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# INDUSTRIAL ENERGY AND ENVIRONMENT EFFICIENCY OF CHINESE CITIES: AN ANALYSIS BASED ON RANGE-ADJUSTED MEASURE

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Industrial energy and environment efficiency evaluation is essential in guiding national and environmental policy making, since the industrial sector is the largest energy consumer and major pollutants producer in China. This study utilizes the Range-Adjusted Measure (RAM) based models to evaluate the energy and environment efficiency of industrial sectors in 31 Chinese major cities. The empirical results show that eastern Chinese cities outperform their western counterparts in terms of industrial energy efficiency, and central Chinese cities outperform their eastern counterparts in terms of industrial environment efficiency. Under natural disposability, 23 cities exhibit decreasing returns to scale, and under managerial disposability, 18 cities exhibit increasing damages to scale.

*Keywords*: Chinese city; energy and environment efficiency; industrial sector; Range-Adjusted Measure (RAM).

## 1. Introduction

Energy and environment (E & E) efficiency evaluation has recently attracted increasing interests both in academic research and policy making in China, since it is considered as the very first step for energy conservation, pollutant reduction, and environment protection. These represents the extraordinary costs China incurs along with its miracle economic growth in the past three decades1-3. As a World Bank survey shows that the combined health and non-health costs of outdoor air and water pollution in China account to around $US100 billion per year, or about 5.8% of China’s GDP4. In a recent study conducted by Yale and Columbia University jointly, China was ranked 116 among all 132 countries and territories in terms of the Environmental Performance Index (EPI), which puts heavy weights on fossil fuel combustion and air and water pollutions5. Environment problems are threatening the sustainable development of this country.

To sustain its development trajectory, China has invested great efforts in improving energy and environment efficiency and controlling environment pollution. It has put forward a strategic target of constructing an environment-friendly and resource-saving society, which was specified in the 11th and 12th Five Year Plan (2006-2010 and 2011-2015): with environment protection as one of its highest priority policy, energy intensity (energy consumption per unit of GDP) should be reduced by 20% during 2006-2010 and 16% during 2011-2015, and these percentages are 10% and 8% respectively for total discharge of major pollutants ($SO_2$, $NO_x$, and COD etc.). In order to realize these targets of energy conservation and pollutant reduction, a series of policy tools, such as E & E regulations and laws, were proposed and implemented within the past single decade. Under such intensive policy intervention, it is necessary to comprehensively evaluate the E & E efficiency as a way to understand China’s current energy and environment management performance, estimate China’s potential in energy conversation and pollution reduction, and therefore, guide further policy making.

This study aims to evaluate the industrial E & E efficiency in China’s major cities, since the industrial sector is the largest consumer of energy and the largest producer of more than half of the major pollutants. The study could also reveal different patterns of E & E efficiency in China as natural resources endowments and economic growth modes vary significantly among Chinese cities.

Data Envelopment Analysis (DEA)[6] has been generally recognized as a successful method to evaluate the efficiency of various decision-making unit (DMU)[7,8], which is also specifically applied in E & E efficiency studies. Ref. 9 had made a good summarization of more than a hundred such applications. E & E efficiency evaluation also flourishes in China with quite extensive investigation in various regions and various sectors. Quite a few studies have contributed to the literatures. For instance, Ref. 10 proposed a total-factor energy efficiency index and evaluated the energy efficiency of 29 Chinese administrative regions based on a DEA model. Ref. 11 investigated the energy efficiency and it changes in China's iron and steel sectors through DEA-based Malmquist index. Ref. 13 utilized a DEA based index to calculate China's regional energy efficiency and then investigated the regional energy efficiency determinants through a second-stage analysis based on an econometric model. Similar DEA based E & E efficiency evaluation researches of China also included Refs. 19-23 and many other articles.

The E & E efficiency is usually recognized as a process that uses the lowest amount of energy inputs to create the greatest amount of desirable outputs (economics outputs), with the least undesirable outputs (negative environmental impacts). Considering undesirable outputs, DEA evaluation process can be classified into two categories[9,16]: conventional DEA with undesirable output transformation approaches and DEA assuming weak disposability. In the first category, undesirable outputs are either modified as negative desirable outputs[12,14]; or treated as inputs[15,17,18]. The second category revises the first one by matching undesirable outputs with desirable outputs under the assumption of weak disposability[24,25] and using directional distance function techniques[36,37]. However, it is not sufficient to assume weak disposability in radial DEA models, since not all DMUs yield a unified abatement on input and/or output factors[26]. In addition, most existing studies have not measured the returns to scale (RTS) or the damages to scale (DTS)[27-30]. Their application is also limited with the methodological difficulty of combining measurement of operational efficiency through desirable output frontier and environmental efficiency from undesirable output frontier in a unified treatment. The Range-Adjusted Measure (RAM) model could help solve these problems as it provides two types of unification for DEA based environmental assessment within a unified DEA framework.

Thus, this study sets up a RAM-DEA model to evaluate sector-specific E & E efficiency with consideration of returns to scale and damages to scale of them in 31 major Chinese cities. City and sector level data input represents another improvement beyond our current understanding of E & E efficiency in China, which is mostly based on general provincial level analysis and lacks of feasibility in more specific situations.

The rest of this paper is organized as follows: Section 2 reviews typical RAM-DEA models for measurement of energy efficiency, environment efficiency and integrated efficiency, with consideration of RTS and DTS. Efficiency indices are also created in this section. Section 3 illustrates the E & E efficiency evaluation framework and computational flows of the RAM models. Section 4 discusses the empirical results and Section 5 concludes this paper.

## 2. RAM-DEA Models for E & E Efficiency Measurement

According to Ref. 30, the strong and weak disposability concepts are proposed for radial DEA based E & E efficiency evaluation that a unified efficiency measure is incorporated and thus the assumption of weak disposability is necessary. However, for non-radial RAM-DEA based E & E efficiency evaluation, there is no necessity to distinguish between weak and strong disposability, since the incorporating of a unified efficiency measure in RAM-DEA is not necessary. In addition, within the radial DEA model, although the directional distance function can be given, the direction for inputs is not specified, which can be further defined under the RAM-DEA model, and thus several new concepts on disposability can be proposed from management and policy making point of view. These new concepts may provide deeper insight into E & E efficiency measures. Furthermore, RAM-DEA models can easily incorporate both energy efficiency and environment efficiency for each DMU in a unified efficiency evaluation structure. Therefore, in this study, the RAM-DEA models, first formally proposed in Ref. 31 and newly developed in Refs. 28 and 30, is utilized to measure the industrial energy and environment efficiency of Chinese major cities.

### 2.1. *Energy efficiency, integrated efficiency under natural disposability and returns to scale*

For evaluating the industrial E & E efficiency of Chinese cities, it is assumed that there are $n$ cities (DMUs), and each of them (DMU$_j$, $j$=1,…,$n$) consumes $m$ kinds of inputs $\boldsymbol{X}_j=(x_{1j},\ldots,x_{mj})$, including energy and non-energy inputs (e.g., labors and capitals), to produce $s$ kinds of desirable outputs $\boldsymbol{G}_j=(g_{1j},\ldots,g_{sj})$ (i.e. industrial added values) and $f$ kinds of undesirable outputs $\boldsymbol{B}_j=(b_{1j},\ldots,b_{fj})$ (e.g. air, water and solid waste pollutions). It is also assumed that all elements in the inputs and outputs vectors are positive. The RAM-DEA model for energy efficiency evaluation of a specific city (DMU$_k$) is presented as following.

$$
\begin{aligned}
\max\ & \sum\nolimits_{i=1}^{m} R_i^x d_i^x + \sum\nolimits_{r=1}^{s} R_r^g d_r^g + \sum\nolimits_{f=1}^{h} R_f^b d_f^b \\
s.t.\ & \sum\nolimits_{j=1}^{n} x_{ij}\lambda_j + d_i^x = x_{ik},\ i=1,\ldots,m, \\
& \sum\nolimits_{j=1}^{n} g_{rj}\lambda_j - d_r^g = g_{rk},\ r=1,\ldots,s, \\
& \sum\nolimits_{j=1}^{n} b_{fj}\lambda_j + d_f^b = b_{fk},\ f=1,\ldots,h, \\
& \sum\nolimits_{j=1}^{n} \lambda_j = 1, \\
& \lambda_j \ge 0,\ j=1,\ldots,n,\quad d_i^x \ge 0, i=1,\ldots,m, \\
& d_r^g \ge 0, r=1,\ldots,s,\quad d_f^b \ge 0,\ f=1,\ldots,h.
\end{aligned}
\tag{2.1}
$$

Where $\lambda_j$ ($j$=1,…,$n$) are intensity variables that connect inputs of each DMU$j$ with its outputs by a convex combination. $d_i^x$ ($i$=1,…,$m$), $d_r^g$ ($r$=1,…,$s$) and $d_f^b$ ($f$=1,…,$h$) are slack variables related to inputs, desirable outputs and undesirable outputs, respectively. $R$s are ranges determined by the upper and lower bounds of inputs, desirable outpus and undesirable outputs. $R_i^x = 1/[(m+s+h)(\overline{x}_i - \underline{x}_i)]$, $R_r^g = 1/[(m+s+h)(\overline{g}_r - \underline{g}_r)]$ , and $R_f^b = 1/[(m+s+h)(\overline{b}_f - \underline{b}_f)]$ , in which $\overline{x}_i = \max_j\{x_{ij}\}$ , $\underline{x}_i = \min_j\{x_{ij}\}$, $\overline{g}_r = \max_j\{g_{rj}\}$, $\underline{g}_r = \min_j\{g_{rj}\}$, $\overline{b}_f = \max_j\{b_{fj}\}$, $\underline{b}_f = \min_j\{b_{fj}\}$.

In Model (2.1), beyond the traditional assumptions of strong and weak disposability, we take a third assumption: natural disposability, which is newly developed by (Refs. 28 and 30). It refers to such a condition that directional vector of inputs decrease along with decrease in the directional vector of undesirable outputs, but directional vector of desirable outputs may increase under this condition. This is referred to as natural disposability. It should be noticed that, in Model (2.1) and under natural disposability, the undesirable outputs are treated as free disposable inputs, which is essentially the same as the strong disposability assumption in the model of Ref. 38. Based on Model (2.1), we created an energy efficiency index and an integrated efficiency index under natural disposability, as shown below:

$$\text{Energy efficiency } (ENEE) = 1 - \left(\sum_{i=1}^{m} R_i^x d_i^{x*} + \sum_{r=1}^{s} R_r^g d_r^{g*}\right) \quad (2.2)$$

$$\text{Integrated efficiency under natural disposability } (IEND) = 1 - \left(\sum_{i=1}^{m} R_i^x d_i^{x*} + \sum_{r=1}^{s} R_r^g d_r^{g*} + \sum_{f=1}^{h} R_f^b d_f^{b*}\right) \quad (2.3)$$

The value of slack variables denoted by * here are determined through optimization of Model (2.1). The index of *IEND* incorporates inputs and both desirable and undesirable outputs, whereas the index of *ENEE* focuses on evaluating energy efficiency but ignores undesirable outputs (environment factors). The dual programming of Model (2.1) is conducted like this:

$$\begin{aligned} &\min \sum_{i=1}^{m} v_i x_{ik} - \sum_{r=1}^{s} u_r g_{rk} + \sum_{f=1}^{h} w_f b_{fk} + \sigma \\ &s.t. \ \sum_{i=1}^{m} v_i x_{ij} - \sum_{r=1}^{s} u_r g_{rj} + \sum_{f=1}^{h} w_f b_{fj} + \sigma \geq 0, \ j = 1,...,n, \\ &\quad v_i \geq R_i^x, i = 1,...,m, \ \ u_r \geq R_r^g, r = 1,...,s, \ \ w_f \geq R_f^b, \ f = 1,...,h. \end{aligned} \quad (2.4)$$

Where, $v_i(i=1,\ldots,m)$, $u_r(r=1,\ldots,s)$, $w_f(f=1,\ldots,h)$, and $\sigma$ are dual variables, with the ranges of the first three variables specified in (2.4) and $\sigma$ unrestricted. We define efficient DMU as those having an *IEND* score of 1, and the type of returns to scale (RTS) for efficient DMU is determined by Model (2.5), which represents the marginal changes of a desirable output due to a unit increase in an input.

$$\begin{aligned} &\max/\min \sigma \\ &s.t. \ \sum_{j=1}^{n} x_{ij}\lambda_j + d_i^x = x_{ik}, i = 1,...,m, \\ &\quad \sum_{j=1}^{n} g_{rj}\lambda_j - d_i^g = g_{rk}, r = 1,...,s, \\ &\quad \sum_{j=1}^{n} \lambda_j = 1, \\ &\quad \sum_{i=1}^{m} v_i x_{ij} - \sum_{r=1}^{s} u_r g_{rj} + \sigma \geq 0, \ j = 1,...,n, \\ &\quad \sum_{i=1}^{m} R_i^x d_i^x + \sum_{r=1}^{s} R_r^g d_r^g = \sum_{i=1}^{m} v_i x_{ik} - \sum_{r=1}^{s} u_r g_{rk} + \sigma, \\ &\quad v_i \geq R_i^x, i = 1,...,m, \ \ u_r \geq R_r^g, r = 1,...,s, \\ &\quad \lambda_j \geq 0, \ j = 1,...,n, \ \ d_i^x \geq 0, i = 1,...,m, \ \ d_r^g \geq 0, r = 1,...,s. \end{aligned} \quad (2.5)$$

Where, $R_i^x = 1/[(m+s)(\bar{x}_i - \underline{x}_i)]$ and $R_r^g = 1/[(m+s)(\bar{g}_r - \underline{g}_r)]$ are different from the ranges in Model (2.1) with the undesirable outputs excluded. For inefficient DMU, with *IEND* score less than one, the type of RTS is determined by Model (2.6) as follows.

$$\begin{aligned} &\max/\min \mu = \sigma + \sum_{f=1}^{h} w_f b_{fj} \\ &s.t. \ \sum_{i=1}^{m} R_i^x d_i^x + \sum_{r=1}^{s} R_r^g d_r^g + \sum_{f=1}^{h} R_f^b d_f^b = \\ &\quad \sum_{i=1}^{m} v_i x_{ik} - \sum_{r=1}^{s} u_r g_{rk} + \sum_{f=1}^{h} w_f b_{kj} + \sigma, \\ &\quad \text{all constraints in (2.1) and (2.4).} \end{aligned} \quad (2.6)$$

Here, the calculations of $R_i^x$, $R_r^g$, and $R_f^b$ are same as those in Model (2.1). Based on the optimized upper bounds $\bar{\sigma}^*$ and $\bar{\mu}^*$, and lower bound $\underline{\sigma}^*$ and $\underline{\mu}^*$ obtained from Model (2.5) and (2.6), respectively, the type of RTS of a specific DMU is determined in this way:

$\underline{\mu}^*(\underline{\sigma}^*) \leq \bar{\mu}^*(\bar{\sigma}^*) < 0 \Rightarrow$ DMU is under increasing RTS.

$\underline{\mu}^*(\underline{\sigma}^*) \leq 0 \leq \bar{\mu}^*(\bar{\sigma}^*) \Rightarrow$ DMU is under constant RTS.

$\bar{\mu}^*(\bar{\sigma}^*) \geq \underline{\mu}^*(\underline{\sigma}^*) > 0 \Rightarrow$ DMU is under decreasing RTS.

### 2.2. *Environment efficiency, integrated efficiency under managerial disposability and damages to scale*

Similar to models for energy efficiency evaluation, the RAM-DEA model for environment efficiency evaluation of a specific city (DMU$_k$) is proposed in this section.

$$\begin{aligned}
&\max \sum\nolimits_{i=1}^{m} R_i^x d_i^x + \sum\nolimits_{r=1}^{s} R_r^g d_r^g + \sum\nolimits_{f=1}^{h} R_f^b d_f^b \\
&s.t.\ \ \sum\nolimits_{j=1}^{n} x_{ij}\lambda_j - d_i^x = x_{ik},\ i = 1,\dots,m, \\
&\qquad \sum\nolimits_{j=1}^{n} g_{rj}\lambda_j - d_r^g = g_{rk},\ r = 1,\dots,s, \\
&\qquad \sum\nolimits_{j=1}^{n} b_{fj}\lambda_j + d_f^b = b_{fk},\ f = 1,\dots,h, \qquad\qquad (2.7) \\
&\qquad \sum\nolimits_{j=1}^{n} \lambda_j = 1, \\
&\qquad \lambda_j \geq 0,\ j = 1,\dots,n,\ \ d_i^x \geq 0, i = 1,\dots,m, \\
&\qquad d_r^g \geq 0, r = 1,\dots,s,\ \ d_f^b \geq 0,\ f = 1,\dots,h.
\end{aligned}$$

Definitions of all variables and parameters in Model (2.7) are the same as those in Model (2.1), with the only difference in the sign of slack $d_i^x$. The difference results from the fact that we adopt a fourth assumption about disposability: managerial disposability, which means that a DMU simultaneously increases its directional vector of inputs but decreases its directional vector of undesirable outputs, so as to increase the directional vector of desirable outputs. This is just opposite to natural disposability. Under this assumption, undesirable outputs take the place of inputs in mathematical calculation of Model (2.7), and the original inputs are placed as outputs. Based on Model (2.7), an environment efficiency index and an integrated efficiency index under managerial disposability can be evaluated as follows.

$$\text{Environment efficiency } (ENVE) = 1 - \left( \sum\nolimits_{i=1}^{m} R_i^x d_i^{x*} + \sum\nolimits_{f=1}^{h} R_f^b d_f^{b*} \right) \qquad (2.8)$$

$$\text{Integrated efficiency under managerial disposability } (IEMD) = 1 - \left( \sum\nolimits_{i=1}^{m} R_i^x d_i^{x*} + \sum\nolimits_{r=1}^{s} R_r^g d_r^{g*} + \sum\nolimits_{f=1}^{h} R_f^b d_f^{b*} \right) \qquad (2.9)$$

Similarly, the slacks denoted by * are determined by optimizing Model (2.7). The index of *IEMD* incorporates inputs and both desirable and undesirable outputs, but the index of *ENVE* ignores desirable outputs. In other words, *ENVE* only evaluates environment efficiency without considering economic factors. Although calculation formulas of *IEMD* in Model (2.7) and *IEND in Model (2.1)* are quite similar, they are essentially different, as the two indexes are derived from different optimization processes. Dual programming of Model (2.7) is conducted as follows:

$$\begin{aligned}
&\min - \sum\nolimits_{i=1}^{m} v_i x_{ik} - \sum\nolimits_{r=1}^{s} u_r g_{rk} + \sum\nolimits_{f=1}^{h} w_f b_{fk} + \sigma \\
&s.t.\ \ -\sum\nolimits_{i=1}^{m} v_i x_{ij} - \sum\nolimits_{r=1}^{s} u_r g_{rj} + \sum\nolimits_{f=1}^{h} w_f b_{fj} + \sigma \geq 0,\ j = 1,\dots,n, \qquad (2.10) \\
&\qquad v_i \geq R_i^x, i = 1,\dots,m,\ \ u_r \geq R_r^g, r = 1,\dots,s,\ \ w_f \geq R_f^b,\ f = 1,\dots,h.
\end{aligned}$$

Here, the definitions of all variables and parameters of Model (2.10) are quite similar with that of Model (2.4), with the only difference in the sign of their first items of the objective and the constraint. In Model (2.10), an efficient DMU is defined as that with an *IEMD* score of one, and its type of damages to scale (DTS) can be determined by Model (2.11) as follows. DTS, which corresponds to the concept of RTS in Model (2.4), represents the marginal change in undesirable output with increase in input.

$$
\begin{aligned}
&\max/\min \sigma \\
&s.t.\ \ \sum\nolimits_{j=1}^{n} x_{ij}\lambda_j - d_i^x = x_{ik}, i=1,\dots,m, \\
&\qquad \sum\nolimits_{j=1}^{n} b_{fj}\lambda_j + d_f^b = b_{fk}, f=1,\dots,h, \\
&\qquad \sum\nolimits_{j=1}^{n} \lambda_j = 1, \\
&\qquad -\sum\nolimits_{i=1}^{m} v_i x_{ij} - \sum\nolimits_{f=1}^{h} w_f b_{fj} + \sigma \geq 0,\ j=1,\dots,n, \\
&\qquad \sum\nolimits_{i=1}^{m} R_i^x d_i^x + \sum\nolimits_{r=1}^{s} R_f^b d_f^b = -\sum\nolimits_{i=1}^{m} v_i x_{ik} - \sum\nolimits_{f=1}^{h} w_f b_{fk} + \sigma, \\
&\qquad v_i \geq R_i^x, i=1,\dots,m, \quad w_f \geq R_f^b, f=1,\dots,h, \\
&\qquad \lambda_j \geq 0,\ j=1,\dots,n, \quad d_i^x \geq 0, i=1,\dots,m, \quad d_f^b \geq 0,\ f=1,\dots,h.
\end{aligned}
\tag{2.11}
$$

Where, $R_i^x = 1/[(m+h)(\overline{x}_i - \underline{x}_i)]$ and $R_f^b = 1/[(m+h)(\overline{b}_f - \underline{b}_f)]$, and the desirable outputs are excluded. For inefficient DMU, with an *IEMD* score less than one, the type of DTS is determined by Model (2.12) as follows:

$$
\begin{aligned}
&\max/\min \tau = \sigma - \sum\nolimits_{r=1}^{s} u_r g_{rk} \\
&s.t.\ \ \sum\nolimits_{i=1}^{m} R_i^x d_i^x + \sum\nolimits_{r=1}^{s} R_r^g d_r^g + \sum\nolimits_{f=1}^{h} R_f^b d_f^b = \\
&\qquad -\sum\nolimits_{i=1}^{m} v_i x_{ik} - \sum\nolimits_{r=1}^{s} u_r g_{rk} + \sum\nolimits_{f=1}^{h} w_f b_{fk} + \sigma, \\
&\qquad \text{all constraints in (2.7) and (2.10).}
\end{aligned}
\tag{2.12}
$$

Calculation of the three ranges of $R_i^x$, $R_r^g$, and $R_f^b$ is the same as that in Model (2.7). Similarly, based on the optimized upper bounds $\overline{\sigma}^*$ and $\overline{\tau}^*$ derived from Model (2.11), and the optimized lower bound $\underline{\sigma}^*$ and $\underline{\tau}^*$ from Model(2.12), DTS of a specific DMU can be determined as follows:

$\underline{\tau}^*(\underline{\sigma}^*) \leq \overline{\tau}^*(\overline{\sigma}^*) < 0 \Rightarrow$ DMU is under decreasing DTS.
$\underline{\tau}^*(\underline{\sigma}^*) \leq 0 \leq \overline{\tau}^*(\overline{\sigma}^*) \Rightarrow$ DMU is under constant DTS.
$\overline{\tau}^*(\overline{\sigma}^*) \geq \underline{\tau}^*(\underline{\sigma}^*) > 0 \Rightarrow$ DMU is under increasing DTS.

## 3. The Framework for E & E Efficiency Evaluation

Figure 1 illustrates the framework for evaluating integrated efficiency, energy efficiency, and environment efficiency. It also explains the process through which RTS and DTS are determined. Computational details are also specified in the figure.

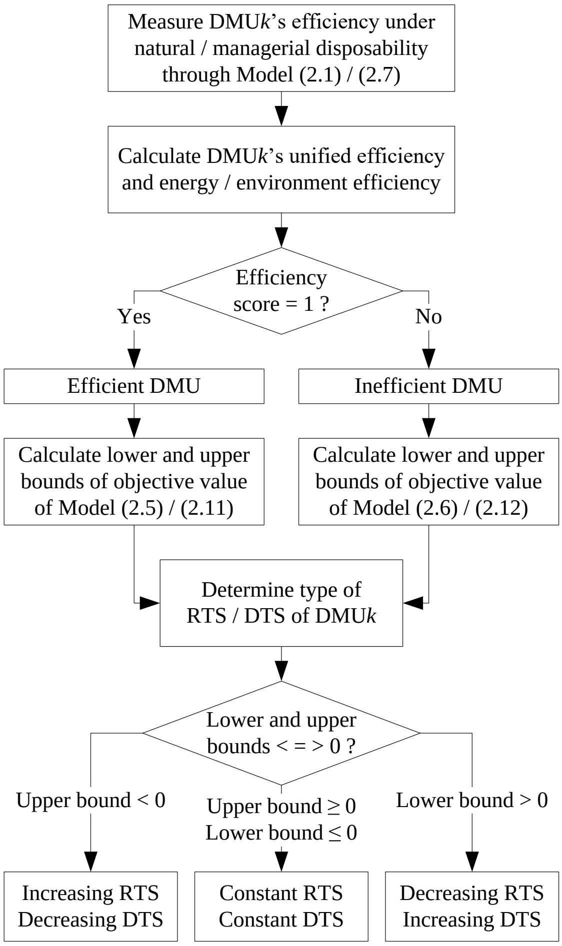


Fig.1. The framework for energy and environment efficiency evaluation.

For evaluation of the integrated efficiency of $DMU_k$ under natural disposability, we first determine all the slacks associated with inputs and outputs by solving Model (2.1). Then, as measurements of integrated and energy efficiency, the indices of *IEND* and *ENEE* are calulated. Based on the value of *IEND*, a $DMU_k$ is determined as either the efficient or inefficient. If it is efficient, the lower and upper bounds of objective value are obtained through solving Model (2.5), otherwise through solving Model (2.6). The type of RTS of a $DMU_k$ is determined by checking the values of its lower and upper bounds. The process of evaluation under managerial disposability is very similarly, with only the substitution of Model (2.1) with Model (2.7), Model (2.5) with Model (2.11), Model (2.6) with Model (2.12), and RTS with DTS.

## 4. Data and Variables

This study takes the capital cities of all the 31 provinces, autonomous regions, and municipalities in mainland China as sample. We focused on their industrial sector and collected data about industrial energy consumption, labor input, fixed assets, added value, and pollutions from gas emission, waste water, and solid wastes, which are summarized in Table 1.

Table 1. Descriptive statistics of input and output factors.

| Inputs and outputs | Input | | | Desirable output | Undesirable output | | |
|---|---|---|---|---|---|---|---|
| | Total industrial energy consumption ($I_1$) | Number of industrial labor ($I_2$) | Net value of industrial fixed assets ($I_3$) | Industrial added value (G) | Total industrial waste gas emission ($B_1$) | Total industrial waste water discharged ($B_2$) | Total industrial solid wastes discharged ($B_3$) |
| Statistics \Units | Million tonnes of coal equivalent | Thousand employees | Billion CNY | Billion CNY | Billion $m^3$ | Million tonnes | Million tonnes |
| Average | 17.79 | 609.95 | 146.45 | 123.06 | 276.71 | 146.15 | 8.62 |
| Std. dev. | 12.93 | 604.80 | 154.54 | 118.94 | 286.67 | 187.63 | 7.20 |
| Max. | 60.35 | 2898.90 | 743.82 | 515.20 | 1258.70 | 799.59 | 25.52 |
| Min. | 0.11 | 11.19 | 7.63 | 1.56 | 0.70 | 4.75 | 0.04 |

Source: China statistical yearbook (2010)[33], China energy statistical yearbook (2010)[34], and China statistical Yearbook on Environment (2010)[35].

The input variables are (i) Total energy consumption includes consumption of coal, oil, natural gas, and other energy. They are all converted to the standard coal equivalent (million tonnes of coal equivalent). Here, coal equivalent is a reference unit for the energetic evaluation of various energy carriers. According to the conversion factors from energy physical unit to calorific value provided in China's national standard: General principles for calculation of total production energy consumption32, 1 kilogram coal equivalent corresponds to a value specified as 29.3 million joules (or 7,000 kilocalories). (ii) Number of employees in industrial sector (thousand people). (iii) Net value of fixed assets in industrial sector (billion Chinese Yuan, CNY). The desirable output variable is industrial added value (billion CNY). Data of the net value of fixed assets and industrial added value are both in current year's price. The undesirable output variables are three major industrial wastes: (i) waste gas (billion cubic meters), (ii) waste water (million tonnes), and (iii) solid wastes (million tonnes). All data of these seven variables are obtained from China Statistical Yearbook33, China Energy Statistical Yearbook34, and China statistical Yearbook on Environment35.

Table 2 lists the correlations between inputs, desirable outputs, and undesirable outputs. All correlations between output and input variables are significant, with just two exceptional pairs: industrial energy consumption and industrial added value, as well as that between industrial energy consumption and industrial waste water. This is considered acceptable in this efficiency evaluation study, as production of desirable output of industrial sector is not just consumes energy, but also other inputs, such as labor and capital. In addition, compared with industrial waste water discharged, the relationship between industrial energy consumption and industrial waste gas emission or solid waste should be much tighter. The positive correlations between input and output variables also satisfy the RAM method requirement that outputs increase along with inputs. Transformation of undesirable outputs is conducted under the instruction from Ref. 38.

Usually, the number of observations under evaluation (DMU) should be more than three times of the number of input and output variables so as to construct an appropriate efficiency frontier. In this study, we have 31 DMUs, three times more than the total number of input and output variables, so the sample is sufficiently large for effective evaluation.

Table 2 Correlation matrix for inputs and outputs.

| *Output* | *Input* | | |
|---|---|---|---|
| | $I_1$ | $I_2$ | $I_3$ |
| $G_1$ | 0.366 | 0.946* | 0.948* |

| | | | |
|---|---|---|---|
| $B_1$ | 0.559* | 0.771* | 0.734* |
| $B_2$ | 0.265 | 0.654* | 0.491* |
| $B_3$ | 0.722* | 0.511* | 0.522* |

*:representsthesignificanceat0.01significantlevel.

## 5. Empirical Results

### 5.1. *Industrial energy and environment efficiency evaluation*

E & E efficiencies in 31 Chinese cities' industrial sectors are presented in Table 3, with the types of RTS and DTS also specified. The first and second columns show the identification of DMUs and name of the cities. The third and fourth columns indicate each city's industrial energy efficiency and integrated efficiency under natural disposability, which are measured by Model (2.1) and related indices ENEE and IEND.

**[Insert Table 3 here]**

Among the 31 capitals, 11 cities, including Tianjin, Shenyang, Changchun, Shanghai, Hefei, Jinan, Zhengzhou, Changsha, Guangzhou, Haikou, and Lhasa, exhibit efficient both in energy efficiency and integrated efficiency under natural disposability (shown in Fig.2), which indicates that (i) without considering pollution, these cities perform efficiently in energy utilization and industrial production; and (ii) under the assumption of natural disposability, these cities perform efficiently both on industrial energy utilization and environment protection.

On the other extreme, Taiyuan performs worst in terms of its efficiency in industrial energy utilization, with an *ENEE* score lower than 0.85. The performance of Wuhan, Chongqing, Beijing, Urumchi, Hangzhou, and Shijiazhuang are similarly poor, with *ENEE* scores lower than 0.95. From a geographic perspective, cities in east China tend to have the highest industrial energy efficiency (E(*ENEE*)=0.978), followed by western cities (E(*ENEE*)=0.967), and finally central cities (*E*(*ENEE*)=0.965). In addition, variance in energy efficiency is significant among central Chinese cities (CV(*ENEE*)= 0.06), and less dismissed among western cities (CV(*ENEE*)=0.02).

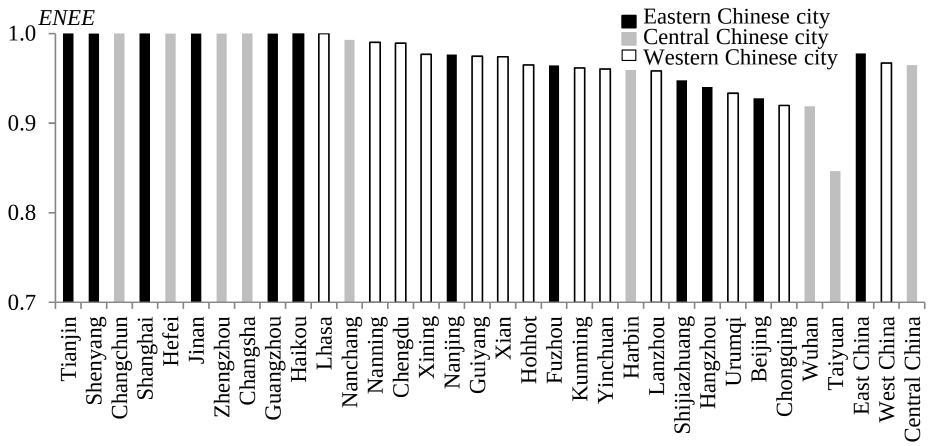

Fig.2. Industrial energy efficiency for 31 Chinese cities.

The eighth and ninth columns of Table 3 indicate the industrial environment efficiency and integrated efficiency under managerial disposability for each Chinese city, which are measured by Model (2.7) and related indices *ENVE* and *IEMD*.

In terms of environment efficiency and integrated efficiency under managerial dsiposability, about half of the cities, including Beijing, Tianjin, Taiyuan, Shenyang, Shanghai, Hefei, Fuzhou, Jinan, Wuhan, Changsha, Guangzhou, Haikou, Lhasa, Yinchuan, and Urumchi achieved efficiency, which indicates that (i) without considering industrial production, these cities all perform efficiently in energy utilization and pollutants emission; and (ii) under the assumption of managerial disposability, these cities perform efficiently both on industrial energy utilization and environment protection.

The other half of the cities performed inefficiently, with Chongqing as the worst one (shown in Fig.3). Its *ENVE* score is even lower than 0.75. Nanjing, Hangzhou, Kunming, and Shijiazhuang did relatively better, with *ENVE* scores between 0.80 and 0.90, but still inefficiently. Interestingly, although the central Chinese cities perform worst in terms of energy efficiency, they constitute the most environmentally efficient region in terms of environment efficiency (E(*ENVE*)=0.984), with eastern China following (E(*ENVE*)=0.963) and western China coming at last (E(*ENVE*)=0.942). The phenomenon repeat here that the region that was least efficient in environmental conservation also has the largest variance in terms of environmental efficiency ($CV(ENVE)_{western}=0.08$), and the best performing one had the lowest variance ($CV(ENVE)_{central}=0.02$).

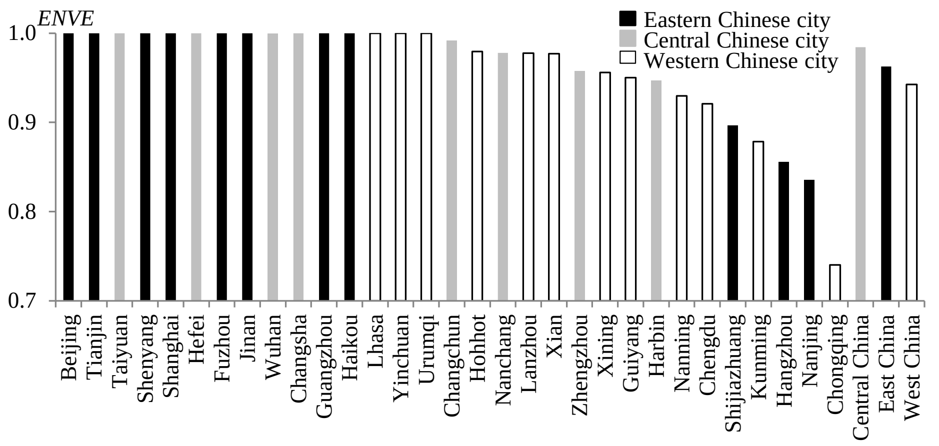


Fig.3. Industrial environment efficiency for 31 Chinese cities.

Combining the evaluation of both energy and environment efficiency, nine cities are efficient both on industrial energy efficiency and industrial environment efficiency, including Tianjin, Shenyang, Shanghai, Hefei, Jinan, Changsha, Guangzhou, Haikou, and Lhasa. Six of them are located in eastern China, two (Hefei and Changsha) in central China, and one (Lhasa) in western China. These nine cities all reached the desirable and undesirable output frontiers, and perform efficiently under both the natural and the managerial disposability assumptions. Therefore, they could serve as the benchmarks for gauging other inefficient Chinese cities to further promote their E & E efficiency in their industrial sectors.

Fig.4 compares the integrated efficiency under natural disposability and managerial disposability for each of the 31 Chinese cities. The radar chart shows that the integrated efficiency under managerial disposability appears more balanced than that under natural disposability. This indicates that the integrated efficiency difference among China’s 31 cities is more significant from the perspective of natural disposability. Taiyuan has the largest gap between the two integrated efficiencies, followed by Wuhan, Beijing and Urumchi. For the four cases, *ENVE* is always higher than *ENEE*, which implies that it is more effective for these cities to promote integrated efficiency by naturally decreasing industrial energy consumptions instead of relying on managerial efforts. In contrast, cities of Zhengzhou, Nanning, Nanjing and Chengdu performed better when evaluated with the criterion of integrated efficiencies under natural disposability than that under managerial disposability, which means that there is more potential in these cities in improving integrated efficiency through management promotion and technology innovation, rather than through naturally decreasing energy consumption.

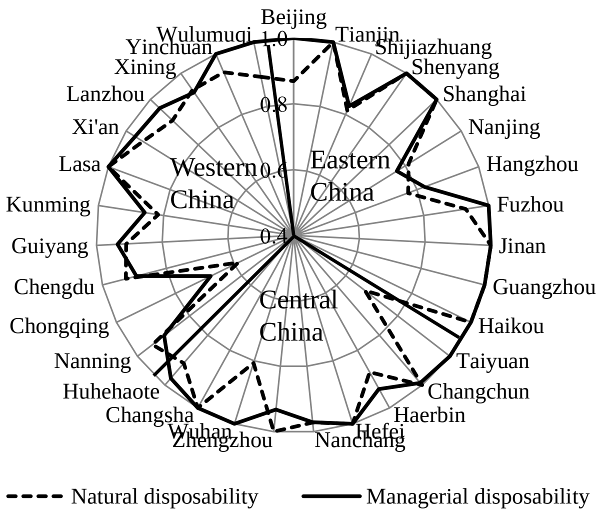


Fig.4. Integrated efficiency under natural and managerial disposability for 31 Chinese cities.

Our study also indicates significant potential for Chinese cities to improve their energy use efficiency. As also illustrated in Table 3, the average integrated efficiency under natural disposability for all sample cities is 0.911, which means they could potentially raise the E & E efficiency by 8.9% in general, if their industrial sectors operate on the desirable output efficiency frontier. In addition, the average integrated efficiency under managerial disposability is 0.947, indicating that if all the inefficient cities place their industrial operation on the undesirable output efficiency frontier, the E & E efficiency could be increased by 5.3%.

### 5.2. *Measurement of returns to scale and damages to scale*

Table 3 also summarizes the types of RTS of industrial sectors of 31 China’s cities. Three different types of increasing, constant and decreasing RTS are indicated in the seventh column of Table 3. Under the assumption of natural disposability, most cities (23 of them) have decreasing RTS in their industrial sectors, such as Beijing, Wuhan, and Chongqing. Another seven cities exhibit constant RTS. Only in Lhasa, RTS in the industrial sector is decreasing (Table 3).

Decreasing RTS under natural disposability implies that the marginal benefit, as measured by industrial added value, from increasing inputs of energy, labor, and physical capital actually decreases. Thus, for the 23 cities with decreasing RTS, further pursuing a large size industrial sector is not recommended. It will not improve their industrial energy efficiency any more. In contrast, increasing RTS under natural disposability indicates increasing marginal benefit from the industrial inputs. Therefore, Lhasa should be particularly promoted to increases the size of its industrial sector, so as to enhance its industrial energy efficiency. For cities with constant RTS, it is better for them to maintain their current size of industrial sector so as to keep their energy efficiency, or alternatively, they should utilize technology innovation so as to further increase their industrial energy efficiency.

In addition, three types (increasing, decreasing and constant) of DTS of industrial sectors of 31 China's cities are also summarized in the last column of Table 3. Under the assumption of managerial disposability, 18 out of the 31 sample cities exhibit increasing DTS, and five with decreasing DTS, another eight with constant DTS (Table 3).

Increasing DTS under managerial disposability indicates that the marginal environmental cost, as measured by the amount of discharge of waste water, waste gas, and solid wastes increases with the input of energy, labor, and physical capital. Thus, the 18 cities with increasing DTS are not recommended to simply extend their industrial production scales, as that will result in over proportionally increase in pollutant discharge, as well as more environment damages. Alternatively, these cities may adopt the innovative technologies in energy conservation and pollutants capture, so as to simultaneously upgrade their industrial production scales and enhance environment efficiency. In contrast to the increasing DTS, decreasing DTS under managerial disposability implies decreasing marginal environmental cost with inputs. Hence, there leave room for Hohhot, Hangzhou, Nanchang, Lhasa, and Lanzhou to enlarge their industrial sectors as a way to improve their environment efficiencies, although this is not recommended either. Extending industrial production would anyway cause more pollution, even at a slower rate. Constant DTS under managerial disposability indicates that constant marginal environmental cost. Thus, for the remaining eight cities, it is not recommended, but acceptable, that they can maintain the current size of industrial production to keep environment efficiency. Certainly, they may also adopt environmental and energy technology innovation or promote energy management to further promote industrial environment efficiency.

## 6. Conclusions

In this paper, we applied the RAM method to evaluate energy efficiency, environment efficiency, and integrated efficiency, under the assumptions of both natural and managerial disposability assumptions, for the industrial sectors of 31 Chinese major cities.

The evaluation results show that: (i) 11 cities exhibit industrial energy efficiency and 15 cities maintain industrial environment efficiency in 2009; (ii) eastern Chinese cities perform best in terms of industrial energy efficiency, followed by western cities, and then central cities; oppositely, central cities perform best in terms of industrial environment efficiency, followed by eastern cities, and then western cities; (iii) central Chinese cities incur great variance in their industrial energy efficiency performance, and the industrial environment efficiency performance varies most among western Chinese cities; (iv) Under natural disposability assumption, most cities exhibit decreasing RTS, whereas under managerial disposability assumption, most cities exhibit increasing DTS. To promote E & E efficiency, our study present the prior potential of applying innovative environmental and energy technologies, instead of simply extending or shrinking the size of industrial sectors, in Chinese cities.

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Table 3.Energy and environment efficiency of industrial sector and type of returns to scale and damages to scale for China's 31 cities.

| DMU No. | Area | City | Model (2.1) & (2.4) | | Model (2.5) & (2.6) | | | Model (2.7) & (2.10) | | Model (2.11) & (2.12) | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | *ENEE* | *IEND* | Upper bound $\bar{\mu}$ ( $\bar{\sigma}$ ) | Lower bound $\underline{\mu}$ ( $\underline{\sigma}$ ) | RTS | *ENVE* | *IEMD* | Upper bound $\bar{\tau}$ ( $\bar{\sigma}$ ) | Lower bound $\underline{\tau}$ ( $\underline{\sigma}$ ) | DTS |
| 1 | E | Beijing | 0.9273 | 0.8687 | 0.1931 | 0.1931 | D | 1 | 1 | 0.1528 | -0.0065 | C |
| 2 | E | Tianjin | 1 | 1 | 0.4813 | -0.0142 | C | 1 | 1 | 1.4724 | 0.0760 | I |
| 3 | E | Shijiazhuang | 0.9473 | 0.8136 | 0.2026 | 0.2026 | D | 0.8968 | 0.8277 | 0.0409 | 0.0409 | I |
| 4 | C | Taiyuan | 0.8461 | 0.6742 | 0.1799 | 0.1799 | D | 1 | 1 | 0.0685 | -0.0014 | C |
| 5 | W | Hohhot | 0.9649 | 0.9127 | 0.0588 | 0.0588 | D | 0.9794 | 0.9725 | -0.0156 | -0.0156 | D |
| 6 | E | Shenyang | 1 | 1 | 0.0614 | 0.0205 | D | 1 | 1 | 0.8465 | -0.0077 | C |
| 7 | C | Changchun | 1 | 1 | 0.2195 | -0.1216 | C | 0.9920 | 0.9912 | 0.0138 | 0.0138 | I |
| 8 | C | Harbin | 0.9595 | 0.8757 | 0.0938 | 0.0938 | D | 0.9468 | 0.9340 | 0.0002 | 0.0002 | I |
| 9 | E | Shanghai | 1 | 1 | 0.4813 | 0.0074 | D | 1 | 1 | 0.1854 | 0.1410 | I |
| 10 | E | Nanjing | 0.9766 | 0.8124 | 0.2452 | 0.2452 | D | 0.8354 | 0.7697 | 0.1083 | 0.1083 | I |
| 11 | E | Hangzhou | 0.9403 | 0.7711 | 0.2660 | 0.2660 | D | 0.8557 | 0.8245 | -0.0117 | -0.0117 | D |
| 12 | C | Hefei | 1 | 1 | 0.0105 | -0.0316 | C | 1 | 1 | 0.0152 | -0.0020 | C |
| 13 | E | Fuzhou | 0.9644 | 0.9291 | 0.0515 | 0.0515 | D | 1 | 1 | 0.1043 | -0.0045 | C |
| 14 | C | Nanchang | 0.9928 | 0.9716 | 0.0319 | 0.0319 | D | 0.9780 | 0.9711 | -0.0130 | -0.0130 | D |
| 15 | E | Jinan | 1 | 1 | 0.2195 | -0.0477 | C | 1 | 1 | 0.0198 | 0.0198 | I |
| 16 | C | Zhengzhou | 1 | 1 | 0.2013 | -0.0477 | C | 0.9578 | 0.9320 | 0.0352 | 0.0352 | I |
| 17 | C | Wuhan | 0.9186 | 0.8068 | 0.2042 | 0.2042 | D | 1 | 1 | 0.9260 | 0.9062 | I |
| 18 | C | Changsha | 1 | 1 | 0.2013 | -0.0103 | C | 1 | 1 | 0.0665 | -0.0077 | C |
| 19 | E | Guangzhou | 1 | 1 | 0.2013 | 0.1926 | D | 1 | 1 | 0.5339 | 0.0253 | I |
| 20 | W | Nanning | 0.9903 | 0.9425 | 0.0529 | 0.0529 | D | 0.9297 | 0.8977 | 0.0342 | 0.0342 | I |
| 21 | E | Haikou | 1 | 1 | 0.0074 | -0.1216 | C | 1 | 1 | 0.0030 | -0.0015 | C |
| 22 | W | Chongqing | 0.9197 | 0.5873 | 0.4618 | 0.4618 | D | 0.7402 | 0.6806 | 0.1284 | 0.1284 | I |
| 23 | W | Chengdu | 0.9891 | 0.9266 | 0.1444 | 0.1444 | D | 0.9209 | 0.8936 | 0.0020 | 0.0020 | I |
| 24 | W | Guiyang | 0.9746 | 0.9092 | 0.0701 | 0.0701 | D | 0.9503 | 0.9355 | 0.0002 | 0.0002 | I |
| 25 | W | Kunming | 0.9617 | 0.8164 | 0.1545 | 0.1545 | D | 0.8786 | 0.8575 | 0.0015 | 0.0015 | I |
| 26 | W | Lhasa | 1 | 1 | -0.0030 | -0.0033 | I | 1 | 1 | -0.0073 | -0.0073 | D |
| 27 | W | Xi'an | 0.9742 | 0.9398 | 0.0471 | 0.0471 | D | 0.9772 | 0.9683 | 0.0274 | 0.0274 | I |
| 28 | W | Lanzhou | 0.9584 | 0.9079 | 0.0554 | 0.0554 | D | 0.9777 | 0.9615 | -0.0131 | -0.0131 | D |
| 29 | W | Xining | 0.9768 | 0.9382 | 0.0360 | 0.0360 | D | 0.9559 | 0.9295 | 0.0418 | 0.0418 | I |
| 30 | W | Yinchuan | 0.9602 | 0.9395 | 0.0241 | 0.0241 | D | 1 | 1 | 0.3281 | 0.0030 | I |
| 31 | W | Urumchi | 0.9334 | 0.8925 | 0.0521 | 0.0521 | D | 1 | 1 | 0.0685 | -0.0021 | C |
| - | Eastern | Mean | 0.9778 | 0.9268 | - | - | - | 0.9625 | 0.9475 | - | - | - |
| | | Std. dev. | 0.0283 | 0.0926 | - | - | - | 0.0657 | 0.0912 | - | - | - |
| - | Central | Mean | 0.9646 | 0.9160 | - | - | - | 0.9843 | 0.9785 | - | - | - |
| | | Std. dev. | 0.0560 | 0.1215 | - | - | - | 0.0214 | 0.0298 | - | - | - |
| - | Western | Mean | 0.9669 | 0.8927 | - | - | - | 0.9425 | 0.9247 | - | - | - |
| | | Std. dev. | 0.0231 | 0.1051 | - | - | - | 0.0736 | 0.0897 | - | - | - |
| - | China | Mean | 0.9702 | 0.9108 | - | - | - | 0.9604 | 0.9467 | - | - | - |
| | | Std. dev. | 0.0351 | 0.1029 | - | - | - | 0.0618 | 0.0799 | - | - | - |

Note: E, C, and W respectively indicate east, central and west China cities; D, C, and I respectively indicate decreasing, constant, and increasing returns or damages to scale.