Ecological Indicators 130 (2021) 108072

Contents lists available at ScienceDirect

Ecological Indicators

journal homepage: www.elsevier.com/locate/ecolind

Industrial eco-efficiency and its determinants in China: A two-stage approach

Ken'ichi Matsumoto [a,b,*], Yueyang Chen [c]

[a] Faculty of Economics, Toyo University, 5–58–20 Hakusan, Bunkyo-ku, Tokyo 112–8606, Japan
[b] Research Institute for Global Change, Japan Agency for Marine-Earth Science and Technology, 3173–25 Showa-machi, Kanazawa-ku, Yokohama, Kanagawa 236-0001, Japan
[c] Graduate School of Fisheries and Environmental Sciences, Nagasaki University, 1–14 Bunkyo-machi, Nagasaki 852–8521, Japan

ARTICLE INFO

Keywords:
Industrial eco-efficiency
Data envelopment analysis
Random-effects Tobit regression
Determinants
Provincial-level analysis
China

ABSTRACT

China has undergone momentous changes and achieved remarkable economic progress since its economic reform and opening-up in 1978. However, the consequent resource depletion and environmental degradation have seriously restricted China's potential for sustainable industrial development. As a practical tool contributing to sustainable development, the concept of eco-efficiency is considered increasingly important for reducing the trend of resource exhaustion and environmental degradation. This study first evaluated industrial eco-efficiency in 30 Chinese provinces during 2005–2015 using data envelopment analysis (DEA), and then identified the determinants of the resulting eco-efficiency scores using random-effects Tobit regression analysis. The DEA results showed that although China's overall industrial eco-efficiency trend was upward, there were great disparities between provinces. Provinces with high industrial eco-efficiency were mainly distributed across the eastern region, while those in the often economically less developed western region had lower industrial eco-efficiency due to technological deficits and weak environmental policies. The Tobit regression results indicated that internal research and development expenditure in industrial enterprises, per capita gross regional product, and investment in wastewater treatment had positive effects on provincial industrial eco-efficiency. By contrast, the proportion of state-owned enterprises and investment in waste gas treatment had negative impacts. These findings provide valuable insights that can help provinces with low industrial eco-efficiency to pursue high-quality, green development.

1. Introduction

1.1. Background

China has undergone momentous changes and achieved remarkable economic progress since its economic reform and opening-up in 1978. The industrial added value rapidly increased sixfold, from 4.03 trillion yuan in 2000 to 23.65 trillion yuan in 2015 (National Bureau of Statistics of China, 2015). Undoubtedly, this rapid industrial growth has greatly contributed to China's economic development. However, the consequent resource depletion and environmental degradation have seriously restricted the country's potential for sustainable economic development. China's industrial energy consumption in 2015 was 2.8 times higher than in 2000 (National Bureau of Statistics of China, 2015). Therefore, the Chinese government must improve the balance between economic development, environmental protection, and energy conservation. China previously emphasized economic development above all since its economic reform and opening-up depended on it. In recent years, however, the government has started to promote environmental control policies, enacting a number of environmental laws and regulations aimed at protecting the environment and achieving sustainable development.

As a practical tool contributing to sustainable development, the concept of eco-efficiency is increasingly considered to be of great importance due to its potential to reduce the trend of resource exhaustion and environmental degradation. Furthermore, to provide governments with practical information to support policymaking related to environmental sustainability, it is important to correctly evaluate industrial eco-efficiency and identify its determinants. To contribute to this effort, this empirical study adopted a two-stage estimation

* Corresponding author at: Faculty of Economics, Toyo University, 5–58–20 Hakusan, Bunkyo-ku, Tokyo 112–8606, Japan.
E-mail address: matsumoto1005@toyo.jp (K. Matsumoto).

https://doi.org/10.1016/j.ecolind.2021.108072
Received 10 November 2020; Received in revised form 19 July 2021; Accepted 2 August 2021
1470-160X/

approach, evaluating industrial eco-efficiency scores in China at the provincial level and then analyzing the factors that influence these scores.

1.2. Literature review

The concept of eco-efficiency was introduced by Stefan and Andreas (1990). It is widely accepted that eco-efficiency is achieved by delivering competitively priced goods and services that satisfy human needs and improve people's quality of life while progressively reducing ecological impacts and resource intensity to a level at least in line with the earth's estimated carrying capacity (Lehni et al., 2000). In other words, eco-efficiency refers to creating more value with less environmental impact. Since eco-efficiency requires comprehensive coordination of the economy, natural resources, and the environment, pursuing more efficient production methods and reducing resource consumption and undesirable outputs (i.e., the environmental impact) should be considered simultaneously (Huang et al., 2018). Eco-efficiency can also be seen as an effective tool for measuring environmental performance (Ball and Lunt, 2020), generally measured as the ratio of the value of what has been produced (e.g., gross domestic product [GDP]) to the environmental effects of that production. A growing body of literature has demonstrated the importance of eco-efficiency. For instance, Huang et al. (2018) showed that eco-efficiency plays an important role in facilitating regional sustainable development. More crucially, measuring eco-efficiency provides critical information for formulating policies that can be integrated into local economic activities and the environment for more sustainable development (Toma et al., 2016).

Data envelopment analysis (DEA) is a method of summarizing various desirable and undesirable effects of production in a single efficiency index. Hence, DEA can be a useful tool for identifying and comprehensively characterizing efficiency by simultaneously considering multiple inputs and outputs. This approach has been applied in various fields. With regard to energy and industrial efficiency, for instance, Hu and Wang (2006) analyzed the energy efficiency of 29 provinces in China for the period 1995–2002 using a traditional DEA and revealed that regional energy efficiency generally improved during the research period, except for the western part of the country. Chen and Golley (2014) combined a standard DEA with the directional distance function to estimate the "green" total factor productivity growth of 38 Chinese industrial sectors from 1980 to 2010 and found that Chinese industry was not yet on a path to sustainable, low-carbon growth. Furthermore, to evaluate industrial eco-efficiency, Dai et al. (2016) employed a super-efficiency DEA model, while Huang et al. (2018) constructed a modified DEA model. Both studies showed that provinces in eastern China had relatively high industrial eco-efficiency. Likewise, Xing et al. (2018a) used a traditional DEA, along with an economic input–output lifecycle assessment, to measure the eco-efficiency of 26 industrial sectors in China, showing that over 70% of them were inefficient and required significant improvement. DEA has thus been widely used to compare a set of homogeneous decision making units (DMUs) by evaluating their relative efficiency (Ebrahimnejad et al., 2014). A common feature of the above studies is that they explored efficiency scores according to various types of DEA but did not analyze the determinants of the scores.

Clarifying the possible determinants of efficiency can provide the government or enterprises with important information to effect improvements. Hence, some studies have further explored the determinants of efficiency scores calculated using DEA. Lv et al. (2012) used a sample of 30 provinces for the period 1998–2009 to measure Chinese regional energy efficiency change and its determinants using a basic DEA and a random-effects Tobit regression model. Their Tobit regression analysis showed that electricity consumption as a proportion of total energy consumption and the proportion of state-owned industrial output relative to an area's gross industrial output had positive impacts on energy efficiency, while the percentage of the added value of the secondary industry as a proportion of GDP had a negative effect. Likewise, Pan et al. (2013) used an extended DEA model and a random-effects Tobit regression model to explore China's provincial industrial energy efficiency and its determinants. Their regression analysis showed that higher energy efficiency resulted from a higher marketization level, a higher per capita GDP, higher research and development (R&D) expenditure per capita, and a lower percentage of coal consumption. However, although Lv et al. (2012) and Pan et al. (2013) used a two-stage approach, they focused on energy efficiency without comprehensively considering undesirable outputs (i.e., environmental issues), such as carbon dioxide (CO_2) and waste emissions, which is inadequate when evaluating the degree of sustainable industrial development. Other studies have also used regression analysis as a second-stage method to explore the determinants of efficiency scores calculated using DEA. By applying the regression method, studies have identified determinants of efficiency in various sectors, such as industrial sectors (Chen and Golley, 2014), Chinese banking (Huang et al., 2014), and tomato production (Raheli et al., 2017).

1.3. Purpose

The purpose of this study was to elucidate the development trend of industrial eco-efficiency in 30 provinces of China and identify effective ways to achieve sustainable industrial development. To that end, this study used a DEA model to evaluate provincial industrial eco-efficiency and a regression model to reveal the determinants of the resulting eco-efficiency scores. Furthermore, since previous studies have only calculated eco-efficiency scores without providing detailed explanations of the results based on region-specific characteristics, this study selected five northern Chinese provinces to obtain further insights into the eco-efficiency scores. The results will allow policymakers to integrate economic activities and better protect the environment.

The remainder of this paper is organized as follows. Section 2 outlines the data and methods, including the DEA and random-effects Tobit models. Section 3 presents the results of the provincial industrial eco-efficiency scores evaluated using DEA, as well as the determinants of eco-efficiency. Section 4 discusses the results. Section 5 concludes the paper and outlines its policy implications.

2. Data and methods

For the empirical analysis, a DEA was used to calculate the regional industrial eco-efficiency scores, and then regression analysis was performed to identify their determinants. Panel data were used for both analyses.

2.1. Variables and data

This section describes the variables selected as inputs and outputs for the DEA model to evaluate China's industrial eco-efficiency and the determinants used in the random-effects Tobit model. The sample consisted of 30 provincial-level administrative units (provinces) in mainland China[1] from 2005 to 2015 (on an annual basis); thus, this study used panel data. See Supplementary Material for the data used in the analyses.

2.1.1. Input and output variables and data used in the DEA model

This study considered both the representativeness and the availability of data to comprehensively evaluate the eco-efficiency of Chinese

[1] This study did not include the Tibet Autonomous Region of mainland China due to data unavailability. Likewise, the two Special Administrative Regions (Hong Kong and Macau) were not considered because they have completely different economic systems from that of mainland China, which makes comparisons difficult.

provincial industries. In the selection of variables for the DEA model, industrial added value, representing the economic value produced by industrial production, was selected as the desirable output variable. Environmental burdens, namely, waste gas, wastewater, solid waste, and CO_2 emissions, were used as undesirable output variables (Chen and Golley, 2014; Feng and Wang, 2017; Lv et al., 2012).

Capital and labor were selected as input variables because they are indispensable for producing economic value (Feng and Wang, 2017; Matsumoto et al., 2020; Zhao et al., 2020).[2] The model also included energy and water consumption as crucial inputs for industrial production (Hu and Wang, 2006; Zou and Cong, 2021).

As no officially published data exist for industrial CO_2 emissions, they were calculated as follows:

$$CARB_r = \sum_j CARB_{rj} = FUEL_{rj} \times SC_j \times SEC_j \times \frac{44}{12} \tag{1}$$

where *CARB* represents CO_2 emissions (in tons of CO_2), *FUEL* represents the total industrial consumption of different energy types (in tons), *SC* represents the conversion coefficient for standard coal for different energy types (in tons of standard coal per ton of energy), *SEC* denotes the carbon emission coefficient (in tons of carbon per ton of standard coal), *r* represents the province, and *j* is the type of fossil fuel.

The coefficients for standard coal conversion and carbon emissions by energy type are shown in Table 1.

Table 2 shows the details of the input and output variables and the data sources, as well as the descriptive statistics. Figure 1 shows the aggregated time-series trends for the input and output variables of the examined provinces. The number of observations for the DEA was 330. The details of the data sources are shown in Table A1.

2.1.2. *Possible determinants and data used in the random-effects Tobit model*

For the random-effects Tobit regression analysis, six independent variables were selected to represent determinants with potentially significant impacts on industrial eco-efficiency according to the DEA: per capita gross regional product (*GRP*), internal R&D expenditure of industrial enterprises (*R&D*), investment in wastewater treatment (*IWW*), investment in waste gas treatment (*IWG*), investment in solid waste treatment (*IWS*), and the proportion of state-owned enterprises (*PSO*). The data sources and descriptive statistics for all independent variables (i.e., possible determinants) are displayed in Table 3. Figure 2 shows the aggregated time-series trends for the independent variables of the examined provinces.

Table 1
Coefficients for standard coal conversion and carbon emissions by energy type.

Energy type	Standard coal conversion coefficient (tons of standard coal/ton of energy)	Carbon emission coefficient (tons of carbon/ton of standard coal)
Coal	0.7143	0.7559
Coke	0.9714	0.8550
Crude oil	1.4286	0.5857
Fuel oil	1.4286	0.6185
Gasoline	1.4714	0.5538
Kerosene	1.4714	0.5714
Diesel	1.4571	0.5921
Natural gas	1.33×10^{-3}	0.4483
Liquefied petroleum gas	1.7143	0.5042

Sources: National Bureau of Statistics of China (2015) for standard coal conversion coefficients and Intergovernmetal Panel on Climate Change (2006) for carbon emission coefficients.

The reasons for selecting these variables as possible determinants of industrial eco-efficiency are as follows. Per capita GRP may have a positive impact on industrial eco-efficiency as a proxy for economic development. With an increase in per capita GRP, residents' expectations of the quality of the environment also increase, and the protection of the environment becomes more important in public opinion. This prompts enterprises to adopt cleaner modes of production.

The internal R&D expenditure of industrial enterprises may also have a positive impact on industrial eco-efficiency. Previous studies have found that R&D has a significant positive effect on the environment (Matsuoka, 2009; Xing et al., 2018b; Zhao et al., 2019). Industrial R&D is the main driver of innovation, and internal expenditure on R&D can function as a key indicator for monitoring the resources allocated to science and technology (Savrul and Incekara, 2015). In this study, R&D investment was considered to have a positive impact on industrial eco-efficiency because environmental performance is closely related to technological progress. A one-year lag (e.g., 2004 data were used for 2005) was applied in the regression model to allow enough time for R&D expenditure to take effect.

Investment in industrial pollution control may also have a positive impact on industrial eco-efficiency, as its objective is to reduce pollution. In this study, three aspects of investment in industrial pollution control were considered: wastewater treatment, waste gas treatment, and solid waste treatment. These factors can contribute to improving industrial eco-efficiency by reducing various pollutants. A one-year lag was also applied in the regression model.

The proportion of state-owned enterprises may have a negative impact on industrial eco-efficiency. Research has shown that state-owned enterprises are less efficient than other types of enterprises (Liu et al., 2020). One reason is that state-owned enterprises are considered to be indirectly owned by the people, and such an ambiguous definition of ownership leads to excessive consumption of resources by the state, managers, and workers (Lin et al., 2020). Another reason is that the controlling shareholder of state-owned enterprises is the government, whose primary aim is not to pursue economic and environmental benefits but to maintain social stability, for example, by reducing unemployment and wage gaps (Lin et al., 1998). Accordingly, a higher proportion of state-owned enterprises may result in a lower industrial eco-efficiency score.

Data for *R&D* and *IWS* were unavailable for some years and provinces. For this reason, 304 observations were used for the regression analysis.

2.2. *Methods*

2.2.1. *Data envelopment analysis*

The DEA model, initially proposed by Charnes et al. (1978), is a popular linear non-parametric mathematical programming approach used to determine the relative efficiency of homogeneous DMUs. It can range from a single-input/single-output technical efficiency measure to a multiple-input/multiple-output measure, and the weights for each DMU input and output are not affected by subjective factors. The most efficient DMUs constitute the efficient frontier, and the efficiency scores of the remaining DMUs represent their relative efficiency.

With the increasing attention to environmental conservation, the development of technologies with smaller undesirable outputs (i.e., environmental burdens) has become a major concern in every area of production. A conventional DEA supposes that producing more outputs with fewer input resources is a criterion of efficiency. In the presence of undesirable outputs, however, technologies with more desirable (good) outputs and fewer undesirable (bad) outputs relative to a lower resource

[2] Although labor with different education levels may affect industrial eco-efficiency differently, we used the total number of employees as an input in the DEA because data for the number of employees by education level were not available. However, given that similar variables have been used in the literature, we believe that this did not degrade the analysis.

Table 2
Input and output (desirable and undesirable) variables used in the DEA model and their data sources and descriptive statistics.

Variable	Unit	Data source	Mean	Standard deviation	Minimum	Maximum
Input						
Total energy consumption	10,000 tons of standard coal equivalent	China Statistical Yearbook (CSY)	8,898.47	6,126.27	465.09	30,070.00
Total assets of industrial enterprises	10,000 yuan	CSY	191,598,596.97	188,537,157.40	7,032,000	1,070,617,273
Annual average number of employees	Person	CSY	293.95	319.56	10.30	1,568.00
Industrial water supply and usage	100 million cubic meters	China Statistical Yearbook on the Environment (CSYE)	46.12	45.03	2.40	239.00
Output (undesirable)						
Industrial waste gas emissions	100 million cubic meters	CSYE	17,263.75	13,948.96	859.7	79,121.3
Industrial wastewater	10,000 tons	CSYE	82,173.26	74,284.33	5,782.20	34,1607.41
Industrial solid waste disposed and kept in storage	10,000 tons	CSYE	3,150.01	4,228.81	10.18	28,237.15
CO_2 emissions	Million tons of CO_2	Own calculation	228.60	163.30	12.00	729.84
Output (desirable)						
Industrial added value	100 million yuan	CSY	6,387.05	6,006.95	176.92	30,259.49

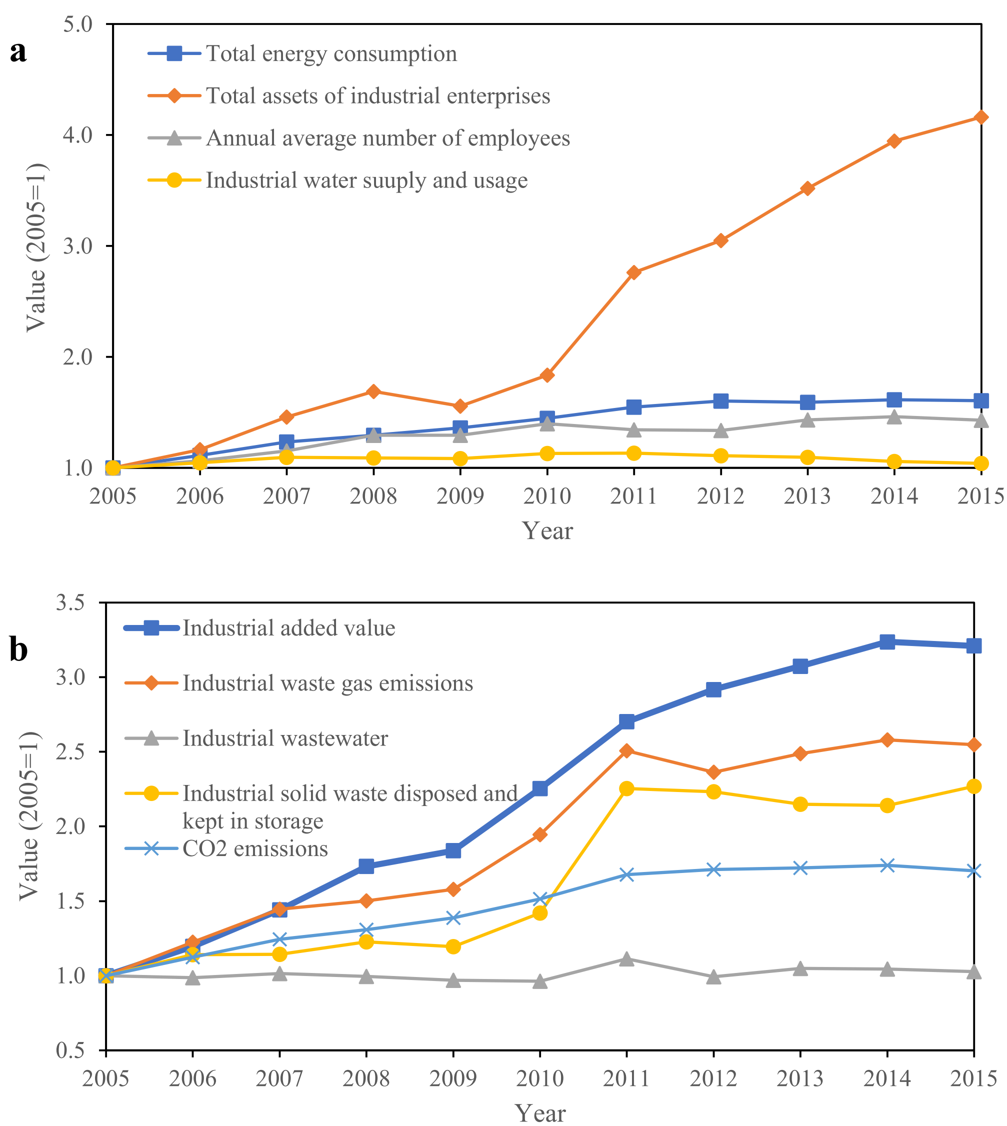

Fig. 1. Aggregated time-series trends for variables used in the DEA model for all examined provinces over the study period (2005 = 1): (a) input variables; (b) output variables.

Table 3
Possible determinants of industrial eco-efficiency and their data sources and descriptive statistics.

Determinant	Unit	Data source	Mean	Standard deviation	Minimum	Maximum
GRP	yuan/person	National Bureau of Statistics of China (2015)	34,941.98	21,574.07	5,052	107,960
R&D	10,000 yuan	China Statistical Yearbook on the Environment (CSYE)	1,971,832.00	3,029,478.00	38	16,500,000
IWW	10,000 yuan	National Bureau of Statistics of China (2015)	48,379.41	47,955.72	90	295,540
IWG	10,000 yuan	National Bureau of Statistics of China (2015)	104,547.60	127,534.10	140	1,281,351
IWS	10,000 yuan	National Bureau of Statistics of China (2015)	7,407.67	10,755.89	1	77,997
PSO	–	National Bureau of Statistics of China (2015)	0.12	0.08	0.01	0.40

GRP: gross regional product; *R&D*: research and development; *IWW*: investment in wastewater treatment; *IWG*: investment in waste gas treatment; *IWS*: investment in solid waste treatment; *PSO*: proportion of state-owned enterprises.

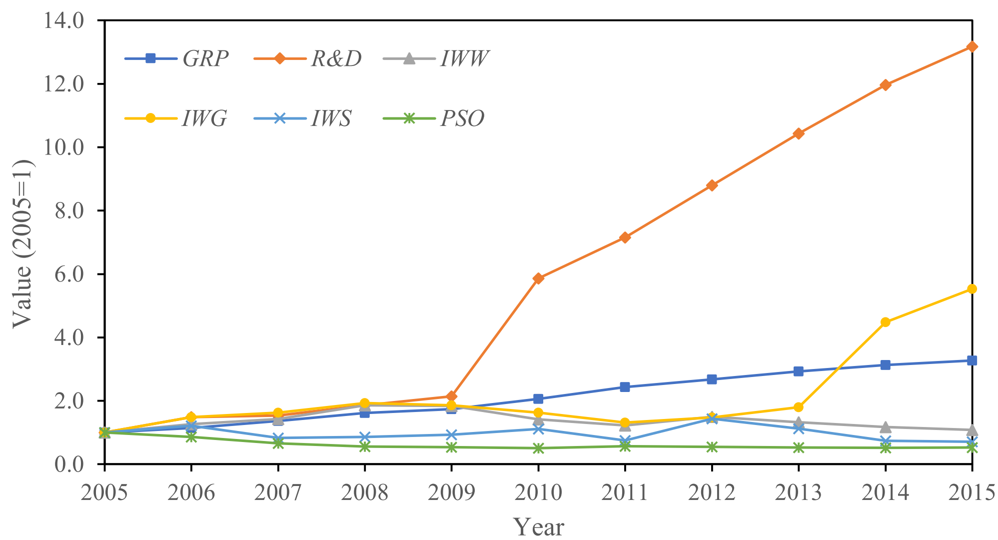

Fig. 2. Aggregated time-series trends for variables (possible determinants) used in the regression model for all examined provinces over the study period (2005 = 1). *GRP*: gross regional product; *R&D*: research and development; *IWW*: investment in wastewater treatment; *IWG*: investment in waste gas treatment; *IWS*: investment in solid waste treatment; *PSO*: proportion of state-owned enterprises.

input are deemed efficient.

The four most commonly used methods for treating undesirable outputs in a DEA are (1) excluding them from the production function, (2) treating them as regular inputs, (3) treating them as normal outputs, and (4) performing the necessary transformations to take them into account (Halkos and Petrou, 2019). In this study, the third option was employed: the undesirable outputs were treated as normal outputs in a slack-based model (SBM).

Suppose that there are n DMUs, each of which has three types of variables (inputs, desirable outputs, and undesirable outputs) represented by vectors $\chi, \gamma^g, and \gamma^b$, respectively. The matrices X, Y^g, and Y^b are defined as $X = (\chi_1, \cdots, \chi_n) \in R^{m\times n}$, $Y^g = (\gamma_1^g, \cdots, \gamma_n^g) \in R^{s_1\times n}$, and $Y^b = (\gamma_1^b, \cdots, \gamma_n^b) \in R^{s_2\times n}$, where m is the number of inputs, s_1 is the number of desirable outputs, and s_2 is the number of undesirable outputs. It was assumed that$X > 0, Y^g > 0, and Y^b > 0$.

The production possibility set (P) was defined as follows:

$$P = \left\{ (\chi, \gamma^g, \gamma^b) | \chi \geq X\lambda, \gamma^g \leq Y^g\lambda, \gamma^b \geq Y^b\lambda, \lambda \geq 0 \right\} \tag{2}$$

where $\lambda \in R^n$ is the intensity vector.

Note that this equation corresponds to constant returns to scale technology.

A $\mathrm{DMU}_o(\chi_o, \gamma_o^g, \gamma_o^b)$ is efficient in the presence of undesirable outputs if there is no vector $(\chi, \gamma^g, \gamma^b) \in P$, such that $\chi_0 \geq \chi, \gamma_o^g \leq \gamma^g, \mathrm{and} \gamma_o^b \geq \gamma^b$, with at least one strict inequality. According to this definition, the SBM was modified to develop an SBM with undesirable outputs as follows:

$$\mathrm{Min}P^* = \frac{1 - \frac{1}{m}\sum_{i=1}^{m}\frac{s_i^-}{\chi_{io}}}{1 + \frac{1}{s_1 + s_2}\left(\sum_{j=1}^{s_1}\frac{s_j^g}{\gamma_{jo}^g} + \sum_{k=1}^{s_2}\frac{s_k^b}{\gamma_{ko}^b}\right)}$$

subject to

$$\chi_o = X\lambda + s^- \tag{3}$$

$$\gamma_o^g = Y^g\lambda - s^g$$

$$\gamma_o^b = Y^b\lambda + s^b$$

$$s^- \geq 0, s^g \geq 0, s^b \geq 0, \lambda \geq 0$$

where i is the index for inputs ($1, 2 \ldots, m$), j is the index for desirable outputs ($1, 2 \ldots, s_1$), k is the index for undesirable outputs ($1, 2 \ldots, s_2$), s^- is the value of slack for the inputs, s^g is the value of slack for the desirable outputs, and s^b is the value of slack for the undesirable outputs.

The vectors $s^- \in R^m$ and $s^b \in R^{s_2}$ correspond to excesses in inputs and undesirable outputs, respectively, while $s^g \in R^{s_1}$ expresses shortages in desirable outputs. P^* reaches 1 only if slacks $s^-, s^g, \mathrm{and} s^b$ are zero for all inputs, desirable outputs, and undesirable outputs.

In DEA, when the number of DMUs is small, the number of units of the dominant or efficient set is relatively large, and the average efficiency is generally high (Alirezaee et al., 1998). Typically, a high proportion of DMUs is considered efficient when the number of DMUs (n) is smaller than the sum of the input (m) and output (s) variables (i.e.,

$n < m + s$), leading to low discrimination between homogeneous units (Matsuoka, 2009). Hence, it is better if $n > m + s$. A rule of thumb in a DEA model is that the number of DMUs should be greater than or equal to $\max\{m \times s, 3 \times (m+s)\}$ (Doyle and Green, 1994). This condition was satisfied in this study.

2.2.2. Random-effects Tobit model

To examine how possible determinants affected the industrial eco-efficiency of provinces, a random-effects Tobit model was used as the second-stage analysis. A two-stage approach combining DEA with a regression model was appealing due to its simplicity and the way in which it describes and interprets efficiency (McDonald, 2009). Since the efficiency scores are bounded, a variety of regression techniques have been used, including the classic ordinary least squares (OLS) and Tobit regression methods (Yahia and Essid, 2019). Since the value of the efficiency scores obtained from DEA is limited to a range from 0 to 1, the DEA scores are censoring variables, and OLS yields biased estimates (Agasisti and Cordero-Ferrera, 2013). For this reason, a limited dependent variable model (Tobit model) was used to avoid this problem. Hoff (2007) noted that, in most cases, the Tobit regression model is sufficient for modeling DEA scores against exogenous variables. Hence, this study used a random-effects Tobit regression model to avoid the bias associated with OLS. The Tobit model is explained as follows:

$$y_{rt} = \beta_o + \beta_1 GRP_{rt} + \beta_2 R\&D_{rt} + \beta_3 IWW_{rt} + \beta_4 IWG_{rt} + \beta_5 IWS_{rt} + \beta_6 PSO_{rt} + \alpha_r + u_{rt}$$
$$\begin{cases} y_{rt} = 0 \text{ if } y^*_{rt} \le 0 \\ y_{rt} = 1 \text{ if } y^*_{rt} \ge 1 \\ y_{rt} = y^*_{rt} \text{ if } 0 < y^*_{rt} < 1 \end{cases} \tag{4}$$

where y_{rt} is the eco-efficiency score evaluated by DEA, y^*_{rt} is the unobserved latent variable, β_o is the constant term, β_{1-6} are the coefficients for the independent variables, α_r is a specified individual random effect, u_{rt} is the error term, and t denotes the year.

3. Results

3.1. Industrial eco-efficiency

First, we checked for possible endogeneity in the DEA (Cordero et al., 2015; Santín and Sicilia, 2017). Spearman's correlation coefficients between the efficiency scores calculated by the DEA and input variables were ≤ 0.30 (0.27 for total energy consumption, 0.30 for total assets of industrial enterprises, 0.28 for annual average number of employees, and 0.17 for industrial water supply and usage). Although the coefficients were positive, they were at an acceptable level (Cordero et al., 2015).

Figure 3 shows a boxplot of each province's industrial eco-efficiency, and Table 4 summarizes the eco-efficiency scores of the provinces from 2005 to 2015. One point of interest is that the industrial eco-efficiency scores of some provinces tended to initially increase dramatically and then decline. For example, the scores for Hebei, Zhejiang, Fujian, Jiangxi, Henan, Hunan, and Guangxi provinces rose dramatically to 1 in 2010 but suddenly dropped in the following year. Another point of interest is that although the overall trend of industrial eco-efficiency was upward, there were considerable regional disparities. With the exception of some provinces, industrial eco-efficiency was generally low. In 2015, Beijing, Tianjin, Inner Mongolia, Hunan, and Guangdong were the most eco-efficient provinces, with a score of 1; on the other end, Ningxia (0.251), Shanxi (0.253), Gansu (0.273), Xinjiang (0.309), and Qinghai (0.356) were the least eco-efficient provinces.

Figure 4 shows the trend of industrial eco-efficiency in the northern provinces during the period 2005–2015. The northern region was selected as an example of the changing trends of industrial eco-efficiency because it includes provinces with both the best and close to the worst eco-efficiency performance. Beijing, Tianjin, and Inner Mongolia experienced significant progress, while Hebei and Shanxi had relatively low eco-efficiency.

3.2. Determinants of industrial eco-efficiency

Using the DEA results as a dependent variable, a panel-data Tobit regression model was performed to explore the external factors that may influence industrial eco-efficiency in China. According to the Hausman test, a random-effects model was selected ($\chi^2 = 0.99$, p = 0.320). Table 5

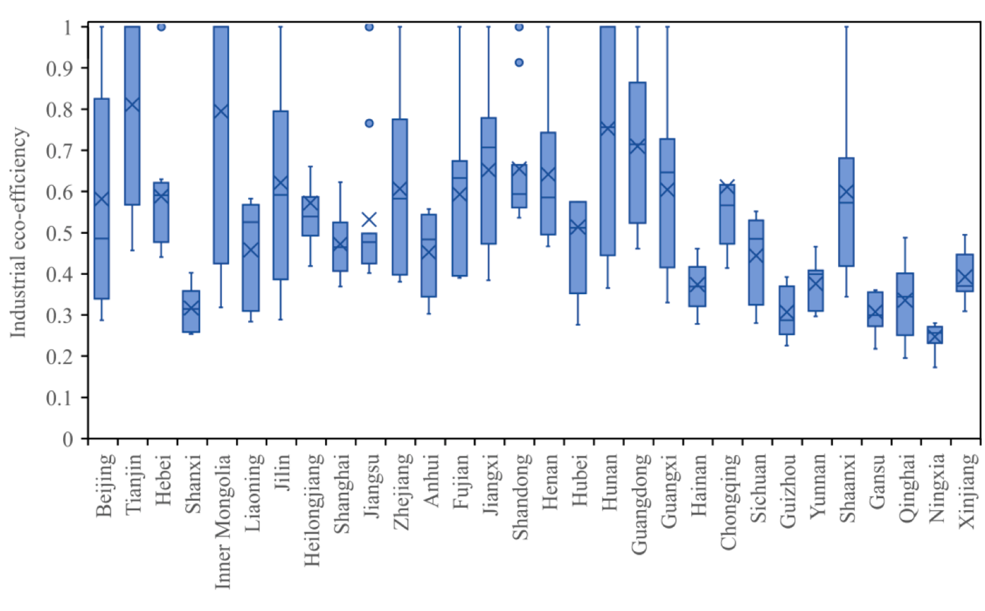

Fig. 3. Boxplot of each province's industrial eco-efficiency scores over the study period. The whiskers represent maximum (top) and minimum (bottom), the lines of the boxes represent the third quartile, median, and first quartile (from top to bottom), the cross marks represent the mean, and the dots represent the outliers.

Table 4
Industrial eco-efficiency scores of 30 Chinese provinces from 2005 to 2015.

Region	Province	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015
North	Beijing	0.287	0.300	0.340	0.371	0.415	0.486	0.606	0.768	0.825	1.000	1.000
	Tianjin	0.457	0.501	0.568	0.774	0.625	1.000	1.000	1.000	1.000	1.000	1.000
	Hebei	0.441	0.471	0.508	0.591	0.616	1.000	0.615	0.621	0.630	0.503	0.477
	Shanxi	0.256	0.259	0.291	0.330	0.311	0.359	0.402	0.368	0.339	0.315	0.254
	Inner Mongolia	0.318	0.362	0.425	0.639	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Northeast	Liaoning	0.284	0.292	0.310	0.362	0.441	0.573	0.526	0.565	0.568	0.582	0.537
	Jilin	0.289	0.327	0.387	0.440	0.592	0.529	0.722	0.795	1.000	1.000	0.752
	Heilongjiang	0.494	0.539	0.536	0.567	0.446	0.553	1.000	0.660	0.587	0.493	0.419
East	Shanghai	0.369	0.390	0.410	0.422	0.407	0.464	0.509	0.525	0.493	0.623	0.584
	Jiangsu	0.402	0.413	0.425	0.443	1.000	0.766	0.460	0.477	0.481	0.487	0.499
	Zhejiang	0.381	0.398	0.392	0.427	0.830	1.000	0.516	0.583	0.630	0.736	0.775
	Anhui	0.303	0.323	0.344	0.360	0.457	0.552	0.516	0.544	0.557	0.539	0.483
	Fujian	0.390	0.395	0.395	0.436	0.752	1.000	0.565	0.635	0.633	0.649	0.674
	Jiangxi	0.384	0.461	0.473	0.526	0.715	1.000	0.782	0.778	0.759	0.707	0.590
	Shandong	0.536	0.594	0.561	0.665	1.000	0.913	0.615	0.621	0.584	0.566	0.551
Central	Henan	0.467	0.527	0.585	0.719	0.801	1.000	0.743	0.704	0.545	0.496	0.470
	Hubei	0.276	0.448	0.318	0.353	1.000	0.495	0.512	0.575	0.544	0.553	0.575
	Hunan	0.366	0.444	0.445	0.538	0.756	1.000	0.733	1.000	1.000	1.000	1.000
South	Guangdong	0.461	0.488	0.524	0.564	0.567	0.714	0.845	1.000	0.777	0.864	1.000
	Guangxi	0.330	0.368	0.416	0.470	0.570	1.000	0.656	0.727	0.647	0.706	0.759
	Hainan	0.278	0.322	0.316	0.351	0.389	0.411	0.437	0.461	0.366	0.417	0.369
Southwest	Chongqing	0.419	0.414	0.473	0.559	0.501	0.616	1.000	1.000	0.579	0.566	0.599
	Sichuan	0.280	0.314	0.325	0.378	0.485	0.551	0.489	0.536	0.530	0.518	0.477
	Guizhou	0.226	0.236	0.253	0.275	0.288	0.364	0.259	0.332	0.370	0.384	0.392
	Yunnan	0.296	0.309	0.310	0.358	0.408	0.466	0.375	0.401	0.399	0.403	0.410
Northwest	Shaanxi	0.344	0.401	0.419	0.492	0.488	0.591	0.681	0.936	1.000	0.673	0.573
	Gansu	0.218	0.257	0.283	0.288	0.300	0.356	0.361	0.357	0.353	0.345	0.273
	Qinghai	0.196	0.215	0.251	0.295	0.299	0.345	0.459	0.488	0.390	0.402	0.356
	Ningxia	0.173	0.200	0.232	0.272	0.257	0.271	0.280	0.272	0.264	0.252	0.251
	Xinjiang	0.352	0.420	0.371	0.376	0.370	0.494	0.463	0.447	0.364	0.358	0.309

Note: Darker blue indicates higher scores (i.e., closer to 1), while darker red indicates lower scores (closer to 0).

summarizes the results.

With regard to economic variables, the effects of both *GRP* and *R&D* on the industrial eco-efficiency score were positive and statistically significant at the 1% and 5% levels, respectively. Regarding investment in pollution control, *IWW* was positive and statistically significant at the 1% level, *IWG* was negative and statistically significant, and *IWS* was not statistically significant. Finally, *PSO* was negative and statistically significant at the 1% level.

4. Discussion

Among the 30 provinces examined, five (Beijing, Tianjin, Inner Mongolia, Hunan, and Guangdong) showed great progress in industrial eco-efficiency, with their scores improving by more than 0.5 from 2005 to 2015. Other provinces, however, did not make equally significant progress. Three provinces (Shanxi, Heilongjiang, and Xinjiang) experienced a decline in industrial eco-efficiency, indicating that although some local governments have begun to seek a balance between environmental protection and economic growth, many provinces are still developing their economies at the cost of producing more undesirable outputs and consuming more inputs. It is also noteworthy that four of the five provinces with the worst industrial eco-efficiency in 2015 (Ningxia, Gansu, Xinjiang, and Qinghai) are located in northwest China, which is characterized by an underdeveloped economy and fragile ecology. In the economically underdeveloped hinterland, insufficient funding and a lack of professional expertise hamper local government

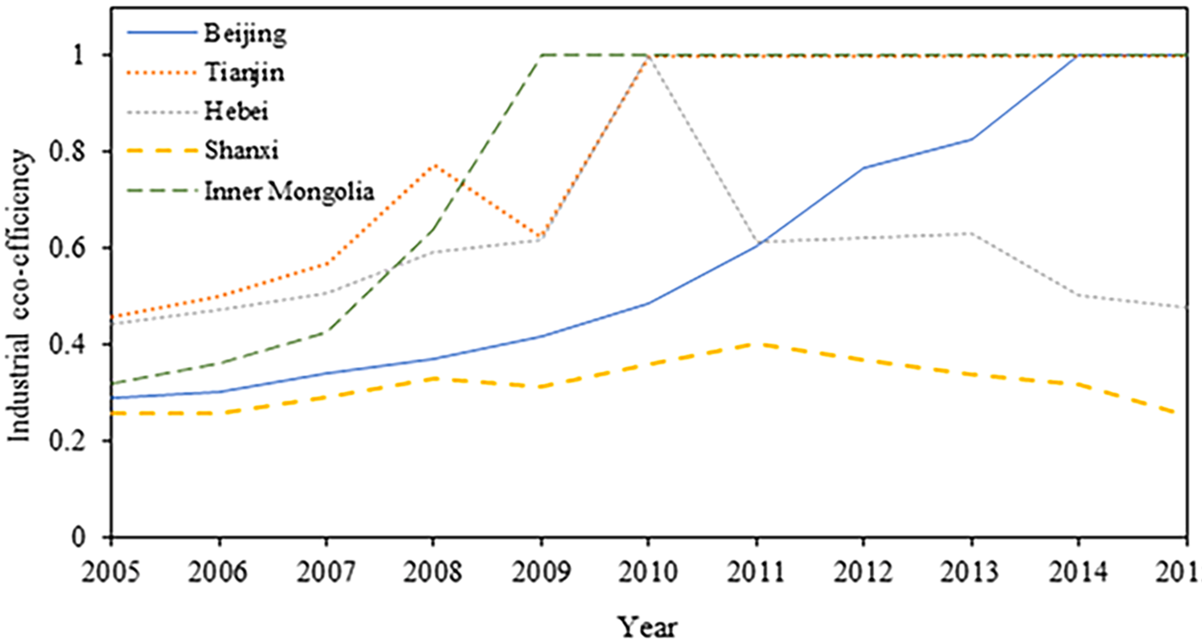

Fig. 4. Industrial eco-efficiency in northern China. The value 1 is the most efficient, while the value 0 is the least efficient.

Table 5
Random-effects Tobit model results.

Determinant	Coefficient		Marginal effect	
GRP	4.74×10^{-6}	**	3.81×10^{-6}	**
	(8.36×10^{-6})		(6.57×10^{-7})	
R&D	1.21×10^{-8}	*	9.78×10^{-9}	*
	(4.78×10^{-9})		(3.87×10^{-9})	
IWW	1.09×10^{-6}	**	8.78×10^{-7}	**
	(3.26×10^{-7})		(2.59×10^{-7})	
IWG	-2.79×10^{-7}	**	-2.25×10^{-7}	**
	(9.05×10^{-8})		(7.30×10^{-8})	
IWS	8.31×10^{-7}		6.69×10^{-7}	
	(1.04×10^{-6})		(8.41×10^{-7})	
PSO	−0.91	**	−0.73	**
	(0.23)		(0.19)	
Constant	0.43	**	–	
	(0.060)			

Notes: Standard errors in parentheses. ** statistical significance at the 1% level; * statistical significance at the 5% level. Observations = 304; log-likelihood = 57.50; Wald $\chi^2 = 146.46$.
GRP: gross regional product; *R&D*: research and development; *IWW*: investment in wastewater treatment; *IWG*: investment in waste gas treatment; *IWS*: investment in solid waste treatment; *PSO*: proportion of state-owned enterprises.

efforts to enforce state-issued environmental regulations, and factory pollution regulations are not strictly observed (Global Environmental Forum, 2004). The results revealed that industrial development in northwest China is extremely deficient in terms of economic, energy, and environmental measures.

The reason that many provinces have not made significant progress or have even experienced a decline in industrial eco-efficiency is presumably a conflict of interest between the central and local governments. In China, national environmental protection laws and regulations are formulated by the central government but are adapted to the actual situation of each region and implemented at the local level (Zheng et al., 2015). This is because the central government represents the general interests of the whole country and the public, while local governments prioritize local economic interests. As a result, some provinces do not fully comply with environmental regulations. Furthermore, in economically developed provinces, local governments are increasingly unfriendly toward low-end, polluting industries, forcing highly polluting enterprises to close or move to other regions. Many provinces, especially in western China, remain economically and institutionally underdeveloped and have little choice but to welcome virtually all investment projects, regardless of their quality, which to some extent hinders the improvement of industrial eco-efficiency.

It is also noteworthy that most provinces in the western region made little progress in industrial eco-efficiency. This is probably the result of industrial transfer from the east to the west of the country. Although the Guiding Opinions of the State Council on Undertaking Industrial Transfer in the Central and Western Regions (State Council, 2010) required adherence to environmental protection regulations and strict control of access in the industrial transfer process, the momentum of pollution transfer was not fundamentally curbed. Jining (2016) found that China's economic development is unbalanced. Some eastern regions have entered the later stages of industrialization, and their environmental quality has improved in recent years, whereas the central and western regions are still in need of economic development. The latter regions were thus willing to welcome the transfer of labor-intensive, high-consumption, high-emission industries from the east.

An important finding from the comparison in the northern region (Fig. 4) was that Beijing achieved great progress during the study period. Its eco-efficiency score was only 0.287 in 2005, which was comparatively low by national standards, but increased rapidly to reach a score of 1 in 2014. This result is consistent with Wu et al. (2018), who found that green development generally improved in Beijing from 2000 to 2014, probably because it continued to improve its environmental protection policies and legislation, strictly supervising their implementation, penalizing polluting businesses, and promoting cleaner production. The Beijing government even mandated the eviction of polluting industries. Beginning in 2006, many large-scale industrial enterprises, such as Beijing Coking and Chemical Plant, Beijing Capital Steel Group's Shougang Shijingshan Plant, and Dongfang Chemical Plant, were closed or moved to other provinces (He et al., 2019). In 2013, 288 polluting enterprises were closed, exceeding the annual goal of eliminating 200 polluting enterprises. These companies belonged to 11 industry sectors, including building materials, chemicals, furniture production, casting, and forging (Beijing Municipal Ecology and Environment Bureau, 2013). Furthermore, the Beijing Clean Air Action Plan, issued in 2011 (People's Government of Beijing Municipality, 2011), contributed to decreasing industrial gas emissions from 489.6 billion m^3

in 2011 to 367.6 billion m^3 in 2015. Moreover, the Municipal People's Congress voted to adopt regulations for the prevention and control of air pollution, which came into effect on March 1, 2014. Since then, the implementation of a catalog of prohibitions and restrictions for new industries has more effectively controlled industrial expansion that does not conform to the strategic positioning of the capital, guiding industries toward a low-carbon, green economy (Beijing Municipal Ecology and Environment Bureau, 2013). Furthermore, in the past 10 years, Beijing has increased its standard sewage charges tenfold. Similarly, a sewage charging policy was implemented step by step to encourage enterprises to progressively adopt advanced technology and to actively control pollution and reduce emissions (Don et al., 2015). Beijing's experience and lessons in the implementation of environmental control policies could be a model for many Chinese provinces.

Tianjin had the highest average industrial eco-efficiency score (0.811) during the study period, not only in the northern region but also in the entire country. As shown in Fig. 4, the province increased its eco-efficiency score throughout the period, except in 2009, and achieved a score of 1 in 2010. This may be explained by Tianjin's implementation of policies to optimize its industrial structure, develop a green economy, strictly control pollution caused by coal combustion, establish strict environmental access mechanisms, and eliminate underdeveloped production facilities. For instance, during the 11th Five-Year Plan period (2006–2010), Tianjin strengthened its energy conservation by focusing on energy utilization efficiency and the development of renewable energy projects, such as wind, solar, and biomass power generation (Tianjin Ecology and Environment Bureau, 2012). As a result, in 2010, its energy consumption relative to the GDP dropped to 0.826 tons of standard coal equivalent per yuan—21% lower than the 2005 level and above the energy-saving target of a 20% reduction during the 11th Five-Year Plan period (Tianjin Ecology and Environment Bureau, 2012). Simultaneously, the quality and efficiency of industrial enterprises significantly improved. In recent years, Tianjin has accelerated the elimination of underdeveloped production facilities and overcapacity, encouraged energy-saving transformations of excessively energy-consuming enterprises, and continuously improved energy utilization methods in key areas.

Significant progress in industrial eco-efficiency has also been made in Inner Mongolia, one of China's most important energy production bases, which experienced remarkable socioeconomic and environmental changes during the study period. The area's industrial eco-efficiency score increased from 0.318 in 2005 to 1 in 2009, which was an achievement of great significance for the development of sustainable industry. In the past, Inner Mongolia had a relatively underdeveloped economy, which developed by wasting resources and damaging the environment (Yang et al., 2012). Since the implementation of the Western Development Strategy in 1999, Inner Mongolia has attracted substantial investment and adopted preferential policies from the national government. Its per capita income grew from 5,861 yuan in 1999 to 71,101 yuan in 2015 (National Bureau of Statistics of China, 2015). This economic growth provided strong support for ecological development, and the level of green development has steadily improved. During the 11th and 12th Five-Year Plans (2006–2010 and 2011–2015), energy consumption per unit of industrial added value decreased by 42.9% and 31.9%, respectively. The province's eco-industrial achievements can serve as an example for other regions in China.

Unlike Beijing, Tianjin, and Inner Mongolia, other provinces are still characterized by low eco-efficiency. For example, Hebei had a relatively low industrial eco-efficiency score (0.477) in 2015. The province has long been known for the consumption of natural resources, backwardness of its environmental infrastructure, and illegal gas emissions from its small enterprises (Li et al., 2020). Pollution fog and haze appear frequently and cause serious damage, threatening people's health and daily living conditions. In 2013, 7 of the 10 most polluted cities in China were located in Hebei (Wang et al., 2013). The province's industrial eco-efficiency score was higher than that of Beijing in 2005 but did not improve. There are several possible reasons for Hebei's relatively low industrial eco-efficiency score. First, its main industries are iron, steel, coke, and cement, which place a high environmental burden. This high proportion of heavy industry has led to an enormous demand for energy and created a large volume of pollutant emissions (Wang et al., 2013). Second, the province's environmental infrastructure is underdeveloped, and many small enterprises produce illegal emissions (Li et al., 2020). Hebei had an eco-efficiency score of 1 in 2010, which dramatically declined in subsequent years, suggesting that its low industrial eco-efficiency was not due to technological limitations but mainly due to insufficient regulation and enforcement.

Finally, Shanxi saw no improvement in industrial eco-efficiency during the study period. Its score slightly increased between 2005 and 2011 but decreased in the following years. Shanxi is one of the leading energy production and consumption regions of China, with its total energy consumption increasing from 45.55 million tons of standard coal in 2000 to 128.23 million tons in 2015 (Zhang et al., 2019b). This seems to be one of the reasons for its low industrial eco-efficiency, as fossil fuel consumption is the primary source of regional air pollution and CO_2 emissions. Furthermore, extensive exploitation of fossil fuels results in environmental deterioration and the discharge of large amounts of wastewater, waste gas, and solid waste. Hence, a resource-dependent region like Shanxi should further improve the natural resource and energy efficiency of its industries by adopting advanced resource-efficient technologies and developing less resource- and energy-intensive industries.

The results also indicate wide gaps in industrial eco-efficiency between provinces, even within the same region. Many provinces have considerable potential to improve their industrial eco-efficiency. Crucially, it is necessary for the central government to address this unbalanced eco-efficiency development of regional industries.

A comparison of our results with those of similar studies reveals both similarities and differences. For example, Huang et al. (2018), who evaluated provincial eco-efficiency in China using five inputs, one desirable output, and one undesirable output, reported similar tendencies in the average scores for Tianjin (first in both studies), Guizhou (29th in both studies), and Guangdong (fourth in this study and second in Huang et al., 2018) and different tendencies for Qinghai (26th and 3rd, respectively), Inner Mongolia (2nd and 24th, respectively), and Hainan (25th and 4th, respectively). The main reason for these inconsistencies is probably the selection of variables (both inputs and outputs). Compared with Huang et al. (2018), as well as Dai et al. (2016), this study included more diversified variables, especially environmental aspects, which allowed a more comprehensive evaluation of eco-efficiency. However, further studies are needed to scrutinize the selection of variables for accurate assessments of industrial eco-efficiency.

The random-effects Tobit regression results showed that, in line with expectations, per capita GRP was positively and significantly associated with industrial eco-efficiency. Along with economic development, public displeasure with environmental degradation has grown (Shi et al., 2020), and the government has been under pressure to satisfy the increasing demands for environmental protection. The growing environmental concerns have led to more stringent environmental regulations, the introduction of cleaner technologies, the replacement of obsolete and polluting technologies, and increased environmental investment (Sinha et al., 2017).

Similarly, in line with our assumptions (see Section 2.1.2), the internal R&D expenditure of industrial enterprises had a positive and statistically significant effect on eco-efficiency. Previous studies have demonstrated that technological innovation provides an avenue for environmental improvement (Zhou and Zhao, 2016) and that R&D investment plays an important role in increasing industrial eco-efficiency (Hobday et al., 2004). Therefore, local governments should introduce measures to encourage enterprise R&D investment.

Investment in wastewater treatment also had a positive and statistically significant impact on industrial eco-efficiency. This is in line with the expectation that investment in pollution control technologies reduces pollutant emissions, thereby improving industrial eco-efficiency. A rather contradictory result was the negative and statistically significant impact of investment in waste gas treatment, perhaps due to China's weak judicial system, extensive corruption, and opaque investment processes (Zhang et al., 2019a).

Finally, the proportion of state-owned enterprises had a negative and statistically significant effect on industrial eco-efficiency. This can be explained by the fact that state-owned enterprises are characterized by a heavy pollution burden, low competition, excessive staff numbers, and poor corporate governance (Lin et al., 2020; Zhong, 2006). In China, state-owned enterprises always enjoy more preferential policies and perform worse than other types of enterprises. Contrary to state-owned enterprises, due to intense market competition, private enterprises are forced to invest in innovation to maintain a competitive advantage (Liu et al., 2020; Zhang et al., 2001). Wu (2017) noted that private enterprises have greater innovative impetus and capabilities than state-owned enterprises, and Konisky and Teodoro (2016) found that private enterprises face higher environmental pressure than state-owned enterprises because they enjoy less protection from the government and are more likely to be penalized for environmental violations. In China, the government controls the bulk of the country's natural resources, most of which are allocated to state-owned enterprises (Zhong, 2006). This uneven allocation of resources lowers the resource usage efficiency of state-owned enterprises. To further improve industrial eco-efficiency, it is essential to minimize governmental market intervention and create a competitive market environment. Furthermore, laws and regulations should not unduly discriminate between state-owned and private enterprises, and privatization can increase competition and efficiency (Zhong, 2006).

5. Conclusion and policy implications

Based on panel data for 30 Chinese provinces from 2005 to 2015, this study adopted a two-stage approach, first using a DEA (SBM) model to determine the provincial industrial eco-efficiency scores and then performing a random-effects Tobit regression analysis to explore the determinants of industrial eco-efficiency. The first-stage results revealed that the overall trend of industrial eco-efficiency was upward. However, with the exception of Beijing, Tianjin, Inner Mongolia, Hunan, and Guangdong, most provinces were still characterized by low industrial eco-efficiency. The second-stage results indicated that per capita GRP, the internal R&D expenditure of industrial enterprises, and investment in wastewater treatment had positive and statistically significant impacts on provincial industrial eco-efficiency. By contrast, the proportion of state-owned enterprises and investment in waste gas treatment had negative impacts. In conclusion, there are great disparities in industrial eco-efficiency between Chinese provinces. Provinces with high industrial eco-efficiency are mainly distributed across the eastern region, while those with low industrial eco-efficiency are located in the often economically less developed western region. The findings of this study have significant policy implications for improving provincial industrial eco-efficiency. The following recommendations aim to help provinces with low industrial eco-efficiency to pursue high-quality, green development.

1. Local governments should encourage enterprises to increase their R&D investment. The regression analysis revealed that R&D investment positively affects industrial eco-efficiency. A previous study indicated that government subsidies facilitate enterprises' R&D investment for developing environmental protection technologies (Wu, 2017). Hence, local governments should provide subsidies to enterprises (particularly private enterprises) that have strong innovative impetus but insufficient resources for innovation (Shi et al., 2020).
2. It is important to construct a responsibility matrix for China's government officials regarding environmental damage. Officials' performance should be judged according to various environment-related indicators, including resource utilization, environmental quality, and ecological protection. This empirical study showed that although some provinces have made great progress in economic development, resource consumption and pollutant emissions remain at high levels. This can be explained by the fact that some local governments pay little attention to environmental protection because the evaluation processes for officials are closely linked to economic achievement and not to environmental performance (Liu, 2017). It is therefore vital that resource and environmental issues should be highlighted in the performance evaluation of officials.
3. Although national anti-pollution regulations apply everywhere in China, regional discrepancies exist in practice. The main reason for this is a lack of expertise (Global Environmental Forum, 2004). It is thus crucial to make technical education available on a wider scale and train more technicians and engineers. At the same time, the Chinese government should take measures to foster technology transfer between provinces to facilitate the flow of knowledge and ideas that contribute to industrial eco-efficiency development. China is at a critical stage of economic restructuring and industrial upgrading. Under the double pressure of environmental pollution and resource scarcity, the government should make substantial efforts to develop science parks and encourage innovation and technology transfer.

CRediT authorship contribution statement

Ken'ichi Matsumoto: Conceptualization, Funding acquisition, Investigation, Methodology, Software, Supervision, Validation, Visualization, Writing - review & editing. **Yueyang Chen:** Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software, Visualization, Writing - original draft.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

The authors thank Professor Michalis Doumpos, Technical University of Crete, Greece, for his fruitful comments on the DEA results in the revision stage. This study was partially supported by the Integrated Research Program for Advancing Climate Models (grant number JPMXD0717935715) of the Ministry of Education, Culture, Sports, Science and Technology of Japan and JSPS KAKENHI (grant numbers JP18K11754 and JP18K11800).

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ecolind.2021.108072.

References

Agasisti, T., Cordero-Ferrera, J.M., 2013. Educational disparities across regions: a multilevel analysis for Italy and Spain. J. Policy Model. 35 (6), 1079–1102.
Alirezaee, M.R., Howland, M., van de Panne, C., 1998. Sampling size and efficiency bias in data envelopment analysis. J. Appl. Math. Decis. Sci. 2 (1), 51–64.
Ball, P., Lunt, P., 2020. Lean eco-efficient innovation in operations through the maintenance organisation. Int. J. Prod. Econ. 219, 405–415.
Beijing Municipal Ecology and Environment Bureau, 2013. Continuous promotion of emission reduction in the clean air industry in Beijing. http://sthjj.beijing.gov.cn/bjhrb/index/xxgk69/zfxxgk43/fdzdgknr2/xwfb/607249/index.html (accessed 5 May 2020).

Charnes, A., Cooper, W.W., Rhodes, E., 1978. Measuring the efficiency of decision making units. Eur. J. Oper. Res. 2 (6), 429–444.
Chen, S., Golley, J., 2014. 'Green' productivity growth in China's industrial economy. Energy Econ. 44, 89–98.
Cordero, J.M., Santín, D., Sicilia, G., 2015. Testing the accuracy of DEA estimates under endogeneity through a Monte Carlo simulation. Eur. J. Oper. Res. 244 (2), 511–518.
Dai, Z., Guo, L.u., Jiang, Z., 2016. Study on the industrial eco-efficiency in East China based on the super efficiency DEA model: an example of the 2003–2013 panel data. Appl. Econ. 48 (59), 5779–5785.
Don, Z., Li, H., Ge, C., 2015. Chinese academy for environmental planning. http://www.cnki.com.cn/Article/CJFDTotal-HJJI201512001.htm (accessed 4 May 2020).
Doyle, J., Green, R., 1994. Efficiency and cross-efficiency in DEA: derivations, meanings and uses. J. Oper. Res. Soc. 45 (5), 567–578.
Ebrahimnejad, A., Tavana, M., Lotfi, F.H., Shahverdi, R., Yousefpour, M., 2014. A three-stage data envelopment analysis model with application to banking industry. Measurement 49, 308–319.
Feng, C., Wang, M., 2017. Analysis of energy efficiency and energy savings potential in China's provincial industrial sectors. J. Clean. Prod. 164, 1531–1541.
Global Environmental Forum, 2004. Overseas environmental measures of Japanese companies. https://www.env.go.jp/earth/coop/coop/document/oemjc/china/e/china_e.pdf (accessed 4 May 2020).
Halkos, G., Petrou, K.N., 2019. Treating undesirable outputs in DEA: a critical review. Econ. Anal. Policy 62, 97–104.
He, K., Zhang, Q., Ming, D., Wu, Y., Witherspoon, C., Foltescu, V., Han, Y., Cheng, J., Qu, Y., 2019. A review of 20 years' air pollution control in Beijing. http://sthjj.beijing.gov.cn/bjhrb/resource/cms/2019/04/2019041916301550241.pdf. (accessed 4 May 2020).
Hobday, M., Rush, H., Bessant, J., 2004. Approaching the innovation frontier in Korea: the transition phase to leadership. Res. Policy 33 (10), 1433–1457.
Hoff, A., 2007. Second stage DEA: comparison of approaches for modelling the DEA score. Eur. J. Oper. Res. 181 (1), 425–435.
Hu, J.-L., Wang, S.-C., 2006. Total-factor energy efficiency of regions in China. Energy Policy 34 (17), 3206–3217.
Huang, J., Chen, J., Yin, Z., 2014. A network DEA model with super efficiency and undesirable outputs: an application to bank efficiency in China. Math. Probl. Eng. 2014, 1–14.
Huang, J., Xia, J., Yu, Y., Zhang, N., 2018. Composite eco-efficiency indicators for China based on data envelopment analysis. Ecol. Indic. 85, 674–697.
Intergovernmetal Panel on Climate Change, 2006. IPCC guidelines for national greenhouse gas inventories 2006. http://www.ipcc-nggip.iges.or.jp/public/2006gl/ (accessed 4 May 2020).
Jining, C., 2016. Taking environmental quality as the core to make up for the weak points of environmental protection. http://www.mee.gov.cn/gkml/sthjbgw/qt/201601/t20160114_326153.htm (accessed 10 May 2020).
Konisky, D.M., Teodoro, M.P., 2016. When governments regulate governments. Am. J. Pol. Sci. 60 (3), 559–574.
Lehni, M., Schmidheiny, S., Stigson, B., Pepper, J., World Business Council for Sustainable Development, 2000. Eco-efficiency: Creating More Value with Less Impact. Conches-Geneva, World Business Council for Sustainable Development.
Li, Y., Huang, S., Yin, C., Sun, G., Ge, C., 2020. Construction and countermeasure discussion on government performance evaluation model of air pollution control: a case study from Beijing-Tianjin-Hebei region. J. Clean. Prod. 254, 120072. https://doi.org/10.1016/j.jclepro.2020.120072.
Lin, J.Y., Cai, F., Zhou, L., 1998. Competition, policy burdens, and state-owned enterprise reform. Am. Econ. Rev. 88 (2), 422–427.
Lin, K.J., Lu, X., Zhang, J., Zheng, Y., 2020. State-owned enterprises in China: a review of 40 years of research and practice. China J. Account. Res. 13 (1), 31–55.
Liu, J., 2017. Smog control more crucial than GDP in officials' evaluation. https://www.chinadaily.com.cn/china/2017-01/16/content_27969082.htm (accessed 15 May 2020).
Liu, Z., Li, X.u., Peng, X., Lee, S., 2020. Green or nongreen innovation? different strategic preferences among subsidized enterprises with different ownership types. J. Clean. Prod. 245, 118786. https://doi.org/10.1016/j.jclepro.2019.118786.
Lv, W., Hong, X., Fang, K., 2012. Chinese regional energy efficiency change and its determinants analysis: Malmquist index and Tobit model. Ann. Oper. Res. 228 (1), 9–22.
Matsumoto, K., Makridou, G., Doumpos, M., 2020. Evaluating environmental performance using data envelopment analysis: the case of European countries. J. Clean. Prod. 272, 122637. https://doi.org/10.1016/j.jclepro.2020.122637.
Matsuoka, M., 2009. Energy and environment R&D toward environmental impact reduction. https://www.ntt-review.jp/archive/ntttechnical.php?contents=ntr200910sf1.html (accessed 10 May 2020).
McDonald, J., 2009. Using least squares and tobit in second stage DEA efficiency analyses. Eur. J. Oper. Res. 197 (2), 792–798.
National Bureau of Statistics of China, 2015. National data. http://data.stats.gov.cn/english/adv.htm?m=advquery&cn=E0103 (accessed 10 May 2020).
Pan, H., Zhang, H., Zhang, X., 2013. China's provincial industrial energy efficiency and its determinants. Math. Comput. Model. 58 (5-6), 1032–1039.
People's Government of Beijing Municipality, 2011. Beijing clean air action plan. http://www.beijing.gov.cn/zhengce/zfwj/zfwj/szfwj/201905/t20190523_72517.html (accessed 10 May 2020).
Raheli, H., Rezaei, R.M., Jadidi, M.R., Mobtaker, H.G., 2017. A two-stage DEA model to evaluate sustainability and energy efficiency of tomato production. Inf. Process. Agric. 4 (4), 342–350.
Santín, D., Sicilia, G., 2017. Dealing with endogeneity in data envelopment analysis applications. Expert Syst. Appl. 68, 173–184.
Savrul, M., Incekara, A., 2015. The effect of R&D intensity on innovation performance: a country level evaluation. Procedia Soc. Behav. Sci. 210, 388–396.
Shi, T., Yang, S., Zhang, W., Zhou, Q., 2020. Coupling coordination degree measurement and spatiotemporal heterogeneity between economic development and ecological environment: empirical evidence from tropical and subtropical regions of China. J. Clean. Prod. 244, 118739. https://doi.org/10.1016/j.jclepro.2019.118739.
Sinha, A., Shahbaz, M., Balsalobre, D., 2017. Exploring the relationship between energy usage segregation and environmental degradation in N-11 countries. J. Clean. Prod. 168, 1217–1229.
State Council, 2010. Guiding Opinions of the State Council on Undertaking Industrial Transfer in the Central and Western Regions. http://www.gov.cn/zhengce/content/2010-09/06/content_1536.htm (accessed 10 May 2020).
Stefan, S., Andreas, S., 1990. Ökologische rationalität: ansatzpunkte zur ausgestaltung von ökologieorientierten managementinstrumenten. Die Unternehmung 44 (4), 273–290.
Tianjin Ecology and Environment Bureau, 2012. The 12th Five-Year Plan of Tianjin Eco-city Construction. http://sthj.tj.gov.cn/env/program_and_plan/planning_plan/201410/t20141022_1977.html (accessed 10 April 2020).
Toma, P., Massari, S., Miglietta, P.P., 2016. Natural resource use efficiency and economic productivity, in: Massari, S., Sonnemann, G., Balkau, F. (Eds.), Life Cycle Approaches to Sustainable Regional Development. Routledge, New York, pp. 143–148.
Wang, L., Yang, J., Zhang, P., Zhao, X., Wei, Z., Zhang, F., Su, J., Meng, C., 2013. A review of air pollution and control in Hebei province, China. Open J. Air Pollut. 02 (03), 47–55.
Wu, A., 2017. The signal effect of government R&D subsidies in China: does ownership matter? Technol. Forecast. Soc. Change 117, 339–345.
Wu, H., Yu, Y., Li, S., Huang, K., 2018. An empirical study of the assessment of green development in Beijing, China: considering resource depletion, environmental damage and ecological benefits simultaneously. Sustainability 10 (3), 719.
Xing, Z., Wang, J., Zhang, J., 2018a. Expansion of environmental impact assessment for eco-efficiency evaluation of China's economic sectors: an economic input-output based frontier approach. Sci. Total Environ. 635, 284–293.
Xing, Z., Wang, J., Zhang, J., 2018b. Total-factor ecological efficiency and productivity in Yangtze River Economic Belt, China: a non-parametric distance function approach. J. Clean. Prod. 200, 844–857.
Yahia, F.B., Essid, H., 2019. Determinants of Tunisian schools' efficiency: a DEA-Tobit approach. J. Appl. Manag. Invest. 8 (1), 44–56.
Yang, X.-j.-l.-t., Xu, M., Han, W., 2012. Pathways to a low-carbon economy for Inner Mongolia, China. Procedia Environ. Sci. 12, 212–217.
Zhang, A., Zhang, Y., Zhao, R., 2001. Impact of ownership and competition on the productivity of Chinese enterprises. J. Comp. Econ. 29 (2), 327–346.
Zhang, H., An, R., Zhong, Q., 2019a. Anti-corruption, government subsidies, and investment efficiency. China J. Account. Res. 12 (1), 113–133.
Zhang, X., Su, B., Yang, J., Cong, J., 2019b. Index decomposition and attribution analysis of aggregate energy intensity in Shanxi Province (2000–2015). J. Clean. Prod. 238, 117897. https://doi.org/10.1016/j.jclepro.2019.117897.
Zhao, P.-J., Zeng, L.-e., Lu, H.-Y., Zhou, Y., Hu, H.-y., Wei, X.-Y., 2020. Green economic efficiency and its influencing factors in China from 2008 to 2017: based on the super-SBM model with undesirable outputs and spatial Dubin model. Sci. Total Environ. 741, 140026. https://doi.org/10.1016/j.scitotenv.2020.140026.
Zhao, S., Jiang, Y., Wang, S., 2019. Innovation stages, knowledge spillover, and green economy development: moderating role of absorptive capacity and environmental regulation. Environ. Sci. Pollut. Res. 26 (24), 25312–25325.
Zheng, S., Yi, H., Li, H., 2015. The impacts of provincial energy and environmental policies on air pollution control in China. Renew. Sust. Energ. Rev. 49, 386–394.
Zhong, H., 2006. Where is the future: China's SOEs reform. J. Washington Inst. China Stud. 1 (1), 105–115.
Zhou, Y., Zhao, L., 2016. Impact analysis of the implementation of cleaner production for achieving the low-carbon transition for SMEs in the Inner Mongolian coal industry. J. Clean. Prod. 127, 418–424.
Zou, D., Cong, H., 2021. Evaluation and influencing factors of China's industrial water resource utilization efficiency from the perspective of spatial effect. Alex. Eng. J. 60 (1), 173–182.