


Measurement of production efficiency and environmental efficiency in China's province-level: a by-production approach

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Abstract The nonconventional by-production approach with respect to the freely disposable inputs but without the weakly disposable and null-joint outputs has been proposed to describe the pollution generating technologies since 2012. To amend the contradictory trade-offs among inputs, intended and unintended outputs, which generate in the previous conventional pollution-generating technologies, the new by-production approach decomposes the general pollution generating technology as classical intended production technology and nature's residual-generation mechanism. In this paper, some production and environmental efficiency indexes will be extended and firstly applied in the study of regional technical efficiency level with considering the energy utilization and air pollutants emission in China. Based on our calculating results, there exists the obvious variation in the regional technical efficiency level with the regional geographic separation. Eastcoast area ranks the highest in production efficiency measurement, and the West has the lowest levels in both production and environmental efficiency. Through conducting some reason discussions, our new efficiency results based on the by-production approach are consistent with the fact of Chinas unbalanced regional development pattern and also reveal the ineffectiveness of current environmental policy implementations.

Keywords By-production · Date envelopment analysis · Production efficiency · Environmental efficiency · Disparity regional development

JEL Classification D2 · O4 · R5

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1 Introduction

In environmental economics study area, it is becoming a conventional view to treat industrial emissions as sorts of undesirable outputs (Färe et al. 2004; Chung et al. 1997). Such treatment leads to some analyses on multilateral industrial productive efficiency and the social well-being changes from “goods” of improvement and “bads” of distortion. Since the undesirable outputs generation depends on the level of input usage, the environmental efficiency index based on the standard axioms production theory can usually be applied to measure the environmental performance.¹

There are plenty of literatures have studied emission generating technologies over several decades.² However, these papers generalize the property of pollution generating technology on the positive relationship between emission and desirable output production. They also advocate even if the disposability of emissions is not free, at least these undesirable outputs should be disposed off in a proportionate to the desirable outputs (usually called “weak-disposability”) and there is no bad output generated if no desirable output produced (“null-jointness”).³ The pollution generating technology with these properties can be referred as “weak-disposability approach”. In many empirical works, nonparametric or parametric specifications of weak-disposability approaches are widely employed for measuring the production efficiency, environmental efficiency, and shadow prices of pollutants generated et al.

Recently, Murty et al. (2012) indicate that the weak-disposability approach treats freely disposable input and weekly disposable and null-jointness outputs might lead to counterintuitive implications for trade-offs between inputs, desirable outputs and undesirable outputs.⁴ To resolving the concerns raised on weak-disposability approach, Murty et al. (2012) propose a set of disposability properties for emission-generating technologies, which reflect the simultaneous play of the emission-generating mechanism of nature and the firm’s desirable production activities. They call this new approach the by-production (BP) approach to modelling emission generating technologies. In this approach, they distinguish explicitly between emission-causing inputs (like fossil fuels) and non-emission causing inputs (such as capital, labour, etc) and decompose the technology into two separated technology sets (1) a standard neo-classical (engineering) desirable production technology which satisfies free disposability with respect to all inputs and desirable outputs and (2) a nature’s emission generating mechanism that violates free disposability of emissions and emission-causing inputs. Rather, BP approach proposes that the latter set should satisfy costly disposability of emissions and emission-causing inputs.

¹ Inputs used in production process can lead to some negative or positive effects on environment (outputs). The environmental efficiency index aims to ranking the economic units by taking account the environmental efficiency level. See, e.g. (Caves et al. 1982; Färe et al. 1989, 2005).

² See, e.g. (Coggins and Swinton 1996; Färe et al. 1989, 1993, 2005; Grosskopf 1996; Murty and Kumar 2002, 2003).

³ See, e.g. (Färe et al. 1996; Tyteca 1997; Färe and Grosskopf 2003).

⁴ The standard single-equation representation of weak-disposability approach shows the non-positive trade-off between input and undesirable output when desirable output held fixed and the non-negative trade-off between desirable output and undesirable output with fixed input. These two trade-offs can be argued to be counter to the emission generation fact (Murty et al. 2012).

However, the paper to propose BP approach mainly focuses on the theoretical modeling and the capability test for the new theory is only according to the artificial data. Therefore, the empirical analyses for testifying applicability of BP approach based on the real data set are still necessary.

As a fast economic developing country, China's environmental issues have caused the extensive concern as well as the Chinese government. Hence, the joint production and environmental efficiency measures identifying technologies and regional locations can provide benchmark purposes within limited resources, and have important implication for designing development and emission policies to promote economic and environmental performance in China. Recently, several literatures contributed to relevant China studies. Hu and Wang (2006) provided a total-factor energy efficiency measurement to analyse the efficiency of China's regional energy usage, but their model only treats the energy as one of multiple inputs and regional GDP as desirable output without considering any emission as undesirable output. Some recent studies proposed the Data Envelopment Analysis (DEA) models to measure the China's regional integrated economic and environmental efficiency, which attempt to decrease the undesirable outputs and increase desirable outputs simultaneously (Bian and Yang 2010; Wang et al. 2012, 2013). However, these models are all based on the "weak-disposability" technologies, which assume there exists a proportionally relation between desirable and undesirable outputs. Since some counterintuitive concerns arose in the "weak-disposability" assumption, the DEA efficiency models in this paper are based on the new BP approach and treat the desirable and undesirable outputs generation as two separated technology sets and measure each technical efficiency, respectively. In terms of efficiency models constructing, there are wide variations between two orientations: "input, desirable and undesirable orientation" and "undesirable orientation" (Nakano and Managi 2012). Weighted Russell Directional Distance (WRDD) models based on the former orientation are recently used in China's environmental efficiency studies (Fujii et al. 2015; Cao et al. 2015). One of the strong points of this efficiency measurement is easily decomposing and detecting the each inefficiency level of input, desirable output and undesirable output individually. The main difference between our study and WRDD method is we separate the total input as non-emission causing inputs and emission causing inputs; the production efficiency measurement for desirable outputs with respect to all inputs and the environmental efficiency measurement for undesirable outputs with only respect to emission causing inputs can be conducted separately, corresponding to the two separate technology sets decomposition under BP emission generating technologies. Hence, the efficiency methods proposed in this paper would be an extension to the previous two orientations.

This paper could fill in the blank of China's regional efficiency studies under BP approach with first applying the actual data of China's 30 province-level regions from 2006 to 2010 to construct the DEA models to measure the provincial technical efficiency. In particular, given the fixed level of capital, labour and energy inputs, the efficiency of China's provincial GDP output with consideration of two main air pollutants (CO_2 and SO_2) will be addressed by employing the new BP technology.

The rest of this paper is organised as follows: Section 2 introduces the characteristics of BP pollution generating technology and how to construct the efficiency measures under BP approach. Section 3 employs the data to evaluate the regional production and environmental efficiency scores and deeply analyses the relevant reasons based on empirical results. According to empirical results presenting, some policy implementations are discussed in Sect. 4.

2 Methodology

2.1 By-production approach

We will assume that there are N inputs, M desirable outputs, and K emission types (undesirable outputs). Input vector is denoted by $x = (x_1, \dots, x_N) \in \mathbb{R}_+^N$, desirable output vector is denoted by $y = (y_1, \dots, y_M) \in \mathbb{R}_+^M$, and undesirable outputs vector is $b = (b_1, \dots, b_K) \in \mathbb{R}_+^K$.⁵

In BP approach, N inputs will be classified into non-emission causing and emission-causing inputs. The first N_1 inputs are non-emission causing, while the last N_2 inputs are emission-causing. Hence, $N = N_1 + N_2$. The input quantity vector $x = \langle x_1, \dots, x_N \rangle \in \mathbb{R}_+^N$ can be partitioned into a vector of non-emission causing inputs, denoted by $x^1 = \langle x_1, \dots, x_{N_1} \rangle \in \mathbb{R}_+^{N_1}$ and a vector of emission-causing inputs, denoted by $x^2 = \langle x_{N_1+1}, \dots, x_N \rangle \in \mathbb{R}_+^{N_2}$. Hence, $x = \langle x^1, x^2 \rangle \in \mathbb{R}_+^N$. When producers use pollution causing inputs, the production of desirable outputs would set a nature's residual mechanism in motion, which will lead to the generation of undesirable outputs (Murty et al. 2012). Therefore, the emission-generating technologies can be separated to two technology sets: T_1 is the conventional production technology set, which reflects the transformation of all inputs into desirable outputs; and T_2 denotes nature's residual generating technology, which shows how emission-causing goods used in T_1 generate emissions in nature.⁶ Hence, the parametric formulation of a BP emission generating technology is given as

$$\begin{aligned} T_{BP} &= T_1 \cap T_2, \quad \text{where} \\ T_1 &= \{ \langle x^1, x^2, y, b \rangle \in \mathbb{R}_+^{N+M+K} \mid f(x^1, x^2, y) \leq 0 \}, \\ T_2 &= \{ \langle x^1, x^2, y, b \rangle \in \mathbb{R}_+^{N+M+K} \mid g(x^2, b) \geq 0 \}. \end{aligned} \quad (1)$$

Functions $f : \mathbb{R}_+^{N+M+K} \rightarrow \mathbb{R}$ and $g : \mathbb{R}_+^{N+M+K} \rightarrow \mathbb{R}$ are the parametric representations of sets T_1 and T_2 , respectively. We assume that both functions are continuously differential and the properties we will impose on functions f and g below will ensure that T_{BP} is non-empty.

We would like to use function f to represent the conventional neo-classical technology set T_1 . Hence, we will assume the following signs for the derivatives of function f :

⁵ Here, the authors only consider the undesirable outputs (emissions) from the production process (e.g. tons of SO₂ and CO₂) and not the externality they might cause.

⁶ This paper does not considerate the pollution reductions, but the model can also be extended to include abatement activities. See, (Murty et al. 2012; Murty 2015).

$$\begin{aligned}
 f_{x_n}(x^1, x^2, y) &\leq 0, \quad \forall n = 1, \dots, N_1, \\
 f_{x_n}(x^1, x^2, y) &\leq 0, \quad \forall n = N_1 + 1, \dots, N, \\
 f_{y_m}(x^1, x^2, y) &\geq 0. \quad \forall m = 1, \dots, M
 \end{aligned}
 \tag{2}$$

The signs of these derivatives imply that all inputs satisfy standard free disposability and all desirable outputs are also freely disposable. In particular, along the frontier of technology T_1 , there is a positive relationship between any input and any desirable output. In addition, the technology set T_1 is independent of the level of emissions, which means emissions do not affect desirable output production.⁷

Set T_2 in (1) reflects the physical and chemical mechanism of pollution generation in nature. In nature, the more the emission-causing goods are used the more are the emissions generated. The function g should capture this. We assume the following signs for the derivatives of function g .

$$\begin{aligned}
 g_{x_n}(x^2, b) &\leq 0, \quad \forall n = N_1 + 1, \dots, N, \\
 g_{b_k}(x^2, b) &\geq 0. \quad \forall b_k = 1, \dots, K.
 \end{aligned}
 \tag{3}$$

Under these sign conventions, the production vectors $\langle x^1, x^2, y, b \rangle \in \mathbb{R}_+^{N+M+K}$ that satisfy $g(x^2, b) = 0$ form the lower frontier of technology T_2 . For every vector of emission-causing inputs, this frontier gives the minimal levels of emissions generated in nature. This property has been called costly disposability of emissions and it captures our intuition that emissions are not freely disposable as outputs. Usage of emission-causing inputs definitely produces some minimal emissions. Employing the implicit function theorem, it can be shown that these sign conventions imply that the trade-off between any emission-causing input and any emission type along the lower frontier of technology T_2 is $-\frac{g_{b_k}}{g_{x_n}}$, which is non-negative, provided $g_{x_n} \neq 0$ for $n = N_1 + 1, \dots, N$. Thus, this captures the positive relation between emission-causing goods such as fossil fuels and emissions such as CO₂ and SO₂.

In Fig. 1, we assume $M = N = K = 1$ and $N_1 = 0$ (that is the single input is emission-causing). For every level of the input, parts (a) and part (b) in Fig. 1 illustrate the maximal level of the desirable output produced in T_1 and minimal level of undesirable outputs generated in T_2 , respectively. Part (c) reflects the output possibility set under BP approach. This shows that given input level x , there is only one combination of the good and the bad output that is efficient, namely, the point A . A indicates the maximal amount of the good output and the minimal amount of the bad output that input level x can produce under T_1 and T_2 , respectively.

2.2 Efficiency measurements under by-production approach

Murty et al. (2012) employ a non-parametric formulation of their BP technology for measuring technical efficiency. The notation that we will employ for a DEA construction of the non-parametric version of the BP technology is as follows: let

⁷ Murty (2015) provides a generalisation of this where emissions from a firm may affect its own desirable production in a beneficial or detrimental manner.

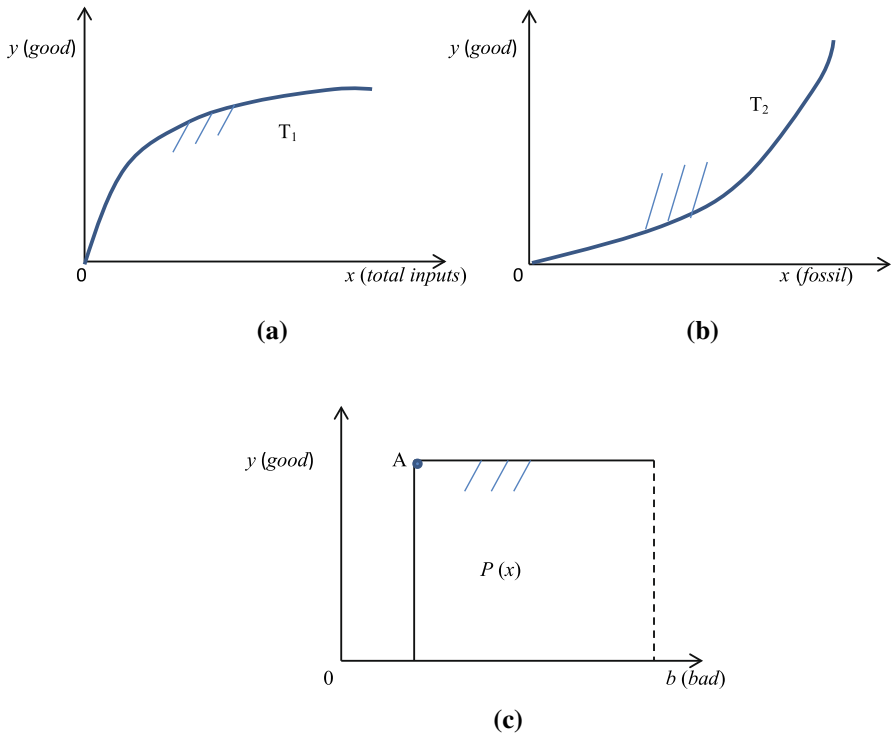


Fig. 1 By-production pollution generating technologies

the matrix of observations on non-pollution causing inputs be denoted by $X_{D \times N_1}^1$ and the pollution causing inputs be denoted by $X_{D \times N_2}^2$. Let the matrices of observations on desirable and undesirable outputs be denoted as before by $Y_{D \times M}$ and $B_{D \times K}$, respectively. Then the standard DEA non-parametric representation of BP can be specified as

$$\begin{aligned}
 T_1 &= \left\{ \langle x, y, b \rangle \in \mathbb{R}_+^{N+M+K} \mid \lambda[X^1, X^2] \leq \langle x^1, x^2 \rangle \wedge \lambda Y \geq y, \quad \lambda \in \mathbb{R}_+^D \right\} \\
 T_2 &= \left\{ \langle x^1, x^2, y, b \rangle \in \mathbb{R}_+^{N+M+K} \mid \mu X^2 \geq x^2 \wedge \mu B \leq b, \quad \lambda \in \mathbb{R}_+^D \right\}
 \end{aligned}
 \tag{4}$$

The overall BP technology is the intersection of T_1 and T_2 . Hence, it is derived under DEA as

$$\begin{aligned}
 T_{BP} = T_1 \cap T_2 &= \left\{ \langle x^1, x^2, y, b \rangle \in \mathbb{R}_+^{N+M+K} \mid \lambda[X^1, X^2] \leq \langle x^1, x^2 \rangle \right. \\
 &\quad \left. \wedge \lambda Y \geq y \wedge \mu X^2 \geq x^2 \wedge \mu B \leq b, \langle \lambda, \mu \rangle \in \mathbb{R}_+^{2D} \right\}.
 \end{aligned}
 \tag{5}$$

Here, $\lambda \in \mathbb{R}_+^D$ and $\mu \in \mathbb{R}_+^D$ here represent the intensity vectors, which are the weights assigned to each decision making unit (DMU) to construct the technically efficient frontiers of T_1 and T_2 under DEA.

Following by the concept of non-parametric technical efficiency measurement under the BP approach, in this paper, we will focus on output-based measures of efficiency and consider two types of efficiency indexes: the hyperbolic (HYP) efficiency index and the modified Färe-Grosskopf-Lovell (FGL) efficiency index.⁸

Since BP approach distinguishes between desirable production technology T_1 and nature’s emission-generating technology T_2 , a technical efficiency index defined under the BP approach can be implicitly or explicitly decomposed into two components: index of desirable output (production) efficiency and an index of undesirable output (environmental) efficiency. In the case of the HYP measure of efficiency in a BP technology, this decomposition is explicit, while in the case of the FGL measure, the decomposition is implicit.

2.2.1 HYP measurement under BP approach

The HYP measure of efficiency decomposes efficiency explicitly into desirable production efficiency, which is defined relative to set T_1 , and environmental efficiency, which is defined relative to T_2 . The former is denoted by $D_{HYP(1)}$ and the latter is denoted by $D_{HYP(2)}$. Intuitively, holding all inputs fixed, $\frac{1}{D_{HYP(1)}}$ measures the maximal factor by which the given desirable output vector can be scaled-up and yet be technologically feasible, while $\frac{1}{D_{HYP(2)}}$ captures the maximal factor by which the bad output vector can be scaled-down and yet be technologically feasible. The overall index of efficiency, denoted by D_{HYP} is obtained by taking the maximum of $D_{HYP(1)}$ and $D_{HYP(2)}$. This implies that $\frac{1}{D_{HYP}}$ is the maximal extent to which the good output vector and the bad output vector can be simultaneously scaled-up and scaled-down, respectively, and yet be technologically feasible.

The mathematical programme to measure hyperbolic efficiency under the BP approach is:

$$\begin{aligned}
 &D_{HYP}(x, y, b; T_{BP}) \\
 &= \inf_{\beta > 0} \{ \beta | \langle x, y/\beta, b\beta \rangle \in T_{BP} \} \\
 &= \inf_{\beta > 0} \{ \beta | \langle x, y/\beta, b\beta \rangle \in T_1 \wedge \langle x, y/\beta, b\beta \rangle \in T_2 \} \\
 &= \max \{ \beta_1, \beta_2 \}. \tag{6} \\
 &D_{HYP(1)} = \inf_{\beta_1 > 0} \{ \beta_1 | \langle x, y/\beta_1, b \rangle \in T_1 \} \\
 &D_{HYP(2)} = \inf_{\beta_2 > 0} \{ \beta_2 | \langle x, y, b\beta_2 \rangle \in T_2 \}
 \end{aligned}$$

⁸ These two efficiency measures indexes have been widely used in study WD approach. In this paper, they will be modified and employed to measure technical efficiency under the BP approach.

where, the last two equalities follow from the fact that, in the BP approach, given a vector of inputs, the output possibility sets corresponding to T_1 and T_2 are independent. When $D_{HYP(1)} = 1$, the observed point is on the weakly efficient frontier of T_1 and when $D_{HYP(2)} = 1$, the observed point is on the weakly efficient lower frontier of T_2 . An observation is inefficient when D_{HYP} is strictly less than one. There might be an observation, for which D_{HYP} equals to one, while $D_{HYP(1)}$ and $D_{HYP(2)}$ might not both equal to one. This implies that the hyperbolic measure will judge this observation as efficient, even when it is inefficient in desirable output production or undesirable output production.

Below, we present the DEA programme for measuring hyperbolic efficiency: for each DMU d' in each different year t , HYP efficiency is measured as

$$\begin{aligned}
 D_{HYP}(x_{d'}^t, y_{d'}^t, b_{d'}^t; T_{BP}) &= \max\{\beta_1, \beta_2\}, \\
 D_{HYP(1)} &= \min_{\lambda, \beta_1} \beta_1 \\
 \text{s.t. } \sum_{t=1}^T \sum_{d=1}^D \lambda_d^t y_{d,m}^t &\geq y_{d',m}^t / \beta_1, \quad \forall m = 1, \dots, M \\
 \sum_{t=1}^T \sum_{d=1}^D \lambda_d^t x_{d,n}^t &\leq x_{d',n}^t, \quad \forall n = 1 \dots N \\
 \lambda_d^t &\geq 0 \quad \forall d = 1, \dots, D.
 \end{aligned} \tag{7}$$

$$\begin{aligned}
 D_{HYP(2)} &= \min_{\mu, \beta_2} \beta_2 \\
 \text{s.t. } \sum_{t=1}^T \sum_{d=1}^D \mu_d^t b_{d,k}^t &\leq b_{d',k}^t \beta_2, \quad \forall k = 1, \dots, K \\
 \sum_{t=1}^T \sum_{d=1}^D \mu_d^t x_{d,n}^t &\geq x_{d',n}^t, \quad \forall n = N_1 + 1, \dots, N \\
 \mu_d^t &\geq 0 \quad \forall d = 1, \dots, D.
 \end{aligned}$$

2.2.2 Modified FGL measurement under BP approach

Murty et al. (2012) consider the output-based version of the FGL approach to construct a modified FGL efficiency index with respect to the BP approach. This index is based on the coordinate-wise expansions of desirable outputs and coordinate-wise contractions of undesirable outputs.⁹ The FGL index decomposes under the BP approach into production and environmental efficiency measures as follows:¹⁰

⁹ The output-oriented version index takes up all slack in output spaces and leaves the slack in inputs spaces.

¹⁰ We denote $y\theta = \langle y_1/\theta_1, \dots, y_M/\theta_M \rangle$ and $b \otimes \gamma = \langle b_1\gamma_1, \dots, b_K\gamma_K \rangle$.

$$\begin{aligned}
 & D_{\text{FGL}}(x, y, b; T_{\text{BP}}) \\
 & =: \frac{1}{2} \min_{\theta, \gamma} \left\{ \frac{\sum_m \theta_m}{M} + \frac{\sum_k \gamma_k}{K} \mid \langle x, y \oslash \theta, b \otimes \gamma \rangle \in T_{\text{BP}} \right\} \\
 & = \frac{1}{2} \min_{\theta} \left\{ \frac{\sum_m \theta_m}{M} \mid \langle x, y \oslash \theta, b \rangle \in T_1 \right\} \\
 & \quad + \frac{1}{2} \min_{\gamma} \left\{ \frac{\sum_k \gamma_k}{K} \mid \langle x, y, b \otimes \gamma \rangle \in T_2 \right\} \\
 & = \frac{1}{2} [D_{\text{FGL}(1)}(x, y, b; T_1) + D_{\text{FGL}(2)}(x, y, b; T_2)].
 \end{aligned} \tag{8}$$

Here, $D_{\text{FGL}(1)}$ measures the production efficiency of the DMU in desirable production, while $D_{\text{FGL}(2)}$ measures its environmental efficiency. The FGL efficiency index takes a simple average of the production efficiency and environmental efficiency to compute the overall efficiency of DMUs. The key feature of this index is that a DMU is judged as efficient if and only if it is efficient in both desirable outputs and environmental directions, i.e., if and only if $D_{\text{FGL}(1)} = D_{\text{FGL}(2)} = 1$. Compare this with the hyperbolic measure of efficiency, where a DMU can be judged efficient even when it is not efficient in the direction of desirable outputs or in the environmental direction.

The DEA algorithm for computing FGL index is given as follows. To compute efficiency of each DMU d' in each year t , we solve the following optimisation problem:

$$\begin{aligned}
 D_{\text{FGL}}(x_d^t, y_d^t, b_d^t; T_{\text{BP}}) & = \min_{\lambda, \theta, \mu, \gamma} \frac{1}{2} \left[\frac{\sum_{m=1}^M \theta_m}{M} + \frac{\sum_{k=1}^K \gamma_k}{K} \right] \\
 \text{s.t. } \sum_{t=1}^T \sum_{d=1}^D \lambda_d^t y_{d,m}^t & \geq y_{d',m}^t / \theta_m \quad \forall m = 1, \dots, M \\
 \sum_{t=1}^T \sum_{d=1}^D \lambda_d^t x_{d,n}^t & \leq x_{d',n}^t \quad \forall n = 1, \dots, N \\
 \sum_{t=1}^T \sum_{d=1}^D \mu_d^t b_{d,k}^t & \leq b_{d',k}^t \gamma_k \quad \forall k = 1, \dots, K \\
 \sum_{t=1}^T \sum_{d=1}^D \mu_d^t x_{d,n}^t & \geq x_{d',n}^t \quad \forall n = N_1 + 1, \dots, N \\
 \lambda_d^t & \geq 0, \mu_d^t \geq 0, \quad \forall d = 1, \dots, D
 \end{aligned} \tag{9}$$

Since the T_1 and T_2 are independent from each other, D_{FGL} could be calculated separately as following:

$$\begin{aligned}
 D_{\text{FGL}(1)} &= \min_{\lambda, \theta} \frac{\sum_{m=1}^M \theta_m}{M} \\
 \text{s.t. } &\sum_{t=1}^T \sum_{d=1}^D \lambda_d^t y_{d,m}^t \geq y_{d,m}^t / \theta_m \quad \forall m = 1, \dots, M \\
 &\sum_{t=1}^T \sum_{d=1}^D \lambda_d^t x_{d,n}^t \leq x_{d,n}^t \quad \forall n = 1, \dots, N \\
 &\lambda_d^t \geq 0, \quad \forall d = 1, \dots, D
 \end{aligned} \tag{10}$$

$$\begin{aligned}
 D_{\text{FGL}(2)} &= \min_{\mu, \gamma} \frac{\sum_{k=1}^K \gamma_k}{K} \\
 &\sum_{t=1}^T \sum_{d=1}^D \mu_d^t b_{d,k}^t \leq b_{d,k}^t \gamma_k \quad \forall k = 1, \dots, K \\
 &\sum_{t=1}^T \sum_{d=1}^D \mu_d^t x_{d,n}^t \geq x_{d,n}^t \quad \forall n = N_1 + 1, \dots, N \\
 &\mu_d^t \geq 0, \quad \forall d = 1, \dots, D
 \end{aligned} \tag{11}$$

When the equal weights are given to measurements in T_1 and T_2 , the coordinate-wise FGL efficiency index could be calculated as $\frac{1}{2}(D_{\text{FGL}(1)} + D_{\text{FGL}(2)})$.

3 Empirical analysis

In this section, the empirical analysis will be carried out by using China's province-level data. The HYP and modified FGL indexes under BP technologies will be implemented to measure the production and environmental efficiency for different provincial regions. We will analyse our results in the context of current Chinese environmental protection regulation reviews and provide some explanations for our empirical results.

3.1 Data

In this study, we consider Chinese 30 provincial administrative divisions as DMUs from 2006 to 2010.¹¹ We also divide these 30 regions into four major parts: Eastcoast, Central, Northeast and West areas from the perspective of China's economic development. The details are shown in Fig. 2.

The annual GDP for each province is considered as one desirable output (y). The data on labour and capital stock are selected for the non-polluting cause inputs (x^1). To eliminate the inflation effect, GDP data is deflated to the price of 2000 and

¹¹ Due to lack of some data on regions such Tibet, Hongkong, Macau and Taiwan, we only consider 30 provincial level regions, including 22 provinces, 4 municipalities and 4 autonomous regions.

measured in hundreds of million CNY.¹² The GDP and labour data could be obtained from the “China Statistical Yearbook”. However, the capital stock could not be gathered directly from the official released data resources. In this paper, we adopt the Perpetual Inventory Method (PIM) to estimate the annual capital stocks for each province during the 2006 to 2010.¹³

The annual total amount of coal, oil and natural gas consumed by each region are selected for polluting cause inputs (x^2). The information of three energy inputs are all from the “China Energy Statistical Yearbook”. The annual net volume of sulfur dioxide (SO₂) and gross volume of carbon dioxide (CO₂) are two undesirable outputs (b). The data on SO₂ could be obtained from the “China Environment Yearbook”.¹⁴ But the data on CO₂ could not be obtained directly. In this paper, we calculate the gross volume of CO₂ emission from the algorithm based on the fossil fuels combustion, which is provided by IPCC (2006).¹⁵ The descriptive statistics of all variables computed from 2006 to 2010 are shown in Table 1.

3.2 Efficiency results under BP approach

Through conducting the optimization problems, HYP and FGL efficiency indexes under BP approach for each province from 2006 to 2010 could be simulated. The 5-year average efficiency scores and descriptive statistics table shows in Tables 2 and 3. As we discussed in theoretical part, given fixed levels of inputs, the output-oriental HYP is defined by the desirable outputs expansions and undesirable outputs contractions by a maximum single scalar, and the FGL is defined by the coordinate-wise expansion of all desirable outputs and contractions of all undesirable outputs. Therefore, the integrated FGL results for each DMU would less or equal to HYP results, which means the HYP efficiency measurement might overestimate the technical efficiency level for each DUM. This can also be observed and proved in Fig. 3. Hence, in this paper, we recommend to focus coordinate-wise FGL index

¹² CNY is an abbreviation for Chinese currency “Yuan”.

¹³ The PIM could be straightforward as

$$K_{i,t} = K_{i,t-1}(1 - \delta_i) + I_{i,t}.$$

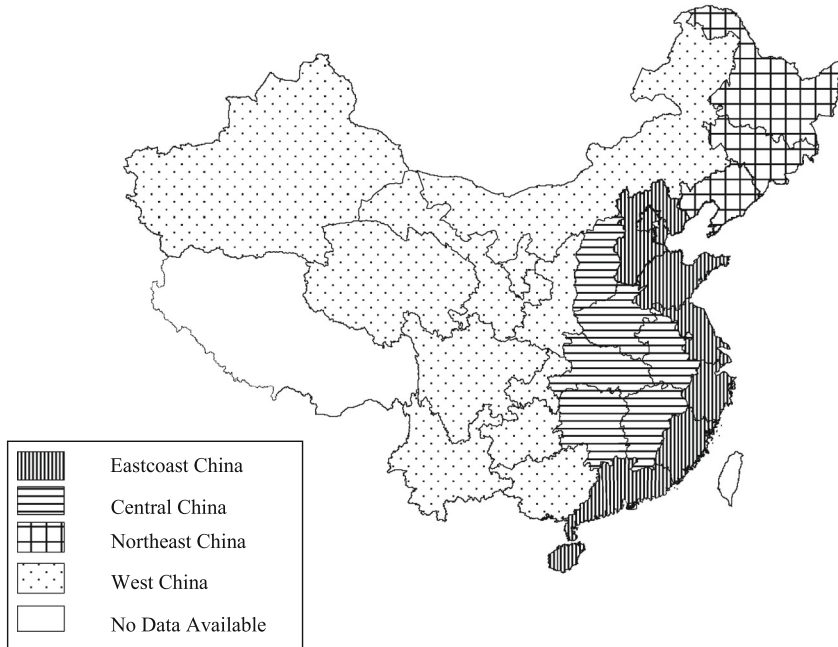
where, i and t represent the i th province and t th year, respectively. K denotes the capital stock. δ and I denote the depreciation rate and capital asset investment of year, respectively. The initial capital stock (based year: 2000) and depreciation rates are derived from Zhang et al. (2004). The annual capital asset investment is obtained from the “China Statistical Yearbook”.

¹⁴ The definition of SO₂ variable can be found in the National Bureau of Statistics of China. Net SO₂ emission refers to volume of sulphur dioxide emission from burning fossil-fuel during production in the premises of enterprises in each region for a given period of time.

¹⁵ The reference approach to calculate the CO₂ emission is designed as

$$CO_{2\text{emission}} = \sum_i (AC_i \cdot CF_i \cdot CC_i) \cdot COF \cdot 44/12.$$

Here, AC_i represents the apparent energy consumption for fossil fuel i . CF_i is the conversion factor for fuel i to energy. CC_i is the carbon content for i fuel. COF is the carbon oxidation factor, usually the value is 1. And $44 / 12$ equals to molecular weight ratio of CO₂ to C . The data on energy consumption are taken from the “China Energy Statistical Yearbook”.



Parts	Province-level regions
Eastcoast	Beijing, Tianjin, Hebei, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, Hainan
Central	Shanxi, Anhui, Jiangxi, Henan, Hubei, Hunan
Northeast	Liaoning, Jilin, Heilongjiang
West	Inner Mongolia, Guangxi, Chongqing, Sichuan, Guizhou, Yunnan, Shaanxi, Gansu, Qinghai, Ningxia, Xinjiang

Fig. 2 Map of China's four economic parts

Table 1 Summary statistics of inputs and outputs variables

Variables ^a	Obs.	Mean	Std. dev.	Min	Max
2006–2010					
GDP	150	8377.93	6872.66	504.85	32,316.06
SO ₂	150	67.32	39.54	2.1	168.7
CO ₂	150	34,455.17	23,683.17	2694.3	117,985.5
Capital	150	27,875.75	21,546.87	2394.62	108,537.9
Labour	150	404.20	233.39	42.92	1086.77
Coal	150	11,250.85	8390.2	332.22	37,327.89
Oil	150	735.88	514.09	76.92	2754.68
Gas	150	28.21	27.81	0.48	175.26

^a Unit of GDP and capital stock is 100 million CNY. Unit of labour is 10,000 person. Unit of SO₂ and CO₂ is 10,000 ton. Unit of coal, oil and gas are 10,000 ton, 10,000 ton and 100 million cu.m, respectively

Table 2 Five-year average calculated HYP and FGL efficiency index under BP approach

Regions	$D_{HYP(1)}$	$D_{HYP(2)}$	D_{HYP}	$D_{FGL(1)}$	$D_{FGL(2)}$	D_{FGL}
2006–2010						
Beijing	0.9497	1.0000	1.0000	0.9497	1.0000	0.9749
Tianjin	0.8319	0.8645	0.8680	0.8319	0.7871	0.8095
Hebei	0.9554	0.8117	0.9554	0.9554	0.7971	0.8762
Shanxi	0.6633	1.0000	1.0000	0.6633	1.0000	0.8317
Inner Mongolia	0.7096	0.9991	0.9991	0.7096	0.8996	0.8046
Liaoning	0.9509	0.6921	0.9509	0.9509	0.6485	0.7997
Jilin	0.6983	0.9379	0.9379	0.6983	0.9257	0.8120
Heilongjiang	0.9607	0.9835	0.9872	0.9607	0.9403	0.9505
Shanghai	1.0000	0.7980	1.0000	1.0000	0.7050	0.8525
Jiangsu	1.0000	0.8383	1.0000	1.0000	0.7835	0.8918
Zhejiang	0.9417	0.9174	0.9417	0.9417	0.8112	0.8764
Anhui	1.0000	0.9155	1.0000	1.0000	0.8884	0.9442
Fujian	1.0000	0.9587	1.0000	1.0000	0.8158	0.9079
Jiangxi	0.9349	0.8212	0.9349	0.9349	0.6517	0.7933
Shandong	0.9722	0.8854	0.9722	0.9722	0.8631	0.9177
Henan	0.9528	0.9076	0.9594	0.9528	0.8324	0.8926
Hubei	0.9996	0.9886	1.0000	0.9996	0.8894	0.9445
Hunan	0.9793	0.8704	0.9793	0.9793	0.7639	0.8716
Guangdong	1.0000	1.0000	1.0000	1.0000	0.7614	0.8807
Guangxi	0.9165	0.9583	0.9711	0.9165	0.6358	0.7762
Hainan	1.0000	0.9936	1.0000	1.0000	0.9763	0.9881
Chongqing	0.6914	1.0000	1.0000	0.6914	0.7696	0.7305
Sichuang	0.8933	0.9626	0.9687	0.8933	0.7595	0.8264
Guizhou	0.6495	0.9144	0.9144	0.6495	0.7465	0.6980
Yunnan	0.7268	0.9294	0.9294	0.7268	0.8507	0.7888
Shaanxi	0.5756	0.8313	0.8313	0.5756	0.6699	0.6228
Gansu	0.7817	0.6582	0.7817	0.7817	0.5625	0.6721
Qinghai	0.5397	0.9852	0.9852	0.5397	0.7959	0.6678
Ningxia	0.4277	0.9424	0.9424	0.4277	0.7940	0.6109
Xinjiang	0.5578	0.8302	0.8302	0.5578	0.6894	0.6236

results to analyse the production and environmental efficiency levels for each region in China.¹⁶

¹⁶ Due to the only one desirable output is chosen ($M = 1$) in this paper, the results of decomposition of FGL production efficiency $D_{FGL(1)}$ for each region in every year are exactly same with $D_{HYP(1)}$ in HYP. Hence, the differences between integrated efficiency scores could be mainly attributed to calculation of environmental efficiency scores under these two methods. If $M \geq 2$, the programming for production efficiency calculation should be designed to take the coordinate-wise distances from each desirable output observation to the corresponding possibility frontier. Hence, $D_{HYP(1)} = D_{FGL(1)}$ is the occasional case with $M = 1$.

Table 3 Summary statistics of calculated HYP and FGL efficiency index under BP approach

Efficiency indexes	Obs.	Mean	Median	Std. dev.	Min	Max
2006–2010						
$D_{HYP(1)}$	150	0.8420	0.9222	0.1730	0.4157	1.0000
$D_{HYP(2)}$	150	0.9065	0.9327	0.1013	0.5258	1.0000
D_{HYP}	150	0.9546	0.9984	0.0703	0.6800	1.0000
$D_{FGL(1)}$	150	0.8420	0.9222	0.1730	0.4157	1.0000
$D_{FGL(2)}$	150	0.8005	0.8004	0.1175	0.5233	1.0000
D_{FGL}	150	0.8212	0.8413	0.1097	0.5629	1.0000

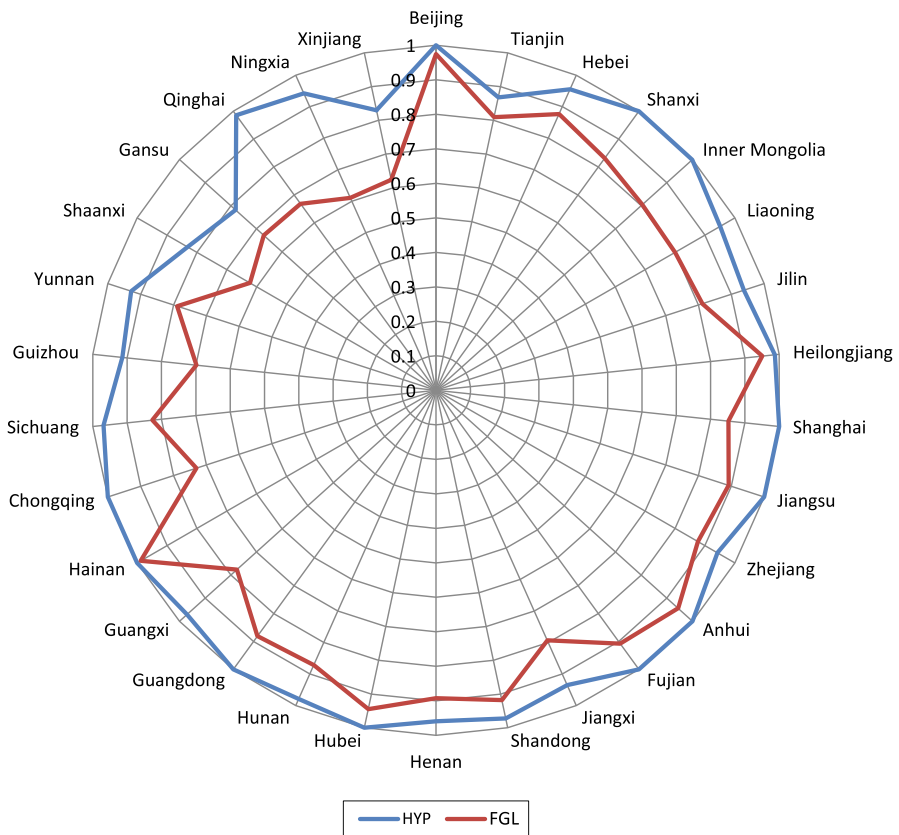


Fig. 3 Five-year average integrated HYP and FGL efficiency scores under BP approach

From the four-part areas respective (Fig. 4), we can observe that the Eastcoast area gets the highest overall technical efficiency level, the Central and Northeast areas are following, and the West area is lowest. Moreover, only the West area is lower than the nation average level, the other three are all higher than the nation

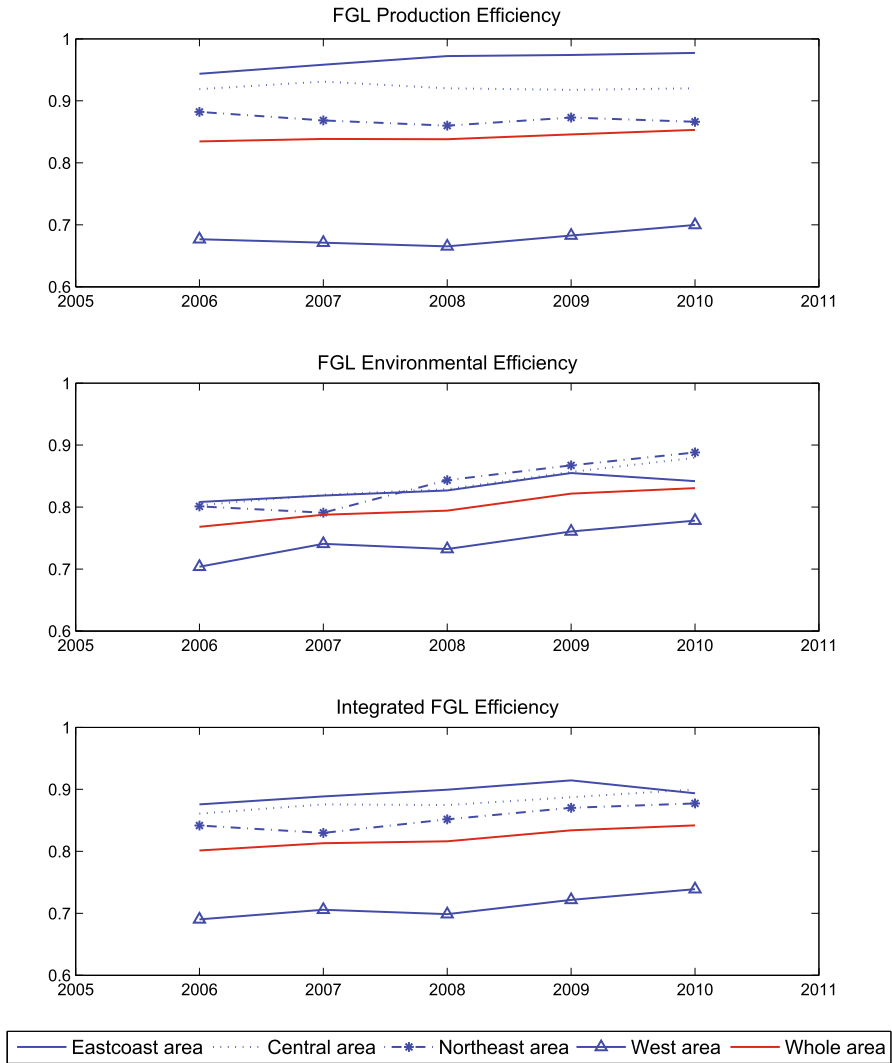


Fig. 4 Average four-part regional FGL efficiency measurements under BP from 2006 to 2010

average efficiency level. Figure 4 also reveals the regional production and environmental efficiencies under FGL. From the production efficiency, we could see the Eastcoast area can get the highest efficiency level, the Central and Northeast areas rank the second and third high position, respectively, and they all above the average nation efficiency level during these 5 years period. Furthermore, the production efficiency level of the West area is lowest, which is the only region lower than the national level during the 5-year study period. On the other hand, the environmental efficiency measurement shows differently. In 2006, the Eastcoast was the highest one, but from 2007 to 2010, it has been exceeded by the Central

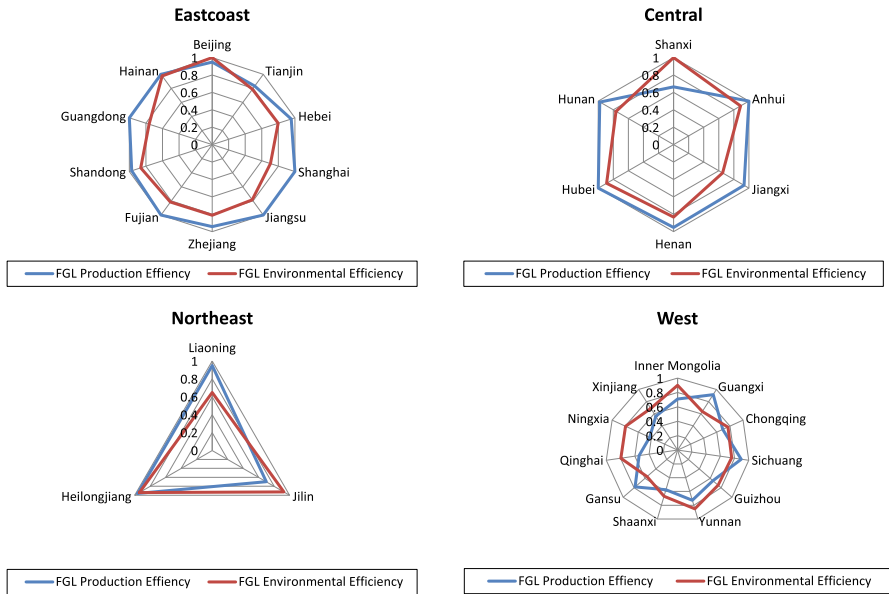


Fig. 5 Five-year average FGL production and environmental efficiency scores of four-part regions

area. Moreover, the Central area has been exceeded by the Northeast since 2008. Only the West area has the relatively poor performance and even below the national levels during these 5 years.

When we target on each province’s efficiency results of four parts in 2010 (Fig. 5), we could find that production efficiency scores for all provinces in Eastcoast are always higher than the environmental efficiency levels. For the Central area, most of provinces are also have the similar characteristics as Eastcoast, except Shanxi, which has the higher environmental efficiency than production efficiency. In Northeast, Liaoning is the only one who gets the higher production efficiency compared to environmental efficiency. But in West, only Gunaxi, Sichuan and Gansu three provinces have higher production efficiency levels than environmental efficiency levels, the other provinces all have higher scores in environmental efficiency than production efficiency. Even though the most West provinces can achieve weakly environmental efficient, the overall environmental efficiency level is still lower than the other three regions and below the national average level.

Therefore, it might be concluded that for most provinces in Eastcoast and Central areas, the production efficiency level is higher than the environmental efficiency level, and in Northeast and West, the most provinces would achieve more environmental efficient than production efficiency measures. Furthermore, from the view of whole country, there are significant gaps on the overall production efficiency levels across all different regions, but in environmental efficiency measurements, the gaps of efficiency levels among four regions are not such obvious as which in production efficiency measures. Finally, we also can find that

the West area is always the least one no matter in production or environmental measurements.

3.3 Reasons discussion

As we discussed above, China's regional development disparity is partially reflected in our BP-FGL results. Eastcoast area can always exhibit a strong advantage in production efficiency. The West area reveals the worst performances in both production and environmental efficiency measurement. From the comprehensive technical efficiency perspective, it can be concluded that the Eastcoast is the best, following by Central and Northeast, and the West is the worst. The gaps of efficiency levels between West to other three regions are always significant.

In fact, the imbalance problem on regional development in China has been pointed out by many relevant researches. Hu and Wang (2006) firstly use total-factor energy efficiency index to measure the China's regional efficiency of energy inputs utilization, and find there exists a variety of the technology levels among the different areas, the East is highest and West and Central are worse. Lu and Lu (2007) use a cross-efficiency measure to the overall technical efficiency in 31 provinces in China, and find that the coastal regions perform on average better than the inland regions for both economic and environmental considerations. Therefore, our empirical results about production efficiency measurement can correctly characterize this regional disparity issue in China and be in correspondence to relevant studies. Some reasons on regional gaps on production efficiency measurements could also be summarized as different regional industrial structures, unequal economic development stages, and government reform policies implemented preferential to the Eastcoast area, etc. (Fleisher and Chen 1997; Kanbur and Zhang 1999, 2005).

Due to the BP approach separates the pollution-generating technologies as two independent parts, our production and environmental efficiency measurements can be conducted to capture each DMU's efficiency based on the two technology parts, respectively. Therefore, from the theoretical view, each province's production technology would not direct influence its environmental efficiency level. The environmental efficiency mainly depends on the different levels of emission generating, given the fixed amounts of fossil fuels usage and pollution reductions. Furthermore, different types of energy resources utilisation and the effectiveness of abatement activities for each province or region should be reflected by the our environmental efficiency measurement results. Table 4 also verifies the the production efficiency ($D_{HYP(1)}$ or $D_{FGL(1)}$) is not correlated to the environmental efficiency ($D_{HYP(2)}$ or $D_{FGL(2)}$).

Therefore, through analysing the deep reasons for various environmental efficiency levels in different regions, this study could make recommendations on the appropriate environmental policy adjustments for Chinese government to improve the regional environmental efficiency levels without harming their production efficiencies.

Table 4 Spearman's correlation tests on 5-year average HYP and FGL efficiency index under BP approach

	$D_{HYP(1)}$	$D_{HYP(2)}$	D_{HYP}	$D_{FGL(1)}$	$D_{FGL(2)}$	D_{FGL}
$D_{HYP(1)}$	1.0000					
$D_{HYP(2)}$	-0.0500	1.0000				
D_{HYP}	0.5903**	0.5975**	1.0000			
$D_{FGL(1)}$	1.0000**	-0.0500	0.5903**	1.0000		
$D_{FGL(2)}$	0.1782	0.6010**	0.4788**	0.1782	1.0000	
D_{FGL}	0.8261**	0.2851	0.6483**	0.8261**	0.6350**	1.0000

* Significant at 10 %

** Significant at 5 %

In terms of fossil fuels usage, many researches indicate that coal consumption always occupies the major percentages of China's energy usage structure. From 1980s to 2014, coal has accounted for around 70 % of the production and consumption of Chinese domestic primary energy sources.¹⁷ The heavily relying on coal usage in China has led to the serious environmental problems. In 2012, China's 79 % total SO₂ emission stems from the direct combustion of coal.¹⁸ Similarly, CO₂ produced by the coal consumption in the long term CO₂ emission generated from energy activities remains about 80 % (IEA 2013). Therefore, various qualities of coal utilisation in different areas may partially lead to the different degrees of emission and environmental efficiency levels. Wang and Li (2001) state that in China, the sulphur content of power coal varies with different regions, the coverage range is between 0.14 and 5.3 %. From the sampling and analysing, they also point out the sulphur content of coal conserving in Northeast is lowest, average to be 0.45 %. Those in Beijing, Jilin, Yunnan etc. average to be 0.5 %. However, the highest sulphur coals (average to be 2.79 %, with individual regions as high as 5.0 %) are mainly observed in Southwest area, like Sichuan Guangxi and Guizhou. The similar results are also found in other literatures (Hong et al. 1993; Xiao and Liu 2011). Due to the different types of coal exploiting and using between the East and West areas, the emission levels from fossil fuel combustion will be influenced. This characteristic can also be reflected in and consistent with our regional environmental efficiency measurements.

In reality, even though the influences on atmospheric environment from coal resource distribution and consumption structure in different areas are inevitable, the strict regulations or policies for controlling low quality coal using and setting up emission standards can also play important roles in forcing the producers to reduce the pollution-causing inputs using and make more efforts on abatement activities to improving the regional efficiency of energy utilisation and environmental quality. To illustrate the reasonability of our environmental

¹⁷ Source from: China National Energy Administration.

¹⁸ Statistical data come from the report of "Coal use contribution to China's air pollution" by China's coal consumption control scheme and policy research, 2014.

Table 5 Descriptive statistics of data for reasons discussion

Variables ^a	Obs.	Mean	Std. dev.	Min	Max
2006–2010					
$D_{FGL(2)}$	150	0.8004	0.1175	0.5233	1.0000
X_1	150	0.4792	0.1997	0	0.8267
X_2	150	1.4632	0.7329	0.582	4.099
X_3	150	1.2333	0.5341	0.46	3.76
X_4	150	0.0871	0.0911	0.0044	0.6954
X_5	150	1.6543	1.0219	0.2812	6.3440

^a Unit of energy intensity (X_2) is tce/10,000 CNY, abbreviation of tons of coal equivalent per 10,000 CNY. The other units are expressed as percentage

efficiency results, we further construct the econometric model to investigate whether our FGL environmental efficiency scores ($D_{FGL(2)}$) will be influenced by such factors as the SO₂ abatement ratio, which is defined by the ratio of annual volume of industrial SO₂ removed to total SO₂ emission (X_1); energy intensity, defined by the annual energy consumption per GDP (X_2); the annual investment in anti-pollution projects as the percentage of GDP (X_3); the ratio of annual pollution discharges levied to GDP (X_4); and the ratio of annual expenditures for indraught of technology to GDP (X_5). All the data of independent variables are all from 2006 to 2010 and collected from “China Statistic Yearbook”, “China Environment Yearbook”, and further calculated by author. The descriptive statistics of data is shown in Table 5 and the specific model form can be given following

$$D_{FGL(2)it} = \beta_0 + \beta_1 X_{1,it} + \beta_2 X_{2,it} + \beta_3 X_{3,it} + \beta_4 X_{4,it} + \beta_5 X_{5,it} + u_{it} \quad (12)$$

where β_0 is constant term; $\beta_1, \beta_2, \beta_3, \beta_4$ and β_5 are coefficient parameters of independent variables, respectively and u is the error term.

The regression results are listed in Table 6. We begin our analysis by estimating the coefficients of such influence factors using simple OLS, fixed effect (FE) and random effect (RE) models. Since our data set is panel data, the OLS may ignore the variations between different regions and lead to estimation bias. Hence, OLS result is only taken as reference. Based on the Hausman test (Hausman 1978), we decide to refer fixed effect model results to analyse which factors would effect our environmental efficiency scores. It can be observed that the SO₂ abatement ratio has a positive relationship with environmental efficiency level, which can be explained as the more efforts conducted by province will lead to a higher environmental efficiency level. Besides, the energy intensity shows a significant negative relation with environmental efficiency, which indicates that if one unit of GDP produced requires more energy consumptions, less environmental efficiency level will be reached. Therefore, readjusting the industrial structure for reducing the proportions of high energy consuming industrials would be an effective way to improve the regional environmental efficiency, especially for some undeveloped western areas. However, our regression results also shows that expenditures for indraught of technology even has a significant negative effect on

environmental efficiency. This result consistent with the previous literature.¹⁹ One possible explanation can be proposed as the variable of expenditure for technology indraught might not concretely reflect the expense on cleaning-technology or eco-friendly technology import and innovation. Furthermore, only expenditures on technology import can not capture the real details of new technology application. The internal technology development and absorptive capacity seem more important (Liao et al. 2012; Fisher-Vanden et al. 2006). When we add region dummies in Panel B and year dummies in Panel C in Table 6, the fixed effects estimation can show consistent results.

Meanwhile, our regression results also reveal the China's current environment regulations do not seem very effective to improve the regional environmental efficiency levels. The total investment in the treatment of environmental pollution and pollution discharge fees neither have significant effects on our environmental efficiency scores.

The reasons on the ineffectiveness of pollution treatment investments could be given as: first, the proportion of total investment to GDP in China is still very low (only 1.2 % of GDP in 2005), which can not play a proper role in the environmental efficiency improvement in a short term (Liu and Diamond 2005). Second, the total investment in pollution treatment shows extremely unbalanced distribution across different regions. In 2010, the total investment on East regions reached to 369.94 billion CNY, which was even greater than the aggregation of other three areas 256.87 billion.²⁰ The unreasonable funding allocation might lead to the insufficiency in some areas but waste in other areas. Third, due to lacking of number of professional and investing management experience, regional pollution control investment might not be planed and implemented reasonably. In addition, China even though established a pollution discharge system, in particular, the discharge fees are still significantly lower than the abatement costs (OECD 2006). According to statistics, the minimal discharge rates for SO₂ and NO_x are 0.63 CNY/kg and 0.60 CNY/kg in 2005, respectively.²¹ Besides, the charges are only incurred on excess emissions, and no charge to the enterprises whose emissions are below the waste standards. Hence, it is difficult to stimulate enterprises maximize emission reduction. Zhang et al. (2001) also indicate that due to the environmental tax has not been levied in China, the current environmental regulatory instruments will neither punish the enterprises which abided by the emission standards nor encourage them seeking for the low-cost pollution control technologies. Once environmental tax could be implemented, every technology innovation means paying less taxes, which might be a new solution to improve the environmental efficiency of energy utilization.

¹⁹ Zeng (2011) uses the input-oriental variable return to scale (VRS) model based on the DEA efficiency measurement of Charnes et al. (1978) to measure China's regional total technical efficiency with bad output consideration. Then, it also employs Tobit regression and finds the technology innovation has a negative effect on regional technology efficiency.

²⁰ Data from: statistical departments in Ministry of Environmental Protection and Ministry of Housing and Urban-rural Development, P. R. China.

²¹ According to the latest statement from Ministry of Environmental Protection of Peoples' Republic of China, the new discharge rate will increase to 1.20 CNY/kg for main air pollutants.

Table 6 Regression analysis of FGL environmental efficiency on selected impact factors from 2006 to 2010

	FE	RE	OLS
Panel A: without dummies			
X_1	0.0836* (0.049)	0.1427*** (0.039)	0.0270 (0.052)
X_2	-0.1234*** (0.039)	-0.0541** (0.026)	-0.0361* (0.018)
X_3	0.0109 (0.009)	0.0146 (0.009)	0.0439** (0.019)
X_4	0.0792 (0.124)	0.1126 (0.118)	0.4189*** (0.143)
X_5	-0.0107* (0.006)	-0.0125** (0.006)	-0.0278** (0.011)
Constant	0.9382*** (0.076)	0.8042*** (0.054)	0.7957*** (0.040)
Observations	150	150	150
R-sq	0.3786	0.3592	0.1128
Hausman Test (Chi-sq) 17.67***			
Panel B: with region dummies			
X_1	0.0836* (0.049)	0.1539*** (0.041)	0.0500 (0.051)
X_2	-0.1234*** (0.039)	-0.0415 (0.029)	0.0235 (0.021)
X_3	0.0109 (0.009)	0.0152 (0.009)	0.0499*** (0.018)
X_4	0.0792 (0.124)	0.1041 (0.121)	0.2276 (0.139)
X_5	-0.0107* (0.006)	-0.0129** (0.006)	-0.0333*** (0.010)
Constant	0.9382*** (0.076)	0.7521*** (0.076)	0.6432*** (0.048)
Observations	150	150	150
R-sq	0.3786	0.3519	0.2552
Panel C: with year dummies			
X_1	0.1093* (0.064)	0.1085* (0.058)	-0.0156 (0.059)
X_2	-0.1404*** (0.044)	-0.0491* (0.027)	-0.0384** (0.018)
X_3	0.0151 (0.010)	0.0123 (0.011)	0.0372** (0.020)
X_4	0.0887 (0.127)	0.1186 (0.121)	0.4380*** (0.144)
X_5	-0.0131* (0.007)	-0.0131* (0.007)	-0.0249** (0.012)

Table 6 continued

	FE	RE	OLS
Constant	0.9542*** (0.079)	0.8073*** (0.055)	0.7941*** (0.042)
Observations	150	150	150
R-sq	0.3893	0.3611	0.1307

Robust standard errors in brackets

* Significant at 10 %

** Significant at 5 %

*** Significant at 1 %

In a word, according to our production and environmental efficiency measurement results, the reasons discussion has been carried out thoroughly. Through constructing the regression model, we concentrate to explain which factors would influence the regional environmental efficiency and find some shortages of China's current environment policy. Besides, some other effective measures to improve environmental efficiency could also be analysed further, such as decomposition the effect factors of elimination policy on different air pollutants from the regional or industrial aspect (Fujii et al. 2013). Furthermore, it is also required to examine the relationship between income or economic growth and environmental quality (Stern et al. 1996; Harbaugh et al. 2002; Rezek and Rogers 2008); and decompose determinants of environmental performance or consider whether environmental policy could be more stringent when the technique effect could not sufficiently reduce emissions (Panayotou 1977; Tsurumi and Managi 2010).

4 Conclusions

This study introduces the characteristics of new by-production approach technologies. Under BP approach, the decomposition of pollution generating technologies based on the multiple production relations could better capture the phenomenon of by production generating than the traditional weak-disposability approach with a single production relation. Under by-production approach, the efficiency indexes are first applied to measure the production efficiency and environmental efficiency by using the DEA algorithm in this study.

In the empirical part, this study employs the hyperbolic index and modified coordinate-wise FGL index under BP technologies to investigate the technical efficiency with emission consideration in China's province-level regions from 2006 to 2010. By classifying four economic areas, the Eastcoast area has the most effective performance in desirable output generation, but the West performs worst in both desirable output and undesirable outputs efficiency measurements. Furthermore, the production efficiency gaps between four areas are very significant, but in environmental efficiency this characteristics is not such obvious. Through conducting reason discussions, we also find that the environmental efficiency levels

are significantly affected by SO₂ abatement activities and energy intensity, but the environment policy factors show less robust. Besides, this paper also testifies China's regional technical efficiency levels are consistent with the regional disparity development pattern and ineffectiveness of current environmental regulations implementations.

According to our findings in this paper, we can provide some policy implications. First, due to such differences between regional development, Chinese central government should release more rights of decision making to sub-national local governments and support them to design more suitable policies for local own development. Since the uniform planing or standards are widely used in Chinas environmental regulation system, some drawbacks of relying on uniform standards might inevitably impact the effectiveness of environmental governance. Therefore, it requires policy makers to pay more concerns on key regions with lower efficiency levels and ensure the environmental regulations in different regions being more purposefully and pertinently. Second, there exists the negative effects between the energy intensity and environmental efficiency level. Adjusting and changing the industrial structure from the high energy consumption industries to high value-added service or technology industries will play a key role in emission reduction and improving the regional environmental efficiency. Third, the current environmental regulations as pollution charges and investment in anti-pollution projects have not achieved the prospective effects. All levels of government and environmental regulators need to constantly improve the level of management in pollution charge system, to ensure the discharge process is reasonable, and meets the real needs of local development. Meanwhile, policy makers should accelerate and promote the enforcement of the environmental taxation in China at appropriate time, which would be a good supplement to the environment pollution charges regulation. For achieving the effectiveness of environmental investment, local governments and relevant enterprises should be more focus on the purpose of the investment and the expected results, rather than blind to expand investment. Forth, local enterprises should remain cautious about introducing new technology from abroad and pay more attention on enhancing the research and development (R&D) strength based on their own situation of development to overcome the dependence on technology import.

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Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest. This study does not contain any studies with human participants or animals performed by any of the authors.

Informed consent Informed consent was obtained from all individual participants included in the study.

References

- Bian Y, Yang F (2010) Resource and environment efficiency analysis of provinces in China: a DEA approach based on Shannon's entropy. *Energy Policy* 38(4):1909–1917
- Cao H, Fujii H, Managi S (2015) A productivity analysis considering environmental pollution and diseases in China. *J Econ Struct* 4(1):1–19
- Caves DW, Christensen LR, Diewert WE (1982) The economic theory of index numbers and the measurement of input, output, and productivity. *Econometrica* 50(6):1393–1414
- Charnes A, Cooper WW, Rhodes E (1978) Measuring the efficiency of decision making units. *Eur J Oper Res* 2(6):429–444
- Chung YH, Färe R, Grosskopf S (1997) Productivity and undesirable outputs: a directional distance function approach. *J Environ Manag* 51(3):229–240
- Coggins JS, Swinton JR (1996) The price of pollution: a dual approach to valuing SO₂ allowances. *J Environ Econ Manag* 30(1):58–72
- Färe R, Grosskopf S (2003) *New directions: efficiency and productivity*. Kluwer Academic Publishers, Boston
- Färe R, Grosskopf S, Hernandez-Sancho F (2004) Environmental performance: an index number approach. *Resour Energy Econ* 26(4):343–352
- Färe R, Grosskopf S, Lovell CK, Pasurka C (1989) Multilateral productivity comparisons when some outputs are undesirable: a nonparametric approach. *Rev Econ Stat* 71(1):90–98
- Färe R, Grosskopf S, Lovell CK, Yaisawarng S (1993) Derivation of shadow prices for undesirable outputs: a distance function approach. *Rev Econ Stat* 75(2):374–380
- Färe R, Grosskopf S, Noh D-W, Weber W (2005) Characteristics of a polluting technology: theory and practice. *J Econom* 126(2):469–492
- Färe R, Grosskopf S, Tyteca D (1996) An activity analysis model of the environmental performance of firms application to fossil-fuel-fired electric utilities. *Ecol Econ* 18(2):161–175
- Fisher-Vanden K, Jefferson GH, Ma J, Xu J (2006) Technology development and energy productivity in China. *Energy Econ* 28(5):690–705
- Fleisher BM, Chen J (1997) The coast-noncoast income gap, productivity, and regional economic policy in China. *J Comp Econ* 25(2):220–236
- Fujii H, Cao J, Managi S (2015) Decomposition of productivity considering multi-environmental pollutants in Chinese industrial sector. *Rev Dev Econ* 19(1):75–84
- Fujii H, Managi S, Kaneko S (2013) Decomposition analysis of air pollution abatement in China: empirical study for ten industrial sectors from 1998 to 2009. *J Clean Prod* 59:22–31
- Grosskopf S (1996) Statistical inference and nonparametric efficiency: a selective survey. *J Product Anal* 7(2–3):161–176
- Harbaugh WT, Levinson A, Wilson DM (2002) Reexamining the empirical evidence for an environmental kuznets curve. *Rev Econ Stat* 84(3):541–551
- Hausman JA (1978) Specification tests in econometrics. *Econom J Econom Soc* 46(6):1251–1271
- Hong Y, Zhang H, Zhu Y (1993) Sulfur isotopic characteristics of coal in China and sulfur isotopic fractionation during coal-burning process. *Chin J Geochem* 12(1):51–59
- Hu J-L, Wang S-C (2006) Total-factor energy efficiency of regions in China. *Energy Policy* 34(17):3206–3217
- IEA (2013) CO₂ emissions from fuel combustion 2013. IEA, Paris. doi:[10.1787/co2_fuel-2013-en](https://doi.org/10.1787/co2_fuel-2013-en)
- IPCC (2006) IPCC guidelines for national greenhouse gas inventories, prepared by the national greenhouse gas inventories programme. Institute for Global Environmental Strategies (IGES), Tokyo, Japan, 2007
- Kanbur R, Zhang X (1999) Which regional inequality? The evolution of rural-urban and inland-coastal inequality in China from 1983 to 1995. *J Comp Econ* 27(4):686–701
- Kanbur R, Zhang X (2005) Fifty years of regional inequality in China: a journey through central planning, reform, and openness. *Rev Dev Econ* 9(1):87–106
- Liao H, Liu X, Wang C (2012) Knowledge spillovers, absorptive capacity and total factor productivity in China's manufacturing firms. *Int Rev Appl Econ* 26(4):533–547
- Liu J, Diamond J (2005) China's environment in a globalizing world. *Nature* 435(7046):1179–1186
- Lu W-M, Lo S-F (2007) A closer look at the economic-environmental disparities for regional development in China. *Eur J Oper Res* 183(2):882–894

- Murty MN, Kumar S (2002) Measuring the cost of environmentally sustainable industrial development in India: a distance function approach. *Environ Dev Econ* 7(3):467–486
- Murty MN, Kumar S (2003) Win-win opportunities and environmental regulation: testing of porter hypothesis for Indian manufacturing industries. *J Environ Manag* 67(2):139–144
- Murty S (2015) On the properties of an emission-generating technology and its parametric representation. *Econ Theory* 60(2):243–282
- Murty S, Robert Russell R, Levkoff SB (2012) On modeling pollution-generating technologies. *J Environ Econ Manag* 64(1):117–135
- Nakano M, Managi S (2012) Waste generations and efficiency measures in Japan. *Environ Econ Policy Stud* 14(4):327–339
- OECD (2006) Environmental compliance and enforcement in China: an assessment of current practices and ways forward. OECD, Paris
- Panayotou T (1997) Demystifying the environmental Kuznets curve: turning a black box into a policy tool. *Environ Dev Econ* 2(04):465–484
- Rezek JP, Rogers K (2008) Decomposing the CO₂ income tradeoff: an output distance function approach. *Environ Dev Econ* 13(04):457–473
- Stern DI, Common MS, Barbier EB (1996) Economic growth and environmental degradation: the environmental Kuznets curve and sustainable development. *World Dev* 24(7):1151–1160
- Tsurumi T, Managi S (2010) Decomposition of the environmental Kuznets curve: scale, technique, and composition effects. *Environ Econ Policy Stud* 11(1–4):19–36
- Tyteca D (1997) Linear programming models for the measurement of environmental performance of firms-concepts and empirical results. *J Product Anal* 8(2):183–197
- Wang K, Yu S, Zhang W (2013) China' regional energy and environmental efficiency: a DEA window analysis based dynamic evaluation. *Math Comput Model* 58(5):1117–1127
- Wang L, Li R (2001) Typical kinds of coal in China and some special coals with their fly ash difficult to precipitate by ESP. In: Presented at the 8th International Conference on Electrostatic Precipitation, 14–17 May 2001
- Wang Q, Zhou P, Zhou D (2012) Efficiency measurement with carbon dioxide emissions: the case of China. *Appl Energy* 90(1):161–166
- Xiao H-Y, Liu C-Q (2011) The elemental and isotopic composition of sulfur and nitrogen in Chinese coals. *Org Geochem* 42(1):84–93
- Zeng X (2011) Environmental efficiency and its determinants across Chinese regions (in Chinese). *Econ Theory Bus Manag* 10:103–110
- Zhang J, Wu G, Zhang J (2004) The estimation of China's provincial capital stock: 1952–2000. *Econ Res J* 10:35–44 (in Chinese)
- Zhang S, He H, Cao J (2001) Environmental policy innovation: discussion on implementing environmental tax in China. *Acta Sci Nat Univ Pekin* 37(4):550–556