The Average Environmental Efficiency Technique and its Application to Chinese Provincial Panel Data

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The average environmental efficiency technique and its application to Chinese provincial panel data

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Abstract

In this study, we propose *average environmental efficiency*, a consistent and robust environmental efficiency measurement, and use it to evaluate the environmental efficiency of Chinese provinces. With the help of a nonparametric directional distance function approach, we can measure all possible environmental efficiency scores of the province by considering all projection directions to the efficient frontier. Then, the mean value of the environmental efficiency scores of a province in all possible projection directions is defined as the average environmental efficiency. Furthermore, we investigate the influencing factors of regional environmental efficiency via a feasible generalized least squares regression approach. The empirical results show that China's national environmental efficiency has a high value of 0.803, and only nine provinces have average environmental efficiency greater than the average of the country. This implies that two-thirds of provinces still have much room for improvement. In addition, the east area achieved the best average environmental efficiency over the studied period, followed in order by the west area, central area, and northeast area. Moreover, we find that the energy consumption structure, government intervention, and economic openness negatively influence the regional environmental efficiency, while higher education positively influences this efficiency at the 1% significance level.

Keywords: Regional environmental efficiency; average environmental efficiency; directional distance function; feasible generalized least squares; provincial panel data

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1. Introduction

China has achieved considerable economic growth in the more than four decades since its "Reform and Opening-up" policy started in 1978. According to data provided by the World Bank, China has become the world's second-largest economy after the United States, and China's gross domestic product (GDP) increased from 365 billion (CNY) in 1978 to 90,030.9 billion (CNY) in 2018. The price of such rapid economic growth has been a huge consumption of energy resources as well as serious environmental pollution problems (Li et al., 2020b). For example, in 2017, China consumed 4.49 billion tons of standard coal equivalent energy and produced 8.75 million tons of SO_2, 69.96 billion tons of effluent water, and 7.96 million tons of dust, as well as other pollutants. In China, 34 provincial administrative regions are mandated by China's central government. These regions are administratively and economically independent, i.e., they have different governance rules and development planning (Wang et al., 2016). The economic development, energy consumption, and environmental pollution present huge differences between provincial-level regions (Li et al., 2020b). How to trade off economic growth, resource conservation, and environmental friendliness is a difficult task for the policymakers in central and local governments. Environmental efficiency measures the coordinated development of economy and environment; improving environmental efficiency is one key way to create economic growth while achieving energy conservation and emission reduction (Meng et al., 2016; Wang et al., 2018; Stergiou and Kounetas, 2021). Therefore, in this study, we address the problems of (1) how to reasonably evaluate the environmental efficiency of provincial regions in China, and (2) what the contributing factors are that determine environmental efficiency.

Data envelopment analysis (DEA) has been widely applied in environmental efficiency evaluation at the macro or micro levels (e.g., Sueyoshi et al., 2017; Zhou et al., 2018) because this method is particularly suitable for efficiency analysis of a set of homogenous decision making units (DMUs) involving multiple inputs (e.g., labor, energy consumption), multiple desirable outputs (e.g., GDP), and multiple undesirable outputs (e.g., dust emission). Within the nonparametric DEA methodology, the efficient frontier is established, and the environmental efficiency of a DMU is evaluated by comparing it with a benchmark on the

efficient frontier. Among various DEA based environmental efficiency models, directional distance function (DDF) in DEA framework received significant attention and has been applied by many scholars in different areas of study (e.g., Chen, 2014; Sun et al., 2017; Sharma and Majumdar, 2021; Stergiou and Kounetas, 2021) because this approach measures the efficiency of DMU along the direction that increases desirable outputs and decreases inputs and undesirable outputs simultaneously (Wang et al., 2019).

Although the DDF approach has been employed in a large body of studies, one crucial issue of applying DDF approach remains that how to justify the choice of an appropriate projection direction along which to measure the environmental efficiency of the DMU. Many researchers have made an attempt to select projection direction for DDF from endogenous or exogenous perspectives (see Wang et al. (2019) for detailed review). However, one main concerns that should be payed attention. That is, prior studies evaluated the DMUs based on different projection directions, thus, the inconsistent projection directions between DMUs will result in unfair and incomparable evaluation results. Specifically, the efficiency value depends considerably on the selection of the projection direction, so one DMU can dominate another along one direction but be dominated along another direction, thus leading to the DMUs have little incentive to accept the evaluation results. Although some scholars proposed to evaluate DMUs based on a common direction (e.g., Chu et al., 2021; Sharma and Majumdar, 2021), other feasible projection directions including relevant information that are helpful for decision support are ignored.

The above discussion motivates a new question: is it possible to evaluate environmental efficiency of a DMU based on all possible projection directions? Taking into account all possible projection directions not only evaluates all DMUs in a same and equitable criterion, increasing the acceptability of evaluation results, but also incorporates all information associated with these directions, offering rich evaluation information for decision makers. Similar problems that the efficiency and ranking of a DMU is sensitive to the input and output weights have been addressed by previous studies (e.g., Lahdelma and Salminen, 2006; Salo and Punkka, 2011; Li et al., 2020b), but the problem of considering all possible projection directions has not been tackled in DDF approach based environmental efficiency evaluation.

To complement the previous research, in this study, we propose an alternative

environmental efficiency measurement, named *average environmental efficiency*, to evaluate the environmental efficiency values of DMUs. According to the research paradigm of Yang et al. (2018) and Lozano and Soltani (2020), within the framework of nonparametric DDF approach, we can measure all possible environmental efficiency scores of a DMU by considering all possible projection directions to the efficient frontier. Then, the mean value of the environmental efficiency scores of a DMU in all possible projection directions is defined as the average environmental efficiency. Because the average environmental efficiency considers all projection directions to the efficient frontier, it not only ensures that all DMUs are evaluated on the same basis but also eliminates the sensitivity issue of the efficiency value. Afterward, the average environmental efficiency is applied to an empirical study of 30 Chinese provincial environmental efficiency using panel data during the period of 2006–2017. Moreover, to provide policymakers with more valuable suggestions on how to improve environmental efficiency, we further examine the determinants of environmental efficiency by using the feasible generalized least squares (FGLS) regression technique. Based on the results of all these analyses, policy implications are given. Overall, this study methodologically and empirically enriches the growing research on regional environmental efficiency evaluation.

The rest of the paper unfolds as follows. In Section 2, we briefly review the studies on environmental efficiency relevant to various DEA models. In Section 3, we present the preliminaries and develop the average efficiency measurement. Section 4 gives the empirical analysis and policy implications. Section 5 concludes this study.

2. Literature review

The concept of environmental efficiency encompasses both economic and environmental aspects (Mardani et al., 2017; Chen et al., 2020). The worsening energy consumption and environmental pollution problems force scholars and practitioners to pay attention to environmental efficiency, the improvement of which is one of the most cost-effective ways to conserve energy and reduce pollution emission and finally achieve sustainable development (Zha et al., 2016; Sueyoshi et al., 2017). As stated aforementioned, DDF in DEA framework has become a popular approach for measuring environmental efficiency of countries, regions, and economic sectors. In this section, we focus on reviewing the literature on environmental

efficiency evaluation by nonparametric DDF methods.

2.1 Environmental efficiency at the national or regional level

Oh (2010) introduced a global Malmquist-Luenberger productivity index based on DDF and applied it to measure dynamic environmental efficiency of 26 OECD countries over 1990 to 2003. Du et al. (2014) employed a nonparametric metafrontier DDF approach to measure the CO_2 emission efficiency and the potential emission reduction of 30 Chinese provinces from 2006 to 2020. Kounetas (2015) estimated the environmental efficiency technology gaps in 25 European countries based on DDF approach. Yu and Choi (2015) proposed a generalized metafrontier DDF approach to measure environmental performance considering regional heterogeneity. Wang et al. (2016) evaluated the carbon emission efficiency of 30 Chinese provinces during 1996–2012 using a nonradial DDF approach. Lee and Choi (2018) measured the environmental efficiency of 16 provinces in Korea by applying a nonradial DDF and examined the pure technical efficiency and scale efficiency. Chen and Xu (2019) used super-efficiency DDF approach to assess the environmental efficiency and Malmquist-Luenberger productivity index of provincial regions in mainland China from 2000 to 2015. Li et al. (2020b) empirically analyzed the regional environmental efficiency in China based on an entropy weight method and nonparametric DDF model, and they found environmental efficiency disparities between regions. Li et al. (2021) developed a bound DDF model to evaluate energy and environmental efficiencies of 30 provinces in mainland China from 2011 to 2015. Sharma and Majumdar (2021) measured the environmental efficiency of 28 Asian countries using DDF and SBM-DEA, in which rice is desirable output and CO_2 is undesirable output.

2.2 Environmental efficiency at the industrial/sectoral level

Also, many scholars have studied environmental efficiency at the industrial/sectoral level. Mandal and Madheswaran (2010) measured the environmental efficiency of the Indian cement industry using both DEA and DDF approaches. Ramli et al. (2013) proposed a scale DDF approach to select optimal direction for each DMU and apply this approach measure the eco-efficiency of the Malaysian manufacturing sector. Beltrán-Esteve and Picazo-Tadeo (2015) analyzed the dynamic environmental efficiency in the transport sectors of 38 countries using

a nonparametric DDF approach based Luenberger productivity indicators. Duan et al. (2016) measured the energy and CO_2 emission performance for China's thermal power industry from static and dynamic perspectives using a bootstrapped DDF approach. Sun et al. (2017) developed a nonradial DDF preference model to evaluate the environmental efficiency of 17 Chinese port enterprises. Song and Wang (2018) proposed a slack-based endogenous DDF model to choose directional vectors and then applied it to measure the environmental efficiency of China's power generation industry. Tovar and Wall (2019) used an output-oriented DDF approach to measure environmental efficiency for a cross section of 28 Spanish port authorities in 2016. Li et al. (2020) used a meta-frontier nonradial DDF approach to measure the static and dynamic CO_2 emission performance of 16 port enterprises in China covering the years of 2013 to 2018. Singh and Gundimeda (2021) measured the environmental efficiency of the grossly polluting Indian leather industry using DDF method under three directional vectors.

2.3 Summary of the literature review

To sum up, the use of nonparametric DDF in environmental efficiency evaluation has attracted increasing attention from scholars in recent decades. The studies pertaining to DDF-based environmental efficiency evaluations include but are not limited to the above research. One critical issue in previous studies has not been well addressed: the environmental efficiency of a DMU is commonly measured along a direction determined by either an exogenous or endogenous mechanism. Each DMU is compared with one efficient target corresponding to its own projection direction. In other words, DMUs are not evaluated in a consistent manner, thus leading to unfair and incomparable results. As a result, the DMUs have little motivation to accept the final environmental efficiency results. Moreover, the environmental efficiency method may lack robustness since it is sensitive to the selection of projection direction. Finally, prior research consider one common direction based on a certain criterion but ignore other projection directions that may reflect information helpful to decision making. To this end, we consider all possible projection directions to estimate the environmental efficiency of a DMU, and propose the average environmental efficiency to enhance the robustness and comparability of the evaluation.

3. Methodology

3.1 Preliminaries

Suppose that there are n DMUs waiting to be evaluated, and each DMU consumes m input resources to produce s desirable outputs and p undesirable outputs. The input vector, desirable output vector, and undesirable output vector of $\mathrm{DMU}_j (j = 1,2,\cdots,n)$ are denoted as $x = (x_{1j}, x_{2j}, \cdots, x_{mj})$, $y = (y_{1j}, y_{2j}, \cdots, y_{sj})$, and $b = (b_{1j}, b_{2j}, \cdots, b_{pj})$. The multi-input and multi-output production technology can be characterized as follows.

$$T = \{(x, y, b): x \text{ can produce } (y, b)\} \tag{1}$$

where T always satisfies the axioms of production theory, such as being closed, bounded, and convex (Färe and Grosskopf, 2006). The strong disposability assumption is imposed on undesirable outputs in this study, and the nonparametric DEA approach is used to construct the strong disposal environmental production technology (Yang and Pollitt, 2010; Sueyoshi and Goto, 2012; Xian et al., 2019; Afzalinejad, 2021; Ma et al., 2021), as follows.

$$T = \left\{ (x, y, b) \middle| \begin{array}{c} \sum_{j=1}^{n} \lambda_j x_j \le x, \\ \sum_{j=1}^{n} \lambda_j y_j \ge y, \\ \sum_{j=1}^{n} \lambda_j b_j \le b, \\ \sum_{j=1}^{n} \lambda_j = 1, \lambda_j \ge 0, j = 1,2,\cdots,n \end{array} \right\} \tag{2}$$

In Eq. (2), $\lambda_j, \forall j$ are the nonnegative intensity variables for constructing the environmental production technology using a convex combination. It can be observed that T is constructed under the assumption of variable returns to scale (VRS). VRS differs from the constant returns to scale (CRS), which is assumed in many previous models, and VRS commonly occurs in the real world (Sun et al., 2017). The above environmental production technology has been extensively used in energy and environment analysis (e.g., Sun et al., 2017).

3.2 Directional distance function with undesirable outputs in data envelopment analysis

The directional distance function (DDF) approach was introduced by Chambers et al. (1996) and further extended by Chung et al. (1997) to measure environmental efficiency. The DDF with undesirable outputs is defined such that it aims to decrease inputs and undesirable outputs and increase desirable outputs simultaneously in the same proportion, as shown below.

$$\vec{D}_T\,(x, y, b; g) = \max\{\beta: (x - \beta g_x, y + \beta g_y, b - \beta g_b) \in T\}, \tag{3}$$

In Eq. (3), $\boldsymbol{g} = (\boldsymbol{g}_x, \boldsymbol{g}_y, \boldsymbol{g}_b) \neq \boldsymbol{0}$ is the directional vector, in which $\boldsymbol{g}_x \in \Re^m$, $\boldsymbol{g}_y \in \Re^s$, $\boldsymbol{g}_b \in \Re^p$; and $\beta(\geq 0)$ measures the inefficiency score of DMU, i.e., $\beta = 0$ means DMU is efficient, while $\beta > 0$ means DMU is inefficient. Combining Eqs. (2) and (3), the following DEA-type model is used to calculate the value of β for a given DMU, denoted as DMU_o.

$$\begin{aligned} \max \quad & \beta \\ \text{s.t.} \quad & \sum_{j=1}^{n} \lambda_j x_{ij} \leq x_{io} - \beta g_i^x, && i = 1,2,\cdots,m \\ & \sum_{j=1}^{n} \lambda_j y_{rj} \geq y_{ro} + \beta g_r^y, && r = 1,2,\cdots,s \\ & \sum_{j=1}^{n} \lambda_j b_{tj} \leq b_{to} - \beta g_t^b, && t = 1,2,\cdots,p \\ & \sum_{j=1}^{n} \lambda_j = 1, \lambda_j \geq 0, && j = 1,2,\cdots,n \end{aligned} \tag{4}$$

In model (4), the value of β is calculated along the directional vector (g_i^x, g_r^y, g_t^b). In previous studies, the observed input and output value of the evaluated DMU_o is always set as a directional vector, i.e., $(g_i^x, g_r^y, g_t^b) = (x_{io}, y_{ro}, b_{to}), \forall i, r, t$, and the environmental efficiency is defined as $E_o = 1 - \beta_o$ (Wang et al., 2019), but other directional vectors such as unit value direction are also applied (e.g., Färe et al., 2006; Halkos and Tzeremes, 2013). In other words, the selection of the directional vector in model (4) is flexible, depending on the purpose of the study (Ray, 2008; Zhang and Choi, 2014; Wang et al., 2019). In addition, the value of β_o may be larger than one thus leading to $E_o = 1 - \beta_o < 0$, i.e., yielding negative efficiency (Cheng and Zervopoulos, 2014). Therefore, Cheng and Zervopoulos (2014) proposed a generalized definition of the efficiency score for the DDF and transformed model (4) to the following model (5).

$$\begin{aligned} \min \quad & \theta_o = \frac{1 - \frac{1}{m}\sum_{i=1}^{m} \beta g_i^x / x_{io}}{1 + \frac{1}{s+p}\left(\sum_{r=1}^{s} \beta g_r^y / y_{ro} + \sum_{t=1}^{p} \beta g_t^b / b_{to}\right)} \\ \text{s.t.} \quad & \sum_{j=1}^{n} \lambda_j x_{ij} \leq x_{io} - \beta g_i^x, && i = 1,2,\cdots,m \\ & \sum_{j=1}^{n} \lambda_j y_{rj} \geq y_{ro} + \beta g_r^y, && r = 1,2,\cdots,s \\ & \sum_{j=1}^{n} \lambda_j b_{tj} \leq b_{to} - \beta g_t^b, && t = 1,2,\cdots,p \\ & \sum_{j=1}^{n} \lambda_j = 1, \lambda_j \geq 0, && j = 1,2,\cdots,n \end{aligned} \tag{5}$$

where θ_o stands for the environmental efficiency, which lies between 0 and 1. Model (5) has a distinctive feature that the efficiency score θ_o depends on the direction of the directional vector, not the length of the directional vector (Cheng and Zervopoulos, 2014; Yang et al., 2018); that is, the value of θ_o will not change whether (g_i^x, g_i^y, g_i^b) or $c * (g_i^x, g_i^y, g_i^b)$ is used, for any constant $c > 0$.

3.3 Average environmental efficiency

Within the DEA DDF framework, the environmental efficiency of a DMU is commonly measured along a direction determined by either an exogenous (e.g., input/output observation value direction) or endogenous (e.g., direction towards the furthest target) mechanism (Wang et al., 2019; Wei et al., 2019). This means that each DMU is evaluated based on its own projection direction, chosen according to the study purpose. Moreover, the environmental efficiency may lack robustness since it changes along with the projection direction (Yang et al., 2018; Lozano and Soltani, 2020). As a result, the evaluation results may lack fairness and comparability, thereby reducing the acceptability of the results to DMUs. As illustrated in Figure 1, for a specific DMU_G, its environmental efficiency is evaluated by comparing it with any benchmark on the efficient frontier $\widehat{HACI}$, i.e., the upper-left projection directions, the entire shadow area, allow DMU_G increase its environmental efficiency by expanding desirable outputs while reducing inputs and undesirable outputs simultaneously. In this study, with the help of model (5), we try to explore all possible projection directions toward the efficient frontier and propose using the average environmental efficiency to compare all the evaluated DMUs.

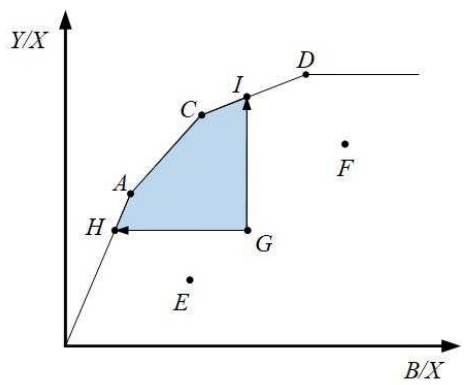

Figure 1 The projections of a specific DMU_G

The efficiency score θ_o obtained from model (5) is independent of the directional vector's length (Cheng and Zervopoulos, 2014). Therefore, as Cheng (2014) suggested, the unit vectors can be regarded as directional vectors and used in model (5). Define the set Θ to include all unit vectors in the nonnegative quadrant of Euclidean space. The unit vector in set Θ is denoted as $\hat{\boldsymbol{g}} = (\bar{g}_1, \bar{g}_2, \cdots, \bar{g}_l)$, where $l = m + s + p$, and $\sum_{k=1}^{l} \bar{g}_k^2 = 1, \bar{g}_k \geq 0$. With the help of a directional vector scanning approach developed by Cheng (2014) and later applied by Yang et al. (2018), uniformly distributed unit vectors can be extracted from Θ. The set containing all uniformly distributed unit vectors is denoted as Ψ, and $\Psi \subset \Theta$, i.e., Ψ is the so-called *directional vector set*. In Ψ, each unit vector $\hat{\boldsymbol{g}}_q$ can be used as a directional vector in model (5) and the corresponding environmental efficiency score $\theta(\hat{\boldsymbol{g}}_q)$ can be obtained. For a certain DMU_o, E_o is a set that includes all environmental efficiency scores corresponding to all directional vectors in Ψ, that is, $E_o = \{\theta_q^o(\hat{\boldsymbol{g}}_q) | \hat{\boldsymbol{g}}_q \in \Psi, \forall q \in Q\}$, and Q is the number of directional vectors in Ψ.

In line with Lahdelma and Salminen (2006), considering all environmental efficiency scores in E_o, the average environmental efficiency of DMU_o, denoted θ_o^{ave}, is defined as the expected value of efficiency scores over the directional vector distributions, as expressed below.

$$\theta_o^{ave} = \int_{\boldsymbol{g} \in \Psi} f(\boldsymbol{g})\, \theta^o(\boldsymbol{g}) dg \tag{6}$$

The average environmental efficiency defined in formula (6) is a comprehensive evaluation result considering all directions to the frontier, which guarantees all DMUs are evaluated using the same criterion. Additionally, this definition avoids the risk of the efficiency score changing with the projection direction selection, i.e., it improves the robustness of the environmental efficiency score. Although formula (6) is a continuous integral, it can be calculated with sufficient accuracy by using a sufficiently high value of Q in the following formula.

$$\theta_o^{ave} \approx \frac{\sum_{q=1}^{Q} \theta_q^o}{Q} \tag{7}$$

The more the number of directional vectors, Q, the more accurate the average efficiency, θ_o^{ave}, but the greater the required calculation time. The value of θ_o^{ave} always lies within the interval 0 and 1, and $\theta_o^{ave} = 1$ means the evaluated DMU_o is efficient while $\theta_o^{ave} < 1$ means

it is inefficient.

4. Empirical analysis

4.1 Sample, variables, and data description

Referring to the previous studies on the environmental efficiency evaluation using DEA methods (e.g., Vlontzos et al., 2014; Li et al., 2020; Liu et al., 2020), three input variables, one desirable output, and two undesirable outputs are considered for environmental efficiency evaluation in this study. Labor, fixed asset investments, and energy consumption are the three inputs; GDP (Gross Domestic Product) is the one desirable output; and SO_2 emission and soot emission are the two undesirable outputs. Due to data availability, this study's sample includes 30 provincial-level administrative regions in China's mainland from 2006 to 2017. (Tibet, Hong Kong, Macau, and Taiwan are excluded because of the missing data. All 30 entities are referred to as *provinces* for convenience in the following analysis.) All data was collected from four sources: the China Statistical Yearbook, DRCNET Statistical Database System, Provincial Statistical Yearbook, and China Labor Statistical Yearbook. A detailed description of inputs and outputs is given below.

(1) Labor input. Labor is a widely accepted input variable of human capital, reflecting the actual utilization of all labor resources within a certain period (Chang et al., 2013). In this study, labor refers to the people in the employed labor force at the end of the year.

(2) Fixed asset investments input. This measure represents the capital stock. As previous studies did (e.g., Lin et al., 2018; Kong et al., 2019; Liu et al., 2020), the capital stock used in this work is calculated by the perpetual inventory method proposed by Goldsmith (1951), shown as follows.

$$K_{j,t} = I_{j,t} + (1-\delta)K_{j,t-1} \tag{9}$$

Here, $K_{j,t}$ represents the capital stock of province *j* at year *t* and $K_{j,t-1}$ represents the capital stock of province *j* at year *t-1*; $I_{j,t}$ is the annual added fixed investment of province *j* at year *t*; and δ is the depreciation rate, which is set at 10.96% in this study. The year 2000 is set as the initial year, and the initial capital stock is calculated by the following equation.

$$K_{j,0} = I_{j,0}/(g_j + \delta) \tag{10}$$

where g_j is the average annual investment growth rate of province j during 2000–2017.

(3) Energy consumption input. The total energy consumption is the total amount of various types of energy consumed in production and daily life, mainly including energy from coal, petroleum, natural gas, and hydroelectric plants. The energy amounts from various sources are converted into total energy consumption, represented by standard coal (Li et al., 2020; Liu et al., 2020).

(4) Desirable output. GDP is an important and widely accepted indicator for measuring economic development. It reflects the economic strength and market size of a country or region. To eliminate the effect of inflation, 2006 is used as the base year to convert the nominal GDP into a real GDP.

(5) Undesirable output. Wastewater, waste gas, and solid waste are commonly used as undesirable outputs. Due to the data availability and completeness, the emissions of SO_2 and of smoke and dust are used as undesirable outputs in this study.

Table 1 summarizes the statistical descriptions for all input and output variables.

Table 1 Descriptive statistics for input and output variables

Variable		Unit	Mean	Std. Dev.	Max	Min
Input	Labor	10^4 person	2629.89	1725.68	6775.60	294.19
	Fixed asset investments	100 million yuan	35659.09	28412.71	152042.39	2230.19
	Energy consumption	10^4 ton	13033.01	8068.63	39423.00	920.00
Desirable output	GDP	100 million yuan	14857.75	13021.09	72252.51	648.50
Undesirable output	SO_2 emission	10^4 ton	66.56	42.83	196.20	1.43
	Smoke and dust emission	10^4 ton	37.55	47.88	813.88	0.90

Note: Provinces=30, Years=12.

In addition, according to the National Bureau of Statistics (2020), mainland China is divided into four areas for purposes of analysis: east, central, west, and northeast. Table 2 lists the provinces and the areas to which they belong.

Table 2 Provinces

Areas	Provinces /municipalities/autonomous regions
East	Beijing, Tianjin, Hebei, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, Hainan
Central	Anhui, Jiangxi, Henan, Hubei, Hunan, Shanxi
West	Inner Mongolia, Guangxi, Chongqing, Sichuan, Guizhou, Yunnan, Shaanxi, Gansu, Qinghai, Ningxia, Xinjiang
Northeast	Liaoning, Jilin, Heilongjiang

4.2 Regional environmental efficiency analysis

In our empirical study, we generate 58,905 unit vectors via the directional vector scanning approach. These are taken as directional vectors and substituted into model (6) to obtain 59,905 environmental efficiency scores for each of the 30 provinces. Figure 2 clearly illustrates the variation of the environmental efficiency of the 30 provinces in 2017. It can be observed that the environmental efficiency varies substantially for the inefficient provinces, indicating that different projection directions yield different environmental efficiency scores. In other words, the environmental efficiency is sensitive to the projection direction, which implies that the environmental efficiency measured along a single projection direction determined by either exogenous or endogenous mechanism lacks fairness and comparability. Therefore, the average environmental efficiency that incorporates all possible projection directions is preferable to measure the environmental efficiency of each province.

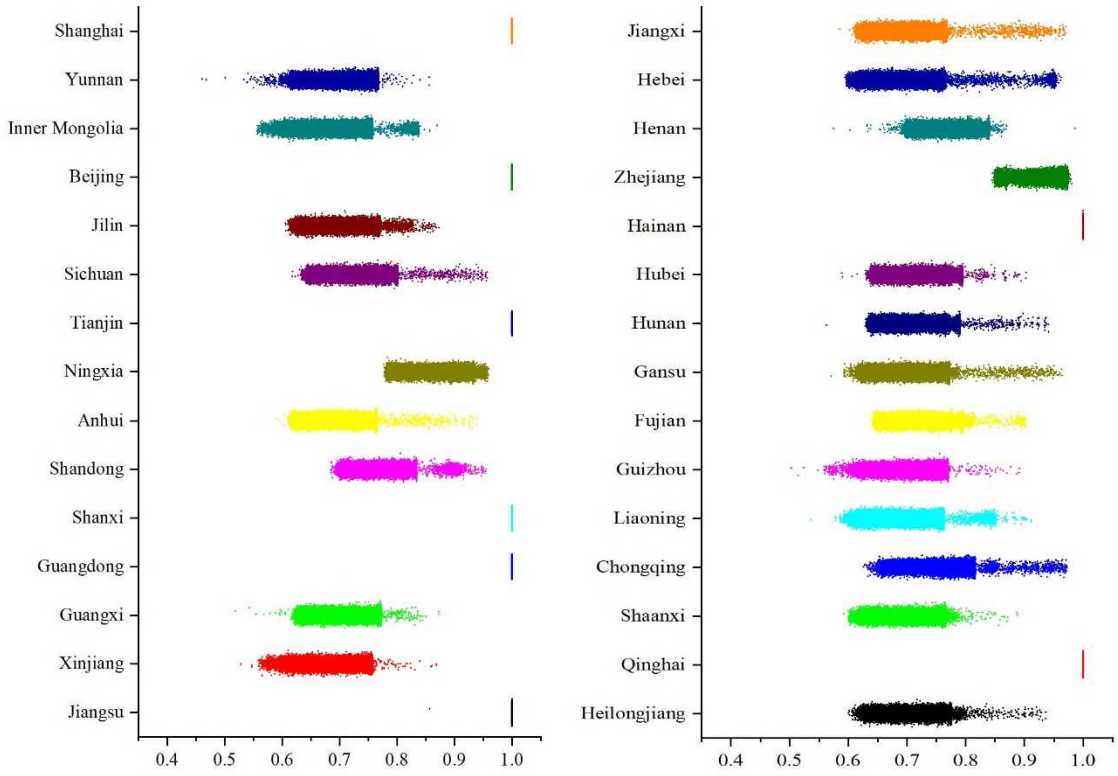

Figure 2 Environmental efficiency scatter plot of 30 Chinese provinces in 2017

Table 3 Environmental efficiencies for 30 provinces from 2006 to 2017

Areas	Provinces	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	Average
East	Shanghai	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
	Beijing	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
	Tianjin	1.000	1.000	0.961	1.000	0.957	1.000	0.965	0.825	0.771	0.792	1.000	1.000	0.939
	Shandong	0.801	0.828	0.847	0.850	0.889	0.769	0.791	0.786	0.756	0.764	0.752	0.779	0.801
	Guangdong	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
	Jiangsu	0.870	0.880	0.907	0.965	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.968
	Hebei	0.727	0.731	0.735	0.736	0.743	0.708	0.710	0.713	0.714	0.711	0.707	0.703	0.720
	Zhejiang	0.904	0.942	1.000	0.926	0.982	0.827	0.880	0.832	0.815	0.836	0.909	0.941	0.899
	Hainan	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
	Fujian	0.802	0.814	0.872	0.792	0.785	0.767	0.761	0.757	0.748	0.749	0.750	0.729	0.777
	Average	0.910	0.920	0.932	0.927	0.936	0.907	0.911	0.891	0.880	0.885	0.912	0.915	0.910
Central	Anhui	0.744	0.740	0.742	0.733	0.729	0.723	0.721	0.721	0.713	0.712	0.712	0.704	0.724
	Shanxi	0.694	0.698	0.704	0.706	0.699	0.698	0.704	0.705	0.705	0.707	0.701	1.000	0.727
	Jiangxi	0.742	0.748	0.760	0.725	0.722	0.716	0.722	0.720	0.715	0.712	0.713	0.707	0.725
	Henan	0.733	0.733	0.740	0.740	0.733	0.735	0.744	0.738	0.726	0.729	0.754	0.778	0.740
	Hubei	0.734	0.741	1.000	0.746	0.763	0.746	0.740	0.736	0.726	0.729	0.734	0.726	0.760
	Hunan	0.744	0.738	0.744	0.745	0.749	0.736	0.743	0.737	0.726	0.730	0.734	0.722	0.737
	Average	0.732	0.733	0.782	0.732	0.733	0.726	0.729	0.726	0.719	0.720	0.725	0.773	0.736
West	Yunnan	0.731	0.733	0.725	0.728	0.724	0.709	0.710	0.703	0.701	0.713	0.713	0.706	0.716
	Inner Mongolia	0.706	0.697	0.703	0.704	0.696	0.696	0.693	0.694	0.749	0.690	0.693	0.689	0.701
	Sichuan	0.721	0.729	0.739	0.750	0.747	0.745	0.766	0.762	0.741	0.742	0.746	0.739	0.744
	Ningxia	1.000	0.995	1.000	1.000	0.839	0.934	0.922	0.904	1.000	1.000	0.866	0.875	0.945
	Guangxi	0.716	0.724	0.724	0.726	0.727	0.729	0.728	0.727	0.712	0.714	0.718	0.709	0.721
	Xinjiang	0.705	0.703	0.703	0.698	0.701	0.689	0.684	0.684	0.710	0.689	0.691	0.688	0.695
	Gansu	0.727	0.732	0.724	0.719	0.721	0.716	0.722	0.717	0.702	0.708	0.713	0.710	0.718
	Guizhou	0.720	0.714	0.707	0.698	0.712	0.718	0.718	0.721	0.705	0.715	0.722	0.721	0.714
	Chongqing	0.731	0.735	0.761	0.764	0.791	0.753	0.758	0.748	0.737	0.739	0.783	0.771	0.756
	Shaanxi	0.710	0.712	0.715	0.729	0.741	0.706	0.706	0.701	0.694	0.697	0.707	0.703	0.710
	Qinghai	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
	Average	0.770	0.770	0.773	0.774	0.764	0.763	0.764	0.760	0.768	0.764	0.759	0.756	0.765
Northeast	Jilin	0.720	0.713	0.723	0.712	0.717	0.712	0.726	0.727	0.724	0.710	0.716	0.709	0.717
	Liaoning	0.715	0.711	0.720	0.719	0.723	0.718	0.717	0.719	0.708	0.706	0.709	0.699	0.714
	Heilongjiang	0.760	0.747	0.744	0.736	0.733	0.722	0.718	0.711	0.709	0.707	0.702	0.717	0.726
	Average	0.732	0.724	0.729	0.722	0.724	0.717	0.721	0.719	0.714	0.708	0.709	0.708	0.719
Average of the whole country		0.805	0.808	0.823	0.812	0.811	0.799	0.802	0.793	0.790	0.790	0.798	0.807	0.803

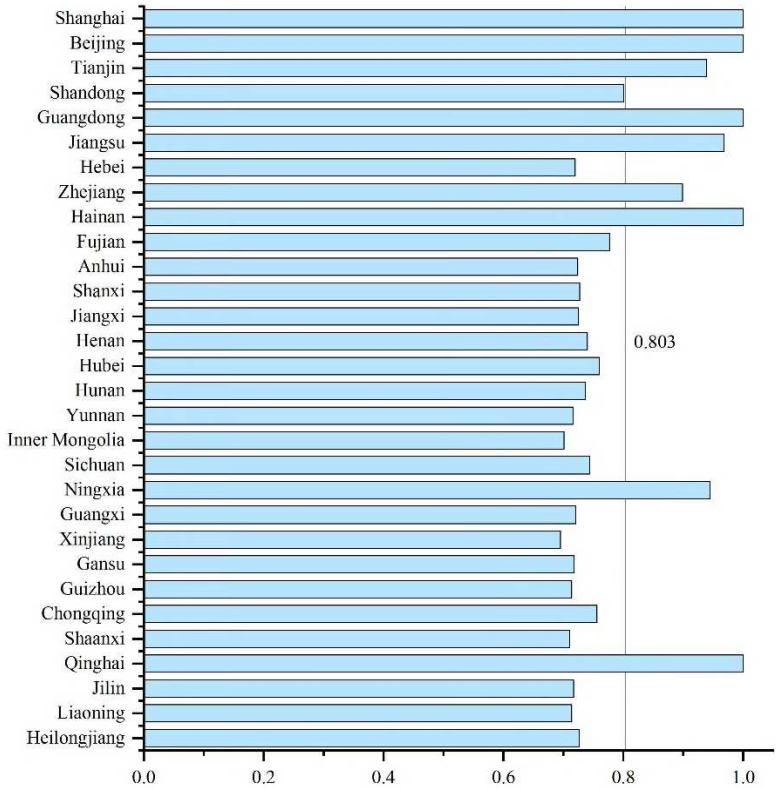

Figure 3 Average environmental efficiency of 30 Chinese provinces during 2006–2017

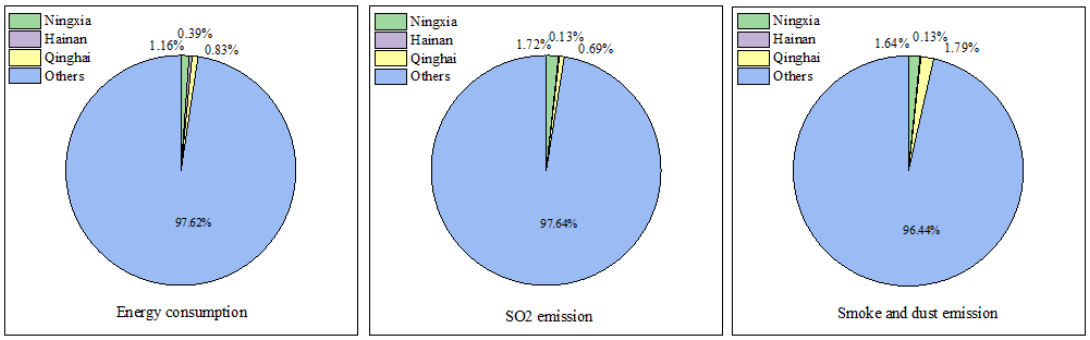

Figure 4 Energy consumption and pollution emissions proportions of 3 provinces

The calculated results for average environmental efficiency from 2006 to 2017 of 30 provinces are reported in Table 3, and Figure 3 clearly shows their average environmental efficiency during the studied span. We can learn from combining Table 3 with Figure 3 that China has a high environmental efficiency score of 0.803. Also, only nine provinces have average environmental efficiency greater than the national average: Shanghai with 1.000, Beijing with 1.000, Tianjin with 0.939, Guangdong with 1.000, Jiangsu with 0.968, Zhejiang with 0.899, Hainan with 1.000, Ningxia with 0.945, and Qinghai with 1.000. This implies that even though the country's environmental efficiency is good, two-thirds of the provinces still have much room for improvement. Shanghai, Beijing, Tianjin, Guangdong, Jiangsu, and

Zhejiang are economically developed regions in China, all of which have advanced environmental management concepts, allowing them to better balance resource consumption, economic growth, and pollution emissions, and thereby attain high environmental efficiency. Unlike the findings in previous studies (e.g., Yu et al., 2019; Li et al., 2020; Liu et al., 2020), our results show that Hainan, Ningxia, and Qinghai achieved very high environmental efficiency during the investigated time span. These three provinces, especially, Ningxia and Qinghai, are underdeveloped regions in China, so they consumed less energy and emitted less pollution. Figure 4 depicts the energy consumption and pollution emission proportions of these three provinces during the studied 12-year period; it can be seen that their energy consumption accounts for about 1~2% and their pollution emission accounts for less than 1%. Additionally, note that Xinjiang is the only province with an environmental efficiency value less than 0.7. We find that the total energy consumption of Xinjiang ranked around tenth among all provinces, and its pollution emissions ranked around fifth, but its GDP ranked in the bottom five during the investigated period. This indicates that Xinjiang did not allocate resources efficiently and paid little attention to clean production, resulting in low environmental efficiency.

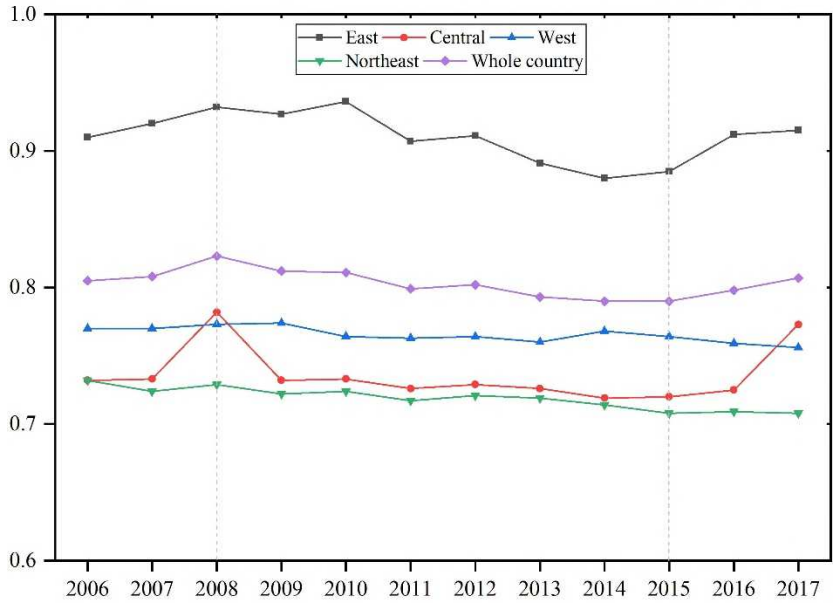

Figure 5 Trends in the environmental efficiency of four areas from 2006 to 2017

Table 3 provides the environmental efficiency of the four areas from 2006 to 2017, and Figure 5 illustrates their environmental efficiency trends. We can find from Table 3 that the east area achieved the best average environmental efficiency over the studied period with the

value of 0.910, followed by the west area (0.765), central area (0.736), and northeast area (0.719). From 2006 to 2017, the east area had the best environmental efficiency each year, followed by the west area, central area, and northeast area, as shown in Figure 5. These findings agree with the conclusion of Yu et al. (2019). The main reason is that the east is an economically developed area; it has advanced production technology, as well as abundant human and material capital, which is good for high environmental efficiency. We also see that the central area performed worse than the west area in terms of environmental efficiency. As part of the Rise of Central China Strategy that was initiated in 2004, the provinces in the central area invested more in infrastructure construction to facilitate economic development. Statistics show that the GDP of the central area increased from 4,321.80 billion (CNY) in 2006 to 17,648.68 billion (CNY) in 2017. However, the rapid economic development came at the cost of excessive resource consumption and excessive pollution emissions, thus lowering the environmental efficiency.

Furthermore, it can be clearly observed in Figure 5 that the environmental efficiency of the whole country and four areas exhibited a downward trend from 2008 to 2015. This is similar to the results of Yu et al. (2019), Zhao et al. (2019), Zhu et al. (2019), and Liu et al. (2020). The 2008 financial crisis occurred all over the world, and China's economy was inevitably hit. To alleviate the adverse effects of the financial crisis, the Chinese government implemented many policies and measures to stimulate the economy, such as increased investments in infrastructure construction. Ecological protection was not taken seriously, and as a result, the environmental efficiency of China was hampered. Additionally, Figure 5 displays that the environmental efficiency of the whole country, as well as the east and central areas showed an upward trend, while the other two areas decreased slightly after 2015. This result agrees with Yu et al. (2019) and Zhao et al. (2019). This achievement may be due to the strict implementation of the "energy conservation and emissions reduction" policy in China's 13th five-year development plan (from 2016 to 2020). That is, compared with 2015, the energy consumption should be limited to 5 billion tons of coal equivalent, and the total chemical oxygen demand, ammonia nitrogen, sulfur dioxide, and nitrogen oxide emissions should be reduced by 10%, 10%, 15%, and 15%, respectively.

4.3 Analysis of influencing factors

To provide more valuable suggestions on the improvement of regional environmental efficiency to policymakers, in this section, we further investigate the factors that may influence the environmental efficiency. Referring to the relevant literature (e.g., Yu et al., 2019; Liu et al., 2020) and considering data availability, the influencing factors this study selected include the energy consumption structure, industrial structure, government intervention, economic openness, and high education. That is, environmental efficiency is a dependent variable, and the above five factors are independent variables. These five variables are described in detail below. All independent variable data points were extracted from the China Statistical Yearbook and Provincial Statistical Yearbook.

Energy consumption structure. As previous literature pointed out, different types of energy are associated with different efficiency, i.e., the energy consumption structure may affect the environmental efficiency (Ma, 2015; Li et al., 2018). This indicator is measured as the ratio of coal consumption to total energy consumption in a province (Yu et al., 2019).

Industrial structure. Secondary industry is a major source of energy consumption and pollution emissions in China, which directly relates to the environmental efficiency in a region (Yu et al., 2019; Liu et al., 2019). The ratio of the total output value of the secondary industry to GDP in a province is used to capture the industrial structure.

Government intervention. This indicator reflects the role of government in environmental governance. Appropriate government intervention contributes to the sustainable development of a region (Liu et al., 2019). Government intervention is measured as the government expenditure divided by the GDP in a province.

Economic openness. Openness not only brings advanced technology in a region but also brings high energy consumption and high pollution emission transfer (Liu et al., 2019). This variable is represented by the proportion of foreign investment to GDP in a province (Montalbano and Nenci, 2019; Liu et al., 2020).

Higher education. High education accelerates the absorption and diffusion of innovative environmental technologies, which is conducive to improving environmental efficiency (Pablo-Romero and Sánchez-Braza, 2015; Salim et al., 2017). It is defined as the

proportion of the population with a college degree or above to the population aged at least six.

The statistical descriptions of independent variables are reported in Table 4, and Table 5 provides the pairwise correlations of dependent and independent variables. Although Table 5 shows that high correlations exist between energy consumption structure and industrial structure, the correlation coefficient is 0.545 and the variance inflation factors (VIF) of all variables are lower than 2.0, much smaller than the recommended cut-off value of 10. In other words, there is no multicollinearity between variables, which can be used for the following regression analysis.

Table 4 Statistics for independent variables

Independent variables	Obs.	Mean	Std. Dev.	Min	Max
Energy consumption structure (*ECS*)	360	0.596	0.176	0.057	0.972
Industrial structure (*IS*)	360	0.463	0.081	0.190	0.593
Government intervention (*GI*)	360	0.222	0.097	0.084	0.627
Economic openness (*EO*)	360	0.025	0.024	0.0004	0.225
Higher education (*HE*)	360	0.112	0.024	0.027	0.476

Table 5 Pairwise correlations of dependent and independent variables

	Variables	1	2	3	4	5	6
1	Environmental efficiency	1.000					
2	Energy consumption structure	-0.470***	1.000				
3	Industrial structure	-0.284***	0.545***	1.000			
4	Government intervention	0.019	-0.243***	-0.232***	1.000		
5	Economic openness	0.243***	-0.112**	-0.043	-0.331***	1.000	
6	Higher education	0.430***	-0.465***	-0.490***	0.007	0.232***	1.000

Note: *p<0.1, **p<0.05, ***p<0.01.

With the selected variables, the specific regression model is expressed as follows.

$$EE_{jt} = \alpha_0 + \alpha_1 ECS_{jt} + \alpha_2 IS_{jt} + \alpha_3 GI_{jt} + \alpha_4 EO_{jt} + \alpha_5 HE_{jt} + \varepsilon_{jt} \quad (11)$$

In Eq. (11), EE_{jt} represents the average environmental efficiency of province j in year t. *ECS*, *IS*, *GI*, *EO*, and *HE* are the energy consumption structure, industrial structure, government intervention, economic openness, and human capital, respectively. The coefficients of independent variables are $\alpha_n (n = 1,2,\cdots,5)$, and ε_{jt} is the error term.

Table 6 Regression results of FGLS regression method

Variables	(1)	(2)	(3)	(4)
	θ^{SBM}	$\theta^{(-x_o,y_o,-b_o)}$	$\theta^{(-1,1,-1)}$	θ^{ave}
ECS	-0.108***	-0.071**	-0.049	-0.056***
	(0.034)	(0.033)	(0.031)	(0.018)
IS	0.026	0.004	-0.075	-0.027
	(0.090)	(0.059)	(0.091)	(0.051)
GI	-0.185***	-0.123***	-0.290***	-0.116***
	(0.061)	(0.039)	(0.068)	(0.044)
EO	-0.918***	-0.442***	-0.222*	-0.344***
	(0.061)	(0.056)	(0.123)	(0.028)
HE	0.381***	0.065	0.150*	0.165***
	(0.071)	(0.067)	(0.089)	(0.050)
Constant	0.628***	0.889***	0.909***	0.869***
	(0.051)	(0.043)	(0.045)	(0.031)
Wald chi2 (5)	320.55	88.65	24.83	192.10
N	360	360	360	360

Note: Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Banker et al. (2019) stated that ordinary least squares (OLS) regression can be used to investigate the effect of contextual variables on index scores. To correct for the autocorrelation and heteroscedasticity that are common in index scores, the feasible generalized least squares (FGLS) approach, an extension of OLS, is applied in this study (Anokhin and Schulze, 2009); the regression results are reported in Table 6. When the average environmental efficiency is used as the dependent variable, we get the results shown in column 5. When the environmental efficiencies measured by the SBM model and DDF model using directional vectors of $(-x_o, y_o, -b_o)$ and $(-1,1,-1)$ are used as dependent variables, the results are as shown in columns 2–4, respectively. We can see from columns 2–4 in Table 6 that the regression results are different when environmental efficiency is measured using different projection directions; in other words, the regression results are sensitive to the selection of projection direction. This also provides evidence for the adoption of average environmental efficiency as an alternative measurement. It can be observed from column 5 that energy consumption structure, government intervention, and economic openness negatively influence the regional environmental efficiency at the 1% significance level, while there is a significant and positive relationship between higher education and regional environmental efficiency. The detailed analysis is unfolded as follows.

The energy consumption structure significantly and negatively influences the regional environmental efficiency; that is, the higher the proportion of coal consumption, the greater the negative impact on environmental efficiency, which is similar to the conclusions of Wang et al. (2019b), Yu et al. (2019), and Zhao et al. (2019). A 1% increase in coal consumption decreases the environmental efficiency by 0.056 when other independent variables remain unchanged. During the period of the centrally planned economy, the low price of coal and abundant coal stocks led China to heavily rely on coal consumption (Crompton and Wu, 2005). In recent years, the Chinese government has been committed to the development and utilization of new energy, but coal consumption still accounts for more than 55% of China's total energy consumption. A high proportion of coal consumption means more pollution and greater environmental damage, thus increasing the difficulty and cost of environmental protection and negatively influencing the environmental efficiency.

Government intervention negatively influences the regional environmental efficiency at the 1% significance level, which consistent with the result of Yu et al. (2019), but some studies (e.g., Liu et al., 2019; Liu et al., 2020) did not find a significant relationship between government intervention and environmental efficiency. When fiscal expenditure is used for education investment and technological upgrading, it will help improve energy utilization and reduce pollutant emissions (Yu et al., 2019). However, using a large amount of fiscal expenditure for infrastructure construction will lead to environmental pollution and ecological damage (Liu et al., 2013). For example, to deal with the adverse effects of the financial crisis of 2008, the government increased investments in infrastructure construction, thus increasing energy consumption and pollutant emissions, which finally hampered environmental efficiency (Liu et al., 2020), as reflected in the downward trend during 2008 to 2015 in Figure 5. In addition, if fiscal expenditures are excessively consumed in administrative management, it may lead to distortions in resource allocation, which causes low environmental efficiency.

There is a significant and negative relationship between economic openness and environmental efficiency. This finding is similar to the conclusion of Liu et al. (2019). Keeping other independent variables unchanged, a 1% increase in economic openness decreases environmental efficiency by 0.344. The pollution haven hypothesis is often adopted to explain the negative relationship between economic openness and environmental efficiency.

Developed countries have stricter environmental regulations and higher labor costs, while developing countries have relatively loose environmental regulations to attract foreign investment (Copeland and Taylor, 1994). To reduce production costs, companies in developed countries are willing to transfer their production with high energy consumption and high pollutions to countries with lower environmental protection requirements (Shahbaz et al., 2015). Such foreign capital inflow inevitably has a negative impact on the host country's environment (Zafar et al., 2020).

Higher education significantly and positively influences regional environmental efficiency, which is similar to the finding of Li et al. (2020). A 1% increase in higher education increases the environmental efficiency by 0.165 when other independent variables are kept unchanged. Pablo-Romero and Sánchez-Braza (2015) proposed that human capital investment is an effective way to save energy and reduce emissions. On the one hand, advanced human capital promotes the research and development of clean energy, accelerates the transformation of energy-saving technologies, and improves energy utilization, which finally reduces pollutant emissions (Li and Lin, 2016). On the other hand, higher education helps to foster awareness of energy conservation and environmental protection (Zografakis et al., 2008). Therefore, expanding higher education will reduce energy consumption and pollutant emissions, which is conducive to improving environmental efficiency (Fang et al., 2017; Li et al., 2020).

5. Conclusions and discussion

5.1 Key findings

The economic development and environmental conditions vary substantially among Chinese provinces. In this study, we propose a consistent and robust environmental efficiency measurement employing a directional distance function approach, naming it the average environmental efficiency measure. We illustrate its use by evaluating the environmental efficiency of Chinese provinces. Further, we examine the influencing factors of environmental efficiency. Our main findings are as follows:

First, the environmental efficiency is sensitive to the projection direction to the frontier, which implies that the environmental efficiency measured along a projection direction

determined by either exogenous or endogenous mechanism lacks fairness and comparability. The average environmental efficiency is consistent and robust because it includes all possible projection directions to measure the environmental efficiency of each province.

Second, the environmental efficiency of the whole country is at a high level of 0.803, and only nine provinces have average environmental efficiency greater than the national average. This implies that even though the country's environmental efficiency is good, two-thirds of provinces still have much room for improvement.

Third, the east area achieved the best average environmental efficiency over the studied period, scoring 0.910, followed by the west area (0.765), central area (0.736), and northeast area (0.719). Furthermore, the results show that the environmental efficiency of China and its four areas all exhibited a downward trend from 2008 to 2015. However, the national environmental efficiency, as well as that of the east area and central area, showed an upward trend, while the other two areas decreased slightly after 2015.

Fourth, using a feasible generalized least squares regression approach, we find that the energy consumption structure, government intervention, and economic openness negatively influence the regional environmental efficiency at the 1% significance level. In contrast, there is a significant and positive relationship between higher education and regional environmental efficiency.

5.2 Policy implications

China is a developing country, and so heavy industries play an important role in its economic development. This role has led to the contradiction between economic development and environmental protection becoming increasingly prominent. Based on the above analysis results, implications are given from the perspectives of the nation and each area.

First, with respect to the whole country, the suggestions are as follows: (i) Fossil fuels account for the largest proportion of energy consumption, and to reduce the pollution generated by fossil fuels, the government needs to increase investment in new energy development, speed up the replacement of traditional energy by clean energy, and balance energy exploitation and energy consumption. (ii) The government should strengthen national environmental protection supervision policies, increase fiscal expenditure on education

investment and technological upgrading, and improve administrative efficiency. (iii) The government should guide foreign investment flow into Chinese industries with low energy consumption and low pollutant emissions. (iv) Higher education is an important subject of technological innovation, and upgrading the human capital is conducive to improving environmental efficiency. On the one hand, the increase in the proportion of highly educated talents can effectively promote the mastery and application of green technology. On the other hand, intergenerational transmission of environmental protection awareness and actions can be realized via higher education, thus saving the costs of education. Therefore, the government should also pay more attention to the popularization and reform of high education.

Second, with respect to each of the four geographical areas in China, we give the following suggestions: (i) The results show that the central area ranks third in environmental efficiency over the studied period. The inter-provincial development pattern in the central area is similar to that in the east area, but the environmental efficiency values of all provinces in the central area are lower than the national average. The central area should learn from the east area regarding environmental protection awareness, managerial experience, and the introduction of foreign investments and talents. (ii) Although the west area has the second-highest environmental efficiency, the environmental efficiency varies substantially among western provinces. The environmental efficiency of Ningxia and Qinghai are far larger than other provinces in the same region, and Xinjiang, which has the lowest environmental efficiency of all Chinese provinces, is also in the west area. Considering the rich tourism resources, the provinces in the west area can increase investments in the tourism industry. Additionally, the government should pay more attention to introducing high-tech talents, developing high education, and utilizing technology spillover effects to coordinate the overall economic development of the west area. (iii) The northeast area, which relies on heavy industry, has the lowest environmental efficiency. The government should actively guide the foreign investment flow, gradually upgrade and transformation of the industrial structure, and increase investments in high education.

5.3 Future research

Several future research directions should be considered. First, restricted by data availability,

we analyze the environmental efficiency and its influencing factors based on a sample of 30 provinces in mainland China. We could extend our study to the city level and provide new implications for scholars and policymakers. Second, in this study, emissions of SO_2 and of smoke and dust are selected as undesirable outputs, but other pollutants, such as CO_2, wastewater, and solid waste, could be considered. Third, this study examines the effect of each factor on environmental efficiency while assuming that the other factors remain unchanged; the configurational path to environmental efficiency under an interplay of factors presents an intriguing path for further research.

Authors' contribution

Jing Tang: Conceptualization, Methodology, Formal analysis Writing-original draft. Feng Yang: Supervision, Writing-review & editing, Funding acquisition. Fangqing Wei: Conceptualization, Methodology, Formal analysis, Writing-review & editing, Funding acquisition.

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Data availability

The datasets analyzed during the current study are available from the corresponding author on reasonable request.

Ethics approval and consent to participate

Not applicable

Consent for publication

Not applicable

Competing interest

The authors declare no competing interests

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