Measuring Environmental Efficiency of Industry: A Case Study of Thermal Power Generation in India

M N, Murty and Kumar, Surender and Dhavala, Kishore

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M N Murty, Surender Kumar and Kishore K. Dhavala

Abstract: Technical and environmental efficiency of some coal-fired thermal power plants in India is estimated using a methodology that accounts for firm's efforts to increase the production of good output and reduce pollution with the given resources and technology. The methodology used is directional output distance function. Estimates of firm-specific shadow prices of pollutants (bad outputs), and elasticity of substitution between good and bad outputs are also obtained. The technical and environmental inefficiency of a representative firm is estimated as 0.10 implying that the thermal power generating industry in Andhra Pradesh state of India could increase production of electricity by 10 per cent while decreasing generation of pollution by 10 percent. This result shows that there are incentives or win-win opportunities for the firms to voluntarily comply with the environmental regulation. It is found that there is a significant variation in marginal cost of pollution abatement or shadow prices of bad outputs across the firms and an increasing marginal cost of pollution abatement with respect to pollution reduction by the firms. The variation in marginal cost of pollution abatement and compliance to regulation across firms could be reduced by having economic instruments like emission tax.

JEL Classification: Q 25

Key words: environmental and technical efficiency, shadow prices of bad outputs, air pollution.

Contact Address of authors:
Institute of Economic Growth,
Delhi University Enclave,
Delhi-110007,
India.
Phone: 91-11-27667268
91-11-27667101
Fax: 91-11-27667410
E-mail: mnm@iegindia.org
kishore@iegindia.org

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1. Introduction

Measurement of the productive efficiency of firms that generate environmental pollution (air and water pollution, and land degradation) and face the environmental regulation has to account for their efficiency in producing good output as well as in reducing pollution, the bad output. A measure of technical efficiency based on conventional input or output-based methods that ignore the firm's efforts to reduce pollution may understate the productive efficiency of firms. For example, Shepard's output distance function with the weak disposability assumption of bad outputs presumes that a firm becomes technically inefficient (efficiency measured in terms of good output production) if it complies with the environmental regulation. There are many studies estimating the technical efficiency of polluting firms using the output distance function. (Coggins and Swinton,1996; Hetemaki, 1996; Swinton, 1998; Boyd and Mclelland, 1999; Murty and Kumar, 2002). Whether the radial expansion of good and bad outputs results in welfare loss or gain depends on the benefits from reducing bad outputs and the cost in terms of reducing the good output (Murty *et al.* 2006). The input based measures of efficiency could be more appropriate in measuring productive efficiency of firms complying with environmental regulation. There are studies that estimate technical efficiency by considering pollution as one of the inputs in the production function (Murty and Kumar, 2006; Murty and Gulati, 2004). The Shepard's input distance function could also be appropriate because a proportional change in inputs with good and bad outputs held constant is an unambiguous indicator of welfare change (Hailu and Veeman, 2001; Murty *et al.* 2006). There are some recent studies using the directional distance function, a generalization of Shepard's output distance function, for estimating the technical and environmental efficiency of polluting firms (Fare and Grosskopf, 2004; Fare *et al.* 2005; Kumar, 2006). The polluting firm's technical efficiency in increasing good output and reducing bad output, namely pollution, could be measured using the directional distance function because it allows one to consider the proportional changes in outputs and allows one output to be expanded while another output is contracted. Since environmental regulation requires the firms to reduce pollution, the technology of firms described by the directional output distance function allows cost minimizing or profit maximizing firms to make choices among different combinations of good and bad outputs in the direction of increasing good output and reducing bad output.

The directional output distance function is estimated in this paper using data from thermal power generating plants in Andhra Pradesh (A.P.) State Of India. It is specified parametrically as a quadratic functional form and is used to estimate the combined environmental and technical efficiency, shadow prices of Suspended Particulate Matter (SPM), Sulphur Dioxide (SO_2) and Nitrous Oxide (NO_x) and the elasticity of substitution between good output, electricity and pollutants. The directional distance function could be estimated either deterministically or stochastically. The deterministic procedure accounts for all deviations from the observed frontier in measuring inefficiency. However, some of the deviations of observed outputs from the frontier outputs might be due to measurement error and random error and therefore, the directional distance function is estimated as a stochastic frontier in this paper.

The main findings are given as follows: The thermal power generating units could reduce emissions of SPM, SO_2, and NO_x further if they improve their technical and environmental efficiency. A representative plant, without increasing resources and developing technology, can annually increase electricity by 18.20 million units and reduce SPM, SO_2 and NO_x by 0.04, 0.053 and 0.008 thousand tonnes respectively. The shadow prices of bad outputs or marginal costs of pollution abatement of a ton of SPM, SO_2 and NOx are estimated respectively as Rs. 4777, 1883 and 6725 at 2003-2004 prices. The average overall elasticity of substitution between electricity and SPM is estimated as -1.159. More than unitary elasticity of substitution between electricity and SPM shows that there could be a significant rise in the marginal cost of abatement of SPM as the plant plans for the higher reductions. The analysis of correlation between firm specific shadow prices of bad outputs or marginal cost of abatement of pollutants and the pollution concentrations and pollution loads shows that there is a rising marginal cost of abatement with respect to pollution concentrations and a falling marginal cost of abatement with respect to pollution loads.

The remaining paper is planned as follows: Section 2 discusses the theoretical model of directional output distance function. Section 3 describes the empirical model and the data used in estimation. Section 4 discusses the results while Section 5 provides conclusions.

2. Theoretical Model

2.1. The Directional Output Distance Function

Let $y = (y_1,..., y_M) \in \Re_+^M$ and $b = (b_1,...,b_J) \in \Re_+^J$ be vectors of good and undesirable outputs respectively and let $x = (x_1,..., x_N) \in \Re_+^N$ be a vector of inputs. The technology of reference is the output possibilities set $P(x)$, which for a given vector of inputs denotes all technically feasible output vectors. This output set is assumed to be convex and compact with $P(0) = \{0,0\}$. Furthermore, inputs and good outputs are assumed to be freely disposable and undesirable outputs only weakly disposable.[1] Finally, good outputs are assumed to be null-joint with the undesirable outputs.[2] This means that good outputs cannot be produced without producing undesirable outputs. The directional output distance function is defined on $P(x)$ as

$$D(x, y,b; g) = \max_{\beta}\{\beta : (y + \beta \cdot g_y ,b - \beta \cdot g_b) \in P(x)\}, \tag{1}$$

which then inherits its properties from $P(x)$. The solution β^*, gives the maximum expansion and contraction of good outputs and undesirable outputs respectively. The vector $g = (g_y ,-g_b)$ specifies in which direction an output vector, $(y,b) \in P(x)$, is scaled so as to reach the boundary of the output set at $(y + \beta^* \cdot g_y ,b - \beta^* \cdot g_b) \in P(x)$, where $\beta^* = D(x, y,b; g)$. This means that the producer becomes more technically efficient

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[1] The output is strongly or freely disposable if $(y,b) \in P(x)$ and $\hat{y} \le y$ imply $(\hat{y}, b) \in P(x)$, this implies that if an observed output vector is feasible, then any output vector smaller than that is also feasible. It excludes production processes that generate undesirable outputs that are costlier to dispose. In contrast concerns about environmental pollutants imply that these should not be considered to be freely disposable. In such cases bad outputs are considered as being weakly disposable and $(y,b) \in P(x)$ and $0 \le \theta \le 1$ imply $(\theta y, \theta b) \in P(x)$ This implies that pollution is costly to dispose and abatement activities would typically divert resources away from the production of desirable outputs and thus lead to lower good output with given inputs.

[2] Null-jointness implies that a firm cannot produce good output in the absence of bad outputs, i.e. *if* $(y,b) \in P(x)$ and $b = 0$ then $y = 0$.

when simultaneously increasing good outputs and decreasing undesirable outputs. The distance function takes the value of zero for technically efficient output vectors on the boundary of $P(x)$, whereas positive values apply to inefficient output vectors below the boundary. The higher the value, the more inefficient is the output vector, i.e., the directional output distance function is a measure of technical inefficiency. Finally, the directional output distance function satisfies the translation property,

$$D(x, y+\alpha \cdot g_y, b-\alpha \cdot g_b; g) = D(x, y, b; g) - \alpha, \tag{2}$$

where α is a positive scalar. The translation property states that if the good output is expanded by αg_y and the bad output is contracted by αg_b, then the value of the distance function will be more efficient with the amount α. It is the additive analogue of the multiplicative homogeneity property of the Shephard's output distance function (Färe *et al.* 2005).

2.2. *The Shadow-pricing Model*

The duality between the distance function and the revenue function is exploited for deriving the shadow-prices of outputs from the directional output distance function. Let $p = (p_1,..., p_M) \in \Re_+^M$ and $q = (q_1,..., q_J) \in \Re_+^J$ represent the absolute prices of the good and undesirable outputs, respectively. Färe *et al.* (2005) showed that the relative shadow prices of undesirable outputs in terms of the m^{th} good output could be derived as,

$$\frac{q_j}{p_m} = -\left(\frac{\partial D(x, y, b; g)}{\partial b_j} \middle/ \frac{\partial D(x, y, b; g)}{\partial y_m} \right), \qquad \begin{array}{l} j = 1,..., J. \\ m = 1,..., M. \end{array} \tag{3}$$

This is the marginal rate of transformation between the jth undesirable output and the mth good output (MRT_{jm}) where $\partial D(\cdot)/\partial y_m < 0$ and $\partial D(\cdot)/\partial b_j \geq 0$. Therefore, the shadow price or the marginal pollution abatement cost (MAC) is measured in terms of decreased production of y_m, which has to be met when reducing b_j marginally, once all inefficiency has been eliminated.

The shadow-pricing model is illustrated in Figure 1. The output possibility set is given by $P(x)$ and (y,b) is the technically inefficient output vector. Given the directional vector, $g = (1,-1)$, the directional output distance function in (1) scales (y,b) until it reaches the boundary of $P(x)$ at A. This particular point has a supporting hyper plane interpreted as a shadow price relation, $q^* - p^*$. The shadow prices of bad outputs or MACs correspond to the tangents on the boundary or the slope of the boundary of the output set at point A.

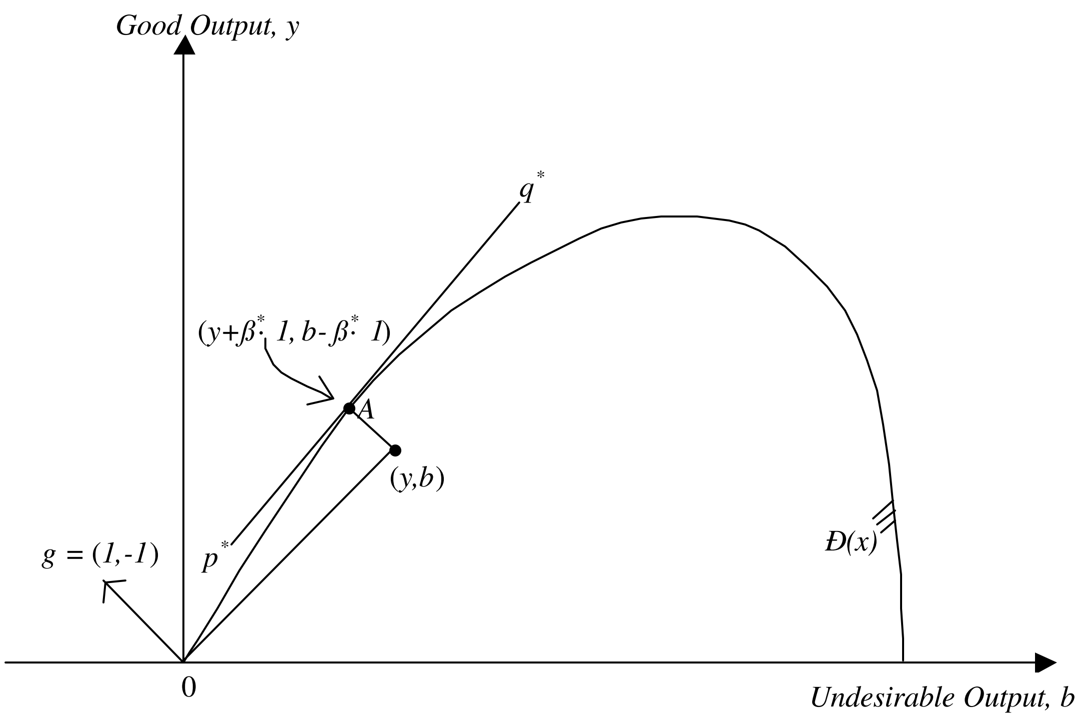

Figure 1: The shadow-pricing model

2.3 Output Elasticity of Substitution

The derivation of the shadow prices of bad outputs is based on the slope of the boundary of the output set. Using the same framework of the directional output distance function we can estimate the output elasticity of substitution (transformation), i.e., the curvature of the boundary of the output set. The curvature measures how the ratio of the shadow prices of good and bad outputs changes as the relative pollution intensity (ratio of bad output to good output) changes. Following Blackorby and Russell (1989) and Grosskopf *et al.* (1995), we define indirect Morishima elasticity of substitution between good output, y and bad output b as follows,

$$M_{by} = \frac{\partial \ln(q/p)}{\partial \ln(y/b)} \tag{4}$$

and in terms of directional output distance function, the Morishima elasticity of substitution, following Färe *et al.* (2005) can be specified as,

$$M_{by} = y^* \left\{ \left(\frac{D_{by}(x, y, b; g)}{D_b(x, y, b; g)} \right) - \left(\frac{D_{yy}(x, y, b; g)}{D_y(x, y, b; g)} \right) \right\} \tag{5}$$

where $y^* = y + D(x, y, b; g)$ and the subscripts on the distance functions refer to partial derivatives with respect to outputs: e.g., $D_{yy}(x, y, b; g)$ is the second order partial derivative of the distance function with respect to y. Given the monotonicity properties[3] of the directional distance function with respect to good and bad outputs, along the positively sloped portion of $P(x)$ (when the bad outputs are assumed to be weakly disposable) the sign of M_{by} should be negative.

The higher values of M_{by} (higher in absolute terms) indicate that a given change in the ratio of outputs will yield higher changes in the shadow price ratio. Therefore, as the elasticity of substitution becomes more negative it becomes more costly for electricity generating plants to reduce the amount of pollution over time.

Here it should be noted that the Morishima and Allen elasticities yield the same result in the two-output case; when the number of outputs exceeds two, however, they no longer coincide. Moreover, the Morishima elasticities may not be symmetric, i.e., $M_{by} \neq M_{yb}$. This is as it should be and allows for the asymmetry in substitutability of different outputs.

[3](i) $D_b(x, y, b; g) \geq 0$; (ii) $D_y(x, y, b; g) \leq 0$; (iii) $D_{yy}(x, y, b; g) \leq 0$; and (iv) $D_{by}(x, y, b; g) \leq 0$. For details on the properties of directional output ditance function see, Färe *et al.* (2005).

3 The Empirical Model and Data

3.1. Empirical Model

Following Färe *et al.* (2005), the directional output distance function is parameterized using a (additive) quadratic flexible functional form. In our case, with one good output, three bad outputs and three inputs, the particular form is,

$$\begin{aligned} D^{kt}(x^{kt}, y^{kt}, b^{kt}; g) = {} & \alpha_0 + \sum_{n=1}^{3}\alpha_n x_n^{kt} + \beta_1 y_1^{kt} + \sum_{j=1}^{3} \gamma_j b_j^{kt} \\ & + \frac{1}{2}\sum_{n=1}^{3}\sum_{n'=1}^{3}\alpha_{nn'} x_n^{kt} x_{n'}^{kt} + \sum_{n=1}^{3}\delta_{n1} x_n^{kt} y_1^{kt} + \sum_{n=1}^{3}\sum_{j=1}^{3} \eta_{nj} x_n^{kt} b_j^{kt} \\ & + \frac{1}{2}\beta_{11} y_1^{kt} y_1^{kt} + \sum_{j=1}^{3} \mu_{1j} y_1^{kt} b_j^{kt} \\ & + \frac{1}{2}\sum_{j=1}^{3}\sum_{j'=1}^{3} \gamma_{jj'} b_j^{kt} b_{j'}^{kt} + \tau_t \end{aligned} \tag{6}$$

where τ is parameter representing time-specific effect. For the translation property to hold, and accounting for the direction vector, the required parameter restrictions are,

$$\beta_1 - \sum_{j=1}^{3}\gamma_j = -1, \sum_{j=1}^{3}\mu_{1j} - \sum_{j'=1}^{3}\gamma_{jj'} = 0, \beta_{11} - \sum_{j=1}^{3}\mu_{1j} = 0,\ j = 1,2,3.$$

In addition to the translation property, we impose symmetry conditions also,

$$\alpha_{nn'} = \alpha_{n'n}, \eta_{nj} = \eta_{jn}, \gamma_{jj'} = \gamma_{j'j}, n, n' = 1,2,3; j, j' = 1,2,3.$$

The function can be computed using both linear programming (LP) and stochastic techniques.[4] Estimating distance functions econometrically has some advantages over the LP approach. Other than allowing for an appropriate treatment of measurement errors and random shocks, several statistical hypotheses can be tested: significance of parameters, separability between outputs and inputs and between good and bad outputs and monotonicity properties of distance functions. Following Kumbhakar and Lovell (2000) and Färe *et al.* (2005), the stochastic specification of the directional distance function takes the form,

$$0 = D(x, y, b; 1, -1) + \varepsilon \tag{7}$$

where $\varepsilon = v - \mu$ and $v \sim N(0, \sigma_v^2)$ and $\mu \sim iidG(P, \theta)$.

[4] The LP estimating procedure is adopted in Färe *et al.* (2001).

To estimate (7) we utilize the translation property of the directional output distance function. As in Färe *et al.* (2005), we choose the directional vector g = (1,-1), where 1 refers to g_y and -1 refers to -g_b, (see Figure 1). This choice of direction is consistent with environmental regulations, which require reduction in bad outputs. The translation property implies that,

$$D(x, y+\alpha, b-\alpha, 1, -1) + \alpha = D(x, y, b; 1, -1)\,. \tag{8}$$

By substituting $D(x, y+\alpha, b-\alpha; 1, -1) + \alpha$ for $D(x, y, b; 1, -1)$ in (7) and taking α to the left hand side, we get

$$-\alpha = D(x, y+\alpha, b-\alpha;\ 1, -1) + \varepsilon \tag{9}$$

where $D(x, y+\alpha, b-\alpha; 1, -1)$ is the quadratic form given by (6) with α added to y and subtracted from b. Thus, one is able to get a variation on the left-hand side by choosing an α that is specific to each electricity generating plant. In our case it may be one of the bad outputs.

The parameters of the quadratic distance function (6) and as well as the value of the directional output distance function which is a measure of technical inefficiency can be estimated using either the corrected ordinary least square (COLS) [5] or the maximum likelihood (ML) methods. The COLS approach is not as demanding as the ML method, which requires numerical maximization of the likelihood function. The ML method is asymptotically more efficient than the COLS estimator but the properties of the two estimators in finite samples can be analytically determined. The finite sample properties of the half-normal frontier model were investigated in a Monte-Carlo experiment by Coelli (1995), in which the ML estimator was found to be significantly better than the COLS estimator when contribution to technical inefficiency effects to the total variance term is large. Greene (2000) shows that the gamma model has the virtue of providing a richer and more flexible parameterization of the inefficiency distribution in the stochastic frontier model than either of the canonical forms, half normal and exponential. Moreover, gamma specification enjoys essentially the same properties as the normal/half-normal model with the additional advantage of the flexibility of a two-parameter distribution.

[5] For an application of COLS to the Shephard output distance function, see Lovell *et al.* (1994) and to the directional output distance function, see Färe *et al.* (2005)

The primary advantage is that it does not require that the firm-specific inefficiency measures be predominately near zero (Greene, 1990). One can test down from the gamma to the exponential by testing if the shape parameter, P, equals 1.0 as the gamma distribution is a generalization of the exponential distribution. The present study adopts the ML estimation approach while assuming gamma distribution for one-sided error term.

3.2. Data

The directional output distance function described above is estimated using data for five coal fired thermal power generating plants belonging to APGENCO (Andhra Pradesh Power Generation Corporation) in A.P, India. The data set used constitutes a panel consisting of monthly observations on variables during the years 1996-97 to 2003-04. It contains 480 observations on electricity produced, air pollutants SPM, SO_2 and NO_x generated as well as coal and other inputs used by the five electricity-generating plants. Electricity generated is considered as a good output while the three pollutants SPM, SO_2 and NO_x generated are taken as bad outputs in the estimation. Table 1 provides the descriptive statistic of the variables used in the estimation of the distance function.

SPM, SO2, and NOx : Monthly loads in tonnes discharged by the power plant. It is computed by multiplying monthly average concentration of the pollutant (mg/NM^3) with the monthly volume of stack discharge (NM^3) for each plant.

Electricity: Electricity produced by the plant during a year in (million units).

Capital: Capital stock of a plant observed at the beginning of a year which is assumed to be fixed for the rest of the year.

Coal: Annual consumption of coal by the plant (in tonnes).

Wage Bill: Annual wage bill of a plant (in million rupees).

Table 1: Descriptive Statistics of the Variables Used in Study

Variable	Unit	Mean	Standard Dev.	Maximum	Minimum
Electricity	Million Units	298.28	13.91	933.58	0.01
SPM	Tonnes	0.653	0.033	3.526	0.018
SO_2	Tonnes	0.874	0.049	4.268	0.004
NO_{xC}	Tonnes	0.139	0.013	1.984	0.001
Coal	Tonnes	223.46	9.93	667.05	0.01
Capital	Rupees millions	1913.231	905.46	62395.28	148.59
Wage Bill	Rupees millions	255.628	111.03	9332.04	344.16

4. Results

The directional output distance function is estimated using mean normalized input and output data since we face convergence problems in the models given the numercial size of the outputs and inputs reported in Table 1 (Färe *et al.* 2005). This normalization implies that $(x, y, b) = (1,1,1)$ for a hypothetical electricity generating plant that uses mean inputs and produces mean outputs.

For the econometric estimation of the directional output distance function, one of the bad outputs is taken as the dependent variable, as specified in equation (9). In the data set, we have three bad outputs and in the available literature there is no guide about the selection of dependent variable while using the translation property. Therefore, we estimate three models considering one of the bad outputs as a dependent variable in each case.

As mentioned above, we follow the ML estimation procedure for the estimation of the directional distance function and the one sided error term is assumed to beindependently and identically gamma distributed (i.i.γ). As the shape parameter P tends to 1.0, the parameter estimates converge towards an exponential distribution of the one-sided error term. On the basis of the loglikelihood test we settle the case either in favor of exponential or gamma distribution of the error term. In *Model 1* (SPM is the dependent variable) and *Model 3* (NO_x is the dependent variable) we go for exponential distribution of the error term, but in *Model 2* (SO_2 is the dependent variable) we have selected the gamma distribution of the error term. Table 2 presents the model selection results.

Table 2: Selection of Model

	Null Hypothesis	Log Likelihood Ratio Test Statistics (λ)	Decision
Model 1	H_0: P=1	-1396.86	Accept H_0
Model 2	H_0: P=1	62.38	Reject H_0
Model 3	H_0: P=1	0	Accept H_0

Note: λ= -2{Log(Likelihood H_0) – Log(Likelihood H_1)}
where *Model 1*: SPM is the dependent variable; *Model 2*: SO_2 is the dependent variable; *Model 3*: NOx is the dependent variables.

In Table 3 the estimated parameters of all the three models are presented. In *Model 2* we have selected the model which assumes gamma distribution of the one-sided error term. In this model we find that the value of shape parameter, P is different from one and it is statistically significant even at the 1% level. Similarly, we find that the other ML estimation parameters are also statistically significant in all the three models. Most of the first order parameters have expected signs and are statistically significant in all the three models. A first look at the parameters in Table 3 indicates that the results obtained for all the three models are very close to each other. Looking at the second order parameters, it appears that they involve interesting results too; these however, require a more detailed analysis to measure their final influence. Thus using the estimated coefficients we are able to verify that the resulting distance functions satify the regulatory conditions for average values.

Table 3 Parameter Estimates of Directional Output Distance Function

Name of Variable	Model 1		Model 2		Model 3	
	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat
Intercept	-0.1233	-5.8580	-0.1565	-7.9800	-0.1301	-5.8620
Y_1	-0.7433	-50.2740	-0.5826	-42.1560	-0.7629	-36.0580
Y_2	0.1317		0.0559	17.8270	0.0824	7.3040
Y_3	0.0839	2.4410	0.3224		0.1578	-0.2210
Y_4	0.0412	3.4630	0.0391	3.8030	-0.0031	
X_1	0.8733	32.3120	0.7544	29.4870	0.8397	25.5310
X_2	-0.1108	-4.0700	-0.1399	-5.0380	-0.2131	-6.9690
X_3	0.3746	5.4420	0.3082	4.5260	0.7547	11.5570
T	-0.0002	-1.3450	-0.0005	-4.0610	0.0001	0.6380
Y_1^2	-0.3229	-53.8390	-0.2969	-55.5240	-0.3282	-56.2120
Y_2^2	0.3981		0.1535	-0.0100	-0.4898	-7.5100
Y_3^2	-0.0670	-3.7500	-0.0002		-0.1133	1.7160
Y_4^2	-0.1300	-11.8500	-0.0876	-7.3360	0.0153	
X_1^2	-0.5576	-17.3710	-0.6735	-18.4610	-0.2452	-7.1830
X_{22}	0.1399	5.2260	0.1683	5.0930	-0.0856	-2.9940
X_3^2	-0.6330	-12.7610	-0.3193	-5.5760	-0.7261	-13.0790
$Y_1 Y_2$	0.0810		-0.0057	-4.7770	-0.2449	-3.5050
$Y_2 Y_3$	0.1901		0.1233		-0.1868	-0.8610
$Y_2 Y_4$	0.1271		0.0359	-7.8510	-0.0582	
$Y_1 Y_3$	-0.1267	-5.3670	-0.1091		-0.0637	33.9210
$Y_1 Y_4$	-0.2772	-14.5140	-0.1821	33.4740	-0.0195	
$Y_1 X_1$	0.3953	33.9510	0.4567	4.3910	0.3429	32.7510
$Y_1 X_2$	0.0633	5.8300	0.0423	-10.4620	0.2549	-0.3610
$Y_1 X_3$	0.0834	7.0820	-0.1063	2.6820	-0.0038	4.9920
$Y_3 Y_4$	0.0202	0.8200	0.0585		0.0930	
$Y_2 X_1$	0.1842		0.1715	7.8580	0.2778	9.8240
$Y_2 X_2$	-0.0032		0.0492	-0.1750	0.1728	-6.2900
$Y_2 X_3$	-0.0229		0.1009	-19.4490	0.1417	-9.2740
$Y_3 X_1$	0.1057	4.7110	0.1765		0.1603	-4.8060
$Y_3 X_2$	0.0746	4.4830	-0.0032		-0.0658	14.0060
$Y_3 X_3$	-0.0667	-3.0330	-0.2754		-0.1285	-1.2340
$Y_4 X_1$	0.1054	8.3270	0.1087	8.4230	-0.0951	

Y_4X_2	-0.0081	-0.7900	-0.0037	-0.3460	0.1479	
Y_4X_3	0.1731	13.9480	0.0682	3.8450	-0.0169	
X_1X_2	-0.4477	-15.4230	-0.4336	-11.8180	-0.6852	-16.8890
X_1X_3	0.1155	3.2860	0.1889	3.5990	-0.0893	-2.1280
X_2X_3	-0.0097	-0.3410	0.0646	1.8540	0.0280	0.9060
θ	15.9290	28.1600	7.3029	19.6420	8.6009	15.4370
P			0.4228	9.9300		
σ_v	0.0174	7.6690	0.0259	13.2280	0.0100	16.6590
Loglikelihood function		733.578		662.343		-409.111

Notes: Underlined parameters are calculated by using the translation property.
Where *Model 1*: SPM is the dependent variable; *Model 2*: SO_2 is the dependent variable; *Model 3*: NOx is the dependent variable.
Y_1: Electricity; Y_2: SPM; Y_3: SO_2; Y_4: NOx; X_1: Coal; X_2: Capital; and X_3: Wage Bill.

From Section 2 we know that for the directional output distance function to be well behaved it needs to be non-negative and the constraints of null-jointness, monotonicity, symmetry and the translation property need to hold. In the deterministic estimation of distance function using the linear programming approach these constraints are imposed. In stochastic estimation of distance functions the properties of non-negativity, translation and symmetry are imposed, and monotonicity and null jointness are tested for afterwards. It may be recalled that null-jointness implies that an output vector belongs to an output set only if the value of the directional output distance function is non-negative. Therefore, an appropriate test is to evaluate $D(x, y, 0; 1, -1)$ for $y > 0$. If $D(x, y, 0; 1, -1) < 0$, then the observation $(y, 0)$ is not in $P(x)$ as implied by null-jointness. Table 4 presents the percentage of observations that satisfies monotonicity and null-jointness conditions for all the three models. We find that the monotonicity condition with respect to electricity is satisfied in all the three models. With respect to SPM, the monotonicity condition is satisfied by all the observations in the first two models but in the third model it is satisfied only by 40 percent of the observations. Similarly, we find that the condition of monotonicity is fulfilled by all the observations in *Model 1*, by 96 percent observations in *Model 2* and only by 44 percent observations in *Model 3* with respect to SO_2. With respect to the third undesirable bad output, NOx we find that in none of the models is the monotonicity condition satisfied by all the observations. However, the highest percentage is for the *Model 1* and it declines in other models.[6] The null-jointness condition is satisfied by 55, 62 and 3 percent of the observations in *Models 1, 2, and 3* respectively.

Table 4: Observations satisfying monotonicity and null-jointness conditions (%)

	Monotonicity Conditions				Null-Jointness Condition
	Y_1	Y_2	Y_3	Y_4	
Model 1	100	100	100	72.50	54.79
Model 2	100	100	95.83	63.13	62.29
Model 3	100	39.79	43.96	55	2.71

Note: Where *Model 1*: SPM is the dependent variable; *Model 2*: SO_2 is the dependent variable; *Model 3*: NOx is the dependent variables. Y_1: Electricity; Y_2: SPM; Y_3: SO_2; Y_4: NOx;

As noted above, we used three models for the purpose of estimating the directional output distance function. This is aimed to shed some light upon the sensitivity of empirical results to the selection of the model. Moreover, the time-series literature is in favor of using the average of the predictions from a number of models. The average of estimates from various models to form predictions may potentially be better than the estimates from any one particular model. For example, in a study discussing various models of combining time-series predictions, Palm and Zellner (1992, p.699) observe "*In many situations a simple average of forecasts will achieve a substantial reduction in variance and bias through averaging out individual bias*".[7] Therefore, all the results reported in the study are averages of the first two models since *Model 3* fails to satisfy most of theoretical properties of the directional output distance function. Moreover, the correlation matrix of technical inefficiency estimated with different models also reveals that there is a high correlation in technical inefficiency estimated with the first two models. However, the correlation between

[6] For the observations that violate the monotonicity conditions, the estimates of directional output distance function are scaling some (those that violate monotonicity) of the observed values of *(y,b)* back to the frontier along the negatively sloped portion of output set (see Figure 1).

[7] The averaging approach is adopted by Coelli and Parelman (1999) in measuring the relative performance of European Railways, by Drake and Simper (2003) in measuring the efficiency of the English and Welsh police force, and by Kumar and Gupta (2004) in measuring the resource use efficiency of US electricity generating plants. Here it should be noted that the averaging is done for the different estimation methods such as parametric linear programming, data evelopment analysis and stochastic estimation. This is the first study which is using the averaging approach for different models using a single estimation technique.

technical inefficiency estimated by *Model 1* and *Model 3* or between *Model 2* and *Model 3* is lower in comparison to the correlation between *Model 1* and *Model 2* (Table 5)

Table 5: Correlation Matrix of Different Model with Regard to Technical Inefficiency

Model	1	2	3
1	1.00	0.91	0.71
2	0.91	1.00	0.60
3	0.71	0.60	1.00

Notes: Model 1: SPM is the dependent variable; *Model 2*: SO_2 is the dependent variable; *Model 3*: NOx is the dependent variables

Tables 6 and 7 present a yearly average and plant-wise average estimates of technical inefficiency based on the first two models and shadow prices of bad outputs. Appendix Table 2 presents the estimates of the Morishima elasticity of substitution between the outputs.[8] For a representative electricity generating plant using the sample mean of inputs to produce the sample mean of outputs, the estimated value of the directional output distance function is 0.061, indicating that the production is not technically and environmentally efficient. This implies that these electricity-generating plants could on average, without changing resources or developing technology, increase electricity by 18.20 MW (298.28×0.061) and reduce SPM, SO2 and NOx by 0.04, 0.053 and 0.008 thousand tonnes respectively. We find that KTPS is the most inefficient and NTS is the least inefficient plant in Andhra Pradesh Electricity Generation Company. Moreover, we also observe that in the latter years, inefficiency has declined in comparison to the earlier years, however, in the last year (2003/04) inefficiency has increased to 10 percent.

Table 6: Yearly Average Estimates of Technical Efficiency and Shadow Prices

Year	Technical and Environmental Inefficiency	Shadow Prices (Rupees)		
		SPM	SO_2	NO_x
1996/97	0.062	2237.60	3741.93	9370.43
1997/98	0.075	3553.32	928.30	4505.75
1998/99	0.055	2805.93	1071.96	2464.48
1999/2000	0.078	5338.02	2574.37	13030.16
2000/01	0.053	8755.13	1089.14	2092.38
2001/02	0.037	4771.03	2729.58	6735.45
2002/03	0.023	5234.24	699.74	2852.05
2003/04	0.100	5521.23	2227.54	12745.67

[8] We presented the Morishima elasticity estimates for *Model 1* only because the monotonicity conditions are satisfied by most of the observations in this model, but in the other two models the monotonicity conditions with respect to SO_2 and NOx are not satisfied by the majority of the observations.

Table 7: Plant-wise Average Estimates of Technical and Environmental Inefficiency and Shadow Prices

Plant	Technical and Environmental Inefficiency	Shadow Prices (Rupees)		
		SPM	SO_2	NO_x
KTPS	0.115	2080.14	1864.56	9210.08
VTPS	0.060	6327.60	1122.97	7929.31
NTS	0.033	132.03	711.88	2830.99
RTS	0.040	14926.68	4889.60	11904.94
RTP	0.054	418.87	825.08	1747.40

Reviewing the shadow prices for SPM, SO2 and NOx, we find that to reduce the emissions of a particular pollutant by one tonne, a representative plant has to spend Rs. 4777, 1883 and 6725 respectively. Moreover, the results reveal that the shadow prices or the marginal abatement costs of pollutants also vary considerably by year and plant. One explanation for this could be that the functional form used is only a local approximation, and the plants that differ significantly from the rest may be assigned extreme shadow prices. These wide variations in the shadow price of pollutants also favor the introduction of market-based instruments to meet the environmental standards in a cost effective way.

This wide variation can be explained by the variation in the degree of compliance as measured by the ratio of pollution load and electricity generated and the different vintages of capital used by the firms for the production of desirable output and pollution abatement. The shadow prices of SPM, SO_2 and NO_x, which may be interpreted as the marginal costs of pollution abatement, are found to be increasing with the degree of compliance of firms. Taking the index of non-compliance by the firms as the ratio of emissions of SPM, SO_2 or NO_x to the electricity generated, it is found that the higher the index, the lower the shadow price. That means, the dirtier the plant, the lower is the shadow price. Considering the logarithm of shadow price as a dependent variable and the emissions to electricity generated ratios as an independent variable, the estimated relationship between the shadow prices and the index of non-compliance for SPM, SO_2 and NO_x are given as follows,

$$Ln(SPMP) = 6.796 - 0.523Ln(SPM/Electricity) - 0.260Ln(SPM)$$
$$(62.15) \quad (-5.015) \quad (-4.391)$$
$R^2 = 0.101$; $F = 26.825$; $N=480$

$$Ln(SO_2P) = 5.815 - 0.642Ln(SO_2/Electricity) - 0.296Ln(SO_2)$$
$$(85.34) \quad (-6.277) \quad (-6.425)$$
$R^2 = 0.143$; $F = 39.915$; $N=480$

$$Ln(NO_XP) = 6.247 - 21.801Ln(NO_X/Electricity) - 0.327Ln(NO_X)$$
$$(24.48) \quad (-4.102) \quad (-5.32)$$
$R^2 = 0.138$; $F = 27.929$; $N=351$

where *SPMP*: shadow price of SPM; SO_2P: shadow price of SO_2; NO_xP: shadow price of NO_x. Figures in parentheses represent *t*-statistics.

Also, the estimates show that the shadow prices of undesirable outputs fall with the pollution load reductions obtained by the firms in the case of all three pollutants. That means that as found in the earlier studies of the Indian water-polluting industries,[9] these results show that there are also scale economies in air pollution abatement, implying that the higher the pollution load reduction, the lower the marginal abatement cost.

Recall that the Morishima elasticity of substitution measures the relative change in the shadow prices of outputs due to relative change in output quantities and its value is expected to be negative. As these are indirect elasticities, the higher is its value (in absolute terms) the more costly it becomes for plants to reduce pollutants. The estimates of Morishima elasticities are presented in Appendix Table A2. The yearly average ranges from –0.237 to –3.24 and the overall average is –1.159 indicating inelasticity in substitution between electricity and SPM. Morever, the plant-wise averages show that NTS has the largest elasticity for substituion between SPM and electricity, i.e., NTS can abate SPM at least cost while for the KTPS it is relatively costly to abate SPM. The yearly average does not present any particular trend. However it has declined (in absolute values) as we find a negative correlation between the values of elasticity and the time trend (-0.155). This indicates that for the plants under study, it is becoming more costly to dispose the pollutants of SPM over time. Moreover, the estimates of Morishima elasticity

[9] Mehta *et al.* (1995), Murty *et al.* (1999), Pandey (1998), and Misra (1999), Murty and Kumar (2002, 2004).

indicate asymmetric behavior in the disposal of bad outputs. For example, the elasticities indicate that there is a complementarity between SPM and NOx.

5. Conclusion

The technology of the air polluting industry, namely the coal fired thermal power generation in India, is modeled in this paper using a methodology that could account for the industry's performance in producing electricity and reducing pollution in measuring the productive efficiency of firms. The methodology used is the directional output distance function which is estimated as a stochastic frontier. An analysis of the effects of environmental regulation on the productive efficiency of industry, shadow prices of bad outputs and elasticity of the substitution of the good and bad outputs with respect to relative shadow prices is attempted. An analysis of correlation between the firm-specific shadow prices or marginal cost of abatement and pollution concentration and pollution loads is undertaken for each bad output to know about the pollution taxes that could be levied on firms for ensuring compliance with the environmental regulation.

The model is estimated by considering that coal-fired thermal power generation produces good output, namely electricity and three bad outputs for example SPM, SO_2 and NO_x. The most important bad output, CO_2 could not be considered in the estimation because of lack of firm specific data on CO_2 emissions. Environmental regulation in India requires the industry to comply with certain standards related to bad outputs. Firm-specific estimates of technical and environmental efficiency show that with the given resources and technology many firms could increase the production of electricity and reduce production of bad outputs from the current levels of production to comply with the regulation. Estimates of elasticity of substitution between the good output and bad outputs show that the changes in output combinations in the industry could significantly affect the marginal costs of abatement (MCA) or shadow prices of bad outputs. The analysis of correlation between the marginal cost of abatement and pollution intensity and electricity generated for each pollutant show that MCA increases with a decrease in pollution concentration and decreases with an increase in firm capacity. This result reveals an increasing marginal cost of air pollution abatement in coal-fired thermal power generation.

The estimates show that there is a significant variation in the technical and environmental inefficiency among the five firms considered (0.033-0.115) with an estimate of 0.10 for the industry on the average during the year 2003-2004. This means that the thermal power generating industry in A.P., India could increase the production of electricity and reduce the pollution loads by 10 percent from the current levels of production with the available resources and technology. This result provides evidence of the existence of incentives and win-win opportunities for the firms to voluntarily comply with environmental regulation. Also, there is a significant variation in the estimates of the shadow prices of bad outputs among the firms with a range of Rs. 14926-132 for SPM, Rs. 4889-711 for SO_2 and Rs. 11904-1747 for NO_x. This variation in the shadow price of bad output among firms could be attributed to different levels of compliance to environmental regulation. The correlation analysis of shadow price of bad output and the pollution intensity of firms show that the higher the pollution intensity the lower is the shadow price. A pollution or emission tax on firms could provide incentives to firms for complying with environmental regulation.

Appendix:

Table A1: Estimates of Technical Efficiency, Shadow Prices and Morishima Elasticity

Plant	Year	Technical Efficiency	Shadow Prices (Rupees)		
			SPM	SO_2	NO_x
KTPS	1996/97	0.067	2503.11	7609.48	37963.38
KTPS	1997/98	0.201	2288.57	258.65	15250.50
KTPS	1998/99	0.155	1017.31	388.72	5177.33
KTPS	1999/2000	0.222	829.07	1818.63	5310.23
KTPS	2000/01	0.109	1578.43	498.38	1116.76
KTPS	2001/02	0.024	1721.67	1836.69	4812.63
KTPS	2002/03	0.027	1839.53	495.72	124.04
KTPS	2003/04	0.118	4863.45	2010.22	3925.80
VTPS	1996/97	0.050	5232.97	514.54	7280.91
VTPS	1997/98	0.058	5679.69	491.39	3709.40
VTPS	1998/99	0.024	3942.77	579.57	4615.02
VTPS	1999/2000	0.040	5494.16	2691.16	7836.43
VTPS	2000/01	0.022	5546.44	293.16	6906.86
VTPS	2001/02	0.081	7736.37	2075.61	12343.94
VTPS	2002/03	0.028	6931.28	407.27	12226.75
VTPS	2003/04	0.178	10057.11	1931.07	8515.16
NTS	1996/97	0.035	55.32	116.71	134.38
NTS	1997/98	0.044	53.50	112.72	2736.44
NTS	1998/99	0.043	39.13	100.62	1909.98
NTS	1999/2000	0.020	197.84	1879.38	5242.19
NTS	2000/01	0.027	67.49	79.94	1514.07
NTS	2001/02	0.027	270.45	1660.14	5037.19
NTS	2002/03	0.019	97.54	64.90	1407.94
NTS	2003/04	0.048	274.98	1680.66	4665.76
RTS	1996/97	0.009	3291.62	10359.11	933.29
RTS	1997/98	0.015	9504.52	3559.66	527.51
RTS	1998/99	0.024	8802.83	4071.30	573.25
RTS	1999/2000	0.091	19694.37	4485.66	43017.93
RTS	2000/01	0.082	36122.65	4270.37	NA
RTS	2001/02	0.040	13470.61	6053.84	7169.65
RTS	2002/03	0.016	16783.73	2464.01	NA
RTS	2003/04	0.042	11743.11	3852.88	43017.93
RTP	1996/97	0.148	104.97	109.80	540.19
RTP	1997/98	0.058	240.33	219.08	304.93
RTP	1998/99	0.030	227.62	219.57	46.84
RTP	1999/2000	0.018	474.66	1997.00	3744.02
RTP	2000/01	0.027	460.62	303.84	924.20
RTP	2001/02	0.012	656.07	2021.65	4313.84
RTP	2002/03	0.027	519.15	66.81	501.49
RTP	2003/04	0.114	667.53	1662.86	3603.69
Overall Average		0.061	4777.06	1882.82	6724.55

Table A2: Estimates of the Morishima Elasticity of Substitution

	M_{y1y2}	M_{y1y3}	M_{y1y4}	M_{y2y1}	M_{y2y3}	M_{y2y4}	M_{y3y1}	M_{y3y2}	M_{y3y4}	M_{y4y1}	M_{y4y2}	M_{y4y3}
Plants												
KTPS	-3.240	-3.240	1.031	-1.179	-3.240	0.021	-3.240	-3.240	-3.240	2.330	0.417	-3.240
VTPS	-1.737	-1.737	0.257	-0.698	-1.737	-0.089	-1.737	-1.737	-1.737	1.595	0.269	-1.737
NTS	-0.237	-0.237	-1.873	-1.447	-0.237	-1.190	-0.237	-0.237	-0.237	-1.689	0.433	-0.237
RTS	-0.283	-0.283	1.213	-1.230	-0.283	-0.165	-0.283	-0.283	-0.283	2.742	1.425	-0.283
RTP	-0.299	-0.299	6.438	-1.578	-0.299	1.540	-0.299	-0.299	-0.299	10.169	3.077	-0.299
Years												
1996/97	-0.958	-0.139	1.369	-1.166	0.066	-1.285	1.615	-1.536	-3.978	2.983	-0.321	-0.016
1997/98	-1.091	-1.268	-0.901	-1.214	-0.011	3.182	0.449	-1.392	-3.044	-0.352	4.333	-0.120
1998/99	0.844	-1.240	4.484	-0.774	-0.004	-0.802	0.446	-1.426	-3.619	7.381	0.302	-0.191
1999/2000	-2.865	-0.797	1.069	-1.658	-0.032	0.099	0.893	-1.338	-3.130	2.558	1.168	1.450
2000/01	-1.570	-7.117	-0.883	-1.366	-0.007	-0.205	0.200	-1.399	-3.171	-0.307	0.958	1.099
2001/02	-1.043	-1.043	-0.656	-1.213	-1.043	-0.302	-1.043	-1.043	-1.043	0.102	0.920	-1.043
2002/03	-1.337	-2.434	-1.536	-1.309	0.086	-0.606	1.637	-1.506	-3.231	-1.180	0.587	1.333
2003/04	-1.253	-1.983	8.363	-1.111	0.073	0.105	0.161	-1.276	-2.814	13.051	1.045	2.541

Note: Y_1: Electricity; Y_2: SPM; Y_3: SO_2; Y_4: NOx

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