Measuring Cost of Environmentally Sustainable Industrial Development in India: A Distance Function Approach*

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Abstract:
This paper attempts to estimate the maintenance cost of water pollution abatement measures to the Indian industry using the methodology of distance function in the theory of production. The distance function is estimated using both programming and stochastic frontier models for a sample of water polluting industries in India. The firm specific shadow prices for pollutants, measures of efficiency and scale economies are estimated. Estimates show that on an average the cost to the Indian industry for reducing one ton of BOD and COD are respectively, Rs 0.246 and 0.077 million. Large differences in the estimates of firm specific shadow prices of pollutants reflect the use of inefficient water pollution abatement technologies. The relationships between firm specific shadow prices or marginal costs of abatement of BOD and COD and the index of compliance (ratio of effluent load to sales value) and the pollution load reductions obtained confirm the earlier empirical results of studies on the water pollution abatement in Indian industries. The earlier studies have found increasing marginal costs with respect to reductions in pollution concentrations and decreasing marginal cost with respect to the pollution loads reduced by the firms.

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environmentally corrected GDP by making use of maintenance cost version of United Nations methodology of `Integrated Environmental and Economic Accounting'.

1. Introduction

It is now known that sustainable industrial development requires the preservation of the environment. Industries create a demand not only for waste receptive services from the environmental media: air, forests, land and water but also for some material inputs supplied by the environmental resources (for example wood in the paper and pulp industry). Environmental resources can ensure a sustainable supply of these services, if they are preserved at their natural regenerative level or the demand for waste receptive services is equal to the waste assimilative capacity of environmental resources. Given that the demand for environmental services from various economic activities can exceed the natural sustainable levels of supply at a given time, and if measures are not taken to reduce this excess demand to zero there can be a degradation of environmental resources. The cost of reducing the demand for environmental services to the natural sustainable level of supply is regarded as the cost of sustainable use of environmental resources and in the case of industrial demand for environmental services, it is the cost of sustainable industrial development. The measurement of this cost of sustainable industrial development is the main objective of this paper.

As a part of environmental regulation, a firm faces a supply constraint on the environmental services in the form of prescribed standards for the effluent quality. The effluent standards are normally fixed such that the demand for the services of environmental media does not exceed the natural sustainable level of supply. The firm has to spend some of its resources to reduce the pollution loads to meet the effluent quality standards. The firm with a resource constraint will be having less resources left for the production of its main product after meeting the standards. Therefore, the opportunity cost of meeting these standards is in the form of a reduced output of the firm. If all the firms in the industry meet the standards, the value of the reduced output of firms is the cost of sustainable industrial development. How to estimate this cost for a competitive firm facing the environmental regulation? It has to be estimated by studying the firm's behaviour in the decision making regarding pollution loads and the choice of pollution abatement technologies. In some of the recent studies, the technology of a polluting firm is modelled on one of the two basic approaches using the conventional methods of the theory of production : (a) Considering effluent as an additional input in the production or profit function, and (b) By including abatement capital as an additional input in a cost function. In some studies, the pollution abatement technology is modelled with the assumption that it is non-separable from the technology of main products while in others it is modelled with the assumption it is separable. In response to environmental regulation, firms may adopt different types of technologies to reduce pollution. Jorgension and Wilcoxen (1990) identify three different responses of firms. First, the firm may substitute less polluting inputs for more polluting ones. Second, the firm may change the production process to reduce emissions. Third, the firm may invest in pollution abatement devices. In practice, a firm may adopt a mix of these methods. The first two methods are non-separable with the production processes of main products while the third method is known as end-of-the pipe method.

There are a number of empirical studies starting from the early eighties examining the impact of environmental regulation on the economic performance of firms.[1] The ultimate aim of these studies has been to measure the effect of pollution regulation on total factor productivity growth (TFP). Most of these studies are based on production, cost or profit functions, with the pollution variable modelled indirectly using abatement capital expenditure as one of the inputs. Ideally, the technology of water or air polluting firms has to be described as one of joint production of good and bad outputs, the bad output being the pollution. The assumption of free disposal (a multi-product firm can produce more of one output without reducing the outputs of other goods) that is normally made in the conventional production theory cannot be applied to describe the technologies of polluting firms. Shephard (1974, p.205) noted that

> ***"...for the future where unwanted outputs of technology are not likely to be freely disposable, it is inadvisable to enforce free disposal of inputs and outputs. Since the production function is a technological statement, all outputs, whether economic goods are wanted or not, should be spanned by the output vector y".***

Also, the conventional studies have implicitly assumed that the firms are operating on the production frontier and the pollution control does not have an impact on production efficiency. However, many recent studies have shown that these assumptions are unlikely to hold in many cases.[2] Finally, the profit or cost functions used to represent production technology require firm specific prices, especially input prices,[3] the reliable data of which is difficult to obtain. As will be shown in this paper, the distance function approach for describing the production technology of a firm will potentially avoid all these problems.

The remaining paper is planned as follows: Section 2 describes the methodology. Section 3 provides information about the data and also highlights the methods of estimation of output distance function. Section 4 presents the estimates of shadow prices of bad outputs, scale economies and technical efficiency for water polluting industries in India. Finally Section 5 provides concluding comments.

2. Methodology

2.1 Output Distance Function

The conventional production function defines the maximum output that can be produced from an exogenously given input vector while the cost function defines the minimum cost to produce the

[1] See Myers and Nakamura, 1980; Pittman, 1981, 1983; Gollop and Roberts, 1983; Conrad and Morrison, 1989; Jorgenson and Wilcoxen, 1990; Barbara and McConnell, 1990, and Gray and Shadbegian, 1993, 1995.

[2] See Fare et al. 1989; Fare et al. 1993; Hakuni, 1994; Yaisawarng and Klien, 1994;Porter and van der Linde, 1995; Coggin and Swinton, 1996, and Surender Kumar 1999.

exogenously given output. The output and input distance functions generalise these notions to a multi-output case. The output distance function describes "how far" an output vector is from the boundary of the representative output set, given the fixed input vector. The input distance function shows how far is the input vector from the input vector corresponding to the least cost for producing a given vector of outputs.

Suppose that a firm employs a vector of inputs $x \in \Re^N_+$ to produce a vector of outputs $y \in \Re^M_+$, $\Re^N_+$, $\Re^M_+$, are non-negative N- and M-dimensional Euclidean spaces, respectively. Let P(x) be the feasible output set for the given input vector x and L(y) is the input requirement set for a given output vector y. Now the technology set is defined as

$$T = \{ (y,x) \in \Re^{M+N}_+ \; y \in P(x)\}. \quad (1)$$

The output distance function is defined as,

$$D_O(x,y) = \min\{\theta > 0 : (y/\theta) \in P(x)\} \; \forall x \in \Re^N_+. \quad (2)$$

Equation (2) characterises the output possibility set by the maximum equi-proportional expansion of all outputs consistent with the technology set (1). We now turn to the properties of output distance function. The output distance function can be used to measure the Debreu-Farrell technical efficiency (DF) (Debreu 1951; Farrell 1957). In terms of the above output set, the Debreu-Farrell measure can be defined as $DF(y,x) = \max\{\theta : \theta y \in P(x)\}$; and in terms of the output distance function $DF(y,x) = 1/ D_O(y,x)$. Thus, the DF measure is the reciprocal of the value of the distance function and it gives the factor by which all output could be expanded proportionately if the production units were operating on the frontier. It is clear that $D_O(y,x) \leq 1$. If $D_O(y,x) = 1$, the firm can be regarded as 100 percent efficient. For $D_O \leq 1$, the firm produces in the interior and could be characterised as $100{*}D_O$ percent efficient.

The output distance function has, among others, the following properties (for a detailed description, see Fare 1998):

1. $D_O(0, y) = +\infty$ for $y \geq 0$, i.e., no free lunch.
2. $D_O(x, 0) = 0$ for all x in $\Re^N_+$ i.e., inaction is possible
3. $x' \geq x$ implies that $D_O(x', y) \leq D_O(x, y)$, i.e., the more input the less efficient.
4. $D_O(x, \mu y) = \mu D_O(x, y)$ for $\mu > 0$, i.e. positive linear homogeneity.
5. $D_O(x, y)$ is convex in y.

3 See recent studies on pollution abatement cost functions in India. For example, Mehta et al. 1995; James & Murty 1998; Pandey, 1998, and Smita Misra, 1999.

The assumptions about the disposability of outputs become very important in the context of a firm producing both good and bad outputs. The normal assumption of strong or free disposability about the technology implies,

$$\text{if } (y_1, y_2) \in P(x) \text{ and } 0 \le y_1^* \le y_1,\ 0 \le y_2^* \le y_2 \Rightarrow (y_1^*, y_2^*) \in P(x).$$

That means, we can reduce some outputs given the other outputs or without reducing them. This assumption may exclude important production processes, such as undesirable outputs. For example, in the case of water pollution, Bio Oxygen Demand (BOD), Chemical Oxygen Demand (COD) and Suspended Solids (SS) are regulated and the firm cannot freely dispose of them. The assumption of weak disposability is relevant to describe such production processes. The assumption of weak disposability implies,

$$\text{if } y \in P(x) \text{ and } 0 \le \theta \le 1 \Rightarrow \theta y \in P(x).$$

That means, a firm can reduce the bad output only by decreasing simultaneously the output of desirable produce.

2.2. Derivation of Shadow Prices of Bad Outputs

The idea of deriving shadow prices using output and input distance functions and the duality results is originally from Shephard (1970). A study by Fare, Grosskopf and Nelson (1990) is the first in computing shadow prices using the (input) distance function and non-parametric linear programming methods. Fare et al. (1993) is the first study deriving the shadow prices of undesirable outputs using the output distance function.

The derivation of absolute shadow prices for bad outputs using distance function requires the assumption that one observed output price is shadow price. Let y_1 denote the good output and assume that the observed good output price (r_1^0) equals its absolute shadow price (r_1^s) (i.e., for m=1, $r_1^0=r_1^s$). Fare et al. (1993) have shown that the absolute shadow prices for each observation of undesirable output (m=2,.....,M) can be derived as[4],

$$(r_m^s) = (r_1^0) \bullet \frac{\partial D_0(x,y) / \partial y_m}{\partial D_0(x,y) / \partial y_1}. \qquad (3)$$

The shadow prices reflect the trade off between desirable and undesirable outputs at the actual mix of outputs, which may or may not be consistent with the maximum allowable under regulation (Fare et al. 1993, p. 376). Further, the shadow prices do not require that the plants operate on the production frontier.

2.3 Scale Economies

[4] See Fare (1988) for derivation.

Economies of scale for a multi-output production firm can be defined in terms of an output distance function[5] as

$$(d\theta/\theta)/(d\varepsilon/\varepsilon) = [\sum_i (\partial D_o/\partial x_i)x_i]/[y_1+\sum_m (\partial D_o/\partial y_m)y_m], \qquad (4)$$

since $D_o(x,y) = y/F(x)$[6]

where:

i= 1, 2,……..,N inputs

m= 2, 3, …..,M outputs

$d\theta/\theta$ = Proportionate increase in outputs

$d\varepsilon/\varepsilon$ = Proportionate increase in inputs

If the value of this function is equal to one, it means the firm is operating under the constant returns to scale, and if its value is greater than or less than one, then there are increasing or decreasing returns to scale respectively. Having estimated the output distance function, the economies of scale for each firm can be computed by this formula.

3. Estimation Methods

3.1 Translog Output Distance Function and Data

In order to estimate the shadow prices of pollutants (bad outputs) for the Indian water polluting industry using equation (3), the parameters of output distance function have to be estimated. The translog functional form[7] is chosen for estimating the output distance function for the Indian water polluting industries which is given as follows:

$$\ln D_o(x, y) = \alpha_0 + \sum\beta_n \ln x_n + \sum \alpha_m \ln y_m + 1/2\sum \sum \beta_{nn'} (\ln x_n) (\ln x_{n'}) + 1/2 \sum \sum \alpha_{mm'} (\ln y_m) (y_{m'}) + \sum \sum \gamma_{nm} (\ln x_n) (\ln y_m) \qquad (5)$$

where x and y are respectively, Nx1 and Mx1 vectors of inputs and outputs.

The data used in this paper is from a recent survey of water polluting industries in India.[8] This survey data provides information of characteristics of the main plant as well as the effluent treatment plant for the year 1994-1995. The data about the main plant are given for sales value, capital stock, wage bill, fuel cost and other material input cost. The data about the effluent treatment plant are given for waste water volume, influent and effluent quality for BOD (bio oxygen demand), COD (chemical oxygen demand) and SS (suspended solids), capital stock, wage

[5] See Pittman (1981) for the definition of scale economies in production function setting for the firms producing multiple outputs.

[6] See Fare, 1988 for proof.

[7] Many earlier studies for estimating shadow prices of pollutants have used the trnaslog functional form for estimating the output distance function. These include Pitman (1981), Fare et al. (1990), and Coggins and Swinton (1996).

bill, fuel and material input cost for a sample of 60 firms. These firms in the sample belong to chemicals, fertilisers, pharmaceuticals, drugs, iron and steel, thermal power, refining and others. For estimating the output distance function, the technology of each plant is described by joint outputs: sales value (good output) and COD, BOD and SS (bad outputs) and inputs: capital, labour, fuel and materials.

The water polluting firms in the Indian industry are supposed to meet the standards set for the pollutants (30mg/l for BOD, 250mg/l for COD, and 1mg/l for SSP) by the Central Pollution Control Board. Command and Control regulatory instruments are used to make the firms realise the standards. All sixty firms in the sample have effluent treatment plants and in addition some firms are using process changes in production to achieve the effluent standards. However, there is a large variation in the degree of compliance among the firms measured in terms of ratio of standard to effluent quality. The laxity of formal environmental regulation by the government, use of command and control instruments, and the absence of informal regulation[9] by the communities in the neighbourhood of the firms can be regarded as factors responsible for large variations in the compliance to the pollution standards by the firms.

3.2 Estimation of Output Distance Function: Programming Model

In this section, a linear programming technique is used to estimate the parameters of a deterministic translog output distance function (Aigner and Chu 1968). This is accomplished by solving the problem,

$$\max \sum [\ln D_o (x , y) - \ln 1], \tag{6}$$

subject to

(I) $\ln Do (x, y) \leq 0$

(ii) $(\partial \ln D_o (x, y))/(\partial \ln y_1) \geq 0$

(iii) $\sum \alpha_m = 1$

$\sum \alpha_{mm} = \sum \gamma_{nm} = 0$

(iv) $\alpha_{mm} = \alpha_{mm}$

$\beta_{nn} = \beta_{nn}$

Here the first output is desirable and the rest of (M-1) outputs are undesirable. 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

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[8] A Survey of Water Polluting Industries in India, Research Project on `Fiscal Instruments for Water Pollution Abatement in India', Institute of Economic Growth, Delhi. 1996.

[9] For empirical evidence about informal regulation by the local communities see Murty et al. (1999) and World Bank, 1999.

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 is done implying the minimisation of sum of deviations of individual observations from the frontier of technology. The constraints in (i) restrict the individual observations to be on or below the frontier of the technology. The constraints in (ii) ensure that the desirable output have a non-negative shadow price. The constraints in (iii) impose homogeneity of degree +1 in outputs (which also ensures that technology satisfies weak disposability of outputs). Finally, constraints in (iv) impose symmetry. There is no constraint imposed to ensure non-negative values to the shadow prices of undesirable outputs. Table 2 provides the linear programming estimates of output distance function for the Indian water polluting industries.

Table 1: Descriptive Statistics of Variables Used in the Estimation of Output Distance Function

Variable	Maximum	Minimum	Mean	Standard Deviation
1.Sales	24197.4	6.32	1335.972	3348.053
2.BOD	1368203.0	138.70	116859.060	234767.140
3.COD	10005560.0	335.80	934810.750	1954634.800
4.SS	15658500.0	642.40	1637753.900	2799843.000
5.Capital Cost	66288.7	11.10	4207.929	11545.509
6.Wage Bill	1341.9	0.05	85.577	191.099
7.Power Cost	16150.0	2.58	779.090	2505.045
8.Materialcost	892.5	0.13	123.360	207.692

Note: Sales, wage bill, power cost, material cost and capital cost are in Rs. million at 1994-1995 prices and BOD, COD and SS are in kilograms.

Table 2: Parametric Estimate of Output Distance Function for Water Polluting Industries in India (Linear Programming).

Variables	Parameters	Values
Y1	$\alpha 1$	0.173
Y2	$\alpha 2$	-0.481
Y3	$\alpha 3$	0.147
Y4	$\alpha 4$	0.160
X1	$\beta 1$	0.191
X2	$\beta 2$	-0.493
X3	$\beta 3$	-0.302
X4	$\beta 4$	-0.560
Y1^2	$\alpha 11$	-0.147
Y2^2	$\alpha 22$	0.097
Y3^2	$\alpha 33$	0.117
Y4^2	$\alpha 44$	-0.013
Y1Y2	$\alpha 12$	1.004
Y1Y3	$\alpha 13$	-0.795
Y1Y4	$\alpha 14$	-0.084
Y2Y3	$\alpha 23$	-0.204
Y2Y4	$\alpha 24$	0.021
Y3Y4	$\alpha 34$	0.003
X1^2	$\beta 11$	0.059
X2^2	$\beta 22$	0.072
X3^2	$\beta 33$	0.132
X4^2	$\beta 44$	-0.131
X1X2	$\beta 12$	-0.005
X1X3	$\beta 13$	0.074

X1X4	β14	0.051
X2X3	β23	0.009
X2X4	β24	-0.178
X3X4	β34	-0.082
Y1X1	γ11	-0.125
Y1X2	γ12	0.045
Y1X3	γ13	-0.215
Y1X4	γ14	0.428
Y2X1	γ21	-0.055
Y2X2	γ22	-0.303
Y2X3	γ23	-0.580
Y2X4	γ24	-0.136
Y3X1	γ31	0.011
Y3X2	γ32	0.245
Y3X3	γ33	0.512
Y3X4	γ34	0.065
Y4X1	γ41	-0.044
Y4X2	γ42	0.083
Y4X3	γ43	0.014
Y4X4	γ44	0.054
Constant	α0	-0.598

Source: Estimated.

where

Y_1: Turnover (Rs. million)
Y_2: BOD (tonnes)
Y_3: COD (tonnes)
Y_4: SS (tonnes)
X_1: Capital Cost (Rs. million)
X_2: Wage Bill (Rs. million)
X_3: Power Cost (Rs. million)
X_4: Material Cost (Rs. million)

3.3 Stochastic Output Distance Function

The stochastic output distance function for estimation is given as follows:

$$D_0 = f(X, Y, \alpha, \beta)+\varepsilon, \quad (7)$$

where D_0 is the distance measure, f (.) is the production technology, X is a vector of inputs, Y is a vector of outputs, α, β are vectors of parameters to be estimated, and ε is the additive error term. The error term may be generated for various reasons. Typically, it may include errors introduced by measurement, data collection, functional form specification, computational procedures, or factors known to the production units but not to the econometrician. Fuss, McFadden, and Mundlak (1978), Brown and Walker (1995) and Griliches, Z. and J. Mairesse (1995) have provided a detailed analysis of the different factors that can generate random errors in production models.

The basic problem with distance functions that concerns econometric estimation is that one does not observe (have data on) the dependent variable. Further, if one sets the distance function equal to its efficient (frontier) value, $D_0 = 1$, the left-hand side of the distance function is invariant, an intercept cannot be estimated, and OLS parameter estimates will be biased. Further, if the distance function is expressed in logarithms, the left-hand side of the distance function will be zero for all observations (i.e., $D_0 = \ln(1) = 0$). In order to avoid these problems, Lovell et al. (1990), Grosskopf et al. (1996), Grosskopf and Hayes 1993), Coelli and Perelman (1996) and Kumar (1999) utilise the property that the output distance function is homogeneous of degree one in outputs. Thus, for each observation to be used in estimating the distance function, a value that is unique to that observation can be used to multiply all output values on the right hand-side and the value of the distance function on the left-hand side. Thus, for an output distance function the following relationship (ignoring the error term) holds:

$$D_0 (\boldsymbol{C}, \lambda \boldsymbol{U}) = \lambda D_0(\boldsymbol{C}, \boldsymbol{U}), \text{ for any } \lambda>0. \quad (8)$$

In the literature, typically one of the outputs is chosen arbitrarily as a scaling variable. For example, if we chose the M-th output, and set $\lambda = 1/Y_M$, equation (8) may be written as,

$$D_0 (\boldsymbol{C}, \boldsymbol{U} / Y_M) = D_0 (\boldsymbol{C}, \boldsymbol{U}) / Y_M . \quad (9)$$

Now assume that we impose some logarithmic functional form on the output distance function, in accordance with most of the empirical literature. Then, equation (9) becomes

$$\ln (D_0/Y_M) = f(X, Y / Y_M, \alpha, \beta), \quad (10)$$

where f denotes some logarithmic functional form, such as translog and α, β the parameters. Alternatively, equation (10) may be expressed as,

$$\ln(D_0) - \ln(Y_M) = f(X, Y/Y_M, \alpha, \beta), \quad (11)$$

or

$$-\ln(Y_M) = f(X, Y/Y_M, \alpha, \beta) - \ln(D_0). \quad (12)$$

Given the data, the parameters in equation (12) can be estimated in various ways, depending on the estimation criteria chosen. Basically, the objective of the estimation method is to generate parameter estimates that fit the data as closely as possible while maintaining the requirement that $0< D_0 \leq 1$, which in the logarithmic case implies $-\infty<\ln D_0 \leq 0$

Aigner et al. (1997) uses the stochastic frontier ML method in a production function context. This approach is based on the composed error term idea, in which a symmetric error term accounts for noise and an asymmetric error term accounts for production inefficiency. For the inefficiency component of the error term, one assumes a functional form and estimates simultaneously all the technology parameters and the parameter(s) of the distribution of the inefficiency term. Adding a symmetric error term, *v*, to equation (12), and denoting the distance to frontier term, - *ln* (D_0), by μ, the stochastic frontier output distance function is obtained as

$$-\ln(Y_M) = f(X, Y / Y_M, \alpha, \beta)+v+\mu. \quad (13).$$

Typically, in the literature it has been assumed that v is distributed $- N(0,\sigma^2_v)$ and independently from μ, while μ is assumed to be either half-normal, truncated normal, exponential, or gamma distributed[10]. It appears that the most popular choice for application has been the half-normal distribution and Maximum Likelihood estimation (Coelli 1995). After having estimated (13), $E(\mu/\mu+v)$ is computed for each plant from which plant specific efficiency measures are calculated as

$$D_o(x, y) = \mathrm{Exp}\{-E(\mu/\mu+v)\}. \quad (14)$$

In order to estimate simultaneously the magnitude of inefficiency and the determinants of inefficiency, the framework proposed by Battese and Coelli (1995) in a production function setting is applied to the distance function framework. Let the equation (14) be defined as

$$\mathrm{Exp}(-\mu) = \exp(-z\delta-w), \quad (15)$$

where the μ's are assumed to be independently distributed, such that μ is obtained by truncation of the normal distribution with mean $z\delta$ and variance σ^2; *z* is a vector of plant specific variables and *w* stands for the unexplained part of the efficiency.

Here the model is estimated with the translog specification and the determinants of inefficiency are taken as the ratios of effluent to influent of all the three pollutants, i.e., BOD, COD, and SS.

[10] See Green, 1993,a,b.

Estimation of ouput distance function is done simultaneously with the model for determinants of inefficiency. The model was estimated using the FRONTIER 4.1 program (Coelli 1995).

Table 3 gives the results from the estimation of full translog specification. The results from the restricted translog and Cobb-Douglas specifications are not presented here, since the values of log likelihood ratio statistics are low for these specifications. The results for the translog model show that some of the parameters associated with the input and output variables are not significant even at the 10 per cent level.

Table3 : Maximum Likelihood Estimate of Stochastic Frontier Output Distance Function for Water Polluting Industries in India.

Variable	Coefficient	Parameter Estimate		T statistic
Constant	β_0	-1.458	*	-3.892
Y_1/Y_4	β_1	0.661	*	3.038
Y_2/Y_4	β_2	0.0096	***	1.775
Y_3/Y_4	β_3	-0.052		- 0.130
X_1	α_1	-0.079	***	1.847
X_2	α_2	-1.167	*	-7.033
X_3	α_3	-0.333		0.667
X_4	α_4	0.738	***	-1.712
$(Y_1/Y_4)^2$	β_{11}	-0.017	***	-1.423
$(Y_2/Y_4)^2$	β_{22}	-0.06		-0.352
$(Y_3/Y_4)^2$	β_{33}	-0.013		0.111
X_1^2	α_{11}	1.029		-0.572
X_2^2	α_{22}	-0.093	***	-1.454
X_3^2	α_{33}	-0.0009		-0.013
X_4^2	α_{44}	-0.150	**	-2.443
Y_1Y_2	β_{12}	-0.058		1.186
Y_1Y_3	β_{13}	0.045		-0.997
Y_1X_1	γ_{11}	-0.031		0.738
Y_1X_2	γ_{12}	0.009		0.292
Y_1X_3	γ_{13}	0.005		0.0901
Y_1X_4	γ_{14}	0.013		-0.379
Y_2Y_3	β_{23}	-0.023		0.082
Y_2X_1	γ_{21}	0.061		-0.533
Y_2X_2	γ_{22}	-0.138		-1.029
Y_2X_3	γ_{23}	-0.142	***	1.321
Y_2X_4	γ_{24}	0.069		0.760
Y_3X_1	γ_{31}	0.073		0.779
Y_3X_2	γ_{32}	0.0141	***	1.323
Y_3X_3	γ_{33}	0.169	***	-1.445
Y_3X_4	γ_{34}	-0.1005	***	-1.221
X_1X_2	α_{12}	-0.168	*	2.760
X_1X_3	α_{13}	0.209	**	-2.029
X_1X_4	α_{14}	-0.061		0.889
X_2X_3	α_{23}	0.045		0.485
X_2X_4	α_{24}	0.008		0.105
X_3X_4	α_{34}	0.217	**	2.171
Constant	δ_0	0.259	*	2.623
BOD ratio	δ_1	-0.0057		-0.198
COD ratio	δ_2	-1.183	*	-3.161

SS ratio	δ_3	0.0046 ***	1.747
	$\gamma=\sigma_\mu^2/\sigma_\mu^2+\sigma_v^2$	0.0018 **	2.366
	Log likelihood	5.98	
	@	9.009 ***	

Note: @ Likelihood ratio test of one-sided error with number of restrictions equal to 5.
*- Significant at 1% level
**-Significant at 5%level
*** Significant at 10% level
where
Y_1: Turnover (Rs. million)
Y_2: BOD (tonnes)
Y_3: COD (tonnes)
Y_4: SS (tonnes)
X_1: Capital Cost (Rs. million)
X_2: Wage Bill (Rs. million)
X_3: Power Cost (Rs. million)
X_4: Material Cost (Rs. million)

4, Estimates of Shadow Prices, Scale Economies and Technical efficiency
4.1 Shadow Prices

Table-4 provides estimates of industry specific shadow prices for bad outputs, BOD and COD based on the parameters of translog distance function estimated using programming approach. These shadow prices are negative, reflecting desirable output and revenue foregone as a result of reducing the effluent by one unit (ton) per year. For instance, the average shadow price for water polluting Indian industries is Rs. 0.246 million for BOD and Rs. 0.0775 million for COD per ton. That means the reduction of BOD by one ton reduces Rs. 0.246 million worth of production of positive output. The average shadow price of total suspended solids (TSS) is zero. This zero shadow price implies that TSS can be disposed at zero cost at margin by the factories.

Alternatively, the pollution abatement process may be such that the reduction of BOD or COD may jointly reduce TSS such that the additional cost of reducing TSS is zero.

There is a wide variation of shadow prices of pollutants across the firms and across the industries as shown in Table 4 and Appendix Table a. The range of shadow prices for BOD is Rs.5266 to 460189 per ton while for COD, it is Rs.528 to 77462 per ton. This wide variation can be explained by the variation in the degree of compliance as measured by the ratio of pollutant effluent load and sales value, and different vintages of capital used by the firms for the production of desirable output and the pollution abatement.

The shadow prices of BOD and COD 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 effluent of BOD or COD to the sales value, it is found that the higher the index, the lower the shadow price. That means, the dirtier the industry, the lower is the shadow price. Considering the logarithm of shadow price as dependent variable and the logarithm of effluent to sales ratios as an independent variable, the estimated relationships between the shadow prices and the index of non-compliance for BOD and COD are given as follows:

$$\ln(\text{BOD Shadow Price}) = \underset{(-0.358)}{-0.226} - \underset{(-4.712)}{0.710}\ln(\text{BOD Effluent to Sales Ratio}), \quad R^2 = 0.277$$

$$\ln(\text{COD Shadow Price}) = \underset{(-3.493)}{-3.531} - \underset{(-0.470)}{0.270}\ln(\text{COD Effluent to Sales Ratio}), \quad R^2 = 0.004$$

(*Note*: Figures in brackets are t values).

In the case of BOD, there is a statistically significant negative relationship between the shadow price and the non-compliance index. However, in the case of COD, the relationship is negative but not statistically significant.

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 BOD and COD. That means as found in the earlier studies of Indian water polluting industries,[11] these results also show that there are scale economies in the water pollution abatement implying that the higher the pollution load reduction, the lower the marginal abatement cost. The logarithms of shadow prices are regressed separately against the logarithms of BOD and COD loads reduced (the difference between the influent and effluent loads) by the firms the results of which are given as follows:

$$\ln\text{BOD Shadow Price} = \underset{(-0.918)}{-0.772} - \underset{(-2.697)}{0.353}\ln(\text{BOD Load Reduced}), \quad R^2 = 0.111$$

$$\ln\text{COD Shadow Price} = \underset{(1.042)}{1.953} - \underset{(-3.215)}{0.448}\ln(\text{COD Load Reduced}), \quad R^2 = 0.151$$

(*Note*: Figures in brackets are t values).

4.2 Technical Efficiency

Given the estimate of econometric model of the output distance function in Section 3, the firm specific measures of technical efficiency can be estimated using equation (4). The technical efficiency scores rely on the value of the unobservable distance function predicted. The descriptive statistics for the technical efficiency scores are given in Table 5, col. 4. The mean level of efficiency for the Indian water polluting industries is 0.899 if all the outputs, i.e., good as well as bad outputs are taken simultaneously. It means that the Indian industries are operating below the frontier and their production of desirable output can be increased.

What do the results of econometric model estimated in Section 3 tell about the technical efficiency and the determinants of inefficiency? The model shows that the inefficiency effects are not a linear function of effluent-influent ratio of various pollutants. It indicates that all the three ratios corresponding to BOD, COD and SS should be included in the model as they are all significant either at the 10 percent or lesser level. The γ parameter defined in Table 3 may be interpreted as the amount of unexplained variation in the technical inefficiency effects (Coelli, 1995). This parameter gets value between zero and one. If it is zero then the variance of effects of inefficiency is zero and the model reduces to the traditional mean response model. On the other hand, a high value for this parameter shows that the model of determinants of inefficiency accounts for the bulk of the variation in the technical inefficiency. In our model specification, the

[11] Mehta et al., 1995; Murty et al., 1999; Pandey, 1998; and Misra, 1999.

Table 4: Shadow Prices of BOD and COD for Water Polluting Industries in India (Rs. Per Ton) (Linear Programming Parameter Estimates)

Industry	No. of Firms	BOD Shadow Prices	COD Shadow Prices
All Firms	60	-246496	-77462
Fertiliser	4	-41343	-10195
Sugar	11	-179433	-66486
Distillery	5	-91606	-34390
Chemical	11	-438988	-127164
Refinery	2	-460189	-163597
Tannery	4	-138681	-72671
Iron and Steel	1	-6785	-528
Paper and Paper Products	16	-5266	-837
Drug	4	-737638	-67774
Others	2	-436806	-68407

Source: Estimated.

Table 5: Scale Economies and Efficiency Measures for Water Polluting Industries in India (Econometric Estimation)

Industry	No. of Firms	Scale Economies	Efficiency
All Firms	60	0.686	0.899
Fertiliser	4	1.017	0.803
Sugar	11	0.999	0.909
Distillery	5	0.338	0.796
Chemical	11	0.421	0.887
Refinery	2	1.173	0.889
Tannery	4	0.66	0.875
Iron and Steel	1	0.551	1.000
Paper and paper products	16	0.527	0.949
Drug	4	0.744	0.893
Others	2	1.236	0.994

Source: Estimated

absolute value of this parameter is very low, i.e., 0.0018 and is statistically significant at the 5 percent level.

The sign of δ_I coefficients in Table 3 are of particular interest. A negative sign for the estimated coefficient shows that an increase in the value of the variable, i.e., ratio of effluent to influent (lower level of regulation) will result in a decrease in the value of the technical inefficiency effect. Thus the more restrictive the regulation, the more inefficient the production process will be. In our estimates, the signs for BOD and COD ratios are negative and for the SS ratio it is positive. This result may be due to the type of regulatory instrument used, for example command and control versus economic instruments. Since in India as of today, only command and control measures are used to control water pollution and it is known that the use of such instruments results in the firms using inefficient pollution abatement technologies, the result found above is expected[12]. However, in a situation of using economic instruments (pollution taxes or marketable pollution permits), the result that the stricter regulation results in the decrease of technical efficiency of polluting firms may not hold good. There are studies arguing that the environmental regulation results in the improvement of technical efficiency of firms, a win-win situation explained by the Porter hypothesis (Porter and Vander Linde, 1995).

4.3 Scale Economies

One more issue of importance in the ongoing debate is about the implication that the pollution control requirements have on economies of scale and barriers to entry. Although this issue has not been as widely debated, but it may have important policy implications. Many industries facing strict pollution control requirements are already characterised by capital intensity and a large minimum efficient size (MES) of plant. A large MES in an industry may act as a barrier to entry, either because of the number of customers that must be pirated away from other suppliers or because of the difficulty in raising the huge sums of money required to build a plant. If entry is difficult, actual and potential competition in the industry may be less vigorous, tacit and explicit collusion may be less difficult, and super-competitive prices and profits may be easier to achieve. Thus if pollution control requirements increase MES in an industry, they may have harmful allocation effects, and the resulting resource costs should be weighed against the benefits of pollution control in policy decisions.

[12] There are now studies to show that the compliance to the pollution standards by the industries in the developing countries including India are due to both formal regulation (command and controls) and the informal regulation by the local communities (Murty et a. 1999, and World Bank, 1999) .

The measure of scale economies may be estimated for each firm in the sample and one may then examine whether firms that show a high level of pollution control are those that have economies of scale in production and controlling pollution. If this association is found, one may conclude that pollution control regulations have increased MES in the sample. Table 3, column 3 and Appendix Table, column 4 provide estimates of scale economies of water polluting industries and firms in the sample.

Three questions are of interest concerning the results of testing for scale economies of joint production.

1. Are the firms in the sample generally operating under conditions of increasing, neutral or decreasing economies of scale ? In the sample, the average figure for this is 0.823.
2. Does any systematic difference in scale economies exist for different firms/industries in the sample ? (e.g. are higher levels of turnover/production associated with increasing or decreasing scale economies). In the sample of 60 firms, the correlation coefficient is 0.047.
3. Are higher levels of pollution control associated with increasing or decreasing scale economies ? Unfortunately, a correct measure of pollution control is not available for answering this question. A low level of pollution may reflect either a high level of pollution control or merely a general low level of production. Obviously, any measure of pollution control must include both levels of influent and effluent. The measure chosen here is the ratio of effluent to influent; a lower value of the ratio reflects a higher level of control. The correlation coefficients between effluent/influent of BOD and COD, and scale economies are -0.197 and -0.098, respectively.

5. Conclusion

The distance function in the theory of production helps to characterise the technology of a firm producing a vector of outputs jointly and to define their shadow prices or opportunity costs. In the case of a firm generating air and water pollution, the output distance function can be used to represent the firm's technology as a joint production of good and bad outputs. With the assumption of weak disposability of outputs, the shadow prices of pollutants can be defined in terms of positive output or revenue foregone.

The distance function approach helps to derive firm specific shadow prices for pollutants. The estimated shadow prices of pollutants have to be equal for all the firms if pollution taxes are levied on all the firms in order to obtain their conformity with the prescribed standards and all the firms reduced pollution loads to meet the standards. Since there are no pollution taxes in India, command and control instruments are used to compel the firms to meet the set standards and a majority of firms do not comply with the standards. The shadow prices of pollutants estimated vary across the firms. The estimated shadow prices of pollutants BOD and COD for all the 60 firms in the sample differ across the firms. The estimated sample averages for shadow prices of BOD and COD are Rs. 0.246 and Rs. 0.077 per a gram of pollutant, respectively. That means as per the current pollution abatement practices, the Indian water polluting industry is forgoing revenue amounting to Rs. 246 and Rs. 77 for reducing one kilogram of BOD and COD, respectively. Large differences in the firm specific shadow prices of pollutants reflect the use of inefficient pollution abatement technologies by the water polluting industries in India. The large differences in the estimates of shadow prices of pollutants bring out clearly the case for using economic instruments like pollution taxes or marketable pollution permits instead of currently used command and control instruments in India.

In an economy in which industries are meeting the pollution standards fixed for the sustainable use of environmental resources, the distance function approach in the theory of production can be used to estimate the maintenance cost of environmental resources. This can be a methodology that can be potentially used for estimating the environmentally corrected GDP by making use of maintenance cost version of United Nations methodology of `Integrated Environmental and Economic Accounting'.

The estimates of production efficiency for water polluting industries in India reported in this paper explain the production efficiency with a joint production of good and bad outputs. For the Indian water polluting industries as a whole, the estimated efficiency index is approximately 90 percent. It means that by employing the same set of inputs, the good output can be further increased by 10 percent. Among the industries for which an efficiency index is estimated, distillery has the lowest while iron and steel has the highest efficiency in the sample of 60 firms from 17 water-polluting industries in India.

The estimates of economies of scale show that the water polluting industry as a whole has decreasing returns to scale. Estimates show that three industries, i.e., fertilisers, refinery and drugs have increasing returns to scale while others have decreasing returns to scale. There is a positive correlation between the economies of scale and the turnover of a firm. Also, there is a positive association between pollution control and economies of scale (the higher the scale economies, lower the effluent-influent quality ratio).

The shadow prices of pollutants estimated in this study may be interpreted as the marginal costs of respective pollutants. The result that there is a negative relationship between pollution load reductions and the shadow prices across the firms found in this study confirm the presence of scale economies in pollution abatement found in the earlier studies on industrial water pollution abatement in India.

Appendix A

Table A_1 : Estimates of Shadow Prices of BOD and COD and Technical Efficiency and Economies of Scale

Industry	Firm	Efficiency Estimates	Economies of Scale	Shadow BOD	Prices COD
Fertilizer	1	0.997	1.028	-0.086	-0.019
	2	1.000	1.451	-0.061	-0.003
	3	0.388	0.686	-0.083	-0.063
	4	0.828	0.903	-0.024	-0.010
Sugar	5	1.000	1.184	-0.414	-0.047
	6	0.763	1.106	-0.799	-0.264
	7	0.902	1.098	-0.099	-0.055
	8	0.790	1.217	-0.250	-0.152
	9	0.983	0.792	-0.007	-0.007
	10	0.994	0.751	0.000	0.000
	11	0.828	0.803	-0.010	-0.006
	12	0.998	1.035	-0.021	-0.015
	13	0.942	0.99	-0.046	-0.018
	14	0.821	1.067	-0.066	-0.024
	15	0.983	0.942	-0.035	-0.013
Distillery	16	0.747	0.575	-0.077	-0.035
	17	1.000	0.343	0.000	0.000
	18	0.718	0.338	-0.325	-0.108
	19	0.738	0.281	-0.001	0.003
	20	0.777	0.155	-0.001	0.000
Chemical	21	0.788	0.623	0.102	-0.017
	22	0.743	0.849	-2.138	-0.406
	23	1.000	-1.477	-0.503	-0.217
	24	0.93	0.823	-0.056	-0.016
	25	0.915	0.348	-0.012	-0.035
	26	0.873	0.645	-0.028	-0.003
	27	0.841	0.64	-0.013	-0.007
	28	0.944	0.348	-0.137	-0.015
	29	0.80	0.572	-0.106	-0.013
	30	0.926	0.937	-0.051	-0.004
	31	0.998	0.748	-0.013	-0.003
Refinery	32	0.862	1.469	-0.471	-0.167
	33	0.916	0.877	-0.024	-0.013
Tannery	34	0.887	0.848	-0.293	-0.149
	35	0.793	0.502	-0.016	-0.008
	36	0.962	0.772	0.000	0.000
	37	0.858	0.509	-0.056	-0.071
Iron and Steel	38	1.000	0.768	-0.007	0.001

Paper and Paper Products	**39**	**0.999**	**0.575**	**-0.005**	**-0.001**
	40	**0.841**	**0.54**	**-0.004**	**-0.001**
	41	**0.936**	**0.481**	**-0.002**	**-0.000**
	42	**0.997**	**0.402**	**-0.000**	**0.000**
	43	**0.803**	**0.460**	**-0.003**	**-0.002**
	44	**1.000**	**0.437**	**-0.001**	**0.000**
	45	**0.802**	**0.372**	**-0.002**	**-0.007**
	46	**1.000**	**0.62**	**-0.006**	**-0.001**
	47	**0.888**	**0.498**	**0.012**	**-0.001**
	48	**1.000**	**0.557**	**-0.002**	**0.000**
	49	**0.998**	**0.386**	**0.000**	**0.000**
	50	**1.000**	**-0.514**	**-0.003**	**-0.000**
	51	**1.000**	**0.62**	**-0.003**	**0.000**
	52	**0.835**	**0.576**	**-0.013**	**-0.001**
	53	**0.867**	**0.601**	**-0.003**	**-0.001**
	54	**0.998**	**0.551**	**-0.005**	**-0.001**
Drug	**55**	**0.645**	**0.418**	**-0.005**	**-0.019**
	56	**1.000**	**1.115**	**-1.090**	**-0.094**
	57	**0.925**	**0.787**	**-0.060**	**-0.014**
	58	**1.000**	**0.657**	**-0.018**	**-0.002**
Misc.	**59**	**1.000**	**0.667**	**-0.088**	**-0.008**
	60	**0.987**	**1.805**	**-1.091**	**-0.182**

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