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Original Research

A PSBM Model for Environmental Efficiency Evaluation and Its Application

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Abstract

The traditional efficiency evaluation model considering undesirable outputs is only able to calculate the efficiency of the overall value of the decision-making units. This paper puts forward a new environmental efficiency evaluation based on the proper slack-based measurement (PSBM) model, which can give the efficiency values of the inputs, desirable outputs, and undesirable outputs. The results from the new model are not only highly correlated with SBM-based evaluation results, but also coincide with reality, which can be used to test the effectiveness of the new model. Our model provides more information for environmental efficiency evaluation analysis.

Keywords: undesirable output, environmental efficiency, proper slack-based measurement model

Introduction

Environmental protection is a global concern. Since the beginning of the 21st century, countries have increasingly begun to face the problems of environmental pollution and ecological degradation. In some developed countries and regions, environmental protections have led to many inefficient or polluting projects being eliminated or required to transfer to developing countries. Many countries are taking the positive steps of developing nuclear power, wind power, and other forms of green energy. They are making efforts to improve the technology for flue gas desulfurization and denitration and to enhance dust-removing technology to reduce nitrogen oxides, dust, and other pollutants. For example, natural gas, a relatively clean source of energy, is used increasingly by cities, and a number of measures have been introduced to control motor vehicle pollution in cities. The above measures alleviate the particle pollution of some countries and regions, and have led to declining concentrations of sulfur dioxide and nitrogen oxides. Ecological degradation is controlled to a certain extent in some areas.

Environmental issues, however, are still of major concern, especially in developing countries and regions. Currently, the total number of vehicles in China has reached 240 million, of which 120 million are cars. Because of exhaust pollution, the atmospheric environmental quality of many cities is causing concern[1]. Every year, from May to June, straw is still burned throughout most rural areas of the country, which results in a significant negative impact on the environment in the spring and autumn. Furthermore, China has become the world's "manufacturing factory." Pollutant emissions not only include national consumer emissions but also emissions arising from production of foreign products. There is a long way for China to go.

It is obvious that the above issues cannot be resolved overnight. Halting the development of the automobile industry or significantly reducing product exports to protect the environment would hinder economic development. These measures would fail to realize sustainable develop-

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[1]According to data released by China's Ministry of Public Security. See http://tv.people.com.cn/n/2013/0130/c39805-20380411.html

ment. Only actively promoting clean production as part of rapid and healthy economic development and prompting the coordination of environmental protection and economic development are consistent with the long-term interests of society. The solution to the environmental problem lies in controlling pollution emissions in the production process using existing technology, that is, effectively improving environmental efficiency.

Many environmental efficiency calculation methods have already been proposed. Although many scholars have expanded on and improved them, they still have not achieved a precise solution that would allow the creation of a specific improvement program for different indicators. This article will explore these issues and propose a new environmental efficiency calculation method to solve this problem.

The second part of this paper is a literature review. We briefly review the development of the evaluation methods of environmental efficiency.

The third part constructs a new environmental efficiency evaluation using a proper slack-based measure (PSBM) model and gives the corresponding propositions.

The fourth analyzes a practical example in China using this new PSBM model.

Finally, the fifth part offers conclusions and directions for further research.

Literature Review

Data envelopment analysis (DEA) is a popular mathematical programming technique for evaluating homogeneous decision-making units (DMUs) [1]. Thus far, DEA has been considered an efficient way to evaluate environmental efficiency [2]. Since the CCR model (developed by and named for Charnes, Cooper, and Rhodes) was put forward based on the mathematical programming model, DEA has undergone many developments and taken many new forms, such as the BCC model (developed by and named for Banker, Charnes, and Cooper) and the additive model [3, 4]. These traditional DEA models are derived from the assumption that inputs must be minimized and outputs maximized, but this does not adequately consider undesirable outputs, which are often produced in the production cycle [5, 6]. In reality, the production cycle usually produces both the desired outputs and undesired outputs such as sulfur dioxide and other polluting emissions. Therefore, the goal is to simultaneously achieve the targets of minimizing investment in production, maximizing desirable outputs, and minimizing undesirable outputs. In recent years, research on this topic has attracted the attention of many scholars [7].

Färe et al. [8] believed that desirable outputs are inevitably accompanied by undesired output generation. They also proposed a nonlinear model based on the curve measure method. Liu and Sharp argued that undesirable inputs and desirable inputs have a certain relationship with undesirable outputs and desirable outputs. They proposed viewing undesirable inputs as desirable outputs or undesirable outputs as desirable inputs and then maximizing the undesirable inputs and desirable outputs while minimizing undesirable outputs and desirable inputs [9]. Liu et al. put forward the extended strong disposability assumption for addressing this kind of problem and proposed a new DEA model based on the ideas of Liu and Sharp [7]. Hailu and Veeman suggested that the need for undesirable output minimization is consistent with the nature of the inputs, so undesirable outputs can be used as inputs [10]. Although this method is simple, it may not be a good approach, because people in the real world cannot completely control undesirable outputs. Golany and Roll and Lovell et al. proposed a non-linear conversion method, taking the reciprocal of undesirable outputs as desirable outputs [11, 12]. Based on this idea, input factors do not increase, desirable outputs are to be as large as possible, and undesirable outputs are as small as possible. Song et al. proposed an evaluation model of environmental efficiency for desirable outputs and undesirable outputs [13]. Seiford and Zhu proposed a linear data transformation function approach; they thought that desirable outputs had a positive impact on efficiency evaluation results, which can take a positive value, and undesirable outputs have a negative impact on the efficiency evaluation results, taking a negative value. Based on the principle of invariance, they proposed introducing an appropriate positive constant to make the undesirable outputs positive, transfer undesirable outputs to desirable outputs, and then build a model for processing [14]. However, with a strong subjective factor, this constant may bring bias to the results, which is not conducive to objective efficiency evaluation. Färe also proposed the distance function, which is premised on the idea that the goal is to maximize desirable outputs and minimize undesirable outputs in the same proportion, and the proportion is the largest, so that desirable outputs increase while undesirable outputs are reduced [15]. Wang et al. argued that governments' environmental regulation policies should consider actual production. Introducing the concept of the retractable coefficient and expansion coefficient, they examined environmental efficiency evaluation in three cases [16].

The above model is established based on the radial and angular; however, in production practice it is difficult to reduce inputs and increase outputs by the same amount. Therefore, these models for the evaluation of DMUs are biased in actual application. Some scholars have suggested that the analytic hierarchy process (AHP) be used to evaluate a multi-criteria decision-making problem [17]. Meanwhile, in order to eliminate the impact of these aspects, some new models have been proposed. Charnes et al. made the early introduction of slack variables. Considering the experience production function's inner structure and the function characteristics of the theory, they proposed a new DEA model for constructing and analyzing the Pareto frontier production function [6]. However, since the calculation process in this model is more complicated, its practical application is limited. Tone improved the objective function of the model and proposed the SBM model [18]. The model directly introduces slack variables into the objective function, avoids interference of the radial and angular, and reflects the production process more accurately, and therefore is used widely in practice [19, 20].

However, the SBM model also has some problems or deficiencies, mainly in three aspects. First, the SBM model only provides average results. If the optimistic objective function value is not equal to 1, the efficiency value and actual practice will have deviations. The SBM model ignores the problem of how to consider inputs and desirable and undesirable outputs, respectively. Second, the information gained by using this model for comprehensive evaluation is not sufficient because there may be a DMU that is not effective as a whole but is efficient for a certain aspect or two of its inputs and desirable and undesirable outputs. Third, although the SBM model provides an overall direction for improvement of non-effective DMUs, that direction is ambiguous; the model cannot propose more specific recommendations on the improvements for inputs or desirable and undesirable outputs. This paper will address the problem of the SBM model. We will build a new DEA model to be able to realize a more precise consideration of undesirable output efficiency evaluation, and give detailed improvements of non-effective DMU inputs and desirable and undesirable outputs to support management decisions.

Model

First, set

$$\theta_i = \frac{x_{i0} - s_i^-}{x_{i0}}, i = 1, \cdots, m$$

$$\theta_t = \frac{y_{t0}^b - s_t^-}{y_{t0}^b}, t = 1, \cdots, k$$

$$\theta_r = \frac{y_{r0}^g + s_r^+}{y_{r0}}, r = 1, \cdots, n$$

...where, *m*, *s*, and *k* represent the indicators of inputs, desirable outputs, and undesirable outputs, respectively.

Set $x_{i0} = x_{ij_0}, y_{r0}^g = y_{rj_0}^g, y_{t0}^b = y_{tj_0}^b$

...where x_{i0} represents the amount of the *i*th investment of the j_0th decision-making unit; s_i^- represents a slack variable of the *i*th investment; y_{r0}^g represents the amount of the *r*th desirable outputs of the j_0th decision-making unit; s_r^+ represents the slack variable of the *r*th output; y_{t0}^b represents the amount of the *t*th undesirable outputs of the j_0th decision-making unit; and s_t^- represents the slack variable of the *t*th outputs. θ_i, $\frac{1}{\theta_r}$, and θ_t represent, respectively, the *i*th input efficiency value of the j_0th decision-making unit, the *r*th desirable outputs efficiency value of the j_0th decision-making unit, and the *t*th undesirable outputs efficiency value of the j_0th decision-making unit.

Slack variables are non-negative, and thus $0 \le \theta_i \le 1$, $0 \le \theta_t \le 1$, and $\theta_r \ge 1$. In order to measure the efficiency of inputs, desirable outputs, and undesirable outputs, we need to set s_i^-, s_r^+, and s_t^-, which should be maximized, thereby minimizing θ_i and θ_t, and maximizing θ_r. In order to measure the overall efficiency value, we build a new objective function as follows:

$$\pi_1 = \min \frac{\frac{1}{m+k}\left(\sum_{i=1}^{m}\theta_i + \sum_{t=1}^{k}\theta_t\right)}{\frac{1}{s}\sum_{r=1}^{s}\theta_r} \tag{1}$$

Theorem 1:
The overall efficiency values of the objective function are between 0 and 1.

Proof:

$\because 0 \le \theta_i \le 1, 0 \le \theta_t \le 1, \therefore 0 \le \sum_{i=1}^{m}\theta_i + \sum_{t=1}^{k}\theta_t \le m+k$, to

thereby obtain $0 \le \frac{1}{m+k}\left(\sum_{i=1}^{m}\theta_i + \sum_{t=1}^{k}\theta_t\right) \le 1$, and $\because \theta_r \ge 1$,

$\therefore \sum_{r=1}^{s}\theta_r \ge s$ that is, $\frac{1}{s}\sum_{r=1}^{s}\theta_r \ge 1$.

From the above, we can obtain:

$$0 \le \frac{\frac{1}{m+k}\left(\sum_{i=1}^{m}\theta_i + \sum_{t=1}^{k}\theta_t\right)}{\frac{1}{s}\sum_{r=1}^{s}\theta_r} \le 1.$$

Further, $\because s_i^-$, s_r^+, and s_t^- as far as possible to maximize $\therefore$, minimize θ_i and θ_t, and maximize θ_r.

In $\therefore \frac{\frac{1}{m+k}\left(\sum_{i=1}^{m}\theta_i + \sum_{t=1}^{k}\theta_t\right)}{\frac{1}{s}\sum_{r=1}^{s}\theta_r}$, the molecular is the minimum and the denominator is the maximum, that is, $\frac{\frac{1}{m+k}\left(\sum_{i=1}^{m}\theta_i + \sum_{t=1}^{k}\theta_t\right)}{\frac{1}{s}\sum_{r=1}^{s}\theta_r}$ is the minimum, and the objective function is $\pi_1 = \min \frac{\frac{1}{m+k}\left(\sum_{i=1}^{m}\theta_i + \sum_{t=1}^{k}\theta_t\right)}{\frac{1}{s}\sum_{r=1}^{s}\theta_r}$.

The overall efficiency values of the objective function are in the interval between 0 and 1. This completes the proof.

Next, the constraint condition of formula (1) will be built. The constraints of the model constructed by Charnes et al. are deformed [6]; the constraints of the model are:

$$s.t. \sum_{j=1}^{n} \lambda_j x_{ij} + s_i^- = x_{i0}, i = 1,2,\cdots,m$$
$$\sum_{j=1}^{n} \lambda_j y_{rj}^g - s_r^+ = y_{r0}^g, r = 1,2,\cdots,s$$
$$\sum_{j=1}^{n} \lambda_j y_{tj}^b + s_t^- = y_{t0}^b, t = 1,2,\cdots,k$$
$$\sum_{j=1}^{n} \lambda_j = 1 \quad (2)$$
$$s_r^+, s_i^-, s_t^-, \lambda_j \geq 0, j = 1,2,\cdots,n$$

Moving all slack variables of formula (2) to the right side of the equation, we can obtain:

$$s.t. \sum_{j=1}^{n} \lambda_j x_{ij} = x_{i0} \text{-} s_i^-, i = 1,2,\cdots,m$$
$$\sum_{j=1}^{n} \lambda_j y_{rj}^g = y_{r0}^g + s_r^+, r = 1,2,\cdots,s$$
$$\sum_{j=1}^{n} \lambda_j y_{tj}^b = y_{t0}^b \text{-} s_t^-, t = 1,2,\cdots,k$$
$$\sum_{j=1}^{n} \lambda_j = 1 \quad (3)$$
$$s_r^+, s_i^-, s_t^-, \lambda_j \geq 0, j = 1,2,\cdots,n$$

Then, through the deformation of formula (3), we can obtain the following form:

$$s.t. \sum_{j=1}^{n} \lambda_j x_{ij} = \frac{x_{i0} \text{-} s_i^-}{x_{i0}} \cdot x_{i0}, i = 1,2,\cdots,m$$
$$\sum_{j=1}^{n} \lambda_j y_{rj}^g = \frac{y_{r0}^g + s_r^+}{y_{r0}^g} \cdot y_{r0}^g, r = 1,2,\cdots,s$$
$$\sum_{j=1}^{n} \lambda_j y_{tj}^b = \frac{y_{t0}^b \text{-} s_t^-}{y_{t0}^b} \cdot y_{t0}^b, t = 1,2,\cdots,k$$
$$\sum_{j=1}^{n} \lambda_j = 1 \quad (4)$$
$$s_r^+, s_i^-, s_t^-, \lambda_j \geq 0, j = 1,2,\cdots,n$$

According to the above assumptions,

$$\theta_i = \frac{x_{i0} - s_i^-}{x_{i0}}, i = 1,\cdots,m;$$

$$\theta_\gamma = \frac{y_{r0}^g + s_r^+}{y_{r0}}, r = 1,\cdots,n; \text{ and}$$

$$\theta_t = \frac{y_{t0}^b - s_t^-}{y_{t0}^b}, t = 1,\cdots,k$$

Formula (4) can be deformed into the following:

$$s.t. \sum_{j=1}^{n} \lambda_j x_{ij} = \theta_i x_{i0}, i = 1,2,\cdots,m$$
$$\sum_{j=1}^{n} \lambda_j y_{rj}^g = \theta_r y_{r0}^g, r = 1,2,\cdots,s$$
$$\sum_{j=1}^{n} \lambda_j y_{tj}^b = \theta_t y_{t0}^b, t = 1,2,\cdots,k$$
$$\sum_{j=1}^{n} \lambda_j = 1 \quad (5)$$
$$0 \leq \theta_i, \theta_t \leq 1, \ \theta_r \geq 1, \lambda_j \geq 0, j = 1,2,\cdots,n$$

Formula (5) is the constraint condition of proposed model (1). Now we give the complete new model (PSBM):

$$\pi_1 = \min \frac{\frac{1}{m+k}\left(\sum_{i=1}^{m}\theta_i + \sum_{t=1}^{k}\theta_t\right)}{\frac{1}{s}\sum_{r=1}^{s}\theta_r}$$

$$s.t. \sum_{j=1}^{n} \lambda_j x_{ij} = \theta_i x_{i0}, i = 1,2,\cdots,m$$
$$\sum_{j=1}^{n} \lambda_j y_{rj}^g = \theta_r y_{r0}^g, r = 1,2,\cdots,s$$
$$\sum_{j=1}^{n} \lambda_j y_{tj}^b = \theta_t y_{t0}^b, t = 1,2,\cdots,k$$
$$\sum_{j=1}^{n} \lambda_j = 1 \quad (6)$$
$$0 \leq \theta_i, \theta_t \leq 1, \ \theta_r \geq 1, \lambda_j \geq 0, j = 1,2,\cdots,n$$

PSBM model production possibility set:

$$T_{PSBM} = \left\{ \left(X, Y^g, Y^b\right) | \sum_{j=1}^{n} \lambda_j X_j = \theta_i X, \sum_{j=1}^{n} \lambda_j Y_j^g = \theta_r Y^g, \right.$$

The model ensures elimination of the problem of the radial and angular and, at the same time, introduces θ_i, θ_r, and θ_t to the objective function and the constraints. The introduction of these three variables can help to solve the efficiency evaluation problem of inputs, desirable outputs, and undesirable outputs.

Theorem 2:
The necessary and sufficient conditions of the effective decision-making unit π_1=1.

Proof:

(i) Adequacy:

When π_1=1, that is, $\min \frac{\frac{1}{m+k}\left(\sum_{i=1}^{m}\theta_i + \sum_{t=1}^{k}\theta_t\right)}{\frac{1}{s}\sum_{r=1}^{s}\theta_r} = 1$,

set θ_i^*, θ_t^*, and θ_r^* to be the optimal solution of θ_i, θ_t, and θ_r.

Moreover, because $0 \leq \frac{1}{m+k}\left(\sum_{i=1}^{m}\theta_i + \sum_{t=1}^{k}\theta_t\right) \leq 1$, $\frac{1}{s}\sum_{r=1}^{s}\theta_r \geq 1$, and $\frac{\frac{1}{m+k}\left(\sum_{i=1}^{m}\theta_i^* + \sum_{t=1}^{k}\theta_t^*\right)}{\frac{1}{s}\sum_{r=1}^{s}\theta_r^*} = 1$, the requirement is $\frac{1}{m+k}\left(\sum_{i=1}^{m}\theta_i + \sum_{t=1}^{k}\theta_t\right) = 1$, $\frac{1}{s}\sum_{r=1}^{s}\theta_r = 1$, where $\therefore$ the maximum values of the slack variables of the inputs, desirable outputs, and undesirable outputs in DMU_{j0} are all 0, so DMU_{j0} is effective.

(ii) Necessity:

When DMU_{j0} is effective, the requirements are that the maximum values of all slack variables s_i^-, s_r^+, and s_t^- in DMU_{j0} should be 0.

Set θ_i^*, θ_t^*, and θ_r^* to be the optimal solution for the θ_i, θ_t, and θ_r and of the PSBM. Obviously:

$$\frac{1}{m+k}\left(\sum_{i=1}^{m}\theta_i^* + \sum_{t=1}^{k}\theta_t^*\right) = 1, \frac{1}{s}\sum_{r=1}^{s}\theta_r^* = 1$$

$$\therefore \pi_1 = \min \frac{\frac{1}{m+k}\left(\sum_{i=1}^{m}\theta_i + \sum_{t=1}^{k}\theta_t\right)}{\frac{1}{s}\sum_{r=1}^{s}\theta_r}$$

Comprehensively, in (i) and (ii) above, the sufficient condition that the DMU_{j0} is effective is $\pi_1=1$. This completes the proof.

When the inputs, desirable outputs, and undesirable outputs of DMU_{j0}, respectively, "project" on the efficient frontier surface, these points can be set to be $\hat{x}_{i0}$, $i = 1,2,...m$; $\hat{y}^g_{r0}$, $r = 1,2,...s$; and $\hat{y}^b_{t0}$, $t = 1,2,...k$. In the "projection" theory, $\hat{x}_{i0} = x_{i0} - s_i^-$, $i = 1,2,...m,$ $\hat{y}^g_{r0} = y^g_{r0} + s_r^+$, $r = 1,2,...s,$ and $\hat{y}^b_{t0} = y^b_{t0} - s_t^-$, $t = 1,2,...k.$ A similar equation (4) to the transformed equation (5) can be defined as follows:

Definition 1: set θ_i^*, θ_r^*, θ_t^* λ^* to be the optimal solution of the PSBM model.

Then,

$$\hat{x}_{i0} = \theta_i^* x_{i0} = \sum_{j=1}^{n}\lambda_j^* x_{ij}, i = 1,2,\cdots m$$,

$$\hat{y}^g_{r0} = \theta_r^* y^g_{r0} = \sum_{j=1}^{n}\lambda_j^* y^g_{rj}, r = 1,2,\cdots s$$, and

$$\hat{y}^b_{t0} = \theta_t^* y^b_{t0} = \sum_{j=1}^{n}\lambda_j^* y^b_{tj}, t = 1,2,\cdots k$$, so there are $m+s+k$ equations. Thus, call ($\hat{X}_0$, $\hat{Y}^g_0$, $\hat{Y}^b_0$) the projection on the efficient frontier of the production possibility set T_{PSBM} of DMU_{j0}.

Because $\hat{x}_{i0}$, $\hat{y}^g_{r0}$, and $\hat{y}^b_{t0}$ are on the efficient frontier surface, we can obtain the projection theorem as follows:

Theorem 3:

The projection of the efficient frontier surface, $\hat{x}_{i0}=\theta_i x_{i0}$, $i = 1,2,...m,$ $\hat{y}^g_{r0} = \theta_r y^g_{r0}$, $r = 1,2,...s,$ $\hat{y}^b_{t0} = \theta_t y^b_{t0}$ $t = 1,2,...k$ is effective.

When DMU_{j0} in the PSBM/SBM model is valid, the maximum values of all its slack variables, s_i^-, s_r^+, and s_t^-, are all 0; thus, it is clear that the SBM objective function value is 1, that is, in the SBM/PSBM model, DMU_{j0} is also effective. It is clear that the PSBM and SBM models are equivalent. Moreover, the PSBM model has advantages over the SBM model, in that it eliminates the problem of the radial and angular and compensates for the SBM model's deficiencies. This new model can not only measure the overall efficiency of the DMUs but also calculate the efficiency value of each input, desirable output, and undesirable output. The PSBM model is solved, and the results are not only the overall efficiency values but also the efficiency values of each input, desirable output, and undesirable output. This provides not only the overall efficiency status quo for management decisions but also quantitative improvement information for each input, desirable output, and undesirable output.

Application

According to (6), we collected the data of 31 provinces, municipalities, and autonomous regions in 2011. We considered the efficiency analysis of undesirable outputs and selected total fixed assets and regional retail sales as the input indicators, GDP as the desirable outputs indicator, and sulfur dioxide emissions, NO_x, and dust as the undesirable outputs indicator. Fixed asset investment amount and GDP are measured in units of 100 million RMB yuan. Data were collected from the China Statistical Yearbook of 2012, the provincial (regional) Statistical Yearbook of 2012, and some statistical surveys.

The environmental efficiency evaluation results are shown in Table 1. The larger the objective function value of the PSBM model, the more efficient the decision-making unit as a whole. For comparison, the overall efficiency values were calculated based on the SBM and PSBM models. The correlation coefficient of the two sets of data was more than 0.991, which again showed that the new model is effective. In Table 1, nine provinces are shown to be effective overall: Beijing, Tianjin, Shanghai, Hainan, Tibet, Shaanxi, Qinghai, Ningxia, and Xinjiang. Among these areas, Tianjin, Shanghai, and Beijing have well-developed economies. They have focused on economic development and considered environmental protection. In Hainan, tourism is a main industry for development, and environmental protection is done well. Tibet, Qinghai, Ningxia, Shaanxi, and Xinjiang belong to the western region. Industry there is not developed well, so pollution is low. The lowest overall efficiency is in Shanxi province, where overall efficiency is less than 0.372, suggesting that the province has a lot of room to improve. Table 1 also shows that most of the provinces' overall efficiency values are below 0.8 and the mean is 0.704. This indicates that China's overall efficiency is not high, and socio-economic development in the future should focus on improving environmental efficiency.

Nine regions have effective fixed assets: Beijing, Tianjin, Shanghai, Hainan, Tibet, Shaanxi, Qinghai, Ningxia, and Xinjiang. Beijing, Tianjin, Shanghai, and Hainan are in coastal areas. Their regional economy is developed, demand for investment in fixed assets is greater, the actual total investment in fixed assets and the ideal total investment in fixed assets are the same, and the total fixed assets investment demand is greater. There is no input redundancy. Tibet, Shaanxi, Qinghai, Ningxia, and

Table 1. Results of environmental efficiency evaluation.

Region	Overall efficiency of SBM	PSBM						
		Overall efficiency	Efficiency of total regional fixed assets	Efficiency of total regional retail sales of consumer goods	Efficiency of regional GDP	Efficiency of SO_2 emission	Efficiency of NO_x emission	Efficiency of Dust emission
Beijing	1.000	1	1.000	1.000	1.000	1.000	1.000	1.000
Tianjin	1.000	1	1.000	1.000	1.000	1.000	1.000	1.000
Hebei	0.532	0.484	0.659	1.000	1.000	0.286	0.370	0.105
Shanxi	0.443	0.372	0.492	1.000	1.000	0.109	0.209	0.049
Inner Mongolia	0.680	0.652	0.946	1.000	1.000	0.393	0.427	0.495
Liaoning	0.424	0.432	0.338	1.000	1.000	0.230	0.444	0.147
Jilin	0.414	0.414	0.427	1.000	1.000	0.237	0.299	0.107
Heilongjiang	0.441	0.425	0.481	1.000	1.000	0.251	0.306	0.086
Shanghai	1.000	1	1.000	1.000	1.000	1.000	1.000	1.000
Jiangsu	0.766	0.795	0.876	1.000	1.000	0.593	0.990	0.516
Zhejiang	0.609	0.674	0.637	1.000	1.000	0.533	0.750	0.452
Anhui	0.537	0.532	0.600	1.000	1.000	0.368	0.501	0.189
Fujian	0.551	0.634	0.463	1.000	1.000	0.554	0.792	0.363
Jiangxi	0.640	0.630	0.813	1.000	1.000	0.449	0.629	0.260
Shandong	0.471	0.497	0.486	1.000	1.000	0.257	0.481	0.259
Henan	0.464	0.452	0.436	1.000	1.000	0.246	0.385	0.193
Hubei	0.437	0.460	0.531	1.000	1.000	0.186	0.354	0.231
Hunan	0.523	0.561	0.483	1.000	1.000	0.380	0.694	0.249
Guangdong	0.759	0.795	0.906	1.000	1.000	0.630	0.708	0.728
Guangxi	0.548	0.558	0.591	1.000	1.000	0.352	0.623	0.223
Hainan	1.000	1	1.000	1.000	1.000	1.000	1.000	1.000
Chongqing	0.744	0.771	0.861	1.000	1.000	0.442	0.868	0.685
Sichuan	0.624	0.654	0.690	1.000	1.000	0.396	0.867	0.318
Guizhou	0.718	0.708	0.982	1.000	1.000	0.274	0.523	0.763
Yunnan	0.706	0.685	0.951	1.000	1.000	0.413	0.625	0.438
Tibet	1.000	1	1.000	1.000	1.000	1.000	1.000	1.000
Shaanxi	1.000	1	1.000	1.000	1.000	1.000	1.000	1.000
Gansu	0.650	0.633	0.865	1.000	1.000	0.311	0.442	0.546
Qinghai	1.000	1	1.000	1.000	1.000	1.000	1.000	1.000
Ningxia	1.000	1	1.000	1.000	1.000	1.000	1.000	1.000
Xinjiang	1.000	1	1.000	1.000	1.000	1.000	1.000	1.000
Mean	0.699	0.704	0.759	1.000	1.000	0.545	0.687	0.529

Data were collected from the China Statistical Yearbook of 2012, provincial (regional) Statistical Yearbook of 2012 and some Statistics Surveys.

Xinjiang are in the western region, where the actual total investment in fixed assets is less. There is no input redundancy. Liaoning's total fixed asset investment efficiency value is the minimum at only 0.338. This indicates that Liaoning has great potential to improve the efficiency of its total investment in fixed assets. The efficiency value of the total investment in fixed assets in most provinces is less than 0.8 and the mean is only 0.759. This indicates the low efficiency of China's total investment in fixed assets. The efficiency value of total retail sales of consumer goods in each province is 1; this may be because the government has many preferential policies to encourage consumption, so the regional total retail sales of consumer goods are not redundant. The GDP efficiency values of the provinces are 1. This may be because potential GDP has been realized in the existing production conditions, so that there is no output abundance.

In terms of sulfur dioxide emissions, there are seven effective areas: Beijing, Shanghai, Hainan, Tibet, Qinghai, Ningxia, and Xinjiang. The lowest efficiency value for sulfur dioxide emissions is in Shanxi Province, where the efficiency value is only 0.109. This may be associated with the province's long-standing coal production and coal-fired power. The efficiency values for sulfur dioxide emissions in most of the provinces are less than 0.60 and the average efficiency value is only 0.545. Designing models for environment policies will impact the effectiveness of environmental management significantly [21]. In order to achieve effective sulfur dioxide emissions, the relevant local governments should create appropriate environmental regulation policies. Analogously, we can analyze the other undesirable factors. The average efficiency value of NO_x emission is only 0.687 and the average efficiency value of dust emission is only 0.529. From these results, we can know the worst performance of undesirable outputs is dust emission. This is consistent with the widespread phenomenon of heavy pollution hazy in almost half of Chinese cities in recent years.

Based on the above analysis of the data results, we can find that the overall environmental efficiency of most provinces and cities has much room for improvement. Moreover, the efficiencies of total fixed asset investment and undesirable outputs, sulfur dioxide emissions, NO_x, and Dust, are not ideal. Each province and city should focus on economic development and at the same time pay more attention to the development of relevant environmental protections.

Discussion of Results

Based on the traditional efficiency evaluation model considering undesirable outputs, this paper proposes a new environmental efficiency evaluation PSBM model. This model not only calculates the overall environment efficiency of DMUs but also gives the efficiency value of inputs, desirable outputs, and undesirable outputs, respectively, which can provide managers with more abundant decision-making information. The case study shows that the model calculation process is easy to understand. The correlation coefficient of calculation results and SBM evaluation results is higher than 0.991, and the calculated results and reality are also highly consistent. This verifies the effectiveness of the new model. Our model will provide a more powerful tool for quantitatively evaluating and analyzing environmental efficiency.

The most important feature of the PSBM model is that it considers all aspects of environmental efficiency, rather than only the overall environmental efficiency. Therefore, it can excavate more useful statistical information from the same amount of indicator data and provide quantitative support for environmental management. However, the new model does not consider the characteristics of the evaluation indicators. For example, we need to determine how to use or extend the PSBM model to evaluate environmental efficiency when some indicator data is integer-based. In addition, we need to determine how to expand the PSBM model to address the phenomenon of the smaller number of DMUs in the environmental efficiency evaluation. Moreover, when more annual data are considered, we need to determine how to investigate the change in environmental efficiency in China. These issues are interesting and we suggest them as avenues for future research.

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