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Innovation and environmental performance: An empirical study of 31 cities in China

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Abstract. After its rapid economic growth, China has been faced with the very serious problem of atmospheric pollution, leading to major long-term atmospheric problems in large cities. Air pollution not only affects normal lives of people, but also has a huge negative impact on their bodies, causing diseases, impacting productivity, and influencing their creativity. In the previous research studies, the influence of environmental variables has been ignored in the discussions of the efficiency of innovation. Accordingly, this study combines energy consumption, economics, environmental variables, innovative research, and development capabilities to analyze and explore the relationship among consumption, environment, economy, and innovative Research and Development (R&D) capabilities. Dynamic Data Envelopment Analysis (DEA) was carried out to calculate energy consumption efficiency, R&D input efficiency, innovation patent output efficiency, carbon dioxide emission efficiency, and Air Quality Index (AQI) efficiency for each city. Also, the cities were compared for their potential of improvement. The results of the study showed that 10 cities had the total efficiency score of one, implying the improvement space of zero, whereas the total efficiency scores of the other 21 cities indicated that there was still much room for improvement with big differences among the cities.

1. Introduction

Innovation capability is considered to be the most important ability for economic growth and social development in the current century as it plays a vital role in sustainable development and acquiring competitive advantages for a nation or society. The development of innovative industries brings forth many employment opportunities and promotes the adjustment of industrial structure. Profit-oriented cities generally shift from traditional industries with high energy consumption and high pollution to high-tech, low-emission industries so as to achieve their own green, sustainable economic structure and economic growth model. After its rapid economic growth, China has been facing a very serious problem of atmospheric pollution with major long-term atmospheric issues appearing in large cities. Air pollution not only affects normal lives of the people, but also has a greater negative impact on their bodies, causing diseases, impacting productivity, and influencing their creativity.

To evaluate the performance of cities or countries in urban economic growth and energy consumption, most research studies have focused on energy consumption and carbon emissions, e.g., [1-18]. Some have conducted studies of the efficiency of urban energy and environmental assessment using sewage, sulfur

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dioxide, etc. as indicators for measuring environmental pollution, e.g., Vardanyan and Noh [19], Rao et al. [20], Long et al. [21], Bi et al. [22], Wu et al. [13], Bian et al. [23], and Wang et al. [24].

Some scholars analyze the impact of heating emission on air quality and explore how to use new technologies or methods in order to reduce air pollution. Li et al. [25] used the Air Quality Index (AQI) heating model to analyze the relationship between AQI and heating system as well as energy conversion in building space through regression model. Li et al. [26] provided a method to accurately quantify the impact of heat emission on air quality in China. Xu et al. [27] made observations to assess the impact of air pollution of Beijing in winter and summer on energy demand. Tong et al. [28] proposed natural ventilation to reduce building energy consumption and maintain a healthy indoor environment. Bidokhti et al. [29] established a framework to observe emissions and urban climate change as well as to mitigate and adapt to climate impacts in Tehran. Ahmadzadehtalatapeh [30] proposed a solar assisted desiccant evaporative cooling system for office buildings providing energy and reducing pollution. Meanwhile, many scholars have suggested that air pollution causes problems for human health. Liao et al. [31] collected data for the Yangtze River Delta region during 2013–2016 to investigate the air quality and health effects. The results showed that public health risks were the highest and O_3 pollution accounted for 70% of the public health problem. Li et al. [32] believed that heating emission would lead to deterioration in environmental quality and human health. He used the heating impact index to evaluate 66 major cities in China and found that when AQI was 45%, the pollution time was 39%. Khreis et al. [33] estimated the number of asthma cases caused by NO_2 and NOx each year in Bradford, England, and found that the increase in the number of asthma cases per year was related to air pollution by traffic. Maji et al. [34] used the exposure-response functions model to assess the relationship between PM2.5 and mortality in 161 cities in China. The results showed that the number of premature deaths associated with PM2.5 was 652,000.

There are certainly many scholars who have conducted in-depth research on innovation efficiency. For example, Laitinen [35] noted that creativity and development capability of a firm could be appropriately quantified by the number of patents. Urpelainen [36] collected data for 22 Organization for Economic Cooperation and Development (OECD) countries during 1991–2007 using statistical analysis to explore the impact of export orientation on energy efficiency innovation. Their empirical results indicated that export orientation had large positive effects on energy efficiency innovation.

Bai and Li [37] used data for 30 regions in China during 1998–2008 in an empirical analysis to explore the impact of government research expenditure on innovation efficiency, stating that Research and Development (R&D) funding from local government had a significantly negative impact on regional innovation efficiency. Chen and Guan [38] collected data for all regions in China and employed the relational network data analysis envelopment model to analyze the innovation efficiency of each region. Bai [39] applied stochastic frontier methods to estimating regional innovation efficiency in China and to investigating the major factors affecting efficiency scores. Moon [40] gathered data about the electronic equipment industry of South Korea using the fuzzy Data Envelopment Analysis (DEA) model to analyze innovation efficiency of the industry. They found out that improving innovation efficiency could lead to saving 28.7% of the input.

Chen and Meng [41] combined the network Slacks Based Measure (SBM) model with DEA window analysis to measure the trend and heterogeneity of technological innovation efficiency based on data for 17 segments of the Chinese high-tech industry. Chen and Kou [42] collected province-level regional data and utilized the two-step hybrid analytical procedure to analyze province-level regional innovation systems of China. The empirical study showed that regional innovation systems of China performed poorly in both technological creation efficiency and technological commercialization. Suh and Kim [43] used the DEA method to estimate innovative activity efficiency of service firms. Wan et al. [44] gathered data for industrial enterprises in China from 2006 to 2010 to explore the impacts of technological innovation modes on the eco-efficiency of industrial enterprises. They concluded that domestic independent innovation had a significantly positive impact on eco-efficiency in the Eastern region. Wang et al. [24] collected data about energy companies in China from 2009 to 2013 and used a two-stage DEA model to construct R&D efficiency, market efficiency, and integrated innovation efficiency indicators for each energy company. The empirical results showed that all companies performed well in terms of R&D efficiency and innovation efficiency.

Kou et al. [45] proposed a new formulation approach to dynamic network DEA and evaluated the innovation efficiency of OECD countries in a multi-period, multi-division context. Huang et al. [46] collected 8601 Chinese firm-year observations from 2007 to 2012 and adopted a two-stage approach to exploring the impact of religion in social environment of a firm on corporate innovation and innovation efficiency. Greco et al. [47] gathered 43,230 European firms to discuss the relationship between public subsidies and open innovation. The empirical results showed that local and national subsidies could improve innovation efficiency. Chen and Lei [48] used the panel quantile regression model to study the impact of renewable energy and technological innovations in 30 countries and explained that technological innovations would affect countries with relatively high CO_2 emissions.

Review of the literature shows that the previous research has mainly focused on the analysis of energy consumption efficiency, the influence of heating emission on air quality, and how to use new technologies or methods to reduce the impact of air pollution on human health and in the area of R&D, only efficiency has been emphasized. Few studies have addressed the relationship among R&D, energy consumption, and air pollution in combination to establish a systematic framework for exploring the correlation of economic and social interactions and for providing more effective government recommendations in policy making.

Thus, this study uses energy consumption, R&D, patents, CO_2 emission, and AQI for 31 cities in China from 2013 to 2015 as input and output variables. Using re-sampling to estimate various indicators in 2016, we employ the dynamic DEA model to calculate energy consumption efficiency, R&D input efficiency, innovation patent output efficiency, carbon dioxide emission efficiency, and AQI efficiency of each city and further compare the cities to find out the space for improvement.

2. Research method

The research method herein is combined with Tone's method [49] in order to propose a re-sampling past-present-future model and it utilizes the SBM dynamic DEA model of Tone and Tsutsui [50]. First, we use the re-sampling method to estimate the input and output data in 2016 and then, 2013–2016 data are utilized to conduct dynamic efficiency analysis. The method is described as follows.

2.1. Resampling past-present-future model

Both the radial and non-radial efficiency measures in DEA have errors in measurement. For example, Simar and Wilson [51,52] proposed a bootstrap method that considered repeated sampling to obtain the most efficient sample distribution. Tziogkidis [53] stated that the bootstrap DEA had significant potential for development and application. However, the method still suffers from some shortcomings. For example, the characteristics of the input and output are not taken into account, while the Decision-Making Units (DMUs) are different. The bootstrapping method, although it is like a re-sampling method, treats existing observations as maternal repeated sampling and in obtaining the original data deficiencies, it cannot explore the characteristics of the data. Tone [49] set up a repeat sampling method to eliminate DEA measurement error. The method can also be used to predict the future efficiency value of a DMU. In addition, it uses past DMU input and output data, $(X^t, Y^t)(t = 1, \cdots, T)$, to predict future DMU input and output values (X^{T+1}, Y^{T+1}) and then, repeats sampling. DEA estimation can find the DMU confidence interval efficiency value.

There are generally three methods for predicting the input and output values of future DMUs:

1. Trend analysis;
2. Weighted average;
3. Average of trend and weighted average.

These three methods offer basically negligible differences. However, the correlation between input and output achieved by the trend analysis method is higher than those by the weighted average method and the integrated average trend. Therefore, this study uses trend analysis and repeated sampling methods to estimate the input and output values of DMUs in 2016 and the DMU confidence interval efficiency value.

2.2. Dynamic DEA

DEA uses the envelope (i.e., isoquant) to project the input and output variables of all evaluated units in space. Depending on whether the projection point falls on the production boundary, a performance index ranging from 0 to 1 is given as a judgment on whether there is efficiency between input and output. Charnes et al. [54] proposed a Charnes, Cooper and Rhodes (CCR) model which determined the architecture of the DEA model and solved multiple inputs and multiple outputs in a linear programming model on a fixed scale of return. However, the scale of change in the production process seems to be the norm in practice and cannot be considered as a fixed scale of compensation. Hence, Banker et al. [55] added the convexity limit of the linear combination, replaced the assumption of constant returns to scale with variable returns to scale, and offered the well-known BCC DEA model. Contrary to the CCR and Banker, Charnes and Cooper (BCC) models, Tone [56] proposed using slacks as non-radial and non-oriented estimation methods to solve the problem in which inputs or outputs could not be adjusted by equal proportions for reaching the most efficient problem. They called it the SBM model. The efficiency value calculated by this model has the following characteristics:

1. **Unit invariance:** The efficiency value of the evaluated unit does not change with the unit of measurement of input and output items;
2. **Monotone:** The rate of oversupply or output shortage is decreasing and monotone, that is, the input or output slacks gradually decrease.

SBM model:

$$\begin{aligned}
\min \quad & \rho = \frac{1 - \frac{1}{m}\sum_{i=1}^{m} s_i^- / X_{io}}{1 + \frac{1}{s}\sum_{r=1}^{s} s_r^+ / Y_{ro}}, \\
\text{s.t.} \quad & X_0 = X\lambda + s^-, \\
& Y_0 = Y\lambda - s^+, \\
& \lambda, s^-, s^+ \geq 0, \qquad (1)
\end{aligned}$$

where ρ is a non-radial slack indicator; m and s are the amounts of input and output, respectively; s_i^- and s_r^+ represent the input slacks and output slacks; and $X\lambda$ and $Y\lambda$ represent values of the efficiency boundary of input and output items.

Tone and Tsutsui [50] extended the model to the SBM dynamic DEA model. They used carry-over as a dynamic period link and classified inputs and outputs as desirable (good), undesirable (bad), discretionary (free), non-discretionary (fixed), etc. The dynamic DEA model is divided into input-oriented, output-oriented, and non-oriented types.

We assess Overall Efficiency (OE) and Term Efficiency (TE) through the non-oriented SBM dynamic DEA approach in this study. Each period has independent input and output in every DMU and there is a carry-over link from period t to $t+1$ so as to find the change across two periods.

The model sets up n DMUs ($j = 1, 2, \cdots, n$) over T periods ($t = 1, 2, \cdots, T$). The DMUs have multiple different and independent inputs and outputs in each term with "good" as a carry-over from period t to period $t+1$ herein. The carry-over is guaranteed by Eq. (2):

$$\sum_{j=1}^{n} z_{ijt}^{\alpha}\lambda_j^t = \sum_{j=1}^{n} z_{ijt}^{\alpha}\lambda_j^{t+1} \quad (\forall; t = 1, \cdots, T-1). \qquad (2)$$

Here, α shows good, bad, free, fix, etc.; the non-oriented OE (δ^*) is calculated by Eq. (3); and ω^t and ω_i are weights of the term t and the input.

$$\delta^* = \frac{\frac{1}{T}\sum_{t=1}^{T}\omega^t\left[1 - \frac{1}{m+nbad}\left(\sum_{i=1}^{m}\frac{\omega_i^- s_{ij}^-}{x_{iot}} + \sum_{i=1}^{nbad}\frac{s_{it}^{bad}}{z_{iot}^{bad}}\right)\right]}{\frac{1}{T}\sum_{t=1}^{T}\omega^t\left[1 - \frac{1}{s+ngood}\left(\sum_{i=1}^{s}\frac{\omega_i^+ s_{ij}^+}{y_{iot}} + \sum_{i=1}^{ngood}\frac{s_{it}^{good}}{z_{iot}^{good}}\right)\right]}. \qquad (3)$$

Eq. (2) is the connection equation between t and $t+1$.

$$x_{iot} = \sum_{j=1}^{n} x_{ijt}\lambda_j^t + s_{it}^- \quad (i = 1, \cdots, m; \quad t = 1, \cdots, T),$$

$$x_{iot}^{fix} = \sum_{j=1}^{n} x_{iot}^{fix}\lambda_j^t \quad (i = 1, \cdots, p; \quad t = 1, \cdots, T),$$

$$y_{iot} = \sum_{j=1}^{n} y_{ijt}\lambda_j^t - s_{it}^+ \quad (i = 1, \cdots, s; \quad t = 1, \cdots, T),$$

$$y_{iot}^{fix} = \sum_{j=1}^{n} y_{iot}^{fix}\lambda_j^t \quad (i = 1, \cdots, r; \quad t = 1, \cdots, T),$$

$$z_{iot}^{good} = \sum_{j=1}^{n} z_{iot}^{good}\lambda_j^t - s_{it}^{good} \quad (i = 1, \cdots, ngood; \quad t = 1, \cdots, T),$$

$$z_{iot}^{bad} = \sum_{j=1}^{n} z_{ijt}^{bad}\lambda_j^t + s_{it}^{bad} \quad (i = 1, \cdots, nbad; \quad t = 1, \cdots, T),$$

$$z_{iot}^{free} = \sum_{j=1}^{n} z_{ijt}^{free}\lambda_j^t + s_{it}^{free} \quad (i = 1, \cdots, nfree; \quad t = 1, \cdots, T),$$

$$z_{iot}^{fix} = \sum_{j=1}^{n} z_{ijt}^{fix}\lambda_j^t \quad (i = 1, \cdots, nfix; \quad t = 1, \cdots, T),$$

$$\sum_{j=1}^{n}\lambda_j^t = 1 \qquad (t = 1, \cdots, T),$$

$$\lambda_j^t \geq 0, \quad s_{it}^- \geq 0, \quad s_{it}^+ \geq 0, \quad s_{it}^{good} \geq 0,$$

$$s_{it}^{bad} \geq 0 \quad \text{and} \quad s_{it}^{free} : free(\forall\, i, t). \qquad (4)$$

The non-oriented TE (ρ^*) follows the following:

$$\rho^* = \frac{1 - \frac{1}{m+nbad}\left(\sum_{i=1}^{m}\frac{\omega_i^- s_{iot}^{-*}}{x_{iot}} + \sum_{i=1}^{nbad}\frac{s_{iot}^{bad*}}{z_{iot}^{bad}}\right)}{1 - \frac{1}{s+ngood}\left(\sum_{i=1}^{s}\frac{\omega_i^+ s_{iot}^+}{y_{iot}} + \sum_{i=1}^{ngood}\frac{s_{iot}^{good*}}{z_{iot}^{good}}\right)}. \qquad (5)$$

3. Empirical study

3.1. Data and variables

Figure 1 illustrates the framework of the inter-temporal efficiency measurement and variables. According to the basic production theory, employees, R&D, and energy are defined as input factors; Gross Domestic Production (GDP) is used as the output factor in the

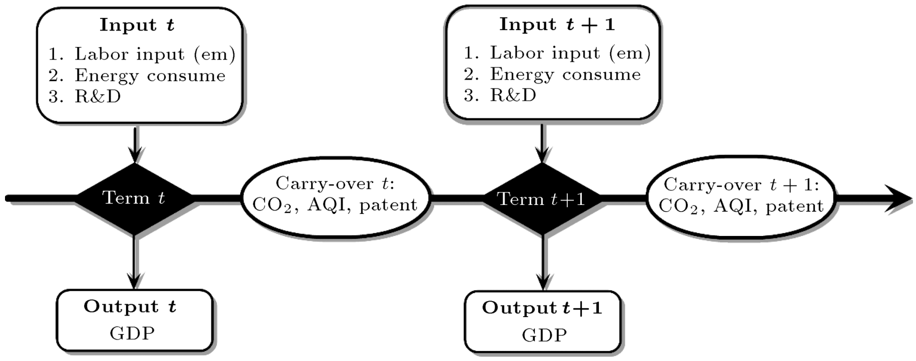

Figure 1. Structural diagram of the dynamic Data Envelopment Analysis (DEA).

evaluation; and CO_2, AQI, and patents are defined as carry-over intermediates, which are outputs of the current period and can be used as inputs to the next period.

3.2. Data sources and description

The study uses panel data for 31 cities that represent the most developed cities in China. Economic and social development data by cities for the years from 2013 to 2016 are collected from the Statistical Yearbook of China, Demographics and Employment Statistical Yearbook of China, and City Statistical Yearbooks. Data for the air pollutants are collected from China Environmental and Protection Bureau Annual Reports and China Environmental Statistical Yearbook.

The 31 sample cities are all capital cities that have the greatest pools of population and the highest aggregations of industries in the regions. The cities together represent the air pollution emission situation in China. The variables (see Table 1) are explained as follows.

Input variables:

- **Labor input (em):** The number of employees in each city by the end of each year (unit: person);
- **Energy consumption (com):** The total energy consumption in each city (unit: 100 million tons), including coal, oil, natural gas, and the total consumption of primary electricity and other energy;
- **R&D expenditure:** Depreciation of the assets used in the R&D process, the raw materials consumed, the wages and welfare expenses, the rent incurred during the development process, and the borrowing costs.

Output variable:

- **GDP:** Market value of all final products (products and services) produced in the economic activity in a certain period (one quarter or one year). GDP is the core indicator of national economic accounting and an important indicator for measuring the economic status and development level of a country or region. It consists of the gross output of the primary, secondary, and tertiary industries calculated at current prices (unit: 100 million CNY). This study uses the GDP of each city to measure its economic status (unit: 100 million Yuan RMB).

Carry-over variables:

- **Patent (Pat):** The protected exclusive rights owned by the pioneers of certain inventions. It is a document issued by a government agency or regional organization representing several countries on the basis of an application, including the content of inventions and creations. In a certain period of time, a legal status is allowed in which patented inventions are created in general. It can only be implemented with the permission of the patent owner. We use the number of patent documents issued by each city in each year as an indicator of the innovation of the city;
- **Carbon emissions (CO_2):** CO_2 emissions data for each city are estimated from energy consumption. CO_2 is seen as the primary cause of the

Table 1. Input and output indices.

Input variable	Desirable output	Carry-over
Labor input (em)	Gross Domestic Production (GDP)	AQI
Energy consumption (com)		CO_2
R&D expenditure		Patent (Pat)

changes in global temperature and the rise in the sea level. Among greenhouse gas emissions, carbon dioxide is the main component; accordingly, CO_2 emissions are used as an indicator for each city;

- **AQI:** A non-linear dimensionless index that quantitatively describes air quality. Larger values of the index indicate higher levels of air quality. On the other hand, darker color of the representation shows that air pollution is more serious and has greater harm to human health. The major pollutants are fine Particulate Matter (PM2.5), PM10, SO_2, NO_2, O_3, CO, etc. (PM2 .5 and PM10 are the 24-hour average concentration). PM2.5 refers to atmospheric particulate matters with a diameter of less than 2.5 micrometers calculated in the unit of micrograms/cubic meter. SO2 refers to sulfur dioxide. It is released naturally by volcanic activity and produced as a by-product of the burning of fossil fuels contaminated with sulfur compounds. NO_2 refers to Nitrogen Dioxide (NO_2) and is within a group of highly reactive gases known as oxides of nitrogen or nitrogen oxides (NO_X). It is an intermediate in the industrial synthesis of nitric acid and millions of tons of it are produced each year. At higher temperatures, it is a reddish-brown gas with a sharp, biting odor and is one of the most prominent air pollutants. AQI is considered with the maximum value in the Individual Air Quality Index (IAQI) for each pollutant. When the AQI is greater than 50, the corresponding pollutant is the primary one and pollutants with IAQIs greater than 100 are considered excessive.

3.3. Statistical description of input and output data

For the years from 2013 to 2016, input variables include energy consumed, labor input, and R&D expenditure. On the other hand, output variables are GDP, patents, CO_2, and AQI, defined as carry-over intermediates. The outputs of the current period can be used as inputs to the next period.

As can be seen in Table 2 and Figure 2, the rise in the maximum value of the index of patents is the highest over time among all input and output indicators. On the other hand, the difference between the maximum and minimum values of this index is considerably great. The maximum GDP and R&D costs in each city grow rapidly and the gap between the maximum and minimum R&D costs is relatively large. The difference between the maximum and minimum values of GDP is smaller than the gap of patents. The average of the two indicators shows an upward trend. Changes in other indicators are relatively flat. We observe that the averages of energy consumption and employed population have increased slightly from 2013 to 2016. The maximum values of CO_2 emissions and

Table 2. Statistics of the indices.

	2013em	**2014em**	**2015em**	**2016em**	**2013com**	**2014com**	**2015com**
Max	635.57	652.2	681.76	702.7	11345.69	11084.63	11387.44
Min	20.41	21.09	21.16	20.57667	171	191.1	156.38
Average	123.80226	126.50968	135.9597	140.9146	3715.788	3758.6002	3735.649
SD	141.93629	147.07432	157.9371	165.1526	2479.046	2519.9475	2586.888
	2016com	**2013R&D**	**2014R&D**	**2015R&D**	**2016R&D**	**2013GDP**	**2014GDP**
Max	11314.34	1487.4	1652.8	1801.2	1970.4	21602.12	23560.94
Min	158.2067	2.3	2.4	3.1	3.4	304.87	347.45
Average	3731.844	382.65806	420.435484	456.56452	493.792473	6365.28355	6951.2813
SD	2653.622	417.46728	461.677069	507.05184	552.511548	5280.10857	5782.6045
	2015GDP	**2016GDP**	**2013pat**	**2014pat**	**2015pat**	**2016pat**	**2013CO_2**
Max	25123.45	26950.167	62671	74661	94031	108481	28820.04
Min	289.46	298.51667	46	48	232	0.94031	496.86
Average	7479.8477	8046.7017	14336.74	14103.58	18540.45	20340.267	9772.36
SD	6215.9718	6700.6092	15202.87	16076.01	20606.31	23469.376	6551.864
	2014CO_2	**2015CO_2**	**2016CO_2**	**2013AQI**	**2014AQI**	**2015AQI**	**2016AQI**
Max	29498.79	29607.344	30096.0313	292	164	133	122.33333
Min	444.6	406.588	359.077333	75	41	39	0.00292
Average	9661.05	9474.7576	9338.45137	149.96774	92.0967742	85.516129	44.74203
SD	6445.519	6617.2677	6650.65642	51.414498	25.9805819	22.4353853	29.37955

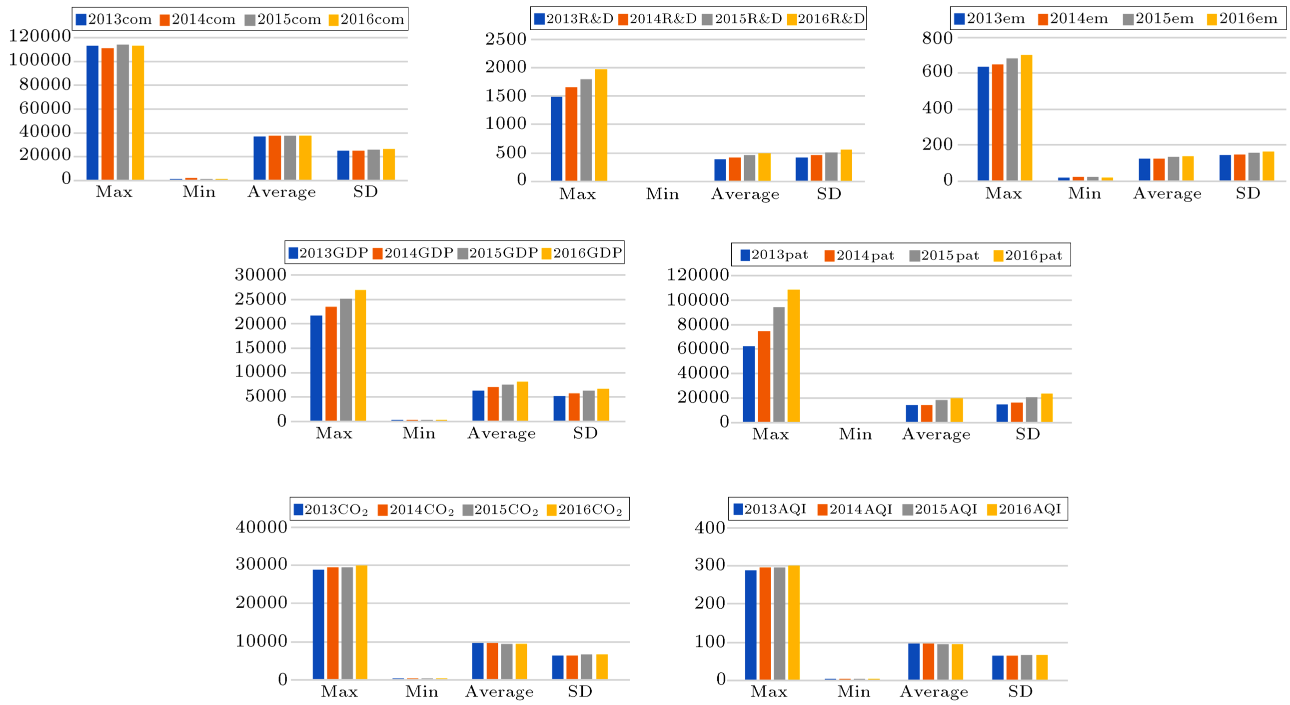

Figure 2. Statistical analysis of input and output indices from 2013 to 2016.

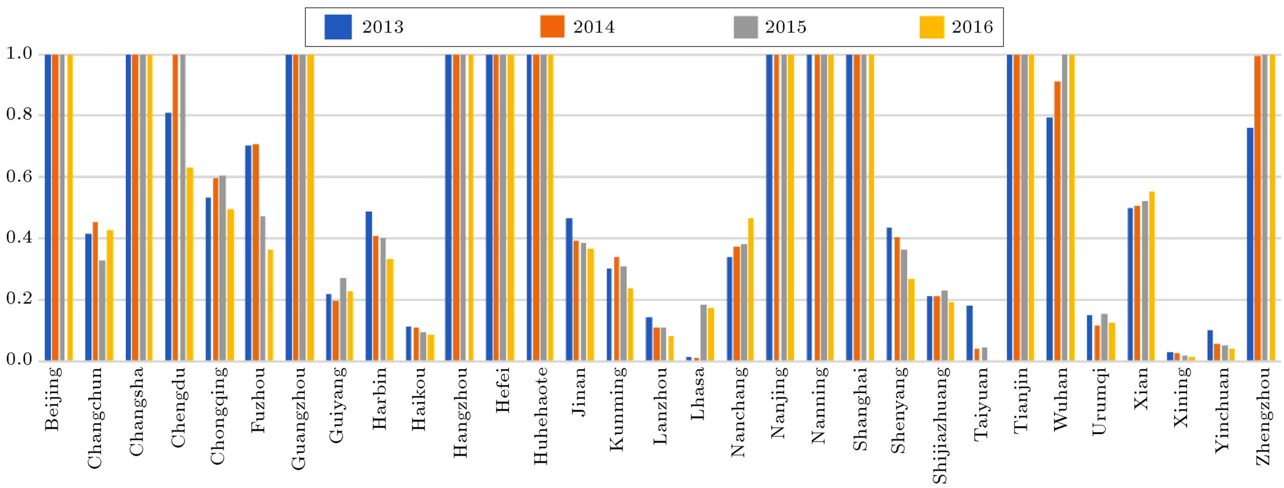

Figure 3. Total efficiency scores of cities during 2013–2016.

AQI have increased over time, but the mean values of these two indicators have shown a downward trend.

3.4. Empirical analysis and results

3.4.1. Total city efficiency scores and evaluation

In Table 3 and Figure 3, we can see that there are big differences between total efficiencies of the cities. The cities with the efficiency score of one include Beijing, Changsha, Guangzhou, Hangzhou, Hefei, Huhehot, Nanjing, Nanning, Shanghai, and Tianjin, indicating that the room for improvement in these cities is zero. Cities with efficiency scores below 0.2 are Haikou, Lanzhou, Lhasa, Taiyuan, Urumqi, Xining, and Yinchuan. The room for improvement in total efficiency of these seven cities is very large. Cities with OE scores of around 0.4 include Changchun, Harbin, Jinan, Kunming, Nanchang, and Shenyang. The efficiency of these cities is only slightly higher than that of the above-mentioned seven cities and they still have room for improvement. There are also cities that have room for improvement, but with a small space, namely Chengdu, Fuzhou, Wuhan, and Zhengzhou.

From the viewpoint of time, there are some cities whose OE is declining. These cities are Lanzhou, Shenyang, Xining, Harbin, Haikou, Jinan, Xining, and Yinchuan. With the changes of Chengdu, Chongqing,

Table 3. Total efficiency of the cities from 2013 to 2016.

DMU	Overall score	Rank	2013(1)	2014(1)	2015(1)	2016(1)
Beijing	1	1	1	1	1	1
Changchun	0.4017	18	0.4165	0.4532	0.3274	0.4281
Changsha	1	1	1	1	1	1
Chengdu	0.8488	13	0.8101	1	1	0.6295
Chongqing	0.5569	14	0.5323	0.5963	0.6056	0.4961
Fuzhou	0.5316	15	0.7024	0.7055	0.4711	0.3605
Guangzhou	1	1	1	1	1	1
Guiyang	0.2242	23	0.2168	0.1955	0.2727	0.2264
Harbin	0.4034	17	0.4887	0.4085	0.3992	0.3327
Haikou	0.0995	27	0.114	0.1067	0.0946	0.0845
Hangzhou	1	1	1	1	1	1
Hefei	1	1	1	1	1	1
Huhehaote	1	1	1	1	1	1
Jinan	0.4005	19	0.4653	0.3929	0.3864	0.3648
Kunming	0.2983	22	0.3028	0.341	0.3103	0.2379
Lanzhou	0.1103	26	0.1422	0.1091	0.1093	0.0804
Lhasa	0.019	29	0.0118	0.0096	0.1847	0.1726
Nanchang	0.3872	20	0.3406	0.3749	0.383	0.4647
Nanjing	1	1	1	1	1	1
Nanning	1	1	1	1	1	1
Shanghai	1	1	1	1	1	1
Shenyang	0.3656	21	0.4359	0.4025	0.3611	0.2671
Shijiazhuang	0.2107	24	0.2114	0.209	0.2287	0.1932
Taiyuan	0.0096	31	0.1816	0.0393	0.0457	0.0018
Tianjin	1	1	1	1	1	1
Wuhan	0.9236	12	0.7961	0.9136	1	1
Urumqi	0.1355	25	0.1499	0.1158	0.1552	0.1247
Xian	0.5185	16	0.498	0.5061	0.5218	0.5526
Xining	0.0187	30	0.0305	0.0246	0.0161	0.0118
Yinchuan	0.0634	28	0.099	0.0567	0.0531	0.04
Zhengzhou	0.9261	11	0.761	0.9936	1	1

Fuzhou, and Kunming over time, their total efficiency has first risen and then declined. The total efficiency of cities such as Changchun, Guiyang, and Urumqi fluctuates greatly. There are also some cities where total efficiency has risen over time, such as Xian, Nanchang, and Wuhan.

3.4.2. Evaluation of the efficiency scores of cities for energy consumption, patents, CO_2 emissions, and AQI

Based on the total efficiency scores of cities, we can state that different cities have a great room for efficiency improvement. In the following, we look at the changes in the efficiency scores of the major input and output indicators for each city. Through re-sampling, we estimate various input and output indicators of each city in 2016 and then, calculate their efficiency scores through the dynamic DEA method, as shown in Table 4. Table 4 and Figure 4 present the scores of energy consumption efficiency, patent efficiency, carbon dioxide efficiency, and AQI efficiency for each city. Also, their changes over time are given. Very large differences can be observed between the indicators in different cities.

In terms of the differences in energy consumption efficiency, cities with the efficiency score of one include Beijing, Changsha, Guangzhou, Hangzhou, Hefei, Huhehot, Nanjing, Nanning, Shanghai, and Tianjin. The room for improvement in energy consumption efficiency of these cities is naturally zero. Cities

Table 4. Comparison of energy consumption efficiency, patent efficiency, CO_2 emissions, and Air Quality Index (AQI) efficiency scores of the cities during 2013–2016.

	Com				**pat**				**CO_2**				**AQI**			
DMU	**2013**	**2014**	**2015**	**2016**	**2013**	**2014**	**2015**	**2016**	**2013**	**2014**	**2015**	**2016**	**2013**	**2014**	**2015**	**2016**
Beijing	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Changchun	0.31	0.27	0.31	1	0.53	0.55	0.36	0.32	0.27	0.36	0.31	1	0.9	0.93	1	0.54
Changsha	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Chengdu	1	1	1	0.87	1	1	1	0.95	1	1	1	0.957	1	1	1	0.51
Chongqing	0.67	0.65	0.61	0.59	0.63	0.71	0.85	0.84	0.65	0.67	0.61	0.608	0.85	0.93	1	0.61
Fuzhou	0.71	0.67	0.59	0.63	0.73	0.79	0.44	0.4	0.67	0.71	0.59	0.671	1	0.82	0.95	0.22
Guangzhou	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Guiyang	0.24	0.23	0.22	0.21	0.22	0.2	0.31	0.32	0.23	0.25	0.27	0.294	1	0.91	0.91	0.48
Harbin	0.73	0.71	0.64	0.63	0.4	0.31	0.34	0.31	0.71	0.72	0.64	0.657	0.96	1	0.88	0.55
Haikou	0.71	0.59	0.49	0.4	0.08	0.07	0.08	0.07	0.59	0.71	0.49	0.489	0.95	1	0.91	0.74
Hangzhou	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Hefei	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Huhehaote	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Jinan	0.31	0.28	0.26	0.42	0.62	0.51	0.55	0.51	0.28	0.31	0.26	0.5	0.87	0.74	0.69	0.26
Kunming	0.4	0.38	0.44	0.45	0.32	0.36	0.34	0.36	0.38	0.4	0.44	0.457	1	0.8	0.87	0.18
Lanzhou	0.15	0.13	0.09	0.08	0.15	0.14	0.16	0.16	0.13	0.15	0.09	0.091	0.89	0.52	0.47	0.1
Lhasa	1	0.8	0.88	0.76	0.01	0.01	0.27	0.31	0.8	1	0.88	1	0.56	0.37	0.32	0.07
Nanchang	0.68	0.62	0.53	0.84	0.28	0.32	0.36	0.38	0.62	0.68	0.53	1	0.83	0.83	0.84	0.52
Nanjing	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Nanning	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Shanghai	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Shenyang	0.68	0.68	0.52	0.53	0.37	0.32	0.35	0.33	0.68	0.66	0.52	0.504	0.89	1	0.78	0.12
Shijiazhuang	0.31	0.32	0.29	0.27	0.26	0.27	0.28	0.29	0.32	0.3	0.46	0.439	0.39	0.35	0.41	0.05
Taiyuan	0.07	0.07	0.06	0.05	0.2	0.05	0.06	0	0.07	0.07	0.06	0.057	1	0.62	0.59	0.13
Tianjin	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Wuhan	0.94	0.9	1	1	0.81	0.91	1	1	0.9	0.99	1	1	0.71	0.99	1	1
Urumqi	0.29	0.27	0.25	0.22	0.14	0.13	0.19	0.19	0.27	0.29	0.25	0.252	0.88	0.52	0.5	0.11
Xian	0.62	0.58	0.55	0.49	0.64	0.63	0.73	0.73	0.58	0.62	0.55	0.485	0.76	0.81	0.84	1
Xining	0.09	0.08	0.07	0.07	0.04	0.04	0.02	0.02	0.08	0.09	0.07	0.077	0.48	0.27	0.27	0.06
Yinchuan	0.19	0.15	0.11	0.13	0.12	0.13	0.15	0.15	0.15	0.19	0.11	0.163	0.45	0.32	0.27	0.08
Zhengzhou	1	0.97	1	1	0.72	1	1	1	0.97	1	1	1	1	1	1	1

with the energy consumption efficiency score of 0.4 or below are Changchun (except for 2016 with the score of one), Guiyang, Jinan, Kunming, Lanzhou, Shijiazhuang, Taiyuan, Xian, Xining, and Yinchuan. This means that energy consumption of these 10 cities can be greatly improved. In addition, the energy consumption efficiencies of the remaining eight cities, namely Chongqing, Fuzhou, Harbin, Haikou, Nanchang, Shenyang, Urumqi, and Wuhan, are around 0.6 or above. Considering time, energy consumption efficiency of Wuhan from 2013 to 2014 is around 0.9, rising to one in 2015 and 2016. For Chengdu, it is one from 2013 to 2015, but declines to 0.87 in 2016. Cities with declining energy consumption efficiencies include Chongqing, Harbin, Haikou, Lanzhou, Taiyuan, Xian, Urumqi, Xining, and Yinchuan, indicating that they still need to make further energy use and energy structure adjustments. There are few cities where

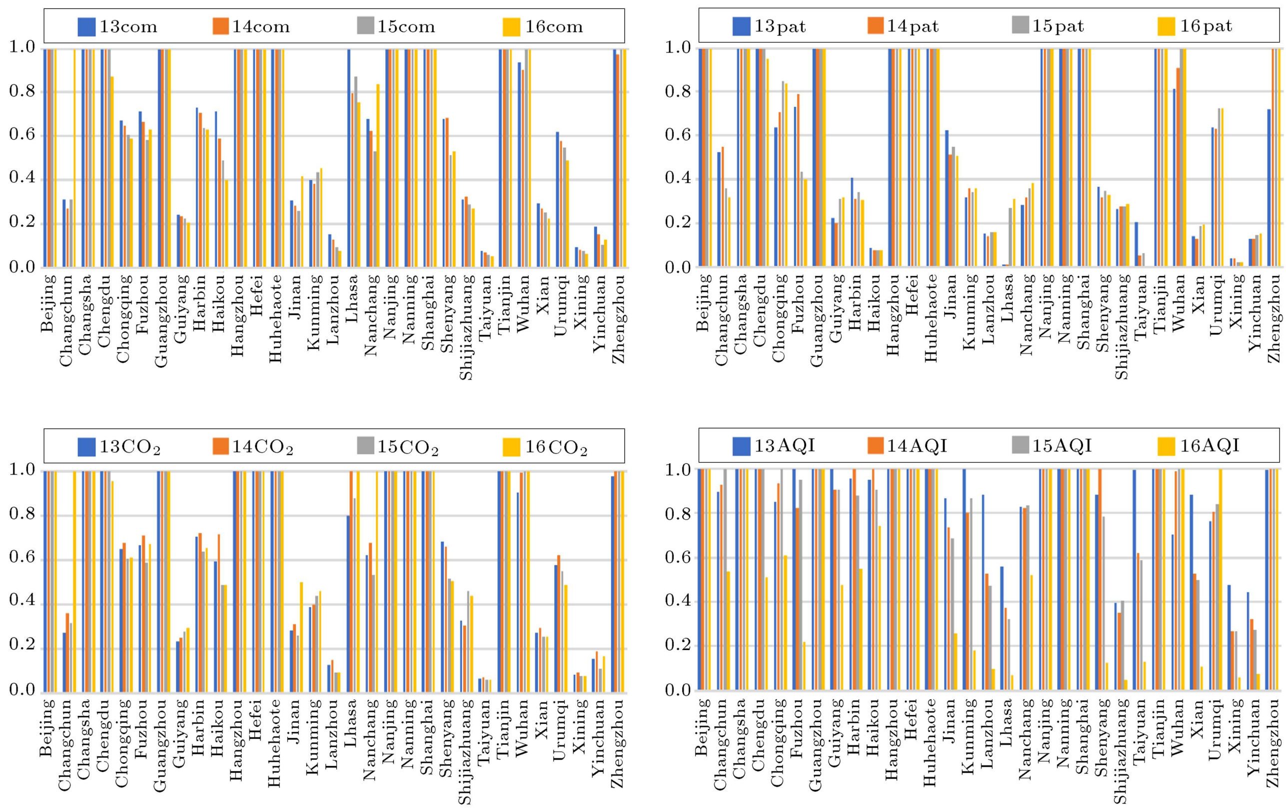

Figure 4. Consumed energy, patents, CO_2, and Air Quality Index (AQI) efficiency in cities during 2013–2016.

energy consumption efficiency is on an upward trend. The overall trend of Kunming and Wuhan is rising. However, Kunming and Wuhan have lower efficiency values in 2014. In 2013, 2015, and 2016, energy consumption efficiency of Wuhan is one.

In terms of patent efficiency, cities with the efficiency score of one are Beijing, Changsha, Guangzhou, Hangzhou, Hefei, Huhehot, Nanjing, Nanning, Shanghai, and Tianjin, indicating no need for improvement in patent efficiency. However, there are many cities with patent efficiencies below 0.4, namely Guiyang, Harbin, Haikou, Kunming, Lanzhou, Lhasa, Nanchang, Shenyang, Shijiazhuang, Taiyuan, Xian, Xining, and Yinchuan. Most of these cities are located in the western highlands of China or the old industrial bases in the northeast and their patent efficiency has great room for improvement. In addition, patent efficiency score of Chongqing exceeds 0.8 in 2015 and is greatly improved in 2016. The patent efficiency score of Urumqi in the first two years is slightly higher than 0.6, but it hits 0.7 in the following two years.

The four-year patent efficiency score of Wuhan exceeds 0.8 and in the last two years, it reaches one. For Zhengzhou, it is about 0.7 in 2013 and reaches one in the following years. Chengdu falls from one in the first three years to 0.95 in 2016. From the point of view of time, cities where patent efficiency is declining are Changchun, Fuzhou, Jinan, Shenyang, and Xining. The cities showing an upward trend are Chongqing, Guiyang, Kunming, Lhasa, Nanchang, Shijiazhuang, Wuhan, Urumqi, and Zhengzhou. Most of them are second-tier western cities that have rapidly developed in recent years. This means that the innovation output of these cities has significantly increased.

In terms of CO_2 emissions, cities with efficiency scores below 0.4 include Changchun, Guiyang, Jinan, Lanzhou, Shijiazhuang, Taiyuan, Xian, Xining, and Yinchuan, meaning that they still have much room for improvement in carbon emission efficiency. Chongqing, Fuzhou, Haikou, Harbin, Nanchang, Shenyang, and Urumqi take slightly higher positions than the previous nine cities and still have much room for improvement. Cities with the efficiency score of one are Beijing, Changsha, Guangzhou, Hangzhou, Hefei, Huhehot, Nanjing, Nanning, Shanghai, and Tianjin.

Considering the progression of time, carbon dioxide efficiency of Chengdu is one in the first three years, but it drops to 0.9 or more in 2016. Wuhan and Zhengzhou rise from about 0.9 in 2013 to one in the next three years. The efficiency score of Changchun in the first three years is below 0.4. However, its efficiency score in the last year is one. CO_2 emissions of Lhasa show some fluctuations to less than one in 2013 and 2015, but hit one in 2014 and 2016. In general, cities with declining trends include Chongqing, Harbin, Haikou, Lanzhou, Shenyang, Taiyuan, Xian, Urumqi, and Xining. On the other hand, Changchun, Guiyang, Jinan, Kunming, Shijiazhuang, Wuhan, and Zhengzhou show an upward trend in efficiency, indicating that they are better controlling CO_2 emissions.

In terms of AQI efficiency, cities with an efficiency score of one include Beijing, Changsha, Guangzhou, Hangzhou, Hefei, Huhehot, Nanjing, Nanning, Shanghai, Tianjin, and Zhengzhou. Cities with a lower AQI score (less than 0.6) are Lanzhou, Lhasa, Shijiazhuang, Taiyuan, Xian, Xining, and Yinchuan. Moreover, the efficiency scores of these cities have dropped rapidly since 2013, falling below 0.2 in 2016. This shows that their AQI efficiency scores are lower than 0.6 for most of the time. More governance measures are thus needed for control and improvement. The efficiency of Changchun, Chongqing, Fuzhou, Guiyang, Harbin, Haikou, Kunming, Nanchang, Shenyang, and Urumqi varies from 0.8 to one.

In terms of time series, the efficiency scores of Changchun, Chengdu, Chongqing, and Nanchang have an increasing trend and are higher than 0.8 in the first three years, but decline in 2016 to lower than 0.6. AQI efficiency of Urumqi rises each year up to 2016. Also, the score for Wuhan reaches one in 2015 and keeps the same value in 2016. Harbin and Haikou show a rise in 2014, but fall in 2015 and 2016. These cities need to pay more attention to improving the efficiency of AQI through the development of innovative and economic processes. Over time, the eight cities of Guiyang, Jinan, Lanzhou, Lhasa, Taiyuan, Xian, Xining, and Yinchuan exhibit declining efficiency scores. For Fuzhou and Kunming, AQI efficiency in 2015 is higher than that in 2014, but in 2016 it drops again. Harbin, Haikou, and Shenyang in 2014 have AQI efficiency scores higher than 2013, but their scores begin to decline afterwards. Only AQI efficiency scores of Wuhan and Urumqi continue to rise. It is noteworthy that, except for the eight cities with efficiency scores of one as well as Wuhan and Urumqi, which follow a rising trend, the AQI efficiency scores of all cities in 2016 are significantly lower than those in the previous years. There are many cities in 2016 with room for improvement in AQI efficiency as their scores drop to around 0.2 or below, including Fuzhou, Guiyang, Jinan, Kunming, Lanzhou, Lhasa, Shenyang, Taiyuan, Xian, Xining, and Yinchuan.

4. Conclusion

Innovative Research and Development (R&D) capabilities are the most important factors in economic activities and the driving force of social development. However, scholars in the past have paid greater attention to the impact of innovative (R&D) capabilities only on economic activities and ignored this impact on the environment. This study combined the variables of energy consumption, economy, environment, and innovative (R&D) capabilities; collected data for 31 cities in China; and used the dynamic SBM DEA model to explore urban efficiency as well as efficiency of variables. After considering input and output indicators such as energy consumption, R&D investment, patent output, CO_2 emissions, and Air Quality Index (AQI), this paper calculated the total efficiency scores of 31 cities in China and presented the scores for each indicator. The scores showed large differences among cities. Our findings were the following.

From the point of view of total efficiency, 10 cities have the score of one, meaning no need for efficiency improvement. However, the total efficiency scores of the other 21 cities show large room for improvement and there are big differences among them. Among these cities, 13 have total efficiencies less than 0.4. With the progression of time, the Overall Efficiency (OE) score of each city changes and we observe significant differences. The total efficiency of eight cities continues to decline, while in four cities it first rises and then declines. In addition, total efficiency of three cities is fluctuating. Finally, only three cities have rising efficiency over time. The efficiency scores for various input and output indicators of the cities are also very different. The development of these various indicators with time in different cities has a broad spectrum. Some cities show an upward trend in some indicators while others show a downward trend. Among the indicators, the number of patents in each city has grown rapidly, but there are still wide differences among the cities.

From the perspective of energy consumption, there are 10 cities with the energy consumption efficiency score of one and 18 cities with efficiency scores of around 0.6 or below. Among the 18 cities, 10 have energy consumption efficiencies lower than 0.4. These cities thus have significant room for improvement. There are few cities with efficiency scores that continue to rise over time and only three cities show fluctuations. In addition, there are at least nine cities whose energy consumption efficiency scores continue to decline, indicating that their energy consumption structure still needs more measures to be taken.

From the perspective of innovative R&D capabilities, the cities with the patent efficiency score of one are exactly those with the energy consumption efficiency score of one. However, there are 14 cities whose patent efficiencies are lower than 0.4. There are five cities whose patent efficiency has continued to decline and nine cities whose patent efficiency has continued to rise with time. This shows that many cities have achieved good results in the field of innovation ability enhancement.

From the perspective of environmental variables, in CO_2 efficiency, 10 cities have the efficiency score of one. However, nine cities have CO_2 efficiency scores lower than 0.4 and seven cities have CO_2 efficiency scores of about 0.6. All the 16 cities have a significant room for improvement. With the progression of time, nine cities have continued to decline in CO_2 efficiency and seven cities have continued to rise. This means that many cities have also made significant progress in CO_2 emission control, but there are still some cities that need to take on more measures to control this pollution.

In terms of AQI efficiency, 11 cities have the efficiency score of one. However, 11 other cities have AQI efficiency scores below 0.6, but their efficiency scores are all higher than 0.2. The AQI efficiency scores of the other cities have been higher at around 0.8 from 2013 to 2015, but the estimated figures in 2016 show a significant decline. Eleven cities have more obvious room for improvement with regard to their AQI efficiency scores. The AQI efficiency scores of two cities have continued to rise, but those of eight cities have continued to decline with time. In 2016, the AQI efficiency scores of all cities have dropped significantly and for many cities, they have fallen below 0.6. There are 11 cities in 2016 with efficiency scores dropping to around 0.2 or below.

The results of this study suggest that, considering the relatively large differences between cities, policies should be formulated to optimize the industrial structure and to explore different industrial advantages, factor endowments, geographic features, demographic characteristics, and cultural characteristics of each city. New technologies can be applied to the use of clean energy and the clean use of traditional energy sources. Priority should be given to the control and prevention of environmental pollution, e.g., by increasing R&D investment as well as improving and optimizing industrial and energy structures. Policymakers must also pay close attention to air pollution and carbon emissions, and formulate policies and measures that are more conducive to the green, ecological, and sustainable economic and social development of all the big cities of China.

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