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Cost of CO_2 Emission Mitigation and its Decomposition: Evidence from Coal-fired Thermal Power Sector in India

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Abstract: We estimate Carbon Mitigation Cost (CMC), and the factors determining change in CMC using environmental production function. The CMC index is defined as the ratio of maximum production of electricity under unregulated and regulated production technology. Change in CMC index is decomposed into technical change, scale change and change in the level of CO_2 emissions. The production function is estimated for 45 coal-fired thermal power plants over the period of 2008 – 2012 using Data Envelopment Analysis. Decomposition of CMC change reveals that impacts of changes in scale of operation and CO_2 emissions were more than the reduced costs realized due to technical changes. We find that the sample plants in Indian coal-fired thermal power sector had to sacrifice about 3.5 percent of electricity production amounting to 2005US$ 1702 million of revenue loss over the 5 years due to regulation of CO_2 emissions.

JEL Classification: C61, D24, Q22, Q54

Key Words: Environmental production function, CO_2 Emission mitigation cost, Decomposition, DEA, Thermal power plants

1. Introduction

Formulation of a cost-effective environmental policy and taxing polluters for environmental damages requires estimates of environmental costs and benefits. Environmental benefits are measured in terms of the economic value of foregone damages accruing to the society when production of bad outputs is reduced. Environmental costs are measured by taking costs borne by the producers for abating or preventing emissions by improving their production practices. Measuring the benefits is difficult to implement as it involves complex ecological and economic consequences (Liu and Sumaila, 2010). We estimate the environmental costs associated with the emissions from coal-fired electricity generation, a major producer of CO_2 emissions in India.

Coal based electricity generation, with an installed capacity of 222 GW, accounts for about three-fourth of total electricity generation (CEA, 2018) and about 40 percent of total CO_2 emissions in India (MoEF, 2010). In India, approximately 20 percent households are still without access to electricity.[1] With about 520 GW capacity of proposed coal-fired power plants, the emissions of carbon are going to increase substantially (WRI, 2012). We intend to provide estimates of the opportunity cost of regulating carbon emissions [also termed as carbon mitigation cost (CMC)] in the coal-fired thermal power sector in India, using an ex-post analysis.[2]

Estimates of CMC are obtained either through survey methods or modelling joint-production of good and bad outputs (Pasurka, 2001; Färe et al., 2016). Färe et al. (2003) have termed these approaches as stated and revealed methods of calculating pollution abatement costs (PAC), respectively.[3] In survey methods, information regarding costs of inputs assigned to emission mitigation is sought from the producers. Survey methods could be useful in collecting the required information for end-of-pipe treatment methods. But, in cases of integrated processes, it is difficult for producers to provide the required information, since inputs are not specifically assigned to mitigation activities. Therefore, we follow a joint-production function approach to estimate CMC of coal-fired thermal power plants in India.

Joint-production models consider that pollution generation is a by-product in the production process. These models relax the assumption of separability of pollution abatement activities from the process of marketed output production.[4] Joint-production models, by avoiding the difficulties associated with the survey methods, do not assign separate inputs for pollution abatement activities, and hence do not require information on abatement technology and costs. Moreover, these models capture synergy among the abatement processes of multiple pollutants (Färe et al., 2003).

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[1] India is able to electrify all the villages in April 2018, yet about 20 percent household have no access to electricity (http://saubhagya.gov.in/ as accessed on May 15, 2018). A village is said to be electrified if electricity is provided to public places and at least 10% of the total number of households are electrified in the village (http://www.ddugjy.gov.in/portal/definition_electrified_village.jsp, accessed on 17.02.2019)

[2] Under the Kyoto Protocol, India was not required to reduce carbon emissions, but at the Paris Agreement, India has pledged to reduce the CO_2 intensity of GDP by about 30-35 percent by 2030 relative to 2005. Reduction in the desired level of the intensity requires India to take some regulatory measures.

[3] Carbon or CO_2 mitigation cost (CMC) and pollution abatement cost (PAC) words are used interchangeably throughout the paper.

[4] Martin et al. (1990) and Bellas (1998) consider pollution abatement activities to be independent from marketed output production processes.

Joint-production models distinguish between regulated and unregulated technologies. Unregulated technology (strong or free disposability of emissions) assumes that pollutants can be disposed of, at no cost to the producer, while the regulated technology (weak or costly disposability of emissions) considers that a producer has to incur costs for reducing pollution, either in terms of reduced marketed output or assigning more inputs to the joint-production process for a given level of good output with a fixed input vector or a combination of both. Reduction in the emissions could be either due to government mandated regulations or voluntarily by the thermal power plant.

The CMC index is defined as the ratio of the maximum marketed outputs under unregulated and regulated technologies. If a thermal power plant is able to throw away the CO_2 emissions without incurring any cost, then the maximum output of electricity under regulated and unregulated technologies is same and the value of CMC index is equal to one. The index value is greater than one, if under the regulated technology, the maximum output of electricity is less than the maximum output under the unregulated technology. The opportunity cost of emission reduction (CMC) is CMC index minus one, multiplied by the output of electricity.[5]

There are about 309 billion tonnes of coal reserves (mostly sub-bituminous) in India[6]. Indian coal, although cheaper than imported coal and natural gas, has low fixed carbon and high ash content. Indian thermal power plants rely largely on domestic coal. Table 1 records electricity generation from coal and CO_2 emissions from power sector during the period of 2005 to 2013 in India.[7] The production of electricity and CO_2 emissions increased by about 71 and 55 percent respectively during this period, indicating a decline in CO_2 intensity of electricity generation by about 10 percent. CO_2 emissions are not formally regulated in India, but there are regulations on emissions of other local pollutants viz. suspended particulate matter (SPM), SO_2 and NO_x emissions. CO_2 and these local pollutants may be related to each other (Kumar and Managi, 2011; Färe et.al. 2012).. Further, Clean Energy Cess (a sort of carbon tax) of Indian Rupees (INR) 50 (about US$ 0.75) per ton of coal/lignite consumed was introduced in India in 2010-11.. This cess was increased to INR 400 (more than US$ 6) per ton of coal/lignite consumed in 2016-17.[8] All coal-fired thermal power plants are making efforts to increase energy efficiency so as to reduce coal consumption, thereby resulting in a reduction in the emissions per unit of electricity. This has been achieved by the addition of units with higher capacity, which are lower in carbon intensity as compared to units of lower generation capacity (Jain and Kumar 2018). Since the CO_2 emission intensity of coal-fired electricity generation has been declining in India, the prevailing technology is assumed to be regulated technology and is compared with a counterfactual unregulated scenario for the purpose of estimating the CMC.[9]

India, after signing climate treaty in Paris in 2016, has pledged to reduce the carbon intensity of its GDP by 30 – 35 percent by 2030 relative to 2005. To achieve this target, the coal-fired

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[5] $\text{CMC} = (\text{CMC index} - 1) \times \text{Electricity Output}$

[6] Statistical Yearbook 2018, Ministry of Statistics and Programme Implementation, accessed from mospi.gov.in

[7] Information on thermal power plants is available on financial year basis in India, starting April of a year and closing in the March of following year. Therefore, 2005 refers to April 2005–March 2006 and 2013 refers to April 2013–March 2014.

[8] The Clean Energy Cess has been replaced by a GST Compensation Cess at the rate of INR 400 per metric ton of coal and lignite with effect from July 01, 2017. (http://www.cercind.gov.in/2018/orders/13SM.pdf as accessed on July 22, 2019)

[9] Considering the prevailing technology as unregulated technology makes the estimates of CMC upward biased (Färe et al., 2003)

electricity sector has to reduce carbon intensity of electricity generation, i.e., emissions per unit of electricity, substantially, which in turn results in changes in CMC index. Therefore, it would be interesting to analyse the factors that contribute to changes in CMC index. One important way to understand the reasons is to decompose change in CMC index into a technical change (TC) index, an input change (IC) index and an undesirable output production change (UPC) index. To decompose CMC index into TC, IC and UPC, we follow Färe et al. (2016). TC and IC measure the changes in CMC index over time due to due to lack of free disposability of CO_2 emissions, while the UPC reflects the change in CMC index due to a change in the levels of CO_2 emissions generated by a thermal power plant over time.

To generate estimates of the CMC index and the components of its change, we employ a joint-production approach, which produces electricity and CO_2 emissions simultaneously. In the regulated technology scenario, we assume that the good and bad outputs are null-joint and jointly weakly disposable, *i.e.*, to reduce CO_2 emissions, the electricity generating plants have to forego the output of electricity, however they can reduce the output of electricity freely. We compute the indices of CMC and the components of its change using a non-parametric linear programming approach, known as data envelopment analysis (DEA).

We find that Indian coal fired thermal power sector sacrificed about 3.5 percent of electricity production for reducing CO_2 emissions during the period 2008 to 2012.[10] There is an increasing trend in the average CMC. CMC is higher for the central government owned thermal power plants relative to the state governments owned plants. On average, thirteen out of 45 plants are reducing their emissions without incurring any cost. The changes in CMC are governed by the changes in IC and UPC, i.e., the changes in IC and UPC offset the changes in TC. Technical change in the Indian thermal power sector helps in reducing the CMC, i.e., the upward shift in the desired output frontier due to technical change is more under the regulated technology compared to the unregulated technology. This finding supports the Porter hypothesis.

The remaining paper is organized as follows: Section 2 reviews the related literature in the areas of interest. The methodology followed in the paper is discussed in Section 3. Section 4 describes the data used in the study, and the results are discussed in Section 5. Section 6 concludes the paper.

2. Related Literature

A number of studies have applied the production theory to measure environmental costs of pollution prevention/abatement during the last four decades. Lowe (1979) is perhaps the earliest attempt in measuring cost of abatement or shadow prices of pollutants using linear programming approach. Pittman (1981) estimates the marginal abatement costs of water pollutants in a joint-production framework, considering the pollutants as inputs. Pittman (1983) calculated adjusted measures of productivity using engineering estimates of shadow prices of bad outputs. Other attempts, using econometric joint-cost function, include Gollop and Roberts (1985), Kolstad and Turnovsky (1998) and Carlson et al. (2000). All these

[10] Descriptive statistics in Table 2, reveals that electricity production and CO_2 emissions were about 12.14 and 9.03 percent respectively, higher in 2012 compared to 2008, implying declining carbon intensity of electricity generation. If the intensity was constant over the period then an average plant had produced 216 thousand tons more of CO_2 than actually produced i.e. 9726 thousand tons of CO_2 emissions were mitigated by sacrificing 3.5 percent of electricity production by the sample 45 plants.

studies use data of the US coal-fired power plants.

Rolf Färe and his co-authors initiated the application of weak disposability of bad outputs in a joint-production framework for estimating shadow prices of pollutants in the early 1980s. There is another strand of literature that applies joint-production approach for measuring efficiency and productivity in the presence of bad outputs. The objective of the second strand of literature is to give credit to the producers for the reduction in environmental externalities and to estimate the opportunity cost of pollution regulation or the impact of regulation on firm’s performance.

A number of studies have used a joint-production framework for estimating the shadow prices of pollutants, starting with the pioneering work of Färe et al. (1993). Zhou et al. (2014) provide a comprehensive survey of the studies estimating shadow prices of pollutants in the energy sector. Earlier studies used an output distance function to model joint-production of good and bad outputs (e.g., Färe et al., 1993; Coggins and Swinton, 1996, Swinton, 2002). Recent studies, following Färe et al. (2005) employ a directional output distance function for measuring shadow prices of pollutants (e.g., 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; Jain and Kumar, 2018).

Färe and Grosskopf (1983) and Färe et al. (1986) estimate the opportunity cost of pollution abatement, when the polluters are restricted to maintain an observed mix of good and bad outputs. Färe et al. (1989) specify hyperbolic measures of performance requiring proportional increases in good outputs and decreases in bad outputs to measure the opportunity cost of pollution abatement. Picazo-Tadeo et al. (2005) and Du et al. (2016) employ a directional output distance function that allows for expansion of marketed outputs and contraction of bad outputs for estimating firm performance and opportunity cost of emission reduction. Du et al. use a meta-frontier parametric programming approach for estimating the opportunity cost. Liu and Sumaila (2010) estimate pollution abatement costs of Norwegian salmon aquaculture industry using a joint-production approach. Note that all these studies provide specific estimates of pollution abatement costs or shadow price of a pollutant, but fail to shed light on the reasons for changes in abatement costs.

Yet another strand of literature, measuring performance in a dynamic setting, includes studies assessing environmentally-sensitive efficiency and productivity change of production entities. These studies include Chung et al. (1997), Ball et al. (2005), Kumar (2006), Kumar and Khanna (2009), Kumar et al. (2015), among others. Most of the studies use data envelopment analysis (DEA), a nonparametric approach, for measuring the performance of the production units.[11] The studies decompose environmentally-sensitive dynamic performance into efficiency change and technical change.

Following the literature on the decomposition of environmentally-sensitive performance, some recent studies decompose pollution abatement cost (PAC) index into a technical change (TC) index, an input change (IC) index and an undesirable production change (UPC) index (Färe et al., 2016, Cui et al., 2018). The decomposition reveals the sources of change in the PAC. It helps in understanding the effects of change in scale of production, change in pollution intensity and change in the production technology on changes in PAC.

[11] Zhou et al. (2008) review the literature on the use of DEA to model environmental performance

In another study, CMC is estimated using a nonparametric DEA technique, wherein change in desired output due to change in the CO_2 emissions is decomposed into carbon productivity (CP) and output elasticity of substitution (Wang et al., 2018). The carbon abatement cost (CAC) in Wang et al. is similar to the UPC component of change in CMC in Färe et al. (2016). These decompositions of CMC and change in CMC are essential inputs for improving the applicability and effective implementation of environmental policy.

Studies estimating carbon mitigation costs are limited in India, though India is supposed to provide a leading role in the global climate policy. To our knowledge, there are only two studies (Gupta, 2006; Jain and Kumar, 2018) that have estimated the shadow prices of CO_2 emissions. Gupta (2006) estimates the shadow price of CO_2 emissions using an output distance function, a radial measure of efficiency. Jain and Kumar (2018) estimate shadow prices of 56 coal-fired thermal power plants for the period of 2000 – 2013, using a directional output distance function. Both the studies use parametric linear programming approach for estimating output distance function and directional output distance function, respectively.

Färe et al. (2016) define PAC as the ratio of maximum output under unregulated to regulated scenarios of emissions. Emissions are considered as outputs and are assumed to be freely disposable under unregulated disposal technology, by treating them equivalent to good output,[12] but their disposability is costly when the technology is assumed to be regulated.

In the present study, we estimate CMC and its decomposition using information of 45 Indian coal-fired thermal power stations for the period 2008 - 2012. This study gathers the required information for these plants, soliciting the Right to Information (RTI) Act 2005[13] and the publications of Central Electricity Authority (CEA) and Central Electricity Regulatory Commission (CERC).

3. Methodology

3.1 Environmental Production Technology and Production Function

As the objective is to find estimates of carbon mitigation costs (CMC), it will be interesting to understand the relationship between mitigation activities and associated changes in production of marketed output (Pasurka, 2008). In this section we discuss the conditions that an environmental production function should satisfy in order to be a conventional production function. An environmental production function (technology) considers *null-jointness* in the

[12] A given technology captures the basic relations between inputs and outputs, based on physical and natural laws. From the technology point of view, emission is not a freely disposable output. It is costly in terms of the good output foregone or in terms of more inputs required to produce same level of good output, i.e., there is a positive trade-off between good output production and emission generation. The prevailing technology is of weak disposability. Strong disposability is a counterfactual case, considered to compute the cost of emission reduction. There are two approaches for modelling free disposability of bad outputs. We follow Färe and Grosskopf (1983) and other subsequent studies in modelling the free disposability of bad outputs, by treating bad outputs equivalent to good outputs. The second approach drops the constraint related to the bad outputs in the maximization of good output or measure of technical efficiency (Färe et. al., 2016).. The difference between these two approaches of modelling free disposability of bad outputs is inclusion of downward sloping frontier of bad output Färe et. al. (2016) follow the later approach, which does not involve bad outputs under free disposability of bad outputs formulation.

[13] Right to Information (RTI) Act 2005 mandates time bound reply to citizen appeals for government information. (http://righttoinformation.gov.in/).

production of electricity and emissions and assumes that electricity and emissions are jointly weakly disposable.

Consider that a coal-fired electricity generating plant produces a vector of good outputs $y = (y_1, \dots \dots, y_M) \in \Re_+^M$ and bad outputs $b = (b_1, \dots \dots, b_J) \in \Re_+^J$ using a vector of inputs $x = (x_1, \dots \dots, x_N) \in \Re_+^N$. The emissions produced by a thermal power plant are considered as bad outputs. The environmental production technology is represented by an output set which is defined as:

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

The output set consists of the combinations of good and bad outputs that can be produced by a given input vector. It satisfies the standard axioms of compactness and free disposability of inputs (Färe et al., 2005). Since the output combination consists of both good and bad outputs, the output set should satisfy the axioms of *null-jointness* in good and bad outputs and weak disposability of bad outputs.

The axiom of *null-jointness* implies that a coal fired thermal power plant inevitably generates CO_2 emissions, when it generates electricity, i.e., $if \; (y, b) \in P(x) \; and \; b = 0, then \; y = 0$. Similarly, the axiom of weak-disposability of bad outputs implies the reduction in CO_2 emissions requires simultaneous proportional reduction in generation of electricity, i.e., electricity generation and CO_2 emissions are jointly weakly disposable: $if \; (y, b) \in P(x) \; and \; 0 \leq \alpha \leq 1, then \; (\alpha y, \alpha b) \in P(x)$. However, the reduction in electricity generation without reducing CO_2 emissions is attainable: $if \; (y, b) \in P(x), then \; for \; y_0 \leq y, (y_0, b) \in P(x)$.

To represent the environmental production technology using the conventional production function,[14] we assume that a thermal power plant produces only one good output, electricity. Considering $y \in \Re_+^M$, an environmental production function is defined as:

$$F(x; b) = \max\{y: (y, b) \in P(x)\} \quad (2)$$

Since $P(x)$ is non-empty and compact, the function $F(x; b)$ exists. Moreover, $F(x; b)$ is non-decreasing in inputs since inputs are freely disposable. The axioms of weak disposability of emissions and *null-jointness* imply that an environmental production function should satisfy the following conditions:

$$if \; y \leq F(x; b) \; and \; 0 \leq \alpha \leq 1, then \; \alpha y \leq F(x; \alpha b) \quad (3)$$

and

$$F(x; 0) = 0 \quad (4)$$

Equation (3) reflects that proportional reduction in good and bad outputs is attainable. Equation (4) depicts the essentiality of bad outputs in the production of good output, following the *null-jointness* axiom, $if \; y = F(x; b) \; and \; b = 0, then \; y = 0$.

[14] An environmental production function is a special case of an environmental directional distance function, which credits for the expansion of good output. This formulation has been chosen as it replicates Indian CO_2 mitigation policy in thermal power sector.

As the good output is freely disposable, $y \leq F(x;b)$; y is feasible. Under this condition, the output set can be recovered by defining:

$$P(x) = \{(y,b): y \leq F(x;b)\} \quad (5)$$

Therefore, an environmental production function is a complete characterization of a single good output environmental production technology and is a special case of environmental directional distance function (Färe et al., 2007). However, contrary to environmental directional distance function, the environmental production function does not directly credit a producer for reduction in emissions. It seeks to maximize the production of good output for an observed level of inputs and bad outputs.

The environmental production function can be estimated parametrically or non-parametrically. Each approach has its own pros and cons. In this study, we use data envelopment analysis (DEA), a nonparametric approach, for the estimation of the production function. Assume there are $k = 1,2,\ldots\ldots,K$ observations of inputs, good output and bad outputs, i.e. $(y^k, b^k, x^k), k = 1, 2, \ldots\ldots, K$, is a production vector. Assuming weak disposability of bad outputs, we consider a regulated production function for observation k' as:

$$F\left(x^{k'}; b^{k'}\right) = \max \sum_{k=1}^{K} z_k y_k \quad (6)$$

Subject to

$$\sum_{k=1}^{K} z_k b_{kj} = b_{k'j}, \quad j = 1,2,\ldots,J$$

$$\sum_{k=1}^{K} z_k x_{kn} \leq x_{k'n}, \quad n = 1, 2, \ldots, N$$

$$z_k \geq 0, \quad k = 1,2,\ldots,K$$

where z_k $(k = 1,2,\ldots,K)$ are the intensity variables or the weights assigned to each observation in the construction of production possibility frontier. We assume constant returns to scale.[15]

The objective function shows the maximum quantity of the good output, which can be produced from the production possibility frontier, constructed from the observations. The first constraint of equality imposes weak disposability of bad outputs. The second constraint in the linear program (LP) is with respect to the inputs employed in the production process; there is a separate constraint for each of the N inputs used by a thermal power plant. The right hand side of the constraint represents the observed amount of inputs used by a producer, while the left hand side of the constraint depicts the theoretical amount of inputs used by an efficient producer. The inequality sign shows that the inputs employed by a theoretical producer must be less than or equal to the inputs employed by a plant, i.e., the inputs are freely disposable. Moreover, to ensure *null-jointness* in good and bad outputs, the following conditions are imposed:

[15] In the measurement of technical efficiency of thermal power plants in India Singh (1991), Shanmugam and Kulshreshtha (2005), Shrivastava et al. (2012) Sahoo et al. (2017) also assume constant returns to scale (CRS). Some studies measure technical efficiency under variable returns to scale (VRS) by adding a convexity constraint to the CRS model. However, adding a convexity constraint to the CRS model under weak disposability is not equivalent to a VRS model under weak disposability (Färe and Grosskopf, 2003). Chen (2013) indicates that VRS model under weak disposability condition is highly non-linear and is difficult to solve, and the production set is non-convex and non-monotonic.

(a) $\sum_{j=1}^{J} b_{kj} > 0, \quad k = 1,2, \dots, K$
(b) $\sum_{k=1}^{K} b_{kj} > 0, \quad j = 1,2, \dots, J$

That is, each row and column has at least one positive element of bad output in plant-level pollutants matrix (i.e. each plant produces at least one bad output and each bad output is produced by at least one plant). *Null-jointness* can be reflected by making $b_{k'j} = 0$ in equation (6). In this case all the intensity variables will be equal to zero, implying that in the absence of bad outputs there is no good output.

In an unregulated production function, the bad outputs are freely disposable. The LP problem for an unregulated production function is:

$$G(x^{k'}; b^{k'}) = \max \sum_{k=1}^{K} z_k y_k \quad (7)$$

Subject to
$$\sum_{k=1}^{K} z_k b_{kj} \geq b_{k'j}, \quad j = 1,2, \dots, J$$
$$\sum_{k=1}^{K} z_k x_{kn} \leq x_{k'n}, \quad n = 1, 2, \dots, N$$
$$z_k \geq 0, \qquad k = 1,2, \dots, K$$

The LP program in equation (7) is similar to equation (6), except for the equality condition with respect to bad outputs. In this case the equality constraint is replaced by an inequality constraint of greater than equal to (≥) sign. This inequality constraint ensures that the quantity of emissions produced by a theoretical producer should be greater than or equal to the amount of emissions produced by the observed producer, i.e., bad outputs are freely disposable.[16]

3.2 CO_2 Emission Mitigation Cost (CMC) and its Decomposition

When CO_2 emissions are not regulated, their disposal is free for polluters but not for the society. But the regulation of emissions makes their disposal costly and polluters have to divert resources from production of marketed output to reduce emissions. The reduction in emissions is achieved at the cost of reduced marketed output. Thus the CMC, an opportunity cost of reducing emissions, is defined as a loss of marketed output, associated with CO_2 emission mitigation activity (Färe et al., 2007; Färe et al., 2016).

$$CMC = G(x^{k'}; b^{k'}) / F(x^{k'}; b^{k'}) \quad (8)$$

Thus, CMC is the ratio of maximum feasible production of marketed output under unregulated to regulated scenario, for a given level of mitigation activity. This ratio is equal to one, if the regulation of emissions is not affecting the production of marketed output, and it is greater than one, when the mitigation of emissions reduces the production of marketed output.

Figure 1 provides the graphical presentation of unregulated and regulated technology frontiers as 0EBUC and 0ABUC respectively in period t. At the observed good and bad

[16] Technologically there is a positive relation between the production of good and bad outputs, irrespective of the state of regulation. Under regulation, to internalize the emissions effect, the good output is reduced for reducing emissions and in an unregulated situation more of good output is produced simultaneously producing more of bad outputs. However, we use free disposability condition as a counter-intuitive case (Färe et al., 2016).

output combination *(y, b)* corresponds to point ‘a’ in period t, the CMC is equal to $\mathrm{rb}'/_{\mathrm{rb}}$ and

if the observed output combination of good and bad output *(y, b)* corresponds to point ‘f’, then CMC is equal to $\mathrm{sf}'/_{\mathrm{sf}}$.

The CMC reflects the cost of emission regulation in terms of marketed output foregone during the year. The change in CMC (ΔCMC_t^{t+1}) index is defined as the ratio of foregone marketed output in year t+1 relative to foregone marketed output in year t, therefore, we define the ΔCMC_t^{t+1} as:

$$\Delta CMC_t^{t+1} = \frac{G^{t+1}(x^{t+1};b^{t+1})/F^{t+1}(x^{t+1};b^{t+1})}{G^t(x^t;b^t)/F^t(x^t;b^t)} = \frac{G^{t+1}(x^{t+1};b^{t+1})/G^t(x^t;b^t)}{F^{t+1}(x^{t+1};b^{t+1})/F^t(x^t;b^t)} \qquad (9)$$

If the value of ΔCMC_t^{t+1} is equal to one, it indicates that between period t and t+1 the cost of regulation is constant, and if it is greater than one, it shows that CMC increases over the period, and, if the value of the index is less than one, CMC decreases over the period. To show the changes in CMC from time t to t+1 graphically, we extend Figure 1; 0WTZV and 0RSTZV represent the production technologies under unregulated and regulated scenarios in period *t+1*. Corresponding to output combinations of good and bad outputs in period *t* and *t+1* at points ‘a’ and ‘i’, respectively, the change in CMC is:

$$\Delta CMC_t^{t+1} = \frac{\mathrm{sj}'/\mathrm{sj}}{\mathrm{rb}'/\mathrm{rb}} = \frac{\mathrm{sj}'/\mathrm{rb}'}{\mathrm{sj}/\mathrm{rb}}$$

Färe et al. (2016) decompose the ΔCMC_t^{t+1} index into TC index, IC index and UPC index as follows:

$$\Delta CMC_t^{t+1} = \left[\left(\frac{G^{t+1}(x^{t+1};b^{t+1})/G^t(x^{t+1};b^{t+1})}{F^{t+1}(x^{t+1};b^{t+1})/F^t(x^{t+1};b^{t+1})}\right)\left(\frac{G^{t+1}(x^t;b^t)/G^t(x^t;b^t)}{F^{t+1}(x^t;b^t)/F^t(x^t;b^t)}\right)\right]^{\frac{1}{2}} \times \left[\left(\frac{G^t(x^{t+1};b^{t+1})/G^t(x^t;b^{t+1})}{F^t(x^{t+1};b^{t+1})/F^t(x^t;b^{t+1})}\right)\left(\frac{G^{t+1}(x^{t+1};b^t)/G^{t+1}(x^t;b^t)}{F^{t+1}(x^{t+1};b^t)/F^{t+1}(x^t;b^t)}\right)\right]^{\frac{1}{2}} \times \left[\left(\frac{G^t(x^t;b^{t+1})/G^t(x^t;b^t)}{F^t(x^t;b^{t+1})/F^t(x^t;b^t)}\right)\left(\frac{G^{t+1}(x^{t+1};b^{t+1})/G^{t+1}(x^{t+1};b^t)}{F^{t+1}(x^{t+1};b^{t+1})/F^{t+1}(x^{t+1};b^t)}\right)\right]^{\frac{1}{2}}$$

$$=(TC_u/TC_r) \times (IC_u/IC_r) \times (UPC_u/UPC_r) = TC \times IC \times UPC \qquad (10)$$

where TC measures the change in CMC associated with technical change in the unregulated technology scenario relative to the regulated technology scenario over time. Similarly, IC measures the changes in CMC due to changes in the marketed output associated with the changes in input levels when the technology is unregulated relative to the regulated technology over time, whereas UPC (undesirable production change) denotes the change in CMC due to changes in good output over time associated with the changes in the emission levels under regulated technology. A value exceeding one for TC, IC or UPC indicates that the component is associated with increasing ΔCMC between the period t and t+1.

To show graphical the components of change in CMC, Figure 1 is extended to include the frontier for unregulated and regulated technologies involving technology of t period and input combination of t+1 period (0PMYN and 0LMYN) and technology of t+1 period and input combination of t period (0KGXH and 0FGXH). Graphical relationship between ΔCMC_t^{t+1} and its different components, viz, TC, IC and UPC is specified as follows:

$$\Delta CMC_t^{t+1} = \frac{\mathrm{sj}'/\mathrm{rb}'}{\mathrm{sj}/\mathrm{rb}} = \left[\left(\frac{\mathrm{sj}'/\mathrm{sh}'}{\mathrm{sj}/\mathrm{sh}}\right)\left(\frac{\mathrm{rc}'/\mathrm{rb}'}{\mathrm{rc}/\mathrm{rb}}\right)\right]^{\frac{1}{2}} \times \left[\left(\frac{\mathrm{sh}'/\mathrm{sf}'}{\mathrm{sh}/\mathrm{sf}}\right)\left(\frac{\mathrm{rd}'/\mathrm{rc}'}{\mathrm{rd}/\mathrm{rc}}\right)\right]^{\frac{1}{2}} \times \left[\left(\frac{\mathrm{sf}'/\mathrm{rb}'}{\mathrm{sf}/\mathrm{rb}}\right)\left(\frac{\mathrm{sj}'/\mathrm{rd}'}{\mathrm{sj}/\mathrm{rd}}\right)\right]^{\frac{1}{2}} (11)$$

Note that in Färe et al. (2016), change in good output due to change in the production of bad output under unregulated technology remains unaffected as they consider only the horizontal part of production frontier. But we take negatively sloping part also in defining strong disposability of bad outputs. Therefore, it is possible that, as a result of change in bad output, the production of good output is also affected. In the negatively sloping segment of the production frontier, reduction in CO_2 emissions could be associated with a higher production of electricity.

Changes in CMC between periods t and t+1 depend upon relative shifts in unregulated and regulated frontiers. If the maximum good output under unregulated technology increases at a faster rate than under the regulated technology, then ΔCMC_t^{t+1} is greater than one, as CMC increases. The index value equal to one indicates that the rate of increase in maximum good output under the strong and weak disposability of bad outputs is the same and the CMC remains constant over time. On the other hand, if the maximum good output increases at faster rate under regulated technology relative to unregulated technology, then CMC decreases over time and the index value is less than one. This case supports the Porter hypothesis, i.e., properly designed environmental regulations, involving technological change, input mix change or good output change, can trigger innovations that may partially or fully offset the costs of environmental compliance (Porter and van der Linde, 1995). We apply the concept of CMC and its decomposition to measure opportunity cost of CO_2 emission reduction in the Indian coal-fired thermal power sector.

4. Data

We need plant level information for outputs and inputs to estimate the opportunity cost of CO_2 emission mitigation. A coal-fired thermal power station inevitably produces CO_2 emissions and electricity, using various inputs such as coal, labour, capital etc. Survey methods require information on expenditure incurred on abatement activities, which is difficult to get for the carbon mitigation activities. Therefore, to get estimates of carbon mitigation costs (CMC), we resort to a joint-production function model. The information required for estimating the opportunity cost was obtained from the individual plants invoking the Right to Information (RTI) Act and various publications of CEA and CERC.

Petitioning via the RTI Act enabled us to acquire the required information on an unbalanced panel of 56 coal-fired thermal power stations for the period of 1999 – 2013. But we could get complete data for a balanced panel of only 45 plants for the period of 2008 – 2012. Out of these 45 plants, 18 plants are owned and operated by the Central government [including 13 by one corporation i.e., National Thermal Power Corporation (NTPC)] and the remaining 27 plants are run by the various state governments.

To estimate the opportunity cost of carbon emission mitigation, we employ plant level information on three inputs: capital, labour and coal, and two outputs: electricity and CO_2 emissions. Net electricity generation[17] is measured in gigawatt hours (GWh). CO_2 emissions, generated by a plant, are measured in tons. The CEA has been collecting the baseline data in order to facilitate the Clean Development Mechanism (CDM) projects since 2001. Details of CO_2 emissions in the coal-fired thermal power sector are given in the User Guide of Baseline Data, published by CEA. [18]

In the sample plants, coal is the primary fuel in electricity generation process and its consumption is measured in tons[19]. We measure labour 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. Capital input is computed following Dhrymes and Kurz (1964).[20]

Table 2 provides the descriptive statistics of the variables for the years 2008 to 2012. We observe that between 2008 and 2012, the average electricity production and CO_2 emissions of sample plants have increased by about 12 and 9 percent respectively.

5. Results and Discussion

We solve linear programs under weak and strong disposability of CO_2 emissions to estimate the opportunity cost of mitigating the emissions. For the computation of CMC and changes in it, we solve the linear programs for the contemporaneous frontiers, i.e., period t+1 technology consists of period t+1 observations and period t technology consists of period t observations. To measure the components of change in CMC we also have to solve the linear programs for t+1 technology consisting of t period observations and t period technology consisting of t+1 period observations.

Table 3 presents geometric means of CMC, ΔCMC and components of ΔCMC at the plant level. We observe significant variations in the opportunity costs among the power plants. We find that out of 45 plants, 13 plants show CMC index value equal to one and remaining 32 plants show a value greater than one. This implies that these 13 plants are able to throw away the CO_2 emissions without incurring any cost, but the remaining plants have to incur mitigation costs for reducing the emissions. On an average, plants run by the State government had to forego the electricity production by about 3 percent per annum whereas plants run by the Central government had to sacrifice the desired output by about 5 percent in a year. Bhusawal thermal power plant in the state sector and Farraka thermal power plant in the central sector have lower CO_2 intensity of electricity generation and these plants have to forego more electricity for a unit of CO_2 reduction; these plants had to lose about 15 percent of their electricity production per year for mitigating the CO_2 emissions. Generally state-

[17] Net electricity generation is defined as gross electricity generation minus auxiliary consumption of electricity which is used by the plant for generation of electricity.
[18] CO_2 Baseline Database for the Indian Power Sector, User Guide, Version 11.0, April 2016, CEA.
[19] Domestic coal, used in thermal power plants in India, is assumed to be homogeneous, almost having same heat content. Since plant-wise data on coal quality and heat rate was not available for the study period, gross consumption of coal has been used. In Indian thermal power plants, use of non-coal fuel is minimal. The plants use oil, only as an ancillary fuel.
[20] Dhrymes and Kurz (1964), compute capital input as a product of total capacity available during the year, its operational availability factor and number of hours of in a year, measured in Gigawatt hours. For details on the data and variable measurement, please see Jain and Kumar (2018).

owned plants are smaller in size and less efficient (or have higher auxiliary consumption of electricity) as compared to centre-owned plants (Jain and Kumar 2018).

We find a positive correlation between carbon productivity (Electricity produced/CO_2 emissions) and CMC.[21] Higher carbon productivity implies lesser scope for emission mitigation per unit of desired output and this may be considered as a measure of regulatory stringency. This implies that as the regulatory stringency increases, the emission mitigation cost increases and it may be one of the reasons of the variations in CMC among the thermal power plants.

The second reason may be related to scale of operation (plant size). We observe a positive correlation between carbon productivity and plant size or electricity produced by the plant; and a positive, but statistically insignificant, correlation between electricity produced and the mitigation cost. This reflects that larger plants use more carbon productive technology and it is costly for them to further reduce emissions. These findings corroborate with the findings of Färe et al (2003). They observe a similar behaviour of opportunity cost, estimated using the joint production framework for the US manufacturing firms.

Table 4 presents the aggregate yearly loss in terms of good output and resultant revenue loss of the sample plants during the period of 2008 – 2012 due to regulations in disposal of CO_2 emissions. Over these five years, if the sample power plants were not involved in any carbon emission mitigation activity, they would have produced about 59152 GW more of electricity and earned an additional revenue of 2005US$ 1702 million.[22] This comprises of 3.88 and 4.35 percent of total electricity production and revenue respectively. Out of a total of 225 observations over the five years, 60 percent observations do not incur emission mitigation costs. Though we could not find any trend in production or revenue loss, the loss has increased by 68 percent in terms of production and about 130 percent in terms of revenue in the terminal year in comparison to the initial years. This reflects that the opportunity cost of carbon emission mitigation is increasing.

Figure 2 fails to discern any trend in CMC index. From the figure it is evident that the thermal power plants owned by the central government have to incur higher opportunity costs for emission reduction, relative to the plants owned by the various state governments. The carbon productivity of the central government owned plants is higher than the plants owned by the state governments and further increasing carbon productivity or reduction in carbon emissions is costly for these plants. Note that the plants owned by the state governments are of smaller size and higher vintages in comparison to the plants owned by the central government, resulting in lower carbon productivity among these plants (Jain and Kumar, 2018).

To understand the reasons of increasing opportunity cost of CO_2 emission mitigation in the

[21] Wang et al. (2018) find that CMC is the product of carbon productivity and output elasticity of substitution of CO_2 emissions. Output elasticity of substitution (OES) is defined as a ratio of changing rate of the frontier's desirable output level due to the changing rate of CO_2 emissions, i.e., $OES = \frac{\%\Delta y}{\%\Delta b}$. OES indicates the substitution relationship between the desirable output and CO_2 emissions. For a plant having higher carbon productivity, the CMC would be higher since the possibilities of substitution will be lower in comparison to a plant having lower carbon productivity.

[22] Year-wise plant level sale price of electricity at current prices was taken from Central Electricity Authority (CEA) and was converted into 2004-05 level prices, using fuel price index of Reserve Bank of India. The losses are converted to $US, to make it understandable to readers globally.

Indian coal-fired thermal power plants, we decompose the changes in the carbon mitigation costs into TC, IC and UPC. ΔCMC measures the change in mitigation cost in year t+1 relative to year t, the ΔCMC index is greater than one if the cost are increasing, it is less than one if the costs are decreasing and it is equal to one if the costs remain constant over time.

Figures 3, 4 and 5 show the average annual trend in ΔCMC and its components for all the plants, for plants owned by the central government and for plants owned by the state governments respectively. For all the plants, we observe that during the period 2008 to 2009 there is about one percent increase in the CMC, but it declines by about 3 percent during the period 2009 to 2010 and it increases again by about 2 percent during the period 2010 to 2011. It remains stagnant during the period 2011 to 2012. It should be noted that the overall changes in the CMC are governed by the technical changes in the production process. A similar kind of trend is visible for the plants owned by the central sector (Figure 4), but for the plants owned by the state governments, ΔCMC is governed by the input changes (Figure 5)

Figure 6 presents the distribution of the cumulative CMC change indices of the 45 thermal power plants during 2008-2012. It varies in a range of 0.7 to 1.64; we define 5 intervals: [0.69 - 0.9], [0.9 – 1.0], [1.0 -1.05], [1.05 – 1.10] and [1.10 – 1.70]. Sixty four percent of the plants fall in the interval of [1.0 - 1.05], revealing that the CMC for these plants increased by five percent. In about 27 percent cases, the CMC has declined and in five percent observations the CMC has increased by more than 10 percent.

Table 3 presents the geometric means for ΔCMC and its components for the individual power plants over the study period. The mean values of ΔCMC vary from 0.9664 to 1.0828 with an overall mean of 1.0031. This shows that the CMC has increased at about 0.31 percent per year. There are large variations in the changes in CMC among the plants. In plants owned by state governments, the CMC increases at about 0.63 percent per annum, but it declines at an annual rate of 0.22 percent in central government owned plants. Of the 27 state governments owned plants, the CMC increases for 11 plants, it declines for 7 plants and the mitigation cost remains constant for 9 plants. But among the plants owned by central government, 4 plants observe no change in the CMC, 06 plants observe a decline in the mitigation cost and increase is observed in 8 plants. In the state governments owned plants, K-Gudem thermal power plant has the largest average decline of 3.36 percent per year in the mitigation costs, but Bhusawal thermal power plant has an average increase of 8.28 percent per year. Similarly, among the central government owned plants, Neyweli-ST2 and Vindhyachal have the largest decline and increase in the magnitude of mitigation cost of about 3 percent and 1.15 percent per year respectively. Variations in the CMC and ΔCMC show that the Indian thermal power sector has potential to reduce the carbon emissions cost effectively provided the Indian environmental or climate policy uses market-based instruments.

Greater than one value of any of the indices of TC, IC or UPC leads to a positive change in the CMC, a value less than one of the index leads to negative change in the CMC and a value equal to one reflects that it does not contribute in the change of CMC in the subsequent year. As stated above, the CMC is increasing for the thermal power plants owned by the state governments but it is declining for the plants owned by the central government. We find that about 71 percent of thermal power plants observe a technical change that leads to decline in the CMC, for both state and central governments owned plants. The overall average TC index of 0.995 indicates that the opportunity cost of reducing CO_2 emissions has been declining due to technical change. The TC index measures the relative shifts of the unregulated and regulated frontiers between periods t and t+1. If both frontiers are shifting outward, a value less than unity indicates that outward shifting of the regulated frontier is faster than that of the unregulated frontier. This may be a reflection of activities undertaken by these plants to enhance carbon productivity. Weak disposability of CO_2 emissions discourages carbon intensive generation of electricity and power plants adopt technology that simultaneously increases output of electricity and reduces CO_2 emissions, and thus the regulated production frontier shifts towards the north-west. This finding supports the Porter hypothesis and concurs with Murty and Kumar (2003), i.e., higher environmental compliance enhances technical efficiency of Indian manufacturing firms.

Note that IC and UPC offset the reduction in CMC due to TC for the thermal power plants owned by the state governments. We find that in the state plants, 16 out of 27 plants observe an IC index value greater than one. Similarly, 11 out of 18 plants owned by the central government experience increase in the CMC due to change in the scale of operation (IC index value is greater than one). That is, due to change in the scale of operation, the production of electricity increases at a higher rate under the unregulated technology relative to the regulated technology and as a result the mitigation costs increase. We find that IC index is higher for the central government owned plants relative to the state governments owned plants. In Bhusawal and Sipat plants, CMC increases by about 20 and 17 percent respectively due to changes in scale of operation. On the other side, change in the scale of operation helps in reducing the CMC by about 6 percent per year in Bhatinda thermal power plant.

The UPC index is greater than one for about 50 percent of all the thermal plants and this ratio is about 67 and 22 percent for the plants owned by state and central governments respectively. Mandatory regulations of CO_2 reduce the production of electricity, as the thermal power plants cannot throw away the emissions freely under weak disposability condition, as they are able to do under the unregulated technology. In the state government owned plants, the regulation of CO_2 emissions increases CMC at the rate of about 0.5 percent per year, while in the central government owned plants the regulation fails to have any significant impact on the CMC. Thus the decomposition of CMC change shows that increase in the CMC due to weak disposability of the CO_2 emissions is offset by the technical change in case of central government owned thermal power plants. These findings imply that effective technology can help in reducing the mitigation costs effectively.

Since majority of the thermal power plants in India are having sub-critical generation technology during the study period, technical change (TC) is not able to offset the changes in CMC due to changes in scale (IC) and CO_2 emissions (UPC). Thus mere addition/augmentation of capacity will not achieve the desired objective of reduction in CO_2 emissions. This calls for introduction of newer technologies viz. super-critical, ultra-super critical etc.[23]

[23] The terms sub-critical, super-critical and ultra-super-critical are related to steam operating conditions in the boiler of a plant defined in terms of pressure and temperature. The main steam pressure (MPa) is less than 22.1 for the sub-critical plants, it lies between 22.1 to 25 for supercritical plants and for ultra-supercritical plants this value is higher than 25. Ultra-supercritical and supercritical technologies are more efficient, require less fuel per unit of electricity generated and produces less emissions relative to subcritical plants. In India, generally the power plants in the capacity of 100-600 MW capacity are sub-critical and of greater than 660 MW capacity are supercritical.

6. Conclusions

Global warming is considered a major challenge to society. Though India's per capita carbon emissions are low in comparison to global average and the emissions in the developed world, being fourth largest emitter of CO2 emissions, it has a major role to play in the mitigation of these emissions. Coal-fired electricity generation is a major source of carbon emissions in India. This study estimates the carbon emission mitigation costs (CMC) and its decomposition using joint production function framework. The estimates of CMC and the factors influencing it could be important inputs in an effective climate policy.

We estimate CMC and the factors determining change in the CMC, using information of 45 coal-fired thermal power stations over the period of 2008 – 2012. The required information is gathered petitioning the Right to Information (RTI) Act. We estimate an environmental production function using data envelopment analysis (DEA), a non-parametric approach under a regulated and unregulated technology. In the estimation of environmental production function, we invoke the axioms of null-jointness in the production of electricity and CO_2 emissions and weak disposability of the emissions. The CMC index is defined as a ratio of maximum desired output produced under unregulated and regulated technologies. The change in the CMC index is decomposed into TC, IC and UPC indices.

We observe that, on an average, out of 45 plants, 32 plants produce more electricity under unregulated technology than regulated technology over the period of 2008 – 2012. Indian thermal power sector has to forego the electricity output by about 3 percent per year as the CMC and change in the CMC are higher for those plants which observe higher electricity output per unit of carbon emissions. This implies that regulatory stringency and scale of operation are the determinants of the CMC. Moreover, the decomposition of change in CMC reflects that in Indian thermal power plants, technical changes favour decline in the CMC, but the changes in the scale of operation and CO_2 emissions result in offsetting the benefits of technical change.

Huge variation in the CMC reveals that the Indian thermal power sector can reduce the emissions cost-effectively by providing economic incentives to the polluters. Similarly, existence of strong disposability in the disposal of bad outputs (due to presence of technical inefficiencies) in the sector presents a case of environmental and managerial improvement. Possibilities of faster shift in the regulated frontier relative to unregulated frontier shows that a properly designed climate policy may produce more of electricity with reduced CO_2 emissions, i.e., sustenance of Porter hypothesis. The results of this study may be essential input for a well-designed climate policy as they provide ex-ante estimates of environmental costs.

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Table 1: Trend in electricity generation and CO_2 Emissions from power sector in India

Year	CO_2 (million tons)	Electricity (million Units)	CO_2 intensity (Kg/KwH)	CO_2 intensity relative to 2005-06
2005-06	469.7	435100	1.080	1
2006-07	494.7	461340	1.072	0.993
2007-08	520.5	486760	1.069	0.991
2008-09	548.6	512530	1.070	0.992
2009-10	580.1	539980	1.074	0.995
2010-11	598.4	561760	1.065	0.987
2011-12	637.8	612880	1.041	0.964
2012-13	696.5	691560	1.007	0.933
2013-14	727.4	746090	0.975	0.903

Source: Compendium of Environment Statistics-2016

Table 2: Descriptive statistics

Variable	Unit	Obs	Mean	Std. Dev.	Min	Max
2008						
Electricity	GW	45	6456.72	5462.56	421.50	24964.11
CO_2	Thousand tons	45	6950.07	5151.37	469.76	23964.90
Coal	Thousand tons	45	5251.72	3974.07	333.50	18044.83
Labour	INR (millions)	45	5236.09	3462.19	76.00	13199.00
Capital	GW	45	7003.34	5259.96	430.35	24040.54
Carbon Productivity (Electricity/CO_2)	GW/1000 tons of CO_2	45	0.87	0.15	0.53	1.15
2009						
Electricity (GW)	GW	45	6605.15	5560.05	460.96	25903.78
CO_2	Thousand tons	45	7113.99	5262.00	499.14	24800.00
Coal	Thousand tons	45	5281.86	4048.25	350.90	18500.00
Labour	INR (millions)	45	53.20	31.31	1.66	152.28
Capital (GW)	GW	45	7233.44	5475.13	468.05	24507.38
Carbon Productivity (Electricity/CO_2)	GW/1000 tons of CO_2	45	0.86	0.15	0.53	1.06
2010						
Electricity (GW)	GW	45	6645.29	5544.13	423.53	25351.68
CO_2	Thousand tons	45	7033.95	5166.93	456.10	24300.00
Coal	Thousand tons	45	5326.27	4034.37	332.61	18300.00
Labour	INR (millions)	45	55.12	31.64	2.84	118.08
Capital (GW)	GW	45	7415.04	5441.53	448.60	24637.78
Carbon Productivity (Electricity/CO_2)	GW/1000 tons of CO_2	45	0.88	0.17	0.53	1.49
2011						
Electricity (GW)	GW	45	6952.52	5654.38	412.27	24282.50
CO_2	Thousand tons	45	7269.30	5255.05	448.60	23300.00
Coal	Thousand tons	45	5548.14	4199.74	325.99	17900.00
Labour	INR (millions)	45	53.93	30.27	2.84	115.42
Capital (GW)	GW	45	8003.47	5744.88	431.25	23985.78
Carbon Productivity (Electricity/CO_2)	GW/1000 tons of CO_2	45	0.89	0.18	0.51	1.48
2012						
Electricity (GW)	GW	45	7240.66	5982.52	397.04	24467.38
CO_2	Thousand tons	45	7577.77	5549.92	447.77	23467.37
Coal	Thousand tons	45	5909.96	4607.00	358.53	18919.76
Labour	INR (millions)	45	5521.53	3125.47	260.00	11329.00
Capital (GW)	GW	45	8399.90	6327.76	425.65	27360.70
Carbon Productivity (Electricity/CO_2)	GW/1000 tons of CO_2	45	0.88	0.18	0.46	1.43
Overall						
Electricity (GW)	GW	225	6780.07	5600.12	397.04	25903.78

CO_2	Thousand tons	225	7189.02	5236.35	447.77	24812.33
Coal	Thousand tons	225	5463.59	4148.86	325.99	18919.76
Labour	INR (millions)	225	5396.52	3158.67	76.00	15228.00
Capital (GW)	GW	225	7611.04	5635.05	425.65	27360.70
Carbon Productivity (Electricity/CO_2)	GW/1000 tons of CO_2	225	0.88	0.16	0.46	1.49

Table 3: Geometric Means of CO_2 mitigation cost (CMC) index and decomposition of ΔCMC

Plant Name	Ownership	CMC	ΔCMC	TC	IC	UPC	Carbon Productivity
Akrimota Lignite	State	1.014	1.0141	0.9851	1.0169	1.0123	0.719
Amarkantak	State	1	1	1.0197	1.0795	0.9084	0.711
Bandel	State	1	1	1	1.0236	0.977	0.657
Bhatinda	State	1	1.0057	0.9978	0.9438	1.0678	0.788
Bhusawal	State	1.145	1.0828	0.9514	1.1979	0.9501	0.780
Chandarpur STPS	State	1.078	0.9989	0.9864	0.9898	1.0231	0.887
DPL	State	1.021	1	1.0006	0.9443	1.0583	0.633
Ennore	State	1.074	0.9858	0.9769	0.9457	1.067	0.606
Gandhinagar	State	1.007	1.0608	0.9852	1.0228	1.0527	0.878
K_gudem	State	1.066	0.9664	0.9781	1.0127	0.9756	0.973
K-Kheda II	State	1.061	1.0119	0.9929	1.0366	0.9831	0.872
Korba-East	State	1.013	0.9872	0.9844	0.9991	1.0037	0.842
Korba-west	State	1	1	1	1	1	0.918
Kota	State	1.026	1	1.0086	0.9989	0.9926	0.946
Kutch Lignite	State	1.003	0.9964	0.9879	1.0032	1.0055	0.593
Nasik	State	1.015	1.0242	0.9916	1.0035	1.0294	0.810
Panipat	State	1	1	0.9991	1.0008	1.0001	0.859
Paras	State	1.036	1.0111	0.9941	1.0452	0.9731	0.841
Parli	State	1.012	1.0152	0.9887	1.0021	1.0247	0.787
R_Gundem- B	State	1	1	1	0.9967	1.0033	0.911
Rajghat	State	1	1	0.9906	0.9989	1.0106	0.696
Rayalseema	State	1.059	0.9921	0.9851	1.001	1.0062	1.049
Sikka REPL	State	1.001	1.0026	0.996	0.9763	1.031	0.759
Suratgarh	State	1	1	1.0548	0.9756	0.9718	0.957
Ukai	State	1	1.0031	1.0008	1.0032	0.9992	0.865
Vijaywada/N Tata Rao	State	1.137	1.027	0.9775	1.0373	1.0128	1.292
Wanakbori	State	1.004	0.9956	0.9494	1.0284	1.0197	0.918
Chandrapura (DVC)	Centre	1.33	1.0106	1.1026	0.995	0.9212	0.832
Dadri (NCTPP)	Centre	1.002	1.0054	0.9959	1.0354	0.975	1.023
Durgapur	Centre	1.018	1.0012	0.9981	0.9819	1.0216	0.801
Farakka STPS	Centre	1.148	0.9793	0.9702	1.0162	0.9933	1.034
Kahalgaon STPS	Centre	1.22	0.9823	1.0197	1.0604	0.9085	1.030
Korba STPS	Centre	1.009	0.9975	0.9871	1.0177	0.993	1.042
Neyveli FST EXT	Centre	1.004	0.9952	0.9862	1.0082	1.001	0.795
Neyveli ST1	Centre	1	1	1.0004	0.9996	1	0.533
Neyveli ST2 (M Cut)	Centre	1.024	0.9706	0.9749	1.0105	0.9852	0.741
R-Gundem STPS	Centre	1	1.0002	0.9973	0.9978	1.0051	1.047
Rihand STPS	Centre	1.0002	1	0.9988	0.9974	1.0039	1.049
Simhadri	Centre	1.038	1.0052	0.981	1.0761	0.9522	1.060
Singrauli STPS	Centre	1.011	0.9874	0.9899	1.0007	0.9969	1.023
Sipat STPS	Centre	1.049	1.0185	1.0069	1.172	0.8631	1.105
Talcher	Centre	1	1	0.9998	0.9985	1.0017	0.829
Tanda	Centre	1	1	1	1	1	0.849

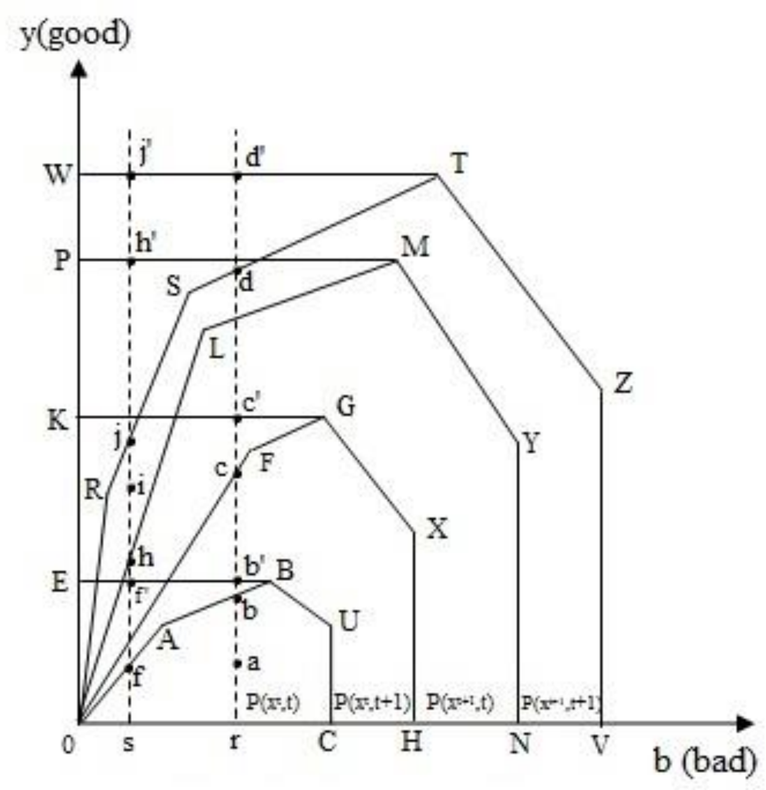
Unchahar	Centre	1.001	1.0005	0.9989	1.0028	0.9988	1.009
Vindhyachal STPS	Centre	1.004	1.0115	0.9946	1.0193	0.9978	1.043
State (Geometric Mean)		1.0278	1.0065	0.9918	1.0095	1.0053	0.834
Centre (Geometric Mean)		1.0443	0.9980	0.9998	1.0208	0.9779	0.944
Overall (Geometric Mean)		1.0344	1.0031	0.9950	1.0140	0.9943	0.875

Table 4: Aggregate opportunity cost of CO_2 emission mitigation (CMC)

Year	Electricity Loss (GW)	%	Resultant Revenue Loss (Million 2005US$)	%	CMC=0 (% observations)
2008	10894.00	3.75	238.36	3.56	56
2009	13625.71	4.58	411.80	5.25	71
2010	4877.78	1.63	154.42	1.96	53
2011	11441.56	3.66	349.56	4.25	49
2012	18312.84	5.62	547.44	6.46	71
Total	59151.88	3.88	1701.58	4.35	60

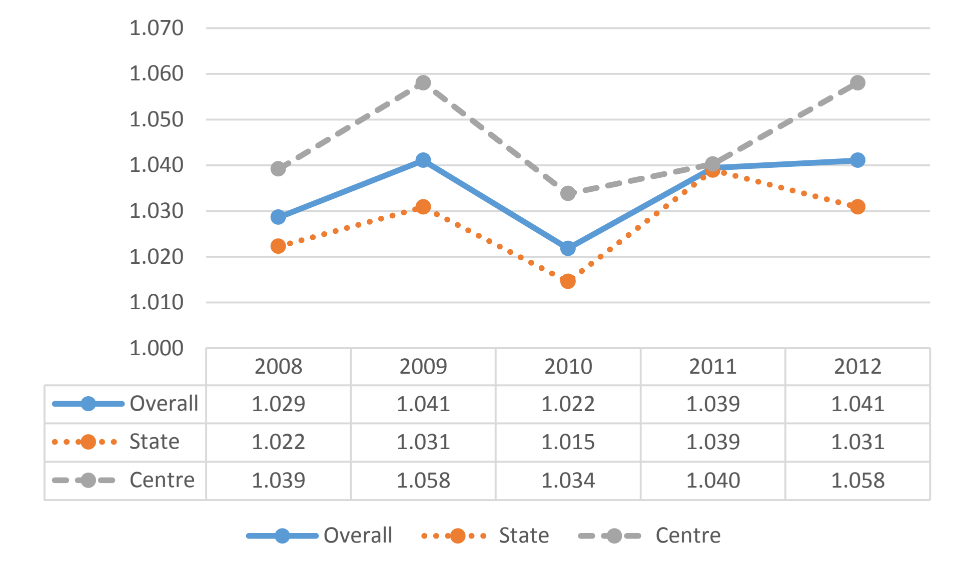
Note: Exchange rate: 1US$=INR65

Figure 1: CO2 mitigation cost (CMC) and its decomposition



Source: Adapted from Färe et al. (2016, Appendix A)

Figure 2: CMC index over the period of 2008 to 2012



	2008	2009	2010	2011	2012
Overall	1.029	1.041	1.022	1.039	1.041
State	1.022	1.031	1.015	1.039	1.031
Centre	1.039	1.058	1.034	1.040	1.058

Figure 3: Change in CMC and its components (Overall)

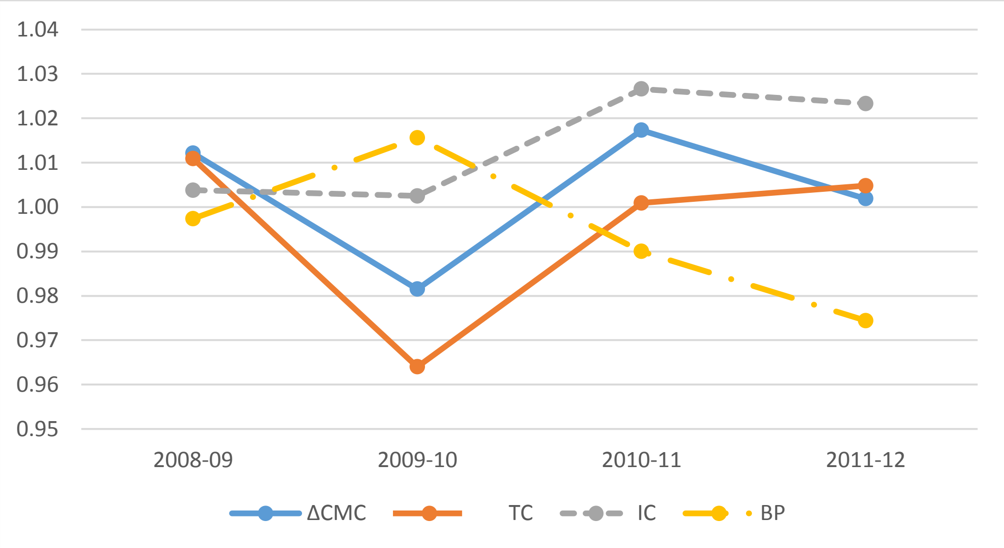


Figure 4: Change in CMC and its components (Central Government owned Plants)

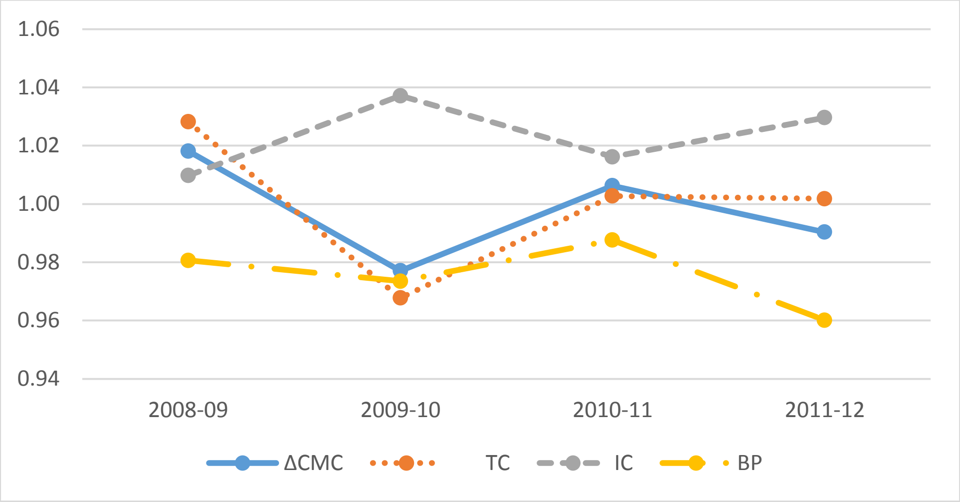


Figure 5: Change in CMC and its components (States Government owned Plants)

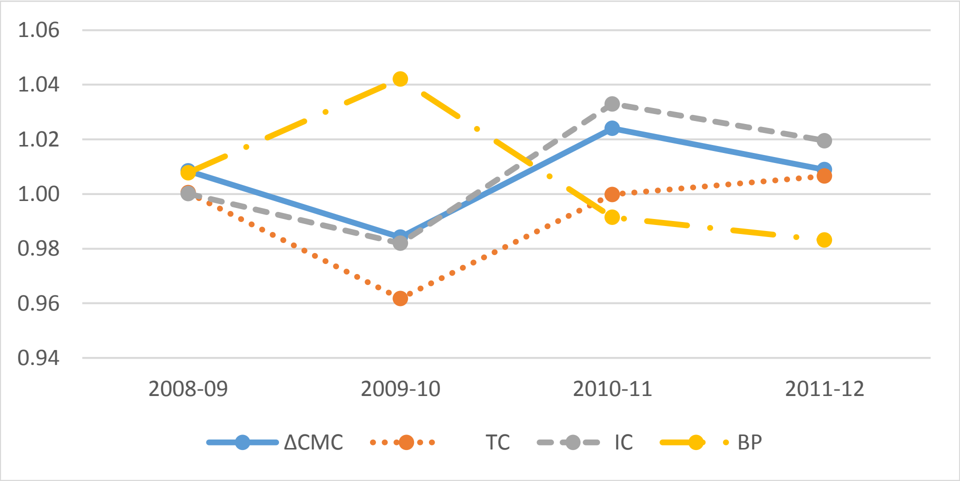


Figure 6: Distribution of ΔCMC