Environmental Regulation, Productive Efficiency and Cost of Pollution Abatement: A Case Study of Sugar Industry in India*

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Abstract

It is shown in this paper that the estimates of technical efficiency, scale economies, and the shadow prices of bad outputs for polluting firms in India are sensitive to the specification of technologies and environmental regulation. The output and input distance functions with the assumption of weak disposability of bad outputs account for the effect of environmental regulation on the productive efficiency of firms. In this context the models of firms' behavior with the strong disposability assumption of bad outputs or relaxed environmental constraints could not accurately explain the input and output choices of firms. That is why the estimates of indicators of firm's performance like technical efficiency, and scale economies are found to be sensitive to the assumptions about the environmental constraints they are facing. In the case of both output and input distance functions, the technical efficiency estimates made with the binding environmental constraint are found to be higher than those made with the relaxed environmental constraint. There are output losses due to binding environmental constraint relating to water pollution in the Indian sugar industry in the range of 3 to 5 percent. In the case of specification of technology of firms by the production functions, the environmental regulation in the form of pollution taxes for instance will make them to consider the waste disposal services as productive inputs for which they have to pay. The generalized production function with the environmental inputs as productive inputs will explain the firm's behavior accurately. The cost of abatement of firms could be accounted and the shadow prices of bad outputs could be estimated using output and input distance functions with the assumption of binding environmental constraints. The output distance function assumes that there is a binding resource constraint on the firm making the reduction of bad output possible only by reducing the production of good output. However, the input distance function allows the firm to obtain additional resources to reduce pollution loads for a given level of good output. The firm specific shadow prices of bad outputs estimated using the distance functions could be used to estimate the marginal cost pollution abatement functions given the firm specific data about pollution loads and concentrations. In the case of taxes standards approach, pollution taxes can be designed using the estimates of marginal cost of abatement functions and pollution standards. In India, the water pollution standards (MINAS) for BOD, COD, and SS are respectively given as 30mg/l, 250mg/l, and 100mg/l. The taxes necessary for making the firms in the Indian sugar industry to comply with these standards are estimated as Rs. 23518, Rs. 45567, and Rs. 7605 respectively per ton of BOD, COD and SS.

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1 Introduction

The effect of environmental regulation on the productive efficiency of firms and the estimates of cost of pollution abatement can be sensitive to the specification of technologies of polluting firms. A case study of sugar industry in India is taken up in this paper for examining the effects of environmental regulation on productive efficiency and the cost of production. Estimates of productive efficiency of firms are obtained under alternative specification of technologies by production function, output distance function and the input distance function. The shadow prices of pollutants of water are estimated using both output and input distance functions.

Productive efficiency is defined and measured either by using output based methods or input based methods. The conventional output based measure computes technical efficiency and technical change in terms of proportional expansion in outputs that can be achieved with the vector of inputs held constant. The input based measure computes technical efficiency and technical change in terms of proportional savings in inputs that can be achieved with the vector of outputs held constant. For the firms producing bad outputs or generating pollution, the traditional output based measure of productive efficiency is not meaningful. Whether the proportional expansion of both good and bad outputs results in welfare loss or gain depends on the benefits from the expansion of good outputs are lower or higher than the damages from the expansion of bad outputs. The input based measure of productive efficiency on the other hand remains to be a meaningful measure because a proportional change in inputs with both good and bad outputs held constant is an unambiguous indicator of welfare change. In contrast to output based methods, the input based method makes it possible to estimate both technical and allocative efficiency of firms. Recently, Hailu and Veeman (2000) have used input distance function to estimate technical efficiency, technical change, and shadow prices of bad outputs for the Canadian paper and pulp industry.

The shadow prices of bad outputs can be estimated using output distance function with the assumption of weak disposability of bad outputs. The assumption of weak disposability in the case of output distance function implies that the disposal of undesirable output involves a cost to the firm in terms of proportional reduction of desirable output. In practice, the firms obtain pollution reductions through the use of additional inputs while increasing or maintaining the production of desirable outputs. Therefore, it requires to go beyond the weak disposability assumption for the complete characterization of technologies of polluting firms. The graphic or hyperbolic measure of efficiency (Fare et al. 1994) accomplishes this by considering simultaneous proportional fall in inputs and bad outputs and increase in good outputs. Hailu and Veeman (2000) have shown that the characterization of input distance function as non-decreasing in bad outputs explains the fact that pollution abatement can also be achieved through the use of additional inputs with good outputs increasing or held constant.

2 Alternative Specification of Technologies of Polluting Firms

Technologies of polluting firms can be specified by using production functions, cost and profit functions, and output and input distance functions. 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,

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

Equation (2) characterises the output possibility set by the maximum equi-proportional expansion of all outputs consistent with the technology set (1).

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,

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

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

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[1],

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

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.

The input distance function can be used to estimate the technical and allocative efficiency of firms. Using the envelope theorem it can also be used to estimate shadow prices of bad outputs. It provides a more general characterization of technology in explaining the firm's ability to reduce bad outputs and inputs and to expand the good output. As mentioned earlier, it also takes in to account the possibilities of the firm using abatement technologies requiring the reduction of good outputs as well as use of additional resources. The input distance function is defined as

$$D(y,x) = \max_{\lambda} \{\lambda \ (y,x / \lambda) \varepsilon \ T, \lambda \varepsilon \ R\} \qquad (4)$$

The input based Farrel measure of technical efficiency is defined as

$$TE(y,x) = 1/ D(y,x) \qquad (5)$$

[1] See Fare (1988) for derivation.

The cost function is dual to the input distance function (Shepard 1953, 1970). The cost function is the solution to the minimization problem

$$C(y,p) = \underset{x}{\mathrm{Min}}\{p.x: D(y,x) \geq 1,\ x \in R_+^N\} \qquad (6)$$

where $p \in R_+^N$ is the input price vector. Equation (6) is the duality relationship between the cost and input distance function. Applying envelope theorem on the first order conditions,

$$\begin{aligned} \nabla_u C(y,p) &= -\Lambda(y,p).\nabla_u D(y,x) \qquad (7) \\ &= -C(y,x).\nabla_u D(y,x) \end{aligned}$$

The second equation in (7) follows from the first equation because the Lagrangian multiplier ($\Lambda(y,p)$) is equal to the optimized cost function in this case. The shadow price of a given output is defined as its marginal cost. Since the input distance function is non-decreasing in bad outputs, the shadow price of bad output is non-positive. From (7) one can write the cost normalized shadow prices of outputs as

$$r_i^* = \partial(y,x)/\partial y_i,\ i = 1,2\ldots.N$$

Alternatively one can use the following formula to calculate the shadow prices of outputs.

$$\frac{r_i^*}{r_j^*} = \frac{\partial(y,x)/\partial y_i}{\partial(y,x)/\partial y_j} \qquad (8)$$

This ratio shows how many units of output j the producer is willing to forego for the right to emit one unit of pollution output. In other words, this ratio is the marginal rate of transformation between the desirable output and the pollution output. Further, if one assumes that the market price of output j is the shadow price, the shadow price of pollution output in monetary terms can be calculated as follows:

$$r_i^* = r_j^* \frac{\partial(y,x)/\partial y_i}{\partial(y,x)/\partial y_j} \qquad (9)$$

A similar procedure is used by Fare et al. (1993), Coggins and Swinton (1996), and Murty and Surender Kumar (2000) for the estimation of shadow prices of bad outputs, but using output distance function. Recently Hailu and Veeman (2000) have used input distance function described above for estimating shadow prices of bad outputs for Canadian paper and pulp industry. The shadow prices computed using the input distance function and the envelope theorem correspond to the output and input levels at the technically efficient frontier of technology. It is so because the cost minimization implies technical and allocative efficiency. In the case of observations below the efficiency frontier, the shadow price formula was evaluated at technically efficient projection of associated input vectors.

The generalized production function with the pollution loads generated by the firms as environmental inputs describes the ability of a firm to minimize the use of inputs including environmental inputs and maximize the output. The hyperbolic graph efficiency given by the distance function H(x,y) similarly explains the ability of a firm to expand outputs (y) and contract inputs (x) simultaneously. It is defined as

$$H(x,y) = \min\{\lambda : (\lambda x, \lambda^{-1} y) \in T\} \qquad (10)$$

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

For the polluting firms, it is convenient to decompose the plant's output vector into two sub-vectors, y = (g, b) which represent the desirable output, g, and undesirable outputs, b, of the production process. The difference between these two types of outputs is captured via the disposability assumptions. Here it is assumed that the desirable outputs are freely disposable and the undesirable outputs may only be weakly disposable. That is, the firm may have to expand resources (or reduce 'good' output) to reduce the bad outputs. In the description of technology of a firm, the ability of the plant to minimize the production of undesirable outputs has to be considered. In this context, a generalized efficiency measure, the hyperbolic measure is defined measuring the ability of a firm to expand desirable output and contract bad outputs and inputs.

$$H(x,g,b) = \min\{\lambda : (\lambda x, \lambda^{-1} g, \lambda b) \in T\} \qquad (11)$$

Environmental regulation results in adoption by a firm the technology satisfying the weak disposability assumption. In case the technology of firms facing environmental regulation is described by assuming free disposability, the inputs used to reduce bad outputs are shown as inputs to produce good output since by assumption bad outputs are freely disposed. As a result, the input output ratios of the plant are higher and the production efficiency of the plant appears lower. The technology described by using free disposability assumption in this case accounts input use separately for the production of good outputs and the reduction of bad outputs and thus making the productive efficiency of the plant higher. The efficiency or potential productivity loss due to regulation is defined by comparing the measures of technical efficiency corresponding to the technologies satisfying weak disposability and free disposability assumptions. The output loss can be measured by the ratio of productivity measure with the free disposability (λ_f) and the productivity measure with the weak disposability (λ_w) assumptions.

$$\text{Output Loss (OL)} = \lambda_f/\lambda_w \qquad (12)$$

If OL = 1, then one can conclude that undesirable outputs (pollutants) are freely disposable, i.e., any regulation concerning the disposability of bad outputs are ineffective. If OL < 1, then undesirable output is not freely disposable, i.e., regulations are effective. The percentage by which 'good' output could have been increased (given OL < 1) can be calculated as (1 – OL) and represents a measure of the opportunity cost of binding regulations to the firm (Fare et al. 1994). These losses can be viewed as implied costs (e.g., labor, capital and material diverted to abatement activities), as well as indirect costs (plant down time, etc.) (Fare et al. 1994; Boyd and McClelland 1999).

3 Estimation Procedures and Data

In order to estimate the shadow prices of pollutants (bad outputs) for the Indian sugar industry using equations (3) and (9), the parameters of output and input distance functions have to be estimated. The translog functional form[2] chosen for estimating these functions is given as follows:

$$\ln D_o(x, y) = \alpha_0 + \sum\beta_n \ln x_n + \sum \alpha_m \ln y_m + 1/2\sum \sum \beta_{nn'} (\ln x_n) (\ln x_{n'}) + 1/2 \sum \sum \alpha_{mm'} (\ln y_m)(y_{m'}) + \sum \sum \gamma_{nm} (\ln x_n) (\ln y_m) + \iota_i D_i \qquad (13)$$

where x and y are respectively, Nx1 and Mx1 vectors of inputs and outputs. There are three inputs: capital, labor, and materials and three outputs: good output, Sugar and bad outputs, BOD, COD, and SS, and D_i is the dummy variable representing the year of data. 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,

$$\max \sum [\ln D_o (x , y) - \ln 1], \qquad (14)$$

[2] 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).

subject to

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

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

(iii) $(\partial \ln D_o\ (x, y))/(\partial \ln y_i) \leq 0$

(iv) $(\partial \ln D_o\ (x, y))/(\partial \ln x_i) \leq 0$

(v) $\sum \alpha_m = 1$

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

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

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

Here the first output is desirable and the rest of (M-1) outputs are undesirable. The objective function minimizes the sum of the deviations of individual observations from the frontier of technology. Since the distance function takes a value of less than or equal to one, the natural logarithm of the distance function is less than or equal to zero, and the deviation from the frontier is less than or equal to zero. Hence the maximization of the objective function is done implying the minimization 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 (iv) restrict that the shadow prices of bad outputs are non-positive, i.e. weak disposability of bad outputs whereas the restrictions in (v) is the derivative property of output distance function with respect to inputs i.e. the derivatives of output distance function with respect to inputs is non-increasing. The constraints in (v) impose homogeneity of degree +1 in outputs (which also ensures that technology satisfies weak disposability of outputs). Finally, constraints in (vi) impose symmetry. There is no constraint imposed to ensure non-negative values to the shadow prices of undesirable outputs.

The parameters of the trans-log input distance function are estimated by solving the problem,

$\min \sum [\ \ln D_I\ (x\ , y) - \ln 1],$

subject to (15)

(i) $\ln D_I\ (x, y) \geq 0$

(ii) $$\frac{\partial \ln D(y,x)}{\partial x_n} \geq 0, \quad n = 1,2,3$$

(iii) $$\frac{\partial \ln D(y,x)}{\partial y_m} \leq 0, \quad m = 1.$$

(iv) $$\frac{\partial \ln D(y,x)}{\partial y_m} \geq 0, \quad m = 2,3,4.$$

(v) $\sum \beta_n = 1$

(vi) $\sum \beta_{nn'} = \sum \gamma_{nm} = 0$

(vii) $\beta_{nn'} = \beta_{n'n}$

(viii) $\alpha_{mm'} = \alpha_{m'm}$

Here first is the desirable and the rest of (M-1) outputs are undesirable and ln D_I (x, y) has an explicit translog functional form. The objective function 'minimizes the sum of the deviations of individual observations from the frontier of technology. Since the distance function takes a value of greater than or equal to one, the natural logarithm of the distance function is greater than or equal to zero. The constraint (i) restricts the individual observations to be on or 'above' the frontier of the technology. Constraint (ii) imposes that input distance function is non-decreasing in inputs. Constraints (iii) and (iv) impose respectively that input distance function is non-increasing in good output and non-decreasing in bad outputs. Constraint (v) imposes homogeneity of degree +1 in inputs. The final set of constraints impose symmetry.

The generalized and conventional production functions are estimated by using the stochastic production function approach. The stochastic frontier production function was proposed first by Aigner, Lovell and Schmidt (1977) and Meeusen and van den Broeck (1977). The original specification involved a production function specified for cross-sectional data having an error term with two components, one to account for random effects and another to account for technical inefficiency. This model can be expressed in the following form:

(1) $Y_i = x_i\beta + (V_i - U_i)$,i=1,...,N, (16)

where Y_i is the production (or the logarithm of the production) of the i-th firm;

x_i is a $k\times1$ vector of (transformations of the) input quantities of the i-th firm;

β is an vector of unknown parameters;

the V_i are random variables which are assumed to be iid. $N(0,\sigma_V^2)$, and independent of the U_i and x_i;

U_i are non-negative random variables which are assumed to account for technical inefficiency in production and are assumed to be iid as truncations at zero of the $N(\mu,\sigma_U^2)$ distribution;

This original specification has been used in a vast number of empirical applications over the past two decades. The specification has also been altered and extended in a number of ways. These extensions include the specification of more general distributional assumptions for the U_i, such as the truncated normal or two-parameter gamma distributions; the consideration of panel data and time-varying technical efficiencies; the extension of the methodology to cost functions and also to the estimation of systems of equations; and so on. A number of comprehensive reviews of this literature are available, such as Forsund, Lovell and Schmidt (1980), Schmidt (1986), Bauer (1990) and Greene (1993).

The data used in this paper are obtained through surveys of polluting industries in India conducted by research teams at the Institute of Economic Growth during the years 1996 and 2000. For sugar industry, the data was collected during the first survey for 60 water polluting firms for the year 1994-95 and in the second survey for 120 firms for the three years 1996-97, 1997-98, and 1998-99. Thus the information collected constitutes unbalanced panel data with 134 observations on all the relevant variables. Table 1 provides the descriptive statistics of variables for which data were collected.

Table 1:Descriptive Statistics for Sugar Industry

	Mean	Median	Maximum	Minimum	Std.Dev.
T	1303.856	461.096	10845.7	5.617	2267.468
M	569.8634	301.41	10094	10.85	1248.68
W	66.50209	33.0737	699.78	2.01	115.9377
KS	757.6216	278.2092	9095.975	0.004257	1337.758
VW	247554.9	202529.2	807100	25200	159699.8

Influent (conc.)					
BOD	995.2575	730	6300	35	1153.933
COD	3070.641	1536	31800	170	5914.944
SS	1001.297	340	65000	62.5	5758.738
Effluent (conc.)					
BOD	89.36701	40	850	3.26	137.2537
COD	303.7958	191	2857	12	414.3622
SS	86.68306	67	760	3	94.45677
Influent load					
BOD	246.3808	166250	2.55E+08	4879	47657554
COD	760.1522	230510	33390000	12250	4829004
SS	247.875	92400	2047500	1487.5	313538.6
Effluent load					
BOD	22.123	11112.5	686035	5	60743.98
COD	75.206	37800	2305885	1680	202225.7
SS	21.458	12299.7	202582.1	5	23810
Pollution load as per standard					
BOD	7.426	6075.878	24213	756	4790.994
COD	61.888	50632.31	201775	6300	39924.95
SS	24.755	20252.92	80710	2520	15969.98

T: Turnover(Rs.million)
M: Material inputs(Rs. Million)
W: Wage-bill(Rs. Million)
K: Capital Stock(Rs. Million)
VW: Waste Water Volume(KL)
BOD Load: Bio-oxygen demand(tons)
COD Load: Chemical oxygen demand(tons)
SS Load: Suspended Solids(tons)
BOD Conc. (mg/l)
COD Conc. (mg/l)
SS Conc. (mg/l)

4 Estimates of Productive Efficiency and Scale Economies under Alternative Specifications of Technologies

Table 2 provides estimates of technical efficiency using output distance function for the Sugar industry. Two estimates of technical efficiency corresponding to free disposability and weak disposability assumptions are reported. The pollution regulation can be represented by the assumption that pollutants are not freely disposable. The potential output loss due to regulation can be estimated by comparing the two efficiency measures. The estimate of technical efficiency with weak disposability assumption (0.793) shows that the sugar industry has become 20.7 percent inefficient as a result of environmental regulation while the estimate with the assumption of strong disposability (0.751) shows that the industry is 24.9 percent inefficient. That means if the environmental constraint is relaxed (free disposability assumption) the inefficiency due to these assumed environmental constraints has increased by 4.2 percent. The output loss measure defined as the ratio of efficiency measure when environmental constraint is not binding and the efficiency measure when it is binding indicates the degree by which the environmental constraint is binding. The ratio is estimated as 0.96 to the Indian Sugar industry implying the efficiency losses equivalent to 4 percent of plant output.

2. Estimates of Technical Efficiency and Output Loss due to Environmental Constraint for Sugar Industry (Output Distance Function Approach)

Variables	Mean	S.D	Maximum	Minimum
EFF(S)	0.7506605	0.22444702	1	0.1040379
EFF(W)	0.7925625	0.2240979	1	0.1535084
(1-OL)	0.0419159	0.1843297	0.5926164	-0.8851361

Table 3 provides estimates of technical and allocative efficiency based on input distance function for Sugar industry. The estimates of technical and allocative efficiency with the assumption of weak disposability are respectively given as 0.847 and 0.801. The over all efficiency that is defined as the product of technical and allocative efficiency is given as 0.681. Again comparing the technical efficiency estimates under the assumptions of weak and free disposability, the output loss due to binding environmental constraint is estimated as 5.1 percent in the case of input distance function.

3: Estimates of Technical and Allocative Efficiency, Output Loss and Scale Economies with Input Distance Function for Sugar

Variables	Mean	S.D	Maximum	Minimum
ITEW	0.8470826	0.1400208	1	0.0659000
ITES	0.8012238	0. 1603786	1	0.0892780
AE	0.8008269	0.8427213	9.004453	0.214947
OE	0.6806075	0.6979109	6.812304	0.0217889
(1-OL)	0.0508594	0.1249106	0.4663419	-0.3539145
SES	0.9641939	0.3189925	2.327978	0.188127
SEW	0.9913976	0.4123881	2.596070	0.104664

The distance function based estimates of technical efficiency are radial measures requiring an equi-proportional reduction of inputs and bad outputs and expansion of good outputs. The technical efficiency measure based on stochastic or frontier production functions is not a radial measure. It shows the degree by which a firm reaches as nearly as possible the efficient production frontier with an ability to vary input and output combinations given the constraints on inputs. With the environmental regulations, a firm has to pay for the waste disposal services offered by the environmental media in the form pollution taxes or the cost of pollution abatement. Therefore, profit maximizing or cost minimizing firms consider waste disposal service as productive input and use it up to the level at which its marginal value productivity is equal to the marginal cost of abatement or the pollution tax. In the production function for the polluting firms subjected to environmental regulation, waste disposal service has to be taken as a productive input along the conventional inputs. Table 3 provides production function based estimates of technical efficiency for Indian sugar industry. The difference between the estimates of technical efficiency made with the generalized production function with waste disposal services as productive inputs and the conventional production function explain the degree at which the environmental constraints are binding. The higher estimate of technical efficiency based on generalized production function (0.718) than the one based on conventional production (0.689) function indicates that the environmental regulation is effective in making the firms to take waste disposal service as a productive input. Since many firms in the sample take in to account the environmental regulation in making the input choices by spending on pollution control, the conventional production function can not accurately explain the firms behavior in making the input and output choices. The production function based estimate of potential efficiency loss due to environmental regulation is 3.4 percent as shown in Table 4.

4. Estimates of Technical Efficiency and Output Loss due to Environmental Constraint Based on Production Function

			Efficiency		
	Mean	Median	Maximum	Minimum	Standard dev
TE (C)	0.688865	0.697	0.883	0.118	0.110066
TE (G)	0.718030	0.736	0.902	0.178	0.106825
OL	0.958752	0.965	1.242	0.664	0.088209
I-OL	0.039083	0.034	0.335	-0.242	0.088035

There are three estimates of technical efficiency made in this paper under alternative specification of technologies of firms: output distance function, input distance function and production function. These estimates are made under free and weak disposability assumptions in the case of distance functions and for generalized and conventional production functions. Using these estimates, the output loss under binding environmental constraints is estimated for each specification of technology. All these estimates are again reported in Table 5 for the sake of comparison. The estimates of technical efficiency have formed a range of 72 to 85 percent while the output loss due to binding environmental constraints form a range of 3 to 5 percent.

Table 5: Technical Efficiency and Output Loss Under Alternative Specification of Technology for Sugar Industry in India

Technology	Technical Efficiency*		Output Loss
	B	R	
Output Distance function	0.793	0.751	0.040
Input Distance function	0.847	0.801	0.051
Production function	0.718	0.689	0.034

* B: Binding environmental constraint
R: Relaxed environmental constraint

The scale economies of Indian Sugar industry can be estimated using estimates of technical efficiency for output and input distance functions. The scale economies can be defined as the ratio of technical efficiency under output distance function and technical efficiency under input distance function. Table 6 reports the estimates of scale economies under binding and relaxed environmental constraints. As evident from the estimates, the Indian Sugar industry has decreasing returns to scale. The weak disposability assumption or the presence of binding environmental constraints increases the scale economies.

Table 6: Estimates of Scale Economies under Binding and Relaxed Environmental Constraints

	Mean	S.D	Maximum	Minimum
SES	0.964	0.125	2.328	0.189
SEW	0.991	0.412	2.596	0.105

SES: Strong disposability
SEW: Weak disposability

6. Estimates of Shadow Prices of Bad Outputs and the Design of Environmental Policy

Shadow prices of bad outputs: BOD, COD and SS are estimated using the parameter estimates of input distance function and output distance function given respectively in the appendix tables, A.1 and A.3. These estimates are reported in tables 7 and 8. The shadow prices based on output distance function account for the cost of all pollution abatement methods used by the firms to meet the prescribed standards, but the firms have resource constraints such that they have to reduce pollution at the cost of reducing the production of good outputs. However, the shadow prices based on input distance function have no restriction on the source of funding the abatement activities of firms, they can raise additional resources to carry on abatement for a given level of good output. The estimates show that the shadow prices of bad outputs are sensitive to the specification of technologies of polluting firms.

Table- 7 Shadow Prices of Bad Outputs for Sugar Industry with Output Distance Function

Variables	Mean	S.D	Minimum	Maximum
SBOD	0.0815653	0.0182817	-0.003	-0.09
SCOD	0.2225652	0.0222683	-0.002	-0.132
SSS	0.0490911	0.0091398	-0.001	-0.055

Table- 8: Shadow Prices of Bad Outputs for Sugar Industry with Input Distance Function

Variables	Mean	S.D	Minimum	Maximum
SBOD	0.089583	0.0523812	0	-0.2458172
SCOD	0.0586339	0.0302463	0	-0.14375
SSS	0.0186339	0.0092362	0	-0.0894495

In Section 2 the shadow prices of bad output is defined as the value of marginal rate of technical transformation between good and bad output at the market price of good output sugar in the current context. This shadow price could also be interpreted as the marginal cost of pollution abatement. Therefore, the marginal cost of abatement function can be estimated for each pollutant given the estimates of shadow prices and data on waste water volumes and pollution concentrations for all the 134 observations in the sample. The estimated marginal cost functions are reported below. The variables BOD, COD and SS represent pollution concentrations in a litre of water and the figures in brackets are t values. Characteristic of panel data, all the three regressions have very low R^2. However, many of the coefficients are significant at either 5 percent or 10 percent level. The signs of all the three pollutants are negative implying that there are raising marginal costs of pollution abatement, the lower the pollution concentration, the higher the marginal cost. However, in the case of waste water volume, there is raising marginal cost in the case of BOD and SS and the falling marginal cost in the case of COD.

$$\ln BOD = -6.450 + 0.312 \ln W - 0.310 \ln BOD \qquad R^2 = 0.03$$
$$(-1.803) \quad (1.105) \qquad (1.445)$$
$$\ln COD = 2.993 - 0.401 \ln W - 0.216 \ln COD \qquad R^2 = 0.03 \qquad (15)$$
$$(0.971) \quad (-1.740) \qquad (-1.063)$$
$$\ln SS = -9.859 + 0.599 \ln W - 0.502 \ln SS \qquad R^2 = 0.03$$
$$(-2.735) \quad (2.077) \qquad (-1.897)$$

The estimates of marginal cost functions reported above can be used to design economic instruments for controlling pollution. Using the taxes-standards approach (Baumol and Oates, and Murty et al. 1999), pollutant specific pollution taxes can be designed given the standards and the estimates of marginal abatement cost functions. In the case of water pollution, the minimum national standards (MINAS) are given as 35mg/l for BOD, 250mg/l for COD and 100mg/l for SS in India (CPCB). The taxes standards method requires the pollution tax to be fixed at the rate equal to the marginal cost of abatement corresponding to the prescribed standard. Table 7.9 reports

Table9: Pollution Taxes for the Sugar Industry for Realizing MINAS Standards for water Pollution

	BOD	COD	SS
Tax (per metric ton in rupees)	23518	45567	7605

the estimates of pollution taxes for BOD, COD and SS. The firms in the Indian Sugar industry can comply with the standards by levying taxes on them equal to Rs 23518, Rs. 45567, and Rs. 7605 respectively for a metric ton of BOD, COD, and SS.

6 Conclusion

Alternative specifications of technologies are considered for the polluting firms with the help of input and output distance functions and the production functions. It is shown that the estimates of technical efficiency, scale economies, and the shadow prices of bad outputs are sensitive to the specification of technologies. It is found that these estimates are also sensitive to the environmental regulation.

The environmental regulation implies that the bad output are not freely disposable. The output and input distance functions with the assumption of weak disposability of bad outputs account for the effect of environmental regulation on the productive efficiency of firms. The firms in the sample are found to respond to environmental regulation by reducing pollution loads at varying degrees of compliance. Therefore, the firms behavior in making input and output choices is better explained by the input or output distance function with the assumption of weak disposability of bad outputs or binding environmental constraint. In this context the models of firms' behavior with the strong disposability assumption of bad outputs or relaxed environmental constraints could not accurately explain the input and output choices of firms. That is why the estimates of indicators of firm's performance like technical efficiency, and scale economies are found to be sensitive to the assumptions about the environmental constraints they are facing. In the case of both output and input distance functions, the technical efficiency estimates made with the binding environmental constraint are found to be higher than those made with the relaxed environmental constraint. There are output losses due to binding environmental constraint relating to water pollution in the Indian sugar industry in the range of 3 to 5 percent.

In the case of specification of technology of firms by the production functions, the environmental regulation in the form of pollution taxes for instance will make them to consider the waste disposal services as productive inputs for which they have to pay. In this case the production function with the conventional inputs alone could not accurately explain the firms behavior in making input and output choices. The generalized production function with the environmental inputs as productive inputs will explain the firm's behavior accurately. That is why the estimate of technical efficiency using generalized production function is found to be higher than the estimate based on conventional production function.

The cost of abatement of firms could be accounted and the shadow prices of bad outputs could be estimated using output and input distance functions with the assumption of binding environmental constraints. The output and input distance functions account for the cost of all pollution abatement activities under taken by the firms. The output distance function assumes that there is a binding resource constraint on the firm making the reduction of bad output possible only by reducing the production of good output. However, the input distance function allows the firm to obtain additional resources to reduce pollution loads for a given level of good output.

The firm specific shadow prices of bad outputs estimated using the distance functions could be used to estimate the marginal cost pollution abatement functions given the firm specific data about pollution loads and concentrations. In the case of taxes standards approach, pollution taxes can be designed using the estimates of marginal cost of abatement functions and pollution standards. In India, the water pollution standards (MINAS) for BOD, COD, and SS are respectively given as 30mg/l, 250mg/l, and 100mg/l. The taxes necessary for making the firms in the Indian sugar industry to comply with these standards are estimated as Rs. 23518, Rs. 45567, and Rs. 7605 respectively per ton of BOD, COD and SS.

Appendix A

Table: A1: Parameter Estimates of Sugar Industry (Weak Disposability)
(Input Distance Function)

Parameter	Value	Parameter	Value
Y_1	-1.102	X_{12}	-0.104
Y_2	-1.0076	X_{13}	-0.007
Y_3	0.102	X_{23}	-0.019
Y_4	-6.99895	Y_1X_1	0.03
X_1	0.564	Y_1X_2	-0.134
X_2	0.358	Y_1X_3	0.016
X_3	0.078	Y_2X_1	0.028
Y_{11}	0.08	Y_2X_2	0.04
Y_{22}	0.001	Y_2X_3	-0.015
Y_{33}	-0.029	Y_3X_1	0.001
Y_{44}	9.899683	Y_3X_2	0.018
X_{11}	-0.02	Y_3X_3	0.00
X_{22}	0.160	Y_4X_1	0.002
X_{33}	-0.002	Y_4X_2	2.567592
Y_{12}	-0.024	Y_4X_3	0.001
Y_{13}	-0.01	D1	0.03
Y_{14}	-0.005	D2	0.016
Y_{23}	0.004	D3	0.065
Y_{24}	-0.003	Constant	-1.135
Y_{34}	0.00		

Table A2 Parameter Estimates of Sugar Industry (Strong Disposability)
(Input Distance Function)

Parameter	Value	Parameter	Value
Y_1	-1.141	X_{13}	-0.018
X_1	0.545	X_{23}	-0.019
X_2	0.357	Y_1X_1	0.129
X_3	0.099	Y_1X_2	-0.151
Y_{11}	0.044	Y_1X_3	0.022
X_{11}	-0.045	D1	-0.093
X_{22}	0.247	D2	0.003
X_{33}	-0.002	D3	0.067
X_{12}	-0.163	Constant	-1.229

Table A3 Parameters Estimates of Output Distance Function (Weak Disposability) (Sugar)

Parameter	Value	Parameter	Value
Y_1	1.059	X_{12}	0.144
Y_2	0.018	X_{13}	0.013
Y_3	-0.058	X_{23}	0.072
Y_4	-0.018	Y_1X_1	-0.117
X_1	0.143	Y_1X_2	0.286
X_2	-1.317	Y_1X_3	-0.126
X_3	0.139	Y_2X_1	-0.014
Y_{11}	-0.033	Y_2X_2	-0.015
Y_{22}	0.005	Y_2X_3	0.008
Y_{33}	0.028	Y_3X_1	-0.013
Y_{44}	-0.001	Y_3X_2	-0.010
X_{11}	0.006	Y_3X_3	0.005
X_{22}	-0.267	Y_4X_1	-0.004
X_{33}	0.024	Y_4X_2	0.002
Y_{12}	0.006	Y_4X_3	-0.002
Y_{13}	0.001	D1	0.71
Y_{14}	0.009	D2	-0.013
Y_{23}	-0.009	D3	-0.019
Y_{24}	0.003	Constant	-2.175
Y_{34}	-0.009		

Table A4 Parameter Estimates of Sugar Industry (Strong Disposability) (Output Distance Function)

Parameter	Value	Parameter	Value
Y_1	1.000	X_{23}	-0.095
X_1	-0.743	Y_1X_1	-0.094
X_2	-0.711	Y_1X_2	0.24
X_3	0.29	Y_1X_3	-0.153
X_{11}	0.006	D1	0.202
X_{22}	-0.104	D2	1.37
X_{33}	-0.002	D3	-0.01
X_{12}	0.04	Constant	-1.189
X_{13}	0.166		

Table A5 Parameter Estimates of Conventional Production Function (Sugar)

Parameter	Coefficient	t-ratio
X_1	1.483	3.69
X_2	0.427	1.049
X_3	-0.411	-2.202
X_{11}	0.0002	0.0069
X_{22}	0.015	0.247
X_{33}	0.031	2.337
X_{12}	-0.226	-3.206
X_{13}	-0.014	-0.174
X_{23}	0.1503	2.54
D_1	-0.2975	-1.576
D_2	0.0702	0.599
D_3	0.0966	0.858
constant	-0.209	-0.248
σ^2	0.447	4.179
γ	0.638	3.748
LR Function	-100.16	
LR Test	3.697	

Table A6 Parameter Estimates of Generalised Production Function (Sugar Industry)

Parameter	Coefficient	t-ratio
Y_2	-0.137	-0.195
Y_3	-1.159	-1.799
Y_4	2.086	4.287
X_1	1.246	2.114
X_2	-0.185	-0.308
X_3	0.121	0.428
Y_{22}	0.0698	1.789
Y_{33}	0.163	1.125
Y_{44}	-0.0579	-2.168
X_{11}	-0.0029	-0.094
X_{22}	0.082	1.174
X_{33}	0.045	3.18
Y_{23}	-0.26	-1.84
Y_{24}	0.308	2.84
Y_{34}	-0.225	-1.745
X_{12}	-0.179	-2.255
X_{13}	-0.099	-1.059
X_{23}	0.153	1.94
Y_2X_1	-0.122	-0.629

Y_2X_2	-0.1198	-0.706
Y_2X_3	0.204	2.195
Y_3X_1	0.45	2.619
Y_3X_2	-0.098	-0.625
Y_3X_3	-0.111	-1.214
Y_4X_1	-0.293	-2.96
Y_4X_2	0.186	1.825
Y_4X_3	-0.114	-1.621
D1	0.0074	3.697
D2	0.0558	0.504
D3	0.052	0.485
constant	0.249	0.151
σ^2	0.339	3.396
γ	0.6412	2.861
LR Function	-81.51	
LR Test	2.011	

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