ISSN No. 2454 - 1427

CDE
March 2019

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Working Paper No. 297

http://www.cdedse.org/pdf/work297.pdf

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Abstract

This paper measures carbon-sensitive efficiency and productivity growth in technologically heterogeneous coal-fired thermal power plants in India for the period of 2000 to 2013. It uses a unique data set of 56 plants, obtained petitioning the Right to Information Act 2005. We apply '*within-MLE*' fixed effects stochastic frontier model to get consistent estimates of meta-directional output distance function. The thermal power plants are grouped in two categories: central sector and state sector. We find that the state sector plants have higher potential to simultaneously increase electricity generation and reduce carbon emission than the central sector plants. If all the state and central sectors plants were made to operate on the meta-frontier, reduction of 98 million tonnes of CO_2 could have been achieved. Carbon-sensitive productivity growth in the central sector plants is higher than the plants in state sector, though in both the sectors productivity growth is governed by carbon-sensitive innovation effect. Commercialisation or autonomy in electricity generation also induces carbon-sensitive productivity growth and reduces carbon-sensitive productivity growth gap.

JEL Classification: C61, D24, Q54

Key Words: Carbon-sensitive productivity, Luenberger productivity indicator, Stochastic meta-frontier, Indian thermal power plants

1. Introduction

India, with a population of about 1.3 billion, has approximately 240 million people without access to electricity supply.[1] Yet India is the fourth largest emitter of green house gases, behind China, USA and European Union. At the Paris Agreement in 2015, India pledged to reduce CO_2 emissions intensity, measured as CO_2 emissions per unit of gross domestic product (GDP), by 30-35 percent by 2030 relative to 2005. Coal-based thermal power generation accounts for about two-third of total electricity production and contributes about half of the CO_2 emissions generated in the country. Therefore, it is imperative to improve performance of Indian thermal power plants with respect to CO_2 emissions. This paper intends to measure carbon-sensitive efficiency and productivity of these plants.[2]

Studies, undertaken to measure carbon-sensitive efficiency and productivity, generally assume that production units share a common production frontier (e.g., Färe et al. 2005, Lee 2005, Sueyoshi et al 2010, Sueyoshi and Goto 2013, Murty et al. 2007, Yang and Pollitt 2009, Wei et al. 2013, Kumar and Managi 2016, Jain and Kumar 2018). They do not consider technological heterogeneity among plants, which are due to differences in ownership, fuel mix, technology, size, vintage and region of operation etc. Studies, which account for group heterogeneity in thermal power sector, are based on deterministic measures of efficiency and productivity (e.g., Du et al. 2016, Zhang and Wang 2015) and thus ignore measurement errors.[3]

The assumption of common production frontier produces biased estimates of efficiency and productivity, if the sample plants use different production processes or are of different vintages (Hayami 1969, Hayami and Ruttan 1970, Pitttman, 1981). Meta-production frontier analysis could be a possible way to consider plant-level heterogeneity (Battese et al. 2004, O'Donnell et al. 2008, Huang et al. 2014, Juo et al. 2015). It envelopes commonly conceived production frontiers and addresses the concerns arising out of incomparability of the performance of various groups. It allows estimation of technical efficiency of a production unit relative to group-specific technology and also technological gap with respect to the best practice technology (Kumbhakar et al., 2015).

To measure group-specific carbon-sensitive productivity, we use Luenberger Productivity Indicator (LPI), derived from directional output distance function (DODF), which does not require price information. LPI is decomposed into efficiency change (catch-up effect) and technological change (innovation effect). We use stochastic meta-frontier to estimate the gap between group-specific frontier and the best practice technology. Meta-Luenberger Productivity Indicator (LPI^M) is sum of group-specific Luenberger Productivity Indicator (LPI^G) and productivity growth gap indicator (PGG). Zhang and Wang (2015) further decompose PGG into efficiency change gap (INECG) and technological change gap (TCG).

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[1] For carbon emissions, please see https://www.carbonbrief.org/guest-post-why-indias-co2-emissions-grew-strongly-in-2017 (as accessed on March 30, 2018) and for energy access see the following link http://www.livemint.com/Industry/mf6g1hQV6OlV6HIW5mQTiN/Indias-economic-growth-is-linked-to-the-fortunes-of-the-ene.html (as accessed on March 13, 2018).

[2] Carbon-sensitive efficiency and productivity measures incorporate both electricity and CO_2 emissions with the assumption of weak disposability of CO_2 emissions.

[3] Studies involving meta-frontier analysis in the thermal power sector are limited, but there are many studies in other areas, such as energy efficiency (e.g., Lin and Du, 2013), agriculture (e.g., Chen and Song, 2008), dairy farming (e.g., Moreira and Bravo-Ureta, 2010), credit unions (e.g., Juo et al, 2015) etc. Most of the studies apply non-parametric deterministic measures of productivity measurement such as Data Envelopment Analysis (DEA).

In India, state and central sectors account for 34.06 and 27.55 percent of total coal-based electricity generation capacity as of January 2017; rest of the production capacity being owned by private sector.[4] We exploit plant-level unbalanced panel data of 56 thermal power plants (37 plants owned by the various state governments and 19 plants owned by the central government, mainly National Thermal Power Corporation (NTPC)), for the period 2000 to 2013. We have classified the plants into two groups: central sector and state sector. We measure carbon-sensitive efficiency and productivity for the two groups, incorporating technological heterogeneity.

Estimation of meta-frontier involves two steps. In the first step, we estimate the production frontier for each group separately using stochastic frontier analysis (SFA). In the second step, we estimate meta-frontier enveloping both groups. Battese et al (2004) and O'Donnell et al (2008) involve stochastic approach in the first step but employ mathematical programming approach in the second step. Du et al. (2016) and Zhang and Wang (2015) use the programming approach in both the steps. Programming approach fails to differentiate between technical efficiency and technological gap arising out of random shocks. Therefore, following Huang et al. (2014), we estimate both the steps econometrically. Huang et al. have proposed stochastic meta-frontier in production function context and for measuring technology gap (TG). We have extended the same for measuring carbon-sensitive efficiency and productivity using DODF. SFA has advantages over mathematical programming, since the statistical properties of the estimates are known to draw relevant statistical inferences.

We find absence of technical inefficiency, also known as managerial inefficiency, within the central sector group, while it is about three percent in state sector group. If the state sector plants were operating at the group-specific frontiers, India could have reduced 54 million tons of CO_2 emissions. The country could have reduced 98 million tons carbon emissions if all the plants (Central and State Sectors) were operating at the meta-frontier. Group-specific frontiers of central and state sectors were almost equally distanced from the meta-frontier. Moreover, we find that in central sector, carbon-sensitive productivity growth was driven only by innovations, while in state sector, the productivity growth was attributed to both catch-up and innovation effects. We find that group specific frontier of the central sector tries to catch-up the meta-frontier over time. It is also noticed that the central sector was more carbon-sensitive innovative than the state sector. The meta-productivity growth in the central sector was also 0.6 percent per annum whereas for the state sector it was about two-third of the central sector. We also observe that carbon-sensitive productivity growth in the Indian thermal power sector is dominated by innovation effect.

The paper is organised as follows: Section 2 describes the methodology of stochastic meta-Luenberger Productivity Indicator for measuring carbon-sensitive group-specific and meta-productivity measures. Section 3 discusses the meta-stochastic frontier estimation approach. Process of obtaining the required information and discussion on variables, used in the study, is carried out in Section 4. Section 5 discusses estimated results of efficiency and productivity in India's thermal power industry. Section 6 concludes the paper.

[4] The information on ownership of coal based electricity is obtained from: http://www.cea.nic.in/reports/monthly/executivesummary/2017/exe_summary-01.pdf (as accessed on February 24, 2018). We could not include private sector owned plants in the study due to non-availability of plant level data.

2. Methodology

2.1 Directional Output Distance Function

Suppose that a thermal power plant generates 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 $x = (x_1, \dots \dots, x_N) \in \Re_+^N$. The environmental production technology is defined as:

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

It is assumed that production technology satisfies the standard assumptions of compactness and free disposability in inputs (Färe et al., 2005). Since production technology generates both good and bad outputs, the assumptions of *null-jointness* in good and bad outputs and weak disposability of bad outputs are taken. The assumption of *null-jointness* implies that in a coal-based thermal power plant CO_2 emissions are inevitably produced when the plants generate electricity, i.e., $if\ (y, b) \in P(x)\ and\ if\ b = 0, then\ y = 0$. Moreover, it is assumed that reduction of electricity without reducing CO_2 emissions is possible i.e. $if\ (y, b) \in P(x), then\ for\ y_0 \leq y, (y_0, b) \in P(x)$. However, reduction in CO_2 emissions requires either simultaneous reduction in electricity or increase in input usage, i.e., electricity and CO_2 emissions are jointly weakly disposable: $if\ (y, b) \in P(x)\ and\ 0 \leq \alpha \leq 1, then\ (\alpha y, \alpha b) \in P(x)$.

To measure carbon-sensitive efficiency and productivity, we use directional output distance function (DODF) as an analytical tool. DODF is defined as maximal distance between actual input-output vector and frontier of the output set in a given directional vector $g \equiv \left(g_y, -g_b\right)$, i.e.

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

where β is non-negative factor, scaled to reach the boundary of the output set $P(x)$. DODF seeks simultaneous maximal expansion of good outputs and reduction in bad outputs. Note that DODF is an additive measure of inefficiency in a given direction g. A zero value of β implies absence of technical inefficiency, whereas a positive value of β reflects the presence of technical inefficiency. It is assumed that 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. DODF also satisfies translation property.

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

where ω is an arbitrary scaling factor. Translation 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.

2.2 Luenberger Productivity Indicator (LPI)

Carbon-sensitive productivity is generally measured using Malmquist-Luenberger (ML) productivity indexes. ML indexes are ratio-based measures of productivity growth and overestimate productivity changes (Bousssemart et al. 2003). Instead, we use difference-based

Luenberger Productivity Indicator (LPI) to measure productivity changes in Indian thermal power sector. LPI was first proposed by Chambers et al. (1996). LPI can be expressed as a Bennet-Bowley Indicator (Färe et al. 2008) and is more robust than ML productivity index (Fujii et al. 2014, Kumar and Managi 2009b).

Considering a case of three inputs, one good output (electricity) and one bad output (CO_2 emissions), we parameterize directional output distance function (DODF) in a quadratic form. Inter-period changes in DODF, applying Diewert (1976) quadratic lemma, can be expressed as:

$$\left(\vec{D}^{t} - \vec{D}^{t+1}\right) = 0.5\left[\frac{\partial \vec{D}^{t}}{\partial y} + \frac{\partial \vec{D}^{t+1}}{\partial y}\right]\left(y^{t} - y^{t+1}\right) + 0.5\left[\frac{\partial \vec{D}^{t}}{\partial b} + \frac{\partial \vec{D}^{t+1}}{\partial b}\right]\left(b^{t} - b^{t+1}\right) + 0.5\sum_{n=1}^{3}\left[\frac{\partial \vec{D}^{t}}{\partial x} + \frac{\partial \vec{D}^{t+1}}{\partial x}\right]\left(x^{t} - x^{t+1}\right) - 0.5\left[\frac{\partial \vec{D}^{t}}{\partial t} + \frac{\partial \vec{D}^{t+1}}{\partial t}\right] \tag{4}$$

where D is short form of D (y, b, x; g, t).

LPI, the productivity growth index is generally defined as difference of weighted average rates of growth in outputs and inputs, where the weights are the derivatives of directional output distance function with respect to good output, bad output and inputs respectively.

$$LPI = 0.5\left[\frac{-\partial \vec{D}^{t}}{\partial y} + \frac{-\partial \vec{D}^{t+1}}{\partial y}\right]\left(y^{t+1} - y^{t}\right) - 0.5\left[\frac{\partial \vec{D}^{t}}{\partial b} + \frac{\partial \vec{D}^{t+1}}{\partial b}\right]\left(b^{t+1} - b^{t}\right) - 0.5\sum_{n=1}^{3}\left[\frac{\partial \vec{D}^{t}}{\partial x} + \frac{\partial \vec{D}^{t+1}}{\partial x}\right]\left(x^{t+1} - x^{t}\right) \tag{5}$$

Equation (5) is rearranged as:

$$LPI = \underbrace{\left(\vec{D}^{t} - \vec{D}^{t+1}\right)}_{EFFC\ or\ catch-up\ effect} + \underbrace{0.5\left[\frac{-\partial \vec{D}^{t}}{\partial t} + \frac{-\partial \vec{D}^{t+1}}{\partial t}\right]}_{TP\ or\ innovation\ effect} \tag{6}$$

Equation (6) provides a decomposition of LPI into efficiency change (EFFC) and technical change (TP). Positive value of EFFC implies technical efficiency improvement. DODF is a measure of technical inefficiency, a negative value of the derivative of DODF with respect to time implies an outward shift of production frontier, i.e., technical progress. For the sake of interpretation, we multiply the estimates of technical progress with minus one. Therefore, the positive value of each of the components and of LPI implies an improvement in TFP.

2.3 Meta Luenberger Productivity Indicator (LPI^M)

Given the concepts of DODF and LPI and its decomposition, group specific and meta-DODF and productivity change measures needs to be defined. Note that group is specified based on the group-specific observations, whereas the meta-frontier is constructed using all the observations of all the groups enveloping all group-frontiers. Group-specific and meta-production technology sets are defined as follows, respectively:

$$P^{G}(x) = \{(y, b): x\ can\ produce\ (y, b)\} \tag{7}$$

$$P^M(x) = \{(y,b): x\ can\ produce\ (y,b)\} \quad (8)$$

where $P^M = (P^1 \cup P^2 \cup \dots \dots \cup P^G)$;

Group-specific DODF and meta-DODF are defined as follows:

$$\vec{D}_O{}^G(x,y,b;g_y,-g_b) = \sup\{\beta : (y+\beta g_y, b-\beta g_b) \in P(x)\} \quad (9)$$

and

$$\vec{D}_O{}^M(x,y,b;g_y,-g_b) = \sup\{\beta : (y+\beta g_y, b-\beta g_b) \in P(x)\} \quad (10)$$

Group-specific DODF and meta-DODF measure technical inefficiency of thermal power plants relative to group-specific and meta-production frontiers. The difference between meta and group-directional output distance functions measures technology gap (TG)[5]:

$$TG = \vec{D}_O{}^M(x,y,b;g_y,-g_b) - \vec{D}_O{}^G(x,y,b;g_y,-g_b) \quad (11)$$

Larger value of TG indicates that the less advanced technology is adopted by plants in a specific group relative to best available technology and vice-versa.

Group-specific and meta- Luenberger productivity indicators (LPI) can be defined as:

$$LPI^G = \underbrace{\left(\vec{D}^t - \vec{D}^{t+1}\right)^G}_{EFFC^G} + \underbrace{0.5\left[\frac{-\partial\vec{D}^t}{\partial t} + \frac{-\partial\vec{D}^{t+1}}{\partial t}\right]^G}_{TP^G} \quad (12)$$

and

$$LPI^M = \underbrace{\left(\vec{D}^t - \vec{D}^{t+1}\right)^M}_{EFFC^M} + \underbrace{0.5\left[\frac{-\partial\vec{D}^t}{\partial t} + \frac{-\partial\vec{D}^{t+1}}{\partial t}\right]^M}_{TP^M} \quad (13)$$

Where $EFFC^G$ and $EFFC^M$ are group-specific and meta-inefficiency changes, and TP^G and TP^M depict group-specific and meta-technological progress. The difference between LPI^M and LPI^G, termed as productivity growth gap (PGG) indicator, is a measure of changes in carbon-sensitive productivity growth gap between group-frontier and meta-frontier over time (Zhang and Wang 2015).

$$LPI^M = LPI^G + PGG \quad (14)$$

A positive value of PGG indicates a decrease in productivity growth gap between group-specific and meta-frontier measures of productivity growth. By combining equations (12) and (13), the PGG can be decomposed into efficiency change gap (ECG) and technical change gap (TCG):

[5] TG measures gap between current and potential technologies adopted by the plants

$$PGG = \underbrace{\left\{\left(\vec{D}^{t} - \vec{D}^{t+1}\right)^{M} - \left(\vec{D}^{t} - \vec{D}^{t+1}\right)^{G}\right\}}_{ECG\ or\ PTCU} + \underbrace{\left\{0.5\left[\frac{-\partial\vec{D}^{t}}{\partial t} + \frac{-\partial\vec{D}^{t+1}}{\partial t}\right]^{M} - 0.5\left[\frac{-\partial\vec{D}^{t}}{\partial t} + \frac{-\partial\vec{D}^{t+1}}{\partial t}\right]^{G}\right\}}_{TCG\ or\ FCU} \quad (15)$$

The first term on the right hand side of equation (15) measures the change in technology gap (TG) overtime and the second term captures the speed of the change in group-specific technology relative to meta-technology. A positive value of ECG indicates a decrease in the technology gap. Similarly, a positive value of TCG indicates that the speed of meta-frontier shift is faster than the group-frontier, i.e., a reduction of *innovation gap*. Chen and Young (2010) have termed the reduction in technology gap as or *pure technological catch-up (PTCU)* and reduction in *innovation gap* as *frontier catch-up (FCU).*

3. Estimation Strategy

3.1 Econometric Estimation of DODF

To obtain estimates of carbon-sensitive productivity growth and technology gap, we estimate DODF econometrically. We employ quadratic form of DODF since it is more generalized, it outperforms relative to translog or linear forms (Färe et al., 2010) and accommodates translation property (Färe et al., 2006).[6] The quadratic form of DODF is expressed as:

$$\vec{D}_o^{kt}(y_{kt}, b_{kt}, x_{kt}; 1, -1, t) = \alpha_k + \sum_{n=1}^{N} \alpha_n x_n^{kt} + \beta_1 y^{kt} + \beta_2 b^{kt} + \gamma_1 t + \frac{1}{2}\sum_{n=1}^{N} \alpha_{nn'} x_n^{kt} x_{n'}^{kt} + \sum_{n=1}^{N} \delta_{n1} x_n^{kt} y^{kt} + \sum_{n=1}^{N} \delta_{n2} x_n^{kt} b^{kt} + \frac{1}{2}\beta_{11} y^{kt} y^{kt} + \beta_{12} y^{kt} b^{kt} + \frac{1}{2}\beta_{22} b^{kt} b^{kt} + \frac{1}{2}\gamma_{11} t^2 + \sum_{n=1}^{N} \gamma_{n1} x_n^{kt} t + \gamma_{y1} y^{kt} t + \gamma_{b1} b^{kt} t \quad (16)$$

where $\vec{D}_o^{kt}(.)$ is the DODF for thermal power plant k in year t; $y^{kt}$is electricity generated at plant k in year t; b^{kt} is CO_2 emissions produced 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). For the symmetric and translation properties to hold, the parameters of the DODF need to satisfy the following conditions:

$$\alpha_{nn'} = \alpha_{n'n};\ \beta_1 - \beta_2 = -1;\ \beta_{11} = \beta_{12} = \beta_{22};\ \gamma_{11} = \gamma_{y1} = \gamma_{b1};\ \delta_{n1} = \delta_{n2}$$

Time-trend variable captures exogenous technological changes. The specification (16) allows for neutral and biased TP. The effect of neutral TP is captured by the coefficients γ_1 and γ_{11}. The extent of input biased TP is estimated by the coefficients γ_{n1}. The effects of changes in output bias TP is estimated by the coefficients $\gamma_{y1}\ and\ \gamma_{b1}$.

The stochastic specification of directional output distance function takes the form;

$$\vec{D}_o^{kt} = f(y_{kt}, b_{kt}, x_{kt}; 1, -1, t) + v \quad (17)$$

where *v* is an error term, $v \sim N(0, \sigma_v^2)$.

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

Since $\vec{D}_o^{kt}$ is unobservable, to estimate equation (16), we utilise the translation property of the directional output distance function expressed in equation (3). By substituting $f\left(y + \omega g_y, b - \omega g_b, x;\ g_y, -g_b, t\right) + \omega$ for $\vec{D}_o^{kt}(y_{kt}, b_{kt}, x_{kt}; 1, -1, t)$ in equation (16) and taking ω to the left hand side, we obtain;

$$-\omega = f\left(y + \omega g_y, b - \omega g_b, x;\ g_y, -g_b, t\right) + v - u \qquad (18)$$

where $f\left(y + \omega g_y, b - \omega g_b, x;\ g_y, -g_b, t\right)$ is the quadratic form given by (16) with ω added to y and subtracted from b; and u=$\vec{D}_o^{kt}$ is one-sided error term, $u \sim N^+(0, \sigma_u^2)$. Thus, one is able to obtain variation on the left-hand side by choosing ω that is specific to each plant. We choose CO_2 variable as ω and estimate equation (16) using stochastic frontier framework.

3.2 Econometric Estimation of Meta-DODF

We follow Huang et al. (2014) for the stochastic estimation of meta-frontier. Estimation of meta-DODF involves two steps: first, we estimate group-specific DODF using the framework described above in Section 3.1. The second step involves estimation of meta-DODF. Following Huang et al. (2015), DODF from equation (11) can be reformulated as:

$$\vec{D}_o^{G*}\left(y + \omega g_y, b - \omega g_b, x;\ g_y, -g_b, t\right) = \vec{D}_o^{M*}\left(y + \omega g_y, b - \omega g_b, x;\ g_y, -g_b, t\right) - TG \quad (19)$$

Though the true value of $\vec{D}_o^{G*}(.)$ is unknown, its estimated value, $\hat{\vec{D}}_o^{G*}(.)$ can be obtained by estimating equation (18), which leads to:

$$\vec{D}_o^{G*}\left(y + \omega g_y, b - \omega g_b, x;\ g_y, -g_b, t\right) = \hat{\vec{D}}_o^{G*}\left(y + \omega g_y, b - \omega g_b, x;\ g_y, -g_b, t\right) + V^M \quad (20)$$

where $V^M = \varepsilon - \hat{\varepsilon}$, denotes the random error arising from the estimation of equation (19) with mean zero and a non-constant variance (Huang et al., 2015). Now substituting equation (20) in equation (19), we obtain:

$$\hat{\vec{D}}_o^{G*}\left(y + \omega g_y, b - \omega g_b, x;\ g_y, -g_b, t\right) = \vec{D}_o^{M*}\left(y + \omega g_y, b - \omega g_b, x;\ g_y, -g_b, t\right) + V^M - U^M \quad (21)$$

where $U^M = TG$.

Equation (21) resembles the standard stochastic frontier model and is estimated using SFA framework. The one-sided non-negative error term U^M is assumed to be distributed half-normal, i.e., $U^M \sim N^+(0, \sigma_2^U)$, and independent of V^M. The estimates of meta-inefficiency or $\vec{D}_o^M$ can be obtained as: $\vec{D}_o^M = \vec{D}_o^G + TG$.

We use panel data stochastic frontier models to estimate the parameters of the quadratic distance functions and the values of DODFs, described in equations (18) and (21). The advantage of panel data models is that they are able to distinguish between time-variant and time-invariant effects, which constitute an important part of individual heterogeneity, though both the effects are unobservable. Earlier panel data stochastic frontier models confounded individual heterogeneity with inefficiency (e.g., Schmidt and Sickles, 1984).

Green (2005a, 2005b) proposes 'true fixed effect' models to differentiate between individual heterogeneity and inefficiency. 'True fixed effect' model is essentially a standard fixed effect panel data model supplemented by inefficiency effect; inefficiency effect is variable over time and over cross-sections. Wang and Ho (2010) and Chen et al. (2014) point out that true fixed effect model may suffer from incidental parameters problem. In the case of maximum likelihood estimation (MLE), though the parameter estimates remain unbiased, '*MLE's of the error variances are biased*' (p66, Chen et al, 2014). In SFA, the error variances are essential components of the inefficiency term, which are extracted from the composite error term.

The literature suggests 'transform the model by *first-differencing* or by *within-transforming'* to remove incidental parameters before estimation. We apply '*within-MLE*' SFA model proposed by Chen et al. (2014), to estimate group specific and meta- quadratic DODFs. '*Within MLE*' removes incidental parameters before estimation and produces consistent estimates of parameters and error variances for fixed time periods by maximizing the likelihood function based on the joint density of the deviations from the individual means of the composite error term, ε (Chen et al. 2014).

4. Data

Electricity sector is in Concurrent List[7] of Indian Constitution. Both, central and state governments are involved in generation of electricity in the country. During early 1990s, electricity sector was opened for private sector as a part of reform and restructuring process to bring efficiency and competition in the sector. In coal-based electricity generation, share of central, state and private sector was about 27.55, 34.06 and 38.39 percent as of January 2017. The central sector has been involved in electricity generation through public sector enterprises (PSEs), mainly National Thermal Power Corporation (NTPC) which has more than 50 GW capacity of electricity generation with 19 coal-based plants.[8]

Central Electricity Authority (CEA) is supposed repository of all the required information, as Section 74 of the Electricity Act, 2003 mandates every generating company or person to furnish all information to CEA as it may require. Other possible sources for the information are Central Electricity Regulatory Commission (CERC), a body for regulation of tariffs of generating companies and the websites of individual thermal power plants or companies. However, none of these sources provided complete information of the required variables at the plant level. Therefore, to get the required information, we had to petition the Right to Information (RTI) Act 2005, besides approaching these sources.[9]

Initially we made a list of 98 thermal power plants; 87 Central government or state government or jointly owned and 11 privately owned thermal power plants, and sent the request for the requisite information to these plants under the RTI Act 2005 for the period of 1999 to 2013 in

[7] In India, the division of responsibilities between central (federal) and state governments is governed by the Constitution of India. Seventh Schedule and Article 246 of the Constitution of India divides the subject areas in three lists: Union List, State List and Concurrent List. Under the Concurrent List, both central and state legislatures can enact laws on wide ranging subjects including electricity generation (Kumar and Managi, 2009a).

[8] https://economictimes.indiatimes.com/industry/energy/power/indias-15-generation-capacity-is-now-from-ntpc/articleshow/57791935.cms (as accessed on March 09, 2017).

[9] According to the Right to Information (RTI) Act 2005, it is mandatory for the governments in India to provide information related to government and public sector in a timely manner. (http://righttoinformation.gov.in/).

2014.[10] Only government owned 56 plants responded back with some information since the RTI Act is applicable only to public sector. NTPC sent information only for power generation and other performance indices i.e., operational availability, forced outage, planned maintenance, plant load factor (PLF)[11] etc. Remaining information about thermal power plants run by NTPC, for the period 2008 to 2012, was obtained from the website of the CERC. We obtained data on CO_2 emissions directly from the office of the CEA. Thus, using various sources, we ended up with information on an unbalanced panel of 56 thermal power plants for the period of 2000 to 2013, comprising a total of 458 observations.

We use plant level information on three inputs: capital, labour and coal, and two outputs: electricity and CO_2 emissions for estimating DODF. Net electricity generation, measured in gigawatt hours (GWh), is the difference between gross electricity generation and auxiliary consumption of electricity in a plant. A power plant may be generating high gross electricity but high auxiliary power consumption, a measure of inefficiency, reduces the availability of electricity to the end user. CO_2 emissions are measured in tons of the emissions produced by a plant. The CEA has been collecting the baseline data in order to facilitate the Clean Development Mechanism (CDM) projects since 2001.[12]

In the sample plants, coal is the primary fuel in electricity generation process and is its consumption is measured in tons. 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.[13] Following Dhryms and Kurz (1964), capital input employed in a thermal power station has been defined as:

$$K = SFT/10^3$$

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, note that in a thermal power plant, different units may be commissioned/decommissioned at different points of time in a year; therefore the capacity of a plant available during a year may differ from its nameplate capacity and is measured as:

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

[10] 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.
[11] Plant Load Factor (PLF) is an indicator of capacity utilization and it depends on installed capacity, age of the plant, plant outrage, availability of fuel and water and past performance. It is defined as a ratio of actual electricity generation to electricity generation if the plants is working at its rated power for the entire year. PLF depends on installed capacity, age of the units, past performance, planned outages, availability of water/fuel, etc.
[12] CO_2 Baseline Database for the Indian Power Sector, User Guide, Version 11.0, April 2016, CEA.
[13] http://labourbureaunew.gov.in/LBO_indtab.pdf as accessed on September 2015

Table 1 provides the descriptive statistics of the variables and reveals that the average plant and unit size of a thermal power station in central sector are 1457 MW and 275 MW respectively, whereas in state sector the average plant size and average unit size are 769 MW and 161 MW respectively. Similarly, we observe large differences in the average values of auxiliary consumption of electricity, CO_2 emission intensities and vintages between central and state sectors. The central sector plants are, on average, newer and have low auxiliary consumption and also low CO_2 emission intensity in comparison to state sector plants. These statistics justify for the application of meta-frontier analysis.

5. Results and Discussion

To get group-specific and meta- estimates of LPI, we estimate different versions of DODF. We use mean normalized input and output data. Normalization of input and output data helps in minimizing the problems of convergence in estimation, given the numerical size of outputs and inputs (see Färe et al., 2005). This normalization implies $(x, y, b) = (1, 1, 1)$ for a hypothetical thermal power plant that uses the mean level of inputs and produces the mean level of outputs.[14]

Table 2 provides the parameter estimates of directional output distance function. We estimate four versions of the DODF. In version 1, we use pooled data of central and state sectors. Versions 2 and 3 present the estimates of DODF for the state and central sectors respectively. Meta-DODF parameter estimates are presented in version 4.

We apply log-likelihood ratio (LR) test to test the null hypothesis that the two groups of thermal power sectors share a common production frontier. Table 2 shows that the value of log-likelihood function for the DODF of the pooled data is 618.43, and the values of log-likelihood functions for the DODF of the data for central and state sectors are 195.48 and 469.93, respectively. The value of the LR test statistics 93.96 decisively rejects the null hypothesis of access to common production technology by both central and state-owned thermal power plants in India and vindicates the application of meta-DODF. We also find that, with the meta-DODF estimates, the statistically significant variance ratio of symmetric error term $\left(\bar{\lambda} = \sigma_v^2 / (\sigma_u^2 + \sigma_v^2)\right)$ rejects the null hypothesis of $V^M = 0$, and supports the treatment of stochastic frontier approach in the second step of estimation over mathematical programming approach (Huang et al, 2014).[15] Moreover we find that the ratio of variance of one-sided error term to total variance is statistically significant for the thermal plants of state sector, but it is insignificant for plant in central sector. It indicates the presence of technical inefficiency in state sector's thermal power plants, but all the plants in central sector are operating at the frontier. This finding is reasonable since all the plants of central sector are managed by a single public sector undertaking namely, NTPC and variation in performance of these plants may be reflection of heterogeneity rather than their efficiency. We are also able to reject the null

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[14] The additive values of DODF cannot directly measure the distance of a particular observation to the frontier in percentage terms. Normalization of inputs and outputs helps in addressing this concern also (Du et al., 2016).

[15] In standard stochastic frontier analysis, the variance ratio $\left(\lambda = \sigma_u^2 / (\sigma_u^2 + \sigma_v^2)\right)$ is used to test the null hypothesis of $U^M = 0$, following Huang et al. (2014), we also use $\left(\bar{\lambda} = \sigma_v^2 / (\sigma_u^2 + \sigma_v^2)\right)$ to test the null hypothesis $V^M = 0$, where $\bar{\lambda} = 1 - \lambda$.

hypothesis of $U^M = 0$, in the case of meta-frontier implying the presence of techology gap (TG), i.e., sectoral frontiers of central and state sectors are enveloped by the meta-frontier.

The parameter estimates of group-specific frontiers and meta-frontier reveal that quadratic DODF fits reasonably well in all the versions. Most of the coefficient estimates are statistically significant. In the group-specific estimates, we observe the presence of coal saving technical progress in state sector, but the coefficient estimates of technical progress are not statistically significant for central sector. For technology gap (TG) frontier, we were able to decisively reject the null hypotheses of absence of capital or coal saving technical progress, but could not reject the null hypothesis of labour-saving technical progress.

5.1 Group Specific Inefficiency Estimates and Technology Gap

Table 3 and Figures 1 report the estimates of DODF which demonstrate carbon-sensitive inefficiencies of Indian thermal power plants relative to the plants located on the frontier of their own group. We also report the inefficiency estimates for the pooled version of the DODF. The pooled version of model reveals that the thermal power plants owned by state governments are more inefficient than the central sector thermal power plants but the difference in performance is trivial. However the inefficiency estimates based on the group-specific frontiers reveal that within group all the central sector plants are on the frontier, but the plants in the state sector have potential to increase the generation of electricity and reduce CO_2 emissions. Note that the efficiency results are not comparable between groups since the group frontiers are different.

It is also observed that among the sample plants in the state group, Parli (in 2009) and Vijayawada (in 2004 to 2007) thermal power plants are the most inefficient plants; they have potential to increase electricity production and reduce carbon emissions by more than 10 percent. On the other side, thermal power plants of Chandrapur (in 2006), K-Gundem (in 2004), Karadi (in 2005 and 2011) and Vijayawada (in 2010 to 2012) are the most efficient plants in the state sector; these plants observe less than 0.5 percent inefficiency and may be considered as defining the frontier of the state group.[16] The average value of DODF for the state sector group is 0.032 (Table 3), i.e., the state sector plants have potential to reduce 3.16 percent CO_2 emissions if all of them were operating on its group frontier, which corresponds to reduction of 55.36 million tons of CO_2 emissions over the study period.[17]

Meta carbon-sensitive inefficiency is defined as the sum of group-specific inefficiency and technology gap (TG). TG, estimated using Equation 21, exhibits the distance between meta-frontier and group-frontiers. From Table 1 and Figure 1, it can be inferred that TG, at the mean level, is slightly higher for the central sector in comparison to the state sector. Moreover, dispersion of TG in the central sector is wider than the state sector (Figure 2, panel a). We also observe that thermal power plant of Vijayawada is on the group-frontier as well as on the meta-frontier in 2011.Chandrapur STPS (0.19) in the state group and Neyveli-ST2 (0.17) in the central group are farthest away from the meta-frontier (Appendix Table A1).

[16] Detailed plant level results are presented in Appendix Table A1 and for each of the plant for each of the year results can be obtained from the authors on request.
[17] CO_2 emission reduction potential of plant, k is calculated as follows: $CO_2^k - CO_2^k(1 - DODF^k)$; where CO_2^k is the observed value of CO_2 emissions of plant k.

Meta-inefficiency results indicate that the plants in the central sector are efficient in comparison to the state sector plants (with average inefficiency score of 0.014 and 0.046, respectively) (Table 3 and Figure). The distribution of efficiency score for the state sector is more dispersed than of the central sector (Figure 2, panel b). Overall, the Indian thermal power sector is about 96 percent carbon efficient. We also find a correlation coefficient of 0.3 between meta-inefficiency and auxiliary consumption[18], statistically significant at 5% level. The comparison of estimates of pooled model with the meta-frontier reveals that for state sector, the estimates of meta-inefficiency are higher than the pooled frontier. But in case of central sector, we find that inefficiency estimates, obtained using pooled model, are higher than the meta-frontier model.

It would be interesting to compare efficiency in the use of coal with the meta-efficiency estimates. Efficiency in use of coal or coal productivity is defined as the ratio of coal consumption per unit of electricity in a plant to minimum coal consumption per unit of output in the sample plants over the study period. Plants revealing higher value of this ratio are associated with reduced coal productivity. We find that the average ratio is 11.16 and 11.46 for the state and central sectors respectively, implying that state sector is efficient than the central sector. Estimates of DODF reflect total factor productivity whereas the coal productivity is an indicator of single factor productivity.

Given the meta-inefficiency values, we calculate CO_2 emission reduction potential for each plant of central and state sectors. We find that the state sector plants could have reduced 79.34 million tons of CO_2 emissions over the study period if they had operated at the meta-frontier and the potential reduction of the emissions in the central sector could have been 18.63 million tons. That is, if all the plants of central and state sectors had operated on the meta-frontier, the Indian thermal power sector could have reduced 98 million tons of CO_2 emissions.

5.2. Estimates of LPI^G and Productivity Growth Gap

Table 4 provides annual average statistics of carbon-sensitive meta-productivity growth, represented by LPI^M, and its decomposition for both central and state sectors. The results suggest an increase in carbon-sensitive meta-productivity growth over the study period 2000 to 2013. On average, the productivity growth in the sector was about 0.44 percent per annum. However, central and state sectors witnessed different productivity growth rates. Carbon-sensitive productivity growth in the central and state sectors was about 0.6 and 0.4 percent per annum, respectively. This reflects that, in general, central sector thermal power plants have shown higher carbon-sensitive productivity growth than the state sector plants.

At plant level, on average, we find that 13 central sector plants (about 72 percent of group) and 26 state sector plants (about 68 percent of group) observed an increase in LPI^M (Appendix Table A1). In central sector only one plant (Tanda) shows negative growth of productivity and but in the state sector about 32 percent of the plants observe negative productivity growth. Neyveli[19] ST2 thermal power plant shows the highest LPI^M (average growth rate about 1.5 percent), but the thermal plant of Vijayawada (in the state sector) shows the highest carbon-sensitive productivity growth rate among both the groups. This plant shows a productivity growth rate of 3 percent per annum. Akrimota, Bhusawal and Rajghat (all in state sector) show

[18] Auxiliary Consumption is defined as the difference between gross and net generation of electricity and is a measure of inefficiency.
[19] Neyveli and Akrimota are lignite-based thermal power stations.

the lowest figure of LPI^M equal to -0.004, indicating that these plants have a negative productivity growth rate of about 0.4 percent per year.

We find a small presence of catch-up effect, which is driven by central sector plants. 12 plants in central sector and 13 plants in state sector show improvement in the technical efficiency. In the thermal power plant of Vijayawada, on average, about 60 percent of the productivity growth is attributed to efficiency improvement. It is also observed that overall carbon-sensitive meta-productivity growth is governed by innovation effect. In central sector, on average, about 80 percent of the productivity growth is due to technical progress. 14 plants in Central Sector and 25 plants in state sector exhibit outward shift of production frontier. Chandrapur STPS in state sector and Neyveli ST2 in central sector reveal highest technical progress of 1.9 and 1.2 percent per year, respectively.

We find that group-specific carbon-sensitive productivity growth rate of the state sector is higher than the central sector and is governed by technical progress. In the central sector, we observe a relatively uniform production technology. Moreover, state sector group shows a slightly higher carbon-sensitive technical progress than the central sector group. Carbon-sensitive productivity growth under the meta-froontier model is observed to be higher than the pooled-frontier model. Based on pooled-frontier model, it is seen that central sector witnesses higher productivity growth than the state sector and is attributed to innovation effect.

The difference between the carbon-sensitive meta-productivity growth and group-specific productivity growth is captured by productivity growth gap (PGG) indicator. A positive value of PGG indicates shrinking gap between the meta and group-specific productivity measures. PGG is further decomposed between ECG and TCG, measuring pure technological catch-up (PTCU) and frontier catch-up (FCU) respectively. We observe that the average ECG is negative (-0.0005) for the state sector group but it is positive (0.0012) for the central sector group, which implies that the PTCU has increased for the state sector group, but the effect has decreased for the central sector group (Table 4). The catch-upeffect is positive for both the groups implying that the technological innovation gap in group-frontier vis-à-vis meta-frontier is dwindling.

Above analysis reveals heterogeneity between state and central sector thermal power plants in India. The kernel density plots confirm obvious differences in the distribution pattern of the indicators of carbon-sensitive productivity growth (Figure 3). For example, the kernel density curves of LPI^M of these two groups show that the curve of the central sector is of a steep shape while that of the state sector shows a gradual pattern (Figure 3, Panel A). Similarly, differences can be observed in the distribution patterns of TP^M, $EFFC^M$, PGG and their components, viz., ECG and TCG.

It would be interesting to compare the dynamic trends in indicators of carbon-sensitive productivity growth among the two groups. Figures 4 to 6 depict dynamic changes in cumulative LPI^M and its two components, $EFFC^M$ and TP^M. We consider the year 2000 as the base year, with the indicator values equal to zero. Figure 4 displays an increasing trend in carbon-sensitive productivity growth for both groups; it is higher for the central sector than the state sector and the gap in carbon-sensitive productivity growth between the two groups is increasing over time. We also observe almost concave shape of the productivity growth curves reflecting that in the beginning the productivity is increasing at an increasing rate and after 2004 it is increasing at a decreasing rate. In the state sector group, the growth rate of carbon-sensitive productivity has almost stagnated after 2008, with little fluctuations.

Figure 5 explains cumulative carbon-sensitive meta-efficiency improvement for the two groups. It reflects that efficiency improvements are almost missing in state sector plants. The trend was slightly positive only for the period of 2004 to 2007 in state sector, while for central sector group, it is increasing during 2001 to 2007, then observe a declining trend (2007 to 2010) and has stagnated subsequently. Combining the results of Figures 4 to 6, we infer that carbon-sensitive innovations govern the productivity growth in Indian thermal power sector. We find that both the groups observe an increasing trend in carbon-sensitive innovations, but the growth rate of innovations in central sector is higher than the state sector (Figure 6).

Figure 7 plots the trends in the components of productivity growth gap (PGG), i.e., technical change gap (TCG) and efficiency change gap (ECG). Central sector group shows a continuous upward trend in TCG and an upward trend in ECG till 2007 and stagnation thereafter, with some fluctuations. However, the state sector observes an 'inverted U' shape of TCG, increasing till 2010 and then shows a declining trend. This shows that the technological gaps of state sector thermal power plants increased after 2010, though before that the gaps were declining. The above analysis reveals the heterogeneity observed in carbon-sensitive productivity growth between central sector and state sector thermal power plants in India.

To examine the determinants of carbon-sensitive meta-productivity growth and its components, we regress meta-carbon-sensitive productivity growth on the lagged value of inefficiency, average size of production unit in a thermal power station, CO_2 intensity of electricity generation, ownership dummy (equal to one if owned by the central government, and equal to 0 if owned by a state government), and a dummy to capture plant specific time-invariant characteristics. Inclusion of lagged technical inefficiency as a determinant of productivity growth helps in restating the convergence theory, i.e., plants away from the production frontier would see higher level of productivity growth than those were nearer the frontier (Lall et al., 2002, Kumar, 2006). Similarly, a positive relationship between productivity growth and ownership dummy establishes the fact that autonomy in operations of thermal power plants helps in achieving higher carbon-sensitive growth. We also regress carbon-sensitive innovations, productivity growth gap and technical change gap on the above stated variables.

Table 5 displays the regression results. From the regression results it is evident that plants away from the frontier observe higher productivity growth, since the coefficient of lagged inefficiency is positive and statistically significant. Similarly, we observe a positive relationship between the lagged technology gap and productivity growth gap. It shows a convergence behaviour in carbon-sensitive productivity growth in coal-based electricity sector in India. We discern a negative relationship between the productivity indicators and average size of production unit. It is also found that the carbon-sensitive productivity growth and carbon-sensitive innovations are negatively associated with CO_2 intensity of electricity generation in the country. We also detect a negative relationship between productivity growth gap/technical change gap and carbon intensity.

The sign of dummy variable of ownership is of particular interest. The central sector owned plants are managed by a public sector enterprise namely, NTPC which runs the business of electricity generation almost on commercial terms. On the other hand, electricity generation business in the plants owned by the various state governments is more or less in the hands of bureaucrats and politicians. This positive relationship discerned between carbon-sensitive productivity growth or its components and the ownership dummy indicates that commercialization of or autonomy in electricity generation is beneficial both from energy and environment perspectives.

6. Conclusion

We measure carbon-sensitive meta- efficiency and productivity of the Indian thermal power industry exploiting a unique data set for 56 thermal power plants over the period of 2000 to 2013, obtained invoking the Right to Information Act. We estimate meta-directional output distance function involving stochastic frontier analysis in both the steps; estimation of meta-frontier requires two-step procedure. The advantage of meta-frontier analysis is that it recognises group heterogeneity. We estimate the meta-stochastic frontier using recently developed 'within' maximum likelihood estimator approach to distinguish between plant heterogeneity and productivity.

We group thermal power plants into two groups: state sector plants and central sector plants. We find that the state sector plants have higher potential to increase electricity generation and reduce carbon emission than the central sector plants. The potential in the state sector plants is the combination of both group-specific inefficiency and technology gap, but in the central sector the potential exists because of technology gap only. If all the state and central sectors plants were made to operate on the meta-frontier, they could have reduced the CO_2 emissions of about 98 million tons during the period of 2000 to 2013. Moreover, it is found that the carbon-sensitive productivity growth in central sector is higher than the state sector, though in both the sectors the productivity growth is governed by the carbon-sensitive innovation effect. This finding is consistent with the fact that state governments owned thermal power plants are older than the plants owned by the central government. Observed concave shape of productivity growth curve is an issue of concern, making further growth in carbon-sensitive productivity difficult, which has already stagnated in state sector. The regression results highlight the fact that commercialisation or autonomy in electricity generation induces carbon-sensitive productivity growth and reduces carbon-sensitive productivity growth gap.

This study has some limitations. First, it covers only the period 2000 to 2013 and it is confined to public sector owned plants. Data is not available at unit level. Future studies should consider unit-level data for a longer period and also involve private sector owned plants in the analysis. Second, we recognise the importance of ownership of different plants in state sector and central sector; it would be interesting for the future studies to divide the groups based on various criteria, such as fuel type, location, technology etc. Thirdly, future studies may also take into consideration other air and water pollutants produced by the sector. Nevertheless, the study is able to highlight the technological heterogeneity in carbon-sensitive productivity growth experienced in the thermal power sector by central and state sector plants. The findings of the study underline the importance of modernization and autonomy/commercialization of the sector to harness the potential of carbon-sensitive productivity growth.

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Table 1: Descriptive Statistics of the Variables

		Overall			Central Sector			State Sector		
Variable	Unit	Obs	Mean	Std. Dev.	Obs	Mean	Std. Dev.	Obs	Mean	Std. Dev.
Electricity (net generation)	GWH	458	5830.81	4973.92	127	9808.59	6351.92	331	4304.60	3229.57
CO_2 Emissions	Tonnes (1000)	458	6421.04	4776.88	127	10200	5785.55	331	4955.8	3324.74
Labour Cost	INR (millions)	458	441.5	281.6	127	667.6	308.7	331	354.8	214.9
Capital	GWH	458	6595.37	5080.49	127	10483.71	6257.20	331	5103.47	3569.96
Coal	Tonnes (1000)	458	4806.61	3850.7	127	8102.44	4575.26	331	3542.05	2599.5
Average Unit Size	MW	458	192.25	109.95	127	274.57	140.56	331	160.66	74.76
Plant Size	MW	458	959.96	682.17	127	1456.73	843.93	331	769.35	491.02
CO_2 intensity	kg/kWH	458	1.23	0.26	127	1.13	0.25	331	1.27	0.25
Vintage	Year	458	24.62	10.31	127	22.05	11.32	331	25.60	9.73
Auxiliary Consumption	Percent	458	9.95	2.51	127	8.26	1.98	331	10.60	2.38

Table 2: Parameter Estimates of the Stochastic Directional Distance Frontier

Model	Pooled Stochastic Frontier (Version 1)		State Group Frontier (Version 2)		Central Group Frontier (Version 3)		Meta Stochastic Frontier (Version 4)	
Variable	Coef.	z-stat.	Coef.	z-stat.	Coef.	z-stat.	Coef.	z-stat.
Electricity	-0.620***	-19.59	-0.640***	-11.17	-0.6347***	-13.79	-0.629***	-49.13
CO_2	0.380	-	0.360	-	0.365	-	0.371	-
Electricity^2, $CO_2{}^2$, Electricity×CO_2	-0.136***	-3.85	-0.079*	-1.7	-0.1449***	-2.88	-0.113***	-7.93
Electricity×Labour, CO_2×Labour	-0.052***	-2.72	-0.125***	-4.06	-0.0046	-0.22	-0.073***	-9.51
Electricity×Capital, CO_2×Capital	0.277***	5.57	0.261***	3.56	0.2613***	3.9	0.270***	11.81
Electricity×Coal, CO_2×Coal	0.053	1.48	0.027	0.58	0.0664	1.05	0.040***	3.65

Electricity×Time, CO_2×Time	0.006**	2.23	0.008	1.37	0.0040	1.16	0.005***	4.61
Labour	0.023	1.11	-0.004	-0.12	0.0892***	2.83	0.002	0.26
Capital	0.089*	1.8	0.003	0.04	0.1515**	2.4	0.080***	3.92
Coal	0.165***	3.04	0.239**	2.35	0.1628*	1.84	0.204***	9.26
Time	-0.005***	-2.62	-0.003	-1.21	-0.0044	-0.82	-0.006***	-6.2
$Time^2$	0.001**	2.42	0.001*	1.9	0.0004	0.65	0.001***	5.78
$Labour^2$	-0.036**	-2.12	0.014	0.39	-0.0508**	-2.5	-0.003	-0.38
Labour×Capital	0.140***	4.12	0.310***	4.76	0.0663*	1.76	0.163***	13.03
Labour×Coal	0.027	1.16	-0.004	-0.1	-0.0102	-0.37	0.022**	2.39
Labour×Time	-0.001	-1.01	-0.002	-1.41	-0.0039*	-1.68	0.000	-0.96
$Capital^2$	-0.449***	-5.26	-0.629***	-4.52	-0.4591***	-4.08	-0.463***	-12.92
Capital×Coal	-0.175***	-2.75	-0.150*	-1.64	-0.1093	-1.37	-0.163***	-6.95
Capital×Time	-0.006	-1.29	0.003	0.33	-0.0046	-0.74	-0.004*	-1.96
$Coal^2$	-0.006	-0.1	0.147*	1.61	-0.1021	-0.99	-0.003	-0.12
Coal×Time	-0.007**	-2.23	-0.022***	-3.13	-0.0006	-0.17	-0.008***	-5.65
$Sigma^2$ $(\sigma^2 = \sigma_u^2 + \sigma_v^2)$	0.002***	8.63	0.002***	6.93	0.0004***	7.31	0.000***	5.17
Lambda $\left(\lambda = \sigma_u^2 \big/ (\sigma_u^2 + \sigma_v^2)\right)$	-3.458***	-3.83	-3.498***	-2.94	-0.0035	0	3.611*	1.81
Log likelihood	618.343		469.925		195.4880		979.772	
Number of Observations	458		331		127		458	

Note: ***: significant at 1% level; **: significant at 5% level; *: significant at 10% level

Table 3: Carbon-sensitive Inefficiency at the Group Level

Group		INEFF	$INEFF^G$	TG	$INEFF^M$
State	Mean	0.0342	0.0323	0.0137	0.0460
	S. D	0.0200	0.0183	0.0077	0.0200
Central	Mean	0.0332	0.0000	0.0141	0.0142
	S. D	0.0171	0.0000	0.0106	0.0106
Total	Mean	0.0339	0.0233	0.0138	0.0372
	S. D	0.0192	0.0212	0.0086	0.0229

Note: INEFF: Inefficiency estimates based on pooled model; $INEFF^G$: Inefficiency estimates based on group specific model; TG: Estimates of Technology Gap; $INEFF^M$: Estimates of Meta-Inefficiency. Mean: Arithmatic Average; S.D.: Standard Deviation.

Table 4: Carbon-sensitive Productivity Growth and its Decomposition at the Group Level

	State		Centre		Total	
	Mean	S.D.	Mean	S.D.	Mean	S.D.
LPI^M	0.0039	0.0215	0.006	0.012	0.0044	0.0197
$EFFC^M$	-0.0001	0.0206	0.0012	0.0111	0.0002	0.0187
TP^M	0.0041	0.0067	0.0048	0.0042	0.0043	0.0062
LPI^G	0.0029	0.0188	0.0022	0.0025	0.0027	0.0164
$EFFC^G$	0.0003	0.0182	0	0	0.0003	0.0159
TP^G	0.0025	0.0046	0.0022	0.0025	0.0025	0.0042
PGG	0.0011	0.0091	0.0038	0.012	0.0017	0.0099
ECG	-0.0005	0.0088	0.0012	0.0111	-0.0001	0.0094
TCG	0.0015	0.0023	0.0026	0.003	0.0018	0.0026
LPI	0.0014	0.0204	0.0023	0.0192	0.0016	0.0201
EFFC	0	0.0203	0.0005	0.0187	0.0001	0.0199
TP	0.0014	0.0022	0.0018	0.0028	0.0015	0.0023

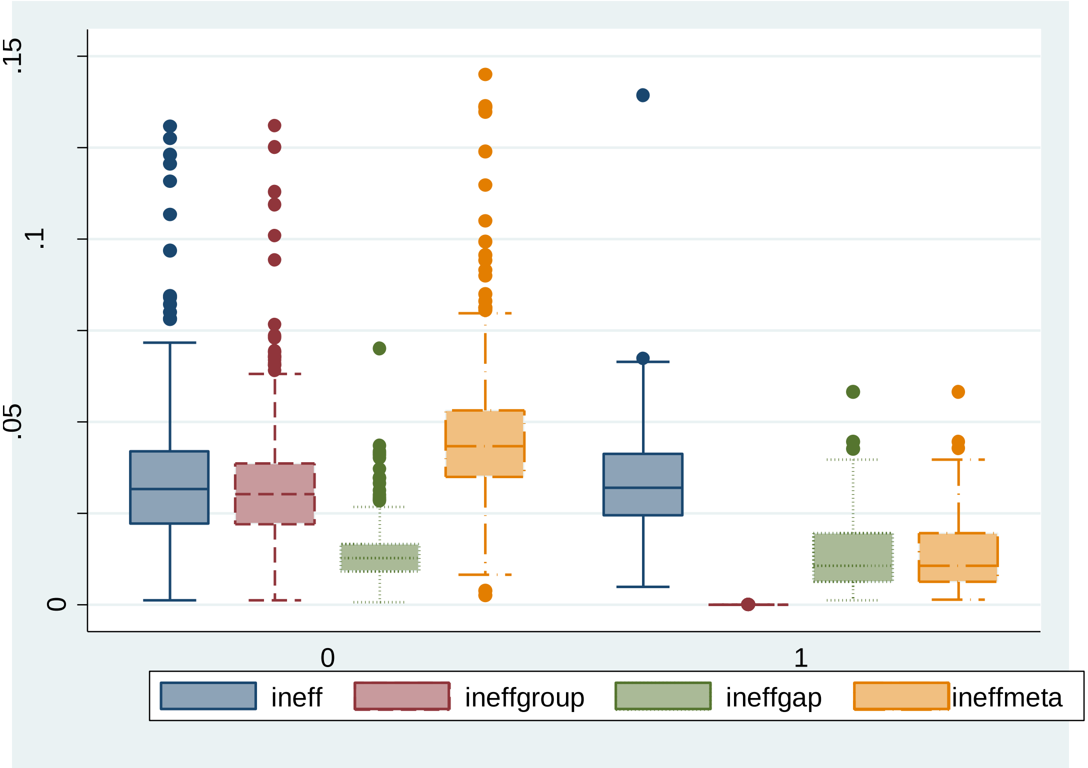
Note: EFFC: Efficiency change based on pooled model; $EFFC^G$: Efficiency change based on group specific model; ECG: Technology change gap; $EFFC^M$: Meta-efficiency change gap; TP: Technical progress based on pooled model; TP^G: Technical progress based on group specific model; TCG: technical change gap; TP^M: Meta technical progress; LPI: Luenberger productivity indicator based on pooled model; LPI^G: Luenberger productivity indicator based on group specific model; PGG: productivity growth gap; LPI^M: Meta Luenberger productivity indicator; Mean: Arithmetic Mean; S. D.: Standard Deviation

Table 5: Determinants of Meta Carbon-sensitive Productivity Growth

	LPI^M		TP^M		PGG		TCG	
	Coef.	t-stat.	Coef.	t-stat.	Coef.	t-stat.	Coef.	t-stat.
$INEFF^M_{t-1}$	0.672***	14.50	-0.0025	-0.24				
TG_{t-1}					0.656***	11.95	0.004	0.41
Ln(Average unit size)	-0.033***	4.99	-0.007***	-4.46	-0.011***	-3.00	-0.004***	5.97
CO_2 intensity kg/kwh	-0.098***	-10.69	-0.005**	-2.42	-0.012**	-2.40	-0.002**	-2.08
Sector dummy (Central=1)	0.032**	2.26	0.014***	4.40	0.019**	2.43	0.013***	8.73
Constant	0.266***	4.01	0.045***	5.20	0.064***	3.05	0.025***	6.38
Plant dummy	Yes		Yes		Yes		Yes	
$F(57,320)$	5.96***		15.62***		3.71***		11.69***	
R^2	0.52		0.74		0.40		0.68	
Obs	378		378		378		378	

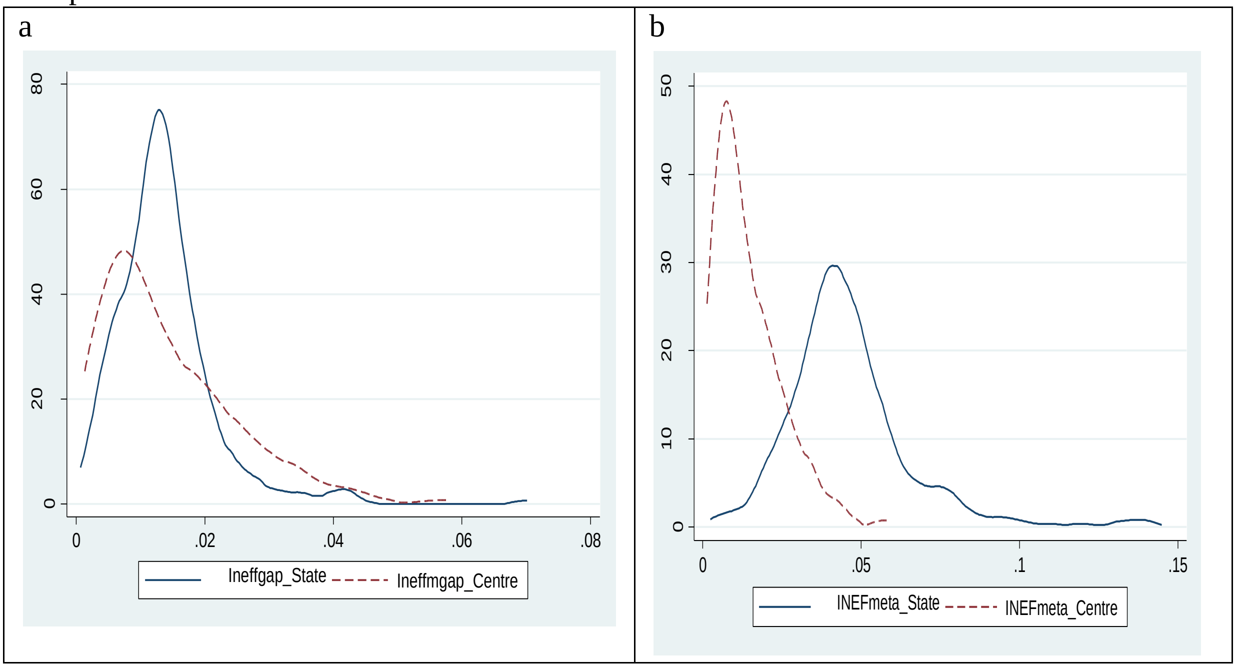
Note: LPI^M: Meta Luenberger productivity indicator; TP^M: Meta technical progress; PGG: productivity growth gap; TCG: technical change gap; TG: Estimates of Technology Gap; $INEFF^M$: Estimates of Meta-Inefficiency.
***: significant at 1% level
**: significant at 5% level
*: significant at 10% level

Figure 1: Various Estimates of Carbon-sensitive Inefficiency Measures



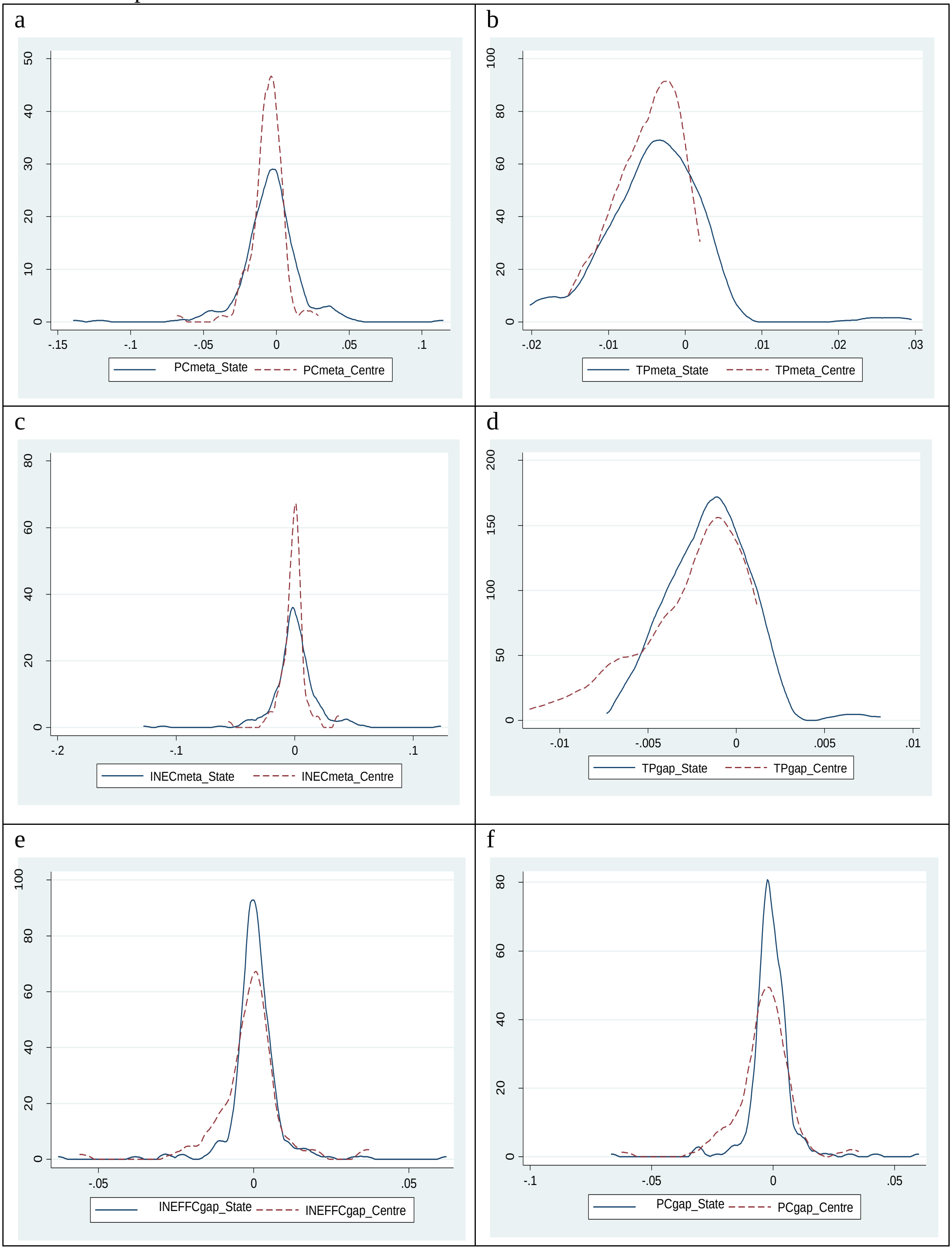
Note: 0: State Group, 1: Central Group; ineff: inefficiency based on pooled model; ineffgroup: inefficiency based on group specific model; ineffgap: technology gap; ineffmeta: meta-inefficiency

Figure 2: Kernel Density Estimates of Carbon-sensitive Inefficiency for State and Central Group



Note: Ineffgap: technology gap; INEFmeta: meta inefficiency

Figure 3: Kernel Density Estimates of Carbon-sensitive Productivity Growth for State and Central Group



Note: PCmeta: Meta Luenberger Productivity Indicator; TPmeta: meta technical progress; INECmeta: meta efficiency change; TPgap: technical progress (change) gap; INEFFCgap: Efficiency change gap; PCgap: Productivity growth gap.

Figure 4: Trends in Cumulative Meta Carbon-sensitive Productivity Growth

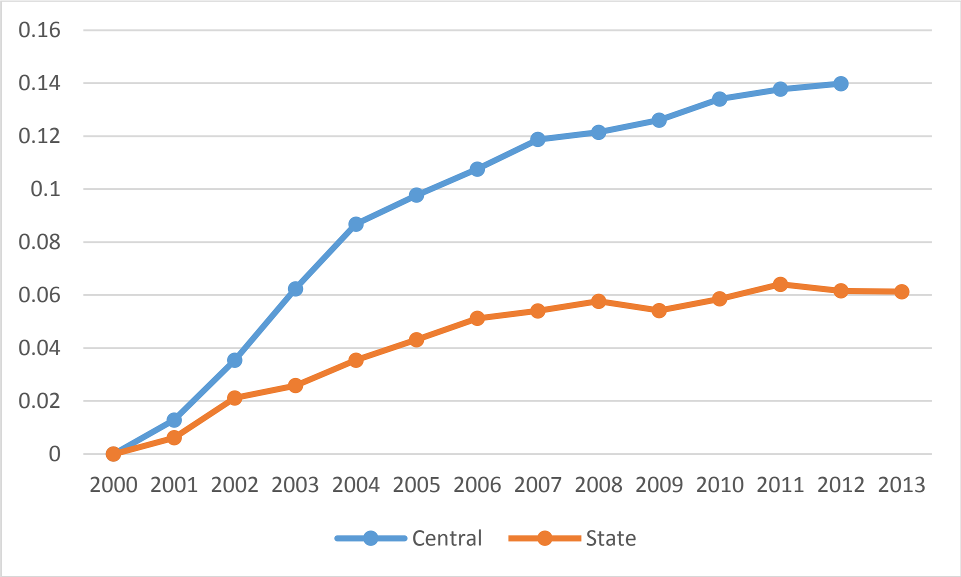


Figure 5: Trends in Cumulative Meta Carbon-sensitive Efficiency Improvement

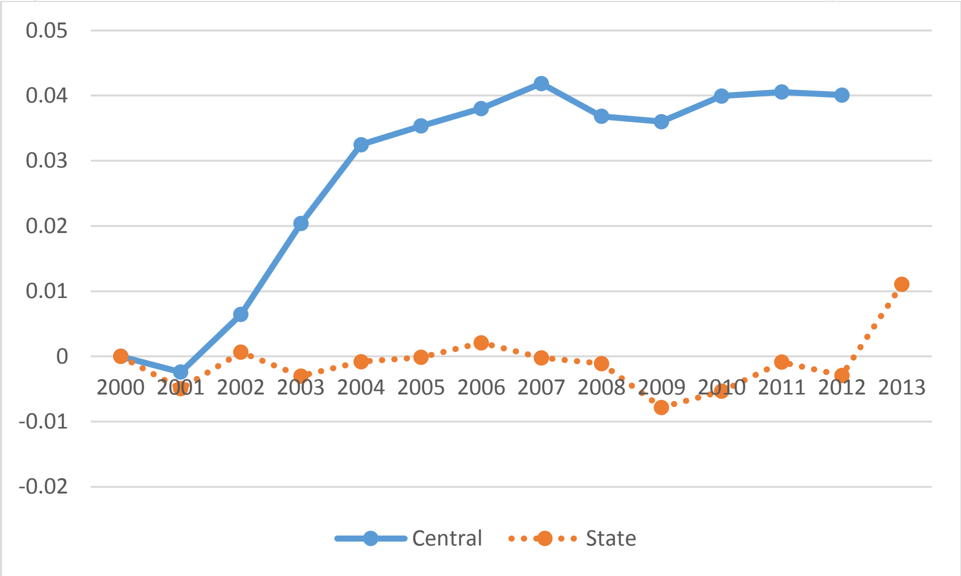


Figure 6: Trends in Cumulative Meta Carbon-sensitive Technical Progress

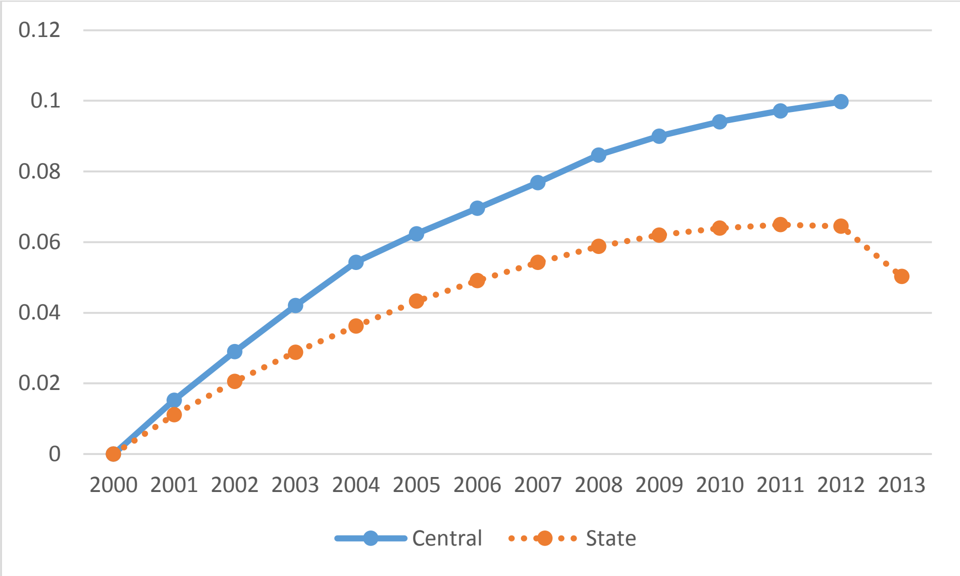
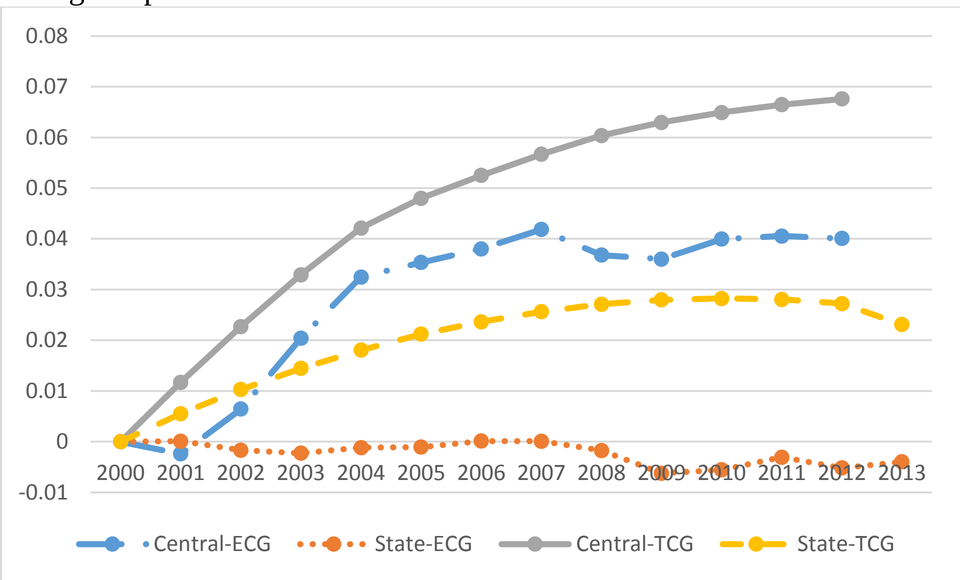


Figure 7: Trends in Cumulative Carbon-sensitive Efficiency Change Gap and Technical Change Gap



Appendix

Table A1: Carbon-sensitive Inefficiency and Decomposition of Productivity Growth at the Plant Level

Plant name	INEFF	$INEFF^{G}$	TG	$INEFF^{M}$	EFFC	$EFFC^{G}$	ECG	$EFFC^{M}$	TP	TP^{G}	TCG	TP^{M}	LPI	LPI^{G}	PGG	LPI^{M}
Badarpur	0.032	0	0.013	0.013	.	.	.	.	.	.	.	.	.	.	.	.
Chandrapura (DVC)	0.033	0	0.013	0.013	0.003	0	0.001	0.001	0.002	0.005	0.001	0.006	0.006	0.005	0.002	0.007
DADRI (NCTPP)	0.033	0	0.013	0.013	-0.011	0	-0.001	-0.001	-0.001	0.002	0	0.002	-0.012	0.002	-0.002	0
Farakka STPS	0.032	0	0.016	0.016	-0.001	0	-0.005	-0.005	0.003	**0.006**	0.003	0.009	0.002	**0.006**	-0.002	0.004
Kahalgaon STPS	0.034	0	0.014	0.014	0.006	0	0.005	0.005	0.006	0.004	0.006	0.009	**0.011**	0.004	0.011	0.015
Korba STPS	**0.039**	0	0.015	0.015	-0.007	0	-0.004	-0.004	0.001	0.002	0.003	0.005	-0.005	0.002	-0.001	0.001
Neyveli FST EXT	0.032	0	0.013	0.013	0	0	0.002	0.002	0.001	0.001	0.001	0.002	0.001	0.001	0.003	0.004
Neyveli ST1	0.032	0	0.014	0.014	0.002	0	0.003	0.003	0.003	0.003	0.004	0.006	0.005	0.003	0.007	0.01
Neyveli ST2	0.034	0	**0.017**	**0.017**	0.002	0	0.003	0.003	**0.006**	0.004	**0.008**	**0.012**	0.008	0.004	0.011	**0.015**
R-Gundem STPS	0.034	0	0.013	0.013	0.002	0	0.001	0.001	-0.002	0	0	0	-0.001	0	0.001	0.001
Rihand STPS	0.032	0	0.013	0.013	0.002	0	0.001	0.001	-0.001	-0.001	0	-0.001	0.001	-0.001	0.002	0
SIMHADRI	0.032	0	0.014	0.014	-0.001	0	0.004	0.004	0	0	0.001	0.001	-0.001	0	0.004	0.005
Singrauli STPS	0.033	0	0.014	0.014	0.005	0	0.002	0.002	0.001	0.002	0.002	0.004	0.005	0.002	0.004	0.006
Sipat STPS	0.035	0	0.013	0.013	**0.008**	0	0.003	0.003	0	0.001	0	0.002	0.008	0.001	0.004	0.005
Talcher STPS	0.033	0	0.016	0.016	0.001	0	**0.009**	**0.009**	0.004	-0.003	0.007	0.005	0.006	-0.003	**0.016**	0.013
Tanda	0.032	0	0.013	0.013	-0.001	0	-0.003	-0.003	0	0.003	0	0.002	-0.002	0.003	-0.004	-0.001
Unchahar	0.032	0	0.014	0.014	-0.006	0	-0.003	-0.003	0	0.003	0	0.003	-0.006	0.003	-0.003	0
Vindhyachal STPS	0.037	0	0.015	0.015	-0.002	0	0.004	0.004	0	-0.003	0.003	0	-0.002	-0.003	0.007	0.004
Akrimota Lignite	0.032	0.03	0.013	0.043	-0.001	-0.002	0.001	-0.002	-0.001	-0.002	-0.001	-0.002	-0.002	-0.004	0	-0.004
Amarkantak	0.032	0.031	0.013	0.044	-0.002	-0.002	0	-0.002	0.001	-0.001	0.001	0.001	-0.001	-0.003	0.001	-0.002
Bandel	0.032	0.031	0.013	0.044	-0.006	-0.007	0	-0.007	-0.001	-0.002	-0.001	-0.003	-0.007	-0.008	-0.001	-0.01
Bhatinda	0.033	0.03	0.013	0.043	0.004	0.003	0	0.003	0.002	0.002	0.002	0.004	0.006	0.005	0.002	0.007
Bhusawal	0.033	0.031	0.013	0.045	-0.006	-0.008	-0.001	-0.009	0.002	0.003	0.002	0.005	-0.003	-0.005	0.001	-0.004
Chandarpur STPS	0.04	0.035	**0.019**	0.054	-0.006	0.002	-0.005	-0.002	**0.005**	**0.014**	**0.006**	**0.019**	-0.001	0.016	0.001	0.017
DPL	0.033	0.031	0.013	0.044	0.001	0.001	0	0.001	0	0	0	0	0.002	0.001	0	0.001
Durgapur	0.032	0.03	0.013	0.043	0.003	0.003	-0.002	0.001	0	0	0	-0.001	0.003	0.003	-0.002	0.001
Ennore	0.032	0.03	0.013	0.043	0	0	0	0	0.003	0.002	0.002	0.004	0.002	0.002	0.002	0.004
Faridabad	0.032	0.03	0.013	0.043	0.004	0.002	0.002	0.004	0.002	0.001	0.002	0.003	0.006	0.003	0.004	0.007
Gandhinagar	0.033	0.031	0.013	0.044	0.007	0.004	0.002	0.006	0.001	0	0.001	0.001	0.008	0.004	0.003	0.007
I B Valley	0.032	0.03	0.013	0.043	-0.001	0.001	-0.002	-0.001	-0.001	0.001	-0.001	0	-0.002	0.002	-0.003	-0.001
K-Kheda II	0.033	0.03	0.014	0.044	-0.003	0.001	-0.003	-0.002	0.002	0.004	0.002	0.006	-0.001	0.005	-0.001	0.004
K_gudem	0.034	0.035	0.016	0.051	-0.009	-0.011	0.002	-0.009	0.004	0.01	0.004	0.014	-0.005	-0.001	**0.006**	0.005

Koradi	0.04	0.037	0.014	0.05	0.001	0	0.003	0.003	0.003	0.005	0.003	0.008	0.004	0.005	0.005	0.011
Korba-East	0.033	0.032	0.013	0.045	0.002	0.001	-0.001	0	0.003	0.006	0.003	0.009	0.005	0.008	0.002	0.009
Korba-west	0.033	0.032	0.013	0.045	0.001	0.003	-0.002	0.001	0.002	0.005	0.002	0.006	0.003	0.008	0	0.007
Kota	0.033	0.031	0.013	0.045	0	0	0	0	0.001	0.003	0.002	0.005	0.001	0.003	0.002	0.005
Kutch Lignite	0.032	0.03	0.013	0.044	-0.002	0	-0.002	-0.002	0	0.001	0	0.001	-0.002	0.002	-0.002	-0.001
Nasik	0.037	0.037	0.013	0.05	-0.001	-0.002	0.001	-0.001	0.002	0.003	0.002	0.006	0.001	0.001	0.003	0.004
Panipat	0.034	0.033	0.013	0.046	-0.001	0	-0.001	-0.001	0.001	0.005	0.002	0.007	0.001	0.005	0.001	0.006
Paras	0.032	0.031	0.014	0.045	0	0.003	-0.003	0	0.001	-0.001	0	0	0.001	0.002	-0.003	-0.001
Paricha	0.032	0.03	0.013	0.043	0.007	0.004	0.003	0.007	0.002	0.001	0.002	0.003	0.01	0.005	0.005	0.01
Parli	0.036	0.034	0.013	0.047	-0.001	-0.002	0	-0.001	0.002	0.002	0.002	0.004	0.001	0.001	0.002	0.002
R_GUNDEM - B	0.032	0.03	0.013	0.043	0	-0.001	0.001	0	0.001	-0.001	0	-0.001	0.001	-0.002	0.001	-0.001
Rajghat	0.032	0.03	0.013	0.043	-0.002	-0.002	0	-0.002	0	-0.002	-0.001	-0.002	-0.002	-0.004	-0.001	-0.004
Rajiv Gandhi Hisar	0.032	0.03	0.013	0.043	0.013	0.01	0.005	0.015	-0.002	-0.001	-0.002	-0.002	0.011	0.01	0.003	0.013
Rayalseema	0.032	0.031	0.014	0.045	0.001	0.004	-0.002	0.001	0.001	0.002	0.001	0.003	0.002	0.006	-0.001	0.004
Sagardighi TPP	0.032	0.03	0.013	0.043	-0.001	0.001	-0.002	-0.002	-0.001	-0.001	-0.001	-0.002	-0.002	0	-0.003	-0.003
Satpura	0.037	0.032	0.015	0.047	-0.006	-0.003	-0.004	-0.007	0.004	0.009	0.004	0.014	-0.002	0.006	0.001	0.007
Sikka REPL	0.032	0.03	0.013	0.043	0	-0.002	0.001	0	0	-0.001	0	-0.002	0	-0.003	0.001	-0.002
Suratgarh	0.032	0.031	0.014	0.045	0	0.001	-0.001	0	0	0.002	0.002	0.003	0.001	0.003	0	0.003
Talcher	0.032	**0**	0.013	0.013	0.002	0	-0.004	-0.004	0	0.005	0	0.005	0.002	0.005	-0.004	0.001
Tenughat	0.032	0.03	0.013	0.043	0.003	0.004	0	0.003	0	-0.001	0	-0.001	0.003	0.002	-0.001	0.002
Tutikorin	0.032	0.03	0.014	0.044	-0.005	-0.001	-0.003	-0.004	0.001	0.005	0.002	0.007	-0.004	0.004	-0.001	0.003
Ukai	0.032	0.03	0.013	0.043	-0.001	-0.001	-0.001	-0.001	0.002	0.002	0.002	0.004	0	0.002	0.001	0.003
Vijaywada	**0.07**	**0.061**	0.017	**0.078**	**0.016**	**0.016**	0.001	**0.018**	0.003	0.009	0.003	0.012	**0.019**	**0.025**	0.005	**0.03**
Wanakbori	0.033	0.03	0.015	0.046	0.006	0.002	**0.005**	0.006	-0.004	-0.009	-0.003	-0.012	0.002	-0.007	0.001	-0.006
Central	0.0332	0.0000	0.0141	0.0142	0.0005	0.0000	0.0012	0.0012	0.0018	0.0022	0.0026	0.0048	0.0023	0.0022	0.0038	0.0060
State	0.0342	0.0323	0.0137	0.0460	0.0000	0.0003	-0.0005	-0.0001	0.0014	0.0025	0.0015	0.0041	0.0014	0.0029	0.0011	0.0039
Total	0.0339	0.0233	0.0138	0.0372	0.0001	0.0003	-0.0001	0.0002	0.0015	0.0025	0.0018	0.0043	0.0016	0.0027	0.0017	0.0044

Note: INEFF: Inefficiency estimates based on pooled model; $INEFF^G$: Inefficiency estimates based on group specific model; TG: Estimates of Technology Gap; $INEFF^M$: Estimates of Meta-Inefficiency; EFFC: Efficiency change based on pooled model; $EFFC^G$: Efficiency change based on group specific model; ECG: Technology change gap; $EFFC^M$: Meta-efficiency change gap; TP: Technical progress based on pooled model; TP^G: Technical progress based on group specific model; TCG: technical change gap; TP^M: Meta technical progress; LPI: Luenberger productivity indicator based on pooled model; LPI^G: Luenberger productivity indicator based on group specific model; PGG: productivity growth gap; LPI^M: Meta Luenberger productivity indicator.