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Spatial–Temporal Evolution Characteristics and Influencing Factors of Industrial Pollution Control Efficiency in China

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Abstract: The green transformation and development of industry form the foundation of sustainable development for a country's society, economy, and environment. Industrial pollution control is one inevitable choice for all industries following the path of sustainable development. Improving industrial pollution control efficiency is also a natural requirement for reducing pollution emissions and achieving carbon peak and carbon neutrality. Based on panel data of 30 provinces in China from 2012–2018, this research applies DEA window analysis to measure the efficiency of industrial pollution control inputs and outputs, and empirically evaluates those factors influencing such efficiency. The findings demonstrate that overall industrial pollution control efficiency in China exhibits a decreasing trend from 2012 to 2018, but there are clear differences among provinces. Industrial pollution control efficiencies in the east and central regions are consistent with the national average, while said efficiencies in the west and northeast regions fluctuate in waves, with the effect of influencing factors in different regions varying significantly. Lastly, based on the results of empirical analysis, this research puts forward the optimization path to further improve industrial pollution control efficiency in China, and to provide new suggestions for its advancement.

Keywords: industrial pollution control; input-output; DEA; window analysis

1. Introduction

The proper coordination of social economic development and ecological environment development is an inevitable requirement of sustainable development [1]. China has implemented a strategy of innovation-driven development, allowing it to become a global manufacturing powerhouse and to inject new impetus into its industrial advancement under the new normal. With the rapid growth of industry and remarkable promotion of its international status, China is now an important engine for driving global economic growth. However, such development consumes a lot of resources and emits a lot of pollutants [2,3], resulting in the degradation of the natural environment. Constraints placed upon resources and the environment are now more and more prominent, and the extensive industrial expansion mode characterized by greater factor inputs has also led to an "unbalanced, uncoordinated, and unsustainable" economy in China [3,4]. The severe increase in environmental pollution is an important issue restricting the country's sustainable economic and social development [5], and is also a challenge that its society must face.

The ninth meeting of the Financial and Economic Commission of the CPC Central Committee stressed that achieving carbon peak and carbon neutrality (CPCN) is a broad and profound goal of systematic economic and social reform, and should be integrated into the overall layout of ecological civilization construction. The sixth plenary session of the nineteenth CPC Central Committee noted that "the CPC Central Committee has made unprecedented efforts to build an ecological civilization, and the building of a beautiful China has taken a major step forward. Ecological and environmental protection in China



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Copyright: © 2022 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (https:// creativecommons.org/licenses/by/ 4.0/). has taken a historic turn and an overall change." CPCN targets need to be transmitted to specific spatial units, and improving industrial pollution control efficiency and promoting green industrial transformation is of great significance to the realization of China's carbon neutrality goal and the overall construction of an ecological civilization. In the context of achieving the goals of CPCN, the CPC Central Committee has carried out a series of fundamental and pioneering works, putting forth unprecedented efforts to prevent and control pollution that have achieved remarkable results. In 2019, national sulfur dioxide emissions hit 4.573 million tons, of which industrial sulfur dioxide emissions were 3.954 million tons, or 86.5% of the total. In 2020, 56.7% of 337 Chinese cities at the prefecture level and above met the required standard, while 43.3% exceeded it.

As shown by various data points, the structural and root pressure of ecological environment protection in China still has not been fundamentally alleviated on the whole, and pollution produced by key industries is still prominent. Industrial pollution control efficiencies in all provinces and cities are generally low, and are unfortunately decreasing year by year [6]. It is thus an arduous task to achieve CPCN when ecological environment protection has a long way to go. How effective is the Chinese government's intensive industrial pollution control? What is the trend of governance efficiency? Are there spatial differences? What are the directions and intensities of the influencing factors? These are questions worth exploring at greater depth.

2. Literature Review

Scholars have conducted a wide range of studies on pollution control efficiency, mainly focusing on its measurement and its influencing factors. In the measurement category, they have drawn differing conclusions from various research perspectives. Masternak-Janus and Rybaczewska-Błażejowska (2017) calculated the eco-efficiency scores of 16 regions in Poland, showing that 11 eco-inefficient regions use too many environmental resources with respect to the produced value of goods and services [7]. Halkos and Polemis (2018) estimated the environmental efficiency of the U.S. power generation sector, with the environmental efficiency level ranging from 0.218 to 0.516 [8]. Moreover, on the basis of comprehensively measuring the efficiency of urban environmental governance in China, Tang (2019) conducted an empirical analysis on its influencing factors, and found that its efficiency in 30 provinces in China exhibited a wave-like rise [9].

There are not only differences between the measured results of pollution control efficiency, but also significant variations across regions. Chen and Jia (2017) evaluated the environmental efficiency of China's industry from 2008 to 2012, noting that the environmental efficiencies are generally low and large differences exist between regions [10]. Zhu et al. (2020) analyzed the energy and environmental efficiency of the industrial sector in 30 provincial-level regions of China, and found large differences between three regions of the country [11]. Zhang et al. (2020) integrated the slack-based model, with undesirable outputs, to estimate the pollution control efficiency in two subsystems of China's provinces from 2011 to 2015. The results showed strong evidence of provincial and regional heterogeneities in pollution control efficiency for both systems [12]. Ma et al. (2021) studied the atmospheric environmental efficiency (AEE) of 30 provinces in China, and discussed the spatial-temporal differences of AEE. The results showed that there are some regional differences in AEE levels in China, with the highest in the east region, followed by west and central regions, and these differences are increasing year by year [13]. Miao et al. (2019) used the Luenberger productivity index to decompose the performance of air pollutant emissions, and, compared to the inland areas of northwest China, the air environmental inefficiency levels in the southeast coastal provinces are generally lower [14].

As for the influencing factors of pollution control efficiency, there are studies on the influential effect of a single factor and on the joint effects of multiple factors. Piao et al. (2019) evaluated environmental efficiency and its dynamic trends in 30 provinces of China. Their results showed, in different regions, that the differentiation of technical characteristics of undesirable outputs has a significant impact on the final environmental efficiency score [15].

Du et al. (2020) constructed a comprehensive index of pollutant emission intensity and carbon emission index, at the enterprise level, to evaluate the impact of environmental regulations on emission reduction and coordinated emission reduction from a micro-level perspective [16]. Li et al. (2021) empirically evaluated the spatial spillover effect of industrial agglomeration on haze pollution [17]. Shen et al. (2021) used the meta-constraint efficiency model to measure China's industrial environmental efficiency, and analyzed the impact of industrial agglomeration externalities on environmental efficiency [18].

Under the joint action of multiple factors, how does the influential effect of pollution control efficiency function? Zhang et al. (2015) employed the super-efficiency DEA model to measure the industrial environmental efficiency of 286 prefecture-level cities in China, and analyzed the spatial convergence and influencing factors of environmental efficiency in these cities. Their results showed that different control variables in different regions have different effects on environmental efficiency [19]. Hao et al. (2018) discussed the impact of environmental regulations on environmental performance, concluding that current environmental control measures and regulations do not achieve the expected goal of controlling and reducing pollution, and that the direct impact of foreign direct investment on China's environment is negative [20]. Zhu et al. (2019) studied and discussed the causal relationship between economic activities and air pollution, and their results showed, in the short term, that there is a one-way causal relationship between foreign trade, economic growth, and industrial structure and pollution, and that there is an inverted U-shape relationship between haze pollution and economic growth [21].

Liu et al. (2019) established a comprehensive environmental pollution index for the discharge of sulfur dioxide, soot, waste water, and solid waste to comprehensively measure the environmental pollution situation in various provinces, and to analyze the main factors affecting environmental pollution. They found a significant spatial correlation between environmental pollution and economic development, an inverse N-shape relationship between environmental pollution and economic development, and that industrial structure and R&D investment have a significant impact on environmental pollution; however, the impact of FDI was not significant [22]. Hao et al. (2020) studied the comprehensive relationships among urbanization development, industrial structure, and environmental pollution, and stated that urbanization aggravates environmental pollution and increases the ratio in favor of the secondary industry, and that there is a non-linear relationship between urbanization and environmental pollution in China [23]. Tang et al. (2020) assessed cleaner production and waste efficiency rates in China's industrial system, and explored what influences cleaner production and waste efficiency rates [24].

The existing research has shown that the theoretical basis of the literature results regarding the efficiency of industrial pollution control is the input-output comparison of industrial pollution control [25-40]. The input and output of the traditional DEA model default indicators occur within the same time period. The model can only statically evaluate the efficiency value in a particular period; it cannot solve the problems associated with multiple periods, such as the scattering of inputs in a particular period in the output of multiple periods, or the concentration of inputs in multiple periods in the output of a particular period. Furthermore, environmental pollution problems cannot be evaluated exclusively through the inputs and outputs of a particular period, as multiple period inputs may occur in one or even multiple period output values. It is thus not reasonable to use cross-sectional data of a particular period to analyze the efficiency value of an environmental pollution problem, and thus panel data are needed to systematically scrutinize the changes in the decision-making units of multiple periods. Some scholars use DEA window analysis to solve such problems, but other scholars subjectively choose a value for the ideal window width; the default value of 3 is usually the ideal window width. However, there is a lag between inputs and outputs, and this lag period leads to large deviations in the results obtained from different window widths in the DEA window method. Different window widths can also produce significant variances in the results, and so it is necessary to make a scientifically informed selection of the ideal window width to minimize the deviation.

This research selects human, financial, and material inputs during the process of industrial pollution control in each province of China as input indicators, and the emissions of industrial pollutants as output indicators. At the same time, by excluding the influence of price factors, we select the ideal window width to evaluate industrial pollution control efficiency in China through DEA window analysis, and empirically analyze the factors influencing this efficiency.

The rest of the paper runs as follows: Section 3 introduces the DEA window analysis method. Section 4 applies the DEA ideal window width to evaluate industrial pollution control efficiency in China, and summarizes the spatial and temporal evolution characteristics of such efficiency. Section 5 analyzes the influencing factors of industrial pollution control efficiency. Section 6 concludes our main findings.

3. DEA Window Analysis Method and Choice of Ideal Window Width

3.1. DEA Window Analysis

Charnes et al. (1985) developed the DEA window analysis (WA) model to examine the efficiency changes of decision-making units (DMUs) in different periods when analyzing the maintenance cases of U.S. Air Force fighters [41]. The aim of this method is to divide the data into successive windows, with overlaps, and to perform DEA for each window separately. By comparing the results of the different windows and analyzing the causes, it finally proposes a corresponding solution path.

The DEA WA model runs as follows. Assume that there are *N* DMUs that need to be analyzed for efficiency in period *T*, where each DMU has *p* inputs and *q* outputs. Next, set the window width to *j* and divide the DMUs in period *T* into a series of windows. The first window contains the panel data of the input–output DMUs in periods 1, 2, ..., *j*. The second window contains the panel data of the input–output DMUs in periods 2, 3, ..., *j* + 1. The last window contains the panel data of the input–output DMU of the T - j + 1, ..., *T* periods.

Assuming that the wth $(1 \le w \le T - j + 1)$ viewport contains the input–output DMU panel data for wth, w + 1, ..., w + j - 1 periods, the input–output matrix becomes:

$$X_{wj} = (x_w^1, x_w^2, \dots, x_w^N, x_{w+1}^1, x_{w+1}^2, \dots, x_{w+1}^N, \dots, x_{w+j}^1, x_{w+j}^2, \dots, x_{w+j}^N)$$
(1)

$$Y_{wj} = (y_w^1, y_w^2, \dots, y_w^N, y_{w+1}^1, y_{w+1}^2, \dots, y_{w+1}^N, \dots, y_{w+j}^1, y_{w+j}^2, \dots, y_{w+j}^N)$$
(2)

The formula for the k^{th} window efficiency value in period T with window width *j* is:

$$\min \theta$$
s.t.

$$\theta \cdot x_t' - X_{wj} \lambda^w \ge 0$$

$$Y_{wj} \lambda^w - y_t' \ge 0$$

$$\sum_{n=1}^N \lambda_n^w = 1$$

$$\lambda_n^w \ge 0$$

$$1 \le t \le T, 1 \le n \le N$$
(3)

From Equation (3), the DMU's efficiency value for each period of the window width from 1 to *T* can be calculated, and the average value of efficiency M_{tj} corresponding to each window width and period can be found, where t denotes period *t* and *j* denotes the window width. Next, we calculate the mean $Mean^t$ of the average efficiency value corresponding to each period. Finally, we measure the deviation ratio of the average efficiency value M_{tj} with window width *j* in period *t*, and the average efficiency value $Mean^t$ corresponding to period *t*, using the following formula:

$$v_{tj} = \frac{M_{tj} - Mean^t}{Mean^t} \times 100\%$$
⁽⁴⁾

We first create a matrix *V*, with the period as the row and the window width as columns, as follows:

$$V = \begin{bmatrix} v_{11} & v_{12} & \cdots & v_{1T} \\ v_{21} & v_{22} & \cdots & v_{2T} \\ & \cdots & & & \\ v_{T1} & v_{T2} & \cdots & v_{TT} \end{bmatrix}_{T:T}$$
(5)

We take the minimum absolute value of the values in each row of the matrix, denoted as v_{ti0} :

$$v_{tj0} = \min_{1 \le j \le T} (|v_{tj}|)$$
(6)

Second, when the value in the matrix V is equal to the absolute minimum of the values in that row, then the value is assigned 1; otherwise, it is assigned 0. The matrix U is thus obtained as:

$$u_{tj} = \begin{cases} 1|v_{tj}| = v_{tj0} \\ 0|v_{tj}| \neq v_{tj0} \end{cases}$$
(7)

$$U = \begin{bmatrix} u_{11} & u_{12} & \cdots & u_{1T} \\ u_{21} & u_{22} & \cdots & u_{2T} \\ & \ddots & \cdots & & \\ u_{T1} & u_{T2} & \cdots & u_{TT} \end{bmatrix}_{T:T}$$
(8)

Third, the sum of all the column values in the matrix is denoted as c_j , and the matrix C is now obtained:

$$c_j = \sum_{t=1}^{I} u_{tj}, (1 \le j \le T)$$
(9)

$$C = (c_1, c_2 \cdots, c_T)_{1 \times T}$$
⁽¹⁰⁾

Lastly, we determine the maximum value c_{i0} of the matrix C:

$$c_{j0} = \max_{1 \le j \le T} (c_j) \tag{11}$$

3.2. Selection of Indicators and Data Processing

Considering the organic combination and mutual correspondence of input and output indicators in industrial pollution control activities, and drawing on existing research results, the input indicators selected in this paper include human forces and financial and material resources invested during the process of industrial pollution control in each province of China, and the output indicators selected include the emissions of industrial pollutants, as follows: "the number of employees in the industry of ecological protection and environmental control sector" is the input indicator, with the unit of persons; the financial input is based on the indicator of "investment in industrial pollution control", with the unit of 10,000 yuan; and the physical indicator, using the indicators "the number of industrial wastewater control facilities" and "the number of industrial waste gas control facilities", is measured in the unit of sets. Output indicators include: the indicator of "industrial wastewater emissions", with the unit of 10 kilotons; the indicator of "industrial sulfur dioxide emissions", in the unit of tons; and the indicator of "comprehensive utilization of industrial solid waste", in the unit of 10 kilotons. Table 1 below lists the details.

Based on data availability, this paper selects input–output panel data of 30 provinces, municipalities, and autonomous regions in China (Tibet, Taiwan, Hong Kong, and Macao are not included in the scope of analysis due to serious missing of data) from 2012 to 2018. The selected data are from the China Environment Statistical Yearbook, China Statistical Yearbook, China Urban Statistical Yearbook, China Population and Employment Statistical Yearbook, and provincial statistical yearbooks from 2013 to 2019. Setting 2010 as the base period, investment in industrial pollution control is deflated according to the fixed asset investment price index. At the same time, the number of industrial wastewater control facilities is combined with the number of industrial waste gas facilities. In the empirical analysis of "three wastes" emissions, we use the linear data conversion function to multiply the data of output indicators by -1 and add a large enough positive value for adjustment. Due to the lack of data for individual indicators in individual years, we calculate the average annual growth rate based on existing data, and then supplement the annual data.

 Table 1. Industrial pollution control efficiency input–output indicators.

Type of Indicator	Primary Indicator	Secondary Indicator	Indicator Unit
	Human resources	Number of employees in the ecological protection and environmental control industry	Persons
Input Output	Financial resources	Investment in industrial pollution control	10,000 yuan
		Number of industrial wastewater control facilities	Set
	Material resources	Number of industrial waste gas control facilities	Set
	Emissions of	Industrial wastewater emissions	10 kilotons
		Industrial sulfur dioxide emissions	Tons
	three wastes	Comprehensive utilization amount of industrial solid waste	10 kilotons

3.3. Ideal Window Width Selection for the DEA Window Analysis Model

The aim of this research is to measure industrial pollution control efficiency in China's provinces. Due to the particularity of industrial pollution control, and the goal to achieve maximum efficiency with minimum input, we chose the Window-IV model, which is inputoriented and based on the ideal window width. Industrial pollution control efficiency in each province of China is measured using Solver Pro5.0 software on input–output panel data from 2012–2018. Here, t denotes the period, and so its value is taken as 2012, 2013, 2014, 2015 2016, 2017, or 2018, while j denotes the window width, and its value can be taken as 1 (2012–2013), 2 (2012–2014), 3 (2012–2015), 4 (2012–2016), 5 (2012–2017), or 6 (2012–2018). Thus, we obtain the efficiency average M_{tj} corresponding to each window width and period, as shown in Table 2. Next, we derive the mean of the average efficiency value corresponding to each period, as seen in Table 3. Finally, we acquire the deviation ratio between M_{tj} and $Mean^t$, such as in Table 4.

Table 2. Mean values of industrial pollution control efficiency in different periods under different window widths.

j	t 2012	2013	2014	2015	2016	2017	2018
1	0.788	0.793	0.736	0.761	0.713	0.724	0.725
2	0.763	0.756	0.727	0.713	0.696	0.664	0.674
3	0.714	0.718	0.716	0.699	0.685	0.651	0.647
4	0.701	0.704	0.700	0.690	0.674	0.642	0.646
5	0.689	0.689	0.689	0.673	0.667	0.634	0.632
6	0.675	0.682	0.681	0.666	0.660	0.634	0.632

Table 3. Mean values of the corresponding average efficiency values for each period at different window widths.

t	2012	2013	2014	2015	2016	2017	2018
Mean	0.722	0.724	0.708	0.700	0.683	0.658	0.660

According to the equations, we conclude that the absolute value of industrial pollution control efficiency reaches the minimum deviation ratio in 2017, when the window width of view is 2. The absolute value of industrial pollution control efficiency reaches the minimum deviation ratio in 2012, 2013, 2014, 2015, 2016, and 2018, when the window width of view is 3. At this point, there is only one maximum value, and so the smallest *j* value is taken as the ideal window width. Therefore, 3 is the ideal window width.

j t	2012	2013	2014	2015	2016	2017	2018
1	0.092	0.096	0.039	0.086	0.044	0.100	0.099
2	0.058	0.045	0.027	0.018	0.020	0.008	0.022
3	-0.011	-0.008	0.011	-0.002	0.003	-0.011	-0.018
4	-0.029	-0.028	-0.012	-0.015	-0.013	-0.024	-0.020
5	-0.045	-0.047	-0.027	-0.039	-0.023	-0.036	-0.041
6	-0.065	-0.057	-0.038	-0.049	-0.033	-0.036	-0.041

Table 4. Proportion of deviation of M_{tj} from $Mean^t$.

4. Evaluation of Industrial Pollution Control Efficiency Based on Ideal Window Width

From the Window-IV model of ideal window width, and according to the determination method of ideal window width, we select 3 as the ideal window width for DEA window analysis of industrial pollution control efficiency. We then employ the input– output panel data from 2012 to 2018 to measure the industrial pollution control efficiency of each province in China. The details appear in Table 5.

Table 5. Industrial pollution control efficiency values and their mean values when ideal window width is 3 in 2012–2018.

Year	2012	2013	2014	2015	2016	2017	2018	Mean	Standard Deviation
Province									Deviation
Beijing	0.561	0.557	0.561	0.556	0.549	0.558	0.543	0.555	0.006
Tianjin	0.578	0.569	0.567	0.554	0.524	0.518	0.517	0.547	0.024
Hebei	0.969	1.000	1.000	1.000	0.951	1.000	0.954	0.982	0.021
Shanxi	1.000	1.000	0.984	0.795	0.708	0.721	0.682	0.841	0.137
Inner Mongolia	0.727	0.752	0.784	0.803	0.729	0.698	0.656	0.736	0.046
Liaoning	0.911	0.886	1.000	0.946	0.780	0.664	0.600	0.827	0.139
Jilin	0.581	0.584	0.597	0.596	0.586	0.547	0.529	0.574	0.024
Heilongjiang	0.603	0.607	0.612	0.611	0.602	0.581	0.596	0.602	0.010
Shanghai	0.599	0.572	0.575	0.567	0.605	0.600	0.519	0.577	0.027
Jiangsu	1.000	1.000	0.986	1.000	0.985	0.917	0.824	0.959	0.061
Zhejiang	0.860	0.873	0.856	0.796	1.000	0.664	0.666	0.816	0.111
Anhui	0.629	0.625	0.617	0.604	0.604	0.579	0.583	0.606	0.018
Fujian	0.646	0.647	0.645	0.641	0.597	0.572	0.610	0.623	0.028
Jiangxi	0.598	0.593	0.583	0.584	0.565	0.546	0.567	0.576	0.017
Shandong	1.000	0.988	1.000	1.000	1.000	1.000	1.000	0.998	0.004
Henan	0.934	0.831	0.843	0.791	0.733	0.697	0.637	0.781	0.093
Hubei	0.633	0.629	0.648	0.629	0.647	0.623	0.609	0.631	0.013
Hunan	0.617	0.607	0.601	0.619	0.578	0.526	0.536	0.584	0.035
Guangdong	1.000	0.960	1.000	1.000	0.948	1.000	1.000	0.987	0.021
Guangxi	0.624	0.636	0.629	0.645	0.613	0.581	0.541	0.610	0.034
Hainan	0.544	0.539	0.541	0.531	0.531	0.528	0.525	0.534	0.007
Chongqing	0.580	0.571	0.567	0.556	0.538	0.530	0.547	0.556	0.017
Sichuan	0.788	1.000	0.932	0.863	1.000	0.761	0.762	0.872	0.099
Guizhou	0.579	0.577	0.570	0.557	0.527	0.529	0.523	0.552	0.023
Yunnan	0.693	0.718	0.728	0.762	0.737	0.714	1.000	0.765	0.098
Shaanxi	0.841	0.859	0.679	0.712	0.629	0.634	0.641	0.714	0.091
Gansu	0.627	0.661	0.671	0.627	0.642	0.614	0.643	0.641	0.019
Qinghai	0.544	0.532	0.529	0.512	0.512	0.501	0.500	0.519	0.015
Ningxia	0.552	0.548	0.558	0.528	0.547	0.526	0.530	0.541	0.012
Xinjiang	0.599	0.606	0.617	0.593	0.578	0.591	0.582	0.595	0.012
Mean	0.714	0.718	0.716	0.699	0.685	0.651	0.647	0.690	0.042

4.1. Time Series Evolutionary Characteristics of Industrial Pollution Control Efficiency

Industrial pollution control efficiency in China's 30 provinces from 2012 to 2018 was overall on a broad downward trend, with efficiency values gradually decreasing. They increased slightly from 0.714 in 2012 to 0.718 in 2013, and then continued to decline to 0.647 in

2018, as shown in Figure 1. In terms of multi-year averages, Shandong, Guangdong, Hebei, and Jiangsu had higher efficiency values, while Qinghai, Ningxia Hui, Hainan, and Tianjin had lower efficiency values. In order to further analyze the industrial pollution control efficiency of the 30 provinces from 2012 to 2018, and to achieve effective improvement of such efficiency, we divide industrial pollution control efficiency into a high-efficiency group (efficiency value greater than 0.9), medium-efficiency group (efficiency value greater than 0.6) according to the high and low industrial pollution control efficiency values in each year, as shown in Figure 2.



Figure 1. National industrial pollution control efficiency values, 2012–2018.

The provinces in the high-efficiency group indicate that the government can accurately grasp the optimal combination of inputs and outputs in the process of industrial pollution control to avoid excessive waste of resources and achieve efficient conversion of inputs and outputs. In terms of multi-year averages, Shandong, Guangdong, and Hebei, which were in the high-efficiency group, ranked in this group during all years. The ranking changes indicate that their industrial pollution control efficiency values did not fluctuate much. At the same time, industrial pollution control inputs and outputs have reached a high conversion rate, and were stable at a certain level. Moreover, in 2012, the efficiency values of Jiangsu, Shandong, Guangdong, and Shanxi reached 1. In 2013, the efficiency values of Hebei, Sichuan, Shanxi, and Jiangsu reached 1. In 2014, the efficiency values of Hebei, Shandong, Guangdong, and Liaoning reached 1. In 2015, the efficiency values of Hebei, Jiangsu, Shandong, and Guangdong reached 1. In 2016, the efficiency values of Zhejiang, Shandong, and Sichuan reached 1. In 2017, the efficiency values of Shandong, Guangdong, and Hebei reached 1. In 2018, the efficiency values of Shandong, Guangdong, and Yunnan reached 1. This shows that these provinces were able to realize the complete conversion of input into output for a certain year.

The results for the provinces in the medium-efficiency group indicate that the government has been able to reasonably transform input factors into output factors in the process of industrial pollution control, and has also been able to control the significant waste of public resources, to a certain extent. However, some redundancy remains; the full value of the input factors is not fully utilized, and it is difficult to achieve high-quality conversion of inputs and outputs. According to the multi-year average value, Hubei, Gansu, Shaanxi, and Inner Mongolia were in the medium-efficiency group in all years. They only changed their rankings in this group, indicating that their industrial pollution control efficiency values did not fluctuate much. Although these values were controlled at a certain level, they did not improve significantly. However, Shanxi, Anhui, and Henan showed a declining trend in terms of change in efficiency values from the medium-efficiency group to the low-efficiency group in all years. This also indicates that blindly increasing inputs cannot effectively improve industrial pollution control efficiency. In order to optimize industrial pollution control inputs and outputs, the joint efforts of many parties will be needed.



Figure 2. Grouping of industrial pollution control efficiency values, 2012–2018.

Provinces in the low-efficiency group, for one thing, neglected environmental damage due to their focus on industrial economic development; in addition, there was a serious waste of public resources due to redundancy of industrial pollution control inputs, and the difficulty of converting them into outputs. This means, in these provinces, that no more than 60% of the inputs can be utilized, and more than 40% of the input elements

will be seriously wasted. In terms of multi-year averages, Qinghai, Hainan, Ningxia Hui, Tianjin, Guizhou, Beijing, Chongqing, Jilin, and Jiangxi were all in the low-efficiency group in each year, without any significant improvement in the conversion rate of industrial pollution control inputs and outputs. Therefore, these provinces should not only strengthen their environmental awareness campaigns, but also rationalize the balance of inputs and outputs. This will avoid inefficient use of resources and accelerate development towards the medium-efficiency group.

4.2. Spatial Evolutionary Characteristics of Industrial Pollution Control Efficiency

There were obvious differences in industrial pollution control efficiency across provinces. We now divide them into four groups, according to the four major economic regions of China, for comparative analysis: east region, central region, west region, and northeast region. Figure 3 illustrates this.



Figure 3. Average industrial pollution control efficiency in the four major economic regions, 2012–2018.

The industrial pollution control efficiency in the east region showed a gradual downward trend, from 0.776 in 2012 to 0.716 in 2018; however, the overall efficiency value was higher than the national average. In terms of multi-year efficiency averages, Shandong, Guangdong, Hebei, and Jiangsu, which were in the high-efficiency group, are located in the east region. Among them, Hebei had an efficiency value of 1 in 2013, 2014, 2015, and 2017; Jiangsu had an efficiency value of 1 in 2012, 2013, and 2015; Zhejiang had an efficiency value of 1 in 2016; Shandong had an efficiency value of 1 in 2012, 2014–2018; and Guangdong had an efficiency value of 1 in 2012 and 2014. Compared with other regions, the economic development level in the east region was high, along with the level of industrial pollution control. Many provinces in this region are able to allocate input factors reasonably. However, there are also several provinces in the region where industrial pollution control is still in an inefficient state, such as Beijing, Tianjin, Shanghai, and Hainan. Therefore, because the east region plays a dominant role in the national economy, those provinces whose industrial pollution control efficiency reaches high efficiency should actively play a major role in driving other provinces in the east region, or even other regional provinces, to achieve high utilization of industrial pollution control input factors.

The industrial pollution control efficiency in the central region maintained consistency with the national average, but also showed a gradual decline, falling from 0.735 in 2012 to

0.602 in 2018. The overall decline was greater than the national average. Among them, only Shanxi had an efficiency value of 1 in 2012 and 2013. Except for Jiangxi and Henan, which were in the high efficiency range, the number of provinces with high efficiency decreased year by year, while the overall efficiency values of the other provinces were in the middle or low levels, even though the investment in industrial pollution control in the central region has increased significantly. However, there was no effective output transformation, and there was a serious resource mismatch. Hence, for the central region, the most important way to improve industrial pollution control efficiency is to reasonably choose the optimal combination of industrial pollution control inputs and outputs that can avoid redundancy of resources caused by blind inputs.

The industrial pollution control efficiency in the west region fluctuated in waves, rising from 0.650 in 2012 to 0.678 in 2013, then gradually decreasing to 0.607 in 2017, and rising significantly to 0.630 in 2018, with the overall efficiency being lower than the national average in all years. The industrial pollution control efficiencies of the provinces within the west region exhibited clearly different characteristics. Even though the overall efficiency level was relatively low, Sichuan had an efficiency value of 1 in 2013 and 2016, and Yunnan had an efficiency value of 1 in 2018. The west region has a comparatively weaker level of economic development, less evident resource endowment advantages, and a significant lack of investment in industrial pollution control. These factors contribute to the generally low efficiency values within the region. Therefore, the west region should increase the input factors in industrial pollution control to a certain extent in order to improve the effective transformation of inputs and outputs within a reasonable range.

Industrial pollution control efficiency in the northeast region also fluctuated in waves, rising from 0.698 in 2012 to 0.736 in 2014, and then declining continuously. Since 2016, it has gradually pulled away from the national level, and dropped to 0.575 in 2018. Among the northeast provinces, Liaoning had a substantial downward trend in its overall efficiency value, despite reaching 1 in 2014, whereas Jilin and Heilongjiang were at a medium–low efficiency level in all years. The dominant role of heavy industry in northeast China inhibits the improvement of its industrial pollution control efficiency, and a large number of inputs cannot be effectively converted into outputs, thus increasing the difficulty of industrial pollution control in the area. Therefore, the northeast region should advocate the new concept of green consumption, and increase the investment in green industries, to guide the adjustment of industrial structure.

China is a country with vast territories in which the efficiency characteristics of environmental protection inputs vary significantly from region to region. Each region should take appropriate environmental protection measures according to local conditions, rather than blindly copying the successful experiences of other regions. This study shows that the regional differences in industrial pollution in cities of China are large, and their dominant factors also vary significantly. The government should thus adopt differentiated strategies when formulating pollution management policies. For example, the east and northeast regions should vigorously optimize the industrial structure and promote innovative emission reduction technologies, while the central and west regions should improve the level of industrial agglomeration, bring into play the energy-saving and emission-reducing effects of positive externalities of agglomeration, assess the quality and efficiency of industries, and curb the disorderly expansion of industrial practices. In addition, there are significant spatial spillover effects of industrial pollution, and thus regional cooperation in environmental management should be enhanced. For example, in terms of environmental protection, China should increase investment in environmental protection, improve the environmental monitoring system, formulate environmental protection laws and pollution emission standards, and also strengthen the joint prevention and control systems between regions in order to effectively curb pollution spillover.

5. Analysis of Factors Affecting Industrial Pollution Control Efficiency

5.1. Variable Selection and Model Selection

This research uses the DEA WA method, applying the ideal window width, to measure the industrial pollution control efficiency in 30 provinces of China. Based on the related literature, we allocate industrial pollution control efficiency (IPCE) as the dependent variable, and select the level of economic development (pgdp), technological innovation (tec), regulation of environmental (*reg*), industrial structure (*is*), urbanization (*urb*), the level of opening up (open), and the level of investment in pollution control (*inv*) as the explanatory variables, in order to conduct an empirical analysis on the factors influencing industrial pollution control efficiency [42–48]. The explanatory variables are measured by GDP per capita, the ratio of R&D internal expenditure to GDP, the ratio of investment completed in the current year in industrial pollution control projects to industrial value added, the ratio of industrial value added to GDP, the ratio of urban population to total population, the ratio of total import and export to GDP, and investment completed in the current year in industrial pollution control projects, respectively. The selected data were obtained from China Statistical Yearbook, China Science and Technology Statistical Yearbook, and the National Bureau of Statistics of China for the years 2013 to 2019. Taking 2010 as the base period, we deflate GDP, per capita GDP, internal R&D expenditures, industrial pollution control projects completed that year, industrial added value, and total imports and exports, in accordance with the corresponding price index:

$$IPCE_{it} = \beta_0 + \beta_1 \ln pgdp_{it} + \beta_2 tec_{it} + \beta_3 reg_{it} + \beta_4 is_{it} + \beta_5 urb_{it} + \beta_6 open_{it} + \beta_7 \ln inv_{it} + \varepsilon_{it}$$
(12)

In (12) *IPCE* is the dependent variable representing industrial pollution control efficiency; lnpgdp, tec, reg, is, urb, open, and lninv are the explanatory variables representing economic development level, technological innovation, environmental regulation, industrial structure, urbanization, opening up, and pollution control investment level, respectively. Here, *i* represents the 30 provinces selected for the study, and *t* represents the seven years selected for the same period. The results of descriptive statistics of the main variables show that the standard deviation of the data is small, that the sample is representative of the overall population, and that the results obtained have a high degree of confidence. Table 6 lists the findings.

Variable	Obs.	Mean	Std. Dev.	Min	Max
IPCE	210	0.6900	0.1628	0.5005	1.0000
ln <i>pgdp</i>	210	4.4661	0.3217	2.3791	4.9580
tec	210	0.0261	0.0174	0.0059	0.1078
reg	210	0.0032	0.0031	0.0004	0.0252
is	210	0.5810	0.1419	0.2010	0.8945
urb	210	0.5768	0.1203	0.3642	0.8961
open	210	0.3362	0.3359	0.0181	1.4782
lninv	210	5.1886	0.4180	3.4769	6.1161

Table 6. Descriptive statistics for each variable.

5.2. Analysis of Empirical Results

We empirically tested industrial pollution control efficiency and its influencing factors through Stata16. The results appear in Table 7.

Variable	National	East	Central	West	Northeast
ln <i>pgdp</i>	0.047	1.138 ***	0.451	0.008	0.955 ***
	0.036	0.167	0.411	0.045	0.241
tec	-1.390	-3.663 ***	15.472 ***	1.012	-18.658 ***
	0.990	0.817	1.914	2.057	5.503
reg	-8.474 **	-1.793	-1.168	-7.284 *	-36.490
	3.433	2.154	9.917	4.086	26.681
is	0.050	-0.009	0.399 ***	0.030	-0.242
	0.075	0.068	0.127	0.137	0.165
urb	-0.47 **	-0.063	-4.883 ***	-0.380	2.495 ***
	0.231	0.265	0.417	0.350	0.439
open	0.065	-0.414 ***	-1.126 ***	-0.181	-0.351
	0.084	0.119	0.402	0.165	0.278
ln <i>inv</i>	0.12 ***	0.039	0.007	0.137 **	0.276 **
	0.033	0.026	0.052	0.061	0.109
_cons	0.146	-4.475 ***	0.717	0.136	-5.948 ***
	0.235	0.751	1.864	0.348	0.952
Log likelihood	198.979 ***	109.886 ***	77.122 ***	86.592 **	49.890 ***

 Table 7. Tobit regression results.

Note: *, **, and *** are significant at 10%, 5%, and 1% respectively.

For the whole country, environmental regulation and urbanization level had a negative inhibitory effect on industrial pollution control efficiency during the study period, passing the 5% significance level. Each 1 percentage point increase in environmental regulation and urbanization level decreased industrial pollution control efficiency by 8.474 and 0.47 percentage points, respectively. The degree of pollution control investment positively contributed to industrial pollution control efficiency, passing the 1% significance level. Each 1 percentage point increase in pollution control investment level increased industrial pollution control efficiency by 0.12 percentage points.

In the east region, the level of economic development had a positive effect on industrial pollution control efficiency during the study period, passing the 1% significance level. Industrial pollution control efficiency rose by 1.138 percentage points for every 1 percentage point increase in the level of economic development. The degrees of technological innovation and opening up have a negative inhibitory effect on industrial pollution control efficiency, passing the 1% significance level. Every 1 percentage point increase in the levels of technological innovation and opening up reduced industrial pollution control efficiency by 3.663 and 0.414 percentage points, respectively.

In the central region, technological innovation and industrial structure had a positive effect on industrial pollution control efficiency during the study period, passing the 1% significance level. Every 1 percentage point increase in technological innovation and industrial structure raised industrial pollution control efficiency by 15.472 and 0.399 percentage points, respectively. Urbanization level and opening up level have a negative inhibitory effect on industrial pollution control efficiency, passing the 1% significance level. Each 1 percentage point increase in the level of urbanization and the level of opening up to the outside world reduced industrial pollution control efficiency by 4.883 and 1.126 percentage points, respectively.

In the west region, environmental regulation had a negative inhibitory effect on industrial pollution control efficiency during the study period, passing the 10% significance level. Each 1 percentage point increase in the level of environmental regulation reduced industrial pollution control efficiency by 7.284 percentage points. The level of pollution control investment had a positive effect on industrial pollution control efficiency, passing the 5% significance level. For every 1 percentage point increase in investment level, industrial pollution control efficiency rose by 0.137 percentage points.

In the northeast region, the economic development level, urbanization level, and pollution control investment level had a positive effect on industrial pollution control efficiency during the study period, passing the significance levels of 1%, 1%, and 5%,

respectively. Every increase of 1 percentage point in the economic development level, urbanization level, and pollution control investment level raised industrial pollution control efficiency by 0.955, 2.495, and 0276 percentage points, respectively. There was a negative inhibitory effect of technological innovation on industrial pollution control efficiency, which passed the 1% significance level. Moreover, each 1 percentage point increase in technological innovation decreased industrial pollution control efficiency by 18.658 percentage points.

6. Conclusions and Recommendations

Based on the panel data of industrial pollution control inputs and outputs of 30 provinces in China from 2012 to 2018, this research adopted DEA window analysis to quantitatively evaluate and examine industrial pollution control efficiency in China, based on the ideal window width. We also carried out empirical analysis of the factors affecting industrial pollution control efficiency. The following conclusions were drawn.

The time series data show that the industrial pollution control efficiencies of 30 provinces in China generally exhibited a decreasing trend over 2012 to 2018, and the efficiency values gradually decreased. According to these values, we divided the 30 provinces into three efficiency groups: high, medium, and low. There were multiple provinces in the highefficiency group, each with an efficiency value of 1 in a certain year, denoting that they achieved complete conversion of input to output; in addition, the efficiency value within the group had a small fluctuation range. Shandong, Guangdong, and Hebei were firmly in the high-efficiency group in all years. Hubei, Gansu, Shaanxi, and Inner Mongolia were in the medium-efficiency group. However, Shanxi, Anhui, and Henan showed a decreasing trend from medium efficiency to low efficiency in each year. Among the low-efficiency group, Qinghai, Hainan, Ningxia Hui, Tianjin, Guizhou, Beijing, Chongqing, Jilin, and Jiangxi were in this group each year. Their industrial pollution control input–output conversion rate did not improve significantly.

In terms of the spatial evolution of industrial pollution control efficiency, there were significant differences among the 30 provinces in China from 2012–2018. The 30 provinces were analyzed according to the four major economic regions: east, central, west, and northeast. The industrial pollution treatment efficiency in the east region was consistent with the national average, showing a gradual decline. Its overall efficiency value was higher than the national average and the other three regions, but there were still many provinces where industrial pollution treatment efficiency remained in a low state. The industrial pollution control efficiency in the central region was consistent with the national average, showing a gradual downward trend. However, its overall fluctuation was greater than the national average, and the overall efficiency values of most provinces in the region were at middle or low levels. Industrial pollution control efficiency in the west region rose, then fell, and then rose in a wave-like fluctuation, and its overall efficiency was lower than the national average in all years. Industrial pollution control efficiency of each province in this region had clearly differentiated features. Industrial pollution control efficiency in the northeast region fluctuated in a wave pattern of rising first, before falling, and, over time, gradually widening its gap with the national level.

This paper offers an empirical analysis of the factors affecting industrial pollution control efficiency across China, as well as the east, central, west, and northeast regions. It shows that the economic and social development of the east and northeast regions has gradually transitioned from a stage of developing at the cost of pollution to a stage of developing while treating the problem, and industrial pollution treatment efficiency has also gradually improved. The impact of technological innovation on industrial pollution control efficiency is positive in the central region and negative in the east and northeast regions, denoting that the direction of technological innovation on industrial pollution control efficiency is not fixed. While investment in technological innovation has increased, the cost of technological innovation should be taken into consideration. The inhibitory effect of technological innovation indicates that the output of technological innovation is less than the input, which includes human, material, and monetary factors. The effect of environmental regulation on industrial pollution control efficiency is negative for both the whole country and in the west region, indicating that environmental regulation increases the cost of industrial enterprises. Industries may choose to increase production to seek more revenue so as to subsidize the cost of environmental pollution. The effect of industrial structure on industrial pollution control efficiency is positive in the central region, showing that the continuous upgrading and optimization of industrial structure can effectively reduce the degree of industrial pollution. The effect of urbanization level on industrial pollution control efficiency is positive in the northeast region, while it is negative nationally and in the central region. This demonstrates that the role of urbanization level on industrial pollution control efficiency is not fixed, and in the process of vigorously promoting urbanization, industrial pollution control may also be ignored during the pursuit of industrial development.

The effect of the level of openness to foreign investment on industrial pollution control efficiency is negatively suppressed in both the east and central regions. It validates the "pollution refuge" hypothesis, which argues that developing countries become the predominant worldwide polluters if they voluntarily impose lower environmental standards. The impact of pollution control investment level on industrial pollution control efficiency is positive in both the east and northeast regions. This indicates that providing a sufficient financial guarantee for industrial pollution control can effectively reduce industrial pollution and improve its control efficiency.

Based on the above findings, this article proposes the following policy recommendations. First, the formation of a regional collaborative governance pattern should be accelerated. Industrial pollution control efficiencies differ in each region and province, and there is also a large gap. Therefore, it is necessary to implement improvements in top-level design and overall planning, give rise to the leading role of the east region, and achieve coordinated governance between regions. The key to synergistic governance is to deal with the relationship between the central government and local governments, the relationships among local governments, and lastly, the relationships among departments and bureaus within a government. This also means balancing overall interests and partial interests, as well as long-term and short-term interests.

Second, governing policies tailored to local conditions should be structured properly. Among the factors influencing industrial pollution control efficiency, different factors have different effects on industrial pollution control efficiency, and the influence of different factors in the many regions varies greatly. Based on local conditions, the authorities should thus execute diverse industrial pollution management policies according to the different factors of each region, such as the level of economic development, technological innovation, environmental regulation, industrial structure, urbanization level, the level of opening up, and the investment situation of pollution management.

Finally, China should adjust the incentive and constraint mechanism appropriately according to the different directions of influencing factors. Positive factors should be used as important so-called pushers to avoid the inhibiting effect of negative influencing factors. Therefore, the government should optimize the industrial layout, encourage green production methods of energy-saving and environmental protection enterprises, reasonably allocate industrial pollution control investments, adjust the national investment structure, and appropriately alter the strength and manner of technological innovation and environmental regulation to avoid counterproductive effects.

Based on the panel data of 30 provinces in China from 2012 to 2018, this study used DEA window analysis to measure the input and output efficiencies of industrial pollution control. From the research findings, this article offers a series of relevant recommendations, which supplement the theoretical results in the field related to environmental governance. However, there are obvious limitations herein. First, this research only conducted a simple linear relationship test when empirically analyzing the factors influencing industrial pollution control efficiency, without comprehensive consideration of the non-linear effects of each influencing factor on this control efficiency. Second, this research did not include the

relationship between control variables when comparing the industrial pollution control efficiency of each province, so that only a simple numerical comparison analysis could be conducted. Finally, this research mainly focused on the implementation effect of China's ecological civilization construction after 2012. In addition, limited data collection failed to help us conduct a more comprehensive study in this field. These elements are needed to achieve a breakthrough in future scholarly endeavors.

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