefficiency. It also allows for a formal statistical testing of hypotheses. Mathematical programming (parametric or non-parametric) is non-stochastic and lump noise and inefficiency together, calling the combination inefficiency. The parametric approaches confound the effects of misspecification of functional form (of both technology and inefficiency) with inefficiency. The DEA approach is non-parametric and less prone to

[1] Strong disposability implies that a firm can dispose of its bad outputs without incurring any cost and weak disposability implies that a firm has to incur some cost for reducing the bad outputs.

specification error. In DEA the number of outlier firms tends to increase as more variables are added to the model. This results in loss of information, in particular when the sample size is small.

Most of the empirical studies are based only one of the above-mentioned methods. We use all the three approaches for the purpose of estimating the components of resource use efficiency. This aims to shed some light upon the sensitivity of empirical results to the selection of estimation method. Moreover, the time-series literature is in favor of using the average of the predictions from a number of models. The average of the various methods to form efficiency predictions may potentially be better than from any one particular method. For example, in a study discussing various methods of combining time-series predictions, Palm and Zellner (1992, p.699) observe that "*In many situations a simple average of forecasts will achieve a substantial reduction in variance and bias through averaging out individual bias*". The averaging approach is adopted by Coelli and Parelman (1999) in measuring the relative performance of European Railways, and by Drake and Simper (2003) in measuring the efficiency of English and Welsh police force.

We measure the RE and its components for a sample of US electricity generating firms during the $SO_2$ allowances trading period.[2] This application helps to test the hypothesis whether EE and TE are compatible and trading of the sulfur emissions has improved the efficiencies.

Previous studies have tried to examine the gains from trading in emissions in comparison to command and control alternatives such as forced scrubbing and a uniform emission rate standard (e.g., Carlson et al., 2000). Some studies have tried to judge whether there remain opportunities to reduce abatement costs through allowance trading even after plant owners have taken advantages of other cost reducing opportunities (e.g., Swinton, 2002; Coggins and Swinton, 1996). Although the trading program seems to be successful in reducing atmospheric emissions of sulfur dioxide, it is not clear, however, whether the program has resulted in minimizing the compliance costs (Swinton, 2004). But none of these studies have tried to examine the impact of trading and reductions in emission rates on RE of these plants.

The paper is organized as follows: Section 2 discusses the concept of resource use efficiency and its components, viz. technical and environmental efficiencies. Section 3 presents the methods of estimation that are considered in the empirical analysis. In Section 4 we briefly discuss the US electricity generation data, while in Section 5 the empirical results are presented and discussed. The final section contains some concluding remarks.

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[2] Title IV of the 1990 Clean Air Act Amendments (CAAA) establishes a market for transferable $SO_2$ emissions allowance among electric utilities. The program is divided in two phases. Phase I affects 110 of the dirtiest plants. The phase I units could emit at the rate of an emission rate of 2.5 pounds of $SO_2$ per million BTUs of heat input; but all other units of fossil-fueled power plants can annually emit at the rate of 1.2 pounds of $SO_2$ per million BTUs of heat input. In phase II, all major plants can emit at the rate of 1.2 pounds of $SO_2$ per million BTUs of heat input. The heat input is based on the 1985-87-reference period. Electricity generating firms can now transfer allowance among their own facilities, sell them to other firm, or bank them for use in future years. Thus the flexibility provided by this program enables the generating units to pursue a variety of compliance options to meet the regulation obligations, including scrubber installation, fuel switching, energy efficiency and allowance trading. Through emissions trading electricity generating firms have the incentive to find the lowest-cost means of achieving compliance and to reap financial rewards for developing those means.

## II. Theoretical Construct

The output enhancing efficiency consists of two components: (i) TE, which reflects the ability of a firm to augment outputs from a given set of inputs, and (ii) allocative efficiency (AE), which measures the ability of a firm to produce the outputs in the optimal proportion, given their respective prices. Similarly, the input saving efficiency consists of two components: (i) TE, which reflects the ability of a firm to contract inputs from a given set of outputs, and (ii) AE, measures the ability of a firm to use the inputs in the optimal proportions, given their respective prices. These two components are then combined to provide a measure of total economic efficiency (overall efficiency). Thus the analysis of efficiency can have an output enhancing or an input-saving orientation. Efficiency is a relative measure; efficiency scores depend on the firms that are compared.

Measurement of output-oriented efficiency requires data on input and output quantities and output prices, which is illustrated in figure 1. First take the case when the firm is producing all the good outputs that have positive prices. Suppose V is one such observation where a firm is operating, the TE of this firm is TE= OV/OD. The overall efficiency (OE) is defined as: OE= $\boldsymbol{ry}/R(\boldsymbol{x,r})$, and is equal to OV/OE. It is the ratio of observed revenue to maximum revenue; where $R(\boldsymbol{x,r})$ is the maximum revenue, $\boldsymbol{ry}$ is the observed revenue of a firm, $\boldsymbol{x}$ and $\boldsymbol{y}$ are the input and output vectors, and $\boldsymbol{r}$ is the output price vector. AE is defined as: AE= $\{\boldsymbol{ry}/TE\}/R(\boldsymbol{x,r})$, and it equal to OD/OE in figure 1. Thus from the figure it follows that, OE= TE.AE.

We extend the case in a situation where a firm is producing one desirable output, $y$ and an undesirable output, $z$ (pollution). There is null-jointness in the production of good and bad outputs, i.e., in the production possibility set there are no points on the left of the line OB, due to technical or biological restrictions. Null-jointness implies that some quantity of bad output is necessarily produced when we are producing some amount of good output. Therefore, point B in figure 1 is the unique point where all of the resources, conventional as well as environmental, are utilized efficiently. Because (i) point B is on the frontier, so the conventional resources (inputs) are used in a technically efficient manner, and also (ii) at this point, environmental resources are used optimally, since it is located on the radial with the lowest production of undesirable outputs per unit of desirable output. Point B in the figure can be defined as

$$(Y1, Z1)\in P(\boldsymbol{x}), \text{ where } R(\boldsymbol{x,r}) = \max\{\boldsymbol{r_y y}+\boldsymbol{r_z z}: (Y1, Z1) \in P(\boldsymbol{x}), \boldsymbol{r_z}\leq 0\}$$

where $\boldsymbol{r_y}$ and $\boldsymbol{r_z}$ are the vector of prices of good and bad outputs[3] respectively, and $R(\boldsymbol{x.r})$ is the revenue function, which is the dual to the output distance function (Färe and Primont, 1995).

In the figure, TE at output bundle V is OV/OD. A firm is environmentally efficient if it is producing the lowest amount of undesirable output per unit of desirable output, i.e. point B. The measure of EE has to relate the point D (equal to the ratio at V) to the maximum ratio at point B. $EE_V$ relates the observed output mix with the optimal output mix for the output bundle V and is equal to:

$$EE_V\,(Y_V,Z_V,X_V,\boldsymbol{r_y},\boldsymbol{r_z}) = \frac{(\mathbf{r_y y_v}+\mathbf{r_z z_v})/TE}{R(\mathbf{x,r})}$$

[3] The good output is priced positively in the market but pollution has either zero or negative price. Its price is negative when a tax in imposed on its generation.

If $\boldsymbol{r_z}$ is equal to zero, the maximum revenue line shifts from aa to BB' and $EE_V$ is given by OD/OF and if $\boldsymbol{r_z}$ is negative, due to costly disposal of bad output, the maximum revenue line shifts to BB'', then $EE_V$ is given by OD/OG. A more negative price of bad output (a more damaging bad output) leads to smaller EE scores.

Recall that point B in the figure is 'resource use efficient' point. We want to compare point V to point B. RE compares the observed revenue at point V to the resource use efficient point B. RE for the output bundle V is equal to

$$RE_V\ (Y_V, Z_V, X_V, \boldsymbol{r_y}, \boldsymbol{r_z}) = \frac{(\mathbf{r}_y\mathbf{y}_v + \mathbf{r}_z\mathbf{z}_v)}{R(\mathbf{x},\mathbf{r})}$$

or OV/OF when the price of bad output is zero and OV/OG when the price of bad output is negative. That is, more negative the price of bad output smaller the RE scores. Therefore, RE can be decomposed into TE and EE, i.e. $RE_V = TE_V.EE_V$. It follows that RE is analogous to OE and EE is analogous to AE.

## III. Measurements and Estimation

*Measurements of TE and EE*

EE can be defined as the ratio of a good and bad outputs quantity indexes. In measuring the TE we scale up all the outputs, but when we measure EE of a firm rather than scaling up all the outputs, we scale-up good outputs and scale down bad outputs separately.

Suppose that a firm employs a vector of inputs $x \in \Re^K_+$ to produce a vector of good outputs $y \in \Re^M_+$, and bad outputs $b \in \Re^N_+$. Let *P(x)* be the feasible output set for the given input vector *x* and *L*(*y*, *b*) is the input requirement set for a given output vector (*y*, *b*). Now the technology set is defined as:[4]:

$$T = \{(x, y, b) : x \text{ can produce } (y, b)\} \qquad (1)$$

The output and input distance functions generalize the production technology of firm that is producing multiple outputs. Both are the radial measures of TE. Both of these measures require data only on the quantities of inputs and outputs. The input distance function provides the measure of input savings that can be achieved for the given level of outputs and output distance function measures the maximum proportional expansion of outputs for the given inputs. Under constant returns to scale they are reciprocal to each other.[5] The output distance function is defined as:

$$D_o(x, y, b) = \inf[\{x, (y, b)/\theta\} \in T] \qquad (2)$$

Equation (2) characterizes the output possibility set by the maximum equi-proportional expansion of all outputs consistent with the technology set (1). The input distance function is defined as:

$$D_i(x, y, b) = \inf[\{x/\lambda, (y, b)\} \in T] \qquad (3)$$

Equation (3) characterizes the input possibility set by the maximum equi-proportional contraction of all inputs consistent with the technology set (1).

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[4] The technology T, meets standard properties like closedness and convexity, see Färe and Primont (1995).
[5] For the properties of input and output distance functions, see Färe and Primont (1995).

For constructing the EE index, one needs to define the good and bad outputs quantity indexes and define the sub-vector distance functions. The sub-vector output distance function on the good outputs is defined as:

$$D_y(x, y, b) = \inf\{\theta : (x, y/\theta, b) \in T\}.$$

This distance function expands good outputs as much while keeping inputs and bad outputs constant. Let $x^0$ and $b^0$ be our given inputs and bad outputs, then the good output index compares two output vectors $y^k$ and $y^l$. The good output quantity index is obtained by taking the ratio of two distance functions, that is:

$$Q_y(x^0, b^0, y^k, y^l) = \frac{D_y(x^0, y^k, b^0)}{D_y(x^0, y^l, b^0)}.$$

This quantity index satisfies some of Fisher's important tests like homogeneity, time reversal, transitivity, and dimensionality.

The index of bad outputs can be constructed using 'input' distance function as the objective is to reduce the quantities of bad outputs. The sub-vector input distance function for bad outputs is defined as:

$$D_b(x, y, b) = \sup\{\lambda : (x, y, b/\lambda) \in T\}.$$

This distance function is homogeneous of degree +1 in bad outputs, and it is defined by finding the maximal contraction in these outputs. Given $(x^0, y^0)$, the quantity index of bad outputs compares $b^k$ and $b^l$ again using the ratios of distance functions i.e.,

$$Q_b(x^0, y^0, b^k, b^l) = \frac{D_b(x^0, y^0, b^k)}{D_b(x^0, y^0, b^l)}.$$

Similar to the good index, the bad output quantity index also satisfies the above-mentioned Fisher tests.

Following Färe et al. (2000) we define the EE index as the ratio of two quantity indexes, i.e.,

$$E^{k.l}(x^0, y^0, b^0, y^k, y^l, b^k, b^l) = \frac{Q_y(x^0, b^0, y^k, y^l)}{Q_b(x^0, y^0, b^k, b^l)}$$

This efficiency index is similar to the index that evaluates how much good output is produced per unit of bad output.

*Estimation Methods*

*Stochastic Frontier Estimation*

To estimate the parameters of output distance function econometrically, we utilize the property that the distance function is homogenous of degree +1 in outputs:

$$\lambda Do(x, y) = Do(x, \lambda y) \qquad (4)$$

Now suppose $\lambda = 1/y_m$, then

$$1/y_m Do(x, y) = Do(x, y/y_m) \qquad (5)$$

From the econometric formulation of output distance function

$$Do(x, y)/y_m \geq Do(x, y/y_m) \qquad (6)$$

Equation (6) can be converted into a stochastic frontier model for Do by introducing the composed error term.

$$\ln (1/y_m) = TL(x, y/y_m)+u+v \qquad (7)$$

where v refers to random shocks and noise, u represents the production inefficiency and TL stands for the translog form of the distance function when the outputs are scaled by the mth output.

It is assumed that v is iid as $N(0, \sigma_v^2)$, and u is assumed to be distributed independently of v and to satisfy $u \leq 0$. After having estimated (7), $E[u_k | v+u]$ is calculated for each plant from which plant-specific measures are computed as

$$Do(x, y) = \exp[-E\{u | v+u\}] \,. \qquad (8)$$

The composed error structure was originally formulated in a production function setting by Aigner et al. (1977) and in the context of the output distance function it was first used by Grosskopf and Hayes (1993).

Similarly, the sub-vector distance functions can be estimated. To estimate the sub vector output distance function when the objective is to increase the good output only, the distance function takes the form of conventional production function in which bad outputs enters as inputs. When we are estimating the sub vector distance function in which the objective is to contract the bad outputs only, the distance function, as mentioned above, behave like an input distance function. The input distance function has also the property of homogeneity of degree one in inputs. By utilizing this property of homogeneity, we estimate this sub vector distance function that takes the form of stochastic cost function, which again can be estimated by the procedure of Aigner et al. (1977).

*Parametric linear programming*

Aigner and Chu (1968) developed and applied the PLP to estimate a single output production frontier. This method involves specifying a parametric form for the production technology and use linear programming to compute parameter values, which provide the closest possible envelopment of the observed data. We specify translog form for the output distance function.

The isoquant of the output set corresponds to $\ln D_0 (x, y, b) = 0$ and the interior points: $-\infty < \ln D_0 (x, y, b) \leq 0$. Therefore, this is accomplished by solving the problem,

$$Max \sum_{i=1}^{I} [\ln D_0 (x, y, b) - \ln 1],$$

*Subject to*

(i) $\ln D_0(x, y, b) \leq 0$

(ii) $\sum_{m=1}^{M} \beta_m + \sum_{j=1}^{J} \gamma_j = 1$

$\sum \alpha_{nn'} = \sum \beta_{mm'} = \sum \gamma_{jj'} = \sum \delta_{nm} = \sum \eta_{nj} = \sum \varphi_{mj} = 0$

(iii) $\alpha_{nn} = \alpha_{nn'}$

$\beta_{mm} = \beta_{mm'}$

$\gamma_{jj} = \gamma_{jj'}$

where: $n=1,2,\ldots\ldots,N$ (number of inputs),

$m=1,2,\ldots\ldots,M$ (number of desirable outputs),
$j=1,2,\ldots\ldots,J$ (number of undesirable outputs)

The objective function minimizes the sum of the deviations of individual observations from the frontier of technology. Since the distance function takes a value of less than or equal to one, the natural logarithm of the distance function is less than or equal to zero, and the deviation from the frontier is less than or equal to zero. Hence the maximization of the objective function implies minimization of the sum of deviations of individual observations from the frontier. The constraints in (i) restrict the individual observations to be on or below the frontier of the technology. The constraints in (ii) impose homogeneity of degree +1 in outputs. Finally, constraints in (iii) impose symmetry.

As stated above output distance function measures the technical efficiency of a firm relative to its colleagues. To measure the environmental efficiency we need to estimate two sub-vector distance functions. To estimate the parameters of the sub-vector output distance function where the objective of the firm is to expand the good output only for the given level of bad outputs and inputs, the constraints in (ii) changes such that only the parameters of good outputs, $\sum_{m=1}^{M} \beta_m=1$. To estimate the parameters of the sub-vector input distance function the objective function is modified such that it becomes minimization problem rather than maximization problem and the constraints in (ii) changes such that only the parameters of bad outputs, $\sum_{j=1}^{J} \gamma_j=1$. In this sub-vector input distance function the firms contract the bad outputs for the given level of good outputs and inputs, and the value of distance function is greater than one or equal to one.

*Data Envelopment Analysis*

For the purpose of estimating resource use efficiency of firms, one needs to compute the three kinds of distance functions: the conventional output distance function, the sub-vector good-output output distance function and the sub-vector bad output input distance function.

Input and output distance functions are reciprocals of Farrell measures of technical efficiencies. Therefore, one can use DEA for computing the distance functions. The conventional technical efficiency for each firm is computed like this

$$(D_y(x^0, y^{k'}, b^{k'}))^{-1} = \max\theta$$

$$st$$

$$\sum_{k=1}^{K} z_k y_m^k \geq \theta y_m^{k'} \qquad m = 1,....,M$$

$$\sum_{k=1}^{K} z_k b_j^k \geq \theta b_j^{k'} \qquad j = 1,....,J$$

$$\sum_{k=1}^{K} z_k x_n^k \leq \mathrm{x}_\mathrm{n}^0 \qquad n = 1,....,N$$

$$\sum_{k=1}^{K} z_k = 1$$

$$z_k \geq 0 \qquad k = 1,......,K$$

The sub-vector good-output output distance functions is computed as:

$$(D_y(x^0, y^{k'}, b^0))^{-1} = \max\theta$$

$$st$$

$$\sum_{k=1}^{K} z_k y_m^k \geq \theta y_m^{k'} \qquad m = 1,....,M$$

$$\sum_{k=1}^{K} z_k b_j^k \leq b_j^0 \qquad j = 1,....,J$$

$$\sum_{k=1}^{K} z_k x_n^k \leq \mathrm{x}_\mathrm{n}^0 \qquad n = 1,....,N$$

$$\sum_{k=1}^{K} z_k = 1$$

$$z_k \geq 0 \qquad k = 1,......,K$$

which is the numerator for $Q_y(x^0, b^0, y^k, y^l)$. The denominator is computed by replacing $y^{k'}$ on the right hand side of the good output constraint with the observed output for the reference firm, i.e., $y^0$. This problem constructs the best practice frontier for a particular firm, and computes the scaling factor on good outputs required for each observation to attain best practice. The sub vector bad output input distance function, for each observation is computed as:

$$
\begin{aligned}
&(D_b(x^0, y^0, b^{k'}))^{-1} = \min \lambda \\
&st \\
&\sum_{k=1}^{K} z_k y_m^k \geq y_m^0 \qquad m = 1,...., M \\
&\sum_{k=1}^{K} z_k b_j^k \leq \lambda b_j^{k'} \qquad j = 1,...., J \\
&\sum_{k=1}^{K} z_k x_n^k \geq \mathrm{x}_\mathrm{n}^0 \qquad n = 1,...., N \\
&\sum_{k=1}^{K} z_k = 1 \\
&z_k \geq 0 \qquad k = 1,......, K
\end{aligned}
$$

which is the numerator for $Q_b(x^0, y^0, b^k, b^l)$. The denominator is computed by replacing $b^{k'}$ on the right hand side of the bad output constraint with the observed bad outputs for the reference firm, i.e., $b^0$. As above, this problem constructs the best practice frontier from the observed data and computes the scaling factor on bad outputs required for each observation to attain best practice[6].

## IV. Data

We are interested in the measurements of TE and EE, whose product constitute RE. We restricted our attention to electricity generating plants for which each generating unit had a minimum installed nameplate generating capacity of 25 megawatts.[7] The deterministic linear programming is sensitive to outliers, to minimize this effect; we examined the ratios of each of output to each input and compared their descriptive statistics across periods. If we observed any abnormality for any plant for a specific year, we excluded that plant from our data set. Thus, the balanced panel data consist of 80 electric generating plants for the years 1995-2001. Out of these 80 plants, 26 plants (including 'compensation and substitution' units) could emit at the rate of 2.5 pounds of $SO_2$ per million BTUs of heat input during the phase I. Phase I of the $SO_2$ trading program covers period 1995 to 1999. The phase II of the trading program started in January 2000 and all the electricity plants had to necessarily participate in the trading.

The data come primarily from two government agencies- the Federal Energy Regulatory Commission (FERC) and the US Environmental Protection Agency (EPA). The FREC maintains an online database of FERC Form 1 for the years 1994 to the present. The Form 1 provides annual information of electricity production activities at the plant level. The EPA maintains emissions database for all majors US pollution sources. Its Aerometric Information Retrieval System (AIRS) database is the source of air pollution data of $SO_2$, $NO_x$ and $CO_2$ for the years

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[6] Note that this index measures the environmental efficiency of each firm relative to the reference firm. Therefore, one can assume the same technology for all the firms and let $k = 1,...., K$ index the firms in the sample. Then, for an arbitrarily chosen base firm, for example *l*, the resultant efficiency scores will provide a cross firm comparison. Färe et al. (2000) use this approach in their application.

[7] Since only the units whose generating nameplate capacity is greater than 25 megawatts are covered under the Allowance program.

1995 to the present. The 1990 CAAA required all affected power plants to install continuous emission monitoring system (CEMS) by 1995. Consequently, all air pollution data from 1995 on are CEMS stack readings.

Variables in the data set include net generation of electricity, emissions of $SO_2$, $NO_x$, $CO_2$, fuel input, labor and capital. We employ total net generation in million kilowatt-hours (kWh), fuel in $10^{12}$ British thermal units (BTUs) of heat content to neutralize the heterogeneous nature of coal as well as to allow for different type of fuel inputs. Labor is measured as the annual average number of employees. Capital is measured in 1996 million dollars. We use this measure of capital rather than the installed nameplate capacity because we are interested not only in the generating capacity of a plant, but also the extent to which the plants have invested in equipment to reduce emissions of air pollutants. The descriptive statistics is provided in Table 1.

## V. Results

Nine different sets of distance functions results are presented here. These are the multi-outputs (good and bad) output distance function, good outputs output distance function, and the bad outputs input distance function. Each is estimated using maximum likelihood estimator (MLE), PLP and DEA.

*Stochastic Frontier Results*

We estimated the transformed distance functions by the maximum likelihood. The parameter estimates and 't' statistics are presented in Table 2. We started with the full translog specification and tested whether some parameters could be deleted. The full translog distance functions were tested to be the most appropriate specification; see Table 3. The hypothesis of the absence of inefficiency is rejected for each model. Most of the parameters of the selected functional forms appeared to be significant (at the 95% significance level). In the estimation process we have assumed the more general truncated normal distribution of the systematic error term as the value of $\mu$ appeared to be significant either at 90% or 95% level of significance. To judge the convexity-concavity property of the models we tested for every observation whether the principal minors of the Hessian matrix are positive or negative and we may conclude that the estimated models appeared to be the most appropriate ones.

We now turn to the estimated results of TE, EE and RE. The yearly geometric means of all the three measures are presented in Table 4. The seven-year average estimates of TE seem reasonable, ranging from 0.747 to 0.964 with a mean of 0.908. Because of the dual relationship between the revenue function and the distance function, this result can be interpreted as a potential of increasing the revenue by 9% due to attaining the efficiency frontier. EE is smaller, on average, than TE with a range from 0.052 to 0.747 and a mean of 0.517. Recall that TE focuses on the utilization of the conventional resources and EE relates the observed output mix to the optimal output mix. Multiplication of TE and EE results in RE. RE ranges from 0.045 to 0.676 with a mean of 0.470. We observe that the yearly average of TE increases up to 1997 and declines in 1998 and then it again starts to increase. But EE and RE are not observing any trend.

The Spearman rank correlation between the different measures of performance is presented in Table 5. The rank correlation coefficient between TE and EE is small and negative. Both TE and EE are positively correlated to RE. The rank correlation coefficient between TE and

RE is very small and insignificant (0.006). A firm that is judged efficient according to TE might not be environmentally efficient. But the high and statistically significant rank correlation coefficient (0.968) between EE and RE shows that if a plant is environmentally efficient, it might be efficient in the use of all kind of resources, i.e. environmental as well as conventional inputs.

*PLP and DEA Results*

In the PLP estimation, we have estimated the distance function for each year separately for the full translog models since in the stochastic estimation it appeared to be the most appropriate model. The estimated parameters of the linear programming models are almost similar to the stochastic models (which can be had from the authors on request). In both the models (MLE and PLP) the firms are not observing constant returns to scale. Therefore, variable returns to scale is assumed in the computation of distance function values through DEA.

A look at the means of TE (Table 4) shows that among the three orientations, the stochastic model produces the largest mean efficiencies in comparison to other two and these differences are generally not small. EE score is highest for PLP and smallest for DEA approach. The differences are generally large between parametric and non-parametric measures.

The rank correlation matrixes between various measures of performance can judge the compatibility between TE and EE. Table 5 shows the consistency between the measures of TE and EE. The rank correlation coefficient between these measures under PLP and DEA is -0.014 and 0.173 respectively. This again, like stochastic measure, reveals that a firm that is technically efficient might not be environmentally efficient. The rank correlation coefficients between TE and RE for both of the deterministic measures are 0.552 and 0.557. We find a high and statistically significant rank correlation between EE and RE; i.e. 0.761 and 0.897 for PLP and DEA measures, respectively.

*A Combination of Efficiency Measures*

Having discussed the various sets of results, one task, which remains so far, is to identify a set of preferred results. We are not taking the side of the proponents of parametric or not parametric, stochastic or deterministic estimation camps. We are constructing geometric means of the three computation techniques for each data point for all the three measures.

The estimates of the overall mean of TE range 0.331 to 0.922 with a mean of 0.737. This implies that there is a potential to increase the revenue by 26%. The mean of EE, on average, is smaller than the mean of TE with a range from 0.127 to 0.539 and a mean of 0.335. RE ranges from 0.042 to 0.436 with a mean of 0.248. For the combined figures also, the rank correlation coefficient between TE and EE is although positive but small (0.213) and insignificant. The rank correlation coefficients between TE and RE, and between EE and RE are large and statistically significant, i.e. 0.617 and 0.877 respectively. This again reveals that if a firm is environmentally efficient, it might be efficient in utilization of all kind of inputs.

One other issue of concern is to determine the factors underlying the changes in the various measures of efficiency. We expect that specific attributes of an individual plant contribute to the economic and environmental performance. Therefore, to further aid an understanding of the results discussed above and to test the hypothesis whether trading of the $SO_2$ emissions has improved the efficiency, we estimated regressions on a panel data set.

Tobit regression is often used with censored data and is suitable for analysis of efficiency scores which are bounded between 0 and 1. The use of Tobit regression for fixed effect model creates further complications. For a sample with a finite number of years, the Tobit model cannot consistently estimate the fixed effects and further more this inconsistency is transmitted to the estimates of coefficients and the variance of error term.[8] Hence heteroskedasticity corrected OLS is a generally accepted estimation procedure in this setting. To examine the relationship between different measures of efficiency and their determinants, we included the dummy variable for phase I plants (TRADE), size of the plant measured in megawatts by the nameplate capacity of the plant (SIZE), environmental performance of the plant measured by the ratio of $SO_2$ emissions in pounds per million BTUs of heat consumption ($SO_2$/HEAT), and time trend (TIME).

Table 6 provides the parameter estimates of the regressions for the efficiency indexes under alternative specifications. For each index, the first column reports the estimation results for the period 1995-1999 (model1) and the last column reports for the period 1995-2001 (model2). These two models were introduced only to judge the robustness of the results. The regression results show that the efficiency indexes are significantly affected by most of the independent variables in both of the models. The significance of F statistics at the 1- % critical level shows the goodness of fit for all of the models. We find that the SIZE variable affects the efficiency indexes positively; indicating that bigger plants are performing better. The positive association between the TIME variables and indexes of efficiency indicates that over time all the measures of efficiency are witnessing an upward trend.

The signs of TRADE and SO2/HEAT variables are of particular interest. TRADE is a significant determinant of TE and to the index it is negatively related. However, it determines EE negatively in model1 but becomes insignificant determinant in model2. There is no expected relationship between the different measures of efficiency and participation of a plant in trading of emissions. Moreover, we find a negative relationship between RE and TRADE. To explain this negative relationship between RE and TRADE, two points should be noted. One, phase I of the $SO_2$ allowance program extracts emissions reductions from the 110 dirtiest power plants in the U.S. These might be the plants those had older production technology and were not able to meet the new performance standards their own, as a result the RE of these plants were lower in comparison to their counterparts who were facing the performance standards. Second, cost effectiveness requires that under the allowance program the variance of emission rate to diverge over time. If plants differ in their ability to accommodate emissions reductions it is expected that the variance of emission rates to rise as owners take advantage of opportunities to trade allowances. From 1995 to 1999 for phase I units, mean and standard deviation of emission rate fell steadily (if 1995 is ignored) (Table 7). This would be expected under a command and control regime. Thus the findings presented here concur with Swinton (2004) in suggesting that market for allowances, *per se*, may not be minimizing compliance cost.

We find that TE is positively associated with the emission rate. The relationship between EE and emission rate is negative implying that as the emission rate declines EE of a plant increases. Thus we find a tradeoff in the sense that the decrease in emission rates leads to

[8] For a comprehensive discussion on limited dependent variables and panel data see Baltagi (1995), pp. 178-187.

decrease in TE but increase in EE. This implies that to decrease emission rates the producers of electricity have to incur abatement costs and these costs leads to improvement in environmental quality. This trade-off raises the question, what is the net impact of decrease in emission rate on the society's resources. The relationship between RE and emission rates may help to answer this question. We find a negative relationship between RE and emission rates in both of the models. In model1, the relationship is statistically insignificant, but in model2 the relationship is statistically significant at 10% critical level. This implies that decrease in emission rates not only increases EE but also leads to increase in RE. This finding concur with the hypothesis that enhancement in environmental performance of a firm leads to increase in the resource use productivity of the firm (Porter and van der Linde, 1995).

## VI. Conclusions

The aim of this paper is to measure RE of US electricity generating plants during the $SO_2$ trading regime. RE is defined as a product of TE and EE. EE is defined as the ratio of good to bad outputs in comparison to the best practicing firm, i.e. the firm that is producing the optimal mix of good and bad outputs. It is analogous to the concept of AE. RE enables the identification of plants that are characterized by efficient use of conventional as well as of natural resources.

The distance functions are used as analytical tools. Three methods are used for the estimation of efficiency indexes: stochastic frontier analysis, deterministic parametric and non-parametric linear programming. An averaging approach is adopted and a simple average of forecasts achieves a substantial reduction in variance and bias through averaging out individual bias.

For the combined figures, the estimate of the overall geometric mean of TE ranges 0.331 to 0.922 and with a mean of 0.737. This implies that an increase in revenue of 26 percent is possible due to attaining the efficiency frontier. The estimates of EE and RE are 0.335 and 0.248 respectively. The rank correlation coefficient between TE, EE and RE is 0.213, 0.617 and 0.877 respectively. This reveals that if a firm is environmentally efficient, it might be efficient in utilization of all kind of inputs. We find that the plants larger in size are more efficient and these efficiency measures are increasing overtime. Moreover, in the regression analyses we observe that phase I units are negatively related to these measures of performance. This suggests that market for allowances, *per se*, may not be minimizing compliance cost. We also find that decrease in $SO_2$ emission rates not only increases EE but also leads to increase in RE. This finding concur with the hypothesis that enhancement in environmental performance of a firm leads to increase in the resource use productivity of the firm.

The analysis of RE may provide the following lessons: (i) Decrease in environmental pollution intensity leads not only improvements in EE, but also increase the RE. (ii) It is not the application of market based instruments (MBIs) *per se* that leads to cost-effectiveness, but it is the flexibility provided in meeting environmental standard that improves the resource utilization in the economy either it is provided through the introduction of MBIs or performance based standards.

## References


Aigner, D. J. and S. F. Chu (1968), 'Estimating the industry production function', *American Economic Review* 58: 826-39.

Aigner, D.J., C.A.K. Lovell and P. Schmidt (1977), 'Formulation and Estimation of Stochastic Frontier Production Function Models', *Journal of Econometrics,* 6:1 (July), 21-37.

Baltagi, B. H. (1995), *Econometrics Analysis of Panel Data*. John Wiley & Sons.

Carlson, C., D. Burtraw, M. Cropper, and K. L. Palmer (2000), "Sulfur Dioxide Control by Electric Utilities: What Are the Gains from Trade?" *Journal of Political Economy* 108(6), 1292–1326.

Coelli, T.J. and S. Parelman (1999), 'A Comparison of Parametric and Non-parametric Distance Functions: With Application to European Railways', *European Journal of Operational Research* 117: 326-339.

Coggins, J.S. and J.R. Swinton (1996), 'The Price of Pollution: A Dual Approach to Valuing $SO_2$ Allowances', *Journal of Environmental Economics and Management* 30:1 (January) 58-72.

Drake, L. and R. Simper (2003), 'The Measurement of English and Welsh Police Force Efficiency: A Comparison of Distance Function Models', *European Journal of Operational Research* 147: 165-186.

Färe, R., S. Grosskopf and F. Hernandez-Sancho (2000), 'Environmental Performance: An Index Number Approach', Department of Economics Working Paper, Oregon State University.

Färe, R., S. Grosskopf, C.A.K. Lovell and C. Pasurka (1989), 'Multilateral Productivity Comparisons When Some Outputs are Undesirable: a Non Parametric Approach', *The Review of Economics and Statistics* 71:1 (February) 90-98.

Färe, R., S. Grosskopf, C. A. K. Lovell and S. Yaisawarng (1993), 'Derivation of Shadow Prices for Undesirable Outputs: a Distance Function Approach', *Review of Economics and Statistics* 75:2 (May), 374-380.

Färe R. and D. Primont (1995), *Multi-Output Production and Duality: Theory and Applications*. Boston: Kluwer Academic Publishers.

Forsund, F. and L. Hjalmarsson (1987) *Analysis of Industrial Structure: A Putty-Clay Approach*. Stockholm: Almquist and Wicksell

Grosskopf, S, and K. Hayes (1993), 'Local public sector bureaucrats and their input choices', *Journal of Urban Economics* 33: 151-66.

Hetemäki, L. (1996) *Essays on the Impact of Pollution Control on a Firm: A Distance Function Approach*. Helsinki: The Finnish Forest Research Institute, Research Papers 609.

Khanna, Madhu; Surender Kumar and Wilma Q. Anton (2002), 'Environmental Self-Regulation: Implications for Environmental Efficiency and Profitability, Working Paper, program in Environmental and Resource Economics', University of Illinois at Urbana-Champaign.

Kumar, Surender and D.N. Rao (2003), 'Environmental Regulation and Production Efficiency: A Case Study of the Thermal Power Sector in India', *Journal of Energy and Development* 29(1): 81-94.

Murty, M. N. and Surender Kumar (2002), 'Measuring cost of environmentally sustainable industrial development in India: a distance function approach', *Environmental and Development Economics* 7: 467-486.

Porter, M. and C. van der Linde (1995), 'Towards a new conception of the environment-competitiveness relationship', *Journal of Economic Perspective* 9: 97-118.

Palm, F.C. and A. Zellner (1992), 'To Combine or Not to Combine? Issues of Combining Forecasts', *Journal of Forecasting* 11: 687-701.

Reinhard, S (1999), 'Econometric Analysis of Economic and Environmental Efficiency of Dutch Dairy Farms', Ph.D. Thesis, Wageningen Agricultural University

Reinhard, S., C.A.K. Lovell and G. Thijssen (1999), 'Econometric Estimation of Technical and Environmental Efficiency: An Application to Dutch Dairy Farms', *American Journal of Agricultural Economics* 81:1 (February), 44-60.

Swinton, J.R. (2002), "The Potential for Cost Savings in the Sulfur Dioxide Allowance Market: Empirical Evidence from Florida", *Land Economics*, 78(3), 390-404.

Swinton, J.R. (2004), 'Phase I Completed: An Empirical Assessment of the 1990 CAAA', *Environmental and Resource Economics*, 27: 3(March), 227-246.

Tyteca, D. (1997), 'Linear Programming Models for the Measurement of Environmental Performance of Firms- Concepts and Empirical Results', *Journal of Productivity Analysis* 8:2 (May), 183-198.

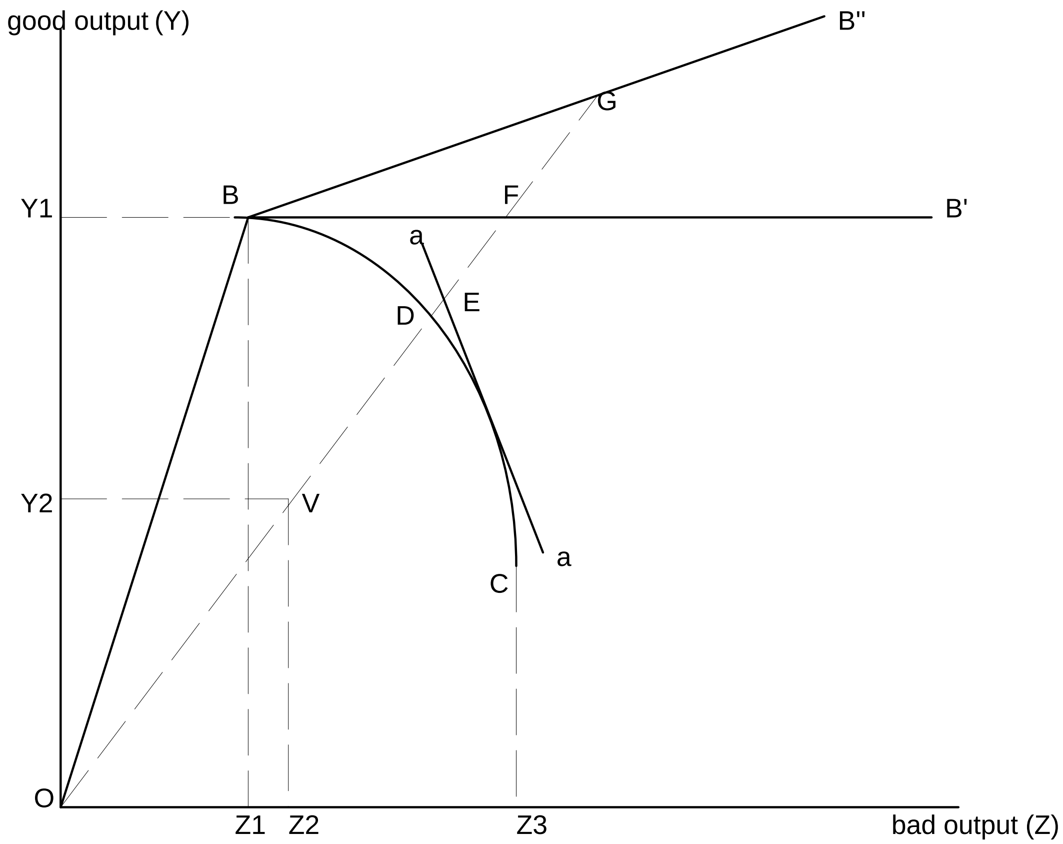

Figure 1: Output Based Resource Use Efficiency Measure

**Table 1 Descriptive Statistics of the Variables Used in the Study**

| | Electricity ($10^6$ kWh) | $SO_2$ (tons) | $NO_x$ (tons) | $CO_2$ (tons) | Labor | Capital (million $) | Heat ($10^{12}$ BTU) |
|---|---|---|---|---|---|---|---|
| **Mean** | 3372.709 | 28342.86 | 11412.36 | 4679370. | 139.982 | 237.506 | 46255983 |
| **Median** | 2308.950 | 13835.00 | 7962.750 | 3475411. | 109.500 | 162.491 | 35133444 |
| **Maximum** | 26631.20 | 183797.0 | 71470.00 | 23868011 | 746.000 | 3218.244 | 2.33E+08 |
| **Minimum** | 0.310 | 11.600 | 27.600 | 9721.300 | 29.000 | 16.860 | 95078.00 |
| **Std. Dev.** | 3338.674 | 35115.30 | 11206.25 | 4457019. | 106.295 | 292.648 | 42926297 |

**Table 2 Maximum Likelihood Estimates of Stochastic Frontier Distance Functions (Full Translog Models)**

| Variable/Parameter | $D_y(x^0, y^{k'}, b^{k'})$ | $D_y(x^0, y^{k'}, b^0)$ | $D_b(x^0, y^0, b^{k'})$ |
|---|---|---|---|
| **$\beta_0$ (Intercept)** | 9.19 (7.20)* | 18.50 (18.30) * | 2.89 (2.06) ** |
| **$\beta_1$ (Y1)** | 0.334 (2.28) ** | -2.45 (-2.77) * | 0.312 (1.74) *** |
| **$\beta_2$ (Y2)** | -2.40 (-8.29) * | 10.20 (11.50) * | 0.748 (-2.08) ** |
| **$\beta_3$ (Y3)** | 2.43 (9.04) * | 1.51 (1.58) | -0.159 (-0.84) |
| **$\beta_4$ (X1)** | -0.437 (-2.23) ** | -11.30 (-14.70) * | -0.136 (-0.86) |
| **$\beta_5$ (X2)** | -0.584 (-1.74) *** | 5.31 (4.77) * | -1.45 (-3.57) * |
| **$\beta_6$ (X3)** | 0.083 (0.353) | -0.889 (-0.90) | 0.399 (1.45) |
| **$\beta_7$ ($Y1^2$)** | 0.015 (4.79) * | -0.0059 (-0.27) | 0.0084 (2.20) ** |
| **$\beta_8$ ($Y2^2$)** | 0.351 (24.42) * | -0.263 (-2.19) ** | 0.264 (14.30) * |
| **$\beta_9$ ($Y3^2$)** | 0.167 (8.83) * | 0.127 (1.29) | -0.0032 (-1.30) |
| **$\beta_{10}$ (Y1*Y2)** | -0.07 (-4.99) * | 0.154 (0.83) | -0.072 (-5.63) * |
| **$\beta_{11}$ (Y1*Y3)** | 0.048 (3.73) * | -0.003 (-0.48) | -0.014 (-2.68) * |
| **$\beta_{12}$ (Y2*Y3)** | -0.507 (-1.91) *** | -0.14 (-0.75) | 0.028 (1.40) |
| **$\beta_{13}$ ($X1^2$)** | 0.016 (1.63) *** | 0.479 (3.77) * | 0.008 (1.43) |
| **$\beta_{14}$ ($X2^2$)** | 0.033 (1.19) | 0.129 (0.97) | 0.042 (1.25) |
| **$\beta_{15}$ ($X3^2$)** | -0.013 (-1.52) | 0.067 (-1.36) | -0.004 (-0.35) |
| **$\beta_{16}$ (X1*X2)** | -0.077 (-3.57) * | 0.131 (0.33) | -0.052 (-1.95) *** |
| **$\beta_{17}$ (X1*X3)** | 0.003 (0.13) | -0.41 (-1.32) | 0.020 (0.93) |
| **$\beta_{18}$ (X2*X3)** | 0.022 (0.78) | 0.016 (0.13) | -0.036 (-1.04) |
| **$\beta_{19}$ (Y1*X1)** | 0.0016 (0.18) | 0.037 (0.20) | 0.009 (0.85) |
| **$\beta_{20}$ (Y1*X2)** | -0.019 (-1.09) | 0.076 (0.93) | -0.009 (-0.42) |
| **$\beta_{21}$ (Y1*X3)** | 0.022 (1.55) | -0.077 (-1.12) | 0.023 (1.26) |
| **$\beta_{22}$ (Y2*X1)** | -0.144 (-4.89) * | -0.17 (-0.82) | -0.159 (-6.04) * |
| **$\beta_{23}$ (Y2*X2)** | 0.229 (6.16) * | -0.64 (-1.31) | 0.313 (7.15) * |
| **$\beta_{24}$ (Y2*X3)** | -0.019 (-0.75) | 0.597 (1.75) *** | -0.072 (-2.57) ** |
| **$\beta_{25}$ (Y3*X1)** | 0.089 (4.10) * | -0.096 (-0.63) | -0.002 (-0.16) |
| **$\beta_{26}$ (Y3*X2)** | -0.137 (-3.50) * | 0.0057 (0.03) | 0.0028 (1.43) |
| **$\beta_{27}$ (Y3*X3)** | -0.033 (-1.34) | 0.071 (0.559) | -0.013 (-0.75) |
| $\sigma_v^2 + \sigma_u^2$ | 0.095 (8.71) * | 4.98 (12.70) * | 0.093 (6.28) * |
| $\gamma = \sigma_u^2 / (\sigma_v^2 + \sigma_u^2)$ | 0.91 (71.40) * | 0.976 (246.0) * | 0.793 (14.50) * |
| $\mu$ | -0.586 (-9.99) * | -4.41 (-11.40) * | -0.543 (-6.45) * |
| **Log Likelihood Fn.** | 314.46 | -599.48 | 206.96 |

**Note:** Values in parentheses are the 't statistics'. *, **, and *** show the level of significance at 1%, 5% and 10 % respectively. In model $D_y(x^0, y^{k'}, b^{k'})$, Y1, Y2, Y3, X1, X2, X3 are respectively the $SO_2$/Electricity, $CO_2$/Electricity, $NO_x$/Electricity, Labor, Capital and Heat respectively. In model $D_y(x^0, y^{k'}, b^0)$ Y1, Y2, Y3, X1, X2, X3 are respectively the $SO_2$, $CO_2$, $NO_x$, Labor, Capital and Heat respectively. In model $D_b(x^0, y^0, b^{k'})$ Y1, Y2, Y3, X1, X2, X3 are respectively the Electricity, $CO_2$/ $NO_x$ , $SO_2$/ $NO_x$, Labor, Capital and Heat respectively.

**Table 3 Specification Tests for Alternative Stochastic Distance Function Models**

| Model | Null Hypothesis | Likelihood Ratio ( $\lambda$ ) | $\chi^2$ Critical Value (95%) | Decision |
|---|---|---|---|---|
| $D_y(x^0, y^{k'}, b^{k'})$ | | | | |
| **Cobb-Douglas** | $\beta_7 = 0, \beta_8 = 0, -- \beta_{27} = 0$ | 557.68 | 32.7 | Rejected |
| **Restricted Translog** | $\beta_{13} = 0, \beta_{14} = 0, -- \beta_{27} = 0$ | 99.14 | 25.0 | Rejected |
| $D_y(x^0, y^{k'}, b^0)$ | | | | |
| **Cobb-Douglas** | $\beta_7 = 0, \beta_8 = 0, -- \beta_{27} = 0$ | 61.4 | 32.7 | Rejected |
| **Restricted Translog** | $\beta_{13} = 0, \beta_{14} = 0, -- \beta_{27} = 0$ | 31.48 | 25.0 | Rejected |
| $D_b(x^0, y^0, b^{k'})$ | | | | |
| **Cobb-Douglas** | $\beta_7 = 0, \beta_8 = 0, -- \beta_{27} = 0$ | 105.72 | 32.7 | Rejected |
| **Restricted Translog** | $\beta_{13} = 0, \beta_{14} = 0, -- \beta_{27} = 0$ | 55.82 | 25.0 | Rejected |

$\lambda$ = -2[Log likelihood ($H_0$)-Log likelihood ($H_1$)]

**Table 4 Yearly Geometric Mean of Various Measures of Efficiency**

| Year | Technical Efficiency | Environmental Efficiency | Resource Use Efficiency |
|---|---|---|---|
| **Stochastic** | | | |
| **1995** | 0.872 | 0.486 | 0.424 |
| **1996** | 0.902 | 0.511 | 0.461 |
| **1997** | 0.917 | 0.467 | 0.428 |
| **1998** | 0.908 | 0.301 | 0.273 |
| **1999** | 0.913 | 0.525 | 0.479 |
| **2000** | 0.917 | 0.591 | 0.542 |
| **2001** | 0.922 | 0.496 | 0.457 |
| **Parametric Linear Programming** | | | |
| **1995** | 0.583 | 0.448 | 0.261 |
| **1996** | 0.673 | 0.520 | 0.350 |
| **1997** | 0.646 | 0.553 | 0.357 |
| **1998** | 0.510 | 0.468 | 0.239 |
| **1999** | 0.712 | 0.584 | 0.416 |
| **2000** | 0.760 | 0.616 | 0.468 |
| **2001** | 0.706 | 0.594 | 0.420 |
| **DEA** | | | |
| **1995** | 0.620 | 0.124 | 0.077 |
| **1996** | 0.634 | 0.383 | 0.081 |
| **1997** | 0.636 | 0.122 | 0.078 |
| **1998** | 0.692 | 0.165 | 0.114 |
| **1999** | 0.652 | 0.130 | 0.085 |
| **2000** | 0.649 | 0.143 | 0.093 |
| **2001** | 0.629 | 0.137 | 0.086 |

| Combined | | | |
|---|---|---|---|
| **1995** | 0.681 | 0.300 | 0.204 |
| **1996** | 0.727 | 0.323 | 0.235 |
| **1997** | 0.722 | 0.316 | 0.228 |
| **1998** | 0.684 | 0.285 | 0.195 |
| **1999** | 0.751 | 0.342 | 0.257 |
| **2000** | 0.768 | 0.374 | 0.287 |
| **2001** | 0.743 | 0.343 | 0.255 |

### Table 5 Spearman Rank Correlation-Matrix of Various Measures of Efficiency

| | **Technical Efficiency** | **Environmental Efficiency** | **Resource Use Efficiency** |
|---|---|---|---|
| **Stochastic** | | | |
| **Technical Efficiency** | 1.000 | -0.177 | 0.006 |
| **Environmental Efficiency** | -0.177 | 1.000 | 0.968* |
| **Resource Use Efficiency** | 0.006 | 0.968* | 1.000 |
| **Parametric Linear Programming** | | | |
| **Technical Efficiency** | 1.000 | -0.014 | 0.552* |
| **Environmental Efficiency** | -0.014 | 1.000 | 0.761* |
| **Resource Use Efficiency** | 0.552* | 0.761* | 1.000 |
| **DEA** | | | |
| **Technical Efficiency** | 1.000 | 0.173 | 0.557* |
| **Environmental Efficiency** | 0.173 | 1.000 | 0.897* |
| **Resource Use Efficiency** | 0.577* | 0.897* | 1.000 |
| **Combined** | | | |
| **Technical Efficiency** | 1.000 | 0.213 | 0.617* |
| **Environmental Efficiency** | 0.213 | 1.000 | 0.877* |
| **Resource Use Efficiency** | 0.617* | 0.877* | 1.000 |

**Note:** * significant at 1% level.

### Table 6 Regression Analyses of Various Measures of Efficiency

| | **Technical Efficiency** | | **Environmental Efficiency** | | **Resource Use Efficiency** | |
|---|---|---|---|---|---|---|
| | **Model 1** | **Model 2** | **Model 1** | **Model 2** | **Model 1** | **Model 2** |
| **Constant** | 0.608 (26.38)* | 0.597 (34.33)* | 0.328 (16.24)* | 0.317 (20.03)* | 0.196 (10.90)* | 0.185 (13.14)* |
| **TRADE** | -3.78E-01 (-2.35)** | -2.78E-01 (-2.03)** | -2.27E-01 (-1.70)*** | -1.03E-01 (-0.88) | -3.20E-01 (-2.63)* | -1.91E-01 (-1.74)*** |
| **SIZE** | 5.30E-04 (3.19)* | 5.48E-04 (4.34)* | 8.96E-04 (6.83)* | 8.95E-04 (8.47)* | 9.53E-04 (7.09)* | 9.52E-04 (8.68)* |
| **$SO_2$/HEAT** | 4.33E-01 (8.54)* | 4.29E-01 (9.79)* | -2.76E-01 (-5.22)* | -3.01E-01 (-6.33)* | -5.51E-02 (-1.20) | -7.94E-02 (-1.94)** |
| **TIME** | 1.15E-01 (2.54)** | 1.51E-01 (4.72)* | 1.55E-02 (0.71) | 6.38E-02 (2.32)** | 5.40E-02 (1.43) | 1.02E-01 (4.05)* |
| **$R^2$** | 0.165) | 0.181 | 0.212 | 0.225 | 0.193 | 0.208 |
| **F** | 19.55 | 30.76 | 26.57 | 40.20 | 23.58 | 36.41 |

**Note:** Values in parentheses are the 't statistics'. *, **, and *** show the level of significance at 1%, 5% and 10 % respectively.

### Table 7 Mean Emission Rates (standard deviation)

| **Year** | **Phase-I Plants** | **All Plants** |
|---|---|---|
| 1995 | 1.94 (1.54) | 1.65 (1.45) |
| 1996 | 2.13 (1.73) | 1.55 (1.35) |
| 1997 | 2.04 (1.61) | 1.53 (1.28) |
| 1998 | 1.88 (1.50) | 1.49 (1.28) |
| 1999 | 1.82 (1.38) | 1.40 (1.08) |