Evaluation of energy efficiency and spatial distribution in China: based on non-separable hybrid DEA model

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Abstract. The increasing tension between energy supply and demand is making it difficult for China to sustain the extensive economic development pattern. The most realistic way of solving the problem lies in increasing the energy efficiency. This paper introduces a non-separable hybrid DEA model that considers undesirable output to measure the energy efficiencies of 285 prefecture or higher-level cities in China during 2003-2016, and then analyses the spatial distribution of energy efficiencies. The results indicate that, for the investigation period, the overall energy efficiency of China with regard to pollutants remained at a low level and presented a “U-shaped” decreasing-increasing trend. To be specific, China’s energy efficiency distribution presented a trend of “high in the east and low in the west”. The energy efficiency of East China changed relatively gently, while the energy efficiencies of Central China and West China changed dramatically. China’s energy efficiency also presented a significant spatial agglomeration effect, i.e., cities with close energy efficiencies are usually adjacent to each other.

1. Introduction
After experiencing an “economic miracle” for more than three decades, China is currently facing the early emergence of both environmental and energy problems. Similar problems have been encountered by all developed countries of the West during their stage of industrialization. The increasing tension between energy supply and demand and the over-drawing of environmental bearing capacity are making it difficult to sustain the extensive economic development pattern. Characterized by high input, high energy consumption, high pollution, and high emission, this pattern has turned China into the world’s largest energy producer and consumer, as well as a major emitter of greenhouse gases and air pollutants (Zheng, 2014[1]). Moreover, due to the price advantage of coal resources, China is not going to change its coal-dominated energy consumption pattern soon. This suggests that the space for realizing energy conservation and emission reduction through the further optimization of the energy structure is very limited, and the most realistic way of solving the problem lies in increasing the energy efficiency (Wang, 2016[2]).

Energy efficiency refers to using less energy for the same amount of service or useful output. In view of its importance, scholars have extensively studied the measure of energy efficiency. One measure is the single-factor energy efficiency method, i.e., adopting the ratio of output to energy input to define energy efficiency. While this index is simple, an economy’s output is determined not just by energy input, but also by the input of factors such as capital, labor, etc. In addition, the single-factor energy efficiency index fails to consider the influence of various “non-efficiency”-related market factors on energy input. For example, the effect of substituting energy as a result of a change in the relative energy price may also render a change in energy efficiency. A second measure is the
total-factor energy efficiency method, i.e., taking the combined effect of various input factors into consideration. This method contains two sub-methods: parametric method and non-parametric method. The non-parametric method of Data Envelopment Analysis (DEA) can calculate the distance between a decision-making unit and the frontier and has thus become a powerful tool in the efficiency literature (Costantini, 2013[3]; Shen, 2015[4]; MarquzeE, 2015[5]; Di, 2018[6]; Huang, 2018[7]). Regarding the strength of existing studies, Tone et al (2001, 2011) [8,9] proposed an SBM-DEA that considers the slackness of input-output, further creating a hybrid DEA model that could not only deal with multiple desirable outputs but also take the non-separability of input-output into account.

Based on existing studies, this paper attempts to introduce a non-separable hybrid data envelopment analysis (DEA) model to measure the energy efficiencies of 285 prefecture or higher-level cities in China during 2003-2016. The method takes radial and non-radial perspectives into account, as well as the non-separability between energy input and undesirable output.

2. Materials and Methods
Farrell (1957) first proposed that a non-parametric linear convex surface could be constructed as production frontier to estimate production efficiency. Based on the study by Farrell, Charnes et al. (1978) developed the first DEA model (CCR) and since then, DEA models have been extensively applied in the field of productivity measurement and evaluation. Based on this CCR, Banker et al (1984) introduced a VCR model for variable returns to scale and after that, other scholars have constantly extended DEA models. Regarding the strength of existing studies, Tone et al (2001, 2011) proposed an SBM-DEA that considers the slackness of input-output, further creating a hybrid DEA model that could not only deal with multiple desirable outputs but also take the non-separability of input-output into account. This model can be described as follows:

The first assumption is that there are \( n \) similar decision-making units in a production system and that the input and output vectors of a decision-making unit in the production process are respectively \( X \in R^{m \times n} \) and \( Y \in R^{l \times n} \). Here, input-output matrices \( X \) and \( Y \) can be decomposed as follows:

\[
X = \begin{pmatrix}
X^F \\
X^B
\end{pmatrix}, \quad Y = \begin{pmatrix}
Y^F \\
Y^B
\end{pmatrix}
\]

where \( X^F \in R^{m \times n} \) and \( X^B \in R^{m \times 2n} \) represent separable and non-separable input matrices, respectively; \( Y^F \in R^{l \times n} \), \( Y^B \in R^{l \times 2n} \), \( Y^FG \in R^{l \times n} \), and \( Y^BF \in R^{l \times 4n} \) represent separable desirable output, separable undesirable output, non-separable desirable output, and non-separable undesirable output, respectively. In this case, the production possibility set of constant returns to scale can be described as:

\[
P_{BF} = \left\{ (x^F, x^B, y^F, y^B, y^{FG}, y^{BF}) \left| \begin{array}{c}
x^F \geq X^F \lambda , \ x^B \geq X^B \lambda , \ y^F \leq Y^F \lambda , y^{FG} \leq Y^{FG} \lambda , y^{BF} \leq Y^{BF} \lambda \\
y^F \lambda = y^B \lambda \\
y^{FG} \lambda = y^{BF} \lambda \\
y^{FG} \lambda \geq y^{BF} \lambda 
\end{array} \right. \right\}
\]

where \( \lambda \) represents the weight vector.

The production possibility set has the following characteristics:

First, Non-separable input-output variables are radial, while separable input-output variables are non-radial;

Second, the decrease of non-separable undesirable output is accompanied by a proportional decrease of non-separable desirable output.

Under the production possibility set, the non-separable validity of the production unit \( DMU_{0}(x_0^F, x_0^B, y_0^F, y_0^B, y_0^{FG}, y_0^{BF}) \) is defined as:

For any \( 0 \leq \theta < 1 \), the production unit will be valid only if \( (x_0^F, \theta x_0^B, y_0^F, y_0^B, \theta y_0^{FG}, \theta y_0^{BF}) \in P_{BF} \) and if there is no \( (x^F, x^B, y^{FG}, y^{BF}) \in P_{BF} \).
that allows any of the strict inequalities $x^F_0 \geq x^F_F$, $y^F_0 \leq y^F_F$, $y^{BF}_0 \leq y^{BF}_F$, $x^{BF}_0 \geq x^{BF}_F$, $y^{BF}_0 \geq y^{BF}_F$ to be established. In this case, $\rho$ represents the energy efficiency value. The model proposed in this paper can be expressed as:

$$\rho^* = \min \left\{ \frac{1}{1 + \mu \left( \sum_{i=1}^{n} \frac{S''_{i}}{y''_{i}} + \sum_{i=1}^{n} \frac{S''_{i}}{y''_{i}} + (1 - \theta) \sum_{i=1}^{n} \frac{S''_{i}}{y''_{i}} + \sum_{i=1}^{n} \sum_{i=1}^{n} \frac{S''_{i}}{y''_{i}} \right) \right\}$$

where $S''_{i}$ represent the slack variables of input-output, respectively (here, surplus variables are collectively referred to as slack variables); $\theta$ represents the reduction coefficient; $\delta$ represents the expansion coefficient of the separable desirable output; $\sum_{r=1}^{k} y^{FG}_{r} + \sum_{r=1}^{k} y^{BG}_{r} = \sum_{r=1}^{k} y^{FG}_{r} + \sum_{r=1}^{k} y^{BG}_{r}$ indicates that the quantity of the desirable output must remain constant.

When $0 \leq \rho^* < 1$, this suggests that the decision-making unit is inefficient and that the input-output of the production process needs to be improved; $\rho^*=1$ suggests that the decision-making unit is efficient and that it is at the production frontier.

The output indices Energy efficiency(EE) include both desirable output and undesirable output. Desirable output selects the gross industrial output value index, adopts the producer price index as price adjustment basis of gross industrial output value, and utilizes 2003 as the base period of the annual average balance of net value of fixed assets, annual average of the employed and industrial SO2 emission, and industrial soot emission. The input indices adopt the producer price indices of provinces to which various cities belong and utilize statistics, this paper adopts panel data of 285 prefecture or higher-level cities in China in 2011/2012, the State Council repealed Chaohu of Anhui Province, and established prefecture-level cities Bijie and Tongren in Guizhou Province and prefecture-level city Sansha in Hainan Province. After that, the number of prefectures or higher-level cities in China changed from 287 to 289. For the sake of consistency in the utilized statistics, this paper adopts panel data of 285 prefecture or higher-level cities in China in 2011/2012, the State Council repealed Chaohu of Anhui Province, and established prefecture-level cities Bijie and Tongren in Guizhou Province and prefecture-level city Sansha in Hainan Province. After that, the number of prefectures or higher-level cities in China changed from 287 to 289. For the sake of consistency in the utilized statistics, this paper adopts panel data of 285 prefecture or higher-level cities in China in 2011/2012, the State Council repealed Chaohu of Anhui Province, and established prefecture-level cities Bijie and Tongren in Guizhou Province and prefecture-level city Sansha in Hainan Province. After that, the number of prefectures or higher-level cities in China changed from 287 to 289. For the sake of consistency in the utilized statistics, this paper adopts panel data of 285 prefecture or higher-level cities in China in 2011/2012, the State Council repealed Chaohu of Anhui Province, and established prefecture-level cities Bijie and Tongren in Guizhou Province and prefecture-level city Sansha in Hainan Province. After that, the number of prefectures or higher-level cities in China changed from 287 to 289. For the sake of consistency in the utilized statistics, this paper adopts panel data of 285 prefecture or higher-level cities in China in 2011/2012, the State Council repealed Chaohu of Anhui Province, and established prefecture-level cities Bijie and Tongren in Guizhou Province and prefecture-level city Sansha in Hainan Province. After that, the number of prefectures or higher-level cities in China changed from 287 to 289. For the sake of consistency in the utilized statistics, this paper adopts panel data of 285 prefecture or higher-level cities in China in 2011/2012, the State Council repealed Chaohu of Anhui Province, and established prefecture-level cities Bijie and Tongren in Guizhou Province and prefecture-level city Sansha in Hainan Province. After that, the number of prefectures or higher-level cities in China changed from 287 to 289. For the sake of consistency in the utilized statistics, this paper adopts panel data of 285 prefecture or higher-level cities in China in 2011/2012, the State Council repealed Chaohu of Anhui Province, and established prefecture-level cities Bijie and Tongren in Guizhou Province and prefecture-level city Sansha in Hainan Province. After that, the number of prefectures or higher-level cities in China changed from 287 to 289. For the sake of consistency in the utilized statistics, this paper adopts panel data of 285 prefecture or higher-level cities in China in 2011/2012, the State Council repealed Chaohu of Anhui Province, and established prefecture-level cities Bijie and Tongren in Guizh
2003-2016 (excluding Chaohu, Bijie, Tongren, Sansha, and Lhasa due to lack of data of previous years). The data is derived from the China Statistical Yearbook, China City Statistical Yearbook and the Comprehensive Statistical Data and Materials on 50 Years of New China over the years. The data for certain years was missing and was supplemented by estimating the average values of the data of their preceding and following years.

3. Empirical Results and Discussion

3.1 Energy Efficiency Measurement Results and Analysis

Based on the above panel data on input-output, this paper uses DEA solver pro5.0 software to solve the model and to obtain the energy efficiency value of Chinese cities considering pollutants during 2003-2016. A division of East China, Central China, and West China is introduced and the mean values were calculated, as the results presented in Tab 1.

For the purpose of comparison, this paper also provides the energy efficiency measurement results without considering pollutants. According to the obtained results (irrespective of pollutants), the average energy efficiency of Chinese cities (0.723) was noticeably higher than the average energy efficiency obtained when considering pollutants (0.605), suggesting that measuring energy efficiency regardless of pollution would be biased. For the country as a whole, the average energy efficiency of China with considering pollutants during 2013-2016 was only 0.605, and its energy efficiency loss reached as high as 0.395; therefore, its overall energy efficiency level during this period was relatively low. By investigating the distribution of energy efficiency across China’s three major regions, the energy efficiency distribution presented a very obvious trend of “high in the east and low in the west” and the annual average energy efficiency values of eastern, central, and western cities were 0.728, 0.456, and 0.469, respectively. This indicates that the energy efficiency of eastern cities was higher than the energy efficiencies of central and western cities, which is consistent with the study results obtained by most scholars. By investigating the intra-regional distribution, it became apparent that the energy efficiencies of East China, Central China, and West China all presented an obvious “U-shaped” decreasing-increasing trend; the energy efficiency of East China changed relatively gently and increased gradually after 2007 (excluding 2007, in which it declined significantly); however, given that it was already at a high level, its increasing velocity remained relatively low; the energy efficiencies of Central China and West China changed dramatically, especially during 2006-2008 (during which they experienced an abrupt drop). Furthermore, they did not begin to slowly pick up until after 2008; after 2014, the energy efficiency of Central China presented a “skipping” increase, while the energy efficiencies of East China and West China maintained a slow increase.

| Year | 285 cities in China | 115 cities in East China | 110 cities in Central China | 60 cities in West China |
|------|---------------------|--------------------------|----------------------------|-----------------------|
|      | considering pollutants | without considering pollutants | considering pollutants | without considering pollutants | considering pollutants | without considering pollutants | considering pollutants | without considering pollutants |
| 2003 | 0.621               | 0.754                    | 0.756                     | 0.808                 | 0.454                 | 0.576                     | 0.476                     | 0.598                     |
| 2004 | 0.606               | 0.757                    | 0.745                     | 0.790                 | 0.445                 | 0.564                     | 0.465                     | 0.589                     |
| 2005 | 0.587               | 0.745                    | 0.732                     | 0.780                 | 0.423                 | 0.534                     | 0.469                     | 0.576                     |
| 2006 | 0.580               | 0.724                    | 0.730                     | 0.767                 | 0.408                 | 0.508                     | 0.454                     | 0.555                     |
| 2007 | 0.565               | 0.709                    | 0.702                     | 0.760                 | 0.389                 | 0.489                     | 0.423                     | 0.523                     |
| 2008 | 0.568               | 0.678                    | 0.711                     | 0.770                 | 0.390                 | 0.502                     | 0.430                     | 0.519                     |
| 2009 | 0.589               | 0.690                    | 0.715                     | 0.778                 | 0.423                 | 0.535                     | 0.438                     | 0.523                     |
| 2010 | 0.598               | 0.712                    | 0.724                     | 0.795                 | 0.456                 | 0.550                     | 0.446                     | 0.529                     |
| 2011 | 0.623               | 0.723                    | 0.720                     | 0.798                 | 0.476                 | 0.576                     | 0.450                     | 0.543                     |
| 2012 | 0.631               | 0.730                    | 0.728                     | 0.812                 | 0.487                 | 0.580                     | 0.468                     | 0.554                     |
| 2013 | 0.643               | 0.726                    | 0.734                     | 0.817                 | 0.490                 | 0.591                     | 0.472                     | 0.560                     |
It remains puzzling why the energy efficiencies of the three major regions (especially those of Central China and West China) declined to varying extents prior to 2008. According to the results obtained in this study, this was mainly because of China’s economic development pattern during this period. During 2003-2016, China was experiencing a rapid development of industrialization and urbanization, and a large volume of productive capital and energy rushed into the industrial sector, especially into the heavy industrial sector. As a result, due to its high energy consumption and low energy efficiency, the heavy industrial sector decreased the energy efficiency of various regions and of the country as a whole. During this period, East China achieved a relatively high economic development level, and many eastern provinces had already entered the late stage of industrialization (moreover, Beijing, Shanghai, and other municipalities or cities have entered the post-industrialization stage); the industrial structure of East China presented an apparent trend of “reducing the secondary industry and promoting the tertiary industry”; therefore, on the whole, the influence of the expansion of the industrial sector of East China remained relatively small; as a result, the amplitude of decline experienced by the energy efficiency of East China during this period was much lower than that experienced by the energy efficiencies of Central China and West China. In contrast, most provinces of Central China and West China were in the early or middle stage of industrialization during this period and their industrial development was mainly driven by the secondary industry; their industrial pattern of “secondary, tertiary and primary” had already taken shape and was continuously being solidified; however, Central China and West China had a generally low technical level and basically, instead of investigating in the high-tech industry and high-end industrial production projects, both areas were only able to engage in the repeated construction of traditional low-level and high-energy consumption heavy industry projects; consequently, their energy efficiencies dropped rapidly. The energy efficiency of China picked up slightly at around 2008, mainly because the large-scale haze hovering over North China around that year triggered a “bottom-up” discussion about the environmental crisis in China and consequently increased the environmental protection awareness of the Chinese population to an unprecedented height; the Chinese government had also realized that the traditional high-input, high-energy consumption, and high-pollution development pattern could no longer be sustained, and that it was extremely urgent to implement energy conservation and emission reduction measures. Several provinces, especially those of Central China, showed a turning point of energy efficiency in 2010, and consequently experienced an accelerated increase of energy efficiency.

3.2 Spatial autocorrelation test

The global Moran’s I was adopted to test whether the energy efficiencies of Chinese cities followed specific spatial distribution laws. The following calculation formula was used:

\[
\text{Moran’s } I = \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} W_{ij} (Y_i - \bar{Y})(Y_j - \bar{Y})}{S^2 \sum_{i=1}^{n} \sum_{j=1}^{n} W_{ij}}
\]

where \(S^2 = \frac{1}{n} \sum_{i=1}^{n} (Y_i - \bar{Y})^2\), \(\bar{Y} = \frac{1}{n} \sum_{i=1}^{n} Y_i\), \(Y_i\) and \(Y_j\) represent the observed energy efficiency values of cities i and j, respectively; \(W_{ij}\) represents the spatial weight matrix. Geoda software was used to measure the global Moran’s I index and the test values of the energy efficiency of China during 2003-2016. According to the test, during the investigated period, the global Moran’s I statistics of the energy efficiencies of Chinese cities all remained positive and passed the significance test of 1%,

| Year | 2014 | 2015 | 2016 | Mean |
|------|------|------|------|------|
| 2014 | 0.641| 0.734| 0.730| 0.605|
| 2015 | 0.654| 0.744| 0.738| 0.673|
| 2016 | 0.666| 0.750| 0.738| 0.663|
thus rejecting the original hypothesis of the absence of spatial autocorrelation in the energy efficiencies of cities. This suggests that the spatial distributions of energy efficiencies of Chinese cities is not random, but rather that it shows an obvious characteristic of spatial agglomeration, i.e., cities of close energy efficiencies are usually adjacent to each other.

In China, the minimum “threshold distance” between cities is 306 km, i.e., it is possible for every city to have at least one geographically adjacent city only when the distance between cities is no less than 306 km. Consequently, this paper calculates both the Moran’s I index and statistical test values of the energy efficiency of China during 2003-2016 under a distance range of 350-1,100 km (see Tab 2). As indicated by the obtained results, the spatial correlation of the energy efficiencies of Chinese cities weakened gradually with increasing geographical distance and as the distance exceeded 1,110 km, the spatial correlation was no longer significant. This not only indicates that the spatial correlation of China’s energy efficiency conforms to “Tobler's first law of geography”, it also verifies that its spatial spillover boundary is about 1,100 km. Thus, it is particularly important to take the differences in geographical distance into account when analyzing the influence of industrial agglomeration on energy efficiency.

### Table 2. The change of Moran’s I index of energy efficiency with geographic distance in China(a)

| year | (0-350) km | (0-500) km | (0-650) km | (0-800) km | (0-950) km | (0-1100) km |
|------|------------|------------|------------|------------|------------|-------------|
| 2003 | 0.165***   | 0.118***   | 0.065***   | 0.027***   | 0.007**    | -0.023      |
| 2004 | 0.177***   | 0.147***   | 0.088***   | 0.046***   | 0.014***   | -0.005      |
| 2005 | 0.190***   | 0.157***   | 0.101***   | 0.064***   | 0.016***   | -0.035      |
| 2006 | 0.197***   | 0.154***   | 0.121***   | 0.087***   | 0.034**    | -0.035      |
| 2007 | 0.202***   | 0.158***   | 0.080***   | 0.065***   | 0.067**    | -0.004      |
| 2008 | 0.217***   | 0.158***   | 0.077***   | 0.065***   | 0.054**    | -0.007      |
| 2009 | 0.219***   | 0.157***   | 0.067***   | 0.045***   | 0.065**    | -0.025      |
| 2010 | 0.225***   | 0.164***   | 0.101***   | 0.076***   | 0.087**    | -0.018      |
| 2011 | 0.230***   | 0.187***   | 0.105***   | 0.064***   | 0.098**    | -0.006      |
| 2012 | 0.241***   | 0.201***   | 0.157***   | 0.123***   | 0.108***   | -0.014      |
| 2013 | 0.265***   | 0.213***   | 0.165***   | 0.132***   | 0.095***   | -0.008      |

### Table 3. The change of Moran’s I index of energy efficiency with geographic distance in China(b)

|     | (0-350) km | (0-500) km | (0-650) km | (0-800) km | (0-950) km | (0-1100) km |
|-----|------------|------------|------------|------------|------------|-------------|
| 2014| 0.254***   | 0.232***   | 0.203***   | 0.165***   | 0.123**    | -0.01       |
| 2015| 0.234***   | 0.201***   | 0.185***   | 0.134***   | 0.103**    | -0.003      |
| 2016| 0.265***   | 0.221***   | 0.212***   | 0.176***   | 0.123**    | -0.001      |

Note: *, **, *** represent significance level of 10%, 5% and 1% respectively

### 4. Conclusions

The increasing tension between energy supply and demand and the overdrawing of environmental bearing capacity are making it difficult to sustain the extensive economic development pattern. The space for realizing energy conservation and emission reduction through the further optimization of the energy structure is very limited, and the most realistic way of solving the problem lies in increasing the energy efficiency. This paper first presents data of 285 prefecture or higher-level cities in China and introduces a non-separable hybrid DEA model that considers undesirable output to measure the energy efficiencies of these cities under pollution emission during 2003-2016. According to the obtained study results, for the investigation period, the overall energy efficiency of China with regard to pollutants remained at a low level and presented a “U-shaped” decreasing-increasing trend. To be specific, China’s energy efficiency distribution presented a trend of “high in the east and low in the west”. The energy efficiency of East China changed relatively gently, while the energy efficiencies of
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