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Shadow Price of CO_2 Emissions in Indian Thermal Power Sector

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Abstract:
This paper estimates production efficiency and shadow prices of CO_2 emissions for thermal power plants in India. It employs a unique sample of 56 power plants for 2000-2013 acquired primarily by invoking the Right to Information (RTI) Act, 2005. It estimates parametric quadratic directional output distance function using linear programming approach. We find that CO_2 intensity of electricity generation could be reduced about 16 and 23 percent if the power plants were made to operate efficiently. The estimated average shadow prices of US$ 14.54 and 18.68 for a ton of CO_2 emission, depending upon a plant's strategies for enhancing electricity and reducing CO_2 emissions, reflects that the prevailing Clean Energy Cess of US$ 6.15 a ton of coal or US$ 3.81 a ton of CO_2 emissions is not enough to induce the required emission mitigation. Significant variation in the estimates of shadow prices calls for the application of economic instruments for cost effective reduction of the emissions.

Keywords: CO_2 emissions, shadow price, directional distance function, thermal power plants, India

JEL Classification: D24, Q25, Q52

1. Introduction

In the energy and climate change debate, the contentious issue that India confronts is of progressing on a low carbon development path. Given large coal reserves, coal based electricity generation contributes about 75 percent of electricity generation and about half of total CO_2 emissions generated in the country (Central Electricity Authority [CEA], 2013). Though CO_2 intensity of electricity generation from thermal power plants has been declining from 1070 gCO_2/kWh in 2009-10 to 1010 gCO_2/kWh in 2014-15 (CEA, 2016), it is much higher than the world averages of 542 and 533 gCO_2/kWh in respective years (IEA, 2015). This paper seeks to explore the possibilities of reducing carbon emissions in coal based power generation cost effectively, a major CO_2 emitting sector in India.

India's emission reduction policies are largely based on command and control (CAC) mechanism and are criticised for lack of economic efficiency (Kumar and Managi, 2009). Therefore, the country has initiated application of market based instruments (MBIs) for realizing goal of energy efficiency and emission reduction in industrial sectors including electricity generation. A program known as PAT (Perform, Achieve and Trade), a market-based energy efficiency trading mechanism, was launched for improving energy efficiency of industrial units in 2012. A sort of carbon tax known as Clean Energy Cess on consumption of coal was introduced. Initially the cess was INR 50 (about US$ 0.75) in 2010-11, which increased to INR 400 (more than US$ 6) in 2016-17. Estimates of marginal abatement cost (MAC) or shadow prices of emissions provide valuable information for devising and improving operations of market based instruments such as carbon taxes or trading (Zhou et al., 2015). This paper intends to estimates shadow prices of CO_2 emissions of thermal power generating plants in India.

There are many ways of estimating MAC[1]; the shadow price of CO_2 emissions may be a reference value to the allowance price in emission trading market or carbon tax rate (Lee et al., 2002). Shadow prices of emissions are derived from the market price of desirable output (e.g., electricity) by exploiting duality between distance and revenue functions. These prices reflect the rate of transformation between desirable output and emissions in a multi-output production setting. Distance functions could be estimated non-parametrically or parametrically by using deterministic or stochastic approaches (Murty et al., 2007; Kumar and Managi, 2010).

We use directional output distance function (DODF) as an analytical tool to derive shadow prices of CO_2 emissions. We parametrically estimate DODF using deterministic approach and exploiting plant level unbalanced panel data of thermal power stations for the period 2000 to 2013. DODF is defined in terms of the translation of a point (corresponding to an output combination) to the frontier along a specified vector. DODF is capable of modelling non-proportional changes in outputs and allows some outputs such as electricity to be expanded while others such as carbon emissions to be contracted in any chosen direction (Chambers et al., 1998; Färe et al., 2005), and provides unambiguous welfare results contrary to output and input distance functions (Murty et al., 2007).

[1] Marginal abatement cost (MAC) means the costs of reducing an additional unit of undesirable output. MAC can be estimated using a computable general equilibrium (CGE) model, a dynamic optimization model, a hybrid model or distance function (Xiao et al., 2017)

Estimates of DODF also inform about deviation of each of the power plants from the boundary of output set, i.e., DODF measures technical and environmental efficiency. The revealed efficiency of thermal power plants helps us to understand the extent of potential to expand electricity generation and contract carbon emissions if the power plants were to operate efficiently. For example, Murty et al. (2007) illustrate that a representative thermal power plant in Andhra Pradesh in India could increase production of electricity by 6 percent while decreasing generation of air pollutants by 6 percent, if they were to operate on the boundary of output set.

We find that thermal power plants in India could reduce emissions of CO_2 and enhance electricity production if they improve their technical and environmental efficiency. A representative average plant has potential to reduce CO_2 intensity of electricity generation by about 16 and 23 percent under strategies 2 and 3 respectively if they were made to operate at the boundary of production set. The estimated average shadow prices of a ton of CO_2 emissions of US$ 2.61, 14.54 and 18.68 respectively for the selected three mitigation strategies imply that the prevailing Clean Energy Cess of about US$ 6.15 on a ton of coal or US$ 3.81 on a ton of CO_2 emissions is not enough to induce a polluter to do the required mitigation.[2] Significant heterogeneity in the estimates of shadow price reflects that economic instruments such as emission trading or carbon emission taxation could be cost effective strategies for accomplishing the pledges taken at the Paris Agreement.

The regression analysis of the determinants of shadow prices of CO_2 emissions reveals that the shadow prices are negatively associated with the load of carbon emissions implying increasing returns to scale in the mitigation. It has been observed that the shadow prices are lower for the plants owned by the central sector than the plants owned by the state governments. We also find a negative association between the average unit size of a plant and the shadow price. From the sample data, it has been witnessed that the average unit size in old plants is low[3], carbon intensity and auxiliary consumption of electricity[4] is high and are using subcritical technology for electricity generation (Figure 1). This calls for renovating and modernizing or retiring the plants that have been using outdated technologies, and adopting new technologies that are efficient in producing higher amount of electricity with less pollution. Application of economic instruments could induce the polluters for modernization and innovation in coal-fired electricity generation in the country.

This study is first in the existing literature on several counts. Firstly, this is perhaps the first study providing comprehensive estimates of marginal abatement costs of CO_2 emissions using a unique set of plant level information of thermal power sector. Secondly, by providing directional vector specific estimates of the shadow prices of CO_2 emissions, it not only examines the robustness of shadow prices but also provides guidance for perspective carbon mitigation strategies to be followed in the sector. Thirdly, we investigate determinates of heterogeneity of the shadow prices in the thermal power sector for each of chosen directional vector. Finally, the estimates of technical and environmental efficiency reflect on the

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[2] Assuming an exchange rate: INR 65 = US$ 1.

[3] Vintage refers to the age of the unit/plant with respect to a reference year (taken to be 2012 in this case). In a thermal power plant, different units are commissioned at different points of time, therefore have different vintages. Therefore, vintage of a plant is the unit size weighted average of the different units in a plant commissioned at different points of time.

[4] Auxiliary power consumption by thermal power stations comprises the power consumption by all the unit auxiliaries as well as the common station requirements such as station lighting, air conditioning etc (CEA, 2016).

potential in the sector of win-win opportunities of expanding electricity output and reduction in CO_2 emissions with given inputs.

Remainder of the paper is organised as follows: In Section 2, we review the related literature. Section 3 describes the analytical model and strategies followed for estimating shadow prices of CO_2 emissions. Process of obtaining the required information and a discussion on variables used in the study has been provided in Section 4. Section 5 discusses estimated results of environmental efficiency and shadow prices of CO_2 in the thermal power industry. Section 6 concludes with some policy implications.

2. Related Literature

Marginal abatement cost (MAC) of CO_2 can be estimated using either production, cost or distance functions. Earlier studies, such as Pittman (1981) and Gollop and Roberts (1985), engaged cost and production functions for estimating shadow prices of water and air pollutants such as BOD, COD, SO_2 and NO_X, respectively. Moreover, the studies conducted in 1980s and 1990s were confined for estimating MAC of criteria air and water pollutants (e.g., Boyd et al., 1996; Färe et al., 1993; Gollop and Roberts, 1985), and empirical studies for estimating shadow prices of CO_2 have intensified recently with an increase in climate change concerns.[5] In the present study we use directional output distance function (DODF) for estimating shadow prices of CO_2 emissions in thermal power sector in India.

There are several studies estimating shadow prices of various pollutants engaging distance function approach both in developed and developing countries, starting with Färe et al. (1993). Application of distance functions for measuring shadow prices of pollutants has been initiated by Färe et al. (1993). Zhou et al. (2014) offer a comprehensive survey of empirical studies estimating shadow prices of undesirable outputs using distance function models in energy sector. Most of the studies are confined to the United States, China, South Korea or other East Asian countries and very few to European countries. Earlier studies (e.g., Färe et al., 1993; Coggins and Swinton, 1996, Swinton, 2002; Kumar and Rao, 2002; Murty and Kumar, 2002; Gupta, 2006) followed same approach and exploited output and input distance functions to estimate shadow prices of pollutants. Output distance function seeks to expand good and bad outputs radially and the welfare gains are ambiguous. However, studies involving directional output distance function allow one to consider non-proportional changes in good and bad outputs and welfare gains are unambiguous. Most of the recent studies, following Färe et al. (2005), employ directional output distance function for estimating shadow prices of bad outputs, environmental and technical efficiency (e.g., Harkness, 2006; Vardanyan and Noh, 2006; Murty et al., 2007; Marklund and Samakovlis, 2007; Park and Lim, 2009; Matsushita and Asano, 2014; Fujii and Managi, 2015; Yagi et al;, 2015; Halkos and Managi, 2017; Johnstone et al., 2017).

Studies estimating shadow prices of pollutants are limited in India, even though India is supposed to provide a leading role in the global climate policy. Kumar and Rao (2002) provide estimates of shadow prices of PM_{10} for 33 thermal power plants for the year 1992-93 using output distance function. Similarly, Gupta (2006) exploiting the radial measure of

[5] For a recent literature survey on the use of distance functions for estimating shadow prices and technical efficiency in the energy sector, see Zhou et al. (2014). This study can also be referred for understanding merits and demerits of various economic tools such as production, cost, input and output distance function and directional distance function in the context.

efficiency, estimates output distance function to calculate the shadow price of CO_2 emissions only for nine thermal power plants operating in the Eastern India for the period of 1990s. Murty and Kumar (2002) offers estimates of shadow prices of water pollutants. However, Murty et al. (2007) is the single study in Indian context that uses DODF for estimating shadow prices of SPM, SO_2 and NO_X and studies only five thermal power plants operating in the state of Andhra Pradesh for the period of 1996-97 to 2003-04. The reason for lack of comprehensive studies estimating shadow prices of carbon emissions could be found in the unavailability of required data. The present study tries to fill the gap using a unique set of information for 56 coal fired thermal power plants for the period of 2000 to 2013. The required information was obtained invoking the Right to Information (RTI) Act 2005[6] and various publications of the CEA and Central Electricity Regulatory Commission (CERC).

Moreover, from the literature it is inferred that shadow price of a pollutant is sensitive to the chosen direction of directional vector in estimation of distance functions (Vardanyan and Noh, 2006; Lee et al., 2014). For example, studies using output distance function (e.g., Coggins and Swinton, 1996) or selecting positive directional vector for both good and bad outputs stipulate lower shadow price of emissions relative to studies that have chosen positive direction for good output and no-change direction for bad output (e.g., Turner, 1994). Boyd et al. (1996) prefer positive direction for good output and negative direction for bad output and offer higher shadow price relative to Turner (1994). Therefore, rather than arbitrarily choosing any particular directional vector in the present study, we choose three different directional vectors consistent with Indian energy and environmental policy in the estimation of environmental efficiency and shadow price of CO_2 emissions. These directional vectors are: positive for both good and bad outputs (strategy 1), positive only for the good output (strategy 2), and positive for good output and negative for bad output (strategy3).

3. Directional Output Distance Function and Shadow Prices

Marginal abatement cost (MAC) of pollutants can be estimated using engineering and economic approaches. Engineering approach requires knowledge on specific abatement technologies and focuses on the capture of technological accomplishments relative to investment cost. Economic approaches involve measured production data for the purpose. Since economic models are based on key factor inputs and outputs, comprehensive characteristics of abatement activities involving production and abatement technologies are captured by these models (Lee et al., 2014). Moreover, presence of technical and environmental inefficiencies could be a reason for the heterogeneity in MAC among polluting firms and economic instruments could be used for smoothing differences in shadow prices (Färe et al., 1993)

Suppose there are K thermal power plants generating a vector of good outputs $y = (y_1, \dots\dots, y_M) \in \Re_+^M$ and bad outputs $b = \left(b_1, \dots\dots, b_J\right) \in \Re_+^J$ using a vector of inputs $x = (x_1, \dots\dots, x_N) \in \Re_+^N$. Transformation of inputs to outputs can be represented through an output correspondence:

$$P(x) = \{(y, b): x \; can \; produce \; (y, b)\}, x \in \Re_+^N \qquad (1)$$

[6] Right to Information (RTI) Act 2005 mandates timely response to citizen requests for government information. (http://righttoinformation.gov.in/).

The output correspondence satisfies the standard assumptions of compactness and free disposability in inputs (Färe et al., 2005). Moreover, it is assumed that the production technology satisfies the condition of null-jointness of good and bad outputs: $if\ (y, b) \in P(x)\ and\ b = 0, then\ y = 0$. This assumption implies that in coal fired thermal power generation sector CO_2 emissions and electricity are generated simultaneously, i.e., in the absence of production of CO_2 emissions in the sector the production of electricity would also be nonexistent. It is also assumed that production of good output is strongly disposable: $if\ (y, b) \in P(x), then\ for\ y_0 \leq y, (y_0, b) \in P(x).$ The condition reflects that the reduction of electricity without reducing CO_2 emissions is attainable. However, with respect to the reduction is CO_2 emissions, it is assumed that any proportional reduction in electricity and CO_2 emissions is attainable, i.e., electricity and CO_2 emissions are jointly weakly disposable: $if\ (y, b) \in P(x)\ and\ 0 \leq \alpha \leq 1, then\ (\alpha y, \alpha b) \in P(x)$. This condition implies that reduction in CO_2 emissions is costly.

Following Färe et al. (2005), directional output distance function (DODF) is defined as the maximal distance between the actual input-output vector and the frontier of the output set in a given directional vector $g \equiv (g_y, -g_b)$, i.e.

$$\vec{D}_O(x, y, b; g_y, -g_b) = \sup\{\beta : (y + \beta g_y, b - \beta g_b)\} \in P(x) \qquad (2)$$

where β is non-negative, scaled to reach the boundary of the output set $P(x)$. DODF seeks to simultaneously maximal expansion of good outputs and maximal reduction in bad outputs. The DODF is an additive measure of inefficiency in a given direction g, where the zero value of DODF implies full efficiency, and a higher value of β means lower technical efficiency. Alternatively DODF could be considered as a measure of technical and environmental inefficiency in the sense that a producer becomes more technically efficient when simultaneously increasing good outputs and decreasing bad outputs. Moreover, DODF is jointly concave in good and bad outputs and non-negative and non-increasing in good outputs and non-decreasing in bad outputs and inputs. It also satisfies translation property.

$$\vec{D}_O(y + \omega g_y, b - \omega g_b, x;\ g_y, -g_b) = \vec{D}_O(y, b, x; g_y, -g_b) - \omega \qquad (3)$$

where ω is a arbitrary scaling factor. This property implies that if good outputs are expanded by ωg_y and bad outputs are reduced by ωg_b then the resulting value of directional output distance function get reduced by ω.

We now turn to the idea of deriving shadow prices of CO_2 emissions by exploiting duality between DODF and revenue function. The idea of using duality between cost function and input distance function or duality between output distance function and revenue function originally comes from Shephard (1970). Färe et al. (1990) is the first study providing estimates of shadow prices using distance function and Färe et al. (1993) is the first study getting shadow prices of bad outputs using duality between output distance function and revenue function. Perhaps Färe et al. (2005) is the first study in the area that derived shadow prices of SO_2 emissions using duality between revenue and directional output distance function. Output distance function projects the observed outputs, including bad outputs, on the boundary of output set by increasing all outputs proportionally, but in case of directional output distance function the projection to the frontier is such that good outputs are expanded but bad outputs are contracted. Therefore, the shadow price reflects a trade-off between good and bad outputs on the boundary of output set $P(x)$. We use duality between revenue function and directional output distance function to retrieve shadow price of CO_2 emissions for thermal power plants in India. The derivation of shadow prices of bad outputs requires an assumption that observed or market price of one of the good output (r_{y1}^{o}) is equal to its shadow price (r_{y1}^{s}), and we assume that the observed electricity price is equal to its shadow price. Then shadow price of j[th] bad output (CO_2 emissions) is:

$$r_{bj}^{s} = r_{y1}^{o} \frac{\partial \vec{D}_O(y,\ b,\ x; g_y, -g_b) \big/ \partial b_j}{\partial \vec{D}_O(y,\ b,\ x; g_y, -g_b) \big/ \partial y_1} \qquad (4)$$

For details on derivation of shadow prices of bad outputs using directional output distance function, see Färe et al. (2005) and Hudgins and Primont (2007).

Equation (4) reveals that the estimated shadow price depends on the slope of output set and direction of change in good and bad outputs. Given the shortage of availability of electricity in India, any mapping rule that constrains expansion of electricity would not be social desirable and politically acceptable. However, with respect to bad outputs (e.g., CO_2 emissions) the country may follow any of three mapping rules or strategies: (i) the bad output is allowed to increase simultaneously with the good output: $\{(g_y, g_b) = (1, 1)\}$, (ii) the bad output remains constant but the good output is allowed to expand: $\{(g_y, g_b) = (1, 0)\}$, and (iii) the bad output is required to be reduced and the good output is expected to expand: $\{(g_y, g_b) = (1, -1)\}$. Under the first strategy, priority is given to stable energy supply even though it results in increase in CO_2 emissions, i.e., CO_2 intensity of electricity generation remains constant if both good and bad outputs expand proportionally, but CO_2 intensity of electricity generation declines under strategy (ii) since only expansion of good output is allowed. However, under strategy (iii) CO_2 emissions decline in absolute terms, though the production of electricity has been expanding. We estimate shadow price of CO_2 emissions following all these three mapping rules or strategies. Depending on the chosen strategy, estimated value of DODF and shadow price of CO_2 emissions vary substantially, and the choice of a particular strategy depends on the prevailing and prospective energy and climate policies in the country.[7] Mapping rule or choice of strategy is important since the shadow price is calculated based on the marginal rate of substitution between good and bad outputs at the point (Lee et al., 2014).

4. Empirical Model and Data

4.1. Parametric Estimation of Directional Output Distance Function

To compute the shadow prices of CO_2 emissions, we need to estimate directional output distance function (DODF) either non-parametrically using Data Envelopment Analysis (DEA) or parametrically. In the present study we adopt parametric approach for the estimation of DODF; parametric approach yields differentials of DODF with respect to input and output factors. Parameters of DODF can be estimated either using deterministic approach

[7] Most of the earlier studies (e.g., Färe et al., 1993; Coggins and Swinton, 1996; Kumar and Rao, 2002, Murty and Kumar 2002) using output distance function follow first strategy (increasing proportionally both good and bad outputs), but most of the studies involving directional output distance function (e.g., Färe et al., 2005, Murty et al., 2007) follow third mapping strategy (increasing good output and reducing bad output) for the purpose.

based on linear programming (LP) or stochastic frontier analysis (SFA). The SFA suffers from the problems of uncertainty of the distributional assumptions for inefficiency and error terms. LP approach, of being a deterministic approach, is free from these distributional assumptions and facilitates modeling of DODF properties. In the deterministic approach, properties such as monotonicity of DODF with respect to good and bad outputs can be imposed through inequality constraints. Therefore, we estimate DODF using linear programming algorithm introduced by Aigner and Chu (1968) in the context of a production function and extended by Färe et al. (2005) in the context of DODF. Moreover, we employ quadratic form of DODF since it is more generalized and outperforms relative to translog or linear forms (Färe et al., 2010) and accommodates translation property of DODF (Färe et al., 2006).[8] The quadratic form of DODF is expressed as:

$$\begin{aligned}\vec{D}_o^{kt}(y_{kt}, b_{kt}, x_{kt}; 1, -1) \\ = \alpha_0 + \sum_{n=1}^{N} \alpha_n x_n^{kt} + \beta_1 y_1^{kt} + \gamma_1 b_1^{kt} + \frac{1}{2}\sum_{n=1}^{N} \alpha_{nn'} x_n^{kt} x_{n'}^{kt} + \sum_{n=1}^{N} \delta_{n1} x_n^{kt} y_1^{kt} \\ + \sum_{n=1}^{N} \eta_{n1} x_n^{kt} b_1^{kt} + \frac{1}{2}\beta_{11} y_1^{kt} y_1^{kt} + \mu_{11} y_1^{kt} b_1^{kt} + \frac{1}{2}\gamma_{11} b_1^{kt} b_1^{kt} + \sum_{t=1}^{T-1} d_t year^t\end{aligned} \tag{5}$$

where $\vec{D}_O(.)$ is the DODF for thermal power plant k in year t; $y_1^{kt}$is the generation of electricity at plant k in year t; b_1^{kt} is the generation of CO_2 emissions at plant k in year t; and $x_n^{kt}$is the nth input use at plant k in year t (n= capital, wage bill, and consumption of coal). Year dummies are introduced to capture the effect of external changes that were happening over the years. Following Aigner and Chu (1968), the parameters of equation (5) are calculated solving the following linear program:

$$\min \sum_{kt=1}^{KT} [\vec{D}_o^{kt}(y_{kt}, b_{kt}, x_{kt}; 1, -1) - 0] \tag{6}$$

Subject to

(i) $\vec{D}_o^{kt}(y_{kt}, b_{kt}, x_{kt}; g_y, -g_b) \geq 0, kt = 1, 2, \dots \dots .., KT;$

(ii) $\partial \vec{D}_o^{kt}(y_{kt}, b_{kt}, x_{kt}; g_y, -g_b) \big/ \partial x_n \geq 0; kt = 1, 2, \dots \dots, KT; n = 1, 2, 3;$

(iii) $\partial \vec{D}_o^{kt}(y_{kt}, b_{kt}, x_{kt}; g_y, -g_b) \big/ \partial y_1 \leq 0; kt = 1, 2, \dots \dots, KT;$

(iv) $\partial \vec{D}_o^{kt}(y_{kt}, b_{kt}, x_{kt}; g_y, -g_b) \big/ \partial b_1 \geq 0; kt = 1, 2, \dots \dots, KT;$

(v) $\beta_1 - \gamma_1 = -1;\ \beta_{11} - \mu_{11} = 0;\ \mu_{11} - \gamma_{11} = 0;\ \sum_{n=1}^{N} \delta_{n1} - \sum_{n=1}^{N} \eta_{n1} = 0; n = 1, 2, 3;$

(vi) $\alpha_{nn'} = \alpha_{n'n}; n = 1, 2, 3$

Restriction (i) ensures that none of the Indian coal fired thermal power plant produces electricity and CO_2 emissions that is not included in the output set $P(x)$. Restrictions (ii) to (iv) impose monotonicity conditions for all inputs, good output and bad output respectively.

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[8] Translation property is used while estimating DODF using stochastic frontier analysis (SFA) (Kumar et al., 2015).

Restrictions (v) and (vi) are due to translation property of DODF and symmetry conditions of the parameters. Restriction (v) satisfies the mapping rule for strategy 3 allowing expansion of electricity generation and contraction in CO_2 emissions. For the other two strategies (i) allowing expansion of both good and bad output, $\{g = (1, 1)\}$ and (ii) allowing expansion only of electricity and no change in the generation of CO_2 emissions, $\{g = (1, 0)\}$, the restriction (v) needs to be altered respectively as:

(v) $\beta_1 + \gamma_1 = -1;\ \beta_{11} + \mu_{11} = 0;\ \mu_{11} + \gamma_{11} = 0;\ \sum_{n=1}^{N} \delta_{n1} + \sum_{n=1}^{N} \eta_{n1} = 0; n = 1, 2, 3$

(v) $\beta_1 = -1;\ \beta_{11} = 0;\ \mu_{11} = 0;\ \sum_{n=1}^{N} \delta_{n1} = 0; n = 1, 2, 3$

4.2. Data

A thermal power plant generates electricity (good/desirable output) while simultaneously producing a number of bad/undesirable outputs viz. GHG gases, suspended particulate matter (SPM) and ash etc. For producing these good and bad outputs, coal-based thermal power plants use a large number of inputs. While price of good output i.e. electricity is available, the prices of bad outputs have to be derived using approach described above. This requires data on inputs and outputs of thermal power plants.

Initially, we made a list of 87 Central government or state government or jointly owned and 11 privately owned thermal power stations for compilation of input-output data and plant level characteristics information for the period 1999 to 2013.[9] Efforts were made to obtain the above information from the publications of Central Electricity Authority (CEA), a statutory authority of Government of India. As per Section 74 of the Central Electricity Act 2003, it is mandatory for every generating company or person to furnish to the CEA such statistics as it may require.

Efforts were also made to obtain the information from the website of various thermal power stations/companies. Simultaneously efforts were also made to get the information for the required variables from the website of Central Electricity Regulatory Commission (CERC), a body for regulation of tariff of generating companies. Price of electricity, and CO_2 emissions details were obtained directly from the office of CEA. Yet, information about a number of variables was not available from these sources. Therefore, requests under the Right to Information (RTI) Act 2005 were sent to the list of 98 thermal power stations for the requisite information. We could get the response only from 55 thermal power stations, and all were government owned. However some variables, particularly manpower costs were not included in the reply of 14 thermal power stations. Therefore information only of 41 stations could be used for further analysis. Moreover, the National Thermal Power Corporation (NTPC), a central government's power generation company, provided information only about power generation and other performance indices i.e., operational availability, forced outage, planned maintenance, plant load factor (PLF)[10] etc. Remaining information about thermal power stations owned by NTPC for the period 2008 to 2012 was obtained from the website of CERC. Based on the information received from various sources, an unbalanced panel data for

[9] In India, data on thermal power plants is available on the financial year basis, starting April of a year and closing in the march of following year. Therefore 1999 refers to 1999-2000 and 2013 refers to 2013-14.

[10] Plant Load Factor (PLF) in the electricity sector is defined as a ratio of actual energy generation to maximum possible energy that can be generated if the plants is working at its rated power and for the entire year. PLF depends on installed capacity, age of the units, past performance, planned outages, availability of water/fuel, etc.

56 thermal power stations having 458 observations has been formed for the period 2000 - 2013.

Considering the process of electricity generation, we use plant level information on three inputs and two outputs for estimation of DODF. Outputs include net electricity generation and CO_2 emissions. Net electricity generation, measured in gigawatt hours (GWh), is defined as the difference between gross electricity generation and auxiliary consumption of electricity at a plant. A power plant may be generating high gross electricity but low net electricity due to high auxiliary power consumption. Using net electricity generation helps us capture plant's inefficiency due to high auxiliary power consumption. CO_2 emissions are measured in tons of emissions generated by a plant. The CEA has been collecting the baseline data in order to facilitate the Clean Development Mechanism (CDM) projects since 2001.[11]

Plants in our sample use coal as their primary fuel and coal consumption is measured in tons. Capital input employed in a thermal power station has been calculated following Dhryms and Kurz (1964), i.e.

$$K = SFT/10^3$$

where K: Capital measured in gigawatt hours (GWh); S: Capacity of a plant available during a year (MW); F = Operational availability factor; and T = number of hours in a year (i.e, 8000 hours (Vogel and Kalb, 2010, p 17). However, different units may be commissioned/decommissioned at different points of time in a year in a thermal power plant; therefore the capacity of a plant available during a year is different from its nameplate capacity and is measured as:

$$\begin{aligned} S = {} & Total\ capacity\ available\ at\ the\ beginning\ of\ a\ year \\ & + \sum (capacity\ of\ units\ commissioned\ during\ the\ year \\ & \times months\ available\ for\ production\ /12) \\ & + \sum (capacity\ of\ units\ decommissioned\ during\ the\ year \\ & \times months\ available\ for\ production\ /12) \end{aligned}$$

Labour in measured in terms of wage bill paid by a thermal power station during a year. Wage bill information is available at current prices and is converted into constant prices using the labour wage index published by the Labour Bureau, Government of India.[12] Similarly electricity prices available in current prices were converted into constant prices by deflating by wholesale price index of fuel and power made available by the Reserve Bank of India.[13] Descriptive statistics of the data used in the study in given in Table 1.

5. Results and Discussion

Parameters of the DODF are obtained by solving the linear program described in equation (6) using GAMS (General Algebraic Modeling System) software and are presented in appendix

[11] CO_2 Baseline Database for the Indian Power Sector, User Guide, Version 11.0, April 2016, CEA

[12] http://labourbureaunew.gov.in/LBO_indtab.pdf as accessed on September 2015

[13] https://dbie.rbi.org.in/DBIE/dbie.rbi?site=publications#!2 as accessed on September 2015

Table A1. Table 2 presents descriptive statistics of technical inefficiency of Indian thermal power sector based on the pooled unbalanced panel data of 458 observations. The value of DODF serves as a measure of technical inefficiency revealing the scope of expansion of electricity generation and contraction of CO_2 emissions, if the plants were made to operate at the boundary of output set. We find an average value of 0.18, 0.19 and 0.13 for DODF for the chosen three directional vectors: (1, 1), (1, 0) and (1, -1) respectively. At the mean level, the CO_2 intensity of electricity generation in Indian thermal power plants comes out 1.101 Kg/kWh, which can be reduced to 0.925 and 0.848 Kg/kWh under mapping rule 2 and 3 respectively. That is, CO_2 intensity of coal fired electricity generation could be reduced by about 16 and 23 percent if the plants were made to operate efficiently. However, under strategy 1, the CO_2 intensity of thermal plants remains constant since both electricity and CO_2 emissions were allowed to increase proportionally. Figure 2 illustrates that over the period of time technical inefficiency of the sector has been increasing, and Figure 3 displays heterogeneity in operations of the sample plants. We find that inefficiency is lower under strategy 3 in comparison to strategy 1 or 2, implying that reduction in CO_2 emissions is costly and the plants that try to reduce the emissions should be credited for their efforts.

The shadow price of CO_2 emissions can be interpreted as marginal abatement cost (MAC) of reducing a ton of the emission in terms of foregone electricity production when the production unit is operating at the boundary of production set. Table 3 summarizes the descriptive statistics of the estimated shadow prices. The average shadow prices for a ton of CO_2 emission are US$ 2.61, 14.54 and 18.68 respectively for the three strategies: (1, 1), (1, 0) and (1, -1) with very high standard deviations. The wide variation in the shadow price supports the introduction of emission trading or emission taxation for emission reduction cost effectively. The average of shadow price obtained from the three directions is US$ 11.94, which is much higher than the Clean Energy Cess levied by Indian Government on the consumption of coal. The present levy is about US$ 6.15 per ton of coal or US$ 3.81 a ton of CO_2 emission, which is not enough to induce the thermal power plants for reducing the emissions.[14]

The value of shadow price for a specific thermal plant is truly varied across three chosen strategies (Figure 4). The rank correlation coefficient between the shadow prices obtained for the different pairs of three directional vectors are: -0.183, -0.317 and 0.981. This finding indicates that the choice of directional vector that allows expansion of both good and bad outputs and the choices that reduce CO_2 intensity (either allowing only the expansion of good output or allowing expansion of good output and contraction of bad output) has strong impact on the ranking of estimated shadow prices, however the ranking is not much different under two other strategies.

Figure 4 displays the CO_2 shadow prices for the chosen three directional vectors. Since the directional vectors cover the different strategeis that the thermal power plants may take to improve production efficiency, the lowest and highest shadow prices attained under the three directional vectors can be considered as lower and upper boundaries of the shadow prices. Lower and upper boundaries are generally achieved under strategies, (1, 1) and (1, -1). Though the mean shadow prices are robust to the choice of directional vectors, arbitrarily choice of directional vector may substantially underestimate the potential for low cost abatement opportunities (Wang et al., 2017).

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[14] Parikh et al. (2009) report a CO_2 emission coefficient of 1.614 for total Indian coal.

Figure 5 graphs the kernel distribution of shadow prices obtained for the three directional vectors. From the graph it is apparent that shadow prices are highly concentrated under strategies (1, 0) and (1, -1) relative to (1, 1). Under strategy 2, an inefficient plant moves vertically to reach on the frontier, and has to relinquish electricity production of about US$18 to reduce one ton of CO_2 emissions. If the plant moves to north-west to reach on the frontier (strategy 3), it has to forego electricity production of about US$ 28, whereas under strategy 1, plant moves to north-east to reach on the frontier has to sacrifice electricity production of only US$ 2.5.

Moreover, we observe that shadow prices obtained under strategy 3 are higher than achieved under strategy 2, which are higher than obtained under strategy 1, implying that the obtained frontier is concave and the direction of movement of a plant given the three directional vectors is from north-east to north and then to north-west. Figure 6 depicts that shadow prices are declining over time for strategy 2 and 3, however the trend got hampered in 2007 and then constancy in the shadow prices has been observed.

Figures 7 and 8 box plot the technical inefficiency and shadow prices of CO_2 emissions categorizing based on ownership and location. The sample thermal power plants are either owned by the central sector[15] or state governments, and are located in all the zones: east, north, south and west. We observe that the plants owned by the state governments are doing better in terms of resource utilization relative to the central sector, but the marginal abatement cost to cut an additional ton of CO_2 emissions are higher for these plants than incurred by the plants of central sector. Here it is worth to note that the plants owned by the state governments have lower average unit size (161 versus 275 MW) and higher CO_2 intensity (1.27 versus 1.13 Kg/kWh) and auxiliary consumption of electricity (10.6 versus 8.26 percent) than the central sector plants. This implies that state owned plants though they are technically efficient relative to central sector plants, but due to lower unit size, they have higher CO_2 intensity and auxiliary consumption, and it is difficult or more costly for them to reduce the emission relative to central sector. In the short-run, the programs like emission trading would be cost effective than command and control, the long-term objective should be to retire or modernize the small size thermal generating units of the plants. Use of economic instruments could also help in realizing the long-term objective since economic instruments encourage innovations in abatement technologies.

In order to further comprehend the determinants of the marginal cost of abatement, we regress the shadow price on plants characteristics coupled with spatial-temporal factors. We hypothesize that the shadow price of CO_2 emissions is the function of multiple variables such as technical efficiency, CO_2 emissions generated, average production unit size, auxiliary consumption of electricity, operation availability, ownership of a plant and fuel quality. Table 4 presents the regression results.

From Table 4, we see that the parameter of the value of directional output distance function (DODF) is positive and weakly significant for the mapping rule (1, 1) (strategy 1), but it is negative and statistically significant for strategies 2 and 3 [mapping rule (1, 0) and (1, -1) respectively] (Figure 9). A negative relationship between technical inefficiency and shadow prices under strategies 2 and 3 imply that an inefficient thermal plant has more option to

[15] Central sector thermal power plants are predominately run by a public sector enterprise, known National Thermal Power Corporation (NTPC). Some plants of central sector are run by Damodar Valley Corporation (DVC) also.

reduce the emissions in comparison to a plant, which is on or near the boundary of production set and use of economic instruments for CO_2 emission mitigation may induce an inefficient plant for realizing those options. However, under the direction vector (1, 1), a positive relationship between the estimated technical inefficiency and the shadow prices implies that an increase in the emissions imposes an additional cost to the plant (Lee et al., 2014).[16]

A negative and statistically significant parameter of load of CO_2 emissions exhibits that the shadow price of the emissions falls with an increase in emissions load for strategies 2 and 3. This implies that the larger plants have lower shadow prices and there exists economies of scale in the mitigation of CO_2 emissions. This finding concurs with existing literature on resource utilization and pollution abatement (e.g., Hettige et al., 1996; Dasgupta et al., 2001; Murty and Kumar, 2002, 2004; Murty et al., 2007; Wei et al., 2013).

We observe a negative association between the shadow price and an average unit size of an electricity generating plant, though it is statistically significant only for strategy 3, implying that larger producing units can reduce the emissions at lower cost relative to smaller units. In India, most of the thermal power plants are of small unit size and use subcritical technology. For the sample plants, average unit size is less than 200 MW (Table 1). Small units suffer from the problems of low plant load factor (PLF) and design deficiencies and higher coal consumption per unit of electricity generation. On the other hand, supercritical technologies have higher production efficiency and lower emissions per unit of electricity generation, i.e., bigger units have more flexibility and can reduce the emissions at lower cost (CEA, 2003).

Auxiliary consumption of electricity at a thermal power plants is a measure of thermal inefficiency which depends on a unit's design heat rate, quality of coal used, and age of the unit (Joskow and Schmalensee 1987). The average age of sample plants is 25 years with a maximum of 46 years and the average auxiliary consumption is about 10 percent (Table 1), which is much higher than the state owned thermal power plants in the US (Chan et al., 2014). Higher vintage and auxiliary consumption implies higher consumption of coal per unit of electricity generation and lesser flexibility in operation making the mitigation of CO_2 emissions difficult. Mittal et al. (2014) also finds that CO_2 emission efficiency of newer plants that use improved technology is better than the old plants. Therefore, as expected, we find a positive association between the shadow prices and auxiliary consumption (Table 4). This finding is consistent with the results of Coggins and Swinton (1996) in context of the US thermal power plants; older plants had higher shadow price of the SO_2 emissions. This finding support the argument that older plants can meet the environmental regulation cost effectively if they are allowed to purchase emission permits from the market rather than abating emissions themselves. Moreover, in a dynamic setting, the emission trading would induce replacement of older and smaller unit size plants with supercritical and/or ultra-supercritical production units.[17]

Moreover, we find a negative association between the shadow prices and the availability of a production unit in a production year. Availability of a plant depends on design and operation of a production unit and newer plants tend to have higher availability factor and have more

[16] Strategy 1 is not compliant with the ongoing environmental trends of reducing CO_2 emissions and further increase in the emissions is irrational since an increase in the emissions imposes a higher mitigation cost (Lee et al. 2014)

[17] Lange and Bellas (2005) observe advancements in scrubber technologies are abatement of SO_2 emissions were observed as of results of emission trading in the US. Kumar and Managi (2010) also observe induced technological advancements due to introduction of SO_2 trading program in the US.

flexibility in reducing CO_2 emissions. Regional factors also bring variability in the shadow prices. The coefficients of time dummies are negative and statistically significant 2008 onwards implying a declining trend in the shadow prices, which is consistent with the installation of generating units of bigger size in the Indian thermal power sector.[18]

6. Conclusions

The augmentation of electricity production and reduction in CO_2 emissions in coal fired thermal power plants is a key step in addressing the challenge of low carbon development path in India. Since the thermal power sector accounts for about half of the total carbon emissions in the country, this sector is expected to bear a greater burden of the emissions reduction for meeting the Paris agreement pledges. Yet to cost-effectively reduce the emissions in this sector, a necessary first step is to analyse the marginal cost of abatement at the plant level.

We parametrically estimate directional output distance function using determinstic framework to compute the reduction potential of CO_2 emissions and shadow price of the emission using a unique data set, retrieved invoking the Right to Information (RTI) Act 2005, of 56 thermal power plants for the period of 2000 to 2013. We find that there exisitng 18, 19 and 13 percent level of inefficiency in the Indian thermal power sector at mean level for the chosen three directional vectors: (1, 1), (1, 0) and (1, -1) respectively. Given the sample CO_2 intensity of electricity generation of 1.101kg/kWh, there is scope to reduce the intensity to 0.925 and 0.848 kg/kWh for the later two directional vectors, i.e., the intensity can be reduced by 16 and 23 percent if the plants were made to operate at the boundary of the output set. This illustrates that there exists a high abatement potential and win-win opportunities in the thermal power sector, and policymakers should provide required incentives to the electricity producers for realizing the potential.

Moreover, the study finds an average shadow price of US$ 2.61, 14.54 and 18.68 respectively for the three chosen directional vector for a ton of CO_2 emissions. The prevailing Clean Energy Cess (CEC) is not enough to induce the polluters to reduce the emissions since the average of shadow price from the chosen directions is much higher than the prevailing rate of CEC. Moreover, it has been observed that there is wide variation in shadow price among the electricity producers, which calls for application of policy instruments such as emission trading or emission taxation in place of prevailing command and control mechanism for cost effectiveness in pollution abatement.

Moreover, the study displays that shadow price of CO_2 emission is dependent on the average production unit size, vintage, production efficiency, ownership, availability of technology etc. There is a negative relationship between shadow price and inefficiency; bigger unit size plants have lower shadow price and are employing newer technologies. These finding call for appropriate allocation of emission reduction targets even in the absence of emission-trading or -taxation system.

[18] The history of 10 biggest thermal power plants in the country: http://www.power-technology.com/features/feature-the-top-10-biggest-thermal-power-plants-in-india/ as accessed on July 27, 2017.

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Table 1: Descriptive statistics

Variable	Mean	Std. Dev.	Min	Max
Inputs				
Capital (GWh)	6595.37	5080.49	329.25	27360.70
Wage bill (INR millions)	441.5	281.6	7.6	1522.8
Coal (tons)	4806611	3850700	235035	19300000
Outputs				
Net Electricity (GWh)	5830.81	4973.92	298.42	25903.78
CO_2 (tons)	6421038	4776882	346321	24800000
Plant Characteristics				
Average unit size (MW)	192.25	109.95	55.00	600.00
Operational availability (%)	82.52	12.29	24.60	98.91
Nameplate Capacity (MW)	959.96	682.17	58.00	3658.63
Lignite (=1, dummy variable)	0.10	0.30	0	1
Imported Coal (=1 if >10%)	0.14	0.35	0	1
Central Sector (=1, dummy variable)	0.28	0.45	0	1
Electricity Prices (INR millions/GWh)	1.9	0.6	0.6	4.6
Indian coal (%)	86.85	29.53	0.00	100.00
Imported coal (%)	3.10	5.39	0.00	23.67
Lignite (%)	10.04	30.09	0.00	100.00
CO_2 intensity (kg/KWh)	1.23	0.26	0.67	2.30
Auxiliary Consumption (%)	9.95	2.51	8.51	20.71

Tale 2: Descriptive statistics value of Directional output distance function and potential changes in electricity and CO_2 emissions

Variable	Mean	Std. Dev.	Min	Max	Potential electricity expansion (Gwh)	Potential change in CO2 emissions (tons)
DODF (strategy 1)	0.18	0.15	0.00	0.75	1049.55	↑1155787
DODF (strategy 2)	0.19	0.17	0.00	0.84	1107.85	No Change
DODF (strategy 3)	0.13	0.12	0.00	0.60	758.01	↓834735

Tale 3: Descriptive statistics shadow price of CO_2 (INR/ton)

Variable	Mean	Std. Dev.	Min	Max
Shadow Price (strategy 1)	169.37 (2.61)	98.76 (1.52)	0.23 (0)	532.38 (8.19)
Shadow Price (strategy 2)	945.01 (14.54)	486.03 (7.48)	12.42 (0.19)	2749.50 (42.3)
Shadow Price (strategy 3)	1214.06 (18.68)	721.59 (11.1)	42.02 (0.65)	4014.71 (61.76)

Note: Values in parentheses are in US$ at an exchange rate of INR 65= US$1; INR: Indian rupees

Table 4: Determinants of shadow prices of CO_2

	Strategy 1		Strategy 2		Strategy 3	
Ln(Shadow price of CO_2)	Coefficient	t-stat.	Coefficient	t-stat.	Coefficient	t-stat.
DODF	0.547*	1.83	-0.775***	-4.35	-1.820***	-6.88
Average unit size	-0.015	-0.5	-0.026	-1.27	-0.061***	-3.04
Ln(CO_2 emissions)	1.014***	9.51	-0.242***	-5.06	-0.300***	-5.9
Auxiliary consumption	0.087***	3.09	0.024**	2.23	0.019*	1.82
Operational availability	-0.015***	-4.74	-0.002	-1.29	-0.003*	-1.74
Central sector (dummy =1)	-0.119	-1.39	-0.463***	-5.57	-0.449***	-6.35
Imported coal (dummy =1 if >10%)	0.446***	6.56	0.380***	5.72	0.393***	6.86
Lignite (dummy =1)	-0.001	-1.33	0.004***	4.1	0.004***	3.93
West (dummy =1)	-0.011	-0.12	0.085	1.23	0.113*	1.81
South (dummy =1)	-0.509***	-4.11	-0.274***	-3.96	-0.277***	-4.12
East (dummy =1)	-0.199**	-2.22	-0.232***	-3.17	-0.210***	-3.21
Year 2001 (dummy =1)	-0.029	-0.18	0.013	0.08	0.014	0.08
Year 2002 (dummy =1)	0.080	0.55	0.087	0.61	0.085	0.6
Year 2003 (dummy =1)	0.051	0.37	0.057	0.38	0.052	0.35
Year 2004 (dummy =1)	-0.099	-0.69	-0.001	-0.01	-0.025	-0.18
Year 2005 (dummy =1)	-0.199	-1.5	-0.168	-1.23	-0.148	-1.08
Year 2006 (dummy =1)	-0.157	-1.15	-0.209	-1.52	-0.186	-1.35
Year 2007 (dummy =1)	-0.114	-0.77	-0.206	-1.51	-0.188	-1.38
Year 2008 (dummy =1)	-0.281*	-1.99	-0.445***	-2.82	-0.362**	-2.54
Year 2009 (dummy =1)	-0.254*	-1.83	-0.279**	-2.06	-0.271*	-1.95
Year 2010 (dummy =1)	-0.289*	-1.84	-0.375***	-2.67	-0.318**	-2.32
Year 2011 (dummy =1)	-0.267*	-1.8	-0.344**	-2.5	-0.310**	-2.29
Year 2012 (dummy =1)	-0.359**	-2.34	-0.403***	-2.82	-0.338**	-2.46
Year 2013 (dummy =1)	0.412	0.65	-0.273	-0.77	-0.307	-1.01
Constant	-10.004***	-6.12	10.979***	15.5	12.329***	16.55
F(24, 433)	24.06***		23.49***		40.74***	
R-squared	0.69		0.59		0.72	
Root MSE	0.53		0.47		0.42	
Number of obs.	458		458		458	

Note: DODF: directional output distance function
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

Figure 1: Vintage - CO2 intensity relationship

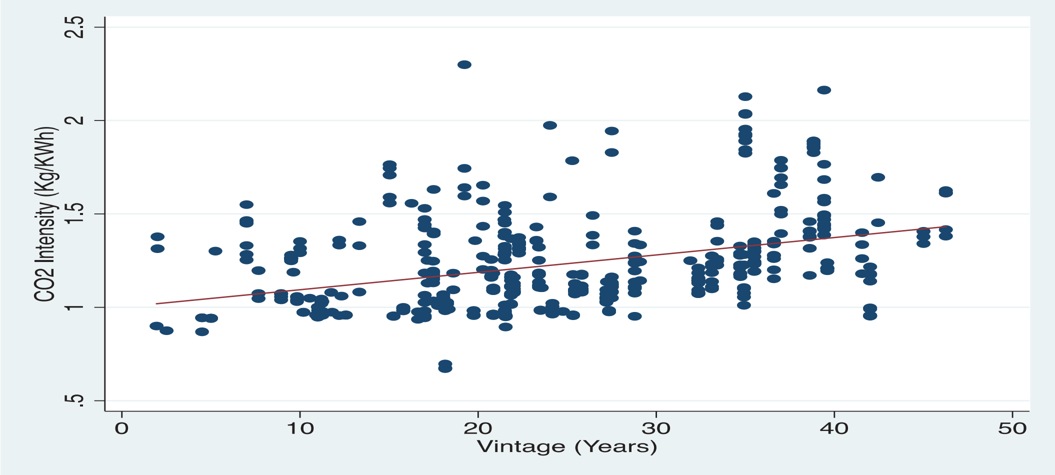


Figure 2: Value of Directional output distance function over time

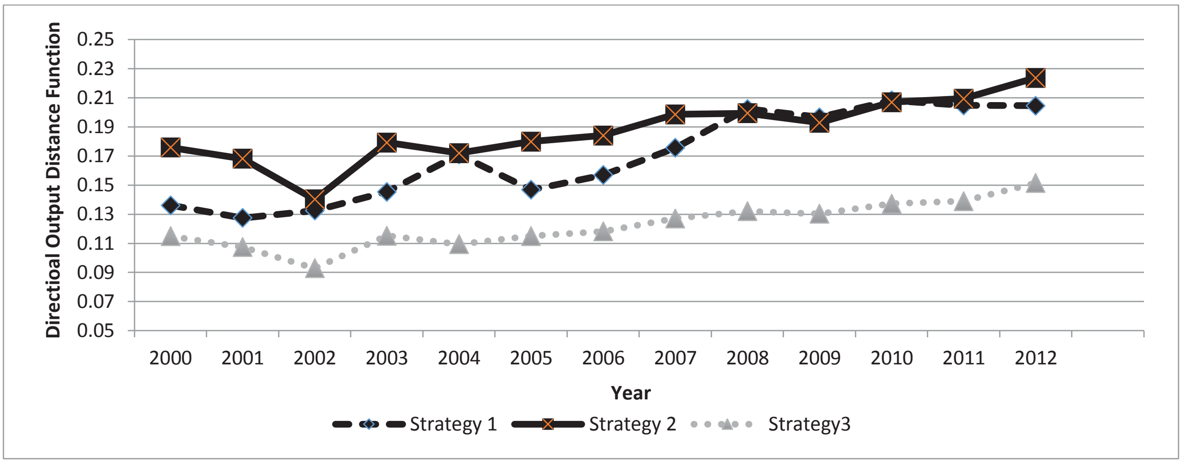


Figure 3: Value of Directional output distance function

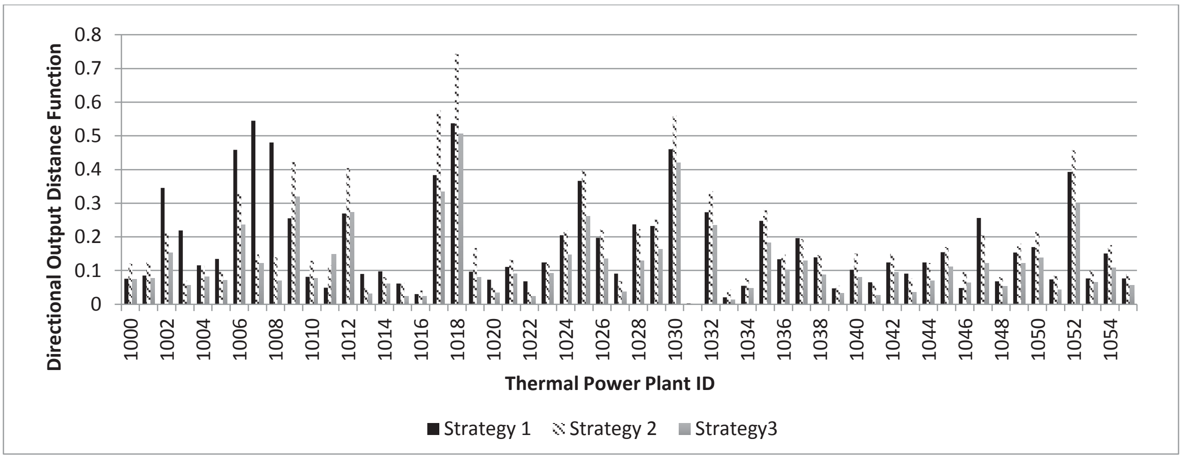
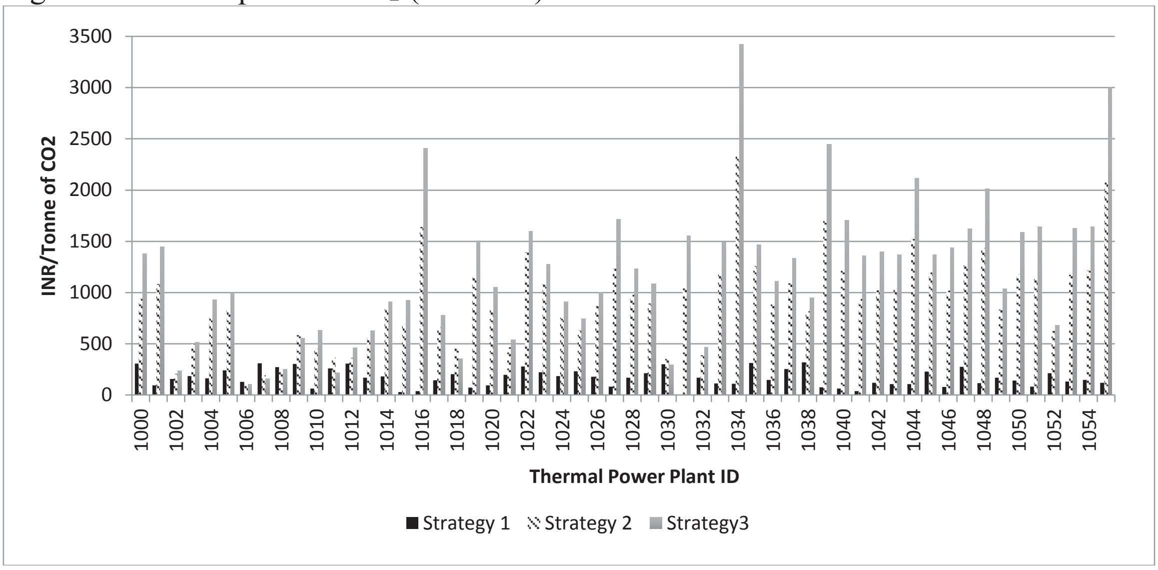
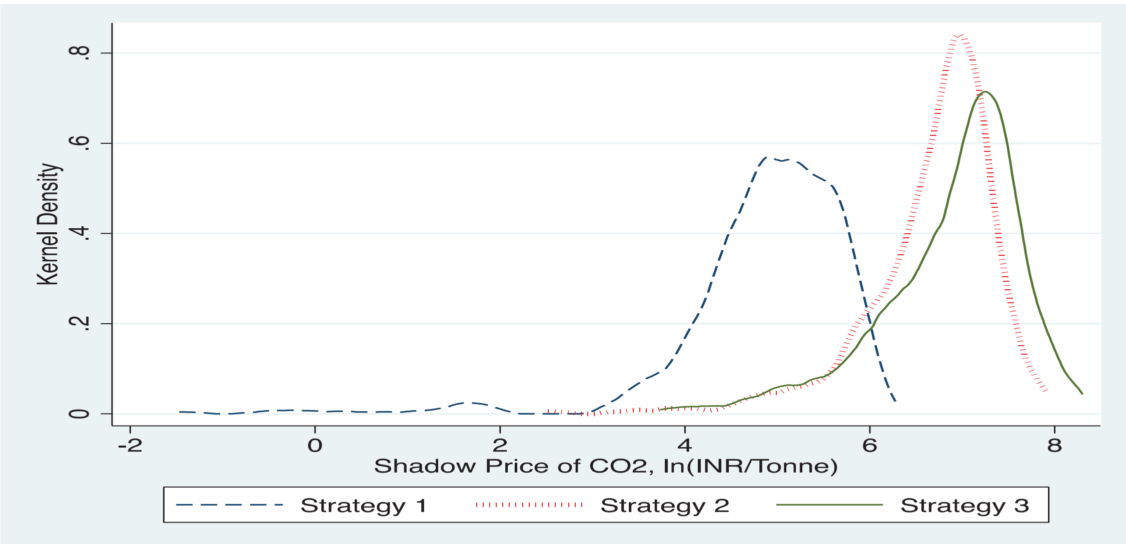


Figure 4: Shadow price of CO_2 (INR/Ton)



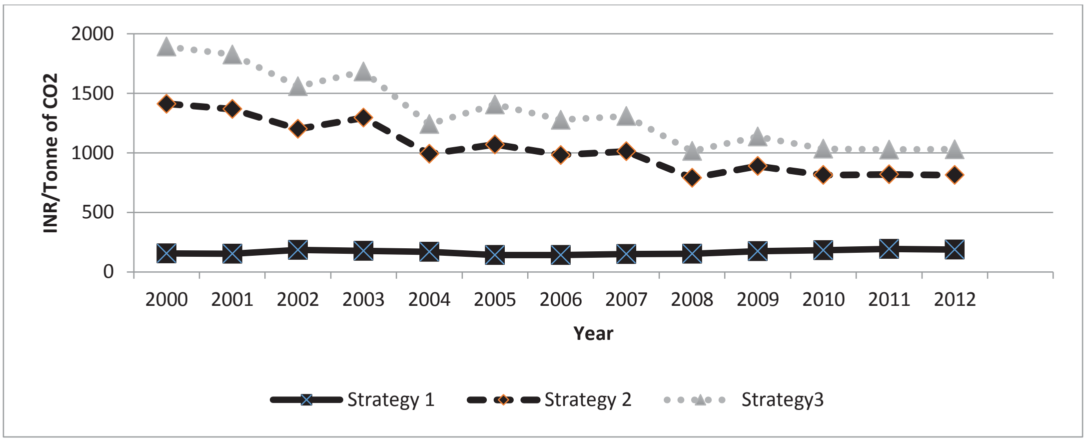
INR: Indian rupees

Figure 5: Distribution of shadow price of CO_2



INR: Indian rupees

Figure 6: Shadow price of CO_2 over time (INR/Ton)



INR: Indian rupees

Figure 7: Directional output distance function over zone and ownership

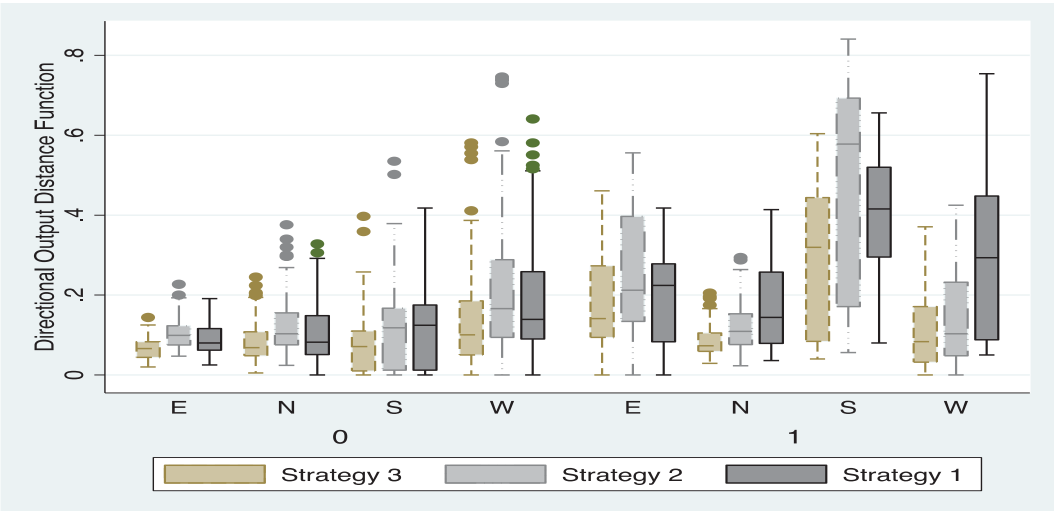
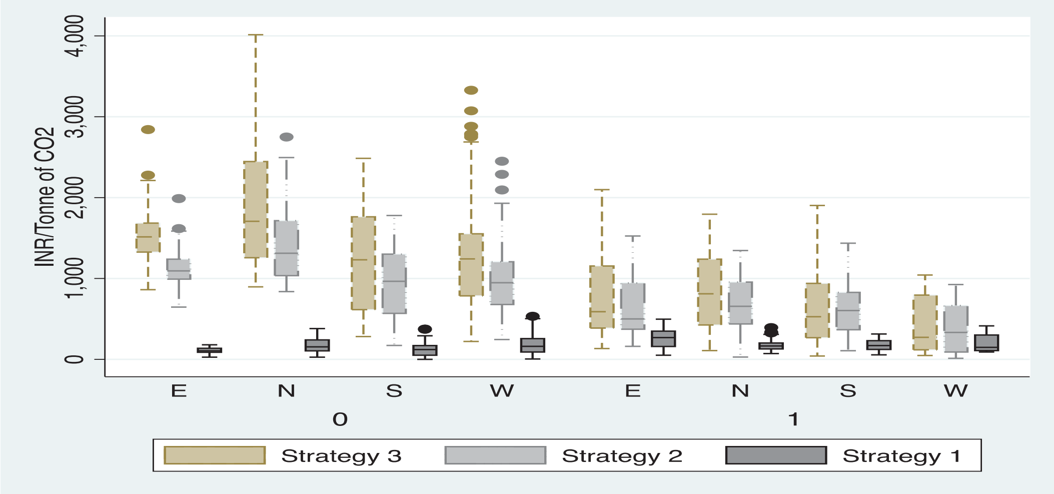
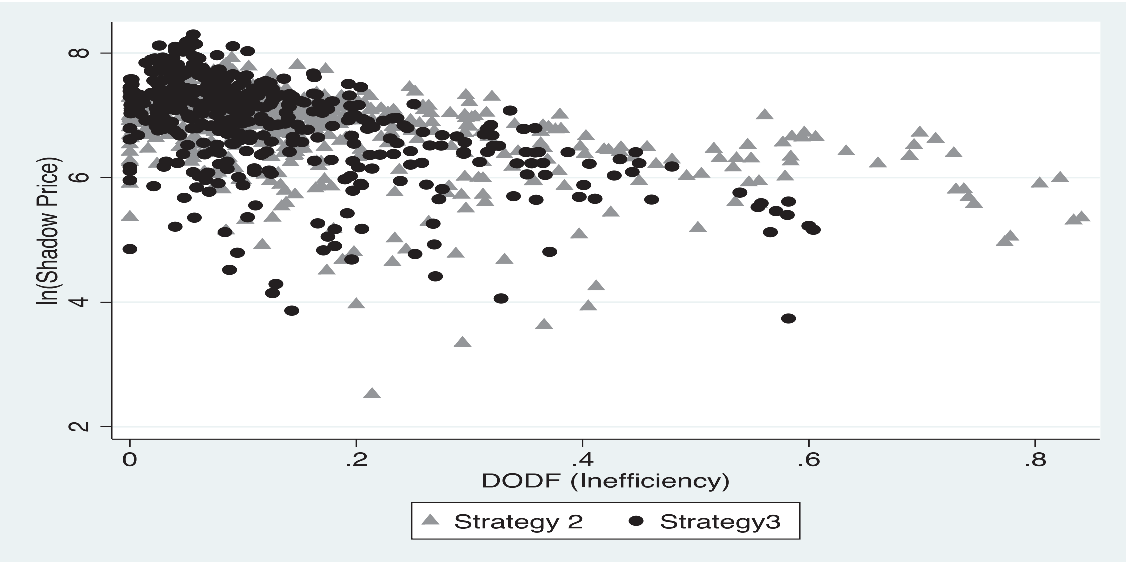


Figure 8: Shadow price of CO_2 over zone and ownership



INR: Indian rupees

Figure 9: Relationship between production inefficiency and shadow prices of CO_2



Appendix

Table A1: Calculated Parameters of Directional Output Distance Function

Variable	Strategy 1	Strategy 2	Strategy 3
Intercept	-0.014	-0.019	-0.016
Coal	0.711	0.101	0.007
Labour	0.056	0.045	0.046
Capital	0.389	0.317	0.004
Electricity	-0.994	-1	-0.47
CO_2	-0.006	0.725	0.53
$Coal^2$	-0.128	0.044	-0.006
Coal × Labour	0.00002	0.233	0.18
Coal × Capital	-0.015	-0.112	0.126
$Labour^2$	-0.07	-0.055	-0.054
Labour ×Capital	0.149	0.127	0.14
$Capital^2$	-0.15	0.038	0.021
$Electricity^2$	0.252	0	0.041
Electricity ×CO_2	-0.252	0	0.041
${CO_2}^2$	0.252	0.098	0.041
Electricity ×Coal	-0.221	0	-0.071
Electricity ×Labour	0.002	0	-0.097
Electricity ×Capital	0.106	0	-0.083
CO2×Coal	0.221	-0.049	-0.071
CO2×Labour	-0.002	-0.217	-0.097
CO2×Capital	-0.106	-0.082	-0.083
Year 2000 (dummy =1)	-0.015	-0.038	-0.03
Year 2001 (dummy =1)	-0.006	0.001	-0.005
Year 2002 (dummy =1)	-0.012	0.011	-0.011
Year 2003 (dummy =1)	-0.002	0.002	0.001
Year 2004 (dummy =1)	-0.003	0.015	0.001
Year 2006 (dummy =1)	-0.001	0.004	-0.005
Year 2007 (dummy =1)	-0.004	0.001	-0.003
Year 2008 (dummy =1)	0.151	0.161	0.071
Year 2009 (dummy =1)	0.017	0.033	0.006
Year 2010 (dummy =1)	0.036	0.06	0.048
Year 2011 (dummy =1)	0.046	0.003	-0.002
Year 2012 (dummy =1)	0.046	0.003	-0.002