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Environmental Efficiency of the Indian Cement Industry: An Interstate Analysis

Sabuj Kumar Mandal
S Madheswaran

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ENVIRONMENTAL EFFICIENCY OF THE INDIAN CEMENT INDUSTRY: AN INTERSTATE ANALYSIS

Sabuj Kumar Mandal[1], **S Madheswaran**[2]

Abstract

Coal combustion, for the production of cement, generates considerable amount of environmentally detrimental carbon dioxide as an undesirable by-product. Thus, this paper aims at measuring environmental efficiency within a joint production framework of both desirable and undesirable output using Data Envelopment Analysis. Carbon dioxide is considered as an input in one context and as an undesirable output in the other with the environmental efficiency being defined accordingly. Using 3 digit sate level data from the Annual Survey of Industries for the years 2000-01 through 2004-05, the proposed models are applied to estimate environmental efficiency of Indian cement industry. Empirical results show that Indian cement industry, if faced with environmental regulation, has the potential to expand desirable output and contract undesirable output with the given inputs. However, regulation has a potential cost in terms of lower feasible expansion of desirable output as compared to unregulated scenario.

Introduction

Indian cement industry witnessed an unprecedented growth as a sequel to government's liberalization policy initiated in the form of partial decontrol in 1982, subsequently culminating in total decontrol in 1989. India has progressed from being the world's eighth largest cement producer in 1979-80 to being the second largest producer at present. However, this huge growth in cement production has exacted a heavy price in the form of massive energy utilization. Among the energy intensive industries in India, cement industry happens to be highly energy-intensive with the second highest share in fuel consumption (15.60%), after Iron and Steel (18.10%), mostly in the form of coal utilization. Its expansion could not have been achieved without a substantial increase in energy input, especially in the form of coal combustion.

This has resulted in severe environmental problems not only in the coal mining regions but also around the cement producing plants. In addition, India's annual emission of green house gases from the cement industry has increased from 7.32 mt in 1993 to 16.73 mt in 2003 and its share in total carbon dioxide (CO_2) emission by India has increased from 3.3% to 4.8% during this period (ICRA, 2006). This raises the question how environmentally efficient Indian cement industry is with respect to carbon dioxide emission.

Globally, cement industry contributes 5% of the total CO_2 generation. Of all the other green house gases, carbon dioxide per se contributes to a very large extent to the global warming process. Anthropogenic activities, primarily the combustion of fossil fuels and the resultant carbon emissions have led to a significant warming of the global climate (IPCC[1], 1995). If India wants to further develop

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[1] Ph.D Fellow, Centre for Economic Studies and Policy, Institute for Social and Economic Change, Nagarabhavi, Bangalore – 560 072; E-mail: sabujecon@gmail.com.

[2] Professor, Centre for Economic Studies and Policy, Institute for Social and Economic Change, Nagarabhavi, Bangalore – 560 072; E-mail: madhes@isec.ac.in.

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this industry without creating much pressure on its scarce resource as well as on its environment, it is necessary to put in substantial efforts in terms of increasing energy use efficiency and thereby reducing carbon dioxide emissions.

However, in the Indian context, not much attention has been devoted to examine the issue of energy related CO_2 emission in general and industrial emission analysis in particular. Paul and Bhattacharya (2004) used decomposition method to decompose the observed changes in the energy-related CO_2 emissions into four factors: pollution coefficient, energy intensity, structural changes and economic activity. The results of their study show that economic growth has the largest positive effect on CO_2 emission changes in all the major economic sectors. Emissions of CO_2 in industrial and transport sectors show a decreasing trend due to improved efficiency and fuel switching. The study of Nag and Parikh (2000) also tries to analyze the impact of different factors such as activity levels, structural changes, energy intensity, and fuel mix and fuel quality on the changes in the aggregate carbon intensity of the economy for the period 1970-1995. Srivastava (1997) presents some indicators of energy use in India including per capita energy consumption levels, the structure of energy consumption as well as the efficiency of its utilization over the recent decades.

Reviewing the existing studies of energy related CO_2 emission in the Indian context, we can conclude that the studies have considered the observed level of CO_2 emission as given and try to identify the factors affecting it. Since carbon dioxide is an undesirable by-product generated as a result of combustion of fossil fuels, efficiency of CO_2 management can be better analyzed within a joint production framework of both desirable and undesirable output. Following the recent developments in Data Envelopment Analysis (DEA) literature, carbon dioxide can be incorporated into the production function either as an input or as an undesirable output. To the best of our knowledge, none of the studies in India has examined the issue of energy related CO_2 emission in this fashion. The present study makes an attempt to construct an environmental performance index in terms of CO_2 emission, which we consider as environmental efficiency of the Indian cement industry across different states. Within the production theoretic framework, we have considered carbon dioxide as an environmentally detrimental input in one context and as an undesirable output (by-product) in the other.

The paper is organized as follows. Section 2 presents different kinds of DEA model formulation for measuring environmental efficiency. Section 3 discusses the data and modeling issues. Section 4 presents empirical results and section 5 provides concluding remarks.

Measuring environmental efficiency using DEA

Carbon dioxide as an environmentally detrimental input

One strand of literature considers emitted CO_2 as one of the inputs in the production function. If emissions are treated as inputs, they serve as a proxy for the use of environment in the form of its assimilative capacity. An increase (decrease) in the quantity of a pollutant emitted represents an increase (decrease) in the use of environment's purification services (Färe *et al* 2007). Pittman (1981), Cropper and Oates (1992) and Reinhard *et al* (2000) followed this approach of considering emissions as input. They specify a production function which includes a vector of conventional inputs and the quantity of waste discharge. Waste emissions are simply treated as another factor of production. According to this line of research, emissions are considered as inputs because like inputs, reduction in these emissions also results in reduced output. But in case of emissions, reduction in output occurs not because emissions have productive use but because firms divert some of their productive resources towards reducing emissions. When we consider carbon dioxide as an input in the production process, the environmental efficiency is defined in either of the two following ways. In the first case, it is defined as the ratio of minimum feasible to observed levels of inputs, conditional on observed level of inputs. In other words, it is computed as the ability of a decision making unit (DMU) to contract both conventional and environmentally detrimental input (here CO_2) equiproportionately for a given level of output, holding input proportions constant. So defined, environmental efficiency is a radial input-oriented measure of technical efficiency that allows for a radial reduction of conventional as well as environmentally detrimental inputs. These models are the original DEA formulation of Banker, Charnes and Cooper (BCC, 1984)[2]. The BCC DEA model for measuring the input oriented technical efficiency of a DMU with the initial input-output bundle (x_0, y_0) is represented by model (1).

BCC DEA Model:

$$\theta^* = \min \theta$$

Subject to the following constraints:

$$\sum_{j=1}^{n} x_{ij}\lambda_j \le \theta x_{i0} \quad \text{; (i= capital, energy, labor, material,)} \qquad \text{(i)}$$

(1)

$$\sum_{j=1}^{n} x_{cj}\lambda_j = \theta x_{c0} \quad \text{; (Carbon dioxide)} \qquad \text{(ii)}$$

$$\sum_{j=1}^{n} y_j\lambda_j \ge y_0 \quad \text{; (Output),} \qquad \text{(iii)}$$

$$\sum_{j=1}^{n} \lambda_j = 1 \qquad \text{(iv)}$$

$$\lambda_j \ge 0,\ j = 1,2,.....,n \qquad \text{(v)}$$

where *j* is indexed as firm.

Model 1 assumes that the objective of the firms is to reduce *all inputs* to the largest extent possible by same proportion. Note that inequality (iii) ensures that the resultant output is no lower than what is actually being produced. Inequality (iv) indicates that the production set is convex and allows for variable return to scale. An efficient DMU will have $\theta^* = 1$ implying that no equiproportionate reduction in inputs is possible, whereas an inefficient DMU will have $\theta^* < 1$. From model (1), the optimal value of θ reveals to us the radial contraction in all inputs that is possible for the firm while producing the given output.

The environmental efficiency measure obtained from model (1) is most appropriate when our objective is to contract all the inputs equiproportionately; but if we are interested in knowing what is the maximum possible reduction in *carbon dioxide* only, and define environmental efficiency as the ability of the producer to contract *carbon dioxide to* the largest extent possible , that will still allow the firm to produce the observed level of output (or more), without requiring any additional quantities of any other inputs, the relevant BCC type DEA model to measure environmental efficiency for a DMU, with the input-output bundle (x_0, y_0), can be developed as in model (2).

DEA Model (2):

$$\beta^* = \min \beta,$$

Subject to the following constraints

$$\sum_{j=1}^{n} x_{cj}\lambda_j = \beta x_{c0} \text{ ; (Carbon dioxide)} \qquad \text{(i)}$$

(2)

$$\sum_{j=1}^{n} x_{ij}\lambda_j \le x_{i0} \text{ ; (i= capital, energy, labor, material,)} \qquad \text{(ii)}$$

$$\sum_{j=1}^{n} y_j\lambda_j \ge y_0 \text{ ; (Output),} \qquad \text{(iii)}$$

$$\sum_{j=1}^{n} \lambda_j = 1 \qquad \text{(iv)}$$

$$\lambda_j \ge 0,\ j = 1,2,.....,n \qquad \text{(v)}$$

The objective here is to reduce only the environmentally detrimental input, carbon dioxide, to the maximum extent possible. In doing so, it is not required that other inputs also be reduced. However, inequality (ii) ensures that the other inputs are not increased at the optimum solution. Inequality (iii) ensures that output produced at the optimum level is no lower than what is actually being produced. Unlike model (1), model (2) provides for non-radial input-oriented measure of technical efficiency that allows for radial contraction of only environmentally detrimental inputs. Models (1) and (2) are appropriate for measuring environmental efficiency when the underlying policy objective is to reduce emissions of carbon dioxide and maintain the quality of environment. In model (1), all inputs are required to be reduced simultaneously while the focus of model (2) is to reduce the emission of carbon dioxide only to the largest extent possible.

Carbon dioxide as an undesirable bad output

The two models, described in the earlier section, consider pollutant as an input in the form of using purification services of the environment. However, this approach has a major drawback because in this approach each unit of pollutant emitted is assumed to use the same quantity of purification services regardless of where or when the emissions are produced. This assumption may not be valid always (Färe *et al* 2007). Moreover, modeling undesirable outputs as inputs seems problematic in the sense that we generally think of inputs that are strongly disposable and production set is not bounded in those inputs. Now, if we think of a total product curve with input on the horizontal axis and output on the vertical axis, unlimited increase in undesirables (keeping other inputs constant) is not technically possible; and hence, violates our assumption of unbounded output set (Färe and Grosskopf, 2004). Due to these technical problems, most of the recent studies avoid considering pollution as an input in the production process. Another body of literature (e.g., Taskin and Zaim, 2000; Zaim and Taskin, 2000) estimates environmental efficiency (considering only undesirable output) and industrial efficiency (considering only desirable output) separately and then take a ratio of the two to calculate efficiency of the production unit in the presence of undesirable output; but this method implicitly assumes that production of undesirable output is independent of the production of desirable output, which calls for further improvements (Watanabe and Tanaka, 2007).

The other strand of literature models the production of desirable and undesirable output in a joint production theoretic framework and extends the traditional analysis of efficiency (Farrell, 1957). The notable contributions include the pioneering work by Färe *et al* (1989). They treat environmental effects as undesirable outputs while developing a hyperbolic efficiency measure defined as the ability of a producer to a simultaneous increase in desirable outputs and reduction in undesirable output by same proportion. They assume both strong and weak disposability condition regarding the disposal of undesirable output and use nonparametric Data Envelopment Analysis (DEA) to construct the best-practice production frontier for calculating hyperbolic efficiency (i.e., graph efficiency) measure based on the frontier. Färe *et al* (1993) also treat pollution as an undesirable output and introduce the use of parametric mathematical programming to calculate hyperbolic efficiency measure and shadow prices of undesirable output. But the hyperbolic efficiency measure does not assume "null-jointness" of desirable and undesirable output which is the more realistic assumption to reflect that any production of desirable output should be accompanied by a positive production of undesirable also.

More recently, the directional (technology) distance function has been applied in the literature to represent the technology. It is based on Luenberger's (1992) benefit function (see Chambers *et al* 1996a; Färe and Grosskopf , 2000; Färe *et al* 2005). The directional distance function is an extension of Shephard's input and output distance function (Chambers *et al* 1996b), which provides a basis for representing the joint production of *desirable* and *undesirables*. In this study, we also employ the directional distance function to estimate the environmental efficiency of the firms where environmental efficiency is defined as the ability of a producer to expand the desirable output and contract the undesirable one by same proportion without increasing the inputs. Advantage of directional distance function is that it helps in measuring not only environmental efficiency but also pollution abatement cost arising from environmental regulation. Färe *et al* (2003) interpret cost of regulation as the foregone output for diverting some of the productive resources towards pollution abatement activities. Picazo-Tadeo *et al* (2005) also define cost of regulation in terms of lower feasible expansion of good output resulting from environmental regulation which prevents free disposal of undesirable outputs. This paper differs from Färe *et al* (2003) and Picazo-Tadeo *et al* (2005) in that it scales both *desirable* output and *undesirable* output instead of scaling only *desirable* output (as done by Färe *et al* 2003) or scaling *desirable* output and *inputs* (as done by Picazo-Tadeo *et al* 2005).

Let us consider a production process that uses a vector of N input $x = (x_1, x_2, \ldots\ldots, x_N) \in \Re_+^N$ to produce a vector of desirable output $y = (y_1, y_2, \ldots. y_M) \in \Re_+^M$ and a vector of undesirable output $b = (b_1, b_2, \ldots b_J) \in \Re_+^J$. The relationship between input and output is represented by the following output set:

$$P(x) = \{(y, b) : x \text{ can produce } (y, b)\}, x \in \Re_+^N . \qquad \text{(a)}$$

The output set is assumed to have the following properties. The first is "null-jointness" which implies that production of a positive amount of desirable output must be accompanied by some amount of undesirable one. Formally, null-jointness implies that:

$$(y, b) \in P(x); b = 0 \Rightarrow y = 0 \qquad \text{(b)}$$

The second assumption is that desirable and undesirable outputs are jointly weakly disposable:

$$(y, b) \in P(x) \text{ and } 0 \leq \theta \leq 1, \text{ then } \theta(y, b) \in P(x) \qquad \text{(c)}$$

This implies that a reduction in undesirable output is not possible without reducing the desirable output. So disposal of undesirable output may not be a free activity. In the face of environmental regulation, reducing undesirable output involves a cost in terms of forgone desirable output. The third assumption is known as strong disposability of desirable output:

$$(y, b) \in P(x) \text{ and } y^0 \leq y, \text{ then } (y^0, b) \in P(x) \qquad \text{(d)}$$

This implies that desirable output can be reduced without reducing the undesirable one. So in our model, desirable and undesirable outputs are treated asymmetrically in terms of their disposal. Fig.1 depicts the output set, $P(x)$, for a case of one desirable output and one undesirable output. Both weak and strong disposability are assumed with respect to the disposal of undesirable output and it is also assumed that under weak disposability of undesirable output firms face environmental regulation and operate under regulated technology, whereas strong disposability of undesirable output implies that disposal of undesirable output is cost free and firms operate under unregulated technology.

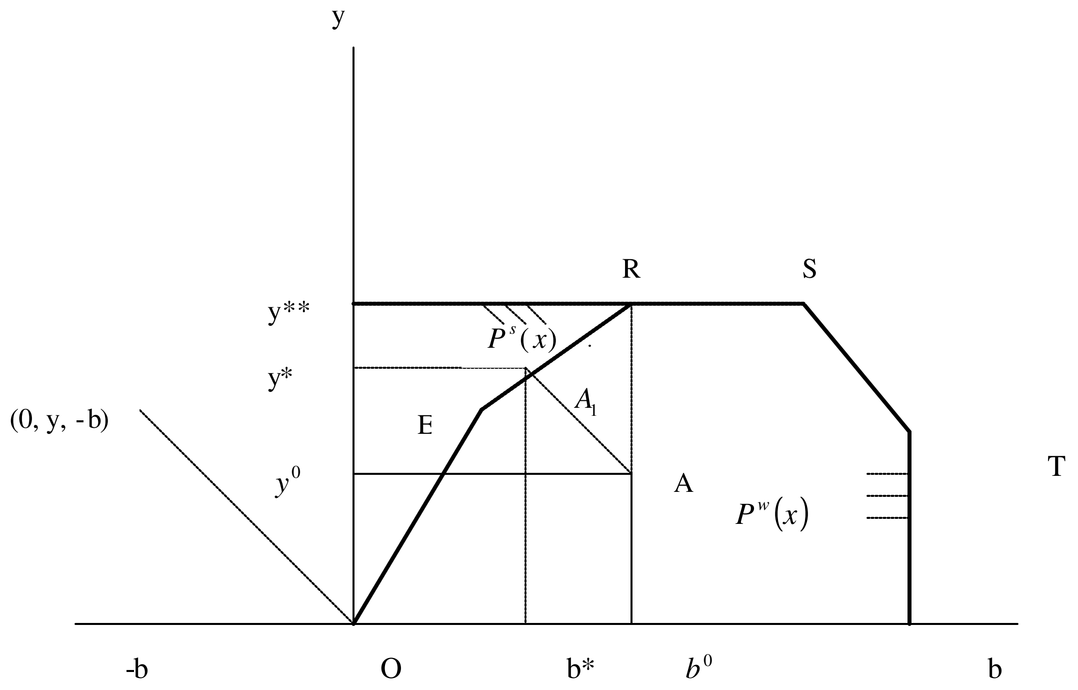

Fig.1. Directional technology distance function and environmental regulation.

In Fig 1, y denotes *desirable* output and b denotes the *undesirable* one. The region Oy**RSTb denotes output set, $P^s(x)$ under unregulated technology and OERSTb denotes output set $P^w(x)$ under regulated technology. The output set under regulated technology satisfies the "null-jointness" property because the only point common between the good output (y-axis) and the output set $P^w(x)$ is the origin O, and b is a by product of y. On the other hand, output set under unregulated technology does not satisfy the "null-jointness" property because there are so many other common points (between O and y**) between the good output (y-axis) and the output set $P^s(x)$. So any production plan between O and y** is not associated with a positive production of bad, implying that unregulated technology may not always be consistent with joint production of good and bad output. Suppose, the initial production plan is at A, where y^0 amount of desirable and b^0 amount of undesirable output is produced, the directional technology distance function locates the productive plan A on the boundary of the regulated output set at A_1. Therefore, the distance $A\ A_1$ measures productive technical inefficiency (Picazo-Tadeo *et al* 2005). Now, assume that firms face no environmental regulation, i.e. undesirable output is freely disposable; under this no regulation scenario, firms' strategy would be to increase good output while maintaining same b^0 amount of undesirable output. So directional technology distance function, under free disposability condition, locates the productive plan A at R which is on the boundary of unregulated output set. It is clear from the diagram that efficient output (y**) under unregulated technology happens to be larger than the efficient output (y*) under regulated technology. So the difference between y** and y* measures the cost of regulation in terms of foregone output. If this difference nullifies to zero, then regulation turns out to be non-binding for that particular productive unit.

In presence of undesirable output, if our objective is to simultaneously expand the desirable output and reduce the undesirable one by same proportion without increasing the inputs, the directional technology distance function becomes

$$\overrightarrow{D_T}(x, y, b; 0, y, -b) = \sup\left[\beta : \left[(1+\beta)\, y, (1-\beta)\, b\right] \in P(x)\right] \qquad \text{(e)}$$

The value β represents technical inefficiency denoted by the distance AA_1 in Fig.1. The direction vector $g = (g_x, g_y, -g_b) = (0, y, -b)$ determines the direction in which efficiency is measured. Given the technology and direction vector, the directional distance function measures the maximum feasible expansion of desirable output and contraction of undesirable output. For an efficient firm, operating on the frontier, the value of directional distance function, β, is zero. The directional distance function, β, is obtained by solving the maximization problem in model (3):

Maximize β

Subject to

$$\sum_{j=1}^{n} \lambda_j y^j - \beta y^0 \geq y^0; \qquad \text{(i)}$$

$$\sum_{j=1}^{n} \lambda_j b^j + \beta b^0 = b^0; \qquad \text{(ii)}$$

$$(3) \qquad \sum_{j=1}^{n} \lambda_j x^j \leq x^0; \qquad \text{(iii)}$$

$$\sum_{j=1}^{n} \lambda_j = 1; \qquad \text{(iv)}$$

$$\lambda_j \geq 0 \quad (j = 1, 2, \ldots.., n) \qquad \text{(v)}$$

Strong disposability of desirable output and weak disposability of undesirable output are imposed through inequality (i) and (ii) respectively in Model (3).

Next, we consider that the firms face no environmental regulation in terms of disposability of undesirable output. Under no regulation scenario, disposal of undesirable output is a free activity, i.e. strong disposability applies to both desirable and undesirable output. Under this new scenario, the distance function, β, is obtained by solving the following programming problem:

Maximize β

Subject to

$$\sum_{j=1}^{n} \lambda_j y^j - \beta y^0 \geq y^0 ; \qquad \text{(i)}$$

$$\sum_{j=1}^{n} \lambda_j b^j + \beta b^0 \leq b^0 \qquad \text{(ii)}$$

(4) $$\sum_{j=1}^{n} \lambda_j x^{j} \leq x^0 ; \qquad \text{(iii)}$$

$$\sum_{j=1}^{n} \lambda_j = 1 ; \qquad \text{(iv)}$$

$$\lambda_j \geq 0 \quad \left(j = 1,2,.....,n\right) \qquad \text{(v)}$$

Where strong disposability of undesirable output has been introduced transforming the equality (3)-(ii) into the inequality (4)-(ii).

Construction of the production frontier

Now, we need to discuss the construction of the production frontier based on which efficiency is measured. First of all, we assume that variable returns to scale hold. Secondly, for each year, we construct a '*sequential frontier'* which assumes all current and past observations as feasible.[3] Starting with a reference sample of 20 observations for the year 2000-01, we successively enlarge the reference sample by including the observations for one more year. For example, sample firms for 2001-02 consist of firms available in 2000-01 plus the existing firms in 2001-02. Conceptually, a sequential frontier amounts to assuming that there is no technical regress, and that any technical regress will be assimilated with inefficiency by this construction.[4]

Data consolidation

The state- level data of the Indian cement industry for the years 2000-01 through 2004-05 has been extracted from the Annual Survey of Industries (1998 NIC code 269) for the relevant years. The study covers 20 major states in terms of cement production. We conceptualize a single output, four input production function for the cement industry in India. Output is measured by value of ex-factory products and by- products in the state, deflated by the whole sale price index for cement. The inputs include (i) capital, (ii) energy, (iii) labor, (iv) materials. Undesirable by-product is measured by carbon dioxide (CO_2)[5]. The capital input is measured as a stock by taking the value of fixed capital, deflated by the wholesale price index for machinery and machine tools. Labor is measured by the total number of production workers. Energy is measured by the expenditure on fuels deflated by the wholesale price index for fuel, power, light and lubricant. Similarly, the material input is measured by the expenditure on materials, deflated by wholesale price index for non-metallic mineral products. All inputs and outputs are divided by the total number of factories in a particular state so that we can examine environmental efficiency of a 'typical firm' within each state.[6] Descriptive statistics of the variables are presented in Table 1.

Table 1: Descriptive statistics of the variables

Variable	Output	CO_2	Capital	Energy	Labor	Material
Mean	3.46	0.24	3.82	0.62	41.00	1.33
Std. Dev.	4.74	0.45	9.05	1.02	22.00	1.13
Min	0.19	0.0025	0.12	0.0035	15.00	0.049
Max	23.09	1.84	72.62	4.34	87.00	5.23

Note: All nominal variables are converted into real variables with 1993-94 as the base. Output, capital, energy and material variables are in Rs.Lakh and labor in number and CO_2 in tonnes.

Calculation of CO_2 emissions[7]

In the present study, CO_2 emission is estimated from the coal use because coal constitutes a major share in the total fuel consumption by the cement industry with the share of other fuels, which also can produce CO_2, being negligible. CO_2 emission is estimated by taking into account the carbon emission factor of coal (25.8), the fraction of oxidized carbon of coal (0.98) and molecular weight ratio of carbon dioxide to carbon (44/12). Following the method of the IPCC (1995), the sectoral CO_2 emission of the i th fuel is obtained from the following relationship:

$$EC_i(t) = C_i(t) \times O_i \times N_i \times M,$$

where $EC_i(t)$ is the carbon dioxide emission of the ith fuel at time t; $C_i(t)$ is the consumption of ith fuel at time t; O_i is the carbon emission factor of the ith fuel; N_i is the fraction of carbon oxidized of the ith fuel and M is the molecular weight ratio of carbon dioxide to carbon (44/12).

According to IPCC (1995) guidelines, the following steps have been performed to calculate CO_2 emissions from the consumption of a particular fuel.

(a) Energy consumption data in million tones of oil equivalent (MTOE) is converted to terajoules (TJ) unit using standard conversion factors.

(b) Total carbon emission (tones of carbon), TC, is estimated by multiplying fuel the fuel consumption (terajoules) by the carbon emission factor (TC/TJ) of the corresponding fuel.

(c) Total carbon emission is then multiplied by the fraction of carbon oxidized and the molecular weight ratio of carbon dioxide to carbon to find the total carbon dioxide emitted from fuel combustion.

Empirical Results

Table 2 presents the input oriented measures of technical efficiency based on DEA model (1). The overall technical efficiency or environmental efficiency of the states under study during the study period was 0.9391 implying that it would be possible to reduce all the inputs, including carbon dioxide, proportionately by 6.09% and still produce the given level of desirable output. However, efficiency varied across years and states. While Gujarat, Kerala, Punjab, Uttaranchal, Uttar Pradesh, Himachal Pradesh, Chattisgarh and West Bengal demonstrated 100% technical efficiency each year, Tamil Nadu, Haryana, and Jammu& Kashmir achieved technical efficiency close to 100%. On the other hand, states like Andhra Pradesh, Karnataka, Maharastra, Madhya Pradesh and Rajasthan were found with the lowest level of technical efficiency. Average environmental efficiency was 0.9590 in 2000-01 but it declined to 0.9538 in 2004-05.

Table 2: Environmental efficiency based on input oriented technical efficiency model

State	2000-01	2001-02	2002-03	2003-04	2004-05	Annual average
AP	0.8824	0.4587	0.4343	0.7359	0.7498	0.6522
AS	1.0000	0.9486	0.8683	0.8768	1.0000	0.9387
BI	1.0000	1.0000	0.8486	0.8633	1.0000	0.9424
CT	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
GU	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
HA	1.0000	0.9017	1.0000	1.0000	1.0000	0.9803
HP	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
JK	1.0000	1.0000	1.0000	1.0000	0.9970	0.9994
JH	0.8161	0.8539	0.9256	0.9417	1.0000	0.9075
KA	0.8198	0.7480	0.7496	0.7752	0.8645	0.7914
KE	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
MP	0.8190	1.0000	0.8239	0.7954	0.9806	0.8838
MA	1.0000	0.7715	0.8565	1.0000	0.7841	0.8824
OR	1.0000	0.7893	0.9402	0.9951	0.8376	0.9125
PU	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
RA	0.8435	1.0000	0.9152	0.8462	0.9241	0.9058
TN	1.0000	0.9836	1.0000	1.0000	0.9392	0.9846
UP	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
UT	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
WB	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
State average	**0.9590**	**0.9228**	**0.9181**	**0.9415**	**0.9538**	**0.9391**

Notes:

1. AP- Andhra Pradesh, AS Assam, BI- Bihar, CT- Chattisgarh, GU- Gujarat, HA- Haryana, HP- Himachal Pradesh, JK- Jammu & Kashmir, JH- Jharkhand, KA- Karnataka, KE- Kerala, MP- Madhya Pradesh, MA- Maharashtra, OR- Orissa, PU-Punjab, RA-Rajasthan, TA- Tamil Nadu, UP- Uttar Pradesh, UT- Uttaranchal, WBWest Bengal.
2. State average is the average efficiency of the 20 states for a given year. Annual average is the average for a given state over 5 years.

While the objective in Model (1) is to contract all inputs, the objective of the firms could be to simply minimize carbon dioxide to the largest extent possible without increasing any other inputs or reducing output. Environmental efficiency based on this definition is estimated using Model (2). The results from this model are presented in Table 3. The average emission efficiency of these states over the 5years is 0.7113. Although the measured efficiency, on an average, is very low, Gujarat, Kerala, Punjab, Uttaranchal, Uttar Pradesh, Himachal Pradesh, and West Bengal achieved 100% environmental efficiency in each year, even by this measure. Jammu & Kashmir followed closely behind with an average efficiency of 99.77%, while Tamil Nadu and Haryana also were found with efficiency of more than 90%. At the other extreme Orissa, Karnataka, Jharkhand, Maharastra and Andhra Pradesh were found to be the worst performers by this measure of environmental efficiency. In this model also, environmental efficiency declined from its initial value of 0.8154 in 2000-01 to 0.7309 in 2004-05. However, by focusing on the carbon dioxide input only, model (2) allows for greater potential for emission reduction at the optimal solution.

Table 3: Environmental efficiency based on carbon dioxide minimization

State	2000-01	2001-02	2002-03	2003-04	2004-05	Annual average
AP	0.6352	0.0363	0.0336	0.2387	0.2122	0.2312
AS	1.0000	0.2166	0.1791	0.1658	0.5518	0.4227
BI	1.0000	0.4873	0.1771	0.3190	1.0000	0.5967
CT	0.5583	0.3995	0.4655	0.4724	0.4659	0.4723
GU	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
HA	1.0000	0.5790	1.0000	1.0000	1.0000	0.9158
HP	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
JK	1.0000	1.0000	1.0000	1.0000	0.9883	0.9977
JH	0.1771	0.2868	0.1660	0.2911	1.0000	0.3842
KA	0.4936	0.5027	0.3678	0.2935	0.2654	0.3846
KE	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
MP	0.5503	0.4637	0.6069	0.5984	0.4574	0.5354
MA	0.2221	0.2246	0.3271	0.4037	0.2325	0.2820
OR	1.0000	0.1781	0.2466	0.4544	0.1092	0.3977
PU	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
RA	0.6722	1.0000	0.6673	0.4182	0.6747	0.6865
TN	1.0000	0.9331	1.0000	1.0000	0.6599	0.9186
UP	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
UT	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
WB	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
State average	**0.8154**	**0.6654**	**0.6619**	**0.6828**	**0.7309**	**0.7113**

The environmental efficiency measures, obtained from the earlier two models, are based on the assumption that carbon dioxide is an input in the production process. Since this assumption is not consistent with the production theory, we have next estimated environmental efficiency of the firms by considering carbon dioxide emission as an undesirable output using model (3) and model (4). These models estimate the value of directional distance function representing environmental inefficiency. Table 4 and Table 5 present values of directional distance function under weak and strong disposability assumption respectively.

Table 4: Values of directional distance function based on weak disposability assumption

State	2000-01	2001-02	2002-03	2003-04	2004-05	Annual average
AP	0.1347	0.7228	0.6351	0.2675	0.2719	0.4064
AS	0.0000	0.1150	0.1592	0.1495	0.0000	0.0847
BI	0.0000	0.0000	0.3511	0.2304	0.0000	0.1163
CT	0.0000	0.3874	0.0000	0.0000	0.0000	0.0775
GU	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
HA	0.0000	0.0919	0.0000	0.0000	0.0000	0.0184
HP	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
JK	0.0000	0.0000	0.0000	0.0000	0.0024	0.0005
JH	0.2384	0.1527	0.0728	0.0534	0.0000	0.1034
KA	0.1845	0.2121	0.2502	0.2381	0.1405	0.2051
KE	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
MP	0.2478	0.2934	0.2048	0.2163	0.1614	0.2247
MA	0.0376	0.2625	0.1046	0.0000	0.2153	0.1240
OR	0.0000	0.2665	0.0390	0.0032	0.2117	0.1041
PU	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
RA	0.1172	0.0000	0.0764	0.1561	0.0686	0.0836
TN	0.0000	0.0141	0.0000	0.0000	0.0579	0.0144
UP	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
UT	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
WB	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
State average	**0.0480**	**0.1259**	**0.0947**	**0.0657**	**0.0565**	**0.0782**

Note: A zero value of directional distance function (DDF) implies 100% efficiency, i.e. neither desirable output can be increased nor undesirable output can be reduced.

Table 4 shows that the average value of the distance function obtained from model (3), which assumes weak disposability of undesirable output, is 0.0782 implying that it is possible to increase the desirable output by 7.82% and contract the undesirable output by 7.82% without increasing the inputs. Therefore, environmental efficiency from weak disposability model is 92.18%. Once again states like Gujarat, Kerala, Punjab, Uttaranchal, Uttar Pradesh, Himachal Pradesh, and West Bengal achieved 100% environmental efficiency in each year because the average values of directional distance function in each year were zero for these states and Tamil Nadu and Jammu& Kashmir achieved environmental efficiency close to 100% with average value of distance function being 0.0144 and 0.0005 respectively.

On the other hand, Table 5 shows average value of the distance function obtained from model (4) which assumes strong disposability of the undesirable output with the average value of the distance function being 0.0883 implying a possibility of increasing the good output by 8.83% and reducing the bad by 8.83% without increasing the inputs. Therefore, environmental efficiency from strong disposability model is 91.17%. The states, which were 100% efficient in earlier models, are found efficient in this model also. But states like Andhra Pradesh, Madhya Pradesh, Karnataka and Bihar show the lowest level of environmental efficiency in both model (3) and model (4). In both the models, average value of the directional distance function increased in 2004-05 as compared to the value in the initial year implying an increase in inefficiency or decrease in efficiency.

Table 5: Values of directional distance function under strong disposability assumption

State	2000-01	2001-02	2002-03	2003-04	2004-05	Annual average
AP	0.1347	0.7228	0.6351	0.2675	0.2719	0.4064
AS	0.0000	0.1434	0.1592	0.1495	0.0115	0.0927
BI	0.0000	0.1083	0.3511	0.2304	0.0000	0.1379
CT	0.0648	0.3909	0.2412	0.2208	0.1274	0.2090
GU	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
HA	0.0000	0.0919	0.0000	0.0000	0.0000	0.0184
HP	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
JK	0.0000	0.0000	0.0000	0.0000	0.0024	0.0005
JH	0.2384	0.1527	0.0728	0.0592	0.0000	0.1046
KA	0.1845	0.2121	0.2502	0.2381	0.1793	0.2128
KE	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
MP	0.2478	0.2934	0.2048	0.2163	0.1919	0.2308
MA	0.0935	0.2625	0.1046	0.0211	0.2153	0.1394
OR	0.0000	0.2665	0.0515	0.0272	0.2282	0.1147
PU	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
RA	0.1172	0.0000	0.0764	0.1561	0.0686	0.0836
TN	0.0000	0.0141	0.0000	0.0000	0.0579	0.0144
UP	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
UT	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
WB	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
State average	**0.0540**	**0.1329**	**0.1073**	**0.0793**	**0.0677**	**0.0883**

In order to verify whether efficiency scores, based on weak disposability assumption, are different from those obtained from strong disposability assumption; the Wilcoxon Rank Sum test[8] has been conducted. The null hypothesis is that efficiency scores obtained from the two models have the same population of relative frequency distribution. The value of Wilcoxon statistic is 3 and the value of two tailed 'p' statistic is 0.0024. So the null hypothesis can be rejected at 1% level, implying that assumption regarding the disposability of the undesirable output brings about significant difference in the value of directional distance function. Under strong disposability assumption, the good output, on an average, can be increased by 8.83% while that can be increased by 7.82% under weak disposability assumption. Therefore, environmental regulation, in the form of costly disposal of bad output, causes a reduction in the capability of expanding good output which can be viewed as the cost of regulation in terms of lower feasible expansion of desirable output. Comparing the environmental efficiency scores obtained from the two different approaches- pollution as an input in one case and undesirable output in the other- we find that pollution as an input produces higher input oriented radial technical efficiency or environmental efficiency, but substantially lower nonradial technical efficiency or environmental efficiency as compared to the situation where pollution is considered as undesirable output.

We have constructed CO_2 emission data from coal consumption with the conversion formula indicating CO_2 emission from a state is a positive linear function of its coal consumption. Now, consumption and efficient use of coal by a state may depend on its level of production, and in that way, production of coal may also influence the environmental performance of a state. So we have, next, examined the correlation between environmental performance of a state and its coal production. Table 6 presents annual coal production (in million tones) of various states over the period 2000-01 to 2004-05. Gujarat, Kerala, Punjab, Uttaranchal, Uttar Pradesh, Himachal Pradesh, and West Bengal are found to be the best performing states in terms of environmental efficiency, but Table 6 also shows that except Uttar Pradesh and West Bengal, all other best performing states happened to be non-producers of coal. On the other hand, Jharkhand, Orissa, Madhya Pradesh and Andhra Pradesh turns out to be the largest producers of coal, but in terms of environmental efficiency they are the worst performers, implying that states with higher availability of coal, experience overall mismanagement of this resource and there by experience poor performance in environmental efficiency.

Table 6: Coal production of various states (in million tonnes)

State	2000-01	2001-02	2002-03	2003-04	2004-05	Annual average
AP	30.3	30.8	33.2	33.9	35.3	32.7
AS	0.7	0.6	0.6	0.7	0.6	0.64
BI	41.9	N.A	N.A	N.A	N.A	N.A
CT	22.8	53.6	56.7	61.5	69.1	52.74
JH	33.5	76.8	78.6	79.5	78	69.28
MP	69.9	44.2	45.7	49.8	52.7	52.46
MA	28.8	30.8	31.4	32.9	34.5	31.68
OR	44.8	47.8	52.2	60.1	66.1	54.2
UP	16.9	16.5	17.8	15.8	16.8	16.76
WB	20.1	21.4	20.5	21.5	23.6	21.42
State Average	**30.97**	**41.59**	**43.27**	**45.87**	**48.69**	**36.88**

Source: Economic Intelligence Service (Energy), Centre for Monitoring Indian Economy (CMIE), 2008(November).

Concluding remarks

Cement production requires massive utilization of energy, mostly in the form of coal, resulting in the generation of a considerable amount of carbon dioxide emission as an undesirable by-product. Thus, this paper makes an attempt to estimate environmental efficiency of the Indian cement industry within a joint production framework of desirable and undesirable output using different types of DEA models. In one context, carbon dioxide is considered as an input in the production process with the environmental efficiency being defined as the ability of a producer to reduce carbon dioxide emission without reducing the desirable output, whereas, pollution is considered as an undesirable by-product in the other context with environmental efficiency being defined as the ability of a producer to simultaneously expand the desirable output and contract the carbon dioxide emission by the same proportion without increasing inputs. Using 3 digit sate level data from the Annual Survey of Industries for the years 2000-01 through 2004-05, the proposed models have been applied to estimate environmental efficiency of Indian cement industry. The empirical results show that compared to the initial year, 2000-01, the average environmental efficiency measures, derived from all the four models, declined in 2004-05. Estimates of environmental efficiency, however, depend on how we model pollution- as an input or as an undesirable output. Regarding the correlation between availability of coal in a state and its environmental performance, results show that, larger the availability of coal in a particular state, lower is the environmental efficiency experienced by it. Results also show that Indian cement industry, if subjected to environmental regulation, has the potential of expanding desirable output and reducing the undesirable one from the given inputs. However regulation has a potential cost in terms of lower feasible expansion of desirable output as compared to unregulated scenario because to control pollution, firms are bound to divert some of their productive resources that could, otherwise, have been used for producing desirable output.

Limitation of the paper is that we have been unable to explain the interstate variations in environmental efficiency using a second stage regression analysis due to two reasons. *Firstly*, lack of systematic state specific data regarding environmental regulation, monitoring and abatement expenditure specifically for controlling CO_2 emission. *Secondly,* in our present context, second stage regression analysis may not be permissible because we have constructed the CO_2 emission data indirectly from the fuel consumption data and hence, it is not an actual observed data regarding CO_2 emission. Different states may undertake different measures for reducing CO_2 emission, and in that case, our indirectly constructed data may not be a true representation of actual CO_2 emission. Nevertheless, this study, using several DEA type linear programming models, highlights the potential for reducing CO_2 emission and thereby improving environmental efficiency of Indian cement industry at the state level.

End Notes

[1] Intergovernmental Panel for Climate Change

[2] For a detailed exposition of DEA, see Ray, 2004 and Coelli et.al. 1998.

[3] The concept of '*sequential frontier*' has been used by Mukherjee (2008) also.

[4] We assume no technical regress because of the short span of our study period where technical regress may not be a conceptually valid assumption. Moreover, the assumption of no technical regress seems to make sense for the sample years under study during which the Indian industrial sector has mostly achieved significant improvement in technology (Mukherjee, 2008).

[5] In our study co_2 emissions data has been constructed from fuel consumption data and emission factor. So level of emission is a linear function of fuel used. This may raise some doubts about the rationale for including both energy and co_2 emission in a DEA model. Since co_2 emission is a major by product of energy use, we include both in a production framework to offer a more realistic and specific characterization of the entire production process (Zhou *et al* 2008).

[6] This approximation of getting firm level data from the industry is not absolutely perfect because, here we are assuming that all firms in a particular state produce equally using equal amount of inputs. In the absence of firm level data within the states, we have used this kind of approximation. Mukherjee (2008), in the context of Indian manufacturing, also used the same approximation.

[7] This section draws heavily from Paul and Bhattacharya (2004).

[8] Wilcoxon Rank-Sum test is a nonparametric alternative to the two sample t-test. This test is based solely on the order in which the observations from the two samples fall. Since DEA efficiency scores are obtained from nonparametric liner programming model, we have used this nonparametric alternative of t-test.

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