Technological and Economic Development of Economy
ISSN: 2029-4913 / eISSN: 2029-4921
2022 Volume 28 Issue 3: 743–774
https://doi.org/10.3846/tede.2022.16594

ENVIRONMENTAL PERFORMANCE OF CHINA'S ECONOMIC SYSTEM: INTEGRATIVE PERSPECTIVE OF EFFICIENCY AND PRODUCTIVITY

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Received 31 March 2021; accepted 06 November 2021

Abstract. The high-quality development of regional economic system is inseparable from the collective efforts of multiple economic sectors. Increasing attention has been paid to the environmental performance evaluation of different administrative levels or economic sectors, but integrated research is scarce. Taking the three industries (the primary, secondary and tertiary industries) into account, this paper proposes a data envelopment analysis (DEA) model with parallel network structure to assess the environmental performance of 30 provinces in China from integrative perspective of efficiency and productivity. Then, the Tobit model is adopted to investigate the effects of external factors on the environmental performance. The results show that environmental efficiency of Chinese economy is only 0.4436 during 2010–2019 and the performance of the secondary industry is the highest, followed by the tertiary and the primary industries. Moreover, the environmental efficiency of eastern region is far higher than that of the central or western regions. Technological progress is the main driver of environmental productivity improvement for China's economic system. Most of the external factors such as energy structure and technology innovation, have different effects on the environmental performance of different regions. Finally, several targeted policy implications are suggested for improving the environmental performance of China's economic system.

Keywords: environmental performance, economic system, efficiency, productivity, parallel network structure, data envelopment analysis (DEA).

JEL Classification: O11, O25, Q55, R11.

Introduction

Nowadays, how to strike a balance between economic development and environmental protection has become a common challenge for policymakers all around the world (Sarkhosh-Sara et al., 2020). As the largest developing country, China's economic growth and environ-

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mental change have a significant effect on the world's economy and environment (Liu & Diamond, 2005). In the past decades, China has experienced a rapid economic boom accompanied by soaring energy consumption and pollutant emission. Thus, the environmental performance of Chinese economy has received increasing attention from scholars at home and abroad (Mi et al., 2017). Having different research objectives, the existing research can be divided into two categories. The first category focuses on the environmental performance of specific economic sector, such as industry (Zhou et al., 2018; Zhang et al., 2020a), agriculture (Zhang & Feng, 2016; Angulo-Meza et al., 2019), and transportation industry (Stefaniec et al., 2020; Wei et al., 2021). The second category focuses on the environmental performance at different administrative levels, including the national (Singpai & Wu, 2021), provincial (Song et al., 2019; Feng et al., 2020), and urban levels (Sueyoshi & Yuan, 2015; Miao et al., 2021). The first category of research is conducive to the environmental improvement of individual economic sector, while the second category provides an overall picture of regional environmental performance. However, the integrated research involving specific administrative level and different economic sectors is seriously lacking.

According to the National Bureau of Statistics of the People's Republic of China and the existing research (Feng et al., 2017; Yang et al., 2019b), all economic sectors in China can be classified into three major industries (primary, secondary, and tertiary industries). And the primary industry consists of agriculture, forestry, animal husbandry, fishery and water conservancy; the secondary industry consists of industry and construction; and the tertiary industry consists of transport, storage and post, wholesale, retail trade and hotel, restaurants, and others. Apparently, the healthy development of regional economy is inseparable from the collective efforts of various economic sectors. In this situation, the regional environmental performance evaluation ignoring different economic sectors may lead to biased results, and it is also difficult to identify the source of inefficiency when economic system performs poorly (Bian et al., 2016).

Several indicators have been used to measure the environmental performance, such as carbon intensity (Gazheli et al., 2016) and energy consumption per capita (Sun et al., 2020a). However, the environmental issues induced by economic activities are affected by such factors as low resource utilization and management efficiency, which may not be captured in full by the environmental performance indicators. As a data-driven non-parametric method, data envelopment analysis (DEA) has been regarded as an effective method to assess the relative performance of a group of decision-making units (DMUs) with multiple inputs and outputs (Chu & Zhu, 2021), which has been widely used to evaluate environmental performance of different fields (Lundgren & Zhou, 2017; Zhou et al., 2017) with most focus on the efficiency, such as Chodakowska and Nazarko (2017). An accurate evaluation of environmental efficiency is helpful for the horizontal comparison between DMUs so as to enable benchmarking, which is of great significance for inefficient DMUs to learn experiences from the best performers to improve (Omrani et al., 2020). In addition, some scholars study the environmental performance from the productivity perspective (Aparicio et al., 2017). Different from the environmental efficiency, which is purely a static measurement, environmental productivity can provide further information about efficiency change and technology change of DMUs over time (Mahlberg & Luptacik, 2014; Wang & Wei, 2016). That is vital to identify the driving factors of environmental performance from within the DMUs. Although a few studies examine the environmental performance of different administrative levels or economic sectors from the efficiency and productivity perspectives, the economic system was treated as a whole, the resulting performance may be overestimated (Kao & Hwang, 2008; Wang et al., 2020). To fill the research gap, this study proposed a parallel relational network DEA model with the undesirable outputs (CO_2) to assess the environmental performance of 30 provinces and their three categories of industries (i.e. the primary, secondary and tertiary industries) from the efficiency and productivity aspects. The key reason for choosing the provincial administrative level is that the macroeconomic policies in China are implemented mainly by the provincial governments (Meng et al., 2015). In addition, considering that the environmental performance is not only affected by selected input and output indicators but also by some external factors (Ji et al., 2021), we also adopt the Tobit model to explore the effect of external influencing factors such as energy structure and environmental regulation.

The main contributions of this paper are twofold. Firstly, the environmental performance of provincial administrative level and their three industries is studied for the first time from the efficiency and productivity perspectives. Secondly, the internal driving factors and the external influencing factors of environmental performance are explored from the national and regional levels. The rest of this paper is organized as follows. Section 1 reviews the literature related to environmental efficiency and environmental productivity. Moreover, the external influencing factors of environmental efficiency are also reviewed. Section 2 gives research method. And Section 3 embodies the empirical analysis. Finally, the conclusions and targeted policy implications are given in the last Section.

1. Literature review

In the economic theory, both efficiency and productivity reflect performance of DMUs and they are two interconnected concepts (Ralević et al., 2020). Efficiency reflects the utilization level of resources in a given year, which can be embodied by the minimum reduction of input under the observed output level or the maximum increase of output under the observed input level (Tone & Tsutsui, 2010). Productivity mainly reflects the dynamic evolution of resource utilization over time (Mavi et al., 2019). In effect, as two important aspects of performance, scholars have examined the efficiency and productivity of different research objects, such as Chinese energy system (Wang et al., 2013a), Australian economic system (Mahlberg & Luptacik, 2014), and so on. In the next, we review the related research on environmental efficiency and environmental productivity of China's economic system.

1.1. The related research of environmental efficiency

Environmental efficiency is formally proposed by the World Economic Council for Sustainable Development, as mentioned by Desimone and Popoff (2000), which means the economic value of unit environmental load. After that, various environmental efficiency indexes have been proposed, such as Air Quality Index, Environmental Performance/Sustainability Index, and have been adopted by most countries. However, these indicators cannot embody the complexity of production activities and the potential substitution effects between different factors (Wang et al., 2013a). To handle these issues, the environmental efficiency based on DEA has drawn much attention in recent years (Sueyoshi et al., 2017). The environmental efficiency at the national level has always been prior research focus, including such subjects as OECD countries (Zaim & Taskin, 2000; Zhou et al., 2006), APEC countries (Jin et al., 2014), European countries (Halkos & Petrou, 2019; Zhang et al., 2021a) and the Belt and Road countries (Singpai & Wu, 2021).

As the world's second-largest economy (Zhu et al., 2020a), environmental efficiency of China also receives extensive research attention. A series of improved DEA models have been proposed to examine the environmental efficiency at the provincial and urban levels. For example, considering the government's different responses to environmental regulations, Wang et al. (2013b) analyze the environmental efficiency and returns to scale of 30 provinces. The same method was also used to assess the environmental efficiency of Chinese provincial capitals (Sueyoshi & Yuan, 2015). Yang et al. (2015) evaluate the environmental efficiency of 30 provinces based on the super-efficiency DEA model to rank the provinces. Taking the technological and environmental heterogeneities of different regions into account, Song et al. (2019) study the environmental efficiency and policy change of 30 provinces. The environmental efficiency of specific areas has also been discussed, such as coastal provinces (Ding et al., 2020), port cities (Kong & Liu, 2021), and resource-based cities (Li et al., 2021).

Prior studies also focus on individual economic sector. Among the different economic sectors, industry, thermal power industry, and transportation industry attracted the most research attention. Early studies often focus on the accurate measurement of environmental efficiency at single stage, taking into account only initial inputs and final outputs (Bi et al., 2012; Chen et al., 2017a; Wu et al., 2019; Long et al., 2018; Sun et al., 2020b; Zhu et al., 2020b; Wei et al., 2021). Later, for the industrial and thermal power sectors, scholars assess environmental efficiency at two sub-stages including economic/electric production and pollution treatment (Wu et al., 2016a; Chen et al., 2018; Bi et al., 2018; Fang, 2020). Some scholars further divide the pollution treatment into wastewater treatment and waste gas treatment to evaluate the eco-environmental efficiency of 36 industrial sectors (Shao et al., 2019). Similar studies can also be found in Wang and Feng (2020) and Tang et al. (2020a). As for the transportation sector, the recent studies examine the environmental efficiency of transportation system as a parallel network including passenger transportation and freight transportation (Wu et al., 2016b; Liu et al., 2020). In addition, the environmental efficiency studies of other economic sectors are also popular, such as the agricultural sector (Li et al., 2018), the construction industry (Yang et al., 2019a), and the service industry (Zhang & Lin, 2018).

1.2. The related research of environmental productivity

Some scholars also adopt the environmental productivity to evaluate environmental performance. One frequently employed approach to evaluate productivity change is the Malmquist index (Kapelko et al., 2015), which is firstly proposed by Malmquist (1953). Based on extended Malmquist index, Beltrán-Esteve et al. (2019) and Oh and Heshmati (2010) analyze the environmental productivity of European Union and OECD countries. The environmental productivities of provincial level (Du et al., 2017), industry (Shen et al., 2019), and manufacturing sector (Du et al., 2018) in China were also investigated in prior studies.

Since efficiency and productivity are two important aspects of performance evaluation (Mavi & Mavi, 2019), the comprehensive research of environmental efficiency and productivity receives increasing attention. For example, based on the non-radial DEA model and Malmquist index, Zhou et al. (2007) assess the environmental performance of OECD countries. Similar method is used to study the environmental efficiency and productivity at the provincial level in China (Song et al., 2018a; Piao et al., 2019). However, the traditional Malmquist index may be infeasible in the calculation (Wang et al., 2019a). Thus, the global Malmquist index, proposed by Pastor and Lovell (2005), has been adopted to analyze the environmental efficiency and productivity at the urban scale in recent years, such as Li et al. (2020) and Miao et al. (2021).

1.3. The external factors of environmental performance

In addition to the measurement of environmental performance, the effects of external influencing factors on environmental performance have also gained much popularity. Given that the scope of environmental efficiency obtained by DEA is between 0 and 1, the use of ordinary least square estimate method would lead to biased and inconsistent results (Huang et al., 2019; Liu et al., 2021). Thus, the Tobit model, proposed by Tobin (1958), is widely used in the research (Xue et al., 2021). For the environmental performance, the effects of a battery of influencing factors have been explored by scholars. For example, using the Tobit model, Song et al. (2013) test the impacts of GDP per capita, industrial structure, and dependence on foreign capital and trade on the environmental efficiency of 28 provinces in China. Zhang et al. (2016) investigate the effects of industrial structure and innovation capability on the regional environmental efficiency in China. Lin and Chen (2020) study the impacts of economic development level, environmental regulation and energy structure on the environmental performance of China's non-ferrous metals industry.

1.4. Literature synthesis and research gap

Great efforts have been made to accurately measure the environmental performance of different administrative levels or economic sectors. However, the integrated research involving both is seriously scarce. To our limited knowledge, only Bian et al. (2016), Xiao et al. (2019) and He et al. (2018) considered the heterogeneity of different economic sectors in their studies. The first research analyzed the energy efficiency of the primary, secondary and tertiary industries in China during 1986–2012. The second explored the CO_2 emission performance at the city level, and only the secondary and service industries were taken into account. Although the last evaluated the environmental efficiency of agriculture, power, industry, residential and transportation through a non-separable bad output DEA model, the study ignored the cooperation between different economic sectors. In fact, the improvement of overall environmental performance of an economic system is inseparable from the joint efforts of various economic sectors. In addition, all these studies analyze the performance of research objects from the efficiency perspective, which can only provide limited information for policymaker. A prior study explored the sources of economic growth in China from the perspective of industries and regions through a three-hierarchy meta-frontier DEA model (Feng et al., 2017), which is different from our research.

2. Methodology

To fill the research gap, this paper proposed a parallel relational network DEA model with the undesirable outputs to evaluate the environmental performance of 30 provinces and their three industries (the primary, secondary and tertiary industries) from the efficiency and productivity perspectives. Moreover, we also employ the Tobit model to test the effects of external influencing factors on environmental performance at the national and regional levels.

2.1. Environmental efficiency modeling

The economic system of China can be regarded as a parallel network structure, including three major parallel industries: primary, secondary and tertiary industries (Bian et al., 2016), as shown in Figure 1.

It is clear that each industry consumes the same input (labor, capital and energy, represented as X_l, X_k, X_e respectively) and produces the same desirable output (GDP, which is expressed as Y_G). Taking each year as the decision-making unit (DMU), Bian et al. (2016) constructed a parallel network DEA model to analyze the energy efficiency of three industries in China from 1986 to 2012. Two key characteristics of economic development are overlooked in their research. Firstly, they ignore the possible pollutants (such as CO_2) in the economic growth, which is not suitable in the real world. Secondly, the research focuses on the energy efficiency at the national level, which is too macro to provide targeted policy recommendations for the provincial governments. In view of this, a new economic structure map of provincial administrative level is given, as shown in Figure 2.

The major difference between Figure 1 and Figure 2 is that the latter takes greenhouse gas, CO_2, into account in the economic development. CO_2 is represented by X_c. The environmental efficiency of different provinces can be obtained through the following parallel relational network DEA model.

$$E=\max\frac{u*(\sum_{p=1}^{3}Y_{g0}^{p})-w*(\sum_{p=1}^{3}B_{c0}^{p})}{v_l*(\sum_{p=1}^{3}X_{l0}^{p})+v_k*(\sum_{p=1}^{3}X_{k0}^{p})+v_e*(\sum_{p=1}^{3}X_{e0}^{p})}$$

$$\text{s.t.}\quad \frac{u*(\sum_{p=1}^{3}Y_{gj}^{p})-w*(\sum_{p=1}^{3}B_{cj}^{p})}{v_l*(\sum_{p=1}^{3}X_{lj}^{p})+v_k*(\sum_{p=1}^{3}X_{kj}^{p})+v_e*(\sum_{p=1}^{3}X_{ej}^{p})}\le 1,\ j=1,\dots,n, \tag{1}$$

$$\frac{u*Y_{gj}^{p}-w*B_{cj}^{p}}{v_l*X_{lj}^{p}+v_k*X_{kj}^{p}+v_e*X_{ej}^{p}}\le 1,\ j=1,\dots,n;\ p=1,2,3,$$

$$u,w,v_l,v_k,v_e\ge 0,$$

where n represents 30, which is the number of provinces. p expresses the industry. The first two constraints ensure that the environmental efficiencies of each province and industry are not greater than 1. And u, w, v_l, v_k, v_e are unknown weight variables, corresponding to desirable output, undesirable output, labor, capital and energy, respectively.

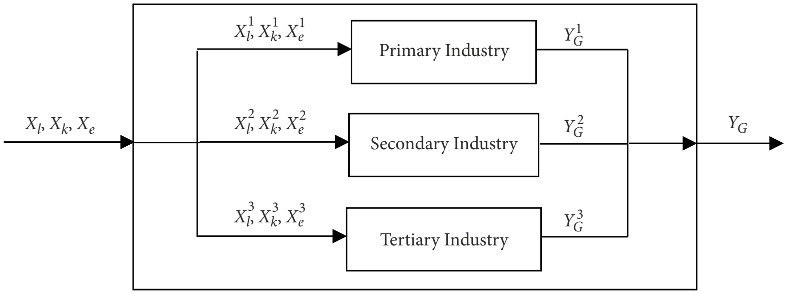

Figure 1. Economic structure in China (adapted from Bian et al., 2016)

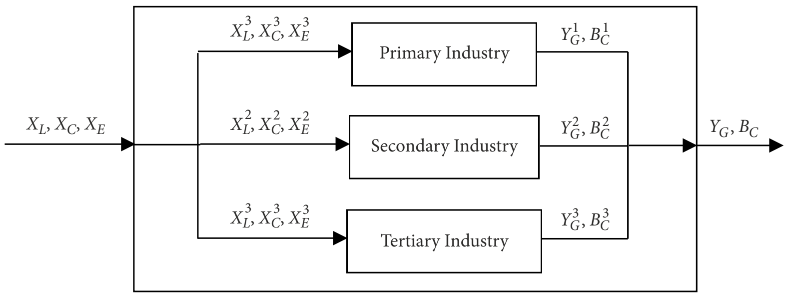

Figure 2. Economic system of provinces in China

In the relational network model, the same factor need to be given the same weight variable, no matter which industry it is connected (Kao & Liu, 2019). Through n iterations, the environmental efficiency of all provinces and industries can be obtained. Model (1) is fractional programming, letting $t = 1/(\nu_l * (\sum_{p=1}^{3} X_{l0}^p) + \nu_k * (\sum_{p=1}^{3} X_{k0}^p) + \nu_e * (\sum_{p=1}^{3} X_{e0}^p))$ and $\upsilon_l = t * \nu_l, \upsilon_k = t * \nu_k, \upsilon_e = t * \nu_e, \mu = t * u, \pi = t * w$, the equivalent linear programming can be shown as follows.

$$
\begin{aligned}
E = \max\ & \mu * (\sum_{p=1}^{3} Y_{g0}^p) - \pi * (\sum_{p=1}^{3} B_{c0}^p) \\
\text{s.t.}\ & \mu * (\sum_{p=1}^{3} Y_{gj}^p) - \pi * (\sum_{p=1}^{3} B_{cj}^p) - \upsilon_l * (\sum_{p=1}^{3} X_{lj}^p) - \upsilon_k * (\sum_{p=1}^{3} X_{kj}^p) - \upsilon_e * (\sum_{p=1}^{3} X_{ej}^p) \le 0, \ j = 1,\ldots,n, \quad (2) \\
& \mu * Y_{gj}^p - \pi * B_{cj}^p - \upsilon_l * X_{lj}^p - \upsilon_k * X_{kj}^p - \upsilon_e * X_{ej}^p \le 0, \ j = 1,\ldots,n;\ p = 1,2,3, \\
& \upsilon_l * (\sum_{p=1}^{3} X_{l0}^p) + \upsilon_k * (\sum_{p=1}^{3} X_{k0}^p) + \upsilon_e * (\sum_{p=1}^{3} X_{e0}^p) = 1, \\
& \mu, \pi, \upsilon_l, \upsilon_k, \upsilon_e \ge 0.
\end{aligned}
$$

With the optimal solution of model (2), $\mu', \pi', \upsilon_l', \upsilon_k', \upsilon_e'$, the environmental efficiencies of the three industries are given through the Eq. (3).

$$E1 = \frac{\mu' * Y_g^1 - \pi' * B_c^1}{\upsilon_l' * X_l^1 + \upsilon_k' * X_k^1 + \upsilon_e' * X_e^1};$$
$$E2 = \frac{\mu' * Y_g^2 - \pi' * B_c^2}{\upsilon_l' * X_l^2 + \upsilon_k' * X_k^2 + \upsilon_e' * X_e^2}; \quad (3)$$
$$E3 = \frac{\mu' * Y_g^3 - \pi' * B_c^3}{\upsilon_l' * X_l^3 + \upsilon_k' * X_k^3 + \upsilon_e' * X_e^3}.$$

When $E = 1$ ($E1 = 1$, $E2 = 1$, $E3 = 1$), the provincial (primary, secondary, tertiary) environmental efficiency is effective. Otherwise, the DMU is ineffective.

2.2. Environmental productivity and its driving

The global Malmquist index (GMI) is used to explore the internal driving factors of environmental performance in this section. As shown in formula (4), we can decompose the GMI into efficiency change (EC) and technological change (TC). The former represents the catching-up effect of the efficiencies of two periods (t, $t + 1$) towards the contemporaneous frontier, which is constructed by the efficient DMUs of one period (t or $t + 1$), while the latter represents the practice gap between the contemporaneous frontier and the global frontier. Unlike the contemporaneous frontier, the global frontier is constructed by the efficient DMUs of all periods.

$$GMI(X^t, Y^t, B^t, X^{t+1}, Y^{t+1}, B^{t+1}) = \frac{E^G(X^{t+1}, Y^{t+1}, B^{t+1})}{E^G(X^t, Y^t, B^t)} =$$
$$\frac{E^{t+1}(X^{t+1}, Y^{t+1}, B^{t+1})}{E^t(X^t, Y^t, B^t)} \times \left(\frac{E^G(X^{t+1}, Y^{t+1}, B^{t+1})}{E^{t+1}(X^{t+1}, Y^{t+1}, B^{t+1})} \times \frac{E^t(X^t, Y^t, B^t)}{E^G(X^t, Y^t, B^t)}\right) = EC^{t,t+1} \times TC^{t,t+1}, \quad (4)$$

where $E^t(X^t, Y^t, B^t)$ and $E^{t+1}(X^{t+1}, Y^{t+1}, B^{t+1})$ represent environmental efficiency in period t and t+1 under the contemporaneous frontier, which can be obtained by the model (2). $E^G(X^t, Y^t, B^t)$ and $E^G(X^{t+1}, Y^{t+1}, B^{t+1})$ mean environmental efficiency in period t and $t + 1$ under the global frontier, the detailed calculations are put in the Appendix.

A value of GMI (EC, TC) greater than, equal to, or less than 1 indicates that the environmental productivity (efficiency, technology) has improved, remained the same, or worsened between periods t and $t+1$, respectively.

2.3. The Tobit model

As the efficiency obtained by DEA ranges from 0 to 1, the Tobit model is suitable to investigate the effects of external factors on the environmental performance (Yang & Wei, 2019). Tobit model is also known as a censored regression model, which is often used to study the situation of dependent variables under certain constraint (Chodakowska & Nazarko, 2017). The model is as follows:

$$E_{it}^{*} = x_{it}\rho + \varepsilon_{it},\ \varepsilon_{it} \sim N(0,\sigma^2),$$
$$E_{it} = E_{it}^{*},\ \text{if } E_{it}^{*} > 0, \tag{5}$$
$$E_{it} = 0,\ \text{if } E_{it}^{*} \le 0,$$

where E_{it}^{*} indicates environmental efficiency of the DMU_i in period t. x_{it} represents influence factor. ρ is the coefficient. $\varepsilon_{it} \sim N(0,\sigma^2)$ indicates that the residuals ε_{it} is independent and subjects to normal distribution.

3. Empirical study

3.1. Data and variables

This paper evaluates the environmental performance of 30 provinces and their three industries in China from 2010 to 2019 and explores the internal and external factors affecting environmental performance. According to our research purpose, labor, capital and energy are selected as input indicators, and the number of employees at the end of the year, the fixed asset investment and the energy consumption (coal, crude oil and natural gas) of three industries are used as the corresponding proxies (Liu et al., 2017; Wang et al., 2019b), respectively. Industrial added-value is selected as the only desirable output (Shao et al., 2019). Considering that CO_2 is the main cause of climate change and global warming (Geng et al., 2017), we take CO_2 as the main undesirable output. Since there is no official data of CO_2, the method of Bian et al. (2013) and Zha et al. (2016) is used in this paper. The data comes from China Statistical Yearbook, China Energy Statistical Yearbook, statistical yearbook and bulletin of each province. The descriptive statistic of indicators is shown in Table 1.

Table 1. Descriptive statistics

Industry	Indicators	Min	Max	Mean	St.d
Primary industry	Labor	37.09	2712	910.63	641.49
	Capital	1.6	2530.8	542	484.93
	Energy	0.01	482.87	69.49	88.38
	Added value	103.88	5116.44	1921.71	1300.05
	CO_2	0.01	1297.61	185.2	237.19
Secondary industry	Labor	52.33	2563.5	789.17	699.99
	Capital	187.70	29467.96	6690.2	5704.4
	Energy	1162.8	970510.26	16813.18	57199.82
	Added value	571	44270.51	10613.8	8764.17
	CO_2	2784.56	2601726.45	42463.79	152342.07
Tertiary industry	Labor	110.2	3378.2	1018.1	622.9
	Capital	527.06	35271.04	9669.03	7028.1
	Energy	1.09	1882.37	368.3	388.04
	Added value	470.88	59773.38	11242.12	10016.43
	CO_2	2.94	4897.59	869.93	1031.14

3.2. Environmental efficiency analysis

Table 2 shows the mean environmental efficiency of Chinese economy in 2010–2019. The results are obtained by lingo software. To gain more information, 30 provinces are divided into three regions (Eastern, central, and western) according to Gao et al. (2021) and Wang et al. (2021), as shown in Table 2.

Table 2. Mean value and ranking of environmental efficiency

DMUs	E	Rank	E1	Rank	E2	Rank	E3	Rank
Eastern (11)								
Beijing	0.9173	2	0.1729	21	0.9956	1	0.9350	2
Tianjin	0.7845	3	0.1340	25	0.8735	4	0.8044	4
Hebei	0.3460	17	0.2449	16	0.4022	25	0.4054	17
Liaoning	0.4952	8	0.3405	8	0.5864	12	0.5912	7
Shanghai	0.9549	1	0.5667	1	0.8934	2	0.9997	1
Jiangsu	0.6649	4	0.2870	10	0.6635	8	0.8461	3
Zhejiang	0.5761	6	0.4072	5	0.5489	14	0.6792	5
Fujian	0.4847	9	0.3414	7	0.6090	11	0.4673	11
Shandong	0.4429	10	0.2480	15	0.4814	18	0.5637	8
Guangdong	0.6521	5	0.4853	2	0.7103	7	0.6439	6
Hainan	0.3357	21	0.4291	4	0.4099	22	0.3491	22
Mean	**0.6049**		**0.3324**		**0.6522**		**0.6623**	
Central (8)								
Shanxi	0.3073	26	0.0566	30	0.4552	19	0.3866	20
Jilin	0.4143	13	0.1328	28	0.7461	6	0.4203	15
Heilongjiang	0.3299	23	0.4465	3	0.2388	30	0.4049	18
Anhui	0.2820	28	0.2721	14	0.3535	28	0.2623	30
Jiangxi	0.3299	22	0.2525	14	0.4028	24	0.3428	23
Henan	0.3202	25	0.2685	13	0.3665	27	0.3320	26
Hubei	0.4050	14	0.2163	18	0.6248	10	0.4228	14
Hunan	0.3895	15	0.2745	9	0.5321	16	0.4262	13
Mean	**0.3472**		**0.2400**		**0.4650**		**0.3747**	
Western (11)								
Chongqing	0.4294	12	0.1548	22	0.6574	9	0.4524	12
Sichuan	0.3485	16	0.3887	6	0.4510	20	0.2841	29
Guizhou	0.2742	29	0.1515	23	0.4062	23	0.3804	21
Yunnan	0.2902	27	0.2393	17	0.4380	21	0.2903	28
Shaanxi	0.4406	11	0.1492	24	0.7956	5	0.5137	10
Gansu	0.2568	30	0.1733	20	0.2999	29	0.3409	24
Qinghai	0.3363	20	0.1330	27	0.5618	13	0.3312	27
Ningxia	0.3204	24	0.0703	29	0.5395	15	0.4159	16
Xinjiang	0.3422	18	0.2052	19	0.4946	17	0.3943	19
Inner Mongolia	0.5002	7	0.1337	26	0.8923	3	0.5595	9
Guangxi	0.3375	19	0.3283	9	0.4011	26	0.3382	25
Mean	**0.3524**		**0.1934**		**0.5398**		**0.3910**	
National mean	**0.4436**		**0.2568**		**0.5610**		**0.4861**	

On the whole, the environmental efficiency of China's economic system is only 0.4436, which indicates that there remains large room for improvement. Shanghai, Beijing, and Tianjin are the three most efficient provinces with the average efficiency of 0.9549, 0.9173 and 0.7845, respectively. And they are all located in the eastern region of China with a higher economic foundation and technological level (Zhang et al., 2020b). In contrast, Gansu, Guizhou, and Anhui perform not well during the study period, which are located in the central and western regions. From the regional perspective, the environmental efficiency of eastern region is highest, followed by the western and the central regions. The similar conclusion is drawn in Song et al. (2016) and Piao et al. (2019). Environmental efficiency of eastern region is better than that of the other two regions. The underlying explanation could be that eastern region has the advantages over the central and western regions in terms of innovative infrastructure, talent and technology (Zhang et al., 2020c), which enables eastern region to achieve the harmonious development of economic growth and environmental protection. Another explanation is the industrial transfer from the eastern region to the central and western regions in recent years (Lin et al., 2013), which optimizes the industrial structure of eastern region, thereby improving the environmental efficiency. Note that although the coordinated development of regions arises increasing attention, and resulting strategy such as "The Development of the Western Region in China" and "The Rise of Central China" have been implemented successively, our research shows that the high-quality development of central and western regions remains a long way to go.

From the industry perspective, the environmental efficiency of the secondary industry is the highest, followed by the tertiary industry and the primary industry, which is in line with the China's development situation. All along, the industry sector is an important pillar of economic growth in China. With the proposal of "made in China 2025", China's industrial development will realize the gradual transformation from made in China to intelligent manufacturing, which imposes higher requirement for the development of industrial sector and even the whole secondary industry. Moreover, the Chinese government has issued a series of environmental regulations to deal with the industrial pollution (Wu et al., 2014), such as the guidelines for the implementation of green manufacturing engineering (Zhang et al., 2020d). In addition, the implementation of most environmental laws is to reduce the pollutants caused by the combustion of fossil energy, such as "The action plan for the prevention and control of air pollution". Although the share of energy consumption of China's secondary industry gradually decreased during the study period, it still reached 68% in 2019 (China Statistical Yearbook, 2020). In this situation, the environmental status of secondary industry has received great attention from policymaker, resulting in the improvement of corresponding environmental efficiency.

From Table 2, we can find that the environmental efficiency of three industries in different regions shows a certain similarity, that is, the environmental efficiency of their primary industry is the lowest. Apparently, the focus of primary industry is different in three regions. The marine industry is an important economic source of most eastern coastal provinces (Ding et al., 2020). The central region is the important food production base in China (Jin & Ma, 2021). For the western region, the forestry development is relatively prosperous (Chen & Wang, 2019). However, their environmental efficiencies are relatively poor. As for the environmental efficiency of the secondary and tertiary industries in different regions, the development of central and western regions is different from that of the eastern region. For the eastern, the environmental efficiency of the tertiary industry is slightly higher than that of the secondary industry. The opposite is true in the central and western regions. Based on the experience of the developed economies, the service industry will play the important role when the industrialization reaches a certain level (Xiao et al., 2019). The industrialization level of eastern region is ahead of that of the other regions, which may be the main reason for the high environmental efficiency of tertiary industry in the eastern region.

For individual provinces, the environmental efficiencies of different industries are quite different. For example, the environmental efficiency of secondary industry in Beijing reaches 0.9956, which has a little improvement room. However, its environmental efficiency of the primary industry is only 0.1729. Similar situations can also be found in Tianjin, Jilin, Shaanxi and so on. As depicted in Table 2, the weak-links of each province is easy to identify. For provinces such as Beijing and Shanghai, the environmental efficiencies of the secondary and the tertiary industry are high. In order to achieve the further improvement of the environmental performance, more attention should be paid to the primary industry. For provinces such as Heilongjiang, the environmental efficiency of the secondary industry is the weakness and should be given top priority. There are also some provinces whose environmental efficiencies of all three industries are not optimistic, such as Henan and Gansu.

There are several common methods to deal with the undesirable outputs (CO_2) in the framework of DEA, such as treating undesirable outputs as negative (Wu et al., 2016b; Zhu et al., 2020b), regarding undesirable outputs as inputs (Xie et al., 2019; Chen et al., 2020) and transforming the undesirable outputs into desirable outputs by the linear transformation method (Chen et al., 2018; Mavi & Mavi, 2019). In order to test the robustness of our results, this study further adopt the latter two methods to obtain the environmental efficiency of China's economic system, as shown in Table 3. The corresponding models are put in the Appendix. At the national level, we can find that the environmental efficiencies of three models are very similar, and the environmental efficiency of the secondary industry is the highest, followed by the tertiary and the primary industries, which is consistent with our previous conclusions. At the regional level, the environmental efficiencies of eastern, western and central regions all decrease in turn under the three models. In addition, for the central and western regions, the trend of environmental efficiencies of three industries is the same as that of the whole country. All these can verify the robustness of the results. Note that the environmental efficiency of secondary industry in the eastern region is highest under the

Table 3. The environmental efficiencies of different models

Regions	Regarding undesirable outputs as inputs				The linear transformation method			
	E	E1	E2	E3	E	E1	E2	E3
National	0.4438	0.2567	0.5616	0.4863	0.4881	0.2869	0.6086	0.4879
Eastern	0.6054	0.3323	0.6536	0.6624	0.6361	0.3508	0.6953	0.6848
Central	0.3473	0.2399	0.4643	0.3754	0.3552	0.2591	0.4694	0.3729
Western	0.3524	0.1933	0.5404	0.3908	0.4367	0.2432	0.6232	0.3748

third model, which is slightly different from the other models. The common linear transformation formula is $B^{*} = -B + M$, where B is the undesirable output and M is a large value to transform the undesirable output into desirable output. Clearly, the efficiencies based on linear transformation method are dependent on the selection of M (Liu et al., 2010), which may be the reason of above differences.

Optimizing industrial structure and narrowing development gaps across regions are the key to ensure the sustainable development of Chinese economy. The coefficient of variation (CV) is expressed as the ratio of the standard deviation to the mean (Ebrahimi et al., 2020) and has become a popular method to measure the unbalanced development of different regions (Huo et al., 2020). Figure 3 shows the CV values and its trends. The larger the value, the more unbalanced development among regions.

Overall, the development gaps of environmental efficiency in China show an upward trend, from the 0.3751 in 2010 to 0.4590 in 2019. The main reason is the significant increase of CV value in the primary industry. It is easy to find that the unbalanced development of the primary industry is obvious for three regions, specifically for the eastern region. The possible explanation for the sharp decline in the CV of the primary industry in 2018 is that Chinese government set up the Ministry of Ecological Environment in this year (Yu et al., 2019). Combined with Table 2 and Figure 3, we can conclude that improving the environmental

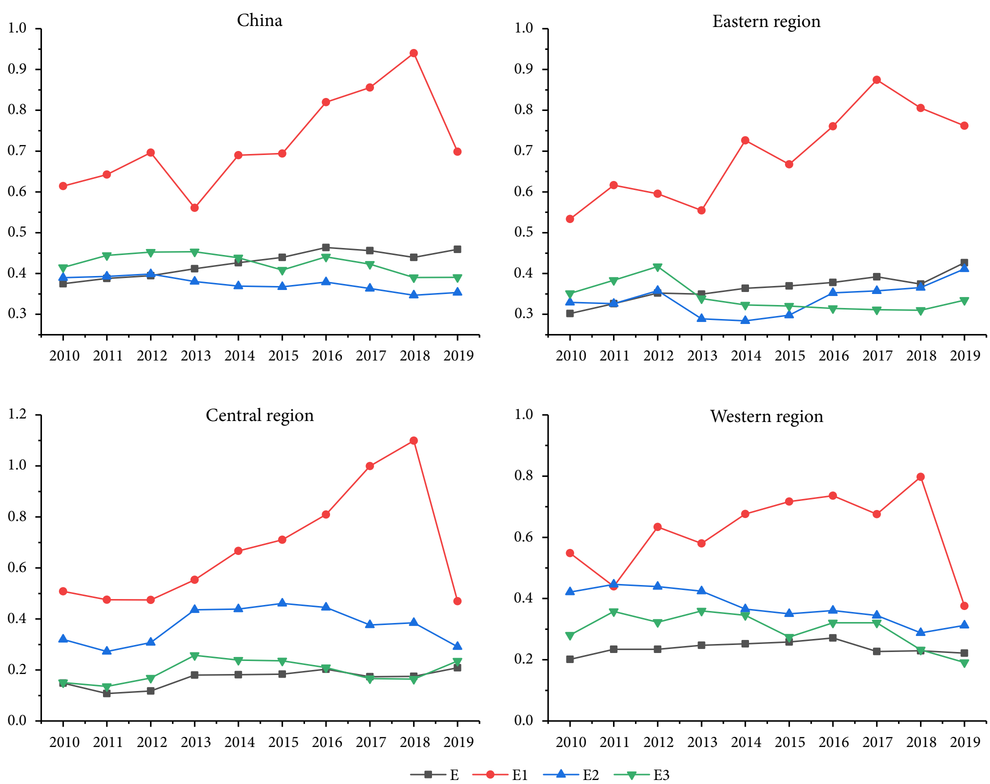

Figure 3. The CV of environemtnal efficiency

efficiency of primary industry and narrowing the development gaps of primary industry have become the urgent issue for China to achieve the high-quality economic development.

From the regional perspective, the development gaps of environmental efficiency in the eastern and central regions increase gradually during the study period. However, except for the role of the primary industry, the increase of eastern region is mainly attributed to the secondary industries, while the increase of central region mainly comes from the tertiary industries. In comparison, the development gaps of the western region narrow gradually no matter for provincial environmental efficiency or the industrial environmental efficiencies. Based on the above findings, we suggest that the eastern region should give more attention to the environmental gaps of the primary industry and the secondary industry in different provinces. For central region, narrowing the development disparity of the primary industry and the tertiary industry is urgent.

3.3. Environmental productivity change

We use the GMI to explore the productivity changes and its driving of Chinese economy and give a more detailed analysis, the results are shown in Table 4.

From the last row, we can find that the mean values of GMI are all greater than 1, indicating that the environmental productivity improves during the study period. The change of productivity shows a U-shaped pattern. During 2010–2013, the productivity experiences an obvious decrease, then a significant increase occurs in 2014–2018. In effect, a series of strict environmental regulations have been issued since 2013, such as "The action plan for the prevention and control of air pollution" and "The action plan for the prevention and control of water pollution". And in 2015, China implemented the most stringent environmental protection law (Wu et al., 2021). All these measures lead to the significant improvement of environmental productivity. Another notable phenomenon is that the productivity change of most provinces is not stable during the study period. For example, the productivity changes of Guangdong experience the decline in 2011–2013, 2014–2015 and 2016–2017. For three regions, the productivity changes of eastern region are greater than 1, while the productivity decline can be found in western region during 2014–2015 and in central region during 2012–2015, respectively. In addition, the period with the highest GMI is different across regions. Since the productivity change depends on both the environmental factors and economic factors (An et al., 2019), the different emphasis on economy and environment in different regions may lead to large differences in productivity.

Figure 4 and Table 5 present the environmental productivity and its driving at national and regional level. From Figure 4, we can conclude that the TC is the main driving of productivity change since they have the similar change trend. Another intuitive phenomenon is that the TC shows a fluctuating upward trend after 2012, while the EC occurs obvious decline during 2012–2016. In order to enhance environmental protection, a revision of Ambient Air Quality Standard was issued in 2012. Moreover, the Ecological Civilization Construction was proposed in the same year. All these means the China's environmental regulations become stricter after 2012 (Tang et al., 2020b). Strict environmental regulations prompted the development of pollution treatment technology, resulting in the improvement of TC.

Table 4. Result of GMI

Provinces	2010–2011	2011–2012	2012–2013	2013–2014	2014–2015	2015–2016	2016–2017	2017–2018	2018–2019
Eastern (11)									
Beijing	1.0969	1.0230	1.0525	1.0764	1.0534	1.0879	1.0695	1.0875	1.1361
Tianjin	1.1654	1.0906	1.0560	1.0634	1.0313	1.0792	1.0438	1.0090	0.7494
Hebei	1.1075	0.9636	0.9648	1.0373	1.0106	1.0747	1.0660	1.0562	0.9759
Liaoning	1.1762	1.0897	1.0561	1.0417	1.0609	0.9993	1.0411	1.0331	0.9335
Shanghai	1.1355	1.0315	0.9723	1.0873	1.0217	1.0830	1.0377	1.0419	1.1620
Jiangsu	1.0161	1.0931	1.0924	1.1012	1.0753	1.1018	1.1105	1.0801	1.0776
Zhejiang	1.0181	0.9539	0.9665	1.0171	1.0617	1.0947	1.0829	1.0752	1.0966
Fujian	1.0053	0.9674	0.9597	1.0507	1.0358	1.1006	1.1116	1.1148	1.1851
Shandong	1.0753	0.9920	0.9892	1.0724	1.0529	1.0731	1.0807	1.1037	0.9541
Guangdong	1.1045	0.9950	0.9777	1.0019	0.9714	1.0352	0.7731	1.2872	1.0712
Hainan	1.0191	0.9335	0.9549	1.0046	1.0250	1.0923	1.0570	1.0513	0.9661
Mean	1.0836	1.0121	1.0038	1.0504	1.0364	1.0747	1.0431	1.0855	1.0280
Central (8)									
Shanxi	1.1358	1.0465	1.0052	1.0005	0.9961	0.9304	1.2607	1.0587	1.0122
Jilin	1.1866	1.1157	1.0481	1.0417	1.0004	1.0378	1.0200	1.0220	0.7854
Heilongjiang	–	–	–	–	0.9877	0.9712	1.0310	1.0537	0.9125
Anhui	1.1976	0.9848	0.9569	0.9800	0.9692	1.0282	1.0992	1.1076	1.2371
Jiangxi	1.2235	0.9594	0.9690	0.9718	1.0038	1.0963	1.0780	1.1021	1.1272
Henan	1.0075	0.9978	0.9544	0.9742	0.9538	0.9969	1.0794	1.0905	1.1539
Hubei	1.0731	0.9703	0.9686	1.0454	1.0878	1.1132	1.0916	1.1198	1.1721
Hunan	1.0969	0.9725	0.9506	0.9742	0.9771	1.1072	1.1013	1.0986	1.1126
Mean	1.1316	1.0067	0.9790	0.9983	0.9970	1.0351	1.0951	1.0816	1.0641
Western (11)									
Chongqing	1.1531	0.9943	1.0460	1.1161	1.0955	1.1236	1.1010	1.0482	1.1629
Sichuan	1.1484	1.0103	0.9846	0.9977	0.9893	1.0069	1.0789	1.1817	1.0633
Guizhou	0.9598	1.1031	0.9978	1.0249	0.9972	1.0823	1.1301	1.0886	1.1256
Yunnan	1.1433	1.0330	0.9803	1.0079	0.9457	0.9646	0.9709	1.0700	1.2987
Shaanxi	1.0993	1.3973	1.0878	1.0548	0.9692	1.0487	1.0974	1.0811	0.9719
Gansu	1.0508	1.0147	0.9553	0.9634	0.9268	1.0366	1.3839	1.1157	1.0162
Qinghai	0.9898	0.9853	1.0929	1.0926	1.0424	1.0440	1.0154	1.0866	1.0334
Ningxia	1.1550	1.0856	1.0713	1.0546	1.0438	1.0686	1.0529	1.0538	0.9944
Xinjiang	1.0808	1.0612	1.0197	1.0584	0.9598	0.9821	1.0868	1.1187	1.0856
Inner Mongolia	1.1368	1.0580	0.9875	1.0025	1.0167	1.0096	0.9121	1.1203	0.9985
Guangxi	0.9086	1.0642	1.1647	0.9842	0.9517	0.8981	0.9848	1.0799	1.0396
Mean	1.0751	1.0734	1.0353	1.0325	0.9944	1.0241	1.0740	1.0950	1.0718
National mean	1.0919	1.0340	1.0098	1.0310	1.0105	1.0456	1.0683	1.0879	1.0537

Note: since the relevant data of Heilongjiang is lack in 2010–2013, the productivity change is given from 2014 to 2019.

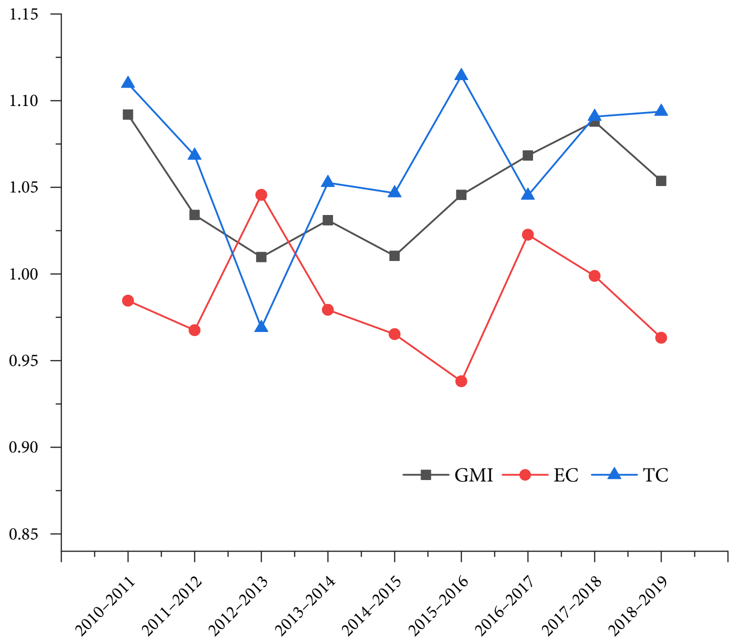

Figure 4. TC and TC in different years

Table 5. The EC and TC of three regions

Regions	Primary industry		Secondary industry		Tertiary industry	
	EC	TC	EC	TC	EC	TC
Eastern	0.9993	1.2308	0.9871	1.0736	1.0170	1.0660
Central	0.9131	1.1406	1.0162	1.0990	1.0161	1.0627
Western	0.9664	1.1662	1.0402	1.0825	1.0377	1.0769

However, huge environmental protection investment may cause the low efficient utilization of resources, which can be verified from the decline of EC from Figure 4. As for different regions, we can find that all TC of different industries are greater than 1, indicating the technology progress play an essential role in the productivity change. The EC of primary industry has obvious improvement room in three regions, and the same conclusion is also applicable to the secondary industry in eastern region.

Figure 5 shows the EC and TC of 30 provinces during study period. According to Figure 5, 30 provinces can be divided into two categories. The first is the provinces with TC and EC exceed 1, including Beijing, Jiangsu, Hubei, Chongqing, and Shaanxi. These provinces not only achieve the catch-up effect for the contemporaneous frontier, but also reduce the gap from the global frontier. In the future, they should continue to play a leading role in technological progress and pay more attention to the improvement of efficiency level. The rest belongs to provinces with TC exceeds 1, while EC is less than 1, accounting for 83.3% of the sample. That means how to improve the management level is urgent for most provinces in China.

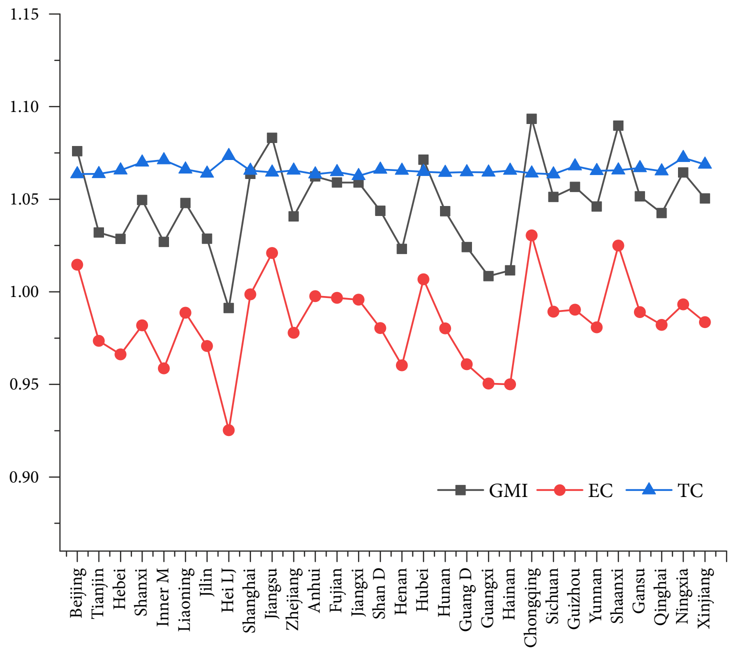

Figure 5. EC and TC of different provinces

3.4. External factor analysis

In this part, the Tobit model is adopted to analyze the influence of external factors on environmental performance from the national and regional perspectives. Corresponding results are obtained by the software Stata 16. According to previous research, six aspects are considered, including economic development level, foreign investment intensity, industrial structure, energy structure, environmental regulation and technological innovation. The selected indicators are shown in Table 6.

Table 6. Influencing factors and explanations

Influencing factors	Sign	Explanation	References
Economic development level	PG	GDP per capita: GDP / total number of people	Song et al. (2018b); Shuai and Fan (2020)
Foreign investment intensity	FG	FDI/GDP	Chen et al. (2021); Wen et al. (2021)
Industrial structure	IP	Added value of tertiary industry/ That of the secondary industry	Zhou et al. (2019); Yuan et al. (2020)
Energy structure	CO	Coal consumption / total energy consumption	Cheng et al. (2020); Tan and Wang (2021)
Environmental regulation	PIG	Investment in pollution treatment/GDP	Feng et al. (2020); Ji et al. (2021)
Technological innovation	TI	R&D expenditure/GDP	Jin et al. (2019); Wu et al. (2020)

In order to ensure the validity of regression results, we firstly perform a Pearson correlation test for the above six indicators. When the correlation coefficients between variables are less than 0.5, it can be concluded that there is no autocorrelation and false regression (Guo et al., 2020). The results show that the maximum correlation coefficient is 0.54, which is slightly higher than the specified value. Secondly, the variance expansion factor (VIF) is used to test the multi-collinearity of indicators. And the minimum and maximum values of VIF are 1.50 and 2.23, both of which are less than the specified value of 10 (Yuan et al., 2020). Thirdly, we also test the stability of each indicator to eliminate the potential bias. Four different unit root tests including LLC, IPS, ADF-Fisher and PP-Fisher are used (Zhang et al., 2021b). The results are shown in Table 7. It is clearly that all indicators pass the significance test after the first-order difference. That is, all indicators are stationary. Finally, to control the heteroscedasticity problem, the natural logarithm of indicators is adopted in the Tobit model (Xue et al., 2021).

Table 8 gives the results of Tobit model at the national and regional level. From the national level, all selected indicators have a significant effect on the environmental efficiency. Except for the energy structure (CO), other indicators have a positive impact, especially for economic development level (PG) and industrial structure (IP). The energy consumption structure dominated by the coal results in a large number of greenhouse gas and other pollutants (Wang et al., 2018a), hindering the healthy development of economic system. The improvement of economic level (PG) can awaken people's environmental awareness (Tian et al., 2016), which is conducive to the improvement of environmental efficiency. Since the main feature of the secondary industry is energy-intensive (Lin & Wang, 2021), an increase in the proportion of tertiary industry is helpful to reduce the energy consumption, thereby improving environmental efficiency. That is also the key reason for Chinese government to optimize the industrial structure. For the foreign investment intensity (FG), on the one hand, it makes up for the shortage of enterprise funds. On the other hand, it is of great significance to the imitation innovation of middle and low-end enterprises in China. The weak environmental regulation (PIG) is regarded as the one of the main reasons for the low environmental efficiency in China (Miao et al., 2019). However, with the gradual strengthening of environmental regulation, it has become an effective way for the government to deal with environmental pollution (Shuai & Fan, 2020). Technological innovation (TI) is a significant tool to improve environmental quality. Both the green upgrading of production line and the R&D of pollution treatment technology are inseparable from the important support of technological innovation.

From the regional perspective, we find that some indicators have different effects on the environmental efficiency in different regions. Firstly, the foreign investment intensity (FG) still has the positive impact on the environmental efficiency of eastern and western regions, but has a negative impact on the central region. Compared with eastern and western regions, many large state-owned heavy industries locate in the central region (Zhang et al., 2020e), making the local eco-environment more fragile. Moreover, the foreign investment is more concentrated in the energy-intensive industries (Zhong et al., 2021). Therefore, the blind introduction of foreign investment may hinder the high-quality development of central region. Secondly, the energy structure (CO) has a significant negative impact on the environmental

Table 7. The results of unit root tests

Tests		E	PG	FG	IP	CO	PIG	TI
LLC	level	−13.666*** (0.000)	−4.094*** (0.000)	−8.519*** (0.000)	−5.409*** (0.000)	−10.014*** (0.000)	−10.767*** (0.000)	−8.157*** (0.000)
	△level	−17.812*** (0.000)	−4.875*** (0.000)	−18.956*** (0.000)	−10.425*** (0.000)	−14.653*** (0.000)	−13.530*** (0.000)	−17.209*** (0.000)
IPS	level	−1.275 (0.101)	−1.876** (0.030)	−0.370 (0.356)	10.700 (1.000)	2.066 (0.981)	−2.565*** (0.005)	−1.888** (0.0296)
	△level	−4.362*** (0.000)	−7.915*** (0.000)	−8.059*** (0.000)	−2.477*** (0.007)	−10.910*** (0.000)	−8.841*** (0.000)	−11.318*** (0.000)
ADF-Fisher	level	141.781*** (0.000)	79.451** (0.032)	149.363*** (0.000)	58.426 (0.460)	115.235*** (0.000)	135.571*** (0.000)	138.854*** (0.000)
	△level	166.245*** (0.000)	135.202*** (0.000)	200.652*** (0.000)	146.670*** (0.000)	171.253*** (0.000)	163.298*** (0.000)	183.817*** (0.000)
PP-Fisher	level	115.706*** (0.000)	253.194*** (0.000)	104.782*** (0.000)	5.758 (1.000)	74.058* (0.076)	83.235** (0.017)	106.060*** (0.000)
	△level	202.183*** (0.000)	404.169*** (0.000)	169.472*** (0.000)	108.340*** (0.000)	400.406*** (0.000)	273.138*** (0.000)	484.715*** (0.000)

Note: △level indicates the first order difference.

Table 8. Result of Tobit

	Environmental efficiency (E)			
Indicators	National	Eastern	Central	Western
PG	0.1972***	0.1322***	0.039	0.0952***
	(11.98)	(5.78)	(1.37)	(7.20)
FG	0.0291***	0.1014***	−0.0402***	0.0071**
	(7.47)	(11.91)	(−3.62)	(2.08)
IP	0.0869**	0.2976***	0.2533***	0.3049***
	(2.47)	(7.12)	(3.72)	(7.11)
CO	−0.0924***	−0.1043***	−0.047*	0.30**
	(−5.82)	(−4.77)	(−1.86)	(2.28)
PIG	0.0353***	0.0037	−0.0161	−0.0073
	(3.72)	(0.33)	(−1.36)	(−0.79)
TI	0.0400***	0.0986***	0.0316**	−0.0007
	(5.34)	(9.94)	(2.45)	(−0.14)
Constant	−0.1112**	0.3031***	0.6005***	0.4763***
	(−2.55)	(−4.25)	(7.94)	(7.61)
Log likelihood	253.474	134.311	115.478	177.423
LR chi2	361.60	238.25	38.35	117.90

Note: t statistics in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

efficiencies of eastern and central regions, but has a significant positive effect on the western region. One possible explanations is that the industrial base of western China is relative weak (Zhang et al., 2020c). Moreover, the western region is an important base of renewable energy such as wind and solar energy (Chen et al., 2017b). All these make western China have a bigger environmental carrying capacity. Since the essence of environmental efficiency is to achieve the harmonious development between economic growth and environmental protection, it is feasible for the western region to appropriately increase fossil energy consumption to realize rapid economic growth. Thirdly, the impact of environmental regulation (PIG) on the environmental efficiency in the eastern region is different from that in the central and western regions, but they are not significant. As the China's economy enters the "New Normal", major changes have taken place in the economic structure and production technology (Wang et al., 2018b). Given that the eastern region has great advantages in talent and technology, it is possible to achieve healthy development of economy system under stricter environmental regulation. Finally, technology innovation (TI) has a significant positive effect on the environmental efficiency in the eastern and central regions, but has an insignificant negative impact on that in the western region. The main characteristics of innovation activities are the high cost and the uncertainty of results (Feng et al., 2021). Moreover, the technology level of western China is still at a low level (Zhang et al., 2020b). Against this background, blindly increasing investment in technological innovation may not be conducive to the improvement of environmental efficiency in the western region.

Conclusions and policy recommendations

The environmental problems caused by the unsustainable development of economy have attracted wide attention all over the world. Although many scholars have studied the environmental performance of specific economic sector or administrative level, the integrated research including both is seriously lacking. Taking China as an example, this study examines the environmental performance of 30 provinces and their three industries (the primary, secondary and tertiary industries) from the efficiency and productivity perspectives. To this end, a parallel relational network DEA model with undesirable outputs is firstly constructed. Then, a global Malmquist index is adopted to explore the environmental productivity change and its driving, which is conducive to figure out the cause of environmental inefficiency from within the DMUs. Finally, a Tobit model is used to analyze the effect of external influencing factors such as industrial structure and environmental regulation on environmental performance from the national and regional levels.

The results show that: 1) During the study period, the environmental efficiency of Chinese economy is only 0.4436, indicating that there remains large room for improvement. 2) On the whole, the environmental efficiency of the secondary industry is the highest, followed by the tertiary industry and the primary industry. Compared to the eastern region, there is still a big gap between the environmental efficiency of the tertiary industry and that of the secondary industry in the central and western regions. 3) The unbalanced development of environmental efficiency across regions presents an obvious upward trend. The main reason for the widening development gap in the eastern region lies in the primary and secondary industries, while the reason for the central region is the primary and tertiary industries. 4)

The environmental productivity of Chinese economy performs well during study period. And technological progress is the main driving of productivity improvement. Improving the management level of primary industry in China is urgent for the high-quality development of economy, and the suggestion is also applicable to the secondary industry in the eastern region. 5) In addition to the positive effect of economic development level (PG) and industrial structure (IP) on environmental efficiency, other external influencing factors, such as foreign investment intensity (FG) and energy structure (CO), have different effects on environmental efficiency of different regions.

Given the empirical findings of the study, the following policy recommendations are given. 1) The environmental efficiency of Chinese economy remains a large room for improvement. For most provinces, the low environmental efficiencies of the primary industry and tertiary industry should arouse attention of the local governments. In this context, some successful experiences from the secondary industry should be introduced into the primary and tertiary industries. For example, it may be helpful to set specific emission reduction targets for the economic sectors of primary industry and tertiary industry, such as marine economic sector and service sector. 2) The development gaps across regions present a clear upward trend during study period. And the main reasons of widening development gaps in each region are different. Under such a situation, narrowing the differences of the primary industry should be given top priority for Chinese government. Meanwhile, the eastern region should also pay more attention to reducing development gaps of the secondary industry. The central region should put emphasis on minimizing development gap in the tertiary industry. 3) Insufficient management level has become the obstacle of environmental productivity improvement in the primary industry for most provinces. Moreover, the eastern region should also focus on the promotion of management capability in the secondary industry. Thus, international and regional cooperation and exchanges should be strengthened so as to explore suitable management mode. 4) According to Tobit results, from both the national and regional levels, insisting on improving the economic development level and optimizing the industrial structure plays an important role in promoting the healthy development of the Chinese economy. However, the central region should carefully evaluate the potential benefits and possible environmental damage in the introduction of foreign investment. In terms of technology innovation, the western region should choose the appropriate innovation path based on its own actual situation. Considering that western region has greater environmental carrying capacity, an appropriate increase in fossil energy consumption at the current stage may be conducive to the rapid development of the local economy. In addition, according to our results, the stricter environmental regulation has a negative impact on the environmental efficiency in the central and western regions. In this situation, we suggest that Chinese government should give local governments more environmental autonomy, that is, allow them to implement corresponding environmental regulation based on their resource endowment and technical level.

There are several limitations in this study. First, limited to incomplete data, only three major industries are analyzed in this paper. Future research covering more industries are meaningful. In addition, some indicators may be imprecise in reality, such as CO_2. Taking the uncertainty of data into account, the obtained environmental performance may be more convincing.

Acknowledgements

This work is supported by the Fundamental Research Funds for the Central Universities (Grant No. HIT.HSS.202104), and The Hong Kong Polytechnic University (Work programme SB3F, Project ID P0035130).

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APPENDIX

The environmental efficiency of period t or $t + 1$ under the global frontier is obtained from the following model.

$$\begin{aligned}
&\underset{l=t \text{ or } t+1}{E^G(X^l, Y^l, B^l)} = \max \frac{u * (\sum_{p=1}^{3} Y_{g0}^{p\,(l)}) - w * (\sum_{p=1}^{3} B_{c0}^{p\,(l)})}{v_l * (\sum_{p=1}^{3} X_{l0}^{p\,(l)}) + v_k * (\sum_{p=1}^{3} X_{k0}^{p\,(l)}) + v * X_{eo}^{(l)}} \\
&\text{s.t.} \quad \frac{u * (\sum_{p=1}^{3} Y_{gj}^{p\,(t)}) - w * (\sum_{p=1}^{3} B_{cj}^{p\,(t)})}{v_l * (\sum_{p=1}^{3} X_{lj}^{p\,(t)}) + v_k * (\sum_{p=1}^{3} X_{kj}^{p\,(t)}) + v_e * (\sum_{p=1}^{3} X_{ej}^{p\,(t)})} \le 1, \; j = 1,...,n; \; t = 1,...,T, \quad \text{(A.1)} \\
&\qquad \frac{u * Y_{gj}^{p\,(t)} - w * B_{cj}^{p\,(t)}}{v_l * X_{lj}^{p\,(t)} + v_k * X_{kj}^{p\,(t)} + v_e * X_{ej}^{p\,(t)}} \le 1, \; j = 1,...,n; \; p = 1,2,3; \; t = 1,...,T, \\
&\qquad u, w, v_l, v_k, v_e \ge 0.
\end{aligned}$$

When the undesirable outputs are regarded as inputs, the resulting model is as follows.

$$\begin{aligned}
&E = \max \frac{u * (\sum_{p=1}^{3} Y_{g0}^{p})}{v_l * (\sum_{p=1}^{3} X_{l0}^{p}) + v_k * (\sum_{p=1}^{3} X_{k0}^{p}) + v_e * (\sum_{p=1}^{3} X_{e0}^{p}) + w * (\sum_{p=1}^{3} B_{c0}^{p})} \\
&\text{s.t.} \quad \frac{u * (\sum_{p=1}^{3} Y_{gj}^{p})}{v_l * (\sum_{p=1}^{3} X_{lj}^{p}) + v_k * (\sum_{p=1}^{3} X_{kj}^{p}) + v_e * (\sum_{p=1}^{3} X_{ej}^{p}) + w * (\sum_{p=1}^{3} B_{cj}^{p})} \le 1, \; j = 1,...,n, \quad \text{(A.2)} \\
&\qquad \frac{u * Y_{gj}^{p}}{v_l * X_{lj}^{p} + v_k * X_{kj}^{p} + v_e * X_{ej}^{p} + w * B_{cj}^{p}} \le 1, \; j = 1,...,n; \; p = 1,2,3, \\
&\qquad u, w, v_l, v_k, v_e \ge 0.
\end{aligned}$$

When the undesirable outputs are transformed into desirable outputs through the linear transformation method ($B' = -B + M$, where B is the undesirable output and M is a large value to transform the undesirable output into desirable output.), the resulting model is as follows.

$$\begin{aligned}
&E = \max \frac{u * (\sum_{p=1}^{3} Y_{g0}^{p}) + w * (\sum_{p=1}^{3} B_{c0}^{p'})}{v_l * (\sum_{p=1}^{3} X_{l0}^{p}) + v_k * (\sum_{p=1}^{3} X_{k0}^{p}) + v_e * (\sum_{p=1}^{3} X_{e0}^{p})} \\
&\text{s.t.} \quad \frac{u * (\sum_{p=1}^{3} Y_{gj}^{p}) + w * (\sum_{p=1}^{3} B_{cj}^{p'})}{v_l * (\sum_{p=1}^{3} X_{lj}^{p}) + v_k * (\sum_{p=1}^{3} X_{kj}^{p}) + v_e * (\sum_{p=1}^{3} X_{ej}^{p})} \le 1, \; j = 1,...,n,
\end{aligned}$$

$$\frac{u^* Y_{gj}^{p} + w^* B_{cj}^{p'}}{v_l^* X_{lj}^{p} + v_k^* X_{kj}^{p} + v_e^* X_{ej}^{p}} \leq 1, \;\; j = 1,\ldots,n; \;\; p = 1,2,3,$$

$$u, w, v_l, v_k, v_e \geq 0.$$

According to existing research, we assume $M = \max B + 1$ (Mavi and Mavi, 2019).

The same method in section 3 can be used to transform the fractional programming into linear programming.