Econometric Estimation of Technical and Environmental Efficiency: An Application to Chemical Industry in and around Mumbai

By
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Abstract

There is a large concentration of chemical firms around Mumbai, and the Maharashtra Pollution Control Board has been actively monitoring them. 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 factors responsible for large variations in the compliance to the pollution standards by the firms might be laxity of formal environmental regulation by the government, use of command and control instruments, and the absence of informal regulation by the communities in the neighbourhood of the firms. The objective of this paper is to compute output-oriented technical efficiency and environmental efficiency using the Stochastic Frontier Approach. In this paper we have incorporated the environmental effects in the stochastic frontier approach and have computed environmental efficiency of the firms. The stochastic production frontier approach allows only one (aggregated) output to be modelled. To incorporate environmental efficiency into a description of the production process of chemical industry, the environmentally detrimental variable has to be specified as an input. Biological oxygen demand (BOD) load and chemical oxygen demand (COD) load is modelled as a conventional input in two different Models. The SFA technical efficiency measure is output augmenting and has to be transformed to allow minimisation of the environmentally detrimental input. The panel data of 50 water-polluting small to medium-scale firms for three-year period of 2004–06 was collected in a primary survey of chemical industries around Mumbai. Finally, we have also estimated "shadow prices" of BOD and COD. These "shadow prices" provide a measure of the cost to firms, in terms of foregone real output, of achieving reductions in BOD and COD and are upper bounds to true shadow prices.

Keywords: *Technical Efficiency; Chemical Industry; Environmental regulation; Porter hypothesis; Stochastic Frontier Production Function*

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1. Introduction

A variety of environmental performance indexes have been proposed in the past, and they can be grouped into two categories: those which adjust conventional indexes 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. The indexes can also be categorize; into those which are calculated using deterministic techniques, which can be either parametric or nonparametric, and those which are estimated using stochastic techniques, which are exclusively parametric

Pittman (1983) was perhaps the first to develop an index of productivity change which takes environmental effects into account. He developed an adjusted Tornqvist productivity index in which environmental effects are treated as additional undesirable outputs whose disposability is costly. However, since undesirable outputs are not generally priced on markets, this approach is feasible only if the undesirable outputs can be valued by their shadow prices. Pittman (1983) used econometric techniques to estimate the shadow price of a single undesirable output, biochemical oxygen demand, generated in the process of converting wood pulp to paper in a sample of thirty Michigan and Wisconsin mills in 1976, where this shadow price was constrained to be constant across all observations.

The objective of this paper is to compute output-oriented technical efficiency and environmental efficiency using the Stochastic Frontier Approach (SFA). . In this paper we shall, therefore, look at a traditional neo-classical production function for incorporate environmental effects and to compute environmental efficiency from the estimation of a stochastic production frontier. Technical efficiency scores reflect the possible increase in outputs conditional on a set of inputs. The stochastic production frontier allows only one (aggregated) output to be modelled. Environmental efficiency, in accordance with existing literature, is defined as the ratio of minimum feasible use to observed use of an environmentally detrimental input, conditional on observed levels of the desirable output and the conventional inputs. If the environmentally detrimental variable is modelled as an input, a single input efficiency score can reflect environmental efficiency Because of the similarities between pollution and conventional inputs in the production function context, BOD and COD (in two different models) are modelled as an environmentally detrimental input in the translog production function. Using primary level panel (time series-cross-section) data of 50 water-polluting firms for three-year period of 2004–06 we shall also estimate the "shadow prices" of BOD and COD. These "shadow prices" provide a measure of the cost to firms, in terms of foregone real output, of achieving reductions in BOD and COD and are upper bounds to true shadow prices.

The next sections are planned as follows: Section 2 briefly deals with the review of literature; Section 3 enumerates the theoretical structure of the model; Section 4 describes the data used for analysis; Section 5 gives us the empirical findings and the last section concludes.

2. Review of Literature

As discussed in the previous section, one of the first attempts to analyse producer environmental performance from an estimated bad output shadow price was made by Pittman (1983). Fare et al. (1989) also treated environmental effects as undesirable outputs, and they developed an "enhanced hyperbolic productive efficiency measure" that evaluates producer performance in terms of the ability to obtain an equiproportionate increase in desirable outputs and reduction in undesirable outputs. They developed their measure on a strongly disposable technology (applicable if undesirable outputs are freely disposable) and on a weakly disposable technology (applicable when it is costly to dispose of undesirable outputs, due perhaps to regulatory action).

Fare et. al. proposed using a nonparametric mathematical programming technique known as data envelopment analysis (DEA) to construct strong-disposal and weak-disposal best-practice production frontiers, and to calculate their enhanced efficiency measure. A comparison of the two values of their measure provides a measure of the cost (in terms of foregone revenue) of a lack of free disposability. They applied their techniques to Pittman's data. Their approach was later applied to U.S. electricity generation data (including SO, emissions as the undesirable output) by Yaisawarng and Klein (1994), who calculated adjusted measures of efficiency and productivity change, and by Turner (1995), who calculated adjusted efficiency measures and marginal abatement costs. This DEA approach has also been applied to aggregate OECD data including CO, emissions by Zofio and Prieto (1996).

Fare et al. (1993) also treated environmental effects as undesirable outputs, and they used a parametric mathematical programming technique to calculate the parameters of a deterministic translog output distance function. This enabled them to calculate an enhanced hyperbolic efficiency measure, and also to calculate the shadow prices of the undesirable outputs. They used Pittman's data to illustrate their techniques. Although these shadow prices could have been used to construct Pittman's adjusted Tornqvist productivity index, they did not undertake such a construction.

Hetemaki (1996) used econometric techniques to estimate deterministic and stochastic variants of a translog output distance function, and to obtain estimates of technical efficiency and the shadow prices of undesirable outputs, in the Finnish pulp and paper industry. The general strategy of the above studies has been to include environmental effects in the output vector, and then to obtain inclusive measures of technical efficiency, and occasionally productivity change, which incorporate the generation of one or more environmental effects as by-products of the production process. This is an accomplishment in itself --- acknowledging that producers produce undesirable as well as desirable outputs when evaluating their performance. However, in several of these studies the shadow prices of the undesirable outputs are also calculated or estimated. This was an additional accomplishment as shadow prices can be used to generate an adjusted index of productivity change, and they can also be interpreted as marginal abatement costs which can be compared with marginal benefit calculations.

In the past, the functional forms most widely used for estimating production relationship have been the Cobb-Douglas and the constant elasticity of substitution (CES) production functions. While these forms are useful and simpler for drawing conclusions, they have in the recent past, been rendered inappropriate for some purposes because of the restrictions that they impose on the data. It has been noted by several researchers that the imposition of constant elasticities of substitution and transformation is particularly restrictive in models specifying more than one output or more than two inputs; it is especially restrictive when one output is an externality. In this paper, as the model includes two outputs (a normal good and water pollution, an externality) and three inputs (capital, labour and materials) a more flexible production function needs to be used. In this paper we shall therefore use the translog production function. It has been established in the literature that this function is “one of a class of general production functions that may be considered second-order approximations to any production function and that impose no restriction on the substitution relationship among inputs”.[1]

How the behaviour of a firm that faces environmental regulation can be modelled, has always been an important component of environmental economics. This is primarily because firms incur costs to comply with regulation. The standard approach in the environmental economics literature characterizes pollution as a public "bad" that results from "waste discharges" associated with the production of private goods. Waste emissions or pollution is treated simply as another factor of production. This is because attempts, for example, to cut back on waste discharges will involve the diversion of other inputs to abatement activities, thereby reducing the availability of these other inputs for the production of goods. Reductions in emissions or waste discharges, in short, should result in reduced output. Similarly, any allowed increase in pollution (like lowering norms of regulation) frees resources that are used for abatement which can be used to increase output. In this paper, therefore the undesirable output will be treated as an input as the behaviour of this output is similar to that of an input.

Stochastic frontier production function has been used by researchers to examine firms’ technical efficiency. Early applications of stochastic frontier production function to economic analysis include those of Aigner et al. (1977) in which they applied the stochastic frontier production function in the analysis of U.S agricultural data. Battese and Corra (1977) applied the technique to the pastoral zone of Eastern Australia. More recently, empirical applications of the technique in efficiency analysis have been reported by Battese and Coelli (1992); Ajibefun and Abdulkadri (1999); and Ojo and Ajibefun (2000). In addition, Shazali et al. (2004) examined the technical efficiency of the Malaysian Furniture Industry using the stochastic frontier production model. They found that actual firm’s output is 20 percent less than maximal output which can be achieved from the existing level of inputs.

In this paper we shall follow the Reinhard, Lovell, and Thijssen (1999) model to estimate the technical and environmental efficiency of a panel of chemical firms in and around

[1] Pittman (1981)

Mumbai. In this analysis, in two different cases, BOD and COD are treated as the environmentally detrimental input. A stochastic translog production frontier is specified to estimate the output-oriented technical efficiency, and the environmental efficiency is calculated using the estimated parameters.

3. Estimation of Technical and Environmental Efficiency

The stochastic frontier production function developed by Aigner et al. (1977), and Meeusen and van den Broeck (1977) was based on an econometric specification of a production frontier. A generalised stochastic production frontier[2] for a frontier production function can be defined as:

$$Y_{it} = F(X_{it}, Z_{it}; b)\exp(V_{it} - U_i) \qquad (1)$$

$$i = 1,2,\ldots..I, \qquad t = 1, \ldots., T$$

In this model, a production frontier defines output as a function of a given set of inputs, X_{it}, (capital, labour and materials) together with technical inefficiency effects. Z_{it} is bad output which, in this model, is taken as an input as discussed in the previous section[3].

The stochastic frontier is also known as the composed error model, because it postulates that the error term is composed of two independent error components, V_{it} and U_i, where V_{it} is a random error term, independently and identically distributed as N $(0, \sigma_v^2)$, represent any stochastic factors beyond the firms' control affecting its ability to produce on the frontier, such as luck and weather, where a symmetric component is normally distributed. It can also account for measurement error in Y_{it} or minor omitted variables. The asymmetric component, U_i, in this case distributed as a half-normal, can be interpreted as pure technical inefficiency. This component has also been interpreted as an unobservable or latent variable, in most cases representing managerial ability. It is a nonnegative random error term, independently and identically distributed as $N^+(\mu, \sigma_u^2)$, intended to capture time invariant technical inefficiency in production, measured with an output orientation as the ratio of observed to maximum feasible output.

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[2] Similar to the characteristics proposed by Battese and Coelli (1992)
[3] Namely BOD in model 1 and COD in model 2

The stochastic version of the output-oriented technical efficiency measure is given by the expression

$$TE_i = Y_{it} / [F(\bullet).\exp(V_i)] = \exp(-U_i) \qquad (2)$$

As the error component U_i , is asymmetric and $U_i \geq 0$, $0 \leq \exp(-U_i) \leq 1$. Technical inefficiency must be separated from statistical noise in the composed error term $(V_{it} - U_i)$ to implement equation (2). Battese and Coelli (1988, 1992) have proposed the technical efficiency estimator

$$TE_i = E[\exp\{-U_{it}\} \,|\, (V_{it} - U_i)] \qquad (3)$$

To derive technical and environmental efficiency in this model, we use the translog stochastic production frontier. These calculations follow the direction of Reinhard, Lovell and Thijssen (1999). Writing equation (1) in translog form, we get

$$\begin{aligned} \ln Y_i = b_0 + \sum_j b_j \ln X_{ij} + b_z \ln Z_i + \frac{1}{2}\sum_j \sum_k b_{jk} \ln X_{ij} \ln X_{ik} + \sum_j b_{jz} \ln X_j \\ + \frac{1}{2} b_{zz} (\ln Z_i)^2 + v_i - u_i \qquad (4) \end{aligned}$$

where $b_{jk} = b_{kj}$. The logarithm of the output of a technically efficient producer (using X_i and Z_i to produce $\hat{Y}_i$) is obtained by setting $u_i = 0$ in the above equation. The logarithm of the output of an environmentally efficient producer (using X_i and Z_i^F to produce Y_{it}) is obtained by replacing Z_i with Z_i^F [4] and setting $u_i = 0$ in the above equation to obtain

$$\begin{aligned} \ln Y_i = b_0 + \sum_j b_j \ln X_{ij} + b_z \ln Z_i^F + \frac{1}{2}\sum_j \sum_k b_{jk} \ln X_{ij} \ln X_{ik} + \sum_j b_{jz} \ln X_j \\ + \frac{1}{2} b_{zz} (\ln Z_i^F)^2 + v_i \qquad (5) \end{aligned}$$

The stochastic measure of environmental efficiency is preferred over the deterministic version because in the former case the farm is compared with an efficient farm encountering identical stochastic conditions. In the latter case the firm is compared with

[4] where Z_i^F is the minimum feasible environmentally detrimental input that would have been used for production if the firm was technically efficient (i.e. producing on the frontier)

an efficient firm without any noise. Thus a farm with bad weather conditions or luck (a negative v), has an output-oriented efficiency score that is larger than in the deterministic case and an environmental efficiency score that is also larger than in the deterministic case.

The logarithm of the stochastic environmental efficiency measure can be defined as:

$$\ln EE_i = \ln Z_i^F - \ln Z_i \qquad (6)$$

To isolate it we can set equations 1 and 2 equal; and we get

$$\frac{1}{2} b_{zz} [(\ln Z_i^F)^2 - (\ln Z_i)^2] + \sum_j b_{jz} \ln X_{ij} [\ln Z_i^F - \ln Z_i] + b_z [\ln Z_i^F - \ln Z_i] + u_i = 0 \qquad (7)$$

which can be rewritten as

$$\frac{1}{2} b_{zz} [\ln Z_i^F - \ln Z_i]^2 + \left[b_z + \sum_j b_{jz} \ln X_{ij} + b_{zz} \ln Z_i \right] [\ln Z_i^F - \ln Z_i] + u_i = 0 \qquad (8)$$

which can be solved for lnEE_i by substituting it for ($\ln Z_i^F - \ln Z_i$) to obtain

$$\ln EE_i = \frac{1}{b_{zz}} \left[-(b_z + \sum_j b_{jz} \ln X_{ij} + b_{zz} \ln Z_i) \pm \left\{ (b_z + \sum_j b_{jz} \ln X_{ij} + b_{zz} \ln Z_i)^2 - 2 b_{zz} u_i \right\}^{0.5} \right] \qquad (9)$$

In this analysis, we have calculated environmental efficiency using the positive root of the formula in the above equation. This is because a technically efficient firm, by definition, is necessarily environmentally efficient. In the above equation, u_i equals to zero implies lnEE_i = 0 only if the positive root of the expression is used. Conditional on (X_{ij}, u_i) or equivalently conditional on (X_{ij}, Y_{ij}), EE_i and Z_i are inversely related. Both relationships hold irrespective of the sign of b_{zz}.

4. Data Descriptions

For the econometric analysis, data for 50 firms for pH levels, BOD, COD, SS, and the amount of oil and grease concentrations of the wastewater were collected from the Maharashtra Pollution Control Board (MPCB) field offices of areas in and around Mumbai where there is high concentration of chemical industries. As we wanted to look at a water polluting industry, the chemical industry was chosen for this study. According to the Central Pollution Control Board, the basic chemical industry constitutes among the 17 major polluting industries in India. The firms in the Basic Chemical industry segment produce intermediate products such as industrial gases, organic and inorganic acids and bases, catalysts, dyes and pigments intermediaries, salts, metal compounds, and other minerals that are needed as inputs in various other industries including Leathers, Textiles, Dyes and Pigments, Paper, Plastics, Rubber, Pharmaceuticals, Food processing, and Chemicals itself. These industries were concentrated in the region in and around Mumbai; namely, Thane, Navi-Mumbai, Raigarh and Kalyan.

Data was finally collected for the areas Thane, Taloja, Patalganga, Roha, Khopoli, Dombivilli, Ambernath, Saravali, Bhiwandi and Pen. The norms followed by the MPCB were 100ng/l for BOD, 250mg/l for COD and 100mg/l for suspended solids. Many firms did not record the absolute load of pollution as there was no compulsion from the MPCB to do so. However, the wastewater volume had to be recorded as there was a limit set by the MPCB on the wastewater generated by the plant. The pollution loads were therefore calculated by multiplying the pollution concentrations with the volume of wastewater generated by each plant.

The plant level data from firms were equally difficult to collect; many of the multi-plant firms, which had available data, refused to give plant level information, citing that these were confidential data. On the other hand, many of the single plant firms were not listed; as a result the method of recording data was extremely poor. They were also suspicious whether such information could be used against them by the authorities or the media. Hence the data that was collected from the plants were only in value terms and not in physical units. They were then normalised using constant base year 1990 prices.

The table below (Table 1) gives us the descriptive statistics of the variables used in the analysis. As there are two important components pollution values that are used in the analysis, we have taken each separately to analyse two models: Model 1 where BOD is used as the environmentally detrimental input and Model 2 where COD is used as the environmentally detrimental input.

Table.1: *Characteristics of the Sample Variables*

	Variables		***Unit***	***Mean***	***Std. Dev.***	***Min.***	***Max.***
	Y	Output	Rupees crores at constant prices	1.529308	2.877675	0.005287	15.86341
	X1	Capital	Rupees crores at constant prices	0.89828	1.624462	0.008796	9.221887
	X2	Labour	Rupees crores at constant prices	0.095338	0.190258	0.00133	0.945651
	X3	Material	Rupees crores at constant prices	0.789654	1.520073	0.001389	8.789243
Model 1	Z	BOD	kg	998.2582	3922.404	0.000604	34640.48
Model 2	Z	COD	kg	2976.725	12223.09	0.001725	115193.8

5. Empirical Findings

The output-oriented technical efficiency of each farm is assumed to be constant during the research period and is allowed to follow a two-parameter half normal distribution. The time-invariant specification is not unreasonable, since there are just three observations per firm available in the data set. A likelihood-ratio test of the hypothesis that inefficiency is absent is rejected, with a test statistic of 1651.53. The estimation results of the first model (Model 1) where BOD is treated as the environmentally detrimental input is reported in Table 2.

It should be noted that the estimated coefficients that are associated with labour or X2 are not significant. Other than that all estimated coefficients are significant. One of the reasons that the estimates associated with labour are not significant could be that in general, the units of labour used for estimation is labour hours and not wage-bill. As we were unable to collect data (as plant level data is generally not disclosed) we had to use wage bill as a proxy, which might not fit the function as well as labour hours.

Table 2: *Parameter Estimates with BOD as polluting input (Model 1)*

Variables	***Coeff. names***	***Coeff. Estimates***	***Significant***
lnX1	b_k	-0.461	**0.021**
lnX2	b_l	0.286	0.189
lnX3	b_m	0.965	**0.001**
lnZ	b_z	0.194	**0.060**
lnX1sq/2	b_{kk}	0.084	**0.040**
lnX2sq/2	b_{ll}	0.012	0.842
lnX3sq/2	b_{mm}	0.230	**0.000**
lnZsq/2	b_{zz}	-0.037	**0.015**
lnX1lnX2	b_{kl}	-0.035	0.350
lnX1lnX3	b_{km}	-0.179	**0.001**
lnX2lnX3	b_{lm}	0.045	0.362
lnX1lnZ	b_{kz}	0.082	**0.001**
lnX2lnZ	b_{lz}	-0.007	0.727
lnX3lnZ	b_{mz}	-0.025	0.110
constant	c	1.897	**0.052**

Before turning to an investigation of technical and environmental efficiency, we first consider the structure of the estimated production technology. Table 3 reports elasticities of output with respect to each input evaluated at output deciles. The elasticities of output with respect to the three inputs (excluding BOD) are positive for 100% of the observations. The sum of the elasticities of output with respect to these four inputs generates an estimated scale elasticity which indicates the presence of decreasing returns to scale except for the last three deciles. It is possible that for the larger plants, it is easier to undertake increased abatement costs through environmental regulation and convert it to benefits accruing to the firm: that cleaner practice reduces costs. Also, for larger plants, the total load of pollution will be higher and as a result, can lead to a negative impact on output.

The estimated scale elasticity increases with a decline in output and has a value of 0.955 at the sample mean. Likelihood ratio tests led to rejections of homotheticity and linear homogeneity in all four inputs significant at 1 percent level.

Table.3: *Elasticities of Output with Respect to Each Input, by Output Deciles (Model 1)*

Output Deciles	***Capital***	***Labour***	***Materials***	***BOD***	***Returns to Scale***
1	0.057	0.173	0.467	0.093	0.790
2	0.000	0.193	0.573	0.078	0.844
3	0.071	0.185	0.535	0.071	0.862
4	0.070	0.196	0.590	0.042	0.898
5	0.068	0.202	0.629	0.033	0.931
6	0.090	0.204	0.641	0.018	0.953
7	0.049	0.219	0.717	0.011	0.996
8	0.071	0.220	0.712	0.019	1.021
9	0.032	0.241	0.822	-0.005	1.090
10	0.198	0.233	0.800	-0.062	1.169

The estimated elasticities of output with respect to BOD are of particular interest. They have a mean value of 0.03, with a standard deviation of 0.014, suggesting that, holding other inputs constant, a 1% reduction in BOD requires a sacrifice of 3/100th of 1% of marketable output. Using mean values reported in Table 1 this estimated abatement cost elasticity implies that a reduction of approximately 10 kilograms of BOD load would "cost" approximately Rs. 4588 at 1990 prices. This, in turn, suggests a "shadow price" of BOD of approximately Rs. 459 per kilogram. The calculated "shadow price" of BOD decreases with plant size because the estimated elasticity of output with respect to BOD decreases with plant size. This can be because of the fact that a larger amount of pollution load (due to a bigger plant size) may affect output adversely.

In Model 2, we take COD as the environmentally detrimental input. A likelihood-ratio test of the hypothesis that inefficiency is absent is rejected, with a test statistic of 1622.50. The parameter estimates, of the second model are reported in Table 4. Here also we see a similar situation regarding the significance of the estimates. The estimated coefficients that are associated with labour or X2 are not significant, similar to Model 1. Other than that all estimated coefficients are significant. As discussed earlier the unit of measurement of labour might be the cause for such discrepancies: that wage bill might not be a good proxy for labour in this analysis.

Table.4: *Parameter Estimates with COD as polluting input (Model 2)*

Variables	***Coeff. names***	***Coeff. Estimates***	***Significant***
lnX1	b_k	-0.5365659	**0.021**
lnX2	b_l	0.1901496	0.445
lnX3	b_m	0.8447446	**0.001**
lnZ	b_z	0.3723596	**0.001**
lnX1sq/2	b_{kk}	0.085888	**0.035**
lnX2sq/2	b_{ll}	0.0000216	0.999
lnX3sq/2	b_{mm}	0.206266	**0.001**
lnZsq/2	b_{zz}	-0.0521102	**0.001**
lnX1lnX2	b_{kl}	-0.041133	0.283
lnX1lnX3	b_{km}	-0.1727	**0.001**
lnX2lnX3	b_{lm}	0.0435051	0.375
lnX1lnZ	b_{kz}	0.0764061	**0.002**
lnX2lnZ	b_{lz}	0.0029543	0.892
lnX3lnZ	b_{mz}	-0.0026228	0.877
constant	c	1.03311	**0.042**

Following the structure of Model 1, we shall first discuss the structure of the production technology. The elasticities of output with respect to the three inputs (excluding COD) are positive for 100% of the observations, similar to Model 1. The sum of the elasticities of output with respect to these four inputs generates an estimated scale elasticity which indicates the presence of decreasing returns to scale except for the last three deciles. As we have discussed earlier, it might be easier for the larger plants to undertake increased abatement costs through environmental regulation and convert it to benefits accruing to the firm: that cleaner practice reduces costs. Also, for larger plants, the total load of pollution will be higher and as a result, can lead to a negative impact on output.

The estimated scale elasticity increases with a decline in output and has a value of 0.942 at the sample mean. Likelihood ratio tests led to rejections of homotheticity and linear homogeneity in all four inputs significant at 1 percent level.

Table 5: *Elasticities of Output with Respect to Each Input, by Output Deciles (Model 2)*

Output Deciles	***Capital***	***Labour***	***Materials***	***COD***	***Returns to Scale***
1	0.073	0.163	0.403	0.109	0.749
2	0.013	0.181	0.511	0.102	0.807
3	0.075	0.175	0.495	0.087	0.833
4	0.079	0.187	0.560	0.051	0.878
5	0.067	0.195	0.607	0.047	0.916
6	0.072	0.198	0.632	0.037	0.939
7	0.037	0.210	0.709	0.032	0.989
8	0.060	0.204	0.718	0.035	1.017
9	0.017	0.222	0.838	0.016	1.093
10	0.172	0.228	0.876	-0.071	1.205

Again, we shall try to calculate the shadow prices using the estimated elasticities of output with respect to COD. The elasticities have a mean value of 0.04, with a standard deviation of 0.016, suggesting that, holding other inputs constant, a 1% reduction in COD requires a sacrifice of 4/100th of 1% of marketable output. Using mean values reported in Table 1 this estimated abatement cost elasticity implies that a reduction of approximately 30 kilograms of COD load would "cost" approximately Rs. 6117 at 1990 prices. This, in turn, suggests a "shadow price" of COD of approximately Rs. 204 per kilogram. The calculated "shadow price" of COD decreases with plant size because the estimated elasticity of output with respect to COD decreases with plant size. This can be because of the fact that a larger amount of pollution load (due to a bigger plant size) may affect output adversely.

The estimated technical and environmental efficiencies are summarized in Table 6 for Model 1 and Table 7 for Model 2. Output-oriented technical efficiency is estimated using equation (3). Estimates of output-oriented technical efficiency are pretty low, with a large variation, ranging from 0.123 to 0.720 with a mean of 0.258 in case of Model 1. In case of Model 2, the results are similar: a low technical efficiency with a large variation, ranging from 0.138 to 0.779 with a mean of 0.283. These low degrees of technical efficiency suggest that a considerable amount of marketable output is sacrificed to resource waste.

Table 6: *Estimates of Technical Efficiency and Environmental Efficiency: Model 1*

	Output-oriented Technical Efficiency	***Environmental Efficiency***
2003-04 mean	0.282	0.062
2004-05 mean	0.285	0.045
2005-06 mean	0.283	0.053
Overall mean	0.258	0.053
Overall minimum	0.123	0.000^{+}
Overall maximum	0.720	0.636

Table 7: *Estimates of Technical Efficiency and Environmental Efficiency in Model 2*

	Output-oriented Technical Efficiency	***Environmental Efficiency***
2003-04 mean	0.283	0.105
2004-05 mean	0.287	0.079
2005-06 mean	0.283	0.088
Overall mean	0.283	0.091
Overall minimum	0.138	0.001
Overall maximum	0.779	0.675

Environmental efficiency is estimated using equation (9). Environmental efficiency is much lower on average and exhibits a similar kind of variability like that of output–oriented technical efficiency, with a range of from 0.00^{+} to 0.636 with a mean of 0.053 in case of Model 1. Similar results were obtained from Model 2: a large variability and a low value. The efficiency values ranged from 0.001 to 0.675 with a mean of 0.091. However the mean value of environmental efficiency in Model 2 is considerably higher than that of Model 1.

It is also interesting to note that the environmental efficiency values were actually fluctuating each year. Environmental efficiency declined from 2003-04 to 2004-05 in both Model 1 and Model 2; however, the values rose from 2004-05 to 2005-06, but not to the level of 2003-04 in both cases. This shows that the measures that were incorporated to reduce pollution were either not working, or some lax monitoring took place between the years. As the technical efficiency values were also low, it might be possible that the firms that were under regulation were simply making abatement expenditures as much as necessary to not be under any penalty, without making any effort to increase their efficiency so that they could continue production. This may be the reason that the smaller firms were facing decreasing returns to scale.

To find out the relationship between size of firms, returns to scale, technical efficiency, environmental efficiency and pollution control intensity, we have calculated the correlation coefficients between these variables. Total turnover of the firm is taken as a proxy of firm size, while pollution control intensity is measured by turnover produced per kg of pollution load. A higher value of the latter ratio reflects a higher level of control. The results are summarized in the tables below:

Table 8: *Correlation matrix for Model 1 (where Z = BOD)*

	Returns to Scale	***Technical Efficiency***	***Environmental Efficiency***	***Firm size***	***Pollution Intensity***
Returns to Scale	N. A.				
Technical Efficiency	Positive and significant	N. A.			
Environmental Efficiency	Negative and significant	Positive and significant	N. A.		
Firm size	Positive and significant	Positive and significant	Negative and significant	N. A.	
Pollution Control Intensity	Negative and significant	Not significant	Positive and significant	Negative and significant	N. A.

Note: All significant levels are at 1 percent.

Table 9: *Correlation matrix for Model 2 (where Z = COD)*

	Returns to Scale	***Technical Efficiency***	***Environmental Efficiency***	***Firm size***	***Pollution Intensity***
Returns to Scale	N. A.				
Technical Efficiency	Positive and significant	N. A.			
Environmental Efficiency	Negative and significant	Positive and significant	N. A.		
Firm size	Positive and significant	Positive and significant	Negative and significant	N. A.	
Pollution Control Intensity	Negative and significant	Not significant	Positive and significant	Negative and significant	N. A.

Note: All significant levels are at 1 percent.

The results are same for both models. We can observe that while the efficiency scores are positively correlated with each other the interesting results come from the relationship between environmental efficiency, pollution intensity and returns to scale. Firms with higher returns to scale as well as larger outputs are associated with low values for pollution intensity as well and environmental efficiency. This may be because of the fact that larger firms are able to get away with any kind of violations because of their clout in the government and a large market share. Also, the process of making large industries pay are very long as undue emphasis is placed on criminal procedure. “The process of taking industry to the court is torturous and drags on for years. We have cases which are pending since 20 years”, says Rashmi Mayur of the International Institute for Sustainable Future, who is involved in many environmental cases in the Mumbai High Court.

6. Summary of Findings

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.

In this paper we have estimated "shadow prices" of BOD and COD. These "shadow prices" provide a measure of the cost to firms, in terms of foregone real output, of achieving reductions in BOD and COD. These "shadow prices" are upper bounds to true shadow prices. The shadow prices of pollutants estimated vary across the firms. The estimated shadow prices of pollutants BOD and COD for all the 50 chemical firms in the sample differ across the firms. The estimated sample averages for shadow prices of BOD and COD are Rs. 0.459 and Rs. 0.204 per a gram of pollutant, respectively. That means as per the current pollution abatement practices, the chemical industry in and around Mumbai is forgoing revenue amounting to Rs. 459 and Rs. 204 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.

The estimates of economies of scale show that the water polluting industry as a whole has decreasing returns to scale. We observe that the average figure in both Model 1 and

Model 2 are 0.955 and 0.942 respectively. However, there is a positive correlation between the economies of scale and the turnover of a firm.

We have also calculated the Environmental efficiency of the firms from the estimated coefficients. We find that the environmental efficiency of this firms to be quite low for both BOD and COD. This again stresses on the fact that the existing command and control instruments in India are unable to control pollution and is causing more harm that good for economic growth as well as the protection of the environment. We find that both return to scale and size of firm have a negative relationship with environmental efficiency. We also observe that returns to scale has a negative relationship with pollution intensity. This again stresses on the fact that the existing command and control instruments in India are unable to control pollution and is causing more harm that good for economic growth as well as the protection of the environment. An increase in environmental efficiency implies cleaner process and not the end-of pipe methods that are generally used by the plants to comply with existing regulations. A cleaner process of production will encourage in win-win situations and higher environmental efficiency while an end-of-pipe method of compliance can lead to a reduction in pollution concentration of effluents which might not always lead to an improvement of the efficiency of firms.

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