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The governance-production nexus of eco-efficiency in Chinese resource-based cities: A two-stage network DEA approach

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ABSTRACT

For decades, resource-based cities in China have significantly contributed to China's socio-economic development. The heavy resource dependence of resource-based cities inevitably leads to a series of environmental problems. Mitigating environmental impacts in an unthinking manner might be disruptive for economic development. Improving eco-efficiency has been a crucial solution for protecting the environment while mitigating its negative economic impact. However, the method commonly used to evaluate the eco-efficiency – that is, the black-box data envelopment analysis (DEA) – cannot examine the inefficiencies of the internal structure, and as a result, the underlying management defects are unclear. To open the black box, this study presents a two-stage network DEA framework incorporating government and industrial sectors and measures the eco-efficiency of 84 resource-based cities during the post-financial crisis period (2007–2015). The results indicate that the average eco-efficiency of China's resource-based cities shows a promising increase, and there is a positive relationship between governance efficiency and production efficiency. The decreasing trend of governance efficiency in the Central, Western, and Northeast regions after 2014 shows the low quality of the government sector in the usage of fiscal income. Proactive disclosure of how the government sector conducts public business and spends taxpayers' money should be made to increase transparency, attract more entrepreneurial resources to carry out production activities, and further improve sustainability. The two-stage network DEA framework helps obtain more insights into the internal management defects of the government and industrial sectors and enhance their cooperation to improve the eco-efficiency precisely.

1. Introduction

Resource-based cities are those whose leading industries involve the exploitation and processing of natural resources, such as minerals, forests, and fossil fuel (The Chinese Government, 2013a). The heavy resource dependence of resource-based cities inevitably leads to a large demand for fossil fuel, a vast quantity of CO_2 emissions, and a series of social-economic problems, such as a monolithic industrial structure, a lack of technological innovation, and a high unemployment rate (Li et al., 2013a; Shao et al., 2020b; Shao and Qi, 2009). These problems are closely interrelated with the unsustainable development mode of resource-based cities (Qin et al., 2019; Ruan et al., 2020; Yan et al., 2019a). Experiences at home and abroad have suggested that resource-based cities should transform from resource-intensive growth patterns to a low-carbon and high value-added economy (The Chinese Government, 2013a).

Eco-efficiency, proposed by Schaltegger and Sturm (1990), is the ability to produce goods and services with minimal natural resource consumption and negative environmental impacts (Kuosmanen, 2005; Long et al., 2017; Oggioni et al., 2011). Improving the eco-efficiency in a

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precise manner provides a solution for this transformation towards sustainable development, as efficiency enhancement can mitigate the negative economic impact of emission constraints (Xiao et al., 2019b; Zhang et al., 2016a). To measure the eco-efficiency, data envelopment analysis (DEA) has attracted great attention based on a total-factor production process (Wang et al., 2016; Wu et al., 2020; Xiao et al., 2019b; Zhou et al., 2008a; Zhou and Ang, 2008). The traditional DEA method used to evaluate the eco-efficiency has some inadequacies because it regards the production process as a black box. The black-box DEA considers production activity as a one-stage process, indicating the use of all inputs and generating all outputs in a single step (Tone and Tsutsui, 2009). However, many production activities include multi-stage processes, which are controlled by corresponding sectors to jointly complete production activities (Adler et al., 2013; Lozano et al., 2013; Tone and Tsutsui, 2009). Previous studies have generally evaluated the eco-efficiency as a single process – that is, focusing on the industrial sector, which directly generates CO_2 emissions – omitting the indispensable role of the government (Li et al., 2013a). The government sector is significant, as it provides public goods and services for a favorable production environment. How the government sector affects the industrial sector or even overall efficiency (the eco-efficiency) is still unknown.

Apart from the inadequacy of research perspective mentioned above, limitations in the emissions data of resource-based cities set a barrier to investigating the eco-efficiency of such cities. Many studies have explored the eco-efficiency of China at the provincial, regional (Guo et al., 2011; Li, 2010; Lin and Du, 2015; Wang et al., 2012), and national levels (Liou and Wu, 2011; Zhou et al., 2010). However, cities in China are considered the basic unit for policy design and CO_2 emission mitigation implementation (Shan et al., 2017; Xiao et al., 2019a, 2019b; Zhou et al., 2018). The lack of comprehensive, consistent, and detailed emissions inventories for resource-based cities makes it impossible to support an in-depth analysis of the eco-efficiency.

Based on the above analysis, we fill two gaps in terms of the eco-efficiency analysis. First, we construct CO_2 emissions inventories for the industrial sectors of 84 resource-based cities in China during 2007–2015. These consistent, transparent, and comparable emissions data can be a basis for emission-related studies. Second, the government's role in sustainable development is included in a two-stage network DEA,[1] the main objective of which is to measure the eco-efficiency, with governance efficiency and production efficiency as its components. This study provides a new perspective on analyzing the low-carbon development situation of resource-based cities by considering the quality of the government sector. Resource-based cities can benefit greatly because of natural resource rent. Whether the government makes good use of this large fiscal income to create an attractive production environment is still unknown. This two-stage network DEA framework can obtain insights into the internal management defects of the government and industrial sectors and enhance cooperation between them to improve the eco-efficiency.

The rest of the paper is structured as follows. Section 2 first compares the methods of the network DEA with two traditional types of DEA (the black-box DEA and the separate DEA), and then, it presents the framework of a two-stage network DEA. Section 3 describes the sample cities, variable selection, and data. Section 4 shows and discusses the results. Section 5 presents the main conclusions and proposes some policy implications.

2. Methodology

DEA is a non-parametric method for evaluating the efficiency of decision-making units (DMUs) that can consume multiple inputs to generate multiple outputs. DEA has been commonly used to measure the eco-efficiency (Zhou et al., 2008b). Long et al. (2017) investigated the eco-efficiency of cement manufacturers in China and found that the Eastern, Central, and Western regions saw a converging trend in the eco-efficiency. Yang et al. (2017) and Zhang et al. (2016) evaluated the eco-efficiency of China's industrial sectors based on DEA. There are two traditional DEA methods for evaluating the eco-efficiency: the black-box DEA and the separate DEA. The black-box DEA considers production activity to be a one-stage step, which means that all inputs are used and all outputs are generated in a single process, regarding the production process as a black box, as illustrated in Fig. 1(A) (Long et al., 2018a, 2020). However, many production activities include multi-stage processes, which are controlled by corresponding sectors to jointly complete the production activities. Using the black-box approach, we cannot evaluate sector-specific inefficiencies. As such, the black-box DEA cannot provide information about potential internal defects for management improvement if a DMU is inefficient. To enable the evaluation of sector-specific inefficiencies and their impacts on overall efficiency, the separate DEA model is used by many studies in the fields of banks (Luo, 2003; Seiford and Zhu, 1999; Tsolas, 2011), companies (Lo and Lu, 2009; Lo and Lu, 2006; Zhu, 2000), and hotels (Keh et al., 2006). The separate DEA can include more than one process, with each process using its own inputs and generating its own outputs, as illustrated in Fig. 1(B). However, the separate DEA regards sectors as being independent of each other, and it neglects the linking structure among them (Tone and Tsutsui, 2009).

Table 1 summarizes the studies on the resource-based regions of China using the DEA method in recent years. These studies provide insightful information for the development of resource-based cities in China. However, the number of related studies is very limited, and all of them use the black-box DEA method to measure different types of efficiencies of China's resource-based cities.

2.1. The black-box DEA

Suppose we deal with N DMUs ($i = 1,2, \dots, N$), and each DMU consumes M inputs to generate E good outputs and F bad outputs. $X = (x_1, x_2, \dots, x_M) \in R_+{}^M$, $G = (g_1, g_2, \dots, g_E) \in R_+{}^E$, and $B = (b_1, b_2, \dots, b_F) \in R_+{}^F$ indicate inputs, good outputs, and bad outputs, respectively. The black-box DEA model evaluates the efficiency of DMUs by using all inputs and generating outputs in a single step. The production technology of a black box process can be formulated following Eq. (1):

$$T = \{(X, G, B) : X \text{ can produce } (G, B)\} \quad (1)$$

[1] Compared with the one-stage DEA, the network DEA can detect the inefficiency of the components in a network system. However, every component of a network system is still a black box. A network system can be regarded as the composition of several black boxes which have interactions.

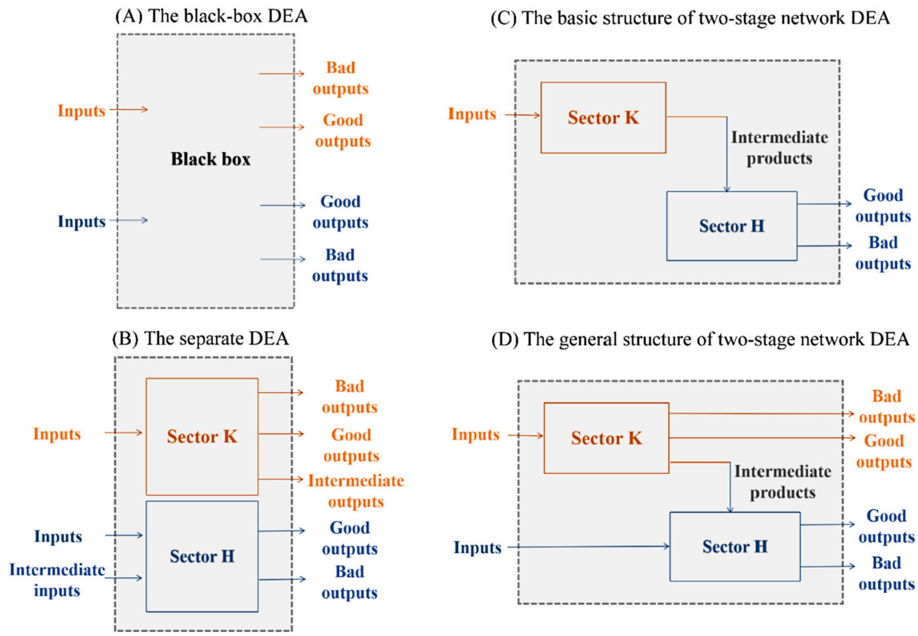

Fig. 1. Illustration of the black-box DEA (A), the separate DEA (B), the basic structure of two-stage network DEA (C), the general structure of two-stage network DEA.

Table 1
Summary of studies on resource-based cities in China using the DEA method.

No.	Authors	Periods	Samples	Topics	Methods
1	Yan et al. (2019a)	2010–2016	105 resource-based cities in China	Measuring total-factor energy efficiency and investigating its determinants	The black-box DEA & panel quantile regression
2	Yan et al. (2019b)	2010–2016	104 resource-based cities in China	Measuring total-factor energy efficiency and examining the spatial variation in it	The black-box DEA & a K-means clustering algorithm
3	Chen et al. (2019)	2006–2015	109 resource-based cities in China	Measuring industrial land use efficiency and investigating its determinants	The black-box DEA & Tobit models
4	Li and Dewan (2017)	2012	116 resource-based cities in China	Measuring total-factor efficiency and investigating its determinants	The black-box DEA & OLS linear regression model
5	Li et al. (2016)	1999–2013	Jiaozuo city in China	Investigating the efficiency of sustainable development after transformation	The black-box DEA
6	Sun et al. (2012)	2000–2008	24 resource-based cities in China	Investigating urban efficiencies and their dynamic change	The black-box DEA

The production technology of the black-box DEA exhibiting constant returns to scale is defined as Eq. (2):

$$T=\left\{\begin{array}{l}(X,G,B):X\geq\sum_{i=1}^{N}\lambda_iX_i,G\leq\sum_{i=1}^{N}\lambda_iG_i,\\ B\geq\sum_{i=1}^{N}\lambda_iB_i,\lambda_i\geq0(i=1,2,\ldots,N)\end{array}\right\} \tag{2}$$

where λ_i indicates the intensity vector.

2.2. *The separate DEA*

The separate DEA model can disassemble the single-stage process into multi-stage processes. For simplicity, assume that there are two sectors, which are sectors k and h, which cooperate in production activities. The production technology of sectors k and h can be expressed as Eqs. (3) and (4).

$$T^k=\left\{\left(X^k,G^k,B^k,Z^k\right):X^k\ can\ produce\ \left(G^k,B^k,Z^k\right)\right\} \tag{3}$$

$$T^h=\left\{\left(X^h,Z^h,G^h,B^h\right):\left(X^h,Z^h\right)\ can\ produce\ \left(G^h,B^h\right)\right\} \tag{4}$$

Intermediate products are generated by sector k and are then used as inputs by sector h. Variables Z^k and Z^h are the intermediate outputs of sector k and the intermediate inputs of sector h, respectively. The production technologies of sector k (T^k) with constant returns to scale can be defined as follows:

$$T^k=\left\{\begin{array}{l}\left(X^k,G^k,B^k,Z^k\right):X^k\geq\sum_{i=1}^{N}\lambda_i^kX_i^k,G^k\leq\sum_{i=1}^{N}\lambda_i^kG_i^k,\\ Z^k\leq\sum_{i=1}^{N}\lambda_i^kZ_i^k,B^k\geq\sum_{i=1}^{N}\lambda_i^kB_i^k,\lambda_i^k\geq0(i=1,2,\ldots,N)\end{array}\right\} \tag{5}$$

The production technologies of sector h (T^h) exhibiting constant returns to scale can be defined as follows:

$$T^h = \left\{ \begin{array}{l} \left(X^h, Z^h, G^h, B^h\right) : X^h \geq \sum_{i=1}^{N} \lambda_i^h X_i^h, Z^h \geq \sum_{i=1}^{N} \lambda_i^h Z_i^h, \\ G^h \leq \sum_{i=1}^{N} \lambda_i^h G_i^h, B^h \geq \sum_{i=1}^{N} \lambda_i^h B_i^h, \lambda_i^h \geq 0 (i = 1, 2, \ldots, N) \end{array} \right\} \tag{6}$$

The main difference between Eqs. (2) and (6) is that the separate DEA considers the existence of several sectors, and each sector consumes its own set of inputs and produces its own set of good and bad outputs. Intermediate products are regarded as good outputs of sector k since they can be used as inputs in sector h. Under the production technology of sectors k and h, the sectoral efficiency can be obtained based on Eqs. (5) and (6), and the overall efficiency is the weighted arithmetic mean of the sectoral efficiency.

2.3. The two-stage network DEA

The early attempt of taking the overall system into the component processes was Charnes et al. (1986), who found that army recruitment had two processes, that is creating awareness through advertisements and creating contracts. Since then, measuring the efficiency by separating a large system into detailed smaller production processes has attracted increasing attention (Färe, 1991; Färe and Grosskopf, 1996; Färe and Whittaker, 1995; Wang et al., 1997). The simplest network system is the basic two-stage network structure, where the outputs of the first production process are all treated as intermediate inputs of the second stage and the inputs of the second production process are all from the first stage (Kao, 2018; Kao, 2017; Kao, 2014a), as shown in Fig. 1(C). The basic two-stage network DEA has been adopted in many research fields, such as commercial banks (Seiford and Zhu, 1999; Tsolas, 2011), firms (Lu, 2009; Tsolas, 2013), retail stores (Keh and Chu, 2003), and hotels (Keh et al., 2006).

However, in the real world, the situation of the system with two production processes can be more complicated. For example, the outputs of the first process can be the final products and partially flow out of the system. Also, some inputs of the second production process can be external but not simply the immediate outputs of the first process. Compared with the basic two-stage network DEA, the general structure of the two-stage network DEA can consider these situations (Kao, 2018, Kao, 2017, Kao, 2014a), as shown in Fig. 1(D). Due to its simple structure and wide application, the general two-stage network DEA has been widely discussed in the literature (Bai-Chen et al., 2012; Chiu et al., 2012; Guan and Chen, 2010; Kao, 2014a). To deal with the situation that has more than two stages and a more complicated structure, the two-stage network system was further extended by including more subprocesses and diverse structures, such as series (Kao, 2009), parallel (Bian et al., 2016; Kao, 2009), mixed (Fare and Grosskopf, 2000; Kao, 2016; Kao, 2009; Lewis and Sexton, 2004), and hierarchical structures (Kao, 2015).

The Network DEA has several advantages over traditional DEA approaches which generally assume production activity as a one-stage process or regards sectors as being independent (Long et al., 2018c; Long et al., 2017; Zhang and Choi, 2013a). First, the constructed network structure is generally closer to a real-world situation. Many production activities include multi-stage processes, which are interrelated, and the realization of one process often depends on the smooth running of other related processes (Adler et al., 2013; Lozano et al., 2013; Tone and Tsutsui, 2009). Additionally, not only does the network DEA consider the existence of multi-stage processes, but it also considers intermediate products simultaneously as inputs in some processes and as outputs in other processes (Tone and Tsutsui, 2009). Second, the network DEA has stronger discriminating power since a DMU is efficient only if all of its sectors are efficient (Kao, 2014b; Moreno and Lozano, 2014; Tone and Tsutsui, 2009). This property helps DMUs examine sector-specific inefficiencies and explore the underlying management defects, which further propose targeted efficiency improvement strategies (Lewis and Sexton, 2004).

The production technology of the general two-stage network DEA showing constant returns to scale is as follows:

$$T^k = \left\{ \begin{array}{l} \left(X^k, X^h, G^k, G^h, B^k, B^h, Z^{(k,h)}\right) : X^k \geq \sum_{i=1}^{N} \lambda_i^k X_i^k, X^h \geq \sum_{i=1}^{N} \lambda_i^h X_i^h, \\ G^k \leq \sum_{i=1}^{N} \lambda_i^k G_i^k, G^h \leq \sum_{i=1}^{N} \lambda_i^h G_i^h, B^k \geq \sum_{i=1}^{N} \lambda_i^k B_i^k, B^h \geq \sum_{i=1}^{N} \lambda_i^k B_i^h, \\ \sum_{i=1}^{N} \lambda_i^k Z_i^{(k,h)} = \sum_{i=1}^{N} \lambda_i^h Z_i^{(k,h)}, \lambda_i^k, \lambda_i^h \geq 0 (i = 1, 2, \ldots, N) \end{array} \right\} \tag{7}$$

The main difference between Eqs. (6) and (7) is that Eq. (7) considers the linking constraints of intermediate products and includes the two sectors, k and h, in the same framework. The superscript (k,h) indicates the flow of intermediate products from sector k to sector h. According to Tone and Tsutsui (2009) and Tone and Tsutsui (2010), there are several ways to deal with the link of intermediate products. In this study, the production technology is under the constraint of the free link value case ($\sum_{i=1}^{N} \lambda_i^k Z_i^{(k,h)} = \sum_{i=1}^{N} \lambda_i^h Z_i^{(k,h)}$). The free link case indicates the situation where the linking activities are freely determined, and their optimal values can be equal, smaller or greater than their observed values (Tone and Tsutsui, 2009). In the real-world situation, government has the capacity to determine the provision of public services and products based on financial budget. Therefore, this study assumes the linking constraints as free link.

To better explore the relationship between different sectors, this study adopts the general two-stage network DEA for the efficiency analysis of resource-based cities. Improving the eco-efficiency of resource-based cities is not a discrete issue but a multifaceted process, requiring the participation of several sectors, such as the industrial and government sectors. The government sector and the industrial sector are regarded as the two components of a city. The government sector is responsible for public goods and services and provides support for the industrial sector, while the industrial sector is in charge of industrial production activities (Avelar-Sosa et al., 2018; The Chinese Government, 2017a; 2016). The government sector uses urban construction land and public finance expenditure to provide support for the industrial sector by providing infrastructure, technology, education, and healthcare. The industrial sector, which uses infrastructure, technology, education, and healthcare as intermediate inputs, also consumes energy, labor, and capital to jointly generate GDP as a good output and CO_2 emissions as a bad output. The general two-stage network system with the government and industrial sectors is illustrated in Fig. 2.

To evaluate the overall efficiency and the sectoral efficiency of a DMU, Tone and Tsutsui (2009) proposed a slack-based network DEA model, named the network slack-based model, to include intermediate products. To simultaneously deal with undesirable output, the objective function is modified accordingly. The eco-efficiency with undesirable outputs using network slack-based model under the constraint of the free link case can be defined as follows:

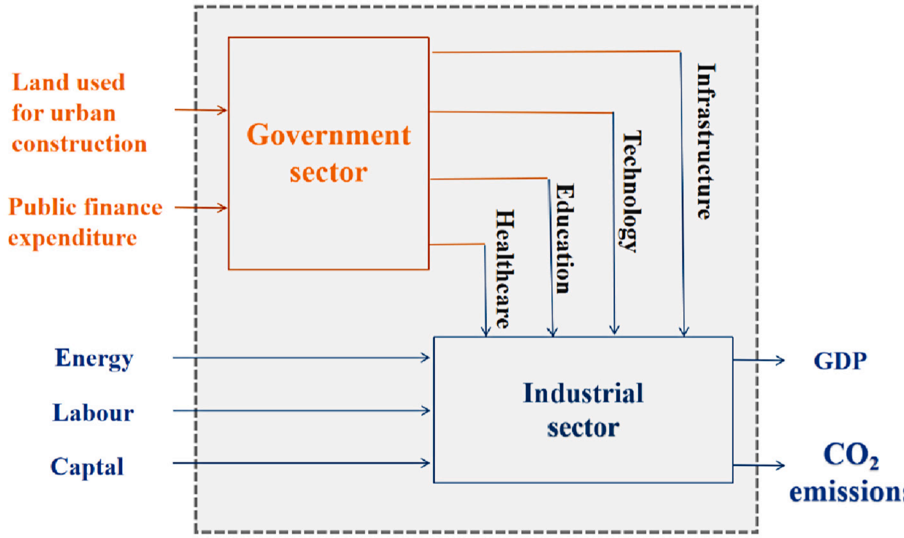

Fig. 2. The general two-stage network structure with the government and industrial sectors.

$$
\begin{aligned}
& Min\frac{w^k\left(1-\frac{1}{M^k}\sum_{m^k=1}^{M^k}\frac{s^{m^k}}{x^{m^k}}\right)+w^h\left(1-\frac{1}{M^h}\sum_{m^h=1}^{M^h}\frac{s^{m^h}}{x^{m^h}}\right)}{w^k\left[1+\frac{1}{E^k+F^k}\left(\sum_{e^k=1}^{E^k}\frac{s^{e^k}}{g^{e^k}}+\sum_{f^k=1}^{F^k}\frac{s^{f^k}}{b^{f^k}}\right)\right]+w^h\left[1+\frac{1}{E^h+F^h}\left(\sum_{e^h=1}^{E^h}\frac{s^{e^h}}{g^{e^h}}+\sum_{f^h=1}^{F^h}\frac{s^{f^h}}{b^{f^h}}\right)\right]} \\
& s.t. X^k=\sum_{i=1}^{N}\lambda_i^k X_i^k+S^{X^k} \quad X^h=\sum_{i=1}^{N}\lambda_i^h X_i^h+S^{X^h} \\
& G^k=\sum_{i=1}^{N}\lambda_i^k G_i^k-S^{G^k} \quad G^h=\sum_{i=1}^{N}\lambda_i^h G_i^h-S^{G^h} \\
& B^k=\sum_{i=1}^{N}\lambda_i^k B_i^k+S^{B^k} \quad B^h=\sum_{i=1}^{N}\lambda_i^h B_i^h+S^{B^h} \\
& \sum_{i=1}^{N}\lambda_i^k Z_i^{(k,h)}=\sum_{i=1}^{N}\lambda_i^h Z_i^{(k,h)} \\
& \lambda_i^k,\lambda_i^h\geq 0 \quad S^{X^k},S^{G^k},S^{B^k}\geq 0
\end{aligned}
\tag{8}
$$

where N indicates the number of DMUs over the whole period. Inputs, good outputs, and bad outputs are denoted as $X=(x_1,x_2,\dots,x_M)\in R_+{}^M$, $G=(g_1,g_2,\dots,g_E)\in R_+{}^E$, and$B=(b_1,b_2,\dots,b_M)\in R_+{}^F$, respectively. Variables M, E, and F indicate the number of inputs, good outputs, and bad outputs, respectively. Variables k and h indicate the government sector and the industrial sector, respectively. The slack variables of all inputs are denoted as $S^X=(s_1,s_2,\dots,s_M)\in R_+{}^M$. Since the government sector may take time to construct infrastructure, promote technology development, and improve the education and healthcare levels, this study considers this lagging effect by using the inputs in the previous year (t − 1) and the outputs in the current year (t) in the government sector.

Variables w^k and w^h are the weights of sectors k and h, respectively ($w^k+w^h=1$, and $w^k,w^h\geq 0$). The methods commonly used to determine the weight can be divided into two categories, endogenous weight method and exogenous weight method (Ang and Chen, 2016; Chen et al., 2018; Kao, 2013; Tone and Tsutsui, 2009). In this study, the weights are exogenous, indicating the weights are pre-determined based on the relative importance among different sectors. The pre-determined weight can be set according to cities' development stages and current main challenges, which serves as guidance in addressing problems. In this study, the weights are set as 1/3 and 2/3 for the governance efficiency and production efficiency, respectively, which are consistent with the weight levels of the separate DEA. The efficiency of the separate DEA equals 1/3 × Sector k + 2/3 × Sector h. The weight of governance efficiency is set to be smaller than that of production efficiency mainly because China has transformed from a planned economy to a socialistic market economy and production activities of entrepreneurs play an increasingly important role in economic structural reform (The Chinese Government, 2017). The weight is not fixed and can be adjusted based on the relative importance of the sector in each city. For a better comparison of the results using different weights, a weight sensitivity analysis ranging from 0.1 to 0.9 has been conducted for the 84 resource-based cities, as shown in Tables A3, A4, and A5. The results show that the overall efficiency will be affected when using different weights, while sectoral efficiency, in some cases, can remain unchanged. These findings are consistent with Guo et al. (2017).

Note that the eco-efficiency obtained from Eq. (8) is the overall efficiency, which can be further decomposed into the governance efficiency (*GE*) and the production efficiency (*PE*) based on Eqs. (9) and (10), respectively (Tone and Tsutsui, 2009). *GE* is to measure the quality of the government sector in providing public goods and services, which can be derived from Eq. (9). If the government sector can produce more public goods and services using limited inputs (e.g., fiscal expenditure), the performance of the government sector will improve. A government-production relationship can be described as that the government provides the road, where the entrepreneurs can drive the car (Lu and Pan, 2016). The outputs of the government sector include a series of public goods and services (Avelar-Sosa et al., 2018; Lu and Pan, 2016; The Chinese Government, 2017a; 2016). The government sector aims to provide fair, accessible, high-quality public goods and services for creating a favorable production environment (Cull et al., 2017; Hu et al., 2017; Lu and Pan, 2016).

The production sector is in charge of the provision of non-public goods and services (Long et al., 2019; Long et al., 2018b; Zhang and Choi, 2013b), whose target is earning profits. The industrial sector is made up of enterprises from diverse industries (e.g., thermal power plants, coal mining plants, and food processing plants), as shown in Table A2, and is one significant component of production sector in resource-based cities. *PE* is defined as the performance of production activities of enterprises in earning profits, *PE* of the industrial sector can be obtained based on Eq. (10). If the enterprises can produce more non-public goods and services with limited inputs, the performance of the production activities will improve.

$$GE = \frac{1 - \frac{1}{M^k} \sum_{m^k=1}^{M^k} \frac{s^{m^k}}{x^{m^k}}}{1 + \frac{1}{E^k + F^k} \left(\sum_{e^k=1}^{E^k} \frac{s^{e^k}}{g^{e^k}} + \sum_{f^k=1}^{F^k} \frac{s^{f^k}}{b^{f^k}} \right)} \tag{9}$$

$$PE = \frac{1 - \frac{1}{M^h} \sum_{m^h=1}^{M^h} \frac{s^{m^h}}{x^{m^h}}}{1 + \frac{1}{E^h + F^h} \left(\sum_{e^h=1}^{E^h} \frac{s^{e^h}}{g^{e^h}} + \sum_{f^h=1}^{F^h} \frac{s^{f^h}}{b^{f^h}} \right)} \tag{10}$$

where *GE* and *PE* lie in the range of [0,1]. If efficiency equals 1, then the

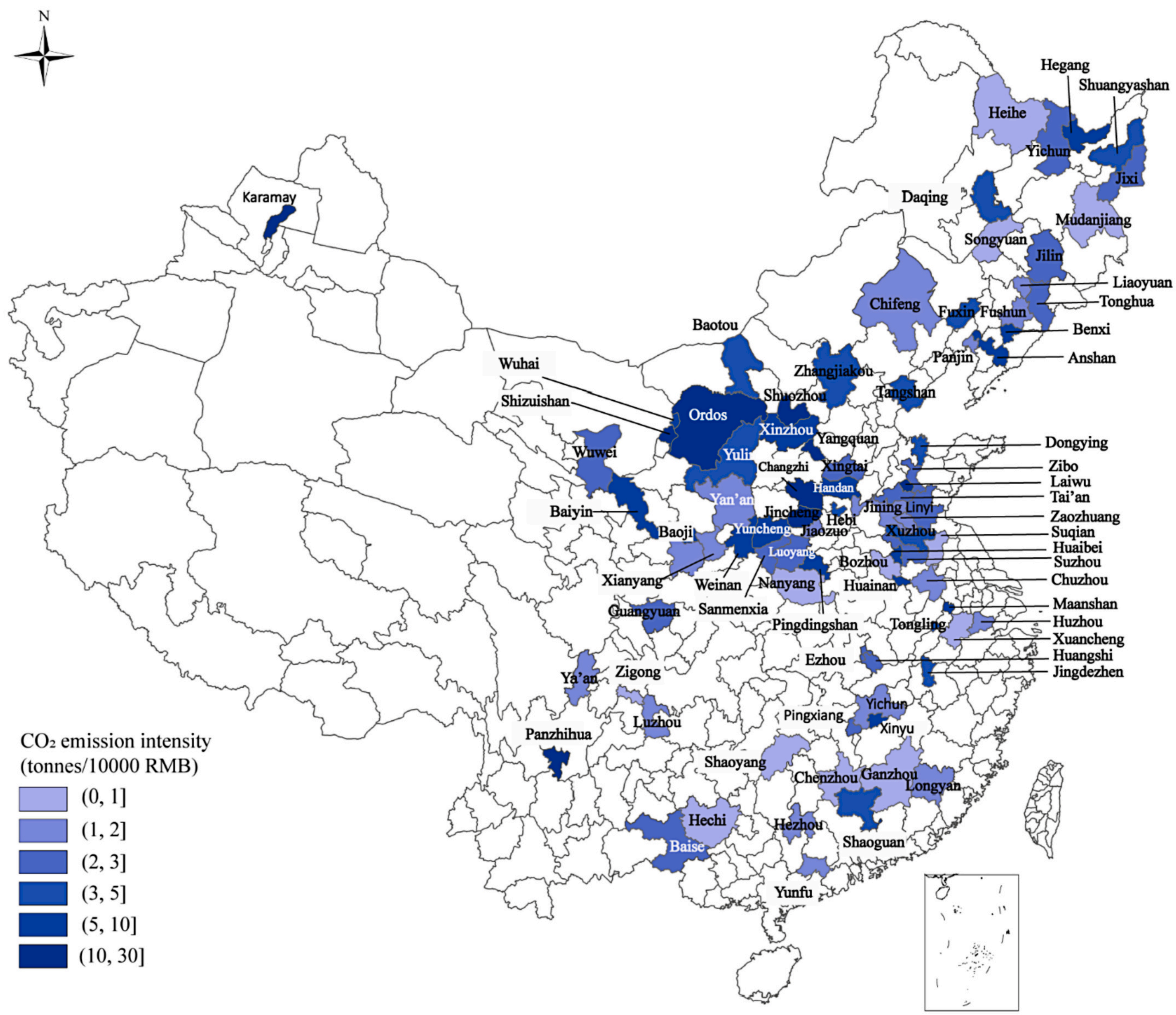

Fig. 3. Spatial distribution and emission intensity of 84 resource-based cities in China in 2015.

DMU is ranked as efficient; otherwise, it has room for improvement.

2.4. Energy inventory construction

We estimate the energy inventories of the industrial sectors of 84 resource-based cities from 2007 to 2015. The energy consumption of industrial sectors is the sum of the energy consumption of 40 subsectors (see Table A2). The energy consumption data are derived from the 'energy balance tables' and 'industrial sectoral energy consumption tables' of city-level statistical yearbooks. For cities that do not have complete data for a specific sector or energy type, this study follows Shan et al. (2017) to deduce 'industry sectoral energy consumption tables' and 'energy balance tables' using one case method involving four cases (Cases A, B, C, and D) and another case method involving three cases (Cases α, β, and γ) based on the corresponding data quality, respectively. To save space, the calculation details are not shown here; more information can be found in Shan et al. (2017). After calculating the energy consumption of 40 subsectors, we transform them into standard coal equivalents and then sum them to obtain the total energy consumption of the industrial sectors of each resource-based city.

2.5. CO_2 emission inventory construction

We further evaluate the CO_2 emissions of the industrial sectors of 84 resource-based cities in China during the 2007–2015 period. The methodology for constructing CO_2 emission inventories that we adopt in this study has been explained in a previous paper of our (Shan et al., 2017), and only the important steps are demonstrated here. The compilation of CO_2 emission inventories is based on the Intergovernmental Panel on Climate Change (IPCC, 2006). The CO_2 emissions of industrial sectors can be divided into two components: energy-related and process-related emissions.

The energy-related CO_2 emissions of the industrial sectors of resource-based cities are constructed as follows.

$$CE_{ij} = \sum_{i=1}^{17} \sum_{j=1}^{40} AD_{ij} \times NCV_i \times CC_i \times O_{ij} \tag{11}$$

In Eq. (11), variables CE_{ij}, NCV_i, CC_i, and O_{ij} are CO_2 emissions, the net caloric value, the carbon content per calorie, and the carbon oxidation ratio, respectively. Variables i and j indicate energy types and socio-economic sectors, respectively. Variable AD_{ij} is the energy consumption amount, which can be obtained following the method discussed in Section 2.4. The emission factors from Liu et al. (2015), which are more in line with China's energy quality (Li et al., 2019; Shan et al., 2019; Shan et al., 2018; Shan et al., 2016), are adopted in this study.

The process-related CO_2 emissions of the industrial sectors of resource-based cites are constructed as follows.

$$CE_{process} = \sum_t AD_t \times EF_t, t \in [1, 9] \tag{12}$$

In Eq. (12), variables $CE_{process}$ and t are CO_2 emissions and the industrial process, respectively (Shan et al., 2017). Variables AD_t and EF_t are activity data and emission factors, respectively. The emission factors are collected from Liu et al. (2015).

3. Sample cities, variable selection, and data

3.1. Sample cities

Since 1949, resource-based cities have generated at least 52.9 billion tonnes of raw coal, 5.5 billion tonnes of crude oil, 5.8 billion tonnes of iron ore, and 2 billion cubic meters of timber (The Chinese Government, 2013a), which significantly contributed to China's economic development (Li et al., 2013b; The Chinese Government, 2013a). The heavy resource dependence of resource-based cities inevitably leads to a large demand for fossil fuel and a vast quantity of CO_2 emissions. A series of social and economic problems also arise, such as an unbalanced industrial structure, a lack of technological innovation, and a high unemployment rate, which are also interrelated with the unsustainable development mode of resource-based cities (Qin et al., 2019; Ruan et al., 2020; Shao and Qi, 2008; Yan et al., 2019a). Natural resource curse theory and its transmission mechanisms (Betz et al., 2015; Shao and Qi, 2009), such as the Dutch disease (Shao et al., 2020b), the crowding-out effect (Shao and Qi, 2008; Shao and Yang, 2014), and the institutional weakening effect (Eregha and Mesagan, 2016; Mehlum et al., 2006), have been used to explain their problems of unsustainable development.

According to the Plan of Sustainable Development for Resource-based Cities in China (2013−2020) issued by the State Council, there are 262 resourced-based prefecture-level administrative units in China, among which 126 cities are prefecture-level administrative units (The Chinese Government, 2013a; 2013b). In this study, based on limitations in data quality, 84 out of 126 prefecture-level administrative units are chosen as sample cities for analysis (see Table A1). All sample cities are

Table 2
Variables selected in existing studies regarding the efficiency of the government sector.

No.	Authors	Inputs	Outputs
1	Ouertani et al. (2018)	Public spending on education; public spending on health; public spending on infrastructure	(1) Education: primary school enrolment; secondary school enrolment (2) Health: life expectancy; electricity transmission power; infant mortality (3) Infrastructure: energy consumption per capita; telephones per 100 habitats
2	Hauner and Kyobe (2010)	Health and education expenditure	(1) Education: primary school enrolment rates; secondary school enrolment rates; the primary completion rate (2) Health: the infant mortality rate; the mortality rate of female adults
3	Rayp and Van De Sijpe (2007)	Central government expenditure per capita in purchasing power parity	(1) Health: immunization against measles; infant mortality (2) Education: secondary school enrolment; the youth illiteracy rate (3) Government performance: government effectiveness (based on survey data evaluating the quality of government services)
4	Afonso and Fernandes (2006)	Per capita municipal expenditures	Total municipal output indicator, which includes four aspects: 'general administration', 'education', 'social activity' and 'basic sanitation and environmental protection'
5	De Borger et al. (1994)	Number of blue- and white-collar workers; space of buildings	(1) Education: the number of students enrolled in local primary schools (2) Infrastructure: the surface of municipal roads; the surface of public recreational facilities (3) Others: the number of beneficiaries of minimal subsistence grants; a centrality index for services delivered to non-residents

Table 3
Variables selected in existing studies regarding the efficiency of the different production sectors.

No.	Authors	Samples	Inputs	Desirable outputs	Undesirable outputs
1	Zhang et al. (2016c)	38 Chinese industrial sectors	Capital; labour; energy	Value added of industrial sectors	CO_2 emissions
2	Xiao et al. (2019b)	Secondary and service industries of cities in the Yangtze River Delta region	Capital; labor; energy	Value added of the secondary and service industries	CO_2 emissions
3	Zhang and Wei (2015)	Transport sectors of 30 provinces in China	Capital; labor; energy	Value added of the transportation industry	CO_2 emissions
4	Zhang et al. (2008)	Industrial system of 30 provinces in China	Water resource, raw mining resource; energy	value added of industry	COD discharge; nitrogen discharge; sulfur dioxide emission; soot emission; dust emission
5	Zhou et al. (2012)	Electricity generation of 129 countries	Fossil fuel	Electricity; heat	CO_2 emissions
6	Hua et al. (2007)	32 paper mills along the Huai River in China	Labour; capital; biochemical oxygen demand emission quota	Paper	Biochemical oxygen demand
7	Liu et al. (2017)	23 coal-fired power plants in China	Generator capacity; operation expenditure	Net generation	SO_2 emissions
8	Fan et al. (2017)	40 Chinese industrial parks	Land; energy; water	Industrial value added	Wastewater discharge; solid waste emissions; chemical oxygen demand emissions; SO_2 emissions

prefecture-level cities, which are Chinese administrative units with built-up urban and rural areas. In 2015, the 84 sample cities accounted for 66.66% of all resource-based cities and 78.33% of their GDP (NBS, 2016a; 2016b), and 21 of them have been listed as resource-exhausted cities (The Chinese Government, 2011). Regarding resource-based cities, there are a variety of natural resource types, such as coal, metal, non-metal, and oil. For decades, these cities have made great contributions to China's economic development by providing natural resource support (Li et al., 2013b; The Chinese Government, 2013a).

The spatial distribution of the 84 resource-based cities is presented in Fig. 3, and the color depth indicates the level of their emission intensity in 2015. Resource-based cities are widely distributed in China. In 2015, the emission intensity of the 84 resource-based cities was, on average, 4.39 t/10^4 RMB, ranging from 0.34 t/10^4 RMB to 25.49 t/10^4 RMB.

This study focuses only on industrial sectors, including 40 subsectors based on China's industrial classification of national economic activities (GB/T 4754-2017) (NAQSIQ, 2017) (see Table A2). This is mainly because industrial sectors consume a large amount of energy and are the most responsible for the high level of CO_2 emissions (Cao and Shen, 2013; Guo, 2015; Shao et al., 2020a), accounting for up to 95.01% of the total CO_2 emissions of resource-based cities in 2015, while the average share for China was 83.91%.[2]

3.2. Variable selection

A variety of inputs and outputs can be selected to measure governance efficiency and production efficiency (Chan and Karim, 2012; Liu et al., 2017; Ouertani et al., 2018). In this study, 11 variables are chosen as the inputs or outputs of the government and industrial sectors, as shown in Table 4. To better understand the choice of these 11 variables, relevant studies on governance efficiency and production efficiency are summarized in Tables 2 and 3, respectively.

For the government sector, the two inputs are public finance expenditure and the area of land used for urban construction, which can be used to provide public goods and services and for city planning. According to the National Bureau of Statistics of China, in 2019, national general public expenditure is mainly on education (14.61%), urban and rural community affairs (10.43%), agriculture, forestry and water conservancy (9.57%), healthcare (6.98%), transport (4.94%), and science and technology (3.99%) (NBSC, 2020). Based on the distribution of public finance, this study chooses education, infrastructure, healthcare, and technology as outputs of the government sector, which are also the intermediate products between the government sector and industrial sector.

The industrial sector, which is mainly composed of a large variety of enterprises, is responsible for the provision of non-public goods and services. For example, thermal power plants can provide electricity during production activities and then sale to residents. During the production process, the industrial sector generates GDP; at the same time, however, the production activities can also generate undesirable outputs, such as CO_2 emissions. In this study, three inputs, specifically capital, energy, and labor, are considered (Du et al., 2014; Li and Lin, 2015; Wang et al., 2013). This study includes CO_2 emissions as the undesirable output and GDP as the desirable output, which have been adopted by many studies (Li and Lin, 2015; Yao et al., 2015; Zhou et al., 2008a).

3.3. Data description

Data on GDP, public finance expenditure, the area of land used for urban construction, the number of students enrolled in institutions of higher education, the number of students enrolled in secondary schools, the number of students enrolled in primary schools, the number of beds in hospitals and health centers, the number of doctors (including licensed doctors and assistant doctors), the area of paved city roads, the capital stock, and the number of employed persons are collected from the China City Statistical Yearbooks from 2006 to 2016. The GDP of industrial sectors is deflated to 2006 prices using the GDP index. The GDP index data are collected from the statistical yearbook of each city and its corresponding province between 2006 and 2016. The innovation index data of cities are collected from Kou and Liu (2017); the innovation index is evaluated through innovation outputs, such as invention patents, utility patents, and design patents. The descriptive statistics and some details regarding variable processing are shown in Table 4.

[2] These data are estimated based on this study, and calculation details can be found in Section 2.5.

Table 4
Descriptive statistics of eleven variables, 2007–2015.

Variable	Unit	Mean	Std. Dev.	Min	Max	Description
Public finance expenditure	100 million yuan	140.09	103.17	13.55	661.84	Public finance expenditure, including expenditure for science, technology, education, social security, transport, and welfare
Land	sq. km	84.56	139.01	1.00	3203.00	Area of land used for urban construction
Education	–	440.00	312.11	41.31	1575.19	Education level$=6\times P+12\times S+16\times H$ P: the number of students enrolled in primary schools S: the number of students enrolled in secondary schools H: the number of students enrolled in institutions of higher education Note: the weighted values (6, 12, and 16) are set based on the length of school years
Infrastructure	10 thousand square meters	1051.87	834.34	14.00	4484.00	Area of paved city roads
Healthcare	–	9841.57	8318.13	1342.00	130,910.00	Healthcare level$=1/2\times B+1/2\times D$ B: the number of beds in hospitals and health centers D: the number of doctors (licensed doctors + assistant doctors)
Technology	–	1.55	2.59	0.01	22.86	The innovation performance is evaluated through innovation outputs, such as invention patents, utility patents, and design patents (Kou and Liu, 2017)
Labour	10 thousand persons	12.43	8.87	1.20	112.26	Employed persons in the industrial sector
Energy	Million tce	2486.71	3450.29	53.17	50,430.74	Energy consumption from the industrial sector (see Section 2.4).
Capital	100 million yuan	730.56	744.03	31.68	6498.82	Capital assets of industrial enterprises
GDP	100 million yuan	1857.67	2091.16	24.48	15,367.87	GDP of industrial sector
CO_2 emissions	Million tonnes	53.82	74.53	0.89	1077.13	CO_2 emissions from the industrial sector (see Section 2.5).

Table 5
Eco-efficiency of resource-based cities using the black-box DEA (blac.), the separate DEA (sepa.), and the two-stage network DEA (netw.) in 2015.

No.	City	Blac.	Sepa.	Netw.	No.	City	Blac.	Sepa.	Netw.
1	Tangshan	0.46	0.21	0.46	43	Jingdezhen	0.30	0.20	0.27
2	Handan	0.42	0.19	0.41	44	Pingxiang	0.54	0.33	0.34
3	Xingtai	0.49	0.24	0.46	45	Xinyu	0.23	0.18	0.26
4	Zhangjiakou	0.44	0.18	0.47	46	Ganzhou	1.00	0.70	0.92
5	Yangquan	0.29	0.19	0.15	47	Yichun-JX	0.75	0.70	0.59
6	Changzhi	0.40	0.17	0.38	48	Zibo	0.80	0.58	0.58
7	Jincheng	0.08	0.19	0.08	49	Zaozhuang	0.59	0.39	0.51
8	Shuozhou	0.28	0.19	0.08	50	Dongying	0.82	0.55	0.76
9	Yuncheng	0.41	0.20	0.42	51	Jining	0.48	0.22	0.47
10	Xinzhou	0.46	0.21	0.13	52	Taian	0.65	0.44	0.53
11	Baotou	0.37	0.16	0.40	53	Laiwu	0.27	0.28	0.28
12	Wuhai	0.22	0.33	0.23	54	Linyi	1.00	0.73	0.64
13	Chifeng	0.57	0.27	0.52	55	Luoyang	0.53	0.31	0.51
14	Ordos	0.45	0.34	0.44	56	Pingdingshan	0.38	0.18	0.39
15	Anshan	0.36	0.14	0.39	57	Hebi	0.42	0.31	0.34
16	Fushun	0.38	0.13	0.39	58	Jiaozuo	1.00	0.73	0.62
17	Benxi	0.21	0.16	0.39	59	Puyang	1.00	0.72	0.61
18	Fuxin	0.13	0.12	0.38	60	Sanmenxia	0.72	0.60	0.51
19	Panjin	0.56	0.36	0.53	61	Nanyang	0.63	0.40	0.60
20	Jilin	0.44	0.21	0.44	62	Huangshi	0.28	0.21	0.27
21	Liaoyuan	0.81	0.70	0.56	63	Ezhou	0.53	0.55	0.40
22	Tonghua	0.58	0.52	0.50	64	Shaoyang	1.00	0.71	0.96
23	Songyuan	0.70	0.70	0.43	65	Chenzhou	1.00	0.69	0.87
24	Jixi	0.08	0.10	0.08	66	Shaoguan	0.40	0.15	0.41
25	Hegang	0.16	0.14	0.07	67	Yunfu	0.50	0.44	0.34
26	Shuangyashan	0.09	0.15	0.09	68	Baise	0.30	0.23	0.31
27	Daqing	0.39	0.23	0.41	69	Hezhou	0.36	0.22	0.36
28	Yichun-HLJ	0.13	0.11	0.06	70	Hechi	0.30	0.25	0.28
29	Mudanjiang	0.36	0.25	0.52	71	Zigong	0.80	0.51	0.58
30	Heihe	0.11	0.12	0.10	72	Panzhihua	0.19	0.19	0.22
31	Xuzhou	1.00	0.72	0.93	73	Luzhou	0.50	0.33	0.55
32	Suqian	1.00	0.71	0.93	74	Guangyuan	0.31	0.21	0.31
33	Huzhou	0.86	1.00	0.64	75	Yaan	0.26	0.17	0.24
34	Huainan	0.09	0.18	0.11	76	Baoji	0.53	0.32	0.51
35	Maanshan	0.29	0.21	0.43	77	Xianyang	0.53	0.32	0.50
36	Huaibei	0.22	0.17	0.22	78	Weinan	0.43	0.16	0.42
37	Tongling	0.54	0.37	0.48	79	Yanan	0.70	0.20	0.63
38	Chuzhou	0.69	0.49	0.58	80	Yulin	0.46	0.29	0.45
39	Suzhou	0.47	0.30	0.43	81	Baiyin	0.15	0.17	0.15
40	Bozhou	0.42	0.28	0.56	82	Wuwei	0.19	0.17	0.20
41	Xuancheng	0.88	0.70	0.61	83	Shizuishan	0.15	0.19	0.17
42	Longyan	0.45	0.29	0.39	84	Karamay	0.25	0.19	0.25
						Average	0.48	0.33	0.42

Notes: Yichun-HLJ (No. 28) refers to the city in Heilongjiang Province, while Yichun-JX (No. 47) refers to the city in Jiangxi Province.

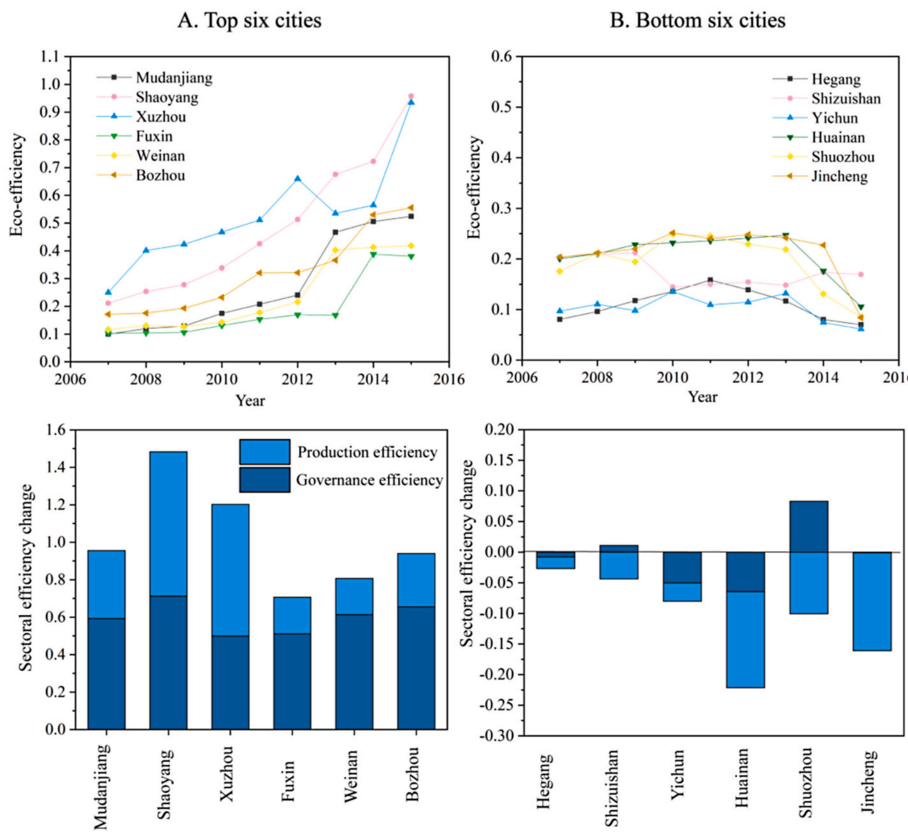

Fig. 4. Top six and bottom six cities in terms of the average annual growth rate of the eco-efficiency during the 2007–2015 period based on the two-stage network DEA (Yichun refers to the city in Heilongjiang Province).

4. Results and discussion

4.1. Comparisons of the eco-efficiency based on three models

Table 5 shows the average eco-efficiency in 2015 using three DEA methods, specifically the black-box, separate, and two-stage network DEA. The average levels of the eco-efficiency using the black-box, separate, and two-stage network DEA models are 0.48, 0.33, and 0.42, respectively (see Table 5), suggesting that there is much room for efficiency improvement. The black-box DEA tends to overestimate efficiency mainly because of the lack of knowledge about internal management defects. The gap between the separate DEA and the two-stage network DEA suggests that there is a 'networking effect' between the two sectors because the separate DEA neglects the links between the government and industrial sectors. The separate DEA fails to depict the full story once there is a 'networking effect' between different sectors.

The discriminating power of the black-box DEA model is inferior to that of the other two models. For example, using the black-box DEA, there are up to eight cities whose eco-efficiency is one (see Table 5), indicating that all of them are the best performers in the eco-efficiency and that the black-box DEA has relatively weak discriminating power when sorting the efficiency levels of DMUs. However, for the separate DEA, there is one city on the best-practice technology frontier (see Table 5). For the two-stage network DEA, all cities are not located on the frontier and still have improvement space (see Table 5), suggesting that this network DEA has a stronger ability to detect interior inefficiency than the black-box and separate DEA. This is because a DMU is efficient in a network system only if all its processes are efficient (Tone and Tsutsui, 2009). The result is consistent with Kao (2014a), Kao, 2014b) and Moreno and Lozano (2014).

Even though the efficiency rankings of these 84 cities using these three DEA models do not always correspond, their rankings change within a relatively small range, suggesting that the results of these three DEA models are robust and reliable. Based on the black-box DEA, eight cities show the best eco-efficiency located along the frontier in 2015: Xuzhou (1.00), Suqian (1.00), Ganzhou (1.00), Linyi (1.00), Jiaozuo (1.00), Puyang (1.00), Shaoyang (1.00), and Chenzhou (1.00) (see Table 5). Based on the separate DEA, Huzhou (1.00), Linyi (0.73), Jiaozuo (0.73), Puyang (0.72), Xuzhou (0.72), Shaoyang (0.71), Suqian (0.71), and Ganzhou (0.70) are the top eight best performers in the eco-efficiency (see Table 5). Based on the two-stage network DEA, Shaoyang (0.96), Xuzhou (0.93), Suqian (0.93), Ganzhou (0.92), Chenzhou (0.87), Dongying (0.76), Linyi (0.64), and Huzhou (0.64) are the top eight most eco-efficient cities (see Table 5).

4.2. The eco-efficiency over time

Based on the two-stage network DEA, the eco-efficiency patterns of the 84 resource-based cities display different characteristics mainly because of their large variation in socio-economic development, resource types, and resource reserves. Fig. 4(A and B) demonstrates the eco-efficiency of the top six and bottom six resource-based cities in terms of their average annual growth rate during the 2007–2015 period, respectively. The stacked bar charts indicate the absolute changes in governance efficiency (bottom part) and production efficiency (top part) in these cities during the 2007–2015 period. The top six resource-based cities that experience the most significant growth from 2007 to 2015 are Mudanjiang, Shaoyang, Xuzhou, Fuxin, Huainan, and Bozhou (see Fig. 4 (A)), while the bottom five cities that witness the most dramatic drop are Hegang, Shizuishan, Yichun, Weinan, Shuozhou, and Jincheng (see Fig. 4(B)).

Among the bottom six cities with the most significant decrease shown in Fig. 4, Yichun- HLJ (in Heilongjiang Province) is a resource-

Table 6
Governance efficiency (GE) and production efficiency (PE) of resource-based cities using the two-stage network DEA in 2015.

No.	City	GE	PE	No.	City	GE	PE
1	Tangshan	0.60	0.40	43	Jingdezhen	0.17	0.30
2	Handan	0.63	0.33	44	Pingxiang	0.26	0.37
3	Xingtai	0.63	0.39	45	Xinyu	0.06	0.33
4	Zhangjiakou	0.66	0.40	46	Ganzhou	0.76	1.00
5	Yangquan	0.10	0.15	47	Yichun-JX	0.69	0.54
6	Changzhi	0.62	0.30	48	Zibo	0.59	0.58
7	Jincheng	0.06	0.09	49	Zaozhuang	0.59	0.48
8	Shuozhou	0.03	0.10	50	Dongying	0.72	0.77
9	Yuncheng	0.73	0.31	51	Jining	0.61	0.40
10	Xinzhou	0.03	0.16	52	Taian	0.62	0.49
11	Baotou	0.58	0.33	53	Laiwu	0.10	0.34
12	Wuhai	0.20	0.24	54	Linyi	0.63	0.65
13	Chifeng	0.68	0.47	55	Luoyang	0.59	0.48
14	Ordos	0.71	0.35	56	Pingdingshan	0.63	0.30
15	Anshan	0.58	0.32	57	Hebi	0.38	0.33
16	Fushun	0.57	0.32	58	Jiaozuo	0.68	0.59
17	Benxi	0.58	0.32	59	Puyang	0.49	0.67
18	Fuxin	0.55	0.32	60	Sanmenxia	0.35	0.59
19	Panjin	0.62	0.48	61	Nanyang	0.69	0.57
20	Jilin	0.56	0.40	62	Huangshi	0.26	0.27
21	Liaoyuan	0.40	0.62	63	Ezhou	0.34	0.42
22	Tonghua	0.60	0.47	64	Shaoyang	0.87	1.00
23	Songyuan	0.29	0.50	65	Chenzhou	0.60	1.00
24	Jixi	0.05	0.09	66	Shaoguan	0.59	0.34
25	Hegang	0.05	0.08	67	Yunfu	0.22	0.39
26	Shuangyashan	0.05	0.10	68	Baise	0.17	0.36
27	Daqing	0.53	0.36	69	Hezhou	0.05	0.48
28	Yichun-HLJ	0.01	0.08	70	Hechi	0.13	0.34
29	Mudanjiang	0.66	0.47	71	Zigong	0.20	0.75
30	Heihe	0.03	0.13	72	Panzhihua	0.05	0.28
31	Xuzhou	0.80	1.00	73	Luzhou	0.61	0.53
32	Suqian	0.78	1.00	74	Guangyuan	0.10	0.38
33	Huzhou	0.65	0.63	75	Yaan	0.07	0.31
34	Huainan	0.12	0.10	76	Baoji	0.63	0.47
35	Maanshan	0.58	0.38	77	Xianyang	0.65	0.44
36	Huaibei	0.10	0.26	78	Weinan	0.70	0.32
37	Tongling	0.30	0.54	79	Yanan	0.71	0.59
38	Chuzhou	0.21	0.74	80	Yulin	0.69	0.36
39	Suzhou	0.60	0.37	81	Baiyin	0.12	0.17
40	Bozhou	0.72	0.49	82	Wuwei	0.07	0.25
41	Xuancheng	0.21	0.80	83	Shizuishan	0.04	0.21
42	Longyan	0.25	0.44	84	Karamay	0.08	0.31
					Average	0.42	0.42

Notes: Yichun-HLJ (No. 28) refers to the city in Heilongjiang Province, while Yichun-JX (No. 47) refers to the city in Jiangxi Province.

exhausted city according to the Chinese government (The Chinese Government, 2011). Yichun, the most important forestry-based city in China, sees a decline in the eco-efficiency, dropping from 0.10 in 2007 to 0.06 in 2015 (see Fig. 4(B)). The decreasing efficiencies of both the government sector and the industrial sector during the 2007–2015 period are responsible for the decline in the eco-efficiency (see Fig. 4 (B)). Yichun used to benefit greatly from the vast extractive industry and timber production, but due to its overdependence on the forestry industry, its industrial foundation for low-carbon and high value-added sectors remains underdeveloped, which may lead to a significant decrease in the efficiency of the government and industrial sectors as the forestry industry declines.

By contrast, Xuzhou, which used to be an old industrial base and a coal city in the Eastern region, is the second best performer in the eco-efficiency among the 84 resource-based cities in 2015 (see Tables 5 and 6). Moreover, it has made substantial improvements in the eco-efficiency and sectoral efficiency during the 2007–2015 period (see Fig. 4(A)). In our interpretation of this result, even though the Jiawang district in Xuzhou has been listed as a resource-depleted region since 2011 (The Chinese Government, 2011), Xuzhou has been performing positive industrial upgrading and transformation, and since 2015, the share of value added of the service industry has increased steadily, overtaking the secondary industry as the dominant industry (NBS, 2016b; The Xuzhou Government, 2017). The government sector of Xuzhou has also contributed to improving the city's eco-efficiency and can be regarded as a 'producer-friendly' government, as opposed to a 'grabber-friendly' government (Mehlum et al., 2006); its efficiency increased by 0.50 (164.51%) during the 2007–2015 period (see Fig. 4 (A)).

4.3. Governance efficiency and production efficiency

The government and industrial sectors are important components of a city and are interdependent on each other. They can perform their functions and give full play to their strengths in a framework in which they are organically combined to jointly promote low-carbon economic and sustainable development.

The outputs of government include a series of public goods and services, such as education, public health, basic science, cutting-edge technology, infrastructure, pollution control, and ecological protection (Avelar-Sosa et al., 2018; The Chinese government, 2016, 2017a; Zhang et al., 2018). Entrepreneurs could achieve great development with a high quality supply of public goods and services from the government. This is even more true for resource-based cities during periods of economic and social transformation (Ruan et al., 2020). It is important for the government to be a 'producer-friendly' government, as opposed to a 'grabber-friendly' government, and to make good use of large fiscal income to create an attractive production environment for entrepreneurs. For a 'producer-friendly' government system, the additional source of income generated from natural resources can produce positive externalities and stimulate production activities (Kaznacheev, 2017).

The industrial sector, which is mainly made up of enterprises from diverse industries, is in charge of the provision of non-public goods and services. During the production process, the industrial sector generates profit; at the same time, however, the production activities can also generate undesirable outputs, such as CO_2 emissions. It is necessary to determine the efficiency of the industrial and government sectors and their relationship to enhance the coordination between them.

The efficiency patterns may differ because China is vast a country with significant regional heterogeneity, so the resource-based cities are categorized into four regions (Lin and Xu, 2020; Long et al., 2013; Luo et al., 2020). Fig. 5 shows the governance efficiency and production efficiency of resource-based cities in the Eastern, Central, Western, and Northeast regions during the 2007–2015 period. The trends over time and the efficiency relationship between these two sectors vary significantly among the four regions. For resource-based cities in the Eastern region, governance efficiency increases by 111.11%, rising from 0.27 in 2007 to 0.57 in 2015 (see Fig. 5). The efficiency of the industrial sector of resource-based cities in the Eastern region also witnesses an increasing trend, rising by 77.63% over the study period (see Fig. 5). Compared with the resource-based cities in the other three regions, the Eastern region is the most efficient in terms of both the government sector and industrial sector (see Fig. 5).

For resource-based cities in the Western region, the efficiency of both the government sector and industrial sector is the lowest among the four regions. The efficiency of the government sector of the Western region experiences an increase from 0.13 in 2009 to 0.36 in 2014, while sees a decrease after 2014. This decreasing trend around 2014 can also be found in the Central and Northeast regions, which is a negative phenomenon for the production activities of industrial sectors. This decreasing trend shows the relatively low quality of the government sector in its usage of fiscal income after 2014. Resource-based cities can benefit greatly because of natural resource rent. The abundance of natural resources may result in rent-seeking behaviors, a waste of fiscal income, and corruption, thereby negatively affecting the quality of governance (Brunnschweiler, 2008). The inefficiency of the government sector as a result of the institutional weakening effect can be one reason for the unsustainable development of resource-based cities (Apergis and

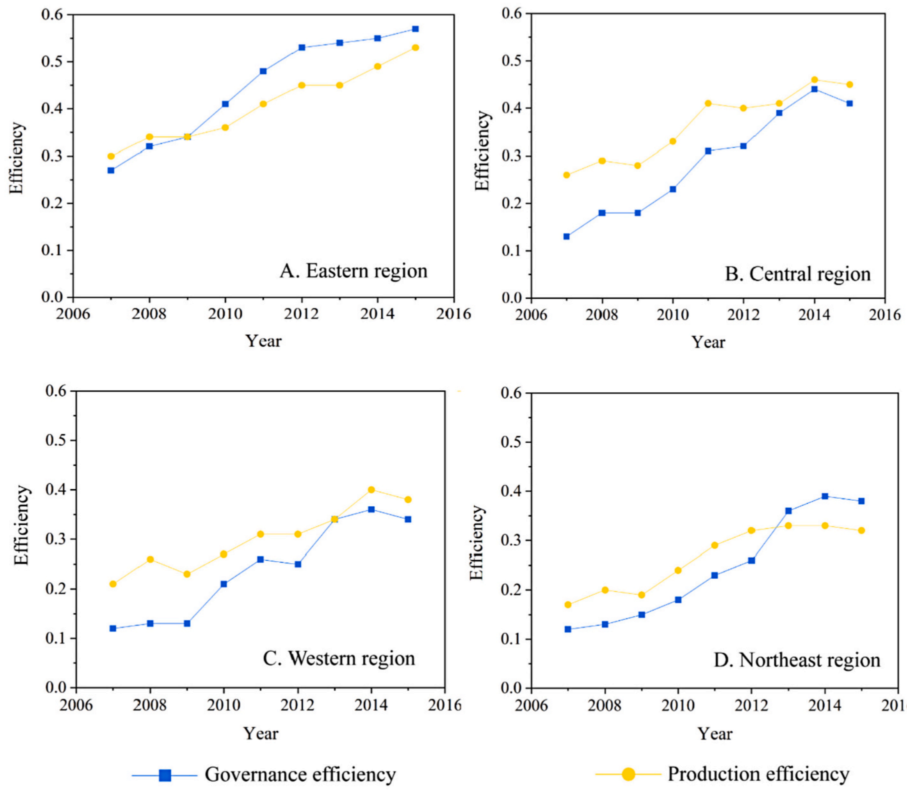

Fig. 5. Governance efficiency and production efficiency of resource-based cities in the Eastern, Central, Western, and Northeast regions from 2007 to 2015 using the two-stage network DEA.

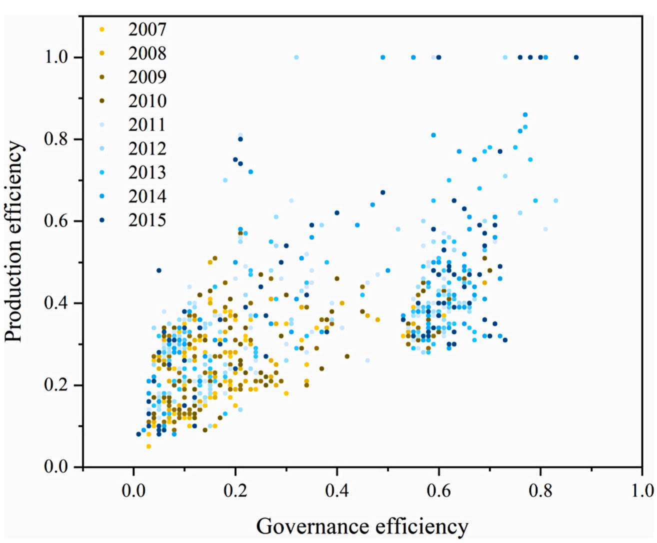

Fig. 6. Relationship between governance efficiency and production efficiency of resource-based cities between 2007 and 2015 using the two-stage network DEA.

Payne, 2014; Brunnschweiler, 2008; Kolstad, 2009; Mehlum et al., 2006). A 'grabber-friendly' government may negatively affect the sustainable development of resource-based cities if few entrepreneurial resources are attracted by the industrial sector (Mehlum et al., 2006). It is very important to make good use of the fiscal advantage coming from natural resource rent to create a more competitive production environment and to achieve a low-carbon economy.

For the Central and Western regions, the governance efficiency and production efficiency witness a sudden decrease in 2009 (see Fig. 5). In our interpretation of this result, the 2008 financial crisis exerted a negative impact on these two sectors. The sudden change in production efficiency of the industrial sector in China around the 2008 financial crisis has also been found by other studies (Zhang et al., 2016b; Zhang et al., 2016a). This sudden decrease can also be found in the Eastern and Northeast regions, but it is not significant.

As shown in Fig. 6, there is a positive relationship between governance efficiency and production efficiency. In other words, higher efficiency of the government sector may bring about more effective production activities of the industrial sector. This positive relationship mainly because the linking structure between these two sectors can affect the flow of intermediate products, such as infrastructure, technology, education, and healthcare, and further affect production activities (see Fig. 2). The decrease in governance efficiency in the Central, Western, and Northeast regions may restrain or even reverse the improvement trend of the production efficiency. Some studies have found that better support from the government has a positive impact on production activities (Avelar-Sosa et al., 2018; Cull et al., 2017) and that cities with lower efficiency are more sensitive to government intervention (Yan et al., 2019a). Improving governance efficiency can be a stepping stone for the normal operation of production activities and further improve the eco-efficiency.

Fig. 6 shows the relationship patterns between governance efficiency and production efficiency of 84 resource-based cities over the whole period. Various colors are used to represent different years. It can be seen that yellow color clusters in the bottom left corner, indicating that resource-based cities do not have an obvious difference in the eco-efficiency in the early period (see Fig. 6). By contrast, blue colors are widely distributed, suggesting that the inequality in efficiency of resource-based cities becomes larger in the later period. In other words, some cities are located on the top right corner with high governance efficiency and production efficiency, while some cities are located on the bottom left corner with low efficiency of both sectors (see Fig. 6). The distribution of resource-based cities in different periods shows that the eco-efficiency gaps of resource-based cities become larger with the development of the city. Some resource-based cities are faced with the dilemmas of resource depletion and struggle for urban transformation, upgrading, and sustainable development. Some resource-based cities have escaped from the institutional lock-in and path-dependence to foster new economic growth points.

Table 6 shows the governance efficiency and production efficiency of 84 resource-based cities using the two-stage network DEA in 2015. The average efficiency of the government sector (0.42) is similar to the production efficiency (0.42). The best performers in the government sector are Shaoyang (0.87) and Xuzhou (0.80). Shaoyang (1.00) and Xuzhou (1.00) are also the best performers in production efficiency. The sectoral efficiencies of these two cities have a value of 1.00, indicating that they are all located on the best-practice technology frontier. It is obvious that Shaoyang and Xuzhou have a 'producer-friendly' government that makes good use of public fiscal income to create a good business environment for production activities. Additionally, the entrepreneurs of Shaoyang and Xuzhou carry out effective production activities. Notably, Xinzhou, Heihe, and Yichun-HLJ perform the worst in terms of the government sector in 2015, with values of 0.03, 0.03, and 0.01, respectively. These three laggards in governance efficiency should shift from a 'grabber-friendly' role to a 'producer-friendly' role by improving the public finance system to offer high-quality public goods and services. Jincheng, Yichun-HLJ, and Hegang had the lowest production efficiency in 2015, with values of 0.09, 0.08, and 0.08, respectively. These three laggards in production efficiency should improve their efficiency by actively performing industrial upgrading, developing the substitution industry, prolonging the industry chain, and forming an ecological industrial circulation system.

5. Concluding remarks

To help China's resource-based cities achieve a low-carbon economy and sustainable development, this study measures the eco-efficiency considering the efficiency of the internal structure, that is, governance efficiency and production efficiency, by opening the black box. First, the CO_2 emission inventories of the industrial sectors of 84 resource-based cities from 2007 to 2015 are constructed. Then, to provide underlying diagnostic information potentially available to management, a two-stage network DEA framework is proposed to measure the eco-efficiency and sectoral efficiency. The empirical results and policy implications are as follows.

First, the average eco-efficiency of China's resource-based cities shows a promising increase from 0.22 in 2007 to 0.42 in 2015. The patterns of the eco-efficiency among the 84 resource-based cities display different characteristics mainly because of their large variation in socio-economic development, resource types, and resource reserves. Shaoyang-HN and Xuzhou-JS have 'producer-friendly' government. They can be a role model since they are the best performers in the eco-efficiency in 2015 and make tremendous improvements during the 2007–2015 period. In contrast, the bottom six cities that witness the most dramatic drop in the eco-efficiency over the study period are Hegang-HLJ, Shizuishan-NX, Yichun-HLJ, Huainan-AH, Shuozhou-SX, and Jingcheng-SX.

Second, there is a positive relationship between governance efficiency and production efficiency. Much attention should be paid to the resource-based cities in the Central, Western, and Northeast regions, in which the governance efficiency and production efficiency of these cities experience a decline after 2014. This trend shows the relatively low quality of the government sector in terms of its usage of fiscal income coming from natural resource rent. These resource-based cities should be alert to the possibility that a continuous decrease in the efficiency of the government sector may restrain or even reverse the increasing trend of production efficiency. This potential risk is mainly because the linking structure between these two sectors can affect the flow of intermediate products, such as infrastructure, technology, education, and healthcare. Proactive disclosure of how the government sector conducts the public business and spends taxpayers' money should be made to increase transparency, attract more entrepreneurial resources to carry out production activities, and further promote sustainable development.

Finally, the inequality in efficiency of resource-based cities becomes larger with the development of the city. Resource-based cities do not show an obvious difference in efficiency in the early period, however, the inequality in efficiency becomes larger in the later period. Some resource-based cities are faced with the dilemmas of resource depletion and struggle for urban transformation, upgrading, and sustainable development. Some resource-based cities have escaped from the institutional lock-in and path-dependence to foster new economic growth points.

Policies for improving eco-efficiency should be differentiated based on sector-specific efficiency as follows. First, improving governance efficiency is an important measure for further deepening systematic reform and facilitating production activities. The government sector should make good use of the fiscal advantage provided by natural resource rent. It is important to move away from a 'grabber-friendly' government and to move towards a 'producer-friendly' government. A reasonable and transparent financial expenditure distribution system should be provided to promote infrastructure construction, technology innovation, human capital accumulation, and sound healthcare system construction. Second, regarding the industrial sector, which directly generates CO_2 emissions, industrial upgrading should be actively performed, the substitution industry should be developed, the industry chain should be prolonged, and an ecological industrial circulation system should be formed. Traditional and ineffective production technology should be replaced by green and advanced technology to consume fewer inputs, generate more desirable outputs, and produce a lower amount of CO_2 emissions. Finally, bilateral cooperation between the government and industrial sectors should be enhanced by strengthening communication. Much attention should be paid to the resource-based cities in the Western, Central, and Northeast regions to contain the decreasing governance efficiency and production efficiency.

This study has some limitations. First, the undesirable outputs generated by the industrial sector vary, and apart from CO_2 emissions, some pollutants, such as sulfur dioxide and solid waste, can be included in future work. Second, this study focuses only on the industrial sectors of resource-based cities, and further studies can explore other sectors to identify similarities and differences.

Acknowledgments

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Table A1
List of 84 sample resource-based cities.

No.	Province	City	No.	Province	City	No.	Province	City
1	Hebei	Tangshan	29	Heilongjiang	Mudanjiang	57	Henan	Hebi
2	Hebei	Handan	30	Heilongjiang	Heihe	58	Henan	Jiaozuo
3	Hebei	Xingtai	31	Jiangsu	Xuzhou	59	Henan	Puyang
4	Hebei	Zhangjiakou	32	Jiangsu	Suqian	60	Henan	Sanmenxia
5	Shanxi	Yangquan	33	Zhejiang	Huzhou	61	Henan	Nanyang
6	Shanxi	Changzhi	34	Anhui	Huainan	62	Hubei	Huangshi
7	Shanxi	Jincheng	35	Anhui	Maanshan	63	Hubei	Ezhou
8	Shanxi	Shuozhou	36	Anhui	Huaibei	64	Hunan	Shaoyang
9	Shanxi	Yuncheng	37	Anhui	Tongling	65	Hunan	Chenzhou
10	Shanxi	Xinzhou	38	Anhui	Chuzhou	66	Guangdong	Shaoguan
11	Inner Mongolia	Baotou	39	Anhui	Suzhou	67	Guangdong	Yunfu
12	Inner Mongolia	Wuhai	40	Anhui	Bozhou	68	Guangxi	Baise
13	Inner Mongolia	Chifeng	41	Anhui	Xuancheng	69	Guangxi	Hezhou
14	Inner Mongolia	Ordos	42	Fujian	Longyan	70	Guangxi	Hechi
15	Liaoning	Anshan	43	Jiangxi	Jingdezhen	71	Sichuan	Zigong
16	Liaoning	Fushun	44	Jiangxi	Pingxiang	72	Sichuan	Panzhihua
17	Liaoning	Benxi	45	Jiangxi	Xinyu	73	Sichuan	Luzhou
18	Liaoning	Fuxin	46	Jiangxi	Ganzhou	74	Sichuan	Guangyuan
19	Liaoning	Panjin	47	Jiangxi	Yichun	75	Sichuan	Yaan
20	Jilin	Jilin	48	Shandong	Zibo	76	Shaanxi	Baoji
21	Jilin	Liaoyuan	49	Shandong	Zaozhuang	77	Shaanxi	Xianyang
22	Jilin	Tonghua	50	Shandong	Dongying	78	Shaanxi	Weinan
23	Jilin	Songyuan	51	Shandong	Jining	79	Shaanxi	Yanan
24	Heilongjiang	Jixi	52	Shandong	Taian	80	Shaanxi	Yulin
25	Heilongjiang	Hegang	53	Shandong	Laiwu	81	Gansu	Baiyin
26	Heilongjiang	Shuangyashan	54	Shandong	Linyi	82	Gansu	Wuwei
27	Heilongjiang	Daqing	55	Henan	Luoyang	83	Ningxia	Shizuishan
28	Heilongjiang	Yichun	56	Henan	Pingdingshan	84	Xinjiang	Karamay

Table A2
List of 40 industrial sectors.

No.	Socioeconomic sectors	No.	Socioeconomic sectors
1	Coal Mining and Dressing	21	Raw Chemical Materials and Chemical Products
2	Petroleum and Natural Gas Extraction	22	Medical and Pharmaceutical Products
3	Ferrous Metals Mining and Dressing	23	Chemical Fiber
4	Nonferrous Metals Mining and Dressing	24	Rubber Products
5	Nonmetal Minerals Mining and Dressing	25	Plastic Products
6	Other Minerals Mining and Dressing	26	Nonmetal Mineral Products
7	Logging and Transport of Wood and Bamboo	27	Smelting and Pressing of Ferrous Metals
8	Food Processing	28	Smelting and Pressing of Nonferrous Metals
9	Food Production	29	Metal Products
10	Beverage Production	30	Ordinary Machinery
11	Tobacco Processing	31	Equipment for Special Purposes
12	Textile Industry	32	Transportation Equipment
13	Garments and Other Fiber Products	33	Electric Equipment and Machinery
14	Leather, Furs, Down, and Related Products	34	Electronic and Telecommunications Equipment
15	Timber Processing, Bamboo, Cane, Palm Fiber, and Straw Products	35	Instruments, Meters, Cultural, and Office Machinery
16	Furniture Manufacturing	36	Other Manufacturing Industry
17	Papermaking and Paper Products	37	Scrap and waste
18	Printing and Record Medium Reproduction	38	Production and Supply of Electric Power, Steam, and Hot Water
19	Cultural, Educational and Sports Articles	39	Production and Supply of Gas
20	Petroleum Processing and Coking	40	Production and Supply of Tap Water

Table A3
The eco-efficiency of the two-stage network DEA using different weights in 2015.

City	(0.1,0.9)	(0.3,0.7)	(0.5,0.5)	(0.7,0.3)	(0.9,0.1)	City	(0.1,0.9)	(0.3,0.7)	(0.5,0.5)	(0.7,0.3)	(0.9,0.1)
Tangshan	0.42	0.45	0.49	0.53	0.54	Jingdezhen	0.38	0.27	0.25	0.20	0.11
Handan	0.35	0.40	0.45	0.50	0.10	Pingxiang	0.45	0.48	0.33	0.27	0.16
Xingtai	0.41	0.45	0.49	0.20	0.12	Xinyu	0.35	0.27	0.22	0.16	0.09
Zhangjiakou	0.42	0.46	0.51	0.16	0.08	Ganzhou	0.98	0.93	0.88	0.83	0.39
Yangquan	0.33	0.15	0.21	0.17	0.12	Yichun-JX	0.55	0.58	0.61	0.38	0.26
Changzhi	0.31	0.37	0.19	0.15	0.10	Zibo	0.58	0.58	0.59	0.59	0.33
Jincheng	0.31	0.36	0.19	0.15	0.11	Zaozhuang	0.48	0.51	0.40	0.34	0.23
Shuozhou	0.35	0.09	0.22	0.17	0.12	Dongying	0.76	0.76	0.62	0.54	0.45
Yuncheng	0.34	0.41	0.15	0.15	0.09	Jining	0.42	0.46	0.50	0.52	0.53
Xinzhou	0.39	0.46	0.11	0.16	0.09	Taian	0.49	0.52	0.54	0.38	0.26
Baotou	0.35	0.39	0.43	0.15	0.08	Laiwu	0.34	0.28	0.24	0.19	0.14
Wuhai	0.45	0.23	0.27	0.19	0.10	Linyi	0.65	0.64	0.64	0.63	0.42
Chifeng	0.48	0.52	0.56	0.22	0.11	Luoyang	0.49	0.51	0.53	0.54	0.16
Ordos	0.38	0.43	0.49	0.53	0.12	Pingdingshan	0.32	0.38	0.20	0.15	0.10
Anshan	0.34	0.38	0.43	0.14	0.07	Hebi	0.41	0.34	0.35	0.28	0.18
Fushun	0.34	0.38	0.12	0.12	0.06	Jiaozuo	0.59	0.61	0.59	0.56	0.49
Benxi	0.34	0.38	0.20	0.15	0.08	Puyang	0.65	0.66	0.58	0.52	0.45
Fuxin	0.34	0.37	0.10	0.12	0.05	Sanmenxia	0.59	0.52	0.47	0.39	0.28
Panjin	0.49	0.52	0.31	0.23	0.15	Nanyang	0.57	0.60	0.61	0.61	0.24
Jilin	0.41	0.43	0.46	0.19	0.10	Huangshi	0.38	0.42	0.25	0.18	0.11
Liaoyuan	0.63	0.56	0.50	0.42	0.30	Ezhou	0.43	0.40	0.38	0.32	0.20
Tonghua	0.47	0.50	0.35	0.31	0.20	Shaoyang	0.99	0.96	0.69	0.57	0.45
Songyuan	0.63	0.64	0.40	0.36	0.26	Chenzhou	0.96	0.88	0.80	0.45	0.29
Jixi	0.29	0.08	0.07	0.11	0.05	Shaoguan	0.36	0.40	0.19	0.15	0.07
Hegang	0.30	0.07	0.06	0.11	0.05	Yunfu	0.44	0.34	0.34	0.27	0.16
Shuangyashan	0.31	0.09	0.08	0.12	0.05	Baise	0.49	0.31	0.26	0.19	0.10
Daqing	0.38	0.40	0.23	0.17	0.10	Hezhou	0.38	0.32	0.27	0.20	0.10
Yichun-HLJ	0.07	0.06	0.05	0.04	0.05	Hechi	0.32	0.29	0.24	0.18	0.44
Mudanjiang	0.49	0.52	0.25	0.20	0.10	Zigong	0.75	0.60	0.50	0.37	0.24
Heihe	0.12	0.10	0.08	0.06	0.05	Panzhihua	0.30	0.21	0.19	0.14	0.08
Xuzhou	0.98	0.94	0.90	0.86	0.82	Luzhou	0.53	0.55	0.34	0.27	0.14
Suqian	0.98	0.93	0.89	0.56	0.44	Guangyuan	0.50	0.32	0.26	0.19	0.09
Huzhou	0.63	0.64	0.55	0.44	0.34	Yaan	0.29	0.25	0.21	0.15	0.07
Huainan	0.35	0.39	0.21	0.15	0.09	Baoji	0.47	0.50	0.35	0.28	0.17
Maanshan	0.39	0.42	0.26	0.20	0.13	Xianyang	0.45	0.49	0.53	0.24	0.14
Huaibei	0.33	0.22	0.20	0.15	0.09	Weinan	0.35	0.41	0.46	0.14	0.08
Tongling	0.55	0.48	0.44	0.34	0.22	Yanan	0.57	0.63	0.14	0.24	0.13
Chuzhou	0.72	0.59	0.49	0.38	0.26	Yulin	0.39	0.44	0.50	0.53	0.10
Suzhou	0.39	0.43	0.30	0.23	0.13	Baiyin	0.41	0.16	0.14	0.16	0.08
Bozhou	0.51	0.55	0.30	0.23	0.13	Wuwei	0.47	0.21	0.18	0.15	0.07
Xuancheng	0.81	0.80	0.51	0.40	0.26	Shizuishan	0.36	0.17	0.21	0.16	0.09
Longyan	0.57	0.39	0.36	0.26	0.14	Karamay	0.33	0.13	0.21	0.16	0.11

Notes: (0.1, 0.9) indicates the weights of government sector and industrial sector are 0.1 and 0.9, respectively.

Table A4
Governance efficiency of the two-stage network DEA using different weights in 2015.

City	(0.1,0.9)	(0.3,0.7)	(0.5,0.5)	(0.7,0.3)	(0.9,0.1)	City	(0.1,0.9)	(0.3,0.7)	(0.5,0.5)	(0.7,0.3)	(0.9,0.1)
Tangshan	0.60	0.60	0.60	0.55	0.55	Jingdezhen	0.61	0.17	0.17	0.06	0.06
Handan	0.64	0.63	0.61	0.55	0.07	Pingxiang	0.73	0.61	0.20	0.10	0.10
Xingtai	0.65	0.63	0.61	0.07	0.07	Xinyu	0.59	0.07	0.06	0.06	0.06
Zhangjiakou	0.66	0.66	0.65	0.04	0.04	Ganzhou	0.76	0.76	0.76	0.76	0.32
Yangquan	0.61	0.10	0.10	0.10	0.10	Yichun-JX	0.73	0.69	0.67	0.26	0.19
Changzhi	0.68	0.64	0.07	0.07	0.07	Zibo	0.61	0.59	0.59	0.58	0.27
Jincheng	0.67	0.61	0.08	0.08	0.08	Zaozhuang	0.64	0.59	0.25	0.23	0.17
Shuozhou	0.69	0.03	0.08	0.08	0.08	Dongying	0.74	0.72	0.41	0.41	0.41
Yuncheng	0.74	0.74	0.05	0.06	0.06	Jining	0.61	0.61	0.59	0.55	0.52
Xinzhou	0.77	0.76	0.03	0.06	0.06	Taian	0.75	0.62	0.59	0.20	0.20
Baotou	0.58	0.58	0.58	0.04	0.04	Laiwu	0.54	0.10	0.10	0.10	0.10
Wuhai	0.57	0.20	0.05	0.05	0.05	Linyi	0.64	0.63	0.63	0.61	0.36
Chifeng	0.74	0.68	0.68	0.09	0.05	Luoyang	0.60	0.59	0.59	0.55	0.10
Ordos	0.72	0.71	0.65	0.56	0.09	Pingdingshan	0.63	0.63	0.07	0.07	0.07
Anshan	0.58	0.58	0.58	0.04	0.04	Hebi	0.66	0.38	0.27	0.14	0.13
Fushun	0.57	0.57	0.08	0.02	0.02	Jiaozuo	0.71	0.68	0.52	0.46	0.46
Benxi	0.59	0.58	0.05	0.05	0.05	Puyang	0.74	0.67	0.44	0.43	0.40
Fuxin	0.55	0.55	0.05	0.01	0.01	Sanmenxia	0.84	0.35	0.33	0.26	0.21
Panjin	0.66	0.62	0.12	0.12	0.10	Nanyang	0.72	0.69	0.63	0.58	0.19
Jilin	0.56	0.56	0.55	0.05	0.05	Huangshi	0.59	0.59	0.07	0.07	0.07
Liaoyuan	0.65	0.40	0.29	0.29	0.22	Ezhou	0.57	0.34	0.28	0.13	0.13
Tonghua	0.63	0.60	0.24	0.20	0.13	Shaoyang	0.87	0.87	0.38	0.38	0.38
Songyuan	0.71	0.62	0.29	0.21	0.21	Chenzhou	0.60	0.60	0.60	0.21	0.21
Jixi	0.54	0.08	0.02	0.02	0.02	Shaoguan	0.60	0.59	0.13	0.03	0.03
Hegang	0.56	0.05	0.05	0.02	0.02	Yunfu	0.76	0.22	0.17	0.15	0.10
Shuangyashan	0.57	0.05	0.05	0.02	0.02	Baise	0.85	0.17	0.07	0.06	0.05
Daqing	0.53	0.53	0.06	0.06	0.06	Hezhou	0.09	0.09	0.09	0.09	0.03
Yichun-HLJ	0.01	0.01	0.01	0.01	0.01	Hechi	0.13	0.13	0.07	0.07	0.38
Mudanjiang	0.66	0.66	0.10	0.06	0.03	Zigong	0.57	0.20	0.18	0.18	0.17
Heihe	0.05	0.03	0.03	0.03	0.01	Panzhihua	0.57	0.09	0.05	0.05	0.05
Xuzhou	0.80	0.80	0.80	0.80	0.80	Luzhou	0.64	0.61	0.15	0.13	0.06
Suqian	0.78	0.78	0.78	0.38	0.38	Guangyuan	0.71	0.10	0.10	0.05	0.03
Huzhou	0.70	0.66	0.29	0.29	0.29	Yaan	0.08	0.07	0.07	0.02	0.02
Huainan	0.57	0.57	0.05	0.05	0.05	Baoji	0.69	0.64	0.17	0.15	0.10
Maanshan	0.59	0.58	0.09	0.09	0.09	Xianyang	0.70	0.65	0.58	0.12	0.09
Huaibei	0.55	0.10	0.06	0.06	0.06	Weinan	0.71	0.70	0.59	0.05	0.05
Tongling	0.58	0.30	0.30	0.15	0.15	Yanan	1.00	0.71	0.05	0.08	0.08
Chuzhou	0.60	0.21	0.21	0.21	0.19	Yulin	0.70	0.69	0.66	0.54	0.07
Suzhou	0.66	0.60	0.17	0.11	0.07	Baiyin	0.58	0.12	0.02	0.04	0.04
Bozhou	0.74	0.72	0.11	0.11	0.07	Wuwei	0.72	0.07	0.07	0.02	0.02
Xuancheng	0.74	0.74	0.21	0.19	0.19	Shizuishan	0.57	0.04	0.06	0.06	0.06
Longyan	0.75	0.25	0.11	0.11	0.07	Karamay	0.58	0.04	0.08	0.08	0.08

Notes: (0.1, 0.9) indicates the weights of government sector and industrial sector are 0.1 and 0.9, respectively.

Table A5
Production efficiency of the two-stage network DEA using different weights in 2015.

City	(0.1,0.9)	(0.3,0.7)	(0.5,0.5)	(0.7,0.3)	(0.9,0.1)	City	(0.1,0.9)	(0.3,0.7)	(0.5,0.5)	(0.7,0.3)	(0.9,0.1)
Tangshan	0.40	0.40	0.40	0.48	0.51	Jingdezhen	0.36	0.30	0.30	0.44	0.45
Handan	0.33	0.33	0.35	0.41	0.32	Pingxiang	0.42	0.43	0.43	0.61	0.61
Xingtai	0.39	0.39	0.41	0.45	0.45	Xinyu	0.33	0.33	0.33	0.33	0.33
Zhangjiakou	0.40	0.40	0.40	0.37	0.37	Ganzhou	1.00	1.00	1.00	1.00	1.00
Yangquan	0.30	0.15	0.30	0.30	0.30	Yichun-JX	0.54	0.54	0.55	0.64	0.87
Changzhi	0.28	0.29	0.28	0.28	0.28	Zibo	0.58	0.58	0.58	0.59	0.84
Jincheng	0.28	0.29	0.28	0.28	0.28	Zaozhuang	0.47	0.48	0.52	0.57	0.74
Shuozhou	0.32	0.10	0.31	0.31	0.31	Dongying	0.77	0.77	0.80	0.80	0.81
Yuncheng	0.31	0.31	0.21	0.29	0.29	Jining	0.40	0.40	0.41	0.47	0.59
Xinzhou	0.36	0.37	0.16	0.33	0.33	Taian	0.47	0.49	0.50	0.75	0.75
Baotou	0.33	0.33	0.33	0.32	0.32	Laiwu	0.33	0.34	0.34	0.34	0.34
Wuhai	0.44	0.24	0.43	0.43	0.43	Linyi	0.65	0.65	0.65	0.67	0.96
Chifeng	0.45	0.47	0.47	0.47	0.56	Luoyang	0.48	0.48	0.48	0.53	0.59
Ordos	0.35	0.35	0.39	0.47	0.33	Pingdingshan	0.30	0.30	0.29	0.29	0.29
Anshan	0.32	0.32	0.32	0.31	0.31	Hebi	0.39	0.33	0.40	0.55	0.55
Fushun	0.32	0.32	0.15	0.31	0.31	Jiaozuo	0.58	0.59	0.66	0.80	0.80
Benxi	0.32	0.32	0.31	0.31	0.31	Puyang	0.64	0.65	0.72	0.73	0.88
Fuxin	0.32	0.32	0.14	0.30	0.30	Sanmenxia	0.57	0.59	0.61	0.70	0.85
Panjin	0.47	0.48	0.49	0.50	0.59	Nanyang	0.56	0.57	0.60	0.65	0.71
Jilin	0.40	0.40	0.40	0.45	0.45	Huangshi	0.37	0.37	0.40	0.40	0.40
Liaoyuan	0.62	0.62	0.71	0.72	1.00	Ezhou	0.42	0.42	0.46	0.69	0.69
Tonghua	0.46	0.47	0.45	0.53	0.75	Shaoyang	1.00	1.00	1.00	1.00	1.00
Songyuan	0.63	0.65	0.50	0.72	0.73	Chenzhou	1.00	1.00	1.00	1.00	1.00
Jixi	0.27	0.08	0.10	0.27	0.27	Shaoguan	0.34	0.34	0.22	0.34	0.34
Hegang	0.28	0.08	0.08	0.27	0.27	Yunfu	0.41	0.39	0.49	0.54	0.75
Shuangyashan	0.29	0.10	0.10	0.28	0.28	Baise	0.46	0.36	0.41	0.42	0.45
Daqing	0.36	0.36	0.36	0.36	0.36	Hezhou	0.40	0.40	0.40	0.40	0.62
Yichun-HLJ	0.08	0.08	0.08	0.08	0.38	Hechi	0.34	0.34	0.41	0.41	1.00
Mudanjiang	0.47	0.47	0.37	0.48	0.64	Zigong	0.77	0.75	0.82	0.82	0.91
Heihe	0.12	0.13	0.13	0.13	0.33	Panzhihua	0.28	0.24	0.28	0.28	0.28
Xuzhou	1.00	1.00	1.00	1.00	1.00	Luzhou	0.52	0.53	0.50	0.53	0.83
Suqian	1.00	1.00	1.00	1.00	1.00	Guangyuan	0.48	0.38	0.38	0.43	0.51
Huzhou	0.62	0.63	0.79	0.79	0.79	Yaan	0.31	0.31	0.31	0.40	0.40
Huainan	0.33	0.33	0.32	0.32	0.32	Baoji	0.45	0.46	0.49	0.52	0.66
Maanshan	0.38	0.38	0.39	0.39	0.39	Xianyang	0.43	0.44	0.48	0.52	0.57
Huaibei	0.31	0.26	0.30	0.30	0.30	Weinan	0.32	0.32	0.38	0.29	0.29
Tongling	0.54	0.54	0.54	0.73	0.73	Yanan	0.52	0.59	0.21	0.60	0.61
Chuzhou	0.73	0.74	0.74	0.74	0.80	Yulin	0.36	0.36	0.38	0.50	0.34
Suzhou	0.36	0.37	0.39	0.45	0.53	Baiyin	0.39	0.17	0.22	0.38	0.38
Bozhou	0.49	0.49	0.46	0.46	0.69	Wuwei	0.45	0.25	0.25	0.38	0.38
Xuancheng	0.82	0.82	0.80	0.89	0.89	Shizuishan	0.34	0.21	0.33	0.33	0.33
Longyan	0.55	0.44	0.56	0.57	0.67	Karamay	0.31	0.16	0.31	0.31	0.31

Notes: (0.1, 0.9) indicates the weights of government sector and industrial sector are 0.1 and 0.9, respectively.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.eneco.2021.105408.

References

Adler, N., Liebert, V., Yazhemsky, E., 2013. Benchmarking airports from a managerial perspective. Omega 41, 442–458. https://doi.org/10.1016/j.omega.2012.02.004.

Afonso, A., Fernandes, S., 2006. Measuring local government spending efficiency: evidence for the Lisbon region. Reg. Stud. 40, 39–53. https://doi.org/10.1080/00343400500449937.

Ang, S., Chen, C.-M., 2016. Pitfalls of decomposition weights in the additive multi-stage DEA model. Omega 58, 139–153. https://doi.org/10.1016/j.omega.2015.05.008.

Apergis, N., Payne, J.E., 2014. The oil curse, institutional quality, and growth in MENA countries: evidence from time-varying cointegration. Energy Econ. 46, 1–9. https://doi.org/10.1016/j.eneco.2014.08.026.

Avelar-Sosa, L., García-Alcaraz, J.L., Mejía-Muñoz, J.M., Maldonado-Macías, A.A., Hernández, G.A., 2018. Government support and market proximity: exploring their relationship with supply chain agility and financial performance. Sustainability 10, 2441. https://doi.org/10.3390/su10072441.

Bai-Chen, X., Ying, F., Qian-Qian, Q., 2012. Does generation form influence environmental efficiency performance? An analysis of China's power system. Appl. Energy Smart Grids 96, 261–271. https://doi.org/10.1016/j.apenergy.2011.11.011.

Betz, M.R., Partridge, M.D., Farren, M., Lobao, L., 2015. Coal mining, economic development, and the natural resources curse. Energy Econ. 50, 105–116. https://doi.org/10.1016/j.eneco.2015.04.005.

Bian, Y., Hu, M., Wang, Y., Xu, H., 2016. Energy efficiency analysis of the economic system in China during 1986–2012: a parallel slacks-based measure approach. Renew. Sust. Energ. Rev. 55, 990–998. https://doi.org/10.1016/j.rser.2015.11.008.

Brunnschweiler, C.N., 2008. Cursing the blessings? Natural resource abundance, institutions, and economic growth. World Dev. 36, 399–419. https://doi.org/10.1016/j.worlddev.2007.03.004.

Cao, Z., Shen, Z., 2013. Industrial carbon emissions status and analysis based on energy consumption. Chin. J. Popul. Resour. Environ. 9, 33–41.

Chan, S.-G., Karim, M., 2012. Public spending efficiency and political and economic factors: evidence from selected East Asian countries. Econ. Ann. 57, 7–23. https://doi.org/10.2298/EKA1293007C.

Charnes, A., Cooper, W.W., Golany, B., Halek, R., Klopp, G., Schmitz, E., Thomas, D., 1986. Two-Phase Data Envelopment Analysis Approaches to Policy Evaluation and Management of Army Recruiting Activities: Tradeoffs between Joint Services and Army Advertising. Cent. Cybern. Stud. Univ. Tex.-Austin Austin Tex, USA.

Chen, K., Kou, M., Fu, X., 2018. Evaluation of multi-period regional R&D efficiency: an application of dynamic DEA to China's regional R&D systems. Omega 74, 103–114. https://doi.org/10.1016/j.omega.2017.01.010.

Chen, Wei, Chen, Wenjun, Ning, S., Liu, E., Zhou, X., Wang, Y., Zhao, M., 2019. Exploring the industrial land use efficiency of China's resource-based cities. Cities 93, 215–223. https://doi.org/10.1016/j.cities.2019.05.009.

Chinese National Administration for Quality Supervision and, Inspection and Quarantine (NAQSIQ), 2017. Industrial classification for national economic activities (GB/T 4754-2017).

Chiu, Y., Huang, C., Chen, Y.-C., 2012. The R&D value-chain efficiency measurement for high-tech industries in China. Asia Pac. J. Manag. 29, 989–1006.

Cull, R., Xu, L.C., Yang, X., Zhou, L.-A., Zhu, T., 2017. Market facilitation by local government and firm efficiency: evidence from China. J. Corp. Financ. 42, 460–480. https://doi.org/10.1016/j.jcorpfin.2015.06.002.

De Borger, B., Kerstens, K., Moesen, W., Vanneste, J., 1994. Explaining differences in productive efficiency: an application to Belgian municipalities. Public Choice 80, 339–358.

Du, K., Lu, H., Yu, K., 2014. Sources of the potential CO_2 emission reduction in China: a nonparametric metafrontier approach. Appl. Energy 115, 491–501. https://doi.org/10.1016/j.apenergy.2013.10.046.

Eregha, P.B., Mesagan, E.P., 2016. Oil resource abundance, institutions and growth: evidence from oil producing African countries. J. Policy Model 38, 603–619.

Fan, Y., Bai, B., Qiao, Q., Kang, P., Zhang, Y., Guo, J., 2017. Study on eco-efficiency of industrial parks in China based on data envelopment analysis. J. Environ. Manag. 192, 107–115. https://doi.org/10.1016/j.jenvman.2017.01.048.

Färe, R., 1991. Measuring Farrell efficiency for a firm with intermediate inputs. Acad. Econ. Pap. 19, 329–340.

Färe, R., Grosskopf, S., 1996. Productivity and intermediate products: a frontier approach. Econ. Lett. 50, 65–70.

Fare, R., Grosskopf, S., 2000. Network DEA. Socio Econ. Plan. Sci. 34, 35–49.

Färe, R., Whittaker, G., 1995. An intermediate input model of dairy production using complex survey data. J. Agric. Econ. 46, 201–213.

Guan, J., Chen, K., 2010. Measuring the innovation production process: a cross-region empirical study of China's high-tech innovations. Technovation 30, 348–358. https://doi.org/10.1016/j.technovation.2010.02.001.

Guo, C., 2015. Estimation of emission reduction potential in China's industrial sector. Chin. J. Popul. Resour. Environ. 13, 223–230.

Guo, C., Abbasi Shureshjani, R., Foroughi, A.A., Zhu, J., 2017. Decomposition weights and overall efficiency in two-stage additive network DEA. Eur. J. Oper. Res. 257, 896–906. https://doi.org/10.1016/j.ejor.2016.08.002.

Guo, X.-D., Zhu, L., Fan, Y., Xie, B.-C., 2011. Evaluation of potential reductions in carbon emissions in Chinese provinces based on environmental DEA. Energy Policy 39, 2352–2360. https://doi.org/10.1016/j.enpol.2011.01.055.

Hauner, D., Kyobe, A., 2010. Determinants of government efficiency. World Dev. 38, 1527–1542. https://doi.org/10.1016/j.worlddev.2010.04.004.

Hu, A., Tang, X., Yang, Z., Yan, Y., 2017. The relationship between the government and the market. In: The Modernization of China's State Governance. Springer, pp. 93–118.

Hua, Z., Bian, Y., Liang, L., 2007. Eco-efficiency analysis of paper mills along the Huai River: an extended DEA approach. Omega 35, 578–587. https://doi.org/10.1016/j.omega.2005.11.001.

Intergovernmental Panel on Climate Change (IPCC), 2006. IPCC Guidelines for National Greenhouse gas Inventories. Institute for Global Environmental Strategies, Hayama (Japan).

Kao, C., 2009. Efficiency decomposition in network data envelopment analysis: a relational model. Eur. J. Oper. Res. 192, 949–962. https://doi.org/10.1016/j.ejor.2007.10.008.

Kao, C., 2013. Dynamic data envelopment analysis: a relational analysis. Eur. J. Oper. Res. 227, 325–330. https://doi.org/10.1016/j.ejor.2012.12.012.

Kao, C., 2014a. Network data envelopment analysis: a review. Eur. J. Oper. Res. 239, 1–16. https://doi.org/10.1016/j.ejor.2014.02.039.

Kao, C., 2014b. Efficiency decomposition in network data envelopment analysis with slacks-based measures. Omega 45, 1–6. https://doi.org/10.1016/j.omega.2013.12.002.

Kao, C., 2015. Efficiency measurement for hierarchical network systems. Omega 51, 121–127.

Kao, C., 2016. Efficiency decomposition and aggregation in network data envelopment analysis. Eur. J. Oper. Res. 255, 778–786.

Kao, C., 2017. Network Data Envelopment Analysis, 10. Springer, pp. 26–33.

Kao, C., 2018. A classification of slacks-based efficiency measures in network data envelopment analysis with an analysis of the properties possessed. Eur. J. Oper. Res. 270, 1109–1121.

Kaznacheev, P., 2017. Curse or Blessing? How Institutions Determine Success in Resource-Rich Economies. Cato Inst. Policy Anal. No 808.

Keh, H.T., Chu, S., 2003. Retail productivity and scale economies at the firm level: a DEA approach. Omega 31, 75–82.

Keh, H.T., Chu, S., Xu, J., 2006. Efficiency, effectiveness and productivity of marketing in services. Eur. J. Oper. Res. 170, 265–276. https://doi.org/10.1016/j.ejor.2004.04.050.

Kolstad, I., 2009. The resource curse: which institutions matter? Appl. Econ. Lett. 16, 439–442. https://doi.org/10.1080/17446540802167339.

Kou, Z., Liu, X., 2017. FIND Report on City and Industrial Innovation in China (2017). Shanghai Fudan Inst. Ind. Dev. Sch. Econ. Fudan Univ.

Kuosmanen, T., 2005. Measurement and analysis of eco-efficiency: an economist's perspective. J. Ind. Ecol. 9, 15–18. https://doi.org/10.1162/108819805775248025.

Lewis, H.F., Sexton, T.R., 2004. Network DEA: efficiency analysis of organizations with complex internal structure. Comput. Oper. Res. 31, 1365–1410. https://doi.org/10.1016/S0305-0548(03)00095-9.

Li, B., Dewan, H., 2017. Efficiency differences among China's resource-based cities and their determinants. Resour. Policy 51, 31–38. https://doi.org/10.1016/j.resourpol.2016.11.003.

Li, H., Long, R., Chen, H., 2013a. Economic transition policies in Chinese resource-based cities: an overview of government efforts. In: Energy Policy, Special section: Long Run Transitions to Sustainable Economic Structures in the European Union and Beyond, 55, pp. 251–260. https://doi.org/10.1016/j.enpol.2012.12.007.

Li, H., Long, R., Chen, H., 2013b. Economic transition policies in Chinese resource-based cities: an overview of government efforts. Energy Policy 55, 251–260. https://doi.org/10.1016/j.enpol.2012.12.007.

Li, K., Lin, B., 2015. Metafroniter energy efficiency with CO_2 emissions and its convergence analysis for China. Energy Econ. 48, 230–241. https://doi.org/10.1016/j.eneco.2015.01.006.

Li, L., Lei, Y., Pan, D., Si, C., 2016. Research on sustainable development of resource-based cities based on the DEA approach: a case study of Jiaozuo, China. Math. Probl. Eng. 1–10. https://doi.org/10.1155/2016/5024837.

Li, L., Shan, Y., Lei, Y., Wu, S., Yu, X., Lin, X., Chen, Y., 2019. Decoupling of economic growth and emissions in China's cities: a case study of the Central Plains urban agglomeration. Appl. Energy 244, 36–45. https://doi.org/10.1016/j.apenergy.2019.03.192.

Li, M., 2010. Decomposing the change of CO_2 emissions in China: a distance function approach. Ecol. Econ. 70, 77–85. https://doi.org/10.1016/j.ecolecon.2010.07.034.

Lin, B., Du, K., 2015. Energy and CO_2 emissions performance in China's regional economies: do market-oriented reforms matter? Energy Policy 78, 113–124. https://doi.org/10.1016/j.enpol.2014.12.025.

Lin, B., Xu, B., 2020. Effective ways to reduce CO_2 emissions from China's heavy industry? Evidence from semiparametric regression models. Energy Econ. 92, 104974. https://doi.org/10.1016/j.eneco.2020.104974.

Liou, J.-L., Wu, P.-I., 2011. Will economic development enhance the energy use efficiency and CO_2 emission control efficiency? Expert Syst. Appl. 38, 12379–12387. https://doi.org/10.1016/j.eswa.2011.04.017.

Liu, X., Chu, J., Yin, P., Sun, J., 2017. DEA cross-efficiency evaluation considering undesirable output and ranking priority: a case study of eco-efficiency analysis of coal-fired power plants. J. Clean. Prod. 142, 877–885. https://doi.org/10.1016/j.jclepro.2016.04.069.

Liu, Z., Guan, D., Wei, W., Davis, S.J., Ciais, P., Bai, J., Peng, S., Zhang, Q., Hubacek, K., Marland, G., Andres, R.J., Crawford-Brown, D., Lin, J., Zhao, H., Hong, C., Boden, T. A., Feng, K., Peters, G.P., Xi, F., Liu, J., Li, Y., Zhao, Y., Zeng, N., He, K., 2015. Reduced carbon emission estimates from fossil fuel combustion and cement production in China. Nature 524, 335–338. https://doi.org/10.1038/nature14677.

Lo, S.-F., Lu, W.-M., 2006. Does size matter? Finding the profitability and marketability benchmark of financial holding companies. Asia Pac. J. Oper. Res. 23, 229–246. https://doi.org/10.1142/S0217595906000930.

Lo, S.-F., Lu, W.-M., 2009. An integrated performance evaluation of financial holding companies in Taiwan. Eur. J. Oper. Res. 198, 341–350. https://doi.org/10.1016/j.ejor.2008.09.006.

Long, X., Oh, K., Cheng, G., 2013. Are stronger environmental regulations effective in practice? The case of China's accession to the WTO. J. Clean. Prod. 39, 161–167. https://doi.org/10.1016/j.jclepro.2012.08.005.

Long, X., Sun, M., Cheng, F., Zhang, J., 2017. Convergence analysis of eco-efficiency of China's cement manufacturers through unit root test of panel data. Energy 134, 709–717. https://doi.org/10.1016/j.energy.2017.05.079.

Long, X., Chen, B., Park, B., 2018a. Effect of 2008's Beijing Olympic Games on environmental efficiency of 268 China's cities. J. Clean. Prod. 172, 1423–1432. https://doi.org/10.1016/j.jclepro.2017.10.209.

Long, X., Luo, Y., Sun, H., Tian, G., 2018b. Fertilizer using intensity and environmental efficiency for China's agriculture sector from 1997 to 2014. Nat. Hazards 92, 1573–1591. https://doi.org/10.1007/s11069-018-3265-4.

Long, X., Wu, C., Zhang, Jijian, Zhang, Jing, 2018c. Environmental efficiency for 192 thermal power plants in the Yangtze River Delta considering heterogeneity: a metafrontier directional slacks-based measure approach. Renew. Sust. Energ. Rev. 82, 3962–3971. https://doi.org/10.1016/j.rser.2017.10.077.

Long, X., Wang, X., Mensah, C.N., Wang, M., Zhang, J., 2019. Spatial and temporal heterogeneity of environmental efficiency for China's hotel sector: new evidence through metafrontier global Malmquist-Luenberger. Environ. Sci. Pollut. Res. 26, 27534–27541. https://doi.org/10.1007/s11356-019-05963-9.

Long, X., Sun, C., Wu, C., Chen, B., Boateng, K.A., 2020. Green innovation efficiency across China's 30 provinces: estimate, comparison, and convergence. Mitig. Adapt. Strateg. Glob. Change 25, 1243–1260. https://doi.org/10.1007/s11027-019-09903-3.

Lozano, S., Gutiérrez, E., Moreno, P., 2013. Network DEA approach to airports performance assessment considering undesirable outputs. Appl. Math. Model. 37, 1665–1676. https://doi.org/10.1016/j.apm.2012.04.041.

Lu, M., Pan, H., 2016. Government-Enterprise Connection: Entrepreneur and Private Enterprise Development in China. Springer, Singapore. https://doi.org/10.1007/978-981-287-658-4.

Lu, W.-C., 2009. The evolution of R&D efficiency and marketability: evidence from Taiwan's IC-design industry. Asian J. Technol. Innov. 17, 1–26.

Luo, X., 2003. Evaluating the profitability and marketability efficiency of large banks: an application of data envelopment analysis. J. Bus. Res. 56, 627–635. https://doi.org/10.1016/S0148-2963(01)00293-4.

Luo, Y., Lu, Z., Long, X., 2020. Heterogeneous effects of endogenous and foreign innovation on CO_2 emissions stochastic convergence across China. Energy Econ. 91, 104893. https://doi.org/10.1016/j.eneco.2020.104893.

Mehlum, H., Moene, K., Torvik, R., 2006. Institutions and the resource curse. Econ. J. 116, 1–20. https://doi.org/10.1111/j.1468-0297.2006.01045.x.

Moreno, P., Lozano, S., 2014. A network DEA assessment of team efficiency in the NBA. Ann. Oper. Res. 214, 99–124.

National Bureau of Statistics of China (NBC), 2020. China Statistical Yearbook of 2020. China Statistics Press, Beijing, China.

National Bureau of Statistics of China (NBS), 2016a. China City Statistical Yearbook. China Statistics Press, Beijing, China.

National Bureau of Statistics of China (NBS), 2016b. Jiangsu Statistical Yearbook. China Statistics Press, Beijing, China.

Oggioni, G., Riccardi, R., Toninelli, R., 2011. Eco-efficiency of the world cement industry: a data envelopment analysis. Energy Policy 39, 2842–2854. https://doi.org/10.1016/j.enpol.2011.02.057.
Ouertani, M.N., Naifar, N., Haddad, H.B., 2018. Assessing government spending efficiency and explaining inefficiency scores: DEA-bootstrap analysis in the case of Saudi Arabia. Cogent Econ. Financ. 6, 1493666. https://doi.org/10.1080/23322039.2018.1493666.
Qin, B., Liu, L., Tao, Y., 2019. Evaluation of sustainable development of resource-based cities in China. J. Environ. Econ. 142–158. https://doi.org/10.19511/j.cnki.jee.2019.03.009.
Rayp, G., Van De Sijpe, N., 2007. Measuring and explaining government efficiency in developing countries. J. Dev. Stud. 43, 360–381. https://doi.org/10.1080/00220380601125230.
Ruan, F., Yan, L., Wang, D., 2020. The complexity for the resource-based cities in China on creating sustainable development. Cities 97, 102571. https://doi.org/10.1016/j.cities.2019.102571.
Schaltegger, S., Sturm, A., 1990. Ecological rationality: approaches to design of ecology-oriented management instruments. Unternehm 4, 273–290.
Seiford, L.M., Zhu, J., 1999. Profitability and marketability of the top 55 U.S. commercial banks. Manag. Sci. 45, 1270–1288. https://doi.org/10.1287/mnsc.45.9.1270.
Shan, Y., Liu, J., Liu, Z., Xu, X., Shao, S., Wang, P., Guan, D., 2016. New provincial CO_2 emission inventories in China based on apparent energy consumption data and updated emission factors. Appl. Energy 184, 742–750. https://doi.org/10.1016/j.apenergy.2016.03.073.
Shan, Y., Guan, D., Liu, Jianghua, Mi, Z., Liu, Z., Liu, Jingru, Schroeder, H., Cai, B., Chen, Y., Shao, S., Zhang, Q., 2017. Methodology and applications of city level CO_2 emission accounts in China. J. Clean. Prod. 161, 1215–1225. https://doi.org/10.1016/j.jclepro.2017.06.075.
Shan, Y., Guan, D., Zheng, H., Ou, J., Li, Y., Meng, J., Mi, Z., Liu, Z., Zhang, Q., 2018. China CO_2 emission accounts 1997–2015. Sci. Data 5, 170201. https://doi.org/10.1038/sdata.2017.201.
Shan, Y., Liu, J., Liu, Z., Shao, S., Guan, D., 2019. An emissions-socioeconomic inventory of Chinese cities. Sci. Data 6, 190027. https://doi.org/10.1038/sdata.2019.27.
Shao, S., Qi, Z., 2008. Energy development and economic growth in Western China: an empirical analysis based on the resource curse hypothesis. Econ. Res. J. 4, 147–160.
Shao, S., Qi, Z., 2009. Energy exploitation and economic growth in Western China: an emprical analysis based on the resource curse hypothesis. Front. Econ. China 4, 125–152. https://doi.org/10.1007/s11459-009-0008-1.
Shao, S., Yang, L., 2014. Natural resource dependence, human capital accumulation, and economic growth: a combined explanation for the resource curse and the resource blessing. Energy Policy 74, 632–642. https://doi.org/10.1016/j.enpol.2014.07.007.
Shao, S., Yang, Z., Yang, L., Zhang, X., Geng, Y., 2020a. Synergetic conservation of water and energy in China's industrial sector: from the perspectives of output and substitution elasticities. J. Environ. Manag. 259, 110045. https://doi.org/10.1016/j.jenvman.2019.110045.
Shao, S., Zhang, Y., Tian, Z., Li, D., Yang, L., 2020b. The regional Dutch disease effect within China: a spatial econometric investigation. Energy Econ. 88, 104766. https://doi.org/10.1016/j.eneco.2020.104766.
Sun, W., Li, Y., Wang, D., Fan, J., 2012. The efficiencies and their changes of China's resources-based cities employing DEA and Malmquist index models. J. Geogr. Sci. 22, 509–520. https://doi.org/10.1007/s11442-012-0943-0.
The Chinese Government, 2011. The Resource-exhausted cities list in China. Retrieved from. http://www.gov.cn/gzdt/2011-03/10/content_1821480.htm>.
The Chinese Government, 2013a. The Sustainable Development Plan for Resources-Based Cities in China (2013–2020) [File Number: State Council, 2013/45].
The Chinese Government, 2013b. Circular of the State Council on printing and distributing the sustainable development plan of resource-based cities in China (2013–2020). Retrieved from< http://www.gov.cn/zwgk/2013-12/03/content_2540070.htm>.
The Chinese Government, 2016. Thirteenth five-year plan (full text). Retrieved from. http://www.gov.cn/xinwen/2016-03/17/content_5054992.htm>.
The Chinese Government, 2017a. Promoting the Equalization of Basic Public Services During "13th Five Year Plan" [File Number: State Council, 2017/09].
The Chinese Government, 2017b. Report to the 19th National Congress of the Communist Party of China. Retrieved from. http://www.gov.cn/zhuanti/19thcpc/baogao.htm>.
The Xuzhou Government, 2017. Jiawang District, Xuzhou: Practical Exploration of Green Transformation Development in Coal Resource Exhausted Cities. Retrieved from. http://www.xzjw.gov.cn/Item/69807.aspx>.
Tone, K., Tsutsui, M., 2009. Network DEA: a slacks-based measure approach. Eur. J. Oper. Res. 197, 243–252. https://doi.org/10.1016/j.ejor.2008.05.027.
Tone, K., Tsutsui, M., 2010. Dynamic DEA: a slacks-based measure approach. Omega 38, 145–156. https://doi.org/10.1016/j.omega.2009.07.003.
Tsolas, I.E., 2011. Relative profitability and stock market performance of listed commercial banks on the Athens Exchange: a non-parametric approach. IMA J. Manag. Math. 22, 323–342. https://doi.org/10.1093/imaman/dpq017.
Tsolas, I.E., 2013. Modeling profitability and stock market performance of listed construction firms on the Athens Exchange: two-stage DEA approach. J. Constr. Eng. Manag. 139, 111–119.
Wang, C.H., Gopal, R.D., Zionts, S., 1997. Use of data envelopment analysis in assessing information technology impact on firm performance. Ann. Oper. Res. 73, 191–213. https://doi.org/10.1023/A:1018977111455.
Wang, K., Wei, Y.-M., Zhang, X., 2012. A comparative analysis of China's regional energy and emission performance: which is the better way to deal with undesirable outputs? Energy Policy 46, 574–584. https://doi.org/10.1016/j.enpol.2012.04.038.
Wang, Q., Su, B., Zhou, P., Chiu, C.-R., 2016. Measuring total-factor CO_2 emission performance and technology gaps using a non-radial directional distance function: a modified approach. Energy Econ. 56, 475–482. https://doi.org/10.1016/j.eneco.2016.04.005.
Wang, Q.W., Zhou, P., Shen, N., Wang, S.S., 2013. Measuring carbon dioxide emission performance in Chinese provinces: a parametric approach. Renew. Sust. Energ. Rev. 21, 324–330. https://doi.org/10.1016/j.rser.2012.12.061.
Wu, F., Zhou, P., Zhou, D.Q., 2020. Modeling carbon emission performance under a new joint production technology with energy input. Energy Econ. 92, 104963. https://doi.org/10.1016/j.eneco.2020.104963.
Xiao, H., Duan, Z., Zhou, Y., Zhang, N., Shan, Y., Lin, X., Liu, G., 2019a. CO_2 emission patterns in shrinking and growing cities: a case study of Northeast China and the Yangtze River Delta. Appl. Energy 251, 113384. https://doi.org/10.1016/j.apenergy.2019.113384.
Xiao, H., Shan, Y., Zhang, N., Zhou, Y., Wang, D., Duan, Z., 2019b. Comparisons of CO_2 emission performance between secondary and service industries in Yangtze River Delta cities. J. Environ. Manag. 252, 109667. https://doi.org/10.1016/j.jenvman.2019.109667.
Yan, D., Kong, Y., Ren, X., Shi, Y., Chiang, S., 2019a. The determinants of urban sustainability in Chinese resource-based cities: a panel quantile regression approach. Sci. Total Environ. 686, 1210–1219. https://doi.org/10.1016/j.scitotenv.2019.05.386.
Yan, D., Kong, Y., Ye, B., Shi, Y., Zeng, X., 2019b. Spatial variation of energy efficiency based on a Super-Slack-Based Measure: evidence from 104 resource-based cities. J. Clean. Prod. 240, 117669. https://doi.org/10.1016/j.jclepro.2019.117669.
Yang, Z., Fan, M., Shao, S., Yang, L., 2017. Does carbon intensity constraint policy improve industrial green production performance in China? A quasi-DID analysis. Energy Econ. 68, 271–282. https://doi.org/10.1016/j.eneco.2017.10.009.
Yao, X., Zhou, H., Zhang, A., Li, A., 2015. Regional energy efficiency, carbon emission performance and technology gaps in China: a meta-frontier non-radial directional distance function analysis. Energy Policy 84, 142–154. https://doi.org/10.1016/j.enpol.2015.05.001.
Zhang, B., Bi, J., Fan, Z., Yuan, Z., Ge, J., 2008. Eco-efficiency analysis of industrial system in China: a data envelopment analysis approach. Ecol. Econ. 68, 306–316. https://doi.org/10.1016/j.ecolecon.2008.03.009.
Zhang, N., Choi, Y., 2013a. Total-factor carbon emission performance of fossil fuel power plants in China: a metafrontier non-radial Malmquist index analysis. Energy Econ. 40, 549–559. https://doi.org/10.1016/j.eneco.2013.08.012.
Zhang, N., Choi, Y., 2013b. Total-factor carbon emission performance of fossil fuel power plants in China: a metafrontier non-radial Malmquist index analysis. Energy Econ. 40, 549–559. https://doi.org/10.1016/j.eneco.2013.08.012.
Zhang, N., Wei, X., 2015. Dynamic total factor carbon emissions performance changes in the Chinese transportation industry. Appl. Energy 146, 409–420. https://doi.org/10.1016/j.apenergy.2015.01.072.
Zhang, N., Wang, B., Chen, Z., 2016a. Carbon emissions reductions and technology gaps in the world's factory, 1990–2012. Energy Policy 91, 28–37. https://doi.org/10.1016/j.enpol.2015.12.042.
Zhang, N., Wang, B., Chen, Z., 2016b. Carbon emissions reductions and technology gaps in the world's factory, 1990–2012. Energy Policy 91, 28–37. https://doi.org/10.1016/j.enpol.2015.12.042.
Zhang, N., Wang, B., Liu, Z., 2016c. Carbon emissions dynamics, efficiency gains, and technological innovation in China's industrial sectors. Energy 99, 10–19. https://doi.org/10.1016/j.energy.2016.01.012.
Zhang, T., Yue, H., Zhou, J., Wang, H., 2018. Technological innovation paths toward green industry in China. Chin. J. Popul. Resour. Environ. 16, 97–108. https://doi.org/10.1080/10042857.2018.1475902.
Zhang, Y., Hao, J., Song, J., 2016. The CO_2 emission efficiency, reduction potential and spatial clustering in China's industry: evidence from the regional level. Appl. Energy 174, 213–223. https://doi.org/10.1016/j.apenergy.2016.04.109.
Zhou, P., Ang, B.W., 2008. Linear programming models for measuring economy-wide energy efficiency performance. Energy Policy 36, 2911–2916. https://doi.org/10.1016/j.enpol.2008.03.041.
Zhou, P., Ang, B.W., Poh, K.L., 2008a. Measuring environmental performance under different environmental DEA technologies. Energy Econ. 30, 1–14. https://doi.org/10.1016/j.eneco.2006.05.001.
Zhou, P., Ang, B.W., Poh, K.L., 2008b. A survey of data envelopment analysis in energy and environmental studies. Eur. J. Oper. Res. 189, 1–18. https://doi.org/10.1016/j.ejor.2007.04.042.
Zhou, P., Ang, B.W., Han, J.Y., 2010. Total factor carbon emission performance: a Malmquist index analysis. Energy Econ. 32, 194–201. https://doi.org/10.1016/j.eneco.2009.10.003.
Zhou, P., Ang, B.W., Wang, H., 2012. Energy and CO_2 emission performance in electricity generation: a non-radial directional distance function approach. Eur. J. Oper. Res. 221, 625–635. https://doi.org/10.1016/j.ejor.2012.04.022.
Zhou, Y., Shan, Y., Liu, G., Guan, D., 2018. Emissions and low-carbon development in Guangdong-Hong Kong-Macao Greater Bay Area cities and their surroundings. Appl. Energy 228, 1683–1692. https://doi.org/10.1016/j.apenergy.2018.07.038.
Zhu, J., 2000. Multi-factor performance measure model with an application to Fortune 500 companies. Eur. J. Oper. Res. 123, 105–124. https://doi.org/10.1016/S0377-2217(99)00096-X.