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Total-factor carbon emission performance of fossil fuel power plants in China: A metafrontier non-radial Malmquist index analysis

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ABSTRACT

This paper proposes the metafrontier non-radial Malmquist CO_2 emission performance index (MNMCPI) for measuring dynamic changes in total-factor CO_2 emission performance over time. The MNMCPI method allows for the incorporation of group heterogeneity and non-radial slack into the previously introduced Malmquist CO_2 emission performance index (MCPI). We derive the MNMCPI by solving several non-radial data envelopment analysis (DEA) models. We decompose the MNMCPI into an efficiency change (EC) index, a best-practice gap change (BPC) index, and a technology gap change (TGC) index, and based on the proposed indices, we examine the dynamic changes in CO_2 emission performance and its decomposition of fossil fuel power plants in China for the 2005–2010 period. The empirical results show a 0.38% increase in total-factor CO_2 emission performance as a whole and a U-shaped MNMCPI curve for the sample period. Because companies owned by the central government lack innovation and technological leadership, the results suggest a missing link in the role of the central government in promoting CO_2 emission performance.

1. Introduction

There is growing concern over the mitigation of climate change in China. During the 11th five-year plan (2006–2010), the Chinese government announced the mandatory goals of a 20% reduction in energy intensity (energy consumption per GDP) from 2006 to 2010 and a 40–45% decrease in carbon intensity (CO_2 emissions per GDP) by 2020 compared to the 2005 level. Based on these goals, the fossil fuel power sector has been under considerable pressure to reduce its energy use and CO_2 emissions because fossil fuel electricity generation accounted for approximately 50% of coal consumption and 48% of CO_2 emissions in China as of 2010 (Liu and Wang, 2011). In this regard, it is crucial for power plants in China to vastly improve their CO_2 emission performance not only for reducing CO_2 emission regulation risks but also for increasing “climate change competitiveness” in the future.

Many indicators such as carbon or energy intensity have been used to monitor CO_2 emission performance at the macroeconomic level (Ang, 1999; Sun, 2005; Tol et al., 2009). Some studies have taken a benchmarking approach to estimate energy or emission efficiency in the global electric power industry by assuming that the efficiency of fossil fuel power plants can reach certain levels (Maruyama and Eckelman, 2009; Ang et al., 2011). These methods may be interpreted as a partial-factor CO_2 emission performance analysis because they can reflect only some aspects of CO_2 emission performance. However, electricity generation is a multi-factor production process using both energy and non-energy inputs such as labor and capital to produce electricity. Therefore, it may be useful to measure CO_2 emission performance within a total-factor integrated production framework. In the literature, Zhou et al. (2010) first propose the Malmquist CO_2 emission performance index (MCPI) for measuring changes in total-factor CO_2 emission performance. This paper attempts to extend the MCPI by incorporating group heterogeneity and non-radial slack to develop a new integrated index called metafrontier non-radial Malmquist CO_2 emission performance index (MNMCPI) for measuring total-factor CO_2 emission performance dynamic change. After introducing the MNMCPI, we also conduct an empirical study for the Chinese fossil fuel power plants case.

The rest of this paper is organized as follows. Section 2 reviews the related literatures and gives the contextual setting. Section 3 introduces the methodology, which consists of the environmental production technology, the non-radial directional distance function, and the MNMCPI. Section 4 takes the proposed approach to empirically analyze the

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dynamic changes in the total-factor CO_2 emission performance of fossil fuel electric power plants in China for the 2005–2010 period, and Section 5 concludes with some suggestions for future study.

2. Literature review and contextual setting

A number of studies have taken the data envelopment analysis (DEA) approach to benchmark energy and environmental performance. Zhou et al. (2008) provide a survey of 100 papers on energy and environmental performance by using the DEA method. In terms of electricity generation, many studies have employed the DEA method to analyze the efficiency of fossil fuel electricity generation (e.g., Barros and Peypoch, 2008; Liu et al., 2010; Sözen et al., 2010; Sueyoshi et al., 2010; Yang and Pollitt, 2010; Sueyoshi and Goto, 2011, 2012; Jaraite and Maria, 2012; Zhou et al., 2012).

However, previous studies have been limited in that they have generally assessed environmental efficiency by using cross-sectional, not time-series data. Therefore, it is not possible to obtain insights into dynamic changes in CO_2 emission performance. Malmquist productivity index proposed by Färe et al. (1994) could be used for measuring dynamic productivity change. The case for using the standard Malmquist index in the power plant industry can be found in Barros (2008). Chung et al. (1997) is the first to propose a Malmquist index with undesirable outputs to measure environmentally sensitive productivity growth: the Malmquist–Luenberger (ML) index. Some empirical studies applying the ML index include Weber and Domazlicky (2001), Färe et al. (2001), Yörük and Zaim (2005), Kumar (2006), and Nakano and Managi (2008) for measuring environmental performance change.

For the carbon emission performance issue, it is the study by Zhou et al. (2010) that first propose the concept total-factor carbon emission performance based on Malmquist CO_2 emission performance index (MCPI), which is later extended by many studies in diverse aspects (e.g. Zhang and Choi, in press). The another contribution of Zhou et al. (2010) is the bootstrapping of MCPI which provides the statistical inference on the total-factor carbon emission performance change and its decomposed components.

The present paper extends the MCPI by incorporating group heterogeneity and non-radial slack. If these two factors are not considered, then the Malmquist index may produce biased estimates. To integrate these two factors with the MCPI, we incorporate the metafrontier Malmquist index (Oh and Lee, 2010) [1] and the non-radial directional distance function (Zhou et al., 2012)[2] into this paper's model. For this reason, we refer to the proposed index as the metafrontier non-radial MCPI (MNMCPI). In addition, following the decomposition of the Malmquist index, we decompose the MNMCPI into several components, including an efficiency change (EC) index, a best-practice gap change (BPC) index, and a technology gap change (TGC) index, to obtain better insights into changes in CO_2 emission performance over time. Based on the proposed approach, we provide an empirical analysis of fossil fuel power plants in China to investigate the effects of China's "carbon reduction" policy on CO_2 emission performance during the 11th five-year plan.

With regard to CO_2 emission efficiency for China based on the frontier approach, some studies have focused on the CO_2 emission performance of China at the national level (Song et al., 2013), provincial level (e.g., Guo et al., 2011; Choi et al., 2012; Wei et al., 2012) or industry level (Lee and Zhang, 2012; Chang et al., 2013). Barros et al. (2013) measure the cost efficiency of Chinese hydroelectric power plant. However, to the best of our knowledge, no study has examined CO_2 emission performance at the plant level for China, and therefore this paper may be the first to investigate the dynamic changes in the CO_2 emission performance of fossil fuel power plants in China.

During the 11th five-year plan (2006–2010), the fossil fuel power industry of China had been under large pressure to reduce the carbon emissions to meet emission reduction targets. The Chinese government introduced a selective concentration policy to meet these targets. The country's "promoting large and closing small" policy implies the closure of small fossil fuel power plants by 2010 and the total loss of 76,830 MW (10.8% of the total capacity). This selective concentration policy during the 11th five-year period was very effective in that, with 2005 as the base year, the fossil fuel power sector reduced its CO_2 emissions by 1.74 billion tons (China Electricity Council, 2011). In this context, we attempt to investigate the effect of carbon emission regulation on the CO_2 emission performance change in China's fossil fuel power plants.

3. Methodology

3.1. Environmental production technology

Suppose that there are N fossil fuel power plants and that each plant uses capital (K), labor (L), and fossil fuel (F) as inputs to generate electricity (E), a desirable output, and CO_2 emissions (C), an undesirable output. Then we can express the multi-output production technology as follows:

$$T = \{(K, L, F, E, C) : (K, L, F) \text{ can produce } (E, C)\} \tag{1}$$

where T is usually assumed to satisfy the standard axioms of production economics theory (Färe and Grosskopf, 2005). Here, because T is a closed set, inactivity is always possible, and finite amounts of inputs can produce only finite amounts of outputs. In addition, inputs and desirable output are often assumed to be strongly or freely disposable. For the reasonable modeling of the joint-production technology, we impose weak-disposability and null-jointness assumptions on T based on Färe et al. (1989). We can express the above two assumptions as follows:

(i) If $(K,L,F,E,C) \in T$ and $0 \leq \theta \leq 1$ then, $(K,L,F,\theta E,\theta C) \in T$
(ii) If $(K,L,F,E,C) \in T$ and $C = 0$, then $E = 0$.

The weak-disposability assumption (i) shifts attention to reducing CO_2 emissions, and the abatement of CO_2 emissions entails an opportunity cost measured by the proportional reduction in electricity generation. The null-jointness assumption (ii) implies that the production of CO_2 emissions is inevitable in fossil fuel electricity generation and that the only way to remove all CO_2 emissions is to completely stop electricity generation.

Once the environmental production technology (T) is defined, we can employ a parametric function or a nonparametric DEA method to specify it. Following Zhou et al. (2012), we can formulate T for N power plants showing constant returns to scale (CRS) as follows:

$$T = \left\{ \begin{array}{l} (K, L, F, E, C) : \sum_{n=1}^{N} z_n K_n \leq K, \sum_{n=1}^{N} z_n L_n \leq L, \\ \sum_{n=1}^{N} z_n F_n \leq F, \sum_{n=1}^{N} z_n E_n \geq E, \sum_{n=1}^{N} z_n C_n = C, z_n \geq 0, n = 1, 2, \cdots, N \end{array} \right\}, \tag{2}$$

where Z_n is an intensity variable for constructing the environmental production technology by a convex combination. The environmental production technology (or the environmental DEA technology) has

[1] Oh and Lee (2010) are the first to present a metafrontier Malmquist index by incorporating group heterogeneity into the conventional Malmquist index. By incorporating undesirable outputs into the metafrontier Malmquist index, Oh (2010) develops a metafrontier Malmquist–Luenberger (ML) index.

[2] The conventional directional distance function is a radial efficiency measure that may overestimate efficiency when there is some slack (Fukuyama and Weber, 2009). Recently, Zhou et al. (2012) make important contributions by providing a formal definition of the non-radial directional distance function with undesirable outputs.

been widely used in energy and environmental research (Färe et al., 2007; Zhou et al., 2010, 2012; Zhang et al., 2012).

If a nonparametric environmental production technology is well constructed, then it is ready to use the directional distance function to calculate CO_2 emission performance.

3.2. Non-radial directional distance function

The directional distance function (DDF), developed by Chambers et al. (1996) and extended by Chung et al. (1997) to environmental efficiency, is a relatively new methodology for measuring performance. Here the traditional DDF is defined such that it maximizes desirable outputs while reducing undesirable ones at the same rate simultaneously:

$$\vec{D}(K,L,F,E,C;g) = \sup\{\boldsymbol{\beta} : ((K,L,F,E,C) + g\cdot\boldsymbol{\beta}) \in T\}. \quad (3)$$

The conventional DDF is a radial efficiency measure that may overestimate efficiency when there is some slack (Fukuyama and Weber, 2009). Non-radial efficiency measures are often advocated to overcome this limitation in measuring energy and environmental performance because of their advantages (Chang and Hu, 2010; Zhang and Choi, 2013). Recently, Zhou et al. (2012) make important contributions by providing a formal definition of the non-radial DDF by considering undesirable outputs. Zhang et al. (2013) extend the non-radial DDF by incorporating the metafrontier approach. Following Zhou et al. (2012), we define the non-radial directional distance function (NDDF) as follows:

$$\vec{D}(K,L,F,E,C;g) = \sup\left\{\mathbf{w}^T\boldsymbol{\beta} : ((K,L,F,E,C) + g\cdot diag(\boldsymbol{\beta}))\in T\right\}, \quad (4)$$

where $\mathbf{w}^T = (w_K, w_L, w_F, w_E, w_C)^T$ denotes a normalized weight vector relevant to the numbers of inputs and outputs; $g = (-g_K, -g_L, -g_F, g_E, -g_C)$ is an explicit directional vector; and $\beta = (\beta_K, \beta_L, \beta_F, \beta_E, \beta_C)^T \geq 0$ denotes a vector of scaling factors representing individual inefficiency measures for inputs and outputs. The symbol *diag* means diagonal matrices. Zhou et al. (2012) incorporate only fossil fuel as the input because they focus on measuring pure energy efficiency. Unlike Zhou et al. (2012), however, the present paper also considers non-energy inputs because its objective is to measure CO_2 emission performance within the total-factor productivity framework.

We can calculate the NDDF value for a specific plant n', denoted as $\vec{D}(K,L,F,E,C;g)$, by solving the following DEA-type model:

$$\begin{aligned}
\vec{D}(K,L,F,E,C;g) = \ & \max w_K\beta_K + w_L\beta_L + w_F\beta_F + w_E\beta_E + w_C\beta_C \\
& \text{s.t.} \sum_{n=1}^{N} z_n K_n \leq K_{n'} - \beta_K g_K \\
& \sum_{n=1}^{N} z_n L_n \leq L_{n'} - \beta_L g_L \\
& \sum_{n=1}^{N} z_n F_n \leq F_{n'} - \beta_F g_F \\
& \sum_{n=1}^{N} z_n E_n \geq E_{n'} + \beta_E g_E \\
& \sum_{n=1}^{N} z_n C_n = C_{n'} - \beta_C g_C \\
& z_n \geq 0, n = 1,2,\cdots,N \\
& \beta_K, \beta_L, \beta_F, \beta_E, \beta_C \geq 0.
\end{aligned} \quad (5)$$

Here we can set the directional vector g in various ways based on different policy goals of emission reductions. If $\vec{D}(K,L,F,E,C;g) = 0$, then the power plant to be evaluated is located along the best-practice frontier in the g direction.

Because there are three inputs (capital, labor, and energy), one desirable output (regional GDP), and one undesirable output (CO_2 emissions), we set the weight vector to (1/9, 1/9, 1/9, 1/3, 1/3) and the directional vectors to $g = (-K, -L, -F, E, -C)$. We follow Zhou et al. (2012) and define the static total-factor CO_2 emission performance index (TCPI) as the ratio of potential target carbon intensity to actual carbon intensity (C/E).[3] Suppose that β_C^* and β_E^* are optimal solutions corresponding to CO_2 emissions and electricity outputs in model (5). Then we can formulate the TCPI as

$$TCPI = \frac{(C-\beta_C^* C)/(E+\beta_E^* E)}{C/E} = \frac{1-\beta_C^*}{1+\beta_E^*}. \quad (6)$$

Eq. (6) seeks to measure maximum possible reductions in carbon intensity, which can be used to measure the CO_2 emission performance of each power plant over a certain period of time which is a static index. Clearly, the TCPI lies between zero and unity, and the higher the TCPI, the better the CO_2 emission performance is. If the TCPI is equal to unity, then the plant shows the best CO_2 emission performance located along the frontier.

Based on Eq. (6), Zhang et al. (2013) develop a static metafrontier CO_2 emission performance. To examine the dynamic changes in CO_2 emission performance over time and consider group heterogeneity at the same time, we propose the MNMCPI, which is discussed in the next subsection.

3.3. Metafrontier non-radial Malmquist CO_2 emission performance index

Three definitions of production technology sets are required for defining and decomposing the MNMCPI. These include the *contemporaneous* production technology, the *intertemporal* production technology, and the *global* production technology.

Based on Tulkens and Vanden Eeckaut (1995) and Oh (2010), we define these three environmental production technology sets as follows: First, we define the contemporaneous environmental production technology of group R_h as $T_{R_h}^c = ((K^t, L^t, F^t, E^t, C^t) : (K^t, L^t, F^t)$ can produce $(E^t, C^t))$, where $t = 1,\ldots T$. This constructs the production technology described in Eq. (2) for the specific group R_h for a specific period t.

We define the intertemporal environmental production technology of group R_h as $T_{R_h}^I = T_{R_h}^1 \cup T_{R_h}^2 \cup \ldots \cup T_{R_h}^T$. This consists of a single technology constructed from observations over the whole period for group R_h. Suppose that there are H distinct intertemporal technologies. Then it is assumed that observations for one intertemporal environmental production technology are unable to access other intertemporal technologies.

We define the global environmental production technology as $T^G = T_{R_1}^I \cup T_{R_2}^I \cup \ldots \cup T_{R_H}^I$, which is constructed from all observations over the whole period for all groups. This means that the global environmental production technology envelops all intertemporal environmental production technologies, and it is assumed that all observations can access the global technology through innovation.

We can express the NDDF described in Eq. (4) based on these three environmental production technologies. We define the contemporaneous NDDF: $\vec{D}^c(.) = \sup\{\mathbf{w}^T\boldsymbol{\beta}^c : ((K,L,F,E,C) + g\cdot diag(\boldsymbol{\beta}^c))\in T_{R_h}^c\}$ based on the contemporaneous environmental production technology ($T_{R_h}^c$) of some specific group R_h and the intertemporal NDDF: $\vec{D}^I(.) = \sup\left\{\mathbf{w}^T\boldsymbol{\beta}^I : \left((K,L,F,E,C) + g\cdot diag\left(\boldsymbol{\beta}^I\right)\right)\in T_{R_h}^I\right\}$ based on the intertemporal environmental production technology ($T_{R_h}^I$) of group R_h. Finally, we define the global NDDF: $\vec{D}^G(.) = \sup\left\{\mathbf{w}^T\boldsymbol{\beta}^G : ((K,L,F,E,C) + g\cdot diag\left(\boldsymbol{\beta}^G\right))\in T^G\right\}$ based on the global environmental production technology (T^G).

[3] The use of the weight vector (0, 0, 1/3, 1/3, 1/3) could measure CO_2 emission performance without changing capital and labor input, which could be regarded as pure CO_2 emission performance measurement (Zhang and Choi, in press).

To compute and decompose the MNMCPI, we solve six different NDDFs: $\vec{D}^C(K^s, L^s, F^s, E^s, C^s)$, $\vec{D}^I(K^s, L^s, F^s, E^s, C^s)$, and $\vec{D}^G(K^s, L^s, F^s, E^s, C^s)$, $S = t, t+1$. As in the case of Eq. (5), we can solve the NDDFs by using the following DEA-type models[4]:

$$\begin{aligned}\vec{D}^d(K^s, L^s, F^s, E^s, C^s; g) = \ & \max w_K\beta_K^d + w_L\beta_L^d + w_F\beta_F^d + w_E\beta_E^d + w_C\beta_C^d \\ \text{s.t.} & \sum_{con} z_n^s K_n^s \le K_{n'} - \beta_K^d g_K \\ & \sum_{con} z_n^s L_n^s \le L_{n'} - \beta_L^d g_L \\ & \sum_{con} z_n^s F_n^s \le F_{n'} - \beta_F^d g_F \\ & \sum_{con} z_n^s E_n^s \ge E_{n'} + \beta_E^d g_E \\ & \sum_{con} z_n^s C_n^s = C_{n'} - \beta_C^d g_C \\ & z_n^s \ge 0, \beta^d \ge 0,\end{aligned} \tag{7}$$

where the superscript d on $\vec{D}^d(.)$ means the type of NDDF that can be contemporaneous, intertemporal, or global. The symbol con under $\sum$ represents the condition for constructing the three environmental production technologies. For the contemporaneous NDDF, we have $d \equiv C$ and $con \equiv \{n \in R_h\}$; for the intertemporal NDDF, we have $d \equiv I$ and $con \equiv \{n \in R_h, s \in [1,2,\ldots,T]\}$; and for the global NDDF, we have $d \equiv G$ and $con \equiv \{n \in [R_1 \cup R_2 \cup \ldots \cup R_H], s \in [1,2,\ldots,T]\}$.

Based on Eq. (5), we set the weight vectors to (1/9, 1/9, 1/9, 1/3, 1/3) and the directional vectors to $g = (-K, -L, -F, E, -C)$. We can solve the six different NDDFs by using Eq. (7). Once the NDDFs are solved, we can obtain six corresponding TCPI values defined in Eq. (6). Based on these six different NDDFs, we have

$$TCPI^d(K^s, L^s, F^s, E^s, C^s) = \left[\frac{\left(C - \beta_C^{d*} C\right) / \left(E + \beta_E^{d*} E\right)}{C/E}\right]^s = \left(\frac{1 - \beta_C^{d*}}{1 + \beta_E^{d*}}\right)^s \tag{8}$$

where $d \equiv (C, I, G)$, $S = t, t+1$. Here we define the MNMCPI based on the global environmental production technology set (T^G) as follows:

$$MNMCPI(K^s, L^s, F^s, E^s, C^s) = \frac{TCPI^G\left(K^{t+1}, L^{t+1}, F^{t+1}, E^{t+1}, C^{t+1}\right)}{TCPI^G(K^t, L^t, F^t, E^t, C^t)}. \tag{9}$$

From Eq. (9), similar to metafrontier Malmquist index (Oh and Lee, 2010), the MNMCPI measures changes of the $TCPI$ on T^G for the period between t and $t+1$. Following the decomposition of the metafrontier Malmquist index in Oh and Lee (2010), we can decompose the MNMCPI into various components: a technical efficiency change (EC) index of CO_2 emissions, a best-practice gap change (BPC) index of CO_2 emission reduction technologies, and a technology gap change (TGC) index of CO_2 emission reductions.[5] Because this decomposition of the MNMCPI requires many notations, we replace $TCPI^G(K^t,L^t,F^t,E^t,C^t)$ as $TCPI^G(.^t)$ to save space.

[4] One alternative method to specify the metafrontier technology is to use the stochastic approach (e.g. Assaf et al., 2010; Huang et al., 2010). The strength of the stochastic metafrontier is that it can provide the statistical inference on the estimated parameters whereas the shortcoming is the relative difficulty to incorporate undesirable output into the stochastic technology. A comparative study between stochastic parametric metafrontier and non-parametric metafrontier could be an interesting topic for the future study. We thank one referee for his suggestion on this point.

[5] As MNMCPI incorporates both metafrontier and non-radial concepts, it could be decomposed into more components based on the production-theoretical decomposition analysis (PDA) which could be considered as the future research topic. We appreciate for one referee's helpful suggestion on this point.

The decomposition process is as follows:

$$\begin{aligned} MNMCPI(K^s, L^s, F^s, E^s, C^s) &= \frac{TCPI^G(.^{t+1})}{TCPI^G(.^t)} \\ &= \left[\frac{TCPI^C(.^{t+1})}{TCPI^C(.^t)}\right] * \left[\frac{TCPI^I(.^{t+1})/TCPI^C(.^{t+1})}{TCPI^I(.^t)/TCPI^C(.^t)}\right] * \left[\frac{TCPI^G(.^{t+1})/TCPI^I(.^{t+1})}{TCPI^G(.^t)/TCPI^I(.^t)}\right] \\ &= \left\{\frac{\left(\frac{1-\beta_C^{C*}}{1+\beta_E^{C*}}\right)^{t+1}}{\left(\frac{1-\beta_C^{C*}}{1+\beta_E^{C*}}\right)^{t}}\right\} * \left\{\frac{\left(\frac{1-\beta_C^{I*}}{1+\beta_E^{I*}}\right)^{t+1} / \left(\frac{1-\beta_C^{C*}}{1+\beta_E^{C*}}\right)^{t+1}}{\left(\frac{1-\beta_C^{I*}}{1+\beta_E^{I*}}\right)^{t} / \left(\frac{1-\beta_C^{C*}}{1+\beta_E^{C*}}\right)^{t}}\right\} * \left\{\frac{\left(\frac{1-\beta_C^{G*}}{1+\beta_E^{G*}}\right)^{t+1} / \left(\frac{1-\beta_C^{I*}}{1+\beta_E^{I*}}\right)^{t+1}}{\left(\frac{1-\beta_C^{G*}}{1+\beta_E^{G*}}\right)^{t} / \left(\frac{1-\beta_C^{I*}}{1+\beta_E^{I*}}\right)^{t}}\right\}. \\ &= \left[\frac{TE^{t+1}}{TE^t}\right] * \left[\frac{BPR^{t+1}}{BPR^t}\right] * \left[\frac{TGR^{t+1}}{TGR^t}\right] = EC * BPC * TGC. \end{aligned} \tag{10}$$

The efficiency change (EC) term in Eq. (10) is a measure of the "*catch-up*" effect in terms of technical efficiency changes in CO_2 emissions for a specific group for two time periods (t, $t+1$). EC captures how close a power plant moves toward the contemporaneous environmental production technology. Here $EC >$ (or $<$) 1 means an efficiency gain (or loss). The best-practice gap change (BPC) index measures changes in the best-practice gap ratio for the CO_2 emission reduction technology between the contemporaneous environmental technology and the intertemporal environmental technology during two periods. Here $BPC >$ (or $<$) 1 means that the contemporaneous technology frontier shifts toward (or far away from) the intertemporal technology frontier. Because BPC measures frontier shifts in a contemporaneous technology, it can be considered an *innovation* effect, as in the case of the technological change (TC) term in the MCPI (Zhou et al., 2010). TGC is a measure of changes in the technology gap ratio for CO_2 emission reductions between the intertemporal environmental production technology frontier and the global frontier during two periods. $TGC >$ (or $<$) 1 indicates a decrease (increase) in the technology gap between the intertemporal technology for a specific group and the global technology. Therefore, TGC measures the technology *leadership* change for a given group.

Fig. 1 shows the MNMCPI and its decomposed components. This is a case of two groups (R_1, R_2) and two time periods (t, $t+1$). Here a_1 and a_2 are observed power plants for the two periods t and $t+1$, respectively, and $T^t_{R_1}$ and $T^{t+1}_{R_1}$ represent the contemporaneous environmental production technology of group R_1 in periods t and $t+1$, respectively. $T^I_{R_1}$ is the intertemporal environmental production technology for group R_1, and T^G_R is the global environmental production technology for two groups. Assume that the coordinates of a1 is (C_{a1}, E_{a1}). Similarly, we can obtain the coordinates of the other points in Fig. 1. The following equation explains the result for the decomposition of the MNMCPI in Fig. 2:

$$\begin{aligned} MNMCPI&(K^s, L^s, F^s, E^s, C^s) \\ &= \frac{TCPI^G(.^{t+1})}{TCPI^G(.^t)} = \left\{\frac{\left[\frac{C_{d2}/E_{d2}}{C_{a2}/E_{a2}}\right]}{\left[\frac{C_{d1}/E_{d1}}{C_{a1}/E_{a1}}\right]}\right\} \\ &= \left\{\frac{\left[\frac{C_{b2}/E_{b2}}{C_{a2}/E_{a2}}\right]}{\left[\frac{C_{b1}/E_{b1}}{C_{a1}/E_{a1}}\right]}\right\} * \left\{\frac{\left[\frac{C_{c2}/E_{c2}}{C_{b2}/E_{b2}}\right]}{\left[\frac{C_{c1}/E_{c1}}{C_{b1}/E_{b1}}\right]}\right\} * \left\{\frac{\left[\frac{C_{d2}/E_{d2}}{C_{c2}/E_{c2}}\right]}{\left[\frac{C_{d1}/E_{d1}}{C_{c1}/E_{c1}}\right]}\right\} \\ &= \left[\frac{TE^{t+1}}{TE^t}\right] * \left[\frac{BPR^{t+1}}{BPR^t}\right] * \left[\frac{TGR^{t+1}}{TGR^t}\right] = EC * BPC * TGC. \end{aligned} \tag{11}$$

4. Empirical analysis

4.1. Data

We employ the methodology proposed in Section 3 to examine the changes in the total-factor CO_2 emission performance of fossil fuel power plants in China during 2005–2010 period. The sample consists of 259 large fossil fuel power plants operating as of 2010 and listed in the

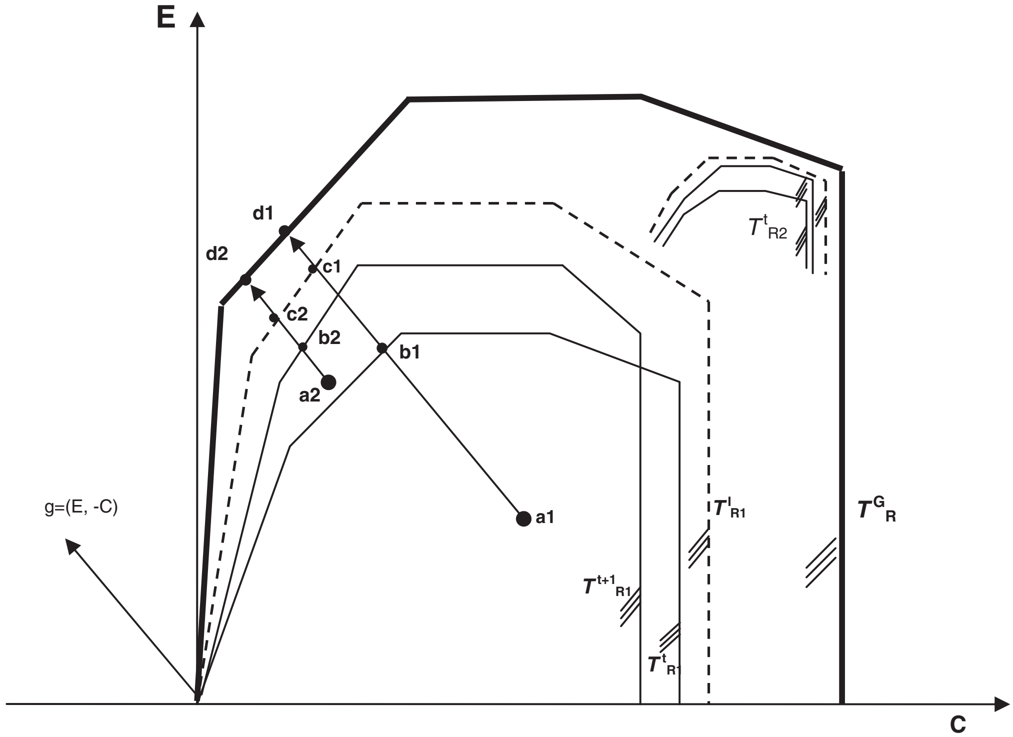

Fig. 1. Illustration of the MNMCPI and its decomposition.

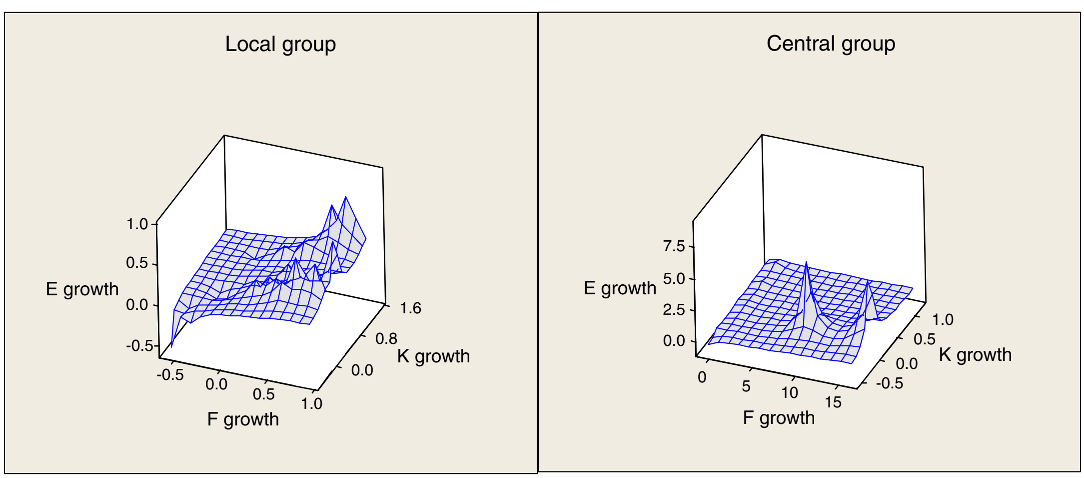

Fig. 2. 3D surface plots of growth rates for two groups.

China Electric Power Yearbook 2011. The generating capacity of these plants exceeds 1 GW. For a balanced panel data, we exclude those plants with incomplete data on variables and obtain a total of 93 fossil fuel power plants and a total of 558 (93 ∗ 6) observations. We measure the electricity output (E) of each power plant by the gross amount of electricity generated and the capital input (K) and the fossil fuel input (F) by the installed generating capacity and fuel consumption, respectively. We measure the labor input (L) by the number of employees for each power plant. We obtain data on E, K, L, and F from the *Compilation of Power industry statistical data, China Electric Power Yearbook, the Chinese Industrial Enterprises Database*, and the *China Electric Power Industry Statistical Analysis*, respectively.[6] Following Yang and Pollitt (2010), we employ the fuel-based carbon calculation model described in IPCC to estimate the CO_2 emissions of power plants. CO_2 emission factors according to major types of carbonaceous fuels for China can

Table 1
Descriptive statistics for variables (2005–2010, $N = 93$).

Variable	Unit	Group	N	Mean	StDev	Min	Max
K	GW	Central	335	1.60	0.68	1.00	4.80
		Local	223	1.59	0.61	1.00	4.20
F	Million tons of standard coal equivalent	Central	335	2.74	1.16	0.07	8.54
		Local	223	2.91	0.98	1.44	7.11
L	Num.	Central	335	654.1	278.1	380	2016
		Local	223	652.7	248.6	370	1764
C	Million tons	Central	335	7.72	3.24	0.34	24.23
		Local	223	8.28	2.83	3.99	21.07
E	GWH	Central	335	8.46	3.53	0.50	26.60
		Local	223	9.13	3.16	4.40	23.70

[6] We also obtain some missed data by contacting the China Electricity Council or the power company via e-mail or phone directly. Finally, for plants not reporting a variable for a given year, we use the average value for that variable from the previous and following years based on the interpolation approach. We employ this method sparingly.

Table 2
Average value and growth rate for variables in two groups (2005–2010).

Group	Num.	E (GWH)		C (10^6 tons)		K (GW)		L (Persons)		F (10^6 tons)	
		Mean	Growth	Mean	Growth	Mean	Growth	Mean	Growth	Mean	Growth
Central	56	8.58	2.8%	7.83	2.5%	1.64	4.1%	663	1.8%	2.78	2.2%
Local	37	9.18	1.8%	8.32	2.1%	1.63	3.4%	629	1.1%	2.92	2.0%
Total	93	8.82	2.3%	8.02	2.2%	1.63	3.8%	660	1.5%	2.84	2.1%

be found in National Development Reform Commission (NDRC) (2007). Table 1 shows the descriptive statistics for the input and output variables.

The sample accounts for a substantial portion of total fossil fuel generation in China. For instance, the total installed capacity of sample plants in 2005 reaches 130,200 MW, accounting for approximately 33.9% of the country's total fossil fuel capacity. The total CO_2 emissions of sample plants in 2005 are 697.5 million tons, accounting for 12.8% of total CO_2 emissions (BP, 2006).

To calculate the MNMCPI, we first characterize groups and determine their members. Here the criterion for grouping a power plant is based on the type of ownership for an enterprise to which the power plant belongs. We consider two types of power companies: companies owned by the central government (central group) and those owned by local governments (local group). The central group includes companies belonging to "five main power groups," which are directly under the control of the State-Owned Assets Supervision and Administration Commission (SASAC) of the State Council. The local group includes companies under the control of local governments. Ownership differences can lead to differences in policies and management strategies for individual power plants. For instance, the local group takes full responsibility for its own profits and losses, whereas the central group enjoys substantial subsidies from the central government. Table 2 shows the average values and growth rates for input and output variables for the two groups.

As shown in Table 2, the two groups show different growth rates for the variables. The central group has a higher growth rate in all the variables than the local group. It is also found that the growth rate of CO_2 emissions is lower than that of electricity output for the central group, while the converse can be observed for the local group. This interesting result indicates that during the research period, the central group i.e. the central power enterprises were under greater pressure to reduce their carbon intensity than the local power enterprises. It suggests that the central state-owned enterprises were facing more stricter environmental regulations than the local enterprises.

To investigate group heterogeneity in greater detail, we consider 3D surface plots of growth rates for *K*, *F*, and *E* for each group. As shown in Fig. 2, each group shows a different growth pattern. For instance, the plots for the central group show a peak in the middle, whereas those for the local group show it along the edge. Therefore, it is meaningful to compare the MNMCPI for these two groups based on the type of ownership. To test whether the two groups are operating under the same technology, we use the non-parametric Mann–Whitney test for efficiency result of the pooled data. The result shows that the null hypothesis of a common technology is rejected, leading us to construct efficiency frontiers separately for each industry group.

Based on the aforementioned discussion, we may obtain biased results if group heterogeneity is not considered when measuring the MNMCPI. This provides a rationale for employing a metafrontier analysis in the context of this paper.

4.2. Empirical results

The Appendix shows the empirical results for the average MNMCPI for the 2005–2010 period and its decomposition for each power plant. For comparative purposes, we also compute the MCPI based on the method in Zhou et al. (2010).[7]

For both methodological approaches, the results indicate an increase in total-factor CO_2 emission performance for the 2005–2010 period. On average, the total-factor CO_2 emission performance of China's power plants increases by approximately 0.38% under the MNMCPI. This means that, on average, the ratio of target carbon intensity to actual carbon intensity increases by 0.38% per year over the sample period. The results for the MCPI show a relatively high growth rate for CO_2 emission performance (0.68%). This difference may be due to the use of different methodologies. Without considering group heterogeneity and non-radial slack for all the variables, the MCPI approach might lead to the overestimation of CO_2 emission performance in this case.

At the plant level, 64 power plants show an increase in CO_2 emission performance under the MNMCPI, whereas 29 plants, a decrease. Wangtan (in Hubei) shows the highest MNMCPI (average growth rate = 6.2%), whereas Latela (in Inner Mongolia), the lowest MNMCPI (average = 0.9914), indicating a 0.86% decrease in CO_2 emission performance.

The average efficiency change (EC) index of CO_2 emission performance is 1.0067 under the MNMCPI framework, indicating an average annual increase in efficiency of approximately 0.67%. The MCPI approach provides similar results, showing an average annual increase of 0.68%. A total of 76 plants show an *EC* index greater than unity, suggesting the movement of these plants toward the contemporaneously environmental technology frontier over the study period and reflecting the catch-up effect. For individual plants, Wangtan (Hubei) shows the best catch-up performance (average growth rate = 6.82% under the MNMCPI and 11.1% under the MCPI). Hancheng (Shaanxi) ranks second with a growth rate of 2.15% under the MNMCPI (6.01% under the MCPI), whereas Fengzhen and Latela (Inner Mongolia) show the poorest catch-up performance (average = 0.9909).

The average best-practice change (BPC) index is approximately 0.9978 under the MNMCPI, indicating a decrease in technology change. This in turn implies a shift in the contemporaneous frontier further away from the intertemporal frontier. The results for the MNMCPI and the MCPI verify some technological decline in fossil fuel electricity generation. A total of 70 power plants show a state of technological decline under the MNMCPI, whereas only 23 show technological progress. The average annual technology gap ratio change (TGC) value is 1.00003, which implies little change in the gap between the global frontier and the intertemporal frontier. Because the TGC index measures changes in technological leadership, this result suggests a lack of technological leadership among power plants in China during the sample period.

We examine the trends in dynamic total-factor CO_2 emission performance and its decomposition. Fig. 3 shows the changes in CO_2 emission performance and the decomposed sources based on the MNMCPI and the MCPI. For total-factor CO_2 emission performance, both the MNMCPI and the MCPI show a U-shaped curve. Between 2005 and

[7] We also calculate the efficiency change results of standard Malmquist index (Barros, 2008) without incorporating the CO_2 emission and find the related average efficiency change is larger than both of MNMCPI and MCPI. It indicates that without taking into the CO_2 emission account, the standard Malmquist might overestimate the real efficiency change. We thank one referee for the suggestion on this point.

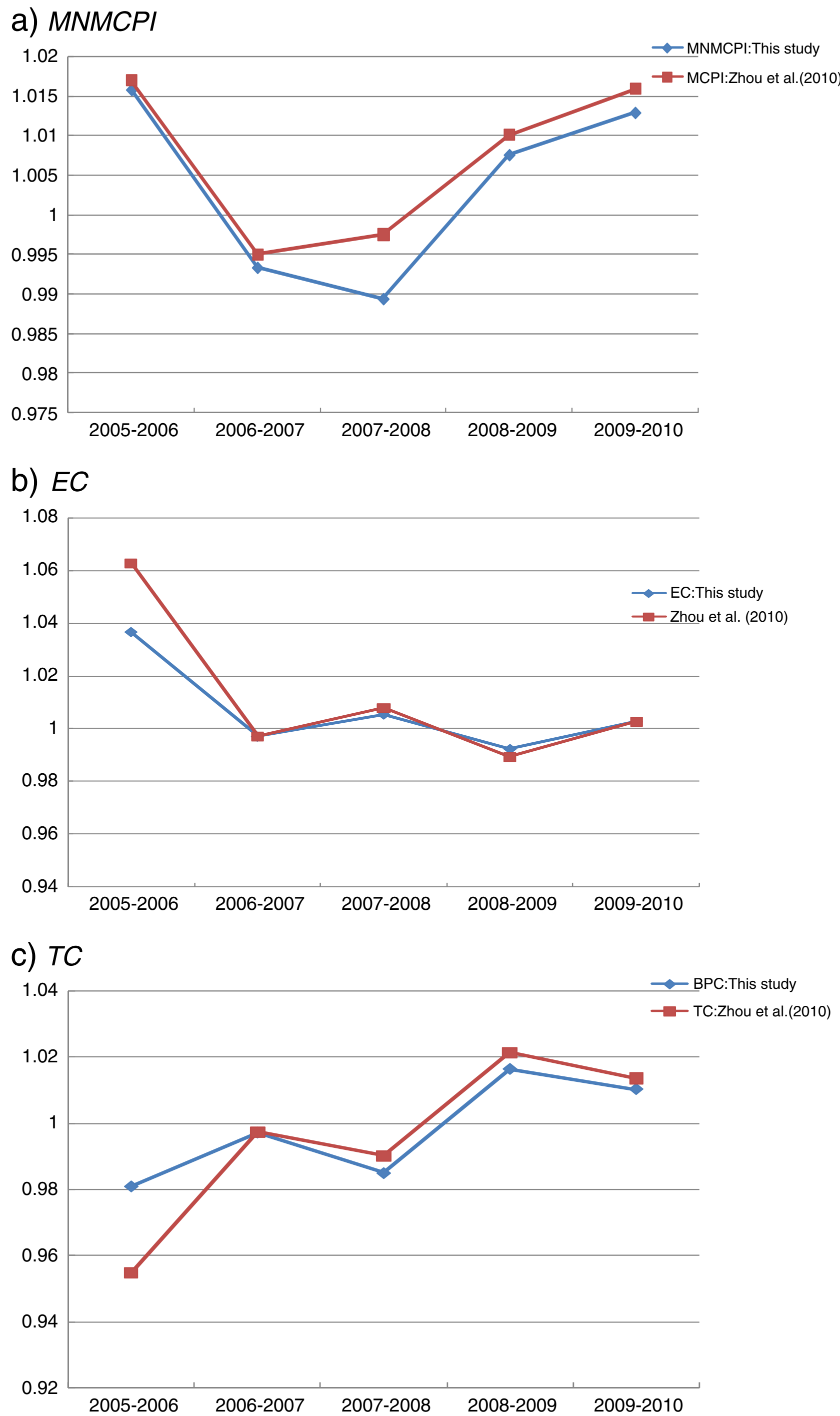

Fig. 3. Changes of MNMCPI and its decomposition.

2006, the MNMCPI and the MCPI show values greater than unity, indicating an increase in CO_2 emission performance. Between 2006 and 2008, however, both indices are less than 1, indicating a decrease in CO_2 emission performance. After 2008, both indices show values greater than unity, and these values continue to increase, implying rapidly increasing CO_2 emission performance. As discussed earlier, the average MCPI exceeds the average MNMCPI, and therefore the former may overestimate performance scores because it does not consider group heterogeneity and non-radial slacks.

The EC index of CO_2 emissions for the 2005–2006 period shows a value greater than unity, indicating good catch-up performance. For the 2006–2007 period, however, the EC index shows a decrease, indicating a decline in efficiency. In each year after 2007, the EC index remains near unity, alternatively going above or below unity. The TC index for the MNMCPI and the MCPI for the 2005–2008 period is less than unity, indicating a period of technological decline, whereas for the 2008–2010 period, the TC index is greater than unity, suggesting technological progress.

Changes in CO_2 emission performance coincide with the EC trends for the 2005–2006 period, whereas they coincide with the TC trends for the 2008–2010 period. This suggests that the increase in total-factor CO_2 emission performance from 2005 to 2006 is driven mainly by efficiency changes, whereas that from 2008 to 2010, by technological advances.

This interesting phenomenon emerges from a paradigm shift in China's policies. As discussed earlier, during the 11th five-year plan (2006–2010), the Chinese government set a reduction target for energy consumption and CO_2 emissions. Therefore, the fossil fuel electricity generation sector was under considerable pressure to reduce its CO_2 emissions. By 2010, this sector reduced its CO_2 emissions by 1.74 billion tons relative to the base year (2005) (China Electricity Council, 2011). This strong regulation had a negative impact on firm performance and innovation because of higher regulatory costs for power plants. According to the empirical results, total-factor CO_2 emission performance and innovation both decrease from 2006 to 2008.

On the other hand, the increases in CO_2 emission performance and innovation after 2008 provide support for the Porter hypothesis (Porter and Van der Linde, 1995), which posits that a stricter environmental regulation means not only cost increases but also improvements in productivity and innovation for more environment-friendly production processes. However, to test the Porter hypothesis accurately we need to conduct future empirical work which is not within our research content.

We compare the MNMCPI and its decomposition at the group level. Table 3 shows the MNMCPI estimation and its decomposition for each group. The central group shows a higher MNMCPI (average annual growth rate = 0.48%). In terms of decomposed factors, the central group shows a higher EC index, indicating a strong catch-up effect, whereas the local group shows a higher BPC index, indicating technological innovation. The changes in the TGC are less than unity for both groups, indicating an absence of technology leadership. The results of group differences could provide useful information for the Chinese government to negotiate with individual power companies as to the carbon emission reduction targets based on their performances. In addition, the results regarding the group difference may provide useful information for the initial quota allocation in China's carbon emission trading scheme with particular reference on the electricity generation companies because the MNMCPI could provide the information for both efficiency and fairness considering the group heterogeneities. The recent study by Zhou et al. (in press) provides a discussion on the impacts of alternative quota allocation methods on the impacts of emission trading.

Fig. 4 shows the trends in the MNMCPI and its decomposition for the two groups. The two groups show similar MNMCPI trends, demonstrating a U-shaped pattern, and have a highly competitive relationship in terms of the MNMCPI in that their rankings change each period. For instance, from 2005 to 2006, the central group shows a higher MNMCPI, whereas the local group shows a higher MNMCPI from 2006 to 2007. This pattern continues in subsequent periods. The two groups show similar EC patterns except for the 2005–2006 period. On average, the central group shows a slightly higher EC index. We find different results for the TC index. The local group shows a higher TC index than the central group except for the 2007–2008 period, indicating that the companies belonging to the local group led innovation. Although both groups show TGC values less than unity, indicating a decrease in the technology leadership effect, the central group shows slightly better technology leadership performance than the local group.

Table 3
Group comparison of the MNMCPI and its decomposition.

Group	MNMCPI	EC	BPC	TGC
Central	1.0048	1.0092	0.9961	0.9998
Local	1.0024	1.0029	1.0004	0.9993
Total	1.0038	1.0067	0.9978	0.9996

In sum, the central group lacks both innovation and leadership, and therefore there is a missing link in the role of the central government of China for power sector. This suggests that the central government should facilitate increased innovation and leadership for its power enterprises because these enterprises form the backbone of the national economy.

We examine plant innovators because the TGC index can indicate only those power plants demonstrating technological leadership. A more in-depth analysis of innovative plants requires a more deliberate examination. There are two types of innovative plants: group and metafrontier innovative power plants. Group innovators refer to outstanding plants within a specific group, and metafrontier innovators can be found in innovative plants from an integrated perspective. According to Färe et al. (1994) and Oh (2010), the three conditions for determining group innovative plants are

$$BPC > 1, \tag{12a}$$

$$\vec{D}^{t}\left(K^{t+1}, L^{t+1}, F^{t+1}, E^{t+1}, C^{t+1}\right) < 0, \tag{12b}$$

$$\vec{D}^{t+1}\left(K^{t+1}, L^{t+1}, F^{t+1}, E^{t+1}, C^{t+1}\right) = 0. \tag{12c}$$

Eq. (12a) suggests that the contemporaneous environmental technology frontier should shift toward the intertemporal environmental technology frontier to become a group innovative power plant. Eq. (12b) indicates that the production activity of innovative plants in period $t+1$ should be outside the contemporaneous frontier in period t. In other words, the technology in period t cannot produce the required quantity of outputs in period $t+1$. Eq. (12c) provides the condition that an innovative plant should be along the contemporaneous technology frontier in period $t+1$.

To choose metafrontier innovative power plants, we include two additional conditions in Eqs. (12a)–(12c):

$$TGC > 1, \tag{13a}$$

$$\vec{D}^{G}\left(K^{t+1}, L^{t+1}, F^{t+1}, E^{t+1}, C^{t+1}\right) = 0. \tag{13b}$$

Eq. (13a) states that a metafrontier innovative power plant should be among technologically leading plants, which implies a decrease in the gap between the intertemporal technology frontier and the global technology frontier. Condition (13b) suggests that a metafrontier innovative plant should be located along the global environmental technology frontier.

Table 4 shows the innovative power plants for each two-year period. In the central group, group innovators vary across periods. In the local group, Huayang Houshi (Fujian) is an innovator twice. Jiangsu Ligang and Zhejiang Taizhou are metafrontier innovators from 2008 to 2009 and from 2009 to 2010, respectively. The results for group and nationwide innovators have some important implications for policymakers regarding power generation. That is, non-innovating power plants can benchmark innovating ones to improve their CO_2 emission performance.

Finally, we conduct a statistical analysis to determine any significant methodological differences between the MNMCPI and the MCPI. For this, we employ the Wilcoxon–Mann–Whitney rank-sum test and compare the difference in decomposition results between the MNMCPI and the MCPI (Table 5). The results reject the null hypothesis at the 5% level, indicating that the results for the two methods show significant differences in rankings in terms of CO_2 emission performance and its

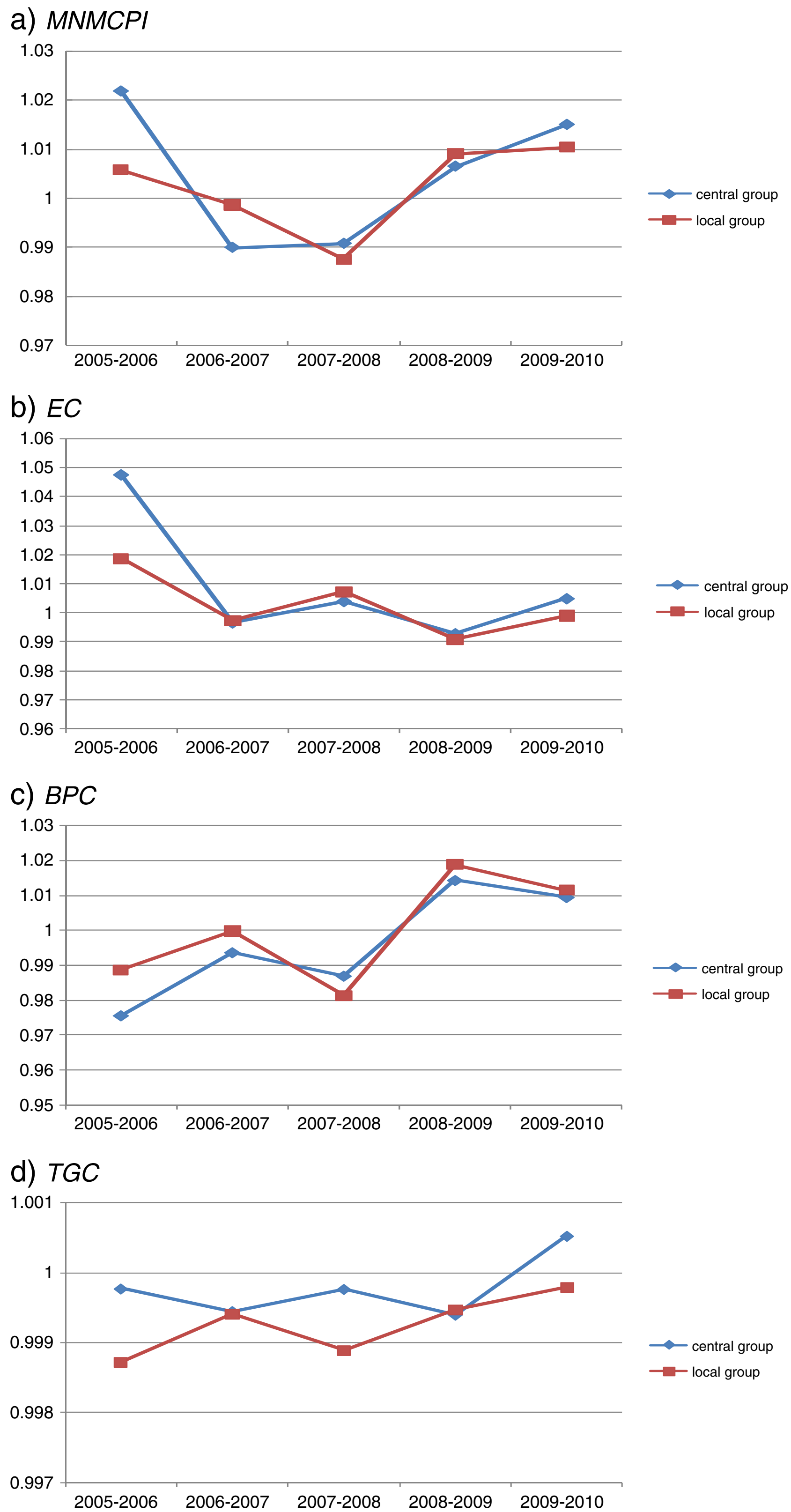

Fig. 4. Trends in the MNMCPI and its decomposition into two groups.

decomposition. The kernel density plot in Fig. 5 indicates some differences in the distribution pattern between the two indices. In addition, the Fan–Ullah test verifies significant differences in the distribution pattern between the MNMCPI and the MCPI.

5. Conclusions

By incorporating group heterogeneity and non-radial slack into the MCPI, we present the MNMCPI, which could be interpreted as a

Table 4
Group and metafrontier innovators.

Year	Group innovator		Metafrontier innovator
	Central group	Local group	
2005–2006	–	–	–
2006–2007	Shitongkou 2nd (Shanghai)	Huayang Houshi (Fujian) Baosteel (Shanghai) Zhangze (Shanxi)	–
2007–2008	–	–	–
2008–2009	Fuzhou power (Fujian)	Ligang (Jiangsu) Huayang Houshi (Fujian)	Ligang (Jiangsu)
2009–2010	Beilun (Zhejiang) Beicang (Zhejiang) Banshan (Zhejiang)	Taizhou (Zhejiang) Jiahua (Zhejiang) Taizhou (Zhejiang)	Taizhou (Zhejiang)

Table 5
Wilcoxon–Mann–Whitney rank-sum test for the MCPI and the MNMCPI.

	Null hypothesis (Ho)	Wilcoxon statistics	*p*-Value
MCPI	MNMCPI = MCPI	7774.0	0.0121
EC	EC of MNMCPI = EC of MCPI	10081.0	0.0002
TC	BPC of MNMCPI = TC of MCPI	10126.0	0.0001

metafrontier total-factor CO_2 emission performance index because it is constructed from the perspective of total-factor metafrontier production efficiency framework. We derive the MNMCPI by solving several non-radial DEA-type models and decompose the MNMCPI into the EC, BPC, and TGC indices.

We employ the proposed approach to analyze the changes in the total-factor CO_2 emission performance of 93 fossil fuel power plants in China for the 2005–2010 period. The results indicate a 0.38% increase in total-factor CO_2 emission performance during the sample period. CO_2 emission performance shows a U-shaped pattern, providing support for the Porter hypothesis. The increase in CO_2 emission performance from 2005 to 2006 is driven mainly by improvements in efficiency, whereas it is driven by technological advances from 2008 to 2010. The central group shows better catch-up performance, whereas the local group, better technological innovation performance. The central group plays a key role in the national economy but lacks innovation and technological leadership. This suggests a missing link in the role of the central government in promoting performance-oriented governance for CO_2 emission efficiency. Thus, the central government should facilitate increased innovation and leadership for its power enterprises.

This study has some limitations. The empirical analysis is based on data only for the 2005–2010 period. Therefore, future research should consider a longer period, by considering a broader plant-level data set, future research can better assess the total-factor CO_2 emission performance of fossil fuel power plants in China. This paper's criterion for grouping power plants is based on the type of ownership. In this regard, future research should consider a wider range of criteria such as generation technologies (e.g., steam, nuclear, and combined cycles) to better reflect different characteristics of power plants in China. An interesting empirical extension to this study would be a regression analysis on the determinants of CO_2 emission performance for fossil fuel power plants or test the Porter hypothesis deeply by statistical analysis. Methodologically, this paper could be further extended in two more directions. One is to bootstrap MNMCPI in order to perform the statistical inference for total-factor CO_2 emission performance and its decompositions. Another is relevant to the decomposition of MNMCPI based on the production-theoretical decomposition analysis (PDA) which has received increasing attention in carbon decomposition analysis (Zhou and Ang, 2008). As MNMCPI incorporates both meta-frontier and non-radial concepts, it could be decomposed in a more detailed way which could be considered as the potential research topic.

Supplementary data to this article can be found online at http://dx.doi.org/10.1016/j.eneco.2013.08.012.

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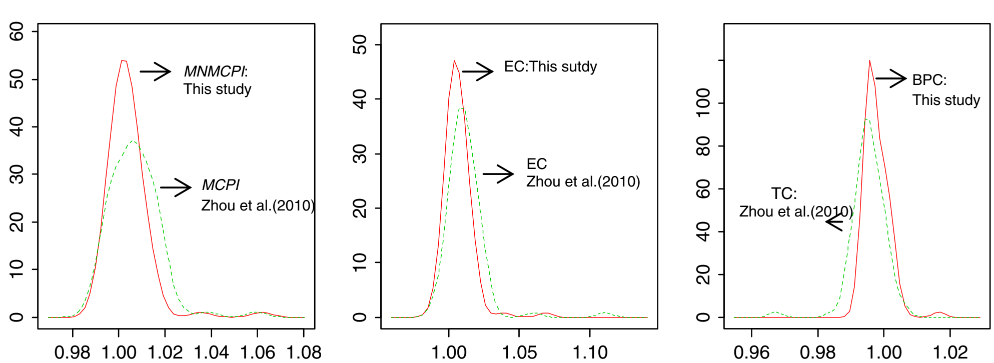

Fig. 5. Kernel density estimation for the MNMCPI and the MCPI.

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