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Total-factor carbon emission performance of the Chinese transportation industry: A bootstrapped non-radial Malmquist index analysis

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ABSTRACT

This paper proposes a non-radial Malmquist CO_2 emission performance index (NMCPI) for measuring dynamic changes in total-factor CO_2 emission performance over time. This index enables the consideration of non-radial slacks in the conventional Malmquist CO_2 emission index (MCPI). The NMCPI is calculated based on a non-radial directional distance function derived by several data envelopment analysis (DEA) models. Furthermore, NMCPI could be decomposed into an efficiency change (EC) index and technological change (TC) index. A bootstrapping approach is conducted to introduce statistical inferences into the NMCPI and its decompositions. Based on the proposed indices, the dynamic CO_2 emission performance change and its decompositions of the Chinese regional transportation industry from 2002 to 2010 are investigated. The empirical results demonstrate that the total-factor carbon emission performance of the transportation industry as a whole decreased by 32.8% over the period, and this reduction was primarily caused by technological decline.

Contents

1. Introduction

Climate change has become one of the most challenging issues facing the world. Increasing numbers of countries are concerned with reducing energy consumption and CO_2 emissions while increasing the efficiency and productivity of the industrial sectors.

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Policy makers have realized the importance of reducing CO_2 emissions in formulating national economic and energy policies, which requires understanding of the patterns of CO_2 emissions and monitoring emission performance. Among all sectors, the transportation sector emits approximately one quarter of the world's CO_2 emissions [1], thereby playing an important role in achieving energy consumption reductions and CO_2 emissions mitigation.

Ten years ago, energy consumption in China was only half of that in the United States, but China became the world's largest energy consumer in 2010 [2]. To address this issue, China seeks a "green and low-carbon development" mode by announcing several new carbon and energy targets based on 2010 emission levels, especially for the transportation industry. An emission offset plan issued by China's Ministry of Transport (MOT) aims to reduce energy consumption and CO_2 emissions per traffic volume for road transport operators by 10% and 11% by 2015 based on 2005 emission levels, respectively. The five-year plan involves several major projects including promoting the use of energy-saving and new energy vehicles, as well as the use of natural gas for taxis and buses; all of these projects would improve the CO_2 emissions performance in the Chinese transportation industry.

To measure energy and CO_2 emissions performance, data envelopment analysis (DEA) has gained considerable popularity [3] because it evaluates the performance within a total-factor production framework, which is more appropriate than a single-factor indicators approach.

Recognizing the importance of evaluating energy and CO_2 emissions efficiency, a number of studies have attempted to address these issues for China based on efficiency measurement via DEA models. For instance, a number of studies have emphasized the province-level. Hu and Wang [4] first employed basic DEA to measure energy efficiency for provinces. Chang and Hu [5] measured energy productivity growth in the dynamic perspective. However, those studies did not consider the undesirable output carbon emissions which are the byproduct of energy use. Several other studies incorporate undesirable outputs into energy or carbon efficiency analysis for Chinese provinces [6–12].

As the industrial sector contributes large carbon emissions, several studies focused on an energy efficiency analysis for the Chinese industrial sector [13–15]. A number of studies analyzed energy efficiency for the Chinese iron and steel industry; for example, Wei et al. [16] analyzed static energy efficiency without considering undesirable output. Smyth et al. [17] estimated the substitutability between energy and classical inputs. He et al. [18] measured energy efficiency and productivity together. Lee and Zhang [19] examined the Chinese manufacturing industries. Several other studies researched the power generation industry [20–23] based on an efficiency analysis.

Although energy and CO_2 emissions efficiency in many sectors have been widely analyzed in China, few studies have focused on the transportation industry [24,52]. Zhou et al. [24] used the undesirable output-oriented DEA models with different returns to scale to measure carbon emission performance for the regional transportation sector; they showed that the number of efficient regions has decreased since 2004, hitting the lowest record in 2006, and improving slightly afterwards. Chang et al. [52] used the SBM-DEA to measure carbon emissions and potential reductions for the regional transport sector; the results indicated that most of the provinces in China do not have an eco-efficient transportation industry. Zhou et al. [53] analyzed energy efficiency and potential energy savings for the Chinese transport industry using the DEA approach. Cui and Li [54] also focused on energy efficiency in the Chinese transport industry by proposing a three-stage virtual frontier DEA.

Nevertheless, these studies also have a number of shortcomings in that they used a static relative carbon performance measure without considering the dynamic performance change. No studies have been conducted on dynamic CO_2 emissions performance change measurement for China's transportation industry. The primary objective of this paper is to analyze the dynamic CO_2 emissions performance change for China's transportation industry.

As mentioned above, most previous studies related to China's CO_2 emission performance efficiency in different industries are within a cross-sectional, rather than a time series, framework. Therefore, we cannot obtain insight regarding the dynamic change of CO_2 emission performance. For measuring the dynamic change of the total-factor CO_2 emission performance, Zhou et al. [25] develop a Malmquist CO_2 emission performance index (MCPI) based on the Shephard carbon distance function. However, this study did not consider the slack variables; thus, the Malmquist index may lead to a biased estimation [26]. Thus, this study proposes a non-radial Malmquist CO_2 emission performance index (NMCPI) by considering slacks based on a non-radial directional distance function. In addition, because NMCPI is a deterministic approach that measures performance relative to an estimate of the true and unobservable production technology, one cannot know whether the CO_2 performance change is statistically significant or not. Therefore, the study adopts the bootstrapping method proposed in Ref. [27] to provide a statistical interpretation of the NMCPI and its decompositions for the Chinese transportation industry.[1] In summary, the contributions of this paper can be divided into two parts: Methodologically, we propose a new approach called the Bootstrapped Non-radial Malmquist index for the first time. Empirically, we first conduct a dynamic CO_2 emission performance change analysis for the Chinese transport industry.

The remainder of this paper is organized as follows. Section 2 presents the methodology, which consists of the concept of environmental production technology and the development of NMCPI. In Section 3, we use the proposed approach to study the CO_2 emission performance of the Chinese transportation industry from 2002 to 2010. Finally, Section 4 presents the conclusions.

2. Methodology

2.1. Environmental production technology

This paper uses non-radial directional distance function to model a transportation technology that jointly produces a desirable and an undesirable output. Following [28], one may think of a transportation system as a production model. Suppose a transportation process where each transport firm employs capital stock (K), labor force (L), and energy (E) as inputs to generate the gross product (Y) of transportation as a desirable output and CO_2 emissions (C) as an undesirable output. The production technology set can be defined as:

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

In production economic theory, the *environmental production technology* (T) is usually assumed to be a closed and bounded set, which indicates that finite inputs can only generate finite outputs. Additionally, inputs and desirable outputs are supposed to be strongly or freely disposable. To model a production technology reasonably that produces both desirable and undesirable outputs, two additional assumptions (i.e., weak disposability and null-jointness) need to be imposed [29]. Technically, the assumptions can be formulated as

(I) If $(K, L, E, Y, C) \in T$ and $0 < \theta \leq 1$, then $(K, L, E, \theta Y, \theta C) \in T$.
(II) If $(K, L, E, Y, C) \in T$ and $C = 0$, then $Y = 0$.

[1] As this study is based on the non-parametric approach, an interesting extension to this study would be the use of parametric DDF to conduct a comparative study in the future [51].

The weak disposability assumption (i) implies that the abatement of undesirable outputs is not free but costly in terms of a proportional reduction in desirable outputs. The null-jointness assumption (ii) implies that producing CO_2 emissions are inevitable in fossil-fuel electricity generation and the only way to remove all the CO_2 emissions is to stop transportation activities. With these assumptions, the production technology for modeling the joint production of $Y$and C has been well-defined conceptually but cannot be directly employed in empirical analysis. A common practice is to characterize the production technology within a nonparametric framework, which can be performed using the piecewise convex combinations (DEA-type) of the observed data. Suppose that there are $n=1,2,\dots,N$ firms and for firm i, the vector of inputs, desirable outputs, and undesirable outputs is $(K_n, L_n, E_n, Y_n, C_n)$. The *environmental production technology* (T) for N transportation firms exhibiting constant returns to scale (CRS) can be formulated as follows:

$$T=\{(K,L,E,Y,C): \sum_{n=1}^{N} z_n K_n \le K \ \sum_{n=1}^{N} z_n L_n \le L \ \sum_{n=1}^{N} z_n E_n \le E \ \sum_{n=1}^{N} z_n Y_n \ge Y \ \sum_{n=1}^{N} z_n C_n = C \ z_n \ge 0, n=1,2,\dots,N\} \tag{2}$$

where Z_n is an intensity variable for constructing the *environmental production technology* (T) by convex combination. Once the environmental production technology is well-constructed, the directional distance functions can be used to calculate the CO_2 emission performance.

2.2. Non-radial directional distance function

The directional distance function (DDF) was originally developed by Chambers et al. [30] and applied by Chung et al. [31] in environmental studies. It is a relatively new methodology for performance and efficiency measurement. The traditional DDF is defined, as it seeks the maximal increase in desirable outputs while reducing the undesirable outputs at the same rate simultaneously:

$$\vec{D}(K,L,E,Y,C;g)=\sup\{\boldsymbol{\beta}: ((K,L,E,Y,C)+g\times\boldsymbol{\beta}))\in T\} \tag{3}$$

The conventional DDF reduces undesirable outputs (inputs) and increase desirable outputs at the same rate, which may still be regarded as a radial efficiency measure with several limitations. One of the limitations is that the radial measure may overestimate the efficiency when non-zero slacks exist [26]. Non-radial efficiency measures are often advocated to overcome this limitation in energy and environmental performance measurement due to its advantages [5,8,32–34]. Recently, Zhou et al. [35] provided a formal definition of the non-radial DDF considering undesirable outputs. Following [35], we define the non-radial directional distance function (NDDF) as follows:

$$N\vec{D}(K,L,E,Y,C;g)=\sup\{\mathbf{w}^T\boldsymbol{\beta}: ((K,L,E,Y,C)+g\times diag\ (\boldsymbol{\beta}))\in T\} \tag{4}$$

where $\mathbf{w}^T=(w_K, w_L, w_E, w_Y, w_C)^T$ denotes the normalized weight vector relevant to the number of inputs and outputs, $g=(-g_K, -g_L, -g_E, g_Y, -g_C)$ is the explicit directional vector, the symbol *diag* means the diagonal matrices, and $\beta=(\beta_K, \beta_L, \beta_E, \beta_Y, \beta_C)^T\ge 0$ denotes the vector of the scaling factors representing the individual inefficiency measure for each input and output. To measure the CO_2 emission performance of transportation, it is better to fix non-energy inputs because capital and labor do not contribute to emissions directly. By setting the directional vector as $g=(0,0,-g_E,g_Y,-g_C)$and the weight vector as (0, 0, 1/3, 1/3, 1/3), we remove the diluting effects of capital and labor from the objective function and constraints.

The value of NDDF of a specific firm n' denoted as $N\vec{D}(K,L,E,Y,C;g)$ can be calculated by solving the following DEA-type model:

$$N\vec{D}(K,L,E,Y,C;g)= \max w_E\beta_E+w_Y\beta_Y+w_C\beta_C$$
$$\begin{aligned} \text{s.t.} \ & \sum_{n=1}^{N} z_n K_n \le K_{n'} \\ & \sum_{n=1}^{N} z_n L_n \le L_{n'} \\ & \sum_{n=1}^{N} z_n E_n \le E_{n'}-\beta_E g_E \\ & \sum_{n=1}^{N} z_n Y_n \ge Y_{n'}+\beta_Y g_Y \\ & \sum_{n=1}^{N} z_n C_n = C_{n'}-\beta_C g_C \\ & z_n\ge 0, n=1,2,\dots,N \\ & \beta_K,\beta_L,\beta_E,\beta_Y,\beta_C\ge 0 \end{aligned} \tag{5}$$

The directional vector g can be set in various ways based on different policy goals of emission reduction. If $N\vec{D}(K,L,E,Y,C;g)=0$, it means that the observation to be evaluated is located at the frontier of best practice in g direction.

Because the weight vector as (0, 0, 1/3, 1/3, 1/3) and the directional vectors are set as$g=(0,0-E,Y,-C)$, we follow [35] to define the total-factor CO_2 emission performance index (TCPI) as the ratio of potential target carbon intensity to actual carbon intensity (C/Y). Suppose that β_C^* and β_Y^* are the optimal solutions corresponding to the CO_2 emissions and the product output of transportation in model (5), the TCPI can be formulated as:

$$\text{TCPI}=\frac{\left(C-\beta_C^*C\right)/\left(Y+\beta_Y^*Y\right)}{C/Y}=\frac{1-\beta_C^*}{1+\beta_Y^*} \tag{6}$$

Eq. (6) seeks to measure the maximal possible reduction in carbon intensity, which can be used to measure the CO_2 emissions performance of each transportation firm for a certain period of time. Clearly, TCPI lies between zero and unity; further, the higher the TCPI, the better is the CO_2 emission performance.

To study the dynamic change in CO_2 emissions performance over time by considering non-radial slacks, we propose a non-radial Malmquist CO_2 emissions performance (NMCPI) in the next sub-section.

2.3. Non-radial Malmquist CO_2 emission performance index

The Malmquist productivity index was first developed by [36] as a ratio of two distance functions for the measurement of productivity. Färe et al. [37] extended it by considering technical inefficiency in productivity measurement within a nonparametric framework. For environmental studies, Chung et al. [31] first proposed a Malmquist index with undesirable outputs named the Malmquist–Luenberger (ML) index to measure environmentally sensitive productivity growth. The ML index has been widely used in environmental studies, and empirical studies of ML index application could be found in Refs. [38,40–43]. The MCPI developed by Ref. [25] could be regarded as a special case of ML index, which is a CO_2 emission sub-vector ML index.

Following the spirit of the nonparametric Malmquist productivity index, we propose a NMCPI for assessing the change in CO_2 emission performance over time. Let t and s ($t<s$) denote two time periods. Assume that $\text{TCPI}^t(K_n^t, L_n^t, E_n^t, Y_n^t, C_n^t)$ and $\text{TCPI}^s(K_n^t, L_n^t, E_n^t, Y_n^t, C_n^t)$ are the total-factor CO_2 emission performance index (TCPI) of firm n based on its inputs and outputs at period t for the production technology at t

and s, respectively. Further assume that $\mathrm{TCPI}^t(K_n^s, L_n^s, E_n^s, Y_n^s, C_n^s)$ and $\mathrm{TCPI}^s(K_n^s, L_n^s, E_n^s, Y_n^s, C_n^s)$ are the TCPI of firm n based on its inputs and outputs at period s for the production technology at t and s, respectively. We define the NMCPI as follows:

$$\mathrm{NMCPI}_n(t,s) = \left[\frac{\mathrm{TCPI}^t(K_n^s, L_n^s, E_n^s, Y_n^s, C_n^s) \times \mathrm{TCPI}^s(K_n^s, L_n^s, E_n^s, Y_n^s, C_n^s)}{\mathrm{TCPI}^t(K_n^t, L_n^t, E_n^t, Y_n^t, C_n^t) \times TCPI^s(K_n^t, L_n^t, E_n^t, Y_n^t, C_n^t)}\right]^{1/2} \tag{7}$$

$\mathrm{NMCPI}_n(t,s)$ can be used to measure the change in the total-factor CO_2 emissions performance of firm n from period t to period s. $\mathrm{NMLCPI}_n(t,s) > 1$ (or $\mathrm{NMLCPI}_n(t,s) < 1$) means that the CO_2 emissions performance has improved (or deteriorated). Similar to the Malmquist productivity index, NMCPI can be decomposed into two components (i.e., efficiency change and technological change) and expressed as:

$$\mathrm{EFFCH}_n(t,s) = \frac{\mathrm{TCPI}^s(K_n^s, L_n^s, E_n^s, Y_n^s, C_n^s)}{\mathrm{TCPI}^t(K_n^t, L_n^t, E_n^t, Y_n^t, C_n^t)} \tag{8}$$

$$\mathrm{TECHCH}_i(t,s) = \left[\frac{\mathrm{TCPI}^t(K_n^s, L_n^s, E_n^s, Y_n^s, C_n^s) \times \mathrm{TCPI}^t(K_n^t, L_n^t, E_n^t, Y_n^t, C_n^t)}{TCPI^s(K_n^s, L_n^s, E_n^s, Y_n^s, C_n^s) \times \mathrm{TCPI}^s(K_n^t, L_n^t, E_n^t, Y_n^t, C_n^t)}\right]^{1/2} \tag{9}$$

The efficiency change term (EC) in Eq. (8) is a measure of the *catch-up* effect in terms of the technical efficiency change of CO_2 emissions within a specific group during two time periods (t, s). EC captures how close an observation moves towards the environmental production technology. EC $>$ (or $<$) 1 means efficiency gain (or loss).

The technological change (TC) component measures the frontier-shift effect, which quantifies the shift in the production technology of observation n over time, from period t to period s. $TC >$ (or $<$) 1 means technological progress gain (or loss).

To calculate NMCPI and its two compositions, four non-radial directional distance functions must be solved (i.e. $\overrightarrow{D}^{l_1}(K^{l_2}, L^{l_2}, E^{l_2}, Y^{l_2}, C^{l_2}; g)$, $l_1, l_2 \in \{s, t\}$). According to Eq. (5) and the environmental production technology given by Eq. (2), we compute $N\overrightarrow{D}^{l_1}(K^{l_2}, L^{l_2}, E^{l_2}, Y^{l_2}, C^{l_2}; g)$ by solving the following DEA-type model:

$$\begin{aligned} N\overrightarrow{D}^{l_1}\left(K^{l_2}, L^{l_2}, E^{l_2}, Y^{l_2}, C^{l_2}; g\right) = \max\ & w_E\beta_E + w_Y\beta_Y + w_C\beta_C \text{ s.t. } \sum_{n=1}^{N} z_n K^{l_1}{}_n \\ & \le K^{l_2}{}_{n'} \sum_{n=1}^{N} z_n L^{l_1}{}_n \le L^{l_2}{}_{n'} \sum_{n=1}^{N} z_n E^{l_1}{}_n \\ & \le E^{l_2}{}_{n'} - \beta_E g_E \sum_{n=1}^{N} z_n Y^{l_1}{}_n \ge Y^{l_2}{}_{n'} \\ & + \beta_Y g_Y \sum_{n=1}^{N} z_n C^{l_1}{}_n = C^{l_2}{}_{n'} - \beta_C g_C\ z_n \ge 0, \\ & n = 1, 2, \ldots, N\ \beta_K, \beta_L, \beta_E, \beta_Y, \beta_C \ge 0 \end{aligned} \tag{10}$$

Note that Eq. (10) is based on the environmental production technology with constant returns to scale, which is the most commonly adopted practice in the literature. Once the NDDFs are solved, we can obtain the four corresponding TCPI defined in (6), that is, $\mathrm{TCPI}^{l_1}(K^{l_2}, L^{l_2}, E^{l_2}, Y^{l_2}, C^{l_2})\ l_1, l_2 \in \{s, t\}$.

According to Ref. [44], the Malmquist productivity index based on the constant returns to scale production technology can be interpreted as a total-factor productivity change index. As a result, the NMCPI can be interpreted as a total-factor CO_2 emission performance change index.

2.4. Bootstrapping NMCPI

Because NMCPI is derived from the non-radial DDF that are calculated based on the estimate of the true production frontier, it will be subject to uncertainties due to the sampling variation of the obtained production frontier. Therefore, it is meaningful to introduce the statistical inference for NMCPI with respect to the sampling variation by bootstrapping the index. The theory and algorithm of bootstrapping Malmquist are developed by [27].

We use the algorithm developed by Simar and Wilson [27] to bootstrap NMCPI. The simplified process for bootstrapping NMCPI is summarized as follows:

(1) Calculate $\mathrm{NMCPI}_i(t,s)$ for $i = 1, 2, \ldots, N$ by using Eqs. (7) and (10).
(2) Based on the bivariate kernel density estimator and the reflection method suggested by [27], we generate two pseudo datasets $\{(K_i^t, L_i^t, E_i^t, Y_i^t, C_i^{t*}),\quad i = 1, 2, \ldots, N\}$ and $\{(K_i^s, L_i^s, E_i^s, Y_i^s, C_i^{s*}),\quad i = 1, 2, \ldots, N\}$ with the normal reference rule of bandwidth.
(3) Compute the bootstrap estimate of $\mathrm{NMCPI}_{i,b}^{*}(t,s)$ of $\mathrm{NMCPI}_i(t,s)$ for $i = 1, 2, \ldots, N$ by solving Eqs. (7) and (10) using the environmental production technologies constructed from the pseudo datasets obtained in Step 2.
(4) Repeat Steps 2–3 B times ($B = 2000$) to provide bootstrapped estimates $\{\mathrm{NMCPI}_{i,b}^{*}(t,s), b = 1, 2, \ldots, B\}$ for $i = 1, 2, \ldots, N$.
(5) From sorting the bootstrapped B estimates of NMCPI, by setting the preferred percentiles, we can construct confidence intervals of NMCPI.

For a specific decision making unit (DMU, hereafter), if one does not fall between the confidence intervals of NMCPI, the improvement or deterioration in the total-factor carbon emission performance index of this DMU is significantly different from unity, under the desired significance level. Similarly, we can also use the estimates to test the significance of the contributing components of NMCPI, such as technical efficiency change (EC) and technological change (TC).

3. Empirical study

3.1. Data

The models described in Section 2 have been applied to examine the total-factor CO_2 emission performance change and its sources in the provincial transportation industry of China[2] from 2002 to 2010. Because the energy data for Tibet cannot be obtained, our dataset covers thirty provinces. The data on gross product (Y)[3] and employees (L) of the transportation industry can be found in Ref. [45]. Total fixed assets in the transportation industry are used for capital stock (K).

The fixed assets of the regional transportation industry were calculated by the perpetual inventory method. Following this method, fixed assets can be calculated as follows:

$$F_t = I_t + (1-\delta)F_{t-1} \tag{11}$$

where F_t, I_t and δ represent the fixed assets, investment in fixed assets, and depreciation rate at time t, respectively. Additionally, F_{t-1} means the fixed assets at time $t-1$. Because the research period starts in 2002, we use the fixed assets in 2002 of each province as the initial fixed assets, which can be found in Ref. [46]. The depreciation rate for each province's transportation shown in

[2] According to the classification of Ref. [45], the transportation industry of China is an integrated industry that includes road transportation, water transportation (inner and sea) and air transportation, as well as the post industry. Therefore, only the data of the integrated transportation industry is available.

[3] Zhou et al. [24] use cargo-km and passenger-km as the good outputs. Our data is from the integrated transportation industry and thus, cargo/passenger-km could be regarded as the intermediate output that can be eventually transformed into gross product value.

Ref. [46] is adopted and the data related to the investment in fixed assets is selected from Ref. [45].

All of the monetary variables, including gross product and capital stock, have been converted into 2002 prices with GDP deflectors. Energy consumption (E) is selected as the energy input, which includes all types of energy, such as coal, oil, and gas [47]. All of these have been converted into tons of standard oil equivalent (TOE), in terms of the corresponding energy folding standard. The official data on provincial CO_2 emissions (C) in the transportation industry is not available in China. Following [24], we employ the fuel-based carbon calculation model described in Refs. [48,49] to estimate the provincial transportation CO_2 emissions. The descriptive statistics of the regional data in the transportation industry are shown in Table 1.

3.2. Dynamic CO_2 emission performance change analysis

To assess the dynamic CO_2 emission performance change of the Chinese provincial transportation industry, we compute the NMCPI for each of the thirty provinces. When solving a mix-period LP problem, the environmental technology constructed by the observations from a period may not enclose all the observations from another period. As a result, some infeasible solutions occur. We therefore follow Ref. [39] to use the three-year "windows" approach to construct the environmental production technologies. Having calculated the NMCPI results for eight two-year pairs from 2002 to 2010 for each province, we use the bootstrapping technology to construct the confidence intervals of the original NMCPI values for testing their significant differences from unity. Table 2 shows the original NMCPI estimates and the statistically significant results.

The NMCPI results indicate a decrease in the total-factor CO_2 emission performance for the period of 2002 to 2010. On average, the total-factor CO_2 emission performance of China's transportation industry decreases by approximately 5.7% under the NMCPI. This result means that on average, the ratio of target carbon intensity to actual carbon intensity decreases by 5.7% per year over the sample period. At the province level, only Ningxia province shows an increase in CO_2 emission performance. All eight two-year periods (i.e., 2002–2003 to 2009–2010) show a decrease in CO_2 emission performance. This indicates that although the incentive policy has allowed the transportation industry to achieve remarkable progress in terms of gross product, transportation was mainly fueled by carbon-intensive development; low-carbon development for the transportation industry has been neglected. The bootstrapping results also confirmed that in most cases, the decrease in CO_2 emission performance is significant. For instance, during 2004–2005, almost all provinces show a significant decrease of NMCPI, except for Inner Mongolia and Shanghai. In other two-year periods, over half of the provinces are found to be a significant DMU of NMPCI below unity.

To investigate the sources of CO_2 emission performance change, the NMCPI estimates have been decomposed into their efficiency change (EC) and technological change (TC) components (Eqs. (8) and (9)) with their bootstrapping results. The efficiency

Table 1
Descriptive statistics of variables (N=270).

Variable	Units	Mean	StDev	Min	Max
L	10^3 persons	262.4	235.1	28.1	1659.0
K	10^9 Yuan	47.0	42.2	1.4	207.3
E	10^3 t	4136.0	3392.0	160.0	17865.0
Y	10^9 Yuan	18.4	13.6	1.3	67.5
C	10^3 t	12675.0	10165.0	517.0	53079.0

Table 2
Changes in NMCPI of provincial transportation industry, 2002–2010.

Provinces	Area	2002–2003	2003–2004	2004–2005	2005–2006	2006–2007	2007–2008	2008–2009	2009–2010	Mean
Beijing	E	1.105*	0.697*	1.083*	0.899*	0.887	0.876*	1.000	0.973	0.940
Tianjin	E	1.185*	0.632*	0.949*	0.982	1.020	0.955	1.000	1.001	0.966
Hebei	E	0.998	0.844*	0.692*	1.087*	1.022*	1.014*	1.048*	1.012	0.965
Shanxi	C	1.042	0.929*	0.991*	0.968*	1.029	0.678*	0.978*	1.003	0.991
Inner Mongolia	W	0.997	0.738*	1.104	1.000	0.945	1.000	0.926	0.818	0.941
Liaoning	E	1.054*	1.031*	0.673*	0.983*	0.831*	0.991	0.967*	0.956*	0.936
Jilin	C	0.889	0.974	0.798*	0.935*	0.872*	0.860	0.891*	0.830*	0.881
Heilongjiang	C	0.868	0.893*	0.805*	0.872*	0.921*	0.999	0.930	0.966	0.907
Shanghai	E	0.947*	0.938*	0.999	0.973*	0.934*	0.972*	0.843*	1.101*	0.963
Jiangsu	E	0.877	0.913	0.892*	0.710*	1.377*	0.995	1.123	1.082	0.996
Zhejiang	E	0.893	1.049	0.905*	1.000	1.000	0.957	0.976	0.898	0.960
Anhui	C	0.980	0.955*	0.957*	0.959	0.888*	0.987	0.867*	0.945*	0.942
Fujian	E	1.010	0.872*	0.737*	1.009	1.019	0.877*	0.954*	0.999	0.935
Jiangxi	C	0.923*	1.072*	0.945*	0.926*	0.981*	1.031*	0.893	0.843*	0.952
Shandong	E	0.633*	1.334*	0.698*	1.075	0.970	1.108	0.847	0.938	0.950
Henan	C	0.996	0.673*	0.904*	1.000	0.936*	0.974	0.791*	0.900*	0.897
Hubei	C	0.951*	1.021*	0.843*	0.991*	0.979*	1.004	1.023*	0.925*	0.967
Hunan	C	1.000	0.953*	0.814*	0.996*	0.957*	1.107*	0.963*	0.941*	0.966
Guangdong	E	0.965	0.914	0.645*	0.977*	0.931*	0.965*	0.953*	0.962*	0.914
Guangxi	W	0.971	0.865*	0.932*	0.950*	0.984*	0.994	0.916*	0.996	0.951
Hainan	E	1.047	0.895*	0.894*	0.976*	0.997*	0.911*	0.908*	1.018*	0.956
Chongqing	W	1.009	0.569*	1.140*	0.990	0.835*	0.987*	1.062*	0.910*	0.938
Sichuan	W	0.809*	0.920	0.811*	0.920	0.814*	0.990	0.936	1.280*	0.935
Guizhou	W	0.650*	0.918*	0.926*	0.909*	0.933*	0.900*	1.284*	0.907*	0.928
Yunnan	W	0.990*	1.245*	0.488*	0.925*	0.936*	1.004*	0.812*	0.822*	0.903
Shaanxi	W	0.715*	0.959*	0.735*	0.968*	0.892*	0.871*	0.922*	0.926*	0.874
Gansu	W	0.994	1.039*	1.143*	0.984	0.938*	1.029	0.892	0.867*	0.986
Qinghai	W	0.936*	0.959*	0.775*	0.959	0.693*	0.799*	0.972*	0.951*	0.881
Ningxia	W	0.952*	1.270*	0.720*	0.927*	0.951*	1.004	1.329*	1.002	1.032
Xinjiang	W	0.908*	0.974*	0.818*	0.945*	0.961*	0.971*	0.997	0.930*	0.938
Mean		0.943	0.938	0.861	0.960	0.948	0.970	0.967	0.957	0.943

* The NMCPI index is significantly different from unity at the 5% significant level.

change (EC) components and corresponding bootstrap results are shown in Table 3. The average efficiency change (EC) index of CO_2 emission performance is 1.012 under our NMCPI framework, showing an average annual increase in efficiency of 1.2%. This result indicates that the movement of these provinces toward the environmental technology frontier over the study period reflects the catch-up effect.

For individual provinces, 17 regions show an increase in efficiency change of CO_2 emission performance, whereas 10 provinces show a decrease. Ningxia shows the highest efficiency change (average growth rate=9.0%), whereas Fujian, the lowest efficiency change (average=0.950%), indicating a 5.0% decrease in efficiency change of CO_2 emission performance.

However, the bootstrapping results lead to a different story. During 2008–2009 and 2009–2010, the original EC index of NMCPI estimates indicates that over half of the provinces have an improvement in their CO_2 emission efficiency change. Nevertheless, the bootstrapping results show that in most cases, the increase is not significant. Only two provinces are found to have significant DMUs in 2008–2009 and 2009–2010.

The TC component of NMCPI is shown in Table 4; it is found that the average TC index is approximately 0.935 under the NMCPI, indicating a decrease in the technological change of CO_2 emission performance. This implies a technological decline in CO_2 emissions reduction in China's transportation industry during the research period. Almost all provinces show a state of technological decline under the NMCPI, whereas only Zhejiang province shows technological progress. This result suggests a lack of technological innovation in low-carbon technology within the transportation industry during the sample period.

The bootstrapping TC index shows some interesting results. Before the 2005–2006 period, bootstrapping results confirm the results of the technological decline of CO_2 emission performance because over half of the provinces show a significant decrease of TC on CO_2 emission performance. Especially during 2004–2005, almost all provinces are found to be significant in the technological decline of CO_2 emission performance. However, after 2006, the bootstrapping results show that in most cases, the technological decline is not significant. For instance, during the 2007–2008 period, only two provinces are found to be significant in the technological decline of CO_2 emissions. In addition, in the 2009–2010 period, no provinces have significant technological decline, whereas two provinces were determined to have significant technological progress of CO_2 emission performance. It seems that the trend of the technological decline of CO_2 emissions reduction had been controlled.

This interesting phenomenon might emerge from a paradigm shift in China's low-carbon policies. Before 2006, the rapid growth of transportation was fueled, which required considerable amounts of energy that lead to huge CO_2 emissions. During the 11th five-year plan (2006–2010), the Chinese government set a reduction target for energy consumption and CO_2 emissions. Therefore, the transportation industry was under considerable pressure to reduce its CO_2 emissions. The pause of technology decline after 2006 might support the Porter hypothesis [50], which posits that a stricter environmental regulation means not only cost increases but also improvements in innovation for more environment-friendly production processes. However, additional empirical work is required to accurately test the Porter hypothesis.

We examine the trends in the cumulative total-factor CO_2 emission performance and its decomposition by setting the 2002 value equal to 1 for the transportation industry. Fig. 1 shows the cumulative changes in CO_2 emission performance and the decomposed sources based on the NMCPI. For the total-factor CO_2

Table 3
Efficiency change component of NMCPI, 2002–2010.

Provinces	Area	2002–2003	2003–2004	2004–2005	2005–2006	2006–2007	2007–2008	2008–2009	2009–2010	Mean
Beijing	E	1.139	0.953	1.222*	1.000	1.000	1.000	1.000	1.000	1.039
Tianjin	E	1.264*	0.699*	1.331*	1.000	1.000	1.000	1.000	1.000	1.037
Hebei	E	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Shanxi	C	1.224*	1.090	1.229*	1.007	1.114	0.677*	1.023	1.067*	1.054
Inner Mongolia	W	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.833	0.979
Liaoning	E	1.151*	1.240*	0.861*	1.024	0.889*	0.981	1.004	1.009	1.020
Jilin	C	1.000	1.000	1.000	1.000	1.000	0.850	1.023	0.941	0.977
Heilongjiang	C	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Shanghai	E	0.964	1.035	1.294*	0.892	0.910	0.965	0.817*	1.167	1.006
Jiangsu	E	1.018	0.997	1.251	0.697*	1.344*	1.051	1.024	1.000	1.048
Zhejiang	E	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.744	0.968
Anhui	C	1.134	1.149	1.357*	0.942	0.924	0.986	0.869*	1.018	1.047
Fujian	E	1.000	1.000	1.000	0.910	0.960	0.865	0.899	1.023	0.957
Jiangxi	C	1.030	1.197*	1.289*	0.940	1.037	1.082	0.929	0.925	1.054
Shandong	E	0.701*	1.427*	1.000	1.000	1.000	1.000	1.000	1.000	1.016
Henan	C	1.186	0.777*	1.288*	1.000	0.974	0.990	0.798*	0.978	0.999
Hubei	C	1.045	1.133*	1.033	1.009	1.030	0.993	1.069*	0.982	1.037
Hunan	C	1.105	1.110	1.157	0.950	0.976	1.102*	0.950	1.012	1.045
Guangdong	E	1.270	1.000	0.807	0.956	0.937	1.019	0.823*	0.862	0.959
Guangxi	W	1.097	0.953*	1.124*	0.973	1.027	0.990	0.933	1.061	1.020
Hainan	E	1.120*	0.947	1.262*	0.874*	0.941	0.902	0.815*	1.012	0.984
Chongqing	W	1.046	0.820*	1.348*	0.914	0.832*	0.976	0.996	0.982	0.989
Sichuan	W	1.000	1.000	1.000	0.936	0.786*	1.060	0.843	1.520*	1.018
Guizhou	W	0.774*	1.027	1.161*	0.947*	0.986	0.893*	1.738*	0.930	1.057
Yunnan	W	1.028	1.382*	0.595*	0.932*	0.977	0.992	0.825*	0.871*	0.950
Shaanxi	W	0.799*	1.140	0.951	1.032	0.996	0.858*	0.977	0.988	0.968
Gansu	W	0.996	1.231*	1.339*	1.047	1.065	1.004	1.000	0.993	1.084
Qinghai	W	1.030	1.136	1.000	1.000	0.730*	0.785*	1.028	1.025	0.967
Ningxia	W	0.944	1.255*	0.936*	0.944	1.017	0.989	1.631*	1.000	1.090
Xinjiang	W	0.950	1.085	0.991	0.970	1.033	0.953	1.043	0.992	1.002
Mean		1.043	1.035	1.013	0.979	0.996	0.986	0.984	0.981	1.012

E: eastern area, C: central area, and W: western area.

* The EC index is significantly different from unity at the 5% significant level.

Table 4
Technological change component of NMCPI, 2002–2010.

Provinces	Area	2002–2003	2003–2004	2004–2005	2005–2006	2006–2007	2007–2008	2008–2009	2009–2010	Mean
Beijing	E	0.971	0.627*	0.688*	0.899*	0.887*	0.876*	1.000	0.973	0.840
Tianjin	E	1.194	0.904	0.664*	0.982	1.020	0.955	1.000	1.001	0.965
Hebei	E	0.998	0.844*	0.692*	1.087	1.022	1.014	1.048	1.012	0.965
Shanxi	C	0.850*	0.852*	0.694*	0.961	0.923	1.001	0.955	0.940	0.897
Inner Mongolia	W	0.997	0.738*	1.104	1.000	0.945	1.000	0.926	0.982	0.962
Liaoning	E	0.916	0.832*	0.781*	0.960	0.934*	1.010	0.963	0.947	0.918
Jilin	C	0.889	0.974	0.798*	0.935	0.872*	1.012	0.871*	0.882	0.904
Heilongjiang	C	0.868*	0.893*	0.805	0.872*	0.921	0.999	0.930	0.966	0.907
Shanghai	E	0.982	0.907	0.772*	1.091	1.027	1.008	1.032	0.944	0.970
Jiangsu	E	0.862*	0.916	0.713*	1.018	1.025	0.946	1.097	1.082	0.957
Zhejiang	E	0.893	1.149	0.905	1.000	1.000	0.957	0.976*	1.208*	1.011
Anhui	C	0.864	0.831*	0.705*	1.017	0.961	1.001	0.998	0.928	0.913
Fujian	E	1.010	0.872*	0.737*	1.110	1.062	1.014	1.061	0.977	0.980
Jiangxi	C	0.896	0.896*	0.733*	0.985	0.946*	0.953	0.961	0.912	0.910
Shandong	E	0.903	0.935	0.698*	1.075	0.970	1.108	0.847*	0.938	0.934
Henan	C	0.840*	0.867*	0.702*	1.000	0.961	0.984	0.992	0.921	0.908
Hubei	C	0.910	0.901	0.816*	0.982	0.951	1.011	0.957	0.942	0.934
Hunan	C	0.905	0.859*	0.703*	1.049	0.981	1.005	1.014	0.930	0.931
Guangdong	E	0.760*	0.914	0.799*	1.023	0.994	0.948	1.158	1.116	0.964
Guangxi	W	0.885*	0.908*	0.829*	0.976	0.958	1.004	0.982	0.939	0.935
Hainan	E	0.935	0.945	0.709*	1.117	1.059	1.010	1.114	1.006	0.987
Chongqing	W	0.965	0.693*	0.692*	1.083	1.003	1.011	1.067	0.927	0.930
Sichuan	W	0.809*	0.920	0.811*	0.983	1.036	0.934*	1.110	1.105*	0.963
Guizhou	W	0.840*	0.894	0.798*	0.960	0.947*	1.008	0.969	0.976	0.924
Yunnan	W	0.964	0.859*	0.820*	0.992	0.959	1.012	0.985	0.943	0.942
Shaanxi	W	0.895*	0.842*	0.772*	0.938*	0.896*	1.015	0.944	0.938	0.905
Gansu	W	0.999	0.843*	0.794*	0.940	0.881*	1.025	0.893	0.873	0.906
Qinghai	W	0.908	0.844*	0.775*	0.959	0.949	1.019	0.946	0.928	0.916
Ningxia	W	1.009	0.881*	0.770*	0.982	0.935	1.015	0.938	1.002	0.941
Xinjiang	W	0.955	0.898*	0.825*	0.974	0.931	1.019	0.956	0.937	0.937
Mean		0.922	0.875	0.763	0.998	0.965	0.996	0.990	0.973	0.935

E: eastern area, C: central area, and W: western area.

* The TC index is significantly different from unity at the 5% significant level.

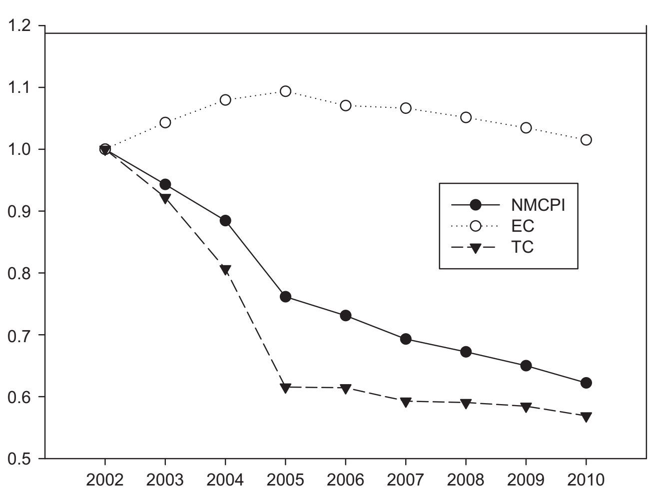

Fig. 1. Trends of cumulative NMCPI and its decomposition, 2002–2010.

emission performance, the NMCPI shows values less than unity, indicating a decrease in CO_2 emission performance. It is found that the sample provinces as a whole show a decrease in CO_2 emission performance by approximately 32.8% from 2002 to 2010.

The EC index of CO_2 emissions for the 2002–2010 periods shows a value greater than unity, indicating good catch-up performance. The TC index for the NMCPI for the whole 2002–2010 period is less than unity, indicating a period of technological decline, whereas for the 2005–2010 periods, the decrease trend of technology seems to be controlled and treated. Taken together, these results indicate that the decrease in the total-factor CO_2 emission performance is primarily caused by technological decline.

The Chinese government announced the mandatory goal of a 40 to 45% decrease in carbon intensity (CO_2 emissions per GDP) by 2020 compared to the 2005 level. The transportation sector will be under considerable pressure to reduce its CO_2 emissions. In this regard, it is crucial for the transportation industry to improve its CO_2 emission performance, not only for reducing CO_2 emission regulation risks but also for increasing "climate change competitiveness" in the future. Because the decrease in the total-factor CO_2 emission performance of the Chinese transportation is caused mainly by technological decline, it is suggested that the government might invest in low-carbon technology for the transportation industry to improve its innovation ability of CO_2 emission performance.

The total-factor CO_2 emission performance change and its decomposition have been compared at the provincial level. Chinese regional classifications are divided into three parts: east, central, and west. The east area is composed of 11 regions: 8 coastal provinces (e.g., Shandong, Jiangsu, and Guangdong) and 3 municipalities (Beijing, Tianjin, and Shanghai). The central area is composed of 8 inland provinces (e.g., Heilongjiang, Jilin, and Hunan). The west area includes 1 municipality (Chongqing) and 11 regions (e.g., Inner Mongolia, Qinghai, Xinjiang, and Sichuan).[4] Compared to the other two areas, this area has the lowest population density and is the least developed region in China.

Fig. 2 demonstrates the MMCPI and its decompositions for each group. From this figure, it is observed that all three areas show a drop in CO_2 emission performance. The eastern area shows the

[4] There are 12 regions in the west area in this study. Tibet is not included because energy data is not available. Therefore, we get 11 regions in the west area in the empirical analysis.

highest NMCPI, with an average annual decrease rate of −16.1%; the central and eastern areas also show negative growth in NMCPI with decrease rates of −23.5% and −24.4%, respectively. This finding indicates that all areas experienced CO_2 emission performance loss.

In Fig. 3, the central area shows the highest efficiency changes (EC) of CO2 emissions with an average growth rate of 23.6%, whereas the east and west areas also enjoy the efficiency gain. Regarding the technological change (TC) in Fig. 4, all areas show a technical decline with a similar decrease rate. After 2005, the decrease rate has slowed down. The east area began to increase its technological change after 2008. In general, all the areas suffer from a deterioration of technology in CO_2 emission performance. This suggests that low-carbon innovation has neglected policy formulation related to the transportation industry.

The TC index only indicates the technologically improved provinces. According to Refs. [25,37], the three conditions for determining the regional innovative provinces are as follows:

$$TC > 1 \tag{12a}$$

$$TCPI^{t}\left(K_i^{t+1}, L_i^{t+1}, E_i^{t+1}, Y_i^{t+1}, C_i^{t+1}\right) > 1 \tag{12b}$$

$$TCPI^{t+1}\left(K_i^{t+1}, L_i^{t+1}, E_i^{t+1}, Y_i^{t+1}, C_i^{t+1}\right) = 1 \tag{12c}$$

Eq. (12a) requires a TC > 1. This suggests that the environmental technology frontier should be shifted towards the direction of more products and less CO_2 emissions to become a regional innovative province. Eq. (12b) means that the production activities of innovative provinces at period $t+1$ should be outside the environmental frontier of the period t. In other words, the technology at period t cannot produce the output at period $t+1$. Eq. (12c) provides the condition that the innovative provinces should be on the environmental technology frontier at the period, $t+1$.

Table 5 lists the innovative provinces for every period. Hebei province is found to be an innovator five times. Beijing, Fujian, Zhejiang and Inner Mongolia are registered as innovative provinces only once. The resulting innovators may provide some implications for regional policy makers and policymaking. Non-innovative provinces can target innovative provinces to improve their carbon performance by ranging their scope for low-carbon development.

Finally, a statistical analysis is carried out to determine any significant methodological differences between the NMCPI proposed in this study and the MCPI developed by Ref. [27]. We employ the Wilcoxon–Mann–Whitney rank-sum test and compare the difference in decomposition results between the NMCPI and the MCPI shown in Table 6. The results of NMCPI (MCPI) and TC reject the null hypothesis at least 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 TC

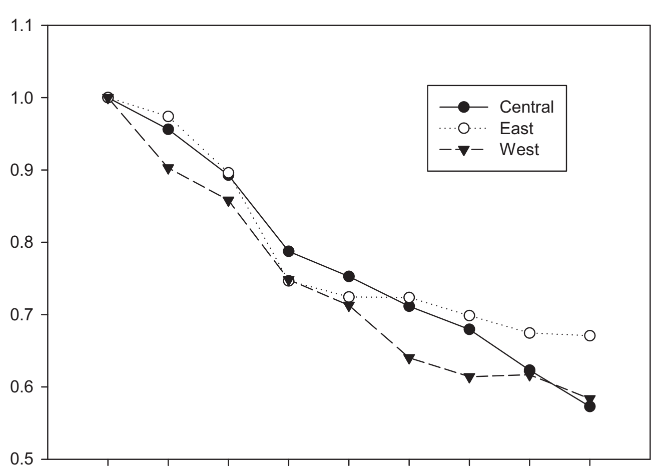

Fig. 2. Trends of cumulative NMCPI at the area level.

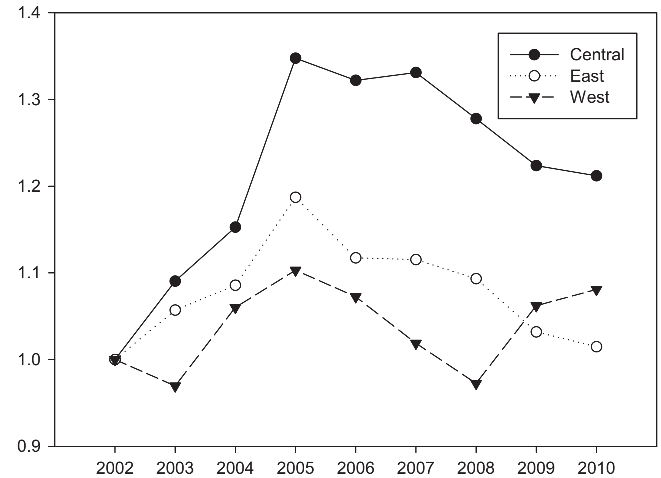

Fig. 3. Trends of cumulative EC in area level.

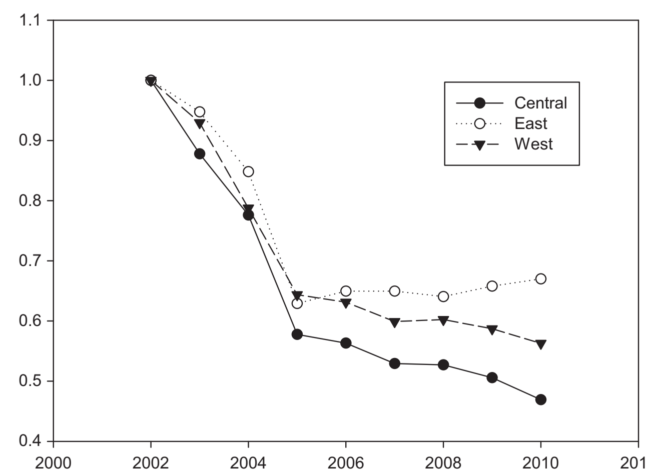

Fig. 4. Trends of cumulative TC in area level.

Table 5
innovators of low-carbon technology

Period	Innovators
2002–2003	Beijing, Fujian
2003–2004	Zhejiang
2004–2005	Inner Mongolia
2005–2006	Hebei
2006–2007	Hebei
2007–2008	Hebei
2008–2009	Hebei
2009–2010	Hebei

Table 6
Wilcoxon–Mann–Whitney rank-sum test for the MCPI and the NMCPI.

	Null hypothesis (Ho)	Wilcoxon statistics	*p*-Value
MCPI	NMCPI = MCPI	67411.0	0.022
EC	EC of NMCPI = EC of MCPI	63849.0	0.160
TC	BPC of NMCPI = TC of MCPI	62461.0	0.002

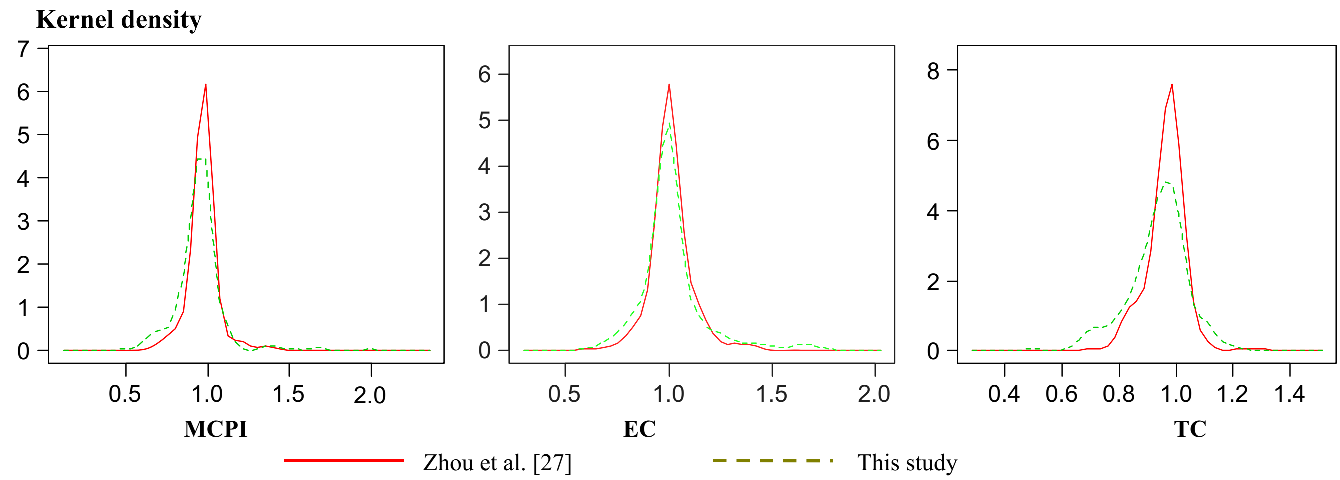

Fig. 5. Kernel density estimation for the NMCPI and the MCPI.

component. However, the significant differences are not observed in the EC component. The average of MCPI is higher than that of NMCPI, which might stem from the lack of non-radial slacks for all the variables. The MCPI approach might lead to the overestimation of CO_2 emission performance in this case.

The kernel density plot in Fig. 5 also 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 NMCPI and the MCPI.

4. Conclusions

By incorporating non-radial slacks into the previous MCPI approach, the study presents the new NMCPI method, which could be interpreted as a non-radial total-factor CO_2 emission performance index because it is constructed from the perspective of the total-factor production efficiency framework. The NMCPI is derived by solving several non-radial DEA-type models and decomposing the NMCPI into the EC and TC indices. The study utilizes bootstrapping NMCPI to perform statistical inferences on non-radial total-factor CO_2 emission performance.

The study employs the proposed approach to analyze the changes in the total-factor CO_2 emission performance of the regional transportation industry in China for the period of 2002 to 2010. The results indicate a 33% cumulative decrease in the total-factor CO_2 emission performance during the sample period. The reduction in CO_2 emission performance is caused by technological decline, which is also confirmed by the bootstrapping NMCPI. The results suggest that the government should develop low-carbon technology for the transportation industry to improve its CO_2 emission performance.

This study also has several limitations. The empirical analysis is based on data from 2002 to 2010; therefore, future research should consider a longer period. Because the empirical work is based on whole transportation industry, consideration in more specific transportation sectors, such as the trucking industry or seaport industry, may be needed. In addition, the second stage regression could also be used to investigate the determinants of CO_2 emission performance.

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References

[1] International Energy Agency (IEA). CO_2 emissions from fuel combustion highlights, Cancún Mexico; 2011.
[2] BP. Statistical review of world energy; 2011. Available at: 〈http://www.bp.com/statisticalreview〉.
[3] Zhou P, Ang BW, Poh KL. A survey of data envelopment analysis in energy and environmental studies. Eur J Oper Res 2008;189:1–8.
[4] Hu JL, Wang SC. Total-factor energy efficiency of regions in China. Energy Policy 2006;34:3206–17.
[5] Chang TP, Hu JL. Total-factor energy productivity growth, technical progress, and efficiency change: an empirical study of China. Appl Energy 2010;87:3262–70.
[6] Hu JL, Lio MC, Yeh FY, Lin CH. Environment-adjusted regional energy efficiency in Taiwan. Appl Energy 2011;88:2893–9.
[7] Guo X, Zhu L, Fan Y, Xie B. Evaluation of potential reductions in carbon emissions in Chinese provinces based on environmental DEA. Energy Policy 2011;39:2352–60.
[8] Li LB, Hu JL. Ecological total-factor energy efficiency of regions in China. Energy Policy 2012;46:216–24.
[9] Choi Y, Zhang N, Zhou P. Efficiency and abatement costs of energy-related CO_2 emissions in China: a slacks-based efficiency measure. Appl Energy 2012;98:198–208.
[10] Wang Q, Zhou P, Zhou D. Efficiency measurement with carbon dioxide emissions: the case of China. Appl Energy 2012;90:161–6.
[11] Wang K, Wei YM, Zhang X. Energy and emissions efficiency patterns of Chinese regions: a multi-directional efficiency analysis. Appl Energy 2013;104:105–16.
[12] Zhang N, Choi Y. Environmental energy efficiency of China's regional economies: a non-oriented slacks-based measure analysis. Soc Sci J 2013;50:225–34.
[13] Shi GM, Bi J, Wang J. Chinese regional industrial energy efficiency evaluation based on a DEA model of fixing non-energy inputs. Energy Policy 2010;38:6172–9.
[14] Wang ZH, Zeng HL, Wei YM, Zhang YX. Regional total factor energy efficiency: an empirical analysis of industrial sector in China. Appl Energy 2012;97:115–23.
[15] Wu F, Fan LW, Zhou P, Zhou DQ. Industrial energy efficiency with CO_2 emissions in China: a nonparametric analysis. Energy Policy 2012;49:164–72.
[16] Wei YM, Liao H, Fan Y. An empirical analysis of energy efficiency in China's iron and steel sector. Energy 2007;32:2262–70.
[17] Smyth R, Marayan P, Shi H. Substitution between energy and classical factor inputs in the Chinese steel sector. Appl Energy 2011;88:361–7.
[18] He F, Zhang Q, Lei J, Fu W, Xu X. Energy efficiency and productivity change of China's iron and steel industry: accounting for undesirable outputs. Energy Policy 2013;54:204–13.
[19] Lee M, Zhang N. Technical efficiency, shadow price of carbon dioxide emissions, and substitutability for energy in the Chinese manufacturing industries. Energy Econ 2012;34:1492–7.
[20] Zhou Y, Xing X, Fang K, Liang D, Xu C. Environmental efficiency analysis of power industry in China based on an entropy SBM model. Energy Policy 2012 (j.enpol.2012.09.060).

[21] Xie B, Fan Y, Qu Q. Does generation form influence environmental efficiency performance? An analysis of China's power system Appl Energy 2012;96: 261–71.

[22] Zhang N, Choi Y. Total-factor carbon emission performance of fossil fuel power plants in China: a metafrontier non-radial Malmquist index analysis. Energy Econ 2013;40:549–59.

[23] Zhang N, Choi Y. A comparative study of dynamic changes in CO_2 emission performance of fossil fuel power plants in China and Korea. Energy Policy 2013;62:324–32.

[24] Zhou G, Chung W, Zhang X. A study of carbon dioxide emissions performance of China's transport sector. Energy 2013;50:302–14.

[25] Zhou P, Ang BW, Han JY. Total factor carbon emission performance: a Malmquist index analysis. Energy Econ 2010;32:194–201.

[26] Fukuyama H, Weber W. A directional slacks-based measure of technical efficiency. Soc-Econ Plann Sci 2009;43:274–87.

[27] Simar L, Wilson PW. Estimating and bootstrapping Malmquist indices. Eur J Oper Res 1999;115:459–71.

[28] Färe R. Directional distance functions and public transportation: a comment. Transp Res D: Transport Environ 2010;15:108–9.

[29] Färe R, Grosskopf S, Lovell CAK. Multilateral productivity comparisons when some outputs are undesirable: a nonparametric approach. Rev Econ Stat 1989;71:90–8.

[30] Chambers R, Chung Y, Färe R. Benefit and distance functions. J Econ Theory 1996;70:407–19.

[31] Chung Y, Färe R, Grosskopf S. Productivity and undesirable outputs: a directional distance function approach. J Environ Manage 1997;51:229–40.

[32] Song ML, Zhang L, An Q, Wang Z, Li Z. Statistical analysis and combination forecasting of environmental efficiency and its influential factors since China entered the WTO: 2002–2010–2012. J Cleaner Prod 2013;42:42–51.

[33] Song ML, An Q, Zhang W, Wang Z, Wu J. Environmental efficiency evaluation based on data envelopment analysis: a review. Renewable Sustainable Energy Rev 2012;16:4465–9.

[34] Zhang N, Zhou P, Choi Y. Energy efficiency, CO_2 emission performance and technology gaps in fossil fuel electricity generation in Korea: a meta-frontier non-radial directional distance function analysis. Energy Policy 2013;56: 653–62.

[35] Zhou P, Ang BW, Wang H. Energy and CO_2 emission performance in electricity generation: a non-radial directional distance function approach. Eur J Oper Res 2012;221:625–35.

[36] Caves DW, Christensen LR, Diewert WE. Multilateral comparisons of output, input and productivity using superlative index numbers. Econ J 1982;92: 73–86.

[37] Färe R, Grosskopf S, Norris M, Zhang Z. Productivity growth, technical progress and efficiency change in industrialized countries. Am Econ Rev 1994;84:66–83.

[38] Weber M, Domazlicky B. Productivity growth and pollution in state manufacturing. Rev Econ Stat 2001;83:195–9.

[39] Färe. R, Grosskopf. S, Pasurka Jr. CA. Accounting for air pollution emissions in measures of state manufacturing productivity growth. J Reg Sci 2001;41:381–409.

[40] Yörük BK, Zaim O. Productivity growth in OECD countries: a comparison with Malmquist indices. J Compar Econ 2005;33:401–20.

[41] Kumar S. Environmentally sensitive productivity growth: a global analysis using Malmquist–Luenberger index. Ecol Econ 2006;56:280–93.

[42] Oh D. A metafrontier approach for measuring an environmentally sensitive productivity growth index. Energy Econ 2010;32:146–57.

[43] Oh D, Heshmati A. A sequential Malmquist–Luenberger productivity index: environmentally sensitive productivity growth considering the progressive nature of technology. Energy Econ 2010;32:1345–55.

[44] Førsund FR. Kittelsen SAC. Productivity development of Norwegian electricity distribution utilities. Resour Energy Econ 1998;20:207–24.

[45] National Bureau of Statistics of China (NBSC). China statistical year book. Beijing: China Statistics Press; 2003–2011.

[46] National Bureau of Statistics of China (NBSC). China economic census year book. Beijing: China Statistics Press; 2004.

[47] National Bureau of Statistics of China (NBSC). China energy statistical year book. Beijing: China Statistics Press; 2001–2010.

[48] IPCC. IPCC guidelines for national greenhouse gas inventories; 2006, available at 〈http://www.ipcc-nggip.iges.or.jp/public/2006gl/pdf/2_Volume2/V2_2_Ch2_Stationary_Combustion.pdf〉.

[49] NDRC. National Greenhouse Gas Inventory of the People's Republic of China. (In Chinese). Beijing: Chinese Environmental Science Press; 2007.

[50] Porter M, van der Linde C. Toward a new conception of the environment: competitiveness relationship. J Econ Perspect 1995;9:120–34.

[51] Wang Q, Zhou P, Shen N, Wang S. Measuring carbon dioxide emission performance in Chinese provinces: a parametric approach. Renewable Sustainable Energy Rev 2013;21:324–30.

[52] Chang Y, Zhang N, Dennis D, Zhang N. Environmental efficiency analysis of transportation system in China: a non-radial DEA approach. Energy policy 2013;58:277–83.

[53] Zhou G, Chung W, Zhang Y. Measuring energy efficiency performance of China's transport sector: a data envelopment analysis approach. Expert Syst Appl 2014;41:709–22.

[54] Cui Q., Li Y. The evaluation of transportation energy efficiency: an application of three-stage virtual frontier DEA. Transp Res: Part D: Transport Environ 29, 1-11.