Innovation and Environment Performance: An empirical study on 31 cities in China

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Abstract:

After its rapid economic growth, China is facing a very serious problem of atmospheric pollution with major long-term atmospheric problems appearing in large cities. Air pollution not only affects people's normal lives, but also has a greater negative impact on their bodies, causing diseases, impacting productivity, and influencing people's creativity. Due to past articles, the discussion on the efficiency of innovation and research has not been considered the impact of environmental variables. This study combines energy consumption, economics, environmental variables and innovative research and development capabilities to analyze and explore the relationship between consumption, environment, economy, and innovative R&D capabilities, this is the feature of this article. This study employ the Dynamic Data Envelopment Analysis (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 each city to find their space for improvement. The results of the study show that 10 cities have a total efficiency score of 1, implying the improvement space is already 0, whereas the total efficiency scores of the other 21 cities mean there is still much room for improvement, and there are big differences among the cities.

Keywords: AQI efficiency; energy efficiency; re-sampling; CO_2 efficiency; innovation efficiency; SBM DEA

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1. Introduction

Innovation capability is considered to be the most important ability for economic growth and social development in this new century, as it plays an extremely important role in sustainable development and acquiring competitive advantages for a nation and 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 and low-emission industries so as to achieve their own green, sustainable economic structure and economic growth model. After its rapid economic growth, China is facing a very serious problem of atmospheric pollution with major long-term atmospheric problems appearing in large cities. Air pollution not only affects people's normal lives, but also has a greater negative impact on their bodies, causing diseases, impacting productivity, and influencing people's creativity.

To evaluate cities' or countries' performances in urban economic growth and energy consumption, most research studies have focused on energy consumption and carbon emissions, such as Hu and Wang [1], Kumar [2], Gomes and Lin [3], Zhou et al. [4], Yeh et al. [5], Zhang et al. [6], Choi et al. [7], Wang et al. [8], Lin and Yang [9], Zhou et al. [10], Pan et al. [11], Wang and Feng[12], Wu et al. [13], Liou et al. [14], Meng et al. [15], Wang et al. [16], Du et al. [17], and Feng et al. [18]. Some have conducted studies on the efficiency of urban energy and environmental assessment using sewage, sulfur dioxide, etc. as indicators for measuring environmental pollution, like 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 to reduce air pollution. Li et al. [25] Using the AQI heating model to analyze the relationship between AQI and heating system and energy conversion in building space through regression model; Li et al. [26] provide a method to accurately quantify the impact of China's heat emission on air quality. Xu et al. [27] used observations to assess the impact of Beijing's air pollution in winter and summer on energy demand; Tong et al. [28] proposed that natural ventilation can reduce building energy consumption and maintain a healthy indoor environment. Bidokhti et al [29] established a framework to observe emissions, urban climate change and mitigate and adapt to climate change in response to climate impacts in Tehran; Ahmadzadehtalatapeh [30] proposed a solar assisted desiccant evaporative cooling system for office building, providing energy and reducing pollution. Meanwhile, many scholars have suggested that air pollution has a problem with human health. Liao et al. [31] collected the Yangtze River Delta region data in 2013-2016 to understand the air quality and health effects. The results showed that public health risks were the highest, and O3 pollution accounted for 70% of the public health problem; Li et al. [32] believe that heating emission leads to deterioration of environmental quality and human health. He used the heating impact index (HII) to evaluate 66 major cities in China and found that when AQI was 45%, the pollution time was 39%. Khveis et al. [33] estimated the number of asthma cases caused by NO2 and NOx each year in Bradford, England, and found that the increase in the number of asthma cases per year is related to air pollution caused by traffic; Maji et al. [34] used the exposure-response functions (ERF) 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 of course many scholars who have conducted in-depth research on innovation efficiency. For example, Laitinen [35] considered that a firm’s creativity and development capability can be appropriately quantified by the number of patents. Urpelainen [36] collected data on 22 OECD countries from 1991-2007, using statistical analysis to explore the impact of export orientation on energy efficiency innovation. Those empirical results found that export orientation has large positive effects on energy efficiency innovation.

Bai and Li [37] used data of 30 regions in China from 1998-2008 for empirical analysis to explore the impact of government research expenditure on innovation efficiency, stating that local government R&D funding has a significantly negative impact on regional innovation efficiency. Chen and Guan [38] collected data from 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 estimate regional innovation efficiency in China and to investigate the major factors affecting efficiency scores. Moon [40] gathered data on South Korea’s electronic equipment industry, using the fuzzy data envelopment analysis (DEA) model to analyze the industry’s innovation efficiency and finding that it can save 28.7% of inputs by improving innovation efficiency.

Chen et al. [41] combined the network SBM model with DEA window analysis to measure the trend and heterogeneity of technological innovation efficiency based on the data of 17 industry segments of China’s high-tech industry. Chen and Kou [42] collected province-level regional data and utilized the two-step hybrid analytical procedure model to analyze China’s province-level regional innovation systems. The empirical study showed that China’s regional innovation systems perform poorly in both technological creation efficiency and technological commercialization. Suh and Kim [43] uses the DEA method to estimate innovative activity efficiency of service firms. Wan et al. [44] took data of industrial enterprises in China from 2006 to 2010 to explore the impacts of technological innovation modes on the eco-efficiency of industrial enterprises, finding that domestic independent innovation has a positive significant impact on their eco-efficiency in the Eastern region. Wang et al. [24] collected data from 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 show that all companies performed well in R&D efficiency and innovation efficiency.

Kou et al. [45] proposed a new formulation approach for dynamic network DEA and evaluated the innovation efficiency of OECD countries in a multi-period and multi-division context. Huang et al. [46] collected 8601 Chinese firm-year observations from 2007 to 2012 and took a two-stage approach to explore the impact of religion in a firm's social environment 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 can 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 found that technological innovations affect countries with relatively high CO2 emissions.

In the past, it was learned from the literature that scholars' research focuses 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. For research and development, only research and development efficiency is emphasized. Few articles combine the relationship between R&D, energy consumption and air pollution to establish a systematic framework to explore the relationship between economic and social interactions and to provide more effective government recommendations in policy.

Thus, this study uses energy consumption, R&D, patents, CO2 emissions, and the AQI index in 31 cities of 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 each city to find out the space for improvement.

2. Research methods

The research method herein is combined with Tone [49] in order to propose a re-sampling past-present-future model and also utilizes the Slack-Based Measures (SBM) Dynamic DEA model of Tone and Tsutsui [50] First, we use the re-sampling method to estimate the data of input and output variables in 2016 and then take 2013-2016 data to conduct dynamic efficiency analysis. We describe this as follows.

2.1 Resample Past-Present-Future Model

Both the radial and non-radial efficiency measures in Data Envelopment Analysis (DEA) have errors in measurement. For example, Simar and Wilson [51,52] proposed a bootstrap method that considers repeated sampling to obtain the most efficient sample distribution. Tziogkidis [53] stated that the bootstrap DEA exhibits very significant development and application. However, these methods still have problems. For example, the characteristics of input and output (that is, DMUs are different) are not taken into account. The bootstrapping method, although it is like a re-sampling method, treats existing observations as maternal repeated sampling. In order to obtain 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, and this method can also be used to predict the future efficiency value of a DMU. This model uses past DMU input and output data, $(X^t, Y^t)(t = 1, \ldots, T)$, 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, and 3) average of trend and weighted average. Essentially, these three methods offer little differences. From the trend analysis method, the correlation between input and output is higher than that from the weighted average method, the integrated average trend, and the weighted average method. 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 in space the input variables and output variables of all evaluated units. Depending on whether the projection point falls on the production boundary, a performance index ranging from 0 to 1 is then given as a judgment on whether there is efficiency between input and output. Charnes et al. [54] proposed their CCR model, which determines the architecture of the DEA model and solves multiple inputs and multiple outputs in a linear programming model with 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 (VRS) by variable returns to scale (VRS), and offered the well-known BCC DEA model. Different from the CCR and BCC models, Tone [56] proposed using slacks as non-radial and non-oriented estimation methods to solve the problem that inputs or outputs cannot be adjusted by equal proportions in order to solve the most efficient problem. They called it the Slacks-Based Measure (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 difference between oversupply or output shortage will incur a decreasing monotone - that is, the input or output slacks gradually decrease.

Slacks-Based Measure (SBM) model:

$$\min \quad \rho = \frac{1 - \frac{1}{m}\sum_{i=1}^{m} s_i^- / X_{io}}{1 + \frac{1}{s}\sum_{r=1}^{s} s_r^+ / Y_{ro}}$$

$$\begin{aligned} s.t. \quad & X_o = X\lambda + s^- \\ & Y_o = Y\lambda - s^+ \\ & \lambda, s^-, s^+ \geq 0 \end{aligned} \qquad (1)$$

ρ is a non-radial slack indicator

m and s are the amount of input and output

s_i^- and s_r^+ represent the input slacks and output slacks

$X\lambda$ and $Y\lambda$ represent values of the efficiency boundary of input and output items.

Tone and Tsutsui [50] extended the model to the Slack-Based Measures (SBM)

D-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 D-DEA model is divided into input-oriented, output-oriented, and non-oriented types.

We assess overall efficiency (OE) and term efficiency (TE) with the non-oriented SBM D-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.

This model sets up n DMUs (j = 1, 2, …, n) over T periods (t = 1, 2, …, T). The DMUs have multiple different and independent inputs and outputs in each term, with the zgood as a carry-over from period t to period t+1 herein. The carry-over is guaranteed by equation (2):

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

Here, symbol α shows good, bad, free, fix, etc., the non-oriented overall efficiency (δ^*) is calculated by equation (3), and ω^t and ω_i are weights to term t and the input.

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

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

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

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

$$y_{iot} = \sum_{j=1}^{n} y_{ijt} \lambda_j^t - s_{it}^+ \qquad (i = 1, \dots, s; t = 1, \dots, T) \qquad (4)$$

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

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

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

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

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

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

$$\lambda_j^t \geq 0, s_{it}^- \geq 0, s_{it}^+ \geq 0, s_{it}^{good} \geq 0, s_{it}^{bad} \geq 0 \text{ and } s_{it}^{free}: \text{free}(\forall i, t),$$

The non-oriented term efficiency (ρ*) follows below:

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

3. Empirical study

3.1 Data and variables

Figure 1 reveals 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; GDP are used as output factors in the evaluation; and CO2, AQI, and patents are defined as carry-over intermediates, which are outputs produced in the current period that can be used as an input for the next period as well.

(Insert Figure 1 here)

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 from the years 2013 to 2016 are collected from the Statistical Yearbook of China, Demographics and Employment Statistical Yearbook of China, and City Statistical Yearbooks. Air pollutants data 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 pool of population and most aggregation of industries in the regions. The cities together represent the air pollution emission situation in China. We explain the variables (see Table 1) herein as follows.

(Insert Table 1 here)

Input variables

Labor input (em): This study uses the numbers of employees in each city by the end of each year. Unit: person.

Energy consume (com): It is calculated from the total energy consumption in each city. Unit: 100 million Ton. It included coal, oil, natural gas, and the total consumption of primary electricity and other energy.

R&D (R&D) expenditure: Research and development expenditure refers to the 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

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

Carry-over Variables

Patent (Pat): Refers to 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, and 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 each year as an indicator of the city's innovation.

Carbon emissions (CO2): CO2 emissions data for each city were estimated from the energy consumption CO2 is seen as a primary cause of changing earth temperatures and rising sea levels. Among greenhouse gas emissions, carbon dioxide is the main component of greenhouse gases, and so CO2 emissions are used as an indicator for each city.

Air Quality Index (AQI): Is a non-linear dimensionless index that quantitatively describes air quality. A larger value, a higher level and category, and a darker color of the representation indicate that air pollution is more serious and has greater harm to human health. The major pollutants are fine Particulate Matter (PM2.5), PM10, SO2, NO2, O3, CO, etc. (PM2 .5 and PM10 are the 24-hour average concentration). PM2.5 refers to atmospheric particulate matter (PM) that has a diameter of less than 2.5 micrometers, written as PM2.5 and with the unit of micrograms / cubic meter. SO2 refers to sulphur dioxide or sulfur dioxide. It is released naturally by volcanic activity and is produced as a by-product of the burning of fossil fuels contaminated with sulfur compounds. NO2 refers to Nitrogen Dioxide (NO2) and is one of a group of highly reactive gases known as oxides of nitrogen or nitrogen oxides (NX). It is an intermediate in the industrial synthesis of nitric acid, and millions of tons of it is produced each year. At higher temperatures it is a reddish-brown gas that has a characteristic sharp, biting odor and is one of the most prominent air pollutants. The AQI was considered to be the maximum value of the Individual air quality index (IAQI) for each pollutant. When the AQI was greater than 50, the corresponding pollutant was the primary pollutant, and pollutants with an IAQI greater than 100 were considered excessive.

3.3 Statistic description of input and output data

From 2013 to 2016, the various input variables include Energy Consumed, Labor Input, and R&D Expenditure, whiles output variables are Gross Domestic Production (GDP), Patents, CO2, and AQI, which are defined as carry-over intermediates that are outputs produced in the current period that can be used as an input for the next term.

As can be seen from the Table 2 and Figure2, the maximum value of the patent's index has risen the most over time in all input and output indicators, but the difference between the maximum and minimum values also varies greatly. The maximum GDP and R&D costs of each city are growing rapidly, and the gap between the maximum and minimum of R&D costs is also relatively large. Relatively speaking, the gap 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 see that the average of energy consumption and employed population increased slightly from 2013 to 2016. The maximum values of CO2 emissions and AQI indices have increased over time, but the mean values of these two indicators have shown a downward trend.

(Insert Figure 2 here)

(Insert Table 2 here)

3.4 Empirical analysis and results

3.4.1 Total city efficiency scores and evaluation

From Table 3 and Figure 3, we can see that there is a big difference in the total efficiency of each city. First, the cities with an efficiency score of 1 include Beijing, Changsha, Guangzhou, Hangzhou, Hefei, Huhehot, Nanjing, Nanning, Shanghai, and Tianjin, indicating that the room of improvement for these cities is 0. Cities with an efficiency score below 0.2 include Haikou, Lanzhou, Lhasa, Taiyuan, Urumqi, Xining, and Yinchuan. The room for improvement in the total efficiency of these 7 cities is very large. Cities with an overall efficiency score of around 0.4 include Changchun, Harbin, Jinan, Kunming, Nanchang, and Shenyang. The efficiency of these cities is only slightly higher than the above 7 cities. However, they still have room for improvement. There are also cities that have room for improvement, but have little room for efficiency improvement, including Chengdu, Fuzhou, Wuhan, and Zhengzhou.

From the perspective of time, there are some cities whose overall efficiency is declining. These cities are Lanzhou, Shenyang, Xining, Harbin, Haikou, Jinan, Xining, and Yinchuan. As Chengdu, Chongqing, Fuzhou, and Kunming changed over time, their total efficiency rose first and then declined. The total efficiency of cities such as Changchun, Guiyang, and Urumqi fluctuates greatly. There are also fewer cities where total efficiency has risen over time, such as Xian, Nanchang, and Wuhan.

(Insert Table 3 here)

(Insert Figure 3 here)

3.4.2 Cities' efficiency score evaluation of energy consumption, patents, CO2 emissions, and AQI

From the total efficiency scores of cities, we can see that different cities' efficiency has great room for improvement. Next, we look at the changes in the efficiency scores of the major input indicators and output indicators for each city. Through re-sampling, we estimate the various input and output indicators of each city in 2016 and then calculate the efficiency scores of various input and output indicators of each city 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 of each city, as well as their changes over time. There are also very large differences between the indicators in different cities.

From the perspective of differences in energy consumption efficiency, cities with an efficiency score of 1 include Beijing, Changsha, Guangzhou, Hangzhou, Hefei, Huhehot, Nanjing, Nanning, Shanghai, and Tianjin. The room for improvement to energy consumption efficiency of these cities is naturally 0. Cities with an energy consumption efficiency score of 0.4 or below are Changchun (except for 2016, when it has 1), Guiyang, Jinan, Kunming, Lanzhou, Shijiazhuang, Taiyuan, Xian, Xining, and Yinchuan. It shows that the energy consumption of these 10 cities can be greatly improved. In addition, the energy consumption efficiencies of 8 cities are around 0.6 or above 0.6, such as Chongqing, Fuzhou, Harbin, Haikou, Nanchang, Shenyang, Urumqi, and Wuhan. From the perspective of time, Wuhan's energy consumption efficiency from 2013 to 2014 is around 0.9, rising to 1 in 2015 and 2016. Chengdu's energy consumption efficiency is 1 from 2013 to 2015, but it 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 these cities still need to further strengthen energy use and energy structure adjustments. There are few cities where 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, Wuhan's energy consumption efficiency is 1 in 2015 and 2016.

In terms of patent efficiency, cities with an efficiency score of 1 include Beijing, Changsha, Guangzhou, Hangzhou, Hefei, Huhehot, Nanjing, Nanning, Shanghai, and Tianjin, indicating no need on room for improvement in patent efficiency. However, there are many cities with patent efficiency below 0.4, such as 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, Chongqing's patent efficiency score exceeds 0.8 in 2015 and 2016 and has greatly improved. The patent efficiency score of Urumqi in the first two years is slightly higher than 0.6, but hit 0.7 in the following two years.

The four-year patent efficiency score of Wuhan exceeds 0.8 and the last two years reaches 1. Zhengzhou's patent efficiency score is only about 0.7 in 2013 and has reached 1. Chengdu fell from 1 in the previous three years to 0.95 in 2016. From the point of view of time, cities where patent efficiency is declining include Changchun, Fuzhou, Jinan, Shenyang, and Xining. Among the cities showing an upward trend are Chongqing, Guiyang, Kunming, Lhasa, Nanchang, Shijiazhuang, Wuhan, Urumqi, and Zhengzhou. Most of these cities are second-tier western cities that have rapidly developed in recent years. It shows that the innovation output of these cities has significantly increased.

From the perspective of CO2 emissions, cities with an efficiency score below 0.4 include Changchun, Guiyang, Jinan, Lanzhou, Shijiazhuang, Taiyuan, Xian, Xining, and Yinchuan, meaning there is still much room for improvement in their carbon emission efficiency. Chongqing, Fuzhou, Haikou, Harbin, Nanchang, Shenyang, and Urumqi are slightly higher than those previous 9 cities, but still have much room for improvement. Cities with an efficiency score of 1 are Beijing, Changsha, Guangzhou, Hangzhou, Hefei, Huhehot, Nanjing, Nanning, Shanghai, and Tianjin.

Judging from the development of time, Chengdu's carbon dioxide efficiency is 1 from the previous 3 years, but drops to 0.9 or more in 2016. Wuhan and Zhengzhou rise from about 0.9 in 2013 to 1 in the next three years. The efficiency score of Changchun in the first three years is below 0.4, however, its last year's efficiency score is 1. Lhasa's CO2 emissions show some fluctuations at less than 1 in 2013 and 2015 and hitting 1 in 2014 and 2016. As a whole, cities with declining trends include Chongqing, Harbin, Haikou, Lanzhou, Shenyang, Taiyuan, Xian, Urumqi, and Xining. Changchun, Guiyang, Jinan, Kunming, Shijiazhuang, Wuhan, and Zhengzhou show an upward trend in efficiency, indicating that they are better controlling CO2 emissions.

In terms of AQI efficiency, cities with an efficiency score of 1 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. It 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 1.

In terms of time series, the efficiency scores of Changchun, Chengdu, Chongqing, and Nanchang increased and are higher than 0.8 in the first three years, but then declined in 2016 to lower than 0.6. Urumqi's AQI efficiency rises each year up to 2016, while Wuhan's also rises to 1 in 2015 and 2016. Harbin and Haikou show a rise in 2014, but then fall in 2015 and 2016 and drop to a lower efficiency score. These cities need to pay more attention to improving the efficiency of AQI through the development of innovation and economic processes. Over time, the above 8 cities of Guiyang, Jinan, Lanzhou, Lhasa, Taiyuan, Xian, Xining, and Yinchuan exhibit declining efficiency scores. For Fuzhou and Kunming, their AQI efficiency in 2015 is higher than in 2014, but in 2016 it drops again. Harbin, Haikou, and Shenyang in 2014 have an AQI efficiency score higher than 2013, but then it begins to decline afterwards. Only Wuhan's and Urumqi's AQI efficiency scores continue to rise. It is noteworthy that, the estimated 2016 efficiency score for each city in 2016, in addition to 8 cities with efficiency scores of 1 and other than Wuhan, Urumqi, the other cities' AQI efficiency scores in the current year were significantly lower than the other years before 2015. There are quite a few cities in 2016 with room for improvement in AQI efficiency, as it drops to around 0.2 or below, including Fuzhou, Guiyang, Jinan, Kunming, Lanzhou, Lhasa, Shenyang, Taiyuan, Xian, Xining, and Yinchuan.

(Insert Table 4 here)

(Insert Figure 4 here)

4. Conclusion

Since innovative research and development capabilities are the most important factor in economic activities and the driving force of social development. However, scholars in the past have paid more attention to the impact of innovative research and development capabilities on economic activities, while ignoring the impact on the environment. This paper combines the variables of energy consumption, economy, environment and innovation research and development capabilities, collects data from 31 cities in China, and uses dynamic SBM DEA model to explore urban efficiency and efficiency of variables. After considering input and output indicators such as energy consumption, R&D investment, patent output, CO_2 emissions, and AQI, this paper calculates the total efficiency scores of 31 cities in China and presents the scores of each indicator, which show large differences and characteristics. Our findings run as follows.

From the point of view of total efficiency, 10 cities have a total efficiency score of 1, 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. Of these, 13 cities have a total efficiency of less than 0.4. As time changes, the overall efficiency score of each city changes, and we see significant differences. The total efficiency of 8 cities continues to decline, while the total efficiency of 4 cities rises first and then declines. In addition, 3 cities' total efficiency fluctuates. However, only three cities have efficiency that continues to rise over time. The efficiency scores of various input and output indicators of the cities are also very different. With the change of time, the development of these various indicators in different cities presents 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 an energy consumption efficiency score of 1 and 18 cities with an efficiency score of around 0.6 or below. Among those 18, 10 cities have energy consumption efficiency of less 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 9 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 research and development capabilities, the cities with a patent efficiency score of 1 are the same cities with an energy consumption efficiency score of 1. However, there are 14 cities whose patent efficiency is lower than 0.4. As time progresses, there are 5 cities whose patent efficiency continued to decline, and 9 cities whose patent efficiency continued to rise. It shows that many cities have achieved good results in the field of innovation ability enhancement.

From the perspective of environmental variables, the CO2 efficiency point of view, the 10 cities mentioned above have an efficiency score of 1. However, 9 cities have a CO2 efficiency score of less than 0.4, and 7 cities have a CO2 efficiency score of about 0.6. All 16 cities have significant room for improvement. With the development of time, nine cities have continued to decline in CO2 efficiency, and seven cities have continued to rise. It shows that many cities have also made significant progress in CO2 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 an efficiency score of 1. However, 11 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 are higher at around 0.8 from 2013 to 2015, but the estimated figures in 2016 show a more significant decline. Eleven cities have more obvious room for improvement due to their AQI efficiency score. As time change, the AQI efficiency scores of two cities continued to rise, but those of eight cities continued to decline. In 2016, the AQI efficiency scores of all cities dropped significantly, as many cities' score fell below 0.6. There are also 11 cities in 2016 with an efficiency score dropping to around 0.2 or below 0.2.

The results of this study suggest that due to the relatively large differences between cities, targeted policies should be formulated to optimize the adjustment of 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, such as increasing R&D investment and 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 construction of green, ecological, and sustainable economic and social development in all the big cities of China.

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Figure Captions

Table Captions

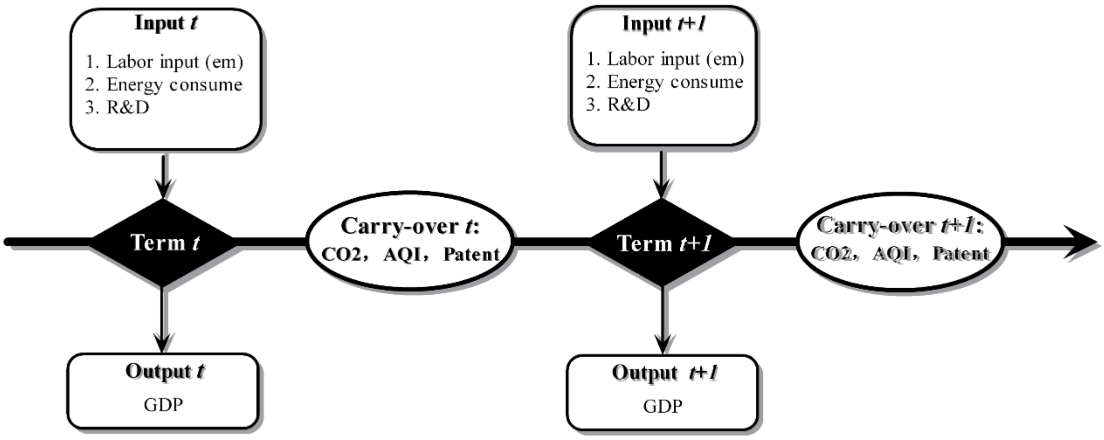

Figure 1: Dynamic Model

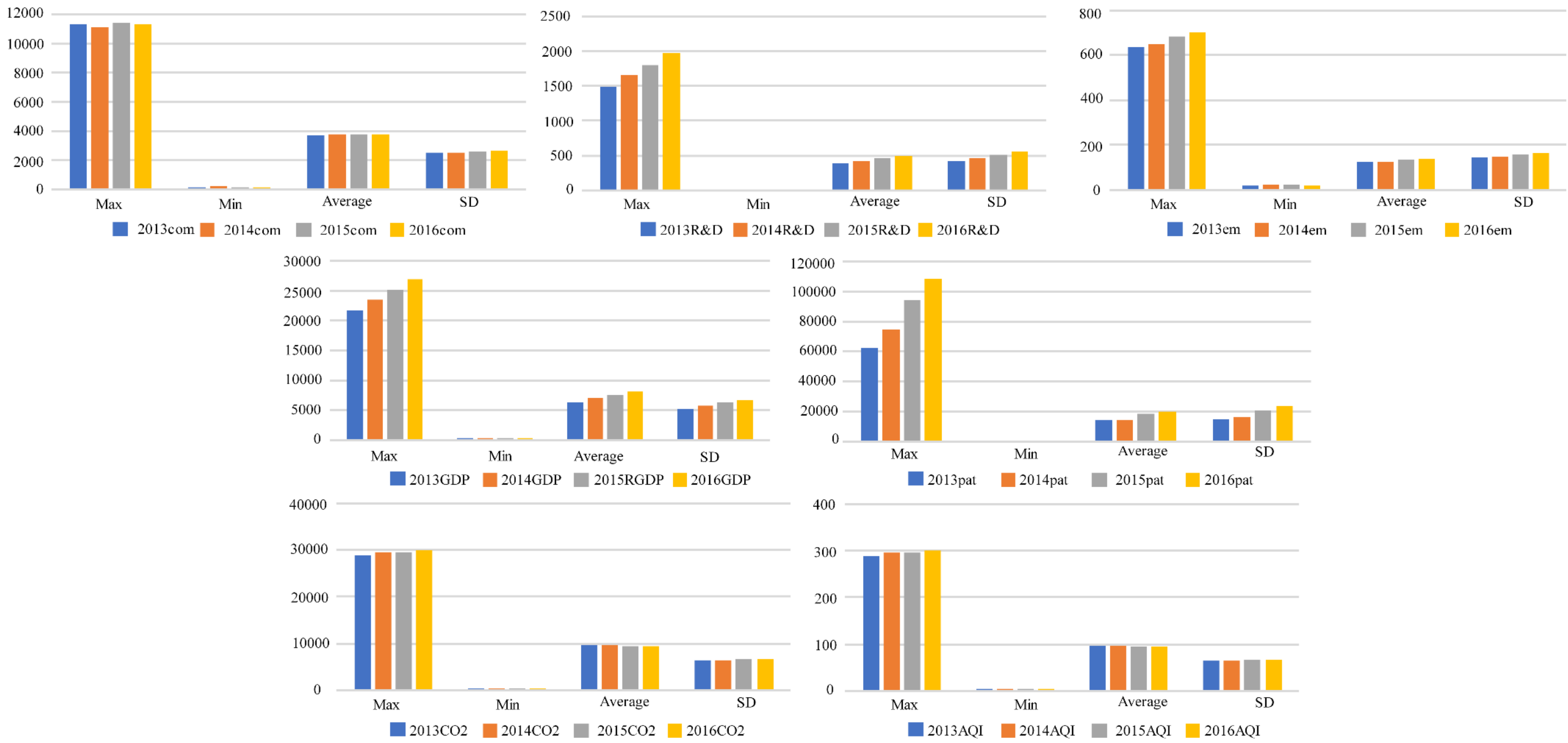

Figure 2: Statistic analysis of input and output indices from 2013 to 2016

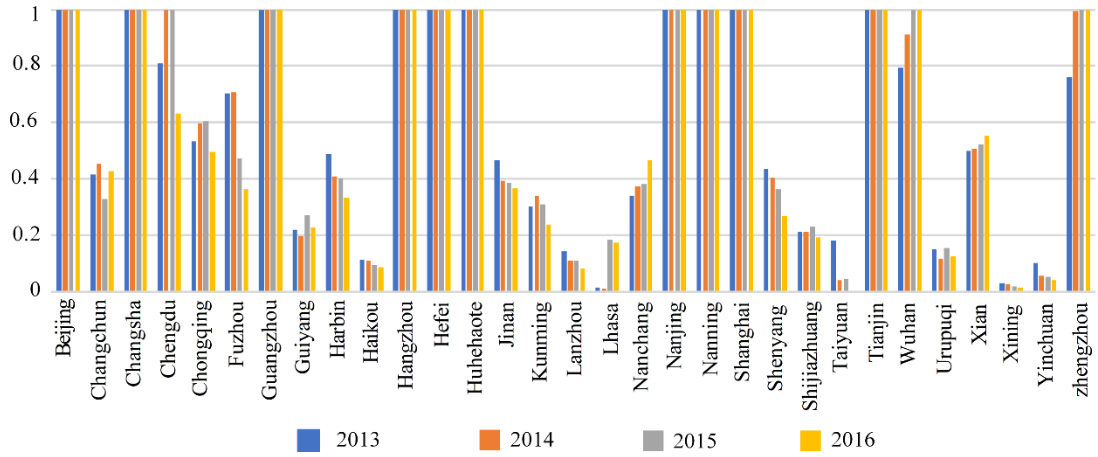

Figure 3: Total efficiency scores of cities in 2013-2016

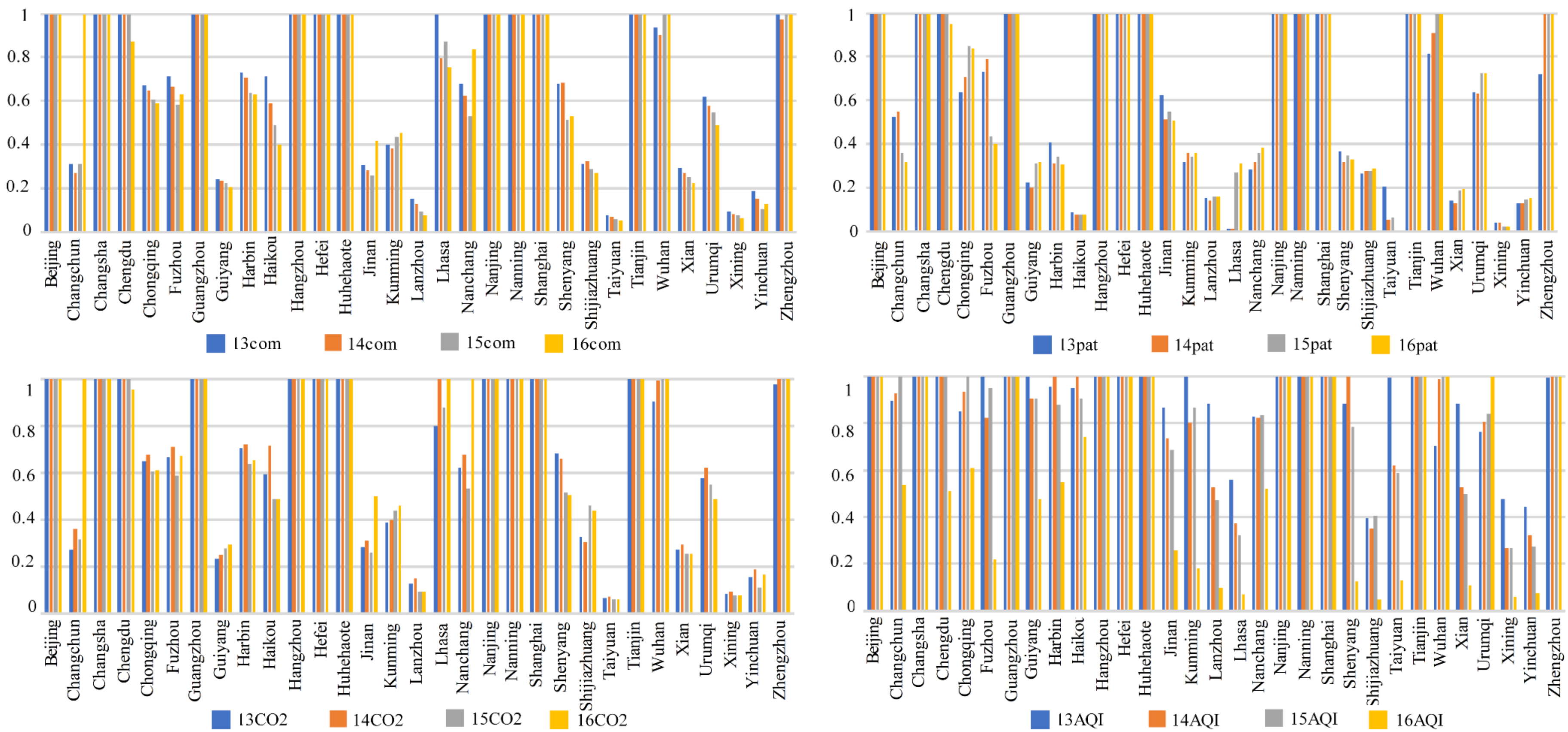

Figure 4: 2013-2016 energy consumed, patents, CO2, and AQI efficiency by cities

Table 1: Input and output indices

Input variable	Desirable output	Carry-over
Labor input (em)	Gross Domestic Production (GDP)	AQI
Energy consume (com)		CO2
R&D expenditure (R&D)		Patent (Pat)

Table 2: Statistics of the indices

	2013em	2014em	2015em	2016em	2013com	2014com	2015com	2016com	2013R＆D	2014R＆D	2015R＆D	2016R＆D	2013GDP	2014GDP
Max	635.57	652.2	681.76	702.7	11345.69	11084.63	11387.44	11314.34	1487.4	1652.8	1801.2	1970.4	21602.12	23560.94
Min	20.41	21.09	21.16	20.57667	171	191.1	156.38	158.2067	2.3	2.4	3.1	3.4	304.87	347.45
Average	123.80226	126.50968	135.9597	140.9146	3715.788	3758.6002	3735.649	3731.844	382.65806	420.435484	456.56452	493.792473	6365.28355	6951.2813
SD	141.93629	147.07432	157.9371	165.1526	2479.046	2519.9475	2586.888	2653.622	417.46728	461.677069	507.05184	552.511548	5280.10857	5782.6045

	2015GDP	2016GDP	2013pat	2014pat	2015pat	2016pat	2013co2	2014co2	2015co2	2016co2	2013AQI	2014AQI	2015AQI	2016AQI
Max	25123.45	26950.167	62671	74661	94031	108481	28820.04	29498.79	29607.344	30096.0313	292	164	133	122.33333
Min	289.46	298.51667	46	48	232	0.94031	496.86	444.6	406.588	359.077333	75	41	39	0.00292
Average	7479.8477	8046.7017	14336.74	14103.58	18540.45	20340.267	9772.36	9661.05	9474.7576	9338.45137	149.96774	92.0967742	85.516129	44.74203
SD	6215.9718	6700.6092	15202.87	16076.01	20606.31	23469.376	6551.864	6445.519	6617.2677	6650.65642	51.414498	25.9805819	22.4353853	29.37955

Table 3: Total efficiency by cities for the years 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

Table 4: Comparison of energy consumption efficiency, patent efficiency, CO2 emissions, and AQI efficiency scores for cities in 2013-2016

	Com				pat				CO2				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

Biographies

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