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

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Abstract

This paper measures resource use efficiency of electricity generating plants in the United States under the SO_2 trading regime. Resource use efficiency is defined as the product of technical efficiency and environmental efficiency, where the latter is the ratio of good output (electricity) to bad output (SO_2) with reference to the best practice firm, i.e., one that is producing an optimal mix of good and bad outputs. This concept of environmental efficiency is similar to that of output oriented allocative efficiency. Using output distance functions we compare three methods for the calculation of resource use efficiency, namely, stochastic frontier analysis (SFA), deterministic parametric programming and non-parametric linear programming. This paper reveals the strengths and weaknesses of these methods for estimating efficiency. Both SFA and linear programming approaches can estimate the efficiency scores. For plants in the dataset the overall geometric mean of the three methods for technical efficiency, environmental efficiency and resource use efficiency is 0.737, 0.335 and 0.248, respectively. The rank correlation coefficient

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between technical efficiency, environmental efficiency and resource use efficiency is 0.213, 0.617 and 0.877, respectively. The regression analyses of performance across plants shows units in phase I of the SO_2 trading programme are negatively related to measures of economic and environmental performance. This suggests that the market for SO_2 allowances, *per se*, may not be minimizing compliance cost. We also find that a decrease in SO_2 emission rates 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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Introduction

The World is witnessing a growing global interest in the potential of market-based instruments (MBIs) for pollution prevention. Cost-effectiveness is advocated the advantage of MBIs in comparison to conventional regulation namely, command and control (CAC) measures. A new alliance of policy makers, enlightened industrialists and environmentalists has emerged, which sees MBIs both as a necessary complement to market-friendly economic policies, and as a powerful tool for reducing environmental damage and conserving natural resources. A number of countries, mainly in Europe and the USA, have instituted pollution prevention policies based on economic incentives and market based instruments. Recent tradable permit schemes in the USA puts the prescription provided by the economists to real test. The experience of USA's tradable permit scheme can be utilized in formulating the environmental policies in developing countries like India, which are looking for the application of MBIs to tackle their environmental problems in a market-oriented environment.

To achieve competitiveness, firms should use marketable inputs (conventional resources) as efficiently as possible, and to be an environment-friendly they should use the environment (natural resources) efficiently. Porter and *van der* Linde (1995) visualise pollution as inefficiency in production process. According to them 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 resources and natural resources efficiently, and whether technical and environmental efficiencies are compatible. Reinhard (1999) has defined the resource use efficiency as the product of technical efficiency and environmental efficiency of production units. Technical efficiency measures how far is a firm from the best practicing of its colleague in terms of the usage of conventional inputs. Environmental efficiency 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. A variety of environmental performance indices have been proposed in the literature, and they can be grouped into two categories: those that adjust conventional indices of productivity change, and those, which adjust conventional measures of technical efficiency. In both cases the adjustment has taken the form of incorporating quantifiable environmental effects into the output vector. To account for more inputs and outputs, Fare *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. They use a nonparametric mathematical programming technique known as Data Envelopment Analysis (DEA) to construct their best-practice frontier (*see* also Ball *et. al*., 1994; Tyteca, 1997; Zaim and Taskin, 2000; Khanna *et. al*., 2002). The literature computes output possibility sets under alternative assumption about output disposability. The technology is assumed to satisfy strong disposability when 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. The ratio of the efficiency scores under strong and weak disposability of bad outputs determines the environmental performance indicator. Mathematical programming techniques are also used to calculate the parameters of an output distance function (*see* Fare *et. al*., 1993; Coggins and Swinton, 1996; Kumar and Rao, 2002; Murty and Kumar, 2002, 2004). In these studies shadow prices of the undesirable outputs are calculated by imposing the weak disposability of the production technology with respect to bad outputs- that is outputs can be disposed of radially. The weak disposability of bad outputs seems to be a reasonable assumption, but Murty and Russell (2002) raise the question on the validity of this assumption and show that such type of specification of production technology is not consistent with the material balance approach. Therefore in the present study for the measurement of environmental performance of firms we do not impose restrictions on the curvature of the output possibility set.

Some studies (e.g., Tyteca, 1997; and Reinhard *et. al*., 1999) define environmental efficiency 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 of environmental efficiency implies technical efficiency and not necessarily a small amount of bad output per unit of good output, and thus the environmental efficiency score differs for the firms who are operating on the same technically efficient frontier. Therefore, we follow Fare *et. al*. (2000) in constructing the index of environmental efficiency. Fare *et. al*. (2000) follows an index number approach for constructing the index of environmental efficiency 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 situation and 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 methods (e.g., Forsund and Hjalmarsson, 1987; Fare *et. al*., 1993; Murty and Kumar, 2003); 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; Murty and Kumar, 2003). According to Lovell (1993), 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. Mathematical programming (parametric or non-parametric) approach is non-stochastic and lump noise and inefficiency together, calling the combination inefficiency. The econometric and parametric mathematical programming approach is parametric, and confounds the effects of misspecification of functional form (of both technology and inefficiency) with inefficiency. Hjalmarsson *et. al*. (1996) argues that one of the main appeals of the stochastic frontier approach is the possibility it offers for a specification in the case of panel data. It also allows for a formal statistical testing of hypotheses. The DEA approach is non-parametric and less prone to this type of specification error. In DEA the number of outlier firms tends to increase as variables are added to the model. This results in loss of information, in particular when the sample size is small.

The vast majority of empirical efficiency measurement literature utilises only one of the above-mentioned methods. In this paper we use all the three approaches for the purpose of estimating the components of resource use efficiency. This aim 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 paper 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 resource use efficiency and its components for a sample of US electricity generating firms during the SO_2 allowances trading period. This application helps to test the hypothesis that environmental efficiency and technical efficiency are compatible and whether trading of the sulfur emissions has affected the various measures of efficiency. 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.

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 or not 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 the resource use efficiency of these plants.

The paper is organized as follows: Section 2 discusses theoretical construct of the concept of resource use efficiency and its components, *viz*. technical efficiency and environmental efficiency. Section 3 presents the measurement and the three 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 concluding remarks.

II. Theoretical Construct

Farrell (1957) developed the basis of standard efficiency methodology. The input saving efficiency consists of two components: (i) technical efficiency, which reflects the ability of a firm to contract inputs from a given set of outputs, and (ii) allocative efficiency, which reflects 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). The output augmenting efficiency consists of two components: (i) technical efficiency, which reflects the ability of a firm to augment outputs from a given set of inputs, and (ii) allocative efficiency, which reflects the ability of a firm to produce the outputs in the optimal proportion, given their respective prices. Thus the analysis of efficiency can have an input-conserving orientation or an output-augmenting orientation. Efficiency is a relative measure; efficiency scores depend on the firms that are compared.

Measurement of output-oriented measures of 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 technical efficiency of this firm is TE= OV/OD. The overall efficiency 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 good output vectors, and $\boldsymbol{r}$ is the output price vector. Allocative output efficiency 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.

Now we extend this case in a situation where a firm is producing one marketable product, *y* along with an undesirable output, *z* (pollution). The desired output has positive market prices but the undesirable output has either zero or negative price. Its price is negative when a tax in imposed on its production. Now we assume that in the production possibility set there are no points on the left of the line OB, due to technical or biological restrictions or we can term it that the production of good and bad outputs are null-joint. The assumption of null-jointness implies that some positive quantity of bad outputs is necessarily produced when we are producing some positive amount of good outputs. Therefore, point B in figure 1 is the single point where all of the resources conventional as well as natural are utilized efficiently. Because (i) point B is on the frontier, so the conventional resources (inputs) are used in a technically efficient manner, and (ii) in point B the natural 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($\boldsymbol{x}$), where R($\boldsymbol{x,r}$) = max{$\boldsymbol{r_y y + r_z z}$: (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 output respectively, and R($\boldsymbol{x.r}$) is the revenue function, which is the dual to the output distance function (Fare and Primont, 1995).

We use output distance function to measure the technical efficiency of a firm. In the figure, the technical output-oriented efficiency measure (TE) at output bundle V is $TE_V(Y_V, Z_V, X) = D_o(Y_V, Z_V, X)$ and is equal to 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 in the figure. The measure of environmental efficiency (EE) has to relate the ratio of good and bad output at point D (equal to the ratio at V) to the maximum ratio at point B. This measure of environmental efficiency relates the observed output mix at the frontier with the optimal output mix, which for the output bundle V is equal to

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

where $R(\boldsymbol{x},\boldsymbol{r}) = \max\{\boldsymbol{r_y y}+\boldsymbol{r_z z}: (Y, Z) \in P(\boldsymbol{x}), \boldsymbol{r_z} \leq 0\}$. 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 a tax on the 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 environmental efficiency scores. Alternatively said, if a firm is environmental efficient at point B then any point of operation of a firm to the right of this point reveals the departure from environmental efficiency.

Recall that point B in the figure is 'resource use efficient', since at this point the conventional resources as well as the natural resources are used efficiently. We want to compare point V to the resource use efficient point B. A convenient measure of resource use efficiency (RE) is the definition of overall output efficiency (Reinhard, 1999). 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 or its production is taxed. That is, more negative the price of bad output smaller the RE score will be. Therefore, resource use efficiency can be decomposed into a technical efficiency and an environmental efficiency component, i.e. $RE_V = TE_V.EE_V$. It follows that RE is analogous to overall economic efficiency and EE is analogous to allocative efficiency.

III. Measurements and Estimation

III.1 Measurements of Technical and Environmental Efficiency

In this section we describe how to measure the technical and environmental efficiency of a polluting firm. In short, we defined the environmental efficiency as the ratio of a good output quantity index and a quantity index of bad outputs. Each of the two indexes is based on distance functions. In measuring the technical efficiency we scale the full output vector, but when we measure environmental efficiency of a firm rather than scaling the full output vector, we scale good and bad outputs separately. Thus our environmental efficiency index is developed using 'sub-vector' distance functions.

Technology of polluting firms can be specified by production, cost and profit functions. The output and input distance functions generalize the production technology of a multi-output firm. Assume that a vector of inputs $x = (x_1,.....,x_N) \in R_+^N$ produces a vector $y = (y_1,....,y_M) \in R_+^M$ of good output and a vector $b = (b_1,....,b_J) \in R_+^J$ of bad outputs, then we define the production technology as

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

In addition to this property on the technology T, we assume that it meets standard properties like closedness and convexity, s*ee* Fare and Primont (1995) for details.

The output distance function is defined as,

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

Equation (2) characterizes the output possibility set by the maximum equi-proportional expansion of all outputs consistent with the technology set (1). Output distance function is non-decreasing, positively linearly homogeneous and convex in outputs and decreasing in inputs. The output distance function takes a value, which is less than or equal to one if the output vector is an element of the feasible production set. Furthermore, the distance function will take a value of unity if output vector is located on the outer boundary of the production possibility set.

The input distance function is defined as

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

Equation (3) characterizes the input possibility set by the maximum equi-proportional contraction of all inputs consistent with the technology set (1). The input distance function is non-decreasing, positively linearly homogenous and concave in inputs and increasing in outputs. The distance function will take a value, which is greater than or equal to one if the input vector is an element of the feasible input set. Furthermore, the distance function will take a value of unity if input bundle is located on the inner boundary of the input set.

Both the input and output distance functions are capable of handling multi-output technologies, and both are the radial measures of technical efficiency. 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 had 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.

To formulize the good output quantity index, we define a sub-vector output distance function on the good outputs as

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

This distance function expands good outputs as much, as is feasible, while keeping inputs and bad outputs constant. Note that it is homogeneous of degree +1 in y. 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. This is done by taking the ratio of two distance functions, and hence, the good output index 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 (1922) important tests like homogeneity, time reversal, transitivity, and dimensionality.

The index of bad outputs is constructed using an 'input' distance function approach. The argument is obvious; it is desirable to reduce such outputs. Thus the input based distance function is defined as

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

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.,

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

Like the good index, $Q_b(x^0, y^0, b^k, b^l)$ satisfies the above-mentioned Fisher tests.

Following Fare, Grosskopf, and Hernandez-Sancho (2000), we define the environmental efficiency 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 follows the tradition of Hicks-Moorsteen[1] by evaluating how much good output is produced per bad output. In the simple case of one good and one bad output, the index takes the following simple form due to homogeneity of the component distance functions

$$E^{k.l} = \frac{y^k / b^k}{y^l / b^l}$$

This one bad one good index shows that the index is the ratio of average good per bad output for k and l firms. In our this case we compare the firms with the firm who is producing the largest quantity of good output per unit of bad output and the environmental efficiency index for this firm is one i.e. it is producing the optimal combination of good and bad outputs.

III. 2 Estimation Models

Stochastic Frontier Estimation Method

The econometric formulation of the output distance function can be expressed as

$$Do = f(x, y)\exp \varepsilon$$

where ε is the random disturbance term and is assumed to be independently and identically distributed (iid) as $N(0, \sigma_\varepsilon^2)$. In econometric estimation, the basic problem with output distance function is the inability to observe the dependent variable. Further if the function is assumed to efficient (i.e. Do = 1), the left hand side of the equation is invariant, an intercept can not be estimated, and the ordinary least squares (OLS) parameter estimates will be biased.

To solve this problem, we utilize the property that the output distance function is homogenous of degree +1 in outputs (Lovell *et al*., 1990; Grosskopf *et al*., 1996; and Kumar and Rao, 2003).

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

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

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

From the econometric formulation of output distance function

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

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

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

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

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

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), and later by Hetemaki (1996), and Kumar and Rao (2003). Like that, the sub-vector output distance function can be estimated. To estimate the sub vector output distance function when the objective is to increase the good output only for the given level of conventional inputs and bad outputs, 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 for the given level of good output and the conventional inputs, 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 utilising 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).

The parametric linear programming method

The method was developed and first applied by Aigner and Chu (1968) to estimate the single output production frontier. It was Fare *et. al*. (1993) who used it for the first time for multi-output production technology using the translog output distance function. This method involves specifying a parametric form for the production technology and use linear programming (LP) to compute parameter values, which provide the closest possible envelopment of the observed data. The translog output distance function for our case is specified as:

$$ln\ D_0\,(x, y, b) = a_0 + \sum_{n=1}^{N} a_n\ ln\ x_n + \frac{1}{2}\sum_{n=1}^{N}\sum_{n'=1}^{N} a_{nn'}\ ln\ x_n\ ln\ x_{n'} + \sum_{m=1}^{M} b_m\ ln\ y_m + \frac{1}{2}\sum_{m=1}^{M}\sum_{m'=1}^{M} b_{mm'}\ ln\ y_m\ ln\ y_{m'} + \sum_{j=1}^{J} g_j\ ln\ b_j + \frac{1}{2}\sum_{j=1}^{J}\sum_{j'=1}^{J} g_{jj'}\ ln\ b_j\ ln\ b_{j'} + \sum_{n=1}^{N}\sum_{m=1}^{M} d_{nm}\ ln\ x_n\ ln\ y_m + \sum_{n=1}^{N}\sum_{j=1}^{J} h_{nj}\ ln\ x_n\ ln\ b_j + \sum_{m=1}^{M}\sum_{j=1}^{J} j_{mj}\ ln\ y_m\ ln\ b_j$$

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

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

Subject to

(i) $ln\ D_0(x, y, b)\ £\ 0$

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

$å\ a_{nn'} = å\ b_{mm'} = å\ g_{jj'} = å\ d_{nm} = å\ h_{nj} = å\ j_{mj} = 0$

(iii) $a_{nn} = a_{nn'}$

$b_{mm} = b_{mm'}$

$g_{jj'} = g_{j'j}$

The objective function minimises 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 maximisation of the objective function implies minimisation 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, $\sum_{m=1}^{M} b_m=1.$ 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, $\sum_{j=1}^{J} g_j=1.$ 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 (DEA)

The DEA involves the use of linear programming methods to construct a piecewise linear envelopment frontier over the data points such that all observed points lie on or below the frontier. In computing the distance functions, we choose the data envelopment analysis (DEA) (or activity analysis) methodology among competing alternatives, so as to take advantage of the fact that the distance functions are reciprocals of Farrell efficiency measures. Thus, the technical efficiency for each firm is computed like this

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

In computing environmental efficiency, we chose the firm that is producing the optimal mix of good and bad output as our reference, i.e., point B in the figure 1. We let $k = 1,....,K$ index the observations (firms) in the sample. Thus for each observation $k^{'} = 1,......,K$, we may compute the distance function for each firm

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

$$st$$

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

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

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

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

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

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, using the observed data on desirable outputs, undesirable outputs and inputs between firms, 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. For the bad index, for a particular firm, for each observation $k' = 1, \ldots\ldots, K$ we compute

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

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.[2]

IV. Data

We are interested in the measurements of technical and environmental efficiency, whose product constitute the resource use efficiency, we restricted our attention to electric generating plants for which each generating unit had a minimum installed nameplate generating capacity of 25 megawatts.[3] We exclude from our sample plants, which have missing data or reporting errors in a specific year. The deterministic linear programming is sensitive to outliers, to minimize the effects of outliers; we first 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 our 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) are the plants that could emit at the rate of 2.5 pounds of SO_2 per million BTUs of heat input during the phase I.

The process of fossil-fueled electricity generation typically uses three conventional inputs; namely, fuel, labor and capital to produce electricity and emissions. The data come primarily from two government agencies- the Federal Energy Regulatory Commission (FERC) and the US Environmental Protection Agency (EPA). These agencies have over the years provided the public with access to data concerning regulated utilities and pollution. 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 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.

In summary, our data set consists of a balanced panel of 80 steam electric utility plants operating during 1995-2001. 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. Labour 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), parametric linear programming (PLP) and Data Envelopment Analysis (DEA).

Stochastic Frontier Results

We estimated the transformed distance functions by the maximum likelihood using the FRONTIER package developed by Coelli (1994). 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 in our models the value of m appeared to be significant either at 90 percent or 95 percent 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 models in this respect.

We now turn to the estimated results of technical, environmental and resource use efficiency measures. The seven-year average estimates of output-oriented technical efficiency 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 an increase of the revenue at the average by 9 percent due to attaining the efficiency frontier. To calculate the environmental efficiency scores, we estimated the two sets of distance functions, one where the maximum expansion in good output for the given level of bad outputs and conventional inputs. The other is the maximum contraction in the bad outputs for the given level of good output and conventional inputs. Environmental efficiency is smaller, on average, than output-oriented technical efficiency, with a range from 0.052 to 0.747 and a mean of 0.517. Recall that the technical efficiency measure focuses on the utilization of the conventional resources and the environmental efficiency measure relates the observed output mix to the optimal output mix. Multiplication of technical and environmental efficiency results in resource use efficiency. The resource use efficiency is by definition smaller than the technical and environmental efficiency measures, ranging from 0.045 to 0.676 and a mean of 0.470. The yearly geometric means of all the three measures are presented in Table 4. We observe that the yearly average of technical efficiency of the plants first increases up to 1997 and declines in 1998 and then it again starts to increase. But with respect to environmental and resource use efficiency we are not observing any trend in the respective series.

The Spearman rank correlation between the distinguished measures of performance is presented in Table 5. The rank correlation coefficient between the technical efficiency and the environmental efficiency scores is small and negative. Technical efficiency and environmental efficiency are positively correlated to the resource use efficiency measure, due to the definition of resource use efficiency. Nonetheless, large differences in the raking according to the technical, environmental and resource use efficiency measures exist. Like that the rank correlation coefficient between technical efficiency and resource use efficiency is very small (0.006). A firm that is judged efficient according to standard technical measures might not be environmentally efficient. But the high rank correlation coefficient between environmental efficiency and resource use efficiency (0.968) 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.

<u>Parametric Linear Programming and DEA Results</u>

The stochastic estimation has the advantage of hypothesis testing but in the deterministic approach we can impose the theoretical restrictions of regularities on the models to be estimated. In the parametric linear programming estimation we have estimated the distance function for each year separately for the full translog models since in the stochastic estimation full translog model 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). We observe that in both the models (MLE and PLP) the firms are not observing constant returns to scale. Therefore in the computation of distance function values in DEA we have put the restriction that the firms are not operating under the condition of constant returns to scale, i.e. we are assuming variable returns to scale.

In Table 4 we have presented the yearly averages of the various measures of efficiency computed through these different estimation techniques and rank correlation coefficients between the various sets of efficiency predictions are presented in Table 5. Looking firstly at the means of technical efficiency (Table 4) we observe that among the three orientations the MLE produces the largest mean efficiencies in comparison to PLP and DEA and these differences are generally not small. But the seven years mean of the sample for environmental efficiency score is highest for the PLP and smallest for the DEA approach. The differences are generally quite large between parametric measures and non-parametric measure.

The rank correlation matrixes between various measures of performance can judge the compatibility between technical and environmental efficiency. We judge from Table 5 the consistency between the measures of technical efficiency and environmental efficiency. 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 efficient environmentally. The rank correlation coefficients between technical efficiency and resource use efficiency for both of the deterministic measures are 0.552 and 0.557. We find a high rank correlation between environmental efficiency and resource use efficiency measures; i.e. 0.761 and 0.897 for parametric linear programming 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 for the purpose of discussing the relative resource use performance of the electricity generating plants of US during the SO_2 trading regime. 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 yearly geometric means of the MLE, PLP and DEA efficiency measures are tabulated in Table 4 for each of the three measures, i.e. technical efficiency, environmental efficiency and resource use efficiency.

The estimates of the overall geometric mean of technical efficiency ranges between 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 geometric mean of environmental efficiency, on average, is smaller than the geometric mean of output-oriented technical efficiency, with a range from 0.127 to 0.539 and with a mean of 0.335. The figures for resource use efficiency ranges from 0.042 to 0.436 with a mean of 0.248. For the combined figures also, the rank correlation coefficient between technical efficiency and environmental efficiency is although positive but small (0.213). The rank correlation coefficients between technical efficiency and resource use efficiency, and between environmental efficiency and resource use efficiency are quite large, i.e. 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.

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 affected the various measures of efficiency, we estimated regressions on a panel data set. The regression analysis also helps to test whether environmental performance is related to various measures of efficiency. Tobit regression is often used with censored data and is suitable for analysis of efficiency scores as these 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.[4] Hence heteroskedasticity corrected OLS is a generally accepted estimation procedure in this setting. The first regression had the technical efficiency scores, the second equation environmental efficiency scores and the third equation resource use efficiency scores as dependent variables. 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 every index, the first column report the estimation results for the period 1995-1999 (model 1) and the last column are the parameter estimates of models for the period 1995-2001 (model 2). Model 1 covers the phase I of the SO_2 trading program, therefore in this model the firms that participated in trading are differentiated by the introduction of dummy variable (TRADE). The phase II of the trading program started in January 2000 and all the electricity plants had to necessarily participate in the trading therefore model 2 covers the period 1995 to 2001. These two models were introduced only to judge the robustness of the results. The regression results show that three efficiency indexes are significantly affected by most of the independent variables in both of the situations. The significance of F statistics at the 1- percent critical level shows the goodness of fit for all of the models. We find that the SIZE variable affects the efficiency index positively, it indicates that the plants that have bigger generation capacities are more efficient not only in terms of technical efficiency but also in terms of environmental and resource use efficiency. 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 SO_2/HEAT variables are of particular interest and require some discussion. We find that the TRADE variable is significant at 5 percent and 10 percent critical levels in determining the technical efficiency index and resource use efficiency index and to both indexes it is negatively related. But this variable is statistically significant in determining the index of environmental efficiency at 10 percent critical level in model 1 and its parameter is statistically insignificant in model 2. There is no expected relationship between the different measures of efficiency and whether a plant could participate in trading of emissions. But as Burtraw (1996) pointed out, there are two aspects of efficiency worth considering. One, allocative efficiency which is equivalent to our measure of environmental efficiency requires that the goal of the policy is indeed the best use of society's resources. The second aspect is cost-effectiveness. To explain the negative relationship between resource use efficiency and the dummy variable of phase I units, 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 resource use efficiency 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 1994 to 1999 for phase I units, the average and standard deviation of emission rate of our sample plants 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.

Now, it is the turn to explain the relationship between various measures of efficiency and SO_2 emission rate of the plants. We find that technical efficiency, which measures the radial expansion in the output vector (good as well as bad outputs) for the given level of inputs, is positively associated with the emission rate. The relationship between the environmental efficiency, which measures the relative optimal mix of good to bad outputs, and emission rate, is negative implying that as the emission rate declines the environmental efficiency of a plant increases. Thus we find a tradeoff in the sense that the decrease in emission rates leads to decrease in technical efficiency but increase in environmental efficiency, that is 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 (environmental as well as conventional resources). The relationship between resource use efficiency and emission rates may help to answer this question. We find a negative relationship between resource use efficiency and emission rates in both of the models. In model 1 that have observations for the period 1995-1999, the relationship is statistically insignificant, but in model 2 as the observations increases, that is for the period 1995-2001, the relationship is statistically significant at 10 percent critical level. This implies that decrease in emission rates not only increases environmental efficiency but also leads to increase in resource use efficiency. 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 resource use efficiency of US Electricity Generating Plants during the SO_2 trading regime. Resource use efficiency is defined as a product of technical efficiency and environmental efficiency. Environmental efficiency 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 and thus it is similar to the concept of output oriented allocative efficiency. This resource use efficiency measure enables the identification of plants that are characterized by efficient use of conventional resources (technical efficiency) and efficient use of natural resources (environmental efficiency).

The distance functions are used as analytical tools to obtain the objective of the paper. We use three methods for the calculation of efficiency; namely Stochastic Frontier Analysis (SFA), deterministic parametric and non-parametric linear programming. The econometric approach is stochastic, and so attempts to distinguish the effects of noise from the effects of inefficiency. Mathematical programming (parametric or non-parametric) approach is non-stochastic and lump noise and inefficiency together, calling the combination inefficiency. The econometric and parametric mathematical programming approach is parametric, and confounds the effects of misspecification of functional form (of both technology and inefficiency) with inefficiency. The econometric approach allows for a formal statistical testing of hypotheses. The DEA approach is non-parametric and less prone to this type of specification error. In DEA the number of outlier firms tends to increase as variables are added to the model. This results in loss of information, in particular when the sample size is small. Therefore, in the present study an averaging approach is adopted since in many situations a simple average of forecasts will achieve a substantial reduction in variance and bias through averaging out individual bias.

For the combined figures, the estimate of the overall geometric mean of technical efficiency ranges between 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 the overall geometric mean of environmental efficiency and resource use efficiency are 0.335 and 0.248 respectively. The rank correlation coefficient between technical efficiency, environmental efficiency and resource use efficiency 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 minimising compliance cost. We also find that decrease in SO_2 emission rates not only increases environmental efficiency but also leads to increase in resource use efficiency. 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 resource use efficiency measurement and analysis provide the following lessons for Indian Environmental Policy. (1) Decrease in environmental pollution intensity leads not only improvements in environmental efficiency, but also increase the resource use efficiency. (2) It is not the application of 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.

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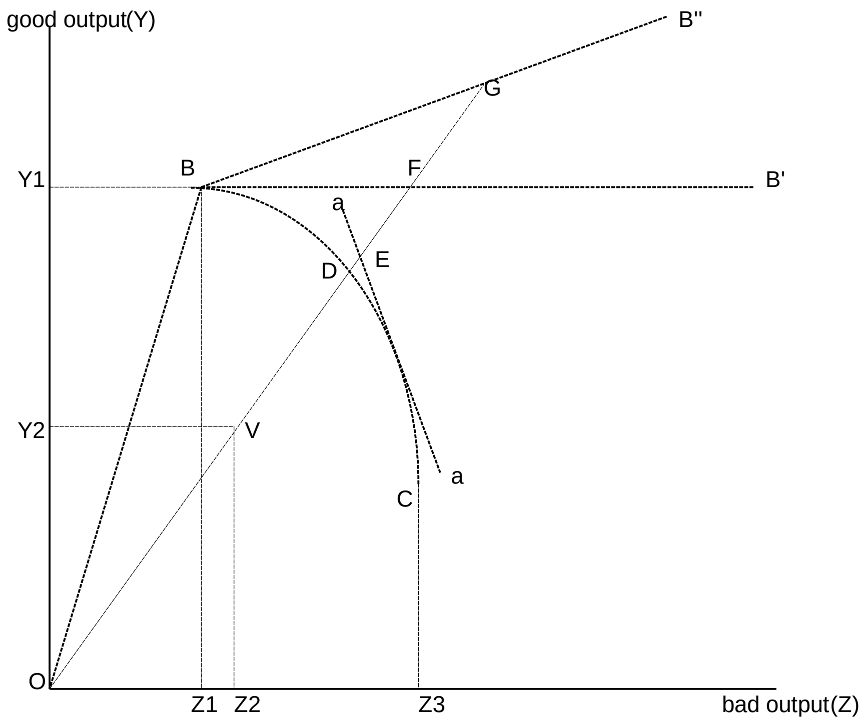

Figure 1: Output Based Resource Use Efficiency Measure

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
Observations	560	560	560	560	560	560	560

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

Variable/ Parameter	$D_y(x^0, y^{k'}, b^{k'})$	$D_y(x^0, y^{k'}, b^0)$	$D_b(x^0, y^0, b^{k'})$
b_0 **(Intercept)**	9.19 (7.20)*	18.50 (18.30) *	2.89 (2.06) **
b_1 **(Y1)**	0.334 (2.28) **	-2.45 (-2.77) *	0.312 (1.74) ***
b_2 **(Y2)**	-2.40 (-8.29) *	10.20 (11.50) *	0.748 (-2.08) **
b_3 **(Y3)**	2.43 (9.04) *	1.51 (1.58)	-0.159 (-0.84)
b_4 **(X1)**	-0.437 (-2.23) **	-11.30 (-14.70) *	-0.136 (-0.86)
b_5 **(X2)**	-0.584 (-1.74) ***	5.31 (4.77) *	-1.45 (-3.57) *
b_6 **(X3)**	0.083 (0.353)	-0.889 (-0.90)	0.399 (1.45)
b_7 **($Y1^2$)**	0.015 (4.79) *	-0.0059 (-0.27)	0.0084 (2.20) **
b_8 **($Y2^2$)**	0.351 (24.42) *	-0.263 (-2.19) **	0.264 (14.30) *
b_9 **($Y3^2$)**	0.167 (8.83) *	0.127 (1.29)	-0.0032 (-1.30)
b_{10} **(Y1*Y2)**	-0.07 (-4.99) *	0.154 (0.83)	-0.072 (-5.63) *
b_{11} **(Y1*Y3)**	0.048 (3.73) *	-0.003 (-0.48)	-0.014 (-2.68) *
b_{12} **(Y2*Y3)**	-0.507 (-1.91) ***	-0.14 (-0.75)	0.028 (1.40)
b_{13} **($X1^2$)**	0.016 (1.63) ***	0.479 (3.77) *	0.008 (1.43)
b_{14} **($X2^2$)**	0.033 (1.19)	0.129 (0.97)	0.042 (1.25)
b_{15} **($X3^2$)**	-0.013 (-1.52)	0.067 (-1.36)	-0.004 (-0.35)
b_{16} **(X1*X2)**	-0.077 (-3.57) *	0.131 (0.33)	-0.052 (-1.95) ***
b_{17} **(X1*X3)**	0.003 (0.13)	-0.41 (-1.32)	0.020 (0.93)
b_{18} **(X2*X3)**	0.022 (0.78)	0.016 (0.13)	-0.036 (-1.04)
b_{19} **(Y1*X1)**	0.0016 (0.18)	0.037 (0.20)	0.009 (0.85)
b_{20} **(Y1*X2)**	-0.019 (-1.09)	0.076 (0.93)	-0.009 (-0.42)

Variable/ Parameter	$D_y(x^0, y^{k'}, b^{k'})$	$D_y(x^0, y^{k'}, b^0)$	$D_b(x^0, y^0, b^{k'})$
b_{21} **(Y1*X3)**	0.022 (1.55)	-0.077 (-1.12)	0.023 (1.26)
b_{22} **(Y2*X1)**	-0.144 (-4.89) *	-0.17 (-0.82)	-0.159 (-6.04) *
b_{23} **(Y2*X2)**	0.229 (6.16) *	-0.64 (-1.31)	0.313 (7.15) *
b_{24} **(Y2*X3)**	-0.019 (-0.75)	0.597 (1.75) ***	-0.072 (-2.57) **
b_{25} **(Y3*X1)**	0.089 (4.10) *	-0.096 (-0.63)	-0.002 (-0.16)
b_{26} **(Y3*X2)**	-0.137 (-3.50) *	0.0057 (0.03)	0.0028 (1.43)
b_{27} **(Y3*X3)**	-0.033 (-1.34)	0.071 (0.559)	-0.013 (-0.75)
$s_v^2 + s_u^2$	0.095 (8.71) *	4.98 (12.70) *	0.093 (6.28) *
$g = s_u^2 / (s_v^2 + s_u^2)$	0.91 (71.40) *	0.976 (246.0) *	0.793 (14.50) *
m	-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, Labour, 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, Labour, Capital and Heat respectively.

Table 3: Specification Tests for Alternative Stochastic Distance Function Models

Model	Null Hypothesis	Likelihood Ratio (l)	c^2 Critical Value (95%)	Decision
$D_y(x^0, y^{k'}, b^{k'})$				
Cobb-Douglas	$b_7 = 0, b_8 = 0,$ $--b_{27} = 0$	557.68	32.7	Rejected
Restricted Translog	$b_{13} = 0, b_{14} = 0,$ $--b_{27} = 0$	99.14	25.0	Rejected
$D_y(x^0, y^{k'}, b^0)$				
Cobb-Douglas	$b_7 = 0, b_8 = 0,$ $--b_{27} = 0$	61.4	32.7	Rejected
Restricted Translog	$b_{13} = 0, b_{14} = 0,$ $--b_{27} = 0$	31.48	25.0	Rejected
$D_b(x^0, y^0, b^{k'})$				
Cobb-Douglas	$b_7 = 0, b_8 = 0,$ $--b_{27} = 0$	105.72	32.7	Rejected
Restricted Translog	$b_{13} = 0, b_{14} = 0,$ $--b_{27} = 0$	55.82	25.0	Rejected

l = -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

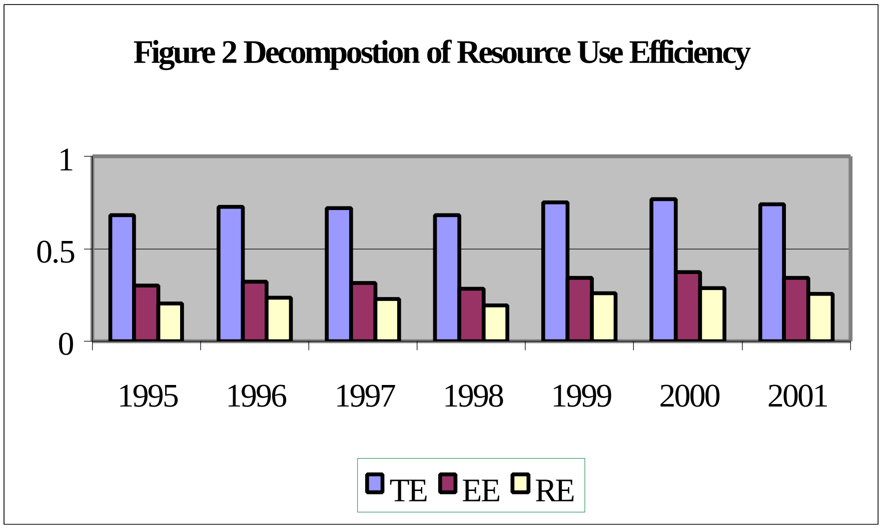

Figure 2. Decomposition of Resource use Efficiency.

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

Table 6: Regression Analysis 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)

End Notes

[1] *See* Fare *et al*. (2000) for a reference.

[2] 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. Fare, Grosskopf, and Hernandez-Sancho (2000) use this approach in their application.

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

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