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Environmental Efficiency Evaluation of China Based on a Kind of Congestion and Undesirable Output Coefficient

Summary: The production "congestion" phenomenon is widespread in reality although few models nowadays consider its influences. In this study, production congestion is introduced into an environmental efficiency evaluation model and a new data envelopment analysis model that considers both production congestion and undesirable output is established so as to measure environmental efficiency evaluation effectively. On this basis, we divide technological change into productive technological change and energy-savings emission-reduction technological change to establish their influences on the congestion phenomenon. The results show that productive technological change cannot relieve the degree of congestion while green technology change that stimulates environmental efficiency improvement can greatly alleviate situations of congestion.

Key words: Congestion, Technological change, Data envelopment analysis (DEA), Environmental efficiency.

JEL: C82, Q56.

In recent decades, the economies of some developing countries have experienced rapid development, resulting in serious environmental pollution. In China, many local governments have taken measures to solve environmental pollution problems, such as building pollution treatment facilities. However, industrial pollution reduction cannot depend solely on last-period treatment because this aggravates enterprises' burdens and prevents improved environmental quality at sources. If undesirable outputs such as wastewater and exhaust gas could be reduced effectively during rather than at the end of the production process, then production efficiency, economic profits, and efficiency of sustainable environmental protection would improve. Thus, it is imperative to develop new production techniques and promote clean production to restrain environmental pollution through constructing an environmentally efficient evaluation system that effectively considers undesirable outputs.

This study applies directed technological change (DTC) theory to solve the congestion phenomenon and establish the optimal input and output adjustment method to realize maximum output by the slightest change of input. We set up a DEA model taking account of the congestion phenomenon to realize the objective of optimal output from the perspective of the weakest relevance between input and output.

1. Literature Review

In most cases, the quantities of desirable and undesirable outputs are highly positively related in production processes. To guarantee that undesirable outputs are controlled within a nominal range, it is necessary to turn a part of production inputs to treatment of undesirable outputs so that the quantity of undesirable outputs could be reduced. In addition, it is necessary to increase production inputs to reduce undesirable outputs but in this case, desirable outputs would not be increased. Instead, a "congestion" phenomenon would appear and consequently, the maximum output could not be realized because of reduction of outputs. The congestion phenomenon reflects incidence relations among each kind of input or output. As the fourth return-to-scale status besides increasing, decreasing, and constant returns to scale, the congestion phenomenon has aroused ongoing attention from many scholars. For environmental protection and the promotion of clean production, it is essential for managers of enterprises to find ways to reduce maximally the inputs and waste of resources resulting from the congestion phenomenon while increasing desirable outputs when making efforts to reduce undesirable outputs.

Then, is technological change the only factor that can relieve the congestion phenomenon? Currently, there is not much literature researching such a problem. The existing literature mainly focuses on the influences of technological change on production efficiency and the efficiency of energy savings and emissions reduction. For example, a series of papers written by Daron Acemoglu (2003, 2007) and Acemoglu et al. (2012) have made significant contributions to develop and improve theories about technological change in energy savings and emissions reduction, named DTC. Under the DTC theoretical framework, technological change is not only uncontrolled but is "directed" as well. Some scholars (Surender Kumar 2006; Peng Zhou, Beng Wah Ang, and Kim Leng Poh 2008; Dong-hyun Oh 2010) measured DTC based on a data envelopment analysis (DEA) model that has developed significantly since its appearance in 1978. Rolf S. Färe, Shawna Grosskopf, and C. A. Knox Lovell (1985) first applied an extended DEA model to the environmental evaluation of the congestion phenomenon but failed to solve incidence relations among desirable outputs, undesirable outputs, and inputs.

Färe and Leif Svensson (1980) first defined the congestion phenomenon of production and showed that it is long term. Some scholars undertook deep analyses from a mathematical economics perspective and constructed a series of models based on the DEA method (Färe and Grosskopf 1983; Färe, Grosskopf, and Lovell 1985). Then, research was extended further and applied by William W. Cooper, Russell G. Thompson, and Robert M. Thrall (1996), Cooper, Lawrence M. Seiford, and Joe Zhu (2000), Cooper, Bisheng Gu, and Shanling Li (2001), and Cooper, Seiford, and Kaoru Tone (2007). However, these models were used mostly to measure the loss of production efficiency resulting from the congestion phenomenon during production processes, and were not used for research from the angle of undesirable outputs.

The awakening of consciousness on environmental protection in recent years has made researchers include pollutant emissions and environmental quality into analyses; how to measure the loss of production efficiency resulting from pollution (undesirable output) has become a hot research topic. Because undesirable output does not satisfy the basic assumption of “reducing inputs while increasing outputs”, many scholars have resorted to the following three kinds of methods for further research. The first is to take undesirable outputs as inputs. This method can realize the goal of minimizing undesirable outputs but it cannot fully reflect real production (Seiford and Zhu 2002). The second method is first, to carry out data transformation of undesirable outputs and then, to use classical DEA efficiency models to evaluate environmental efficiency; this is a better method than the first one but the transformed data have no real practical meaning (Zhongsheng Hua, Yiwen Bian, and Liang Liang 2007). The third method puts forward a weak disposability hypothesis that considers undesirable outputs instead of a strong disposability hypothesis. Under this hypothesis, undesirable outputs can be reduced but at the cost of reduction of desirable outputs (Färe and Grosskopf 2003). Recently, much relevant research has been carried out using the third method. In order to achieve both an increase of desirable outputs and a reduction of undesirable outputs, Färe, Grosskopf, and Francesc Hernandez-Sancho (2004) constructed a distance function that can meet a series of ideal features when evaluating environmental performance. Färe, Grosskopf, and Carl A. Pasurka Jr. (2007) compared an environmental production function, which considers only increasing desirable outputs, and a directional environmental distance function, which simultaneously considers the increase of desirable outputs and the reduction of undesirable outputs. Then, they carried out a technical efficiency evaluation and calculated the cost of emissions reduction. Thereafter, an undesirable output model was put forward by Finn R. Førsund (2009) considering pollution and multi-output variables, and an extended DEA model by Toshiyuki Sueyoshi and Mika Goto (2011) was used to measure returns to scale of desirable outputs and damages to scale of undesirable outputs simultaneously.

The issue of how to reduce pollutant emissions maximally without a reduction of output is a problem for many scholars. Acemoglu et al. (2012) tried to solve the issue from an economic perspective by establishing endogenous growth models assuming that clean technology and pollutive technology (i.e., productive technology) compete with each other. The more clean technology costs, the less pollutive technology costs. This theoretically proved the existence of the congestion phenomenon and was the first to combine it with DTC theory. It was also proved that it is feasible to relieve production congestion through DTC. On this basis, Acemoglu et al. (2014) introduced DTC into environmentally restricted and resource-limited growth models and analyzed the costs and profits of both clean and pollutive technologies under different environmental policies. Moreover, they investigated the influences of DTC on costs and time for CO_2 emissions reduction from an angle of output. Mads Greaker and Tom-Reiel Heggedal (2012) considered that clean technology would be effective in the long term, and thus, detracted from the argument for excessive subsidies for research and development of clean technology suggested by Acemoglu et al. (2014).

Nevertheless, the abovementioned research carried out congestion analysis only theoretically and without properly measuring congestion. Then, the key to such research becomes the avoidance of congestion to the greatest extent by measuring the efficiency loss resulting from congestion during the production phase and energy-savings and emissions reduction phase. Moreover, earlier research carried out congestion analysis on inputs and outputs without discussing the incidence relations between inputs and inputs or between outputs and outputs. Hence, some of their conclusions are probably inaccurate. This study develops a new DEA model to consider congestion and undesirable outputs (CUODEA) to gain more accurate evaluation results.

2. Model Construction

Measuring performance of decision-making units (DMUs) by the DEA approach has been accepted widely. However, in reality, desirable outputs are often accompanied by unexpected by-products, that is, undesirable outputs. Undesirable outputs can negatively affect production efficiency because they would be increased in the pursuit of the maximization of desirable outputs, which differs from our objective of maximizing desirable outputs and minimizing undesirable outputs. Usually, there is productive dependency between desirable outputs and undesirable outputs. In practice, environmental pollution results from the inevitable discharge of pollutants during the production of desirable outputs. In the extreme, if undesirable outputs were to trend toward zero, the corresponding desirable outputs would trend toward zero as well.

In order to evaluate environmental efficiency considering the production congestion problem, we define X as an input and Z as undesirable outputs. Then, the production possibility set (PPS) is shown in Figure 1.

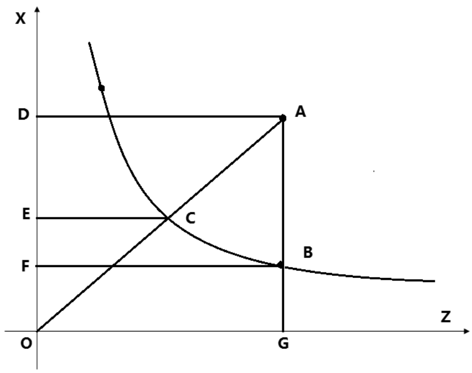

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Figure 1 Production Congestion Phenomenon and Undesirable Outputs

In Figure 1, DMUs B and C are located at the production frontier while DMU A is not. The production efficiency evaluation of the classical DEA radial model for DMU A can be expressed as follows:

$$\theta = \frac{OC}{OA}. \tag{1}$$

At this time, the input redundancy of DMU A is DE (see Figure 1). Considering that Z represents undesirable outputs, comparing DMUs A and B is meaningful because this considers which inputs have less equal undesirable outputs. Compared with this method, DMU A's input redundancy is DF.

Then, we define input and output indexes of the CUODEA model as follows.

Input $x_j = \left(x_{1j}, x_{2j}, ..., x_{mj}\right)$ is the m - dimension vector, desirable output $y_j = \left(y_{1j}, y_{2j}, ..., y_{s_1 j}\right)$ is the s_1- dimension vector, and undesirable output $z_j = \left(z_{1j}, z_{2j}, ..., z_{s_2 j}\right)$ is the s_2- dimension vector.

The production possibility set is:

$$T = \{(\hat{x}, \hat{y}, \hat{z}) | \hat{x}_i \geq \sum_j \lambda_j x_{ij}, i = 1,2,...,m; \hat{y}_r \leq \sum_j \lambda_j y_{rj}, r = 1,2,...,s_1, \hat{z}_k \leq \sum_j \lambda_j z_{kj}, k = 1,2,...,s_2; \lambda_j \geq 0\}$$

The overall efficient set is:

$$T^{eff} = \left\{ \begin{array}{l} (\hat{x}, \hat{y}, \hat{z}) \in T \,\middle|\, \forall (\overline{x}, \overline{y}, \overline{z}) \in T,\ \ if: \overline{x} \leq \hat{x} \text{ and } \overline{y} \geq \hat{y} \text{ and } \overline{z} \leq \hat{z}, \\ \text{there will be } (\overline{x}, \overline{y}, \overline{z}) = (\hat{x}, \hat{y}, \hat{z}) \end{array} \right\}$$

The lock undesirable output efficient set is:

$$T_z^{eff} = \left\{ \begin{array}{l} (\hat{x}, \hat{y}, \hat{z}) \in T \,\middle|\, \forall (\overline{x}, \overline{y}, \overline{z}) \in T,\ \ if: \overline{x} \leq \hat{x} \text{ and } \overline{y} \geq \hat{y} \text{ and } \overline{z} = \hat{z}, \\ \text{there will be } (\overline{x}, \overline{y}, \overline{z}) = (\hat{x}, \hat{y}, \hat{z}) \end{array} \right\}$$

The lock input efficient set is:

$$T_x^{eff} = \left\{ \begin{array}{l} (\hat{x}, \hat{y}, \hat{z}) \in T \,\middle|\, \forall (\overline{x}, \overline{y}, \overline{z}) \in T,\ \ if: \overline{x} = \hat{x} \text{ and } \overline{y} \geq \hat{y} \text{ and } \overline{z} \leq \hat{z}, \\ \text{there will be } (\overline{x}, \overline{y}, \overline{z}) = (\hat{x}, \hat{y}, \hat{z}) \end{array} \right\}$$

Then, the efficiency evaluation formula considering production congestion and undesirable output would be:

$$\theta^* = \frac{\theta_1 + \theta_2 + \theta_3}{3}. \tag{2}$$

In Equation (2), θ^* is the congestion and undesirable output (CUO) coefficient. The smaller θ^* is, the more obvious is the congestion phenomenon.

Three steps can be taken to calculate the value of θ^*. They are shown as follows.

Step 1: Calculate the value of θ_1 by classical DEA model, taking undesirable outputs as inputs. The formula is:

$$
\begin{aligned}
&\min \theta_1 = \theta - \varepsilon\left(\sum s_i^x + \sum s_r^y + \sum s_i^z\right) \\
&s.t.\ \sum_{j=1}^{n} \lambda_j x_{ij} = \theta x_{i0} - s_i^x,\ i = 1,2,\ldots,m \\
&\sum_{j=1}^{n} \lambda_j y_{ij} = y_{i0} + s_i^+,\ i = 1,\ldots,s_1 \\
&\sum_{j=1}^{n} \lambda_j z_{ij} = \theta z_{i0} - s_i^z,\ i = 1,2,\ldots,s_2 \\
&\lambda_j \geq 0,\ j = 1,\ldots,n \\
&s_i^x, s_i^y, s_i^z \geq 0\,.
\end{aligned} \tag{3}
$$

Step 2: Add constraint $\sum_{j=1}^{N} \lambda_j z_{ij} = z_{i0}$ ($i = 1, 2, \ldots, s_2$) and analyze production efficiency under the same undesirable output condition. The formula is:

$$
\begin{aligned}
&\min \theta_2 = \theta - \varepsilon\left(\sum s_i^x + \sum s_r^y\right) \\
&s.t.\ \sum_{j=1}^{n} \lambda_j x_{ij} = \theta x_{i0} - s_i^x,\ i = 1,2,\ldots,m \\
&\sum_{j=1}^{n} \lambda_j y_{ij} = y_{i0} + s_i^y,\ i = 1,\ldots,s_1 \\
&\sum_{j=1}^{n} \lambda_j z_{ij} = z_{i0},\ i = 1,2,\ldots,s_2 \\
&\lambda_j \geq 0,\ j = 1,\ldots,N \\
&s_i^x, s_i^y \geq 0\,.
\end{aligned} \tag{4}
$$

Step 3: Add constraint $\sum_{j=1}^{N} \lambda_j x_{ij} = x_{i0}$ ($i = 1, 2, \ldots, m$) and analyze the degree of reduction of undesirable outputs under the same input condition. The formula is:

$$
\begin{aligned}
&\min \theta_3 = \theta - \varepsilon\left(\sum s_i^y + \sum s_r^z\right) \\
&s.t.\ \sum_{j=1}^{n} \lambda_j x_{ij} = x_{i0},\ i = 1,2,\ldots,m \\
&\sum_{j=1}^{n} \lambda_j y_{ij} = y_{i0} + s_i^y,\ i = 1,\ldots,s_1 \\
&\sum_{j=1}^{n} \lambda_j z_{ij} = \theta z_{i0} - s_i^z,\ i = 1,2,\ldots,s_2 \\
&\lambda_j \geq 0,\ j = 1,\ldots,N \\
&s_i^y, s_i^z \geq 0\,.
\end{aligned} \tag{5}
$$

Proposition 1: (x_0, y_0, z_0) locks undesirable output efficient when and only when $\theta = 1$, $s_i^x = 0, s_i^y = 0$ for linear program (5):

Proof:

(1) If $\theta = 1$, $s_i^x = 0, s_i^y = 0$, (x_0, y_0, z_0) locks undesirable output efficient.

If (x_0, y_0, z_0) is undesirable output inefficient, according to the definition of lock, there would be $(\overline{x}, \overline{y}, \overline{z}) \in T$, $\overline{x} \le \hat{x}$, $\overline{y} \ge \hat{y}$, and $\overline{z} = \hat{z}$. One of the two inequalities would be strictly correct. Because $(\overline{x}, \overline{y}, \overline{z}) \in T$ and $\overline{z} \le \hat{z}$, there would be λ_1^*, $\lambda_2^*, \cdots,$ λ_N^*, which results in:

$$\begin{aligned}
&\sum_{j=1}^{N} \lambda_j^* x_{ij} \le \overline{x}_i \quad i = 1,2,...,m \\
&\sum_{j=1}^{N} \lambda_j^* y_{ij} \ge \overline{y}_i \quad i = 1,2,...,s_1 \\
&\sum_{j=1}^{N} \lambda_j^* z_{ij} = \overline{z}_i = z_{i0} \quad i = 1,2,...,s_2 \\
&\lambda_j^* \ge 0 \quad j = 1,2,...,N.
\end{aligned} \tag{6}$$

Moreover, there are $\overline{x} \le \hat{x}$ and $\overline{y} \ge \hat{y}$ (one of the two inequalities is strictly correct). Therefore,

$$\begin{aligned}
&\sum_{j=1}^{N} \lambda_j^* x_{ij} \le x_{i0} \quad i = 1,2,...,m \\
&\sum_{j=1}^{N} \lambda_j^* y_{ij} \ge y_{i0} \quad i = 1,2,...,s_1 \\
&\sum_{j=1}^{N} \lambda_j^* z_{ij} = z_{i0} \quad i = 1,2,...,s_2 \\
&\lambda_j^* \ge 0 \quad j = 1,2,...,N.
\end{aligned} \tag{7}$$

In addition, one of the first two inequalities is strictly correct, that is, $\theta = 1$, $s_i^x = 0, s_i^y = 0$. Therefore, (x_0, y_0, z_0) locks undesirable output efficient.

(2) If $\theta \ne 1$ or $s_i^x \ne 0$ or $s_i^y \ne 0$, then (x_0, y_0, x_0) locks undesirable output inefficient.

As per the definition, we know that $(\theta x_0 \text{-} s_i^x, y_0 + s_i^y, z_0) \in T$, if $\theta \ne 1$ or $s_i^x \ne 0$ or $s_i^y \ne 0$, then $(\theta x_0 \text{-} s_i^x, y_0 + s_i^y, z_0) \ne (x_0, y_0, z_0)$. As per the definition of T_z^{eff}, we know that (x_0, y_0, z_0) locks undesirable output inefficient.

Proposition 2: $T^{eff} = T_z^{eff} \cap T_x^{eff}$.

Proof:

$\forall(\hat{x}, \hat{y}, \hat{z}) \in T^{eff}$ and $\forall(\bar{x}, \bar{y}, \bar{z}) \in T$. If $\bar{x} \le \hat{x}$, $\bar{y} \ge \hat{y}$ and $\bar{z} = \hat{z}$, from the definition of T^{eff} , we know that $(\bar{x}, \bar{y}, \bar{z}) = (\hat{x}, \hat{y}, \hat{z})$, which satisfies the definition of T_z^{eff} . Therefore, $(\hat{x}, \hat{y}, \hat{z}) \in T_z^{eff}$.

$(\hat{x}, \hat{y}, \hat{z}) \in T_x^{eff}$ can be proved in a similar way. Therefore, $T^{eff} \subset (T_z^{eff} \cap T_x^{eff})$.

$\forall(\hat{x}, \hat{y}, \hat{z}) \in (T_z^{eff} \cap T_x^{eff})$ and $\forall(\bar{x}, \bar{y}, \bar{z}) \in T$, if $\bar{x} \le \hat{x}$, $\bar{y} \ge \hat{y}$, and $\bar{z} \le \hat{z}$, then, there would be $(\bar{x}, \bar{y}, \hat{z}) \in T$. From the definition of T_z^{eff} , we know that $(\bar{x}, \bar{y}, \hat{z}) = (\hat{x}, \hat{y}, \hat{z})$. Therefore, $\bar{x} = \hat{x}$ and $\bar{y} \ge \hat{y}$, $\bar{z} \le \hat{z}$. Furthermore, from the definition of T_x^{eff} , we know that $(\bar{x}, \bar{y}, \bar{z}) = (\hat{x}, \hat{y}, \hat{z})$, which satisfies the definition of T^{eff} . Therefore, $(\hat{x}, \hat{y}, \hat{z}) \in T^{eff}$.

3. Chinese Industrial Wastewater Treatment Efficiency

In this section, we analyze the degree of congestion of industrial water consumption in each province of China by using the CUODEA model constructed in Section 2. For simplicity, we research only conditions during the treatment of wastewater. In this phase, water circulation, as the basic requirement for wastewater treatment, must make treated wastewater as recyclable as possible. In fact, only partial wastewater can reach recycling standards. We take gross water consumption and wastewater treatment facilities as inputs, gross industrial production as desirable output, and total amount of sub-standard wastewater discharge as undesirable output. When the input of gross water consumption increases, the output of industrial products increases and gross industrial production is higher; when the quantity of wastewater treatment facilities increases, the amount of sub-standard wastewater discharge decreases but gross industrial production is not increased. Then, there would be conditions that inputs increase while outputs do not, that is, the congestion phenomenon.

As per the data in each year's China Statistical Yearbook and the China Environmental Statistical Yearbook from 2001 to 2014, we select total industrial water consumption and quantity of wastewater treatment facilities as input indexes; gross industrial production as a desirable output index; and total discharged wastewater as an undesirable output index. For simplicity, we take input and output data in 2010 as an example and calculate the efficiency value of CUODEA. Specific data are shown in Table 1 and the CUO coefficients are shown in Table 2.

Table 1 Values of Input and Output Indexes

Area	Total water consumption	Quantity of waste water treatment facilities	GDP	Total discharged industrial waste water	Under-standard waste water discharge
	X1	X2	Y	Z	Z1
Beijing	5.20	514	2693.15	8367	43633
Tianjin	3.81	875	3821.07	20433	17667
Hebei	25.22	5822	8777.42	121172	131028
Shanxi	13.47	2797	4265.77	41150	93550
Inner Mongolia	20.46	836	4271.03	29167	175433
Liaoning	24.66	1822	7512.11	83073	163527
Jilin	19.27	629	3064.63	38353	154347
Heilongjiang	57.55	990	4365.90	38910	536590
Shanghai	79.56	1790	6235.92	41871	753729
Jiangsu	209.40	6469	16663.81	259999	1834001
Zhejiang	61.03	7630	11580.33	200488	409812
Anhui	85.40	1795	4137.35	67007	786993
Fujian	75.44	4196	5415.77	139997	614403
Jiangxi	59.92	1767	3414.88	68681	530519
Shandong	24.69	4590	17702.17	176977	69923
Henan	51.40	3211	10477.92	133144	380856
Hubei	96.98	2050	4963.61	93687	876113
Hunan	82.04	3149	4933.08	92340	728060
Guangdong	137.19	9968	18402.64	213314	1158586
Guangxi	51.70	2552	3037.74	205745	311255
Hainan	4.90	293	434.40	5991	43009
Chongqing	45.98	1550	2433.27	67027	392773
Sichuan	57.74	4757	5790.10	108700	468700
Guizhou	33.75	1798	1408.71	11695	325805
Yunan	22.11	2032	2451.09	32996	188104
Tibet	1.32	13	115.76	924	12276
Shanxi	12.87	2780	3842.08	48477	80223
Gansu	13.07	747	1471.43	16405	114295
Qinghai	7.805	148	529.40	7098	71402
Ningxia	3.33	380	581.24	20448	12852
Xinjiang	9.78	775	2086.74	22875	74925

Source: China Statistical Yearbook (2011)[1].

[1] **National Bureau of Statistics of China.** 2011. *China Statistical Yearbook*. Beijing: China Statistics Press.

Table 2 CUODEA Efficiency Values

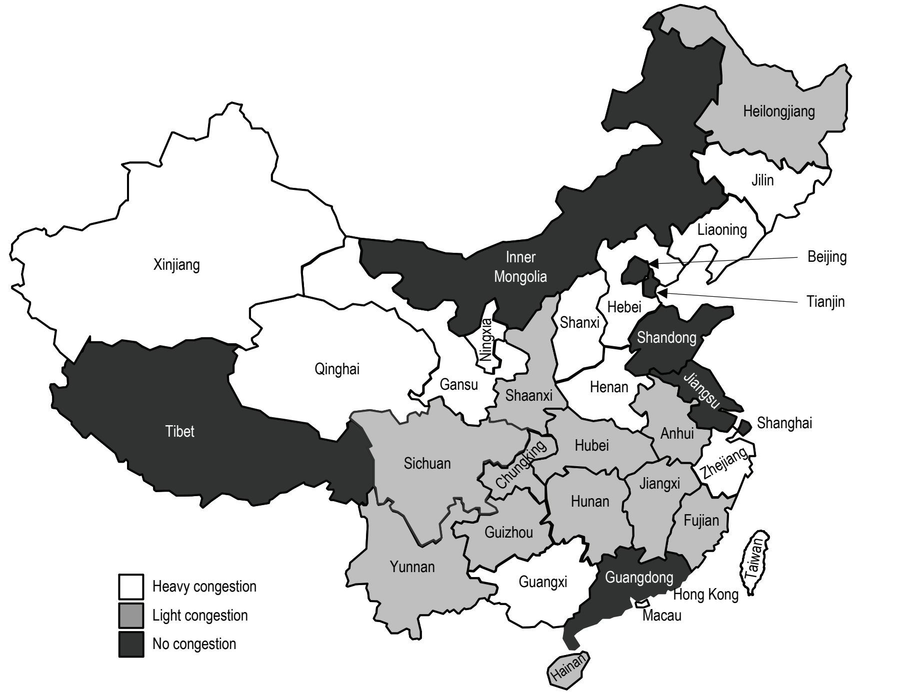
DMU	θ_1	θ_2	θ	DMU	θ_1	θ_2	θ
Beijing	1.000	1.000	1.000	Hubei	0.613	0.576	0.913
Tianjin	1.000	1.000	1.000	Hunan	0.510	0.393	0.807
Hebei	0.737	0.496	0.522	Guangdong	1.000	1.000	1.000
Shanxi	0.834	0.416	0.284	Guangxi	1.000	0.292	0.000
Inner Mongolia	1.000	1.000	1.000	Hainan	0.288	0.279	0.988
Liaoning	1.000	0.963	0.000	Chongqing	0.422	0.356	0.898
Jilin	1.000	0.941	0.000	Sichuan	0.428	0.327	0.850
Heilongjiang	0.912	0.905	0.926	Guizhou	0.245	0.183	0.924
Shanghai	0.812	0.812	1.000	Yunnan	0.303	0.287	0.978
Jiangsu	0.929	0.929	1.000	Tibet	1.000	1.000	1.000
Zhejiang	1.000	0.646	0.000	Shanxi	0.465	0.390	0.877
Anhui	0.539	0.537	0.996	Gansu	0.818	0.393	0.300
Fujian	0.355	0.332	0.966	Qinghai	1.000	0.653	0.000
Jiangxi	0.484	0.449	0.936	Ningxia	1.000	0.313	0.000
Shandong	1.000	1.000	1.000	Xinjiang	1.000	0.557	0.000
Henan	0.876	0.821	0.693				

Source: China Statistical Yearbook (2011) and China Environmental Statistical Yearbook (2011)[2].

Provinces in which CUO coefficients are one are defined as efficient provinces without production congestion. In these areas, undesirable outputs generated from production activities are reduced to the minimal level compared with other provinces; provinces in which CUO coefficients are in the range of 0.8 to 1 are defined as provinces with little production congestion; and provinces in which CUO coefficients are lower than 0.8 are defined as provinces with severe production congestion. For a visual reference, refer to Figure 2 for the distribution of provinces with different levels of production congestion.

In Figure 2, areas without production congestion are in dark color, areas with little production congestion are in light color, and areas with severe production congestion are in white. Economic and technological levels in the areas of Beijing, Tianjin, Shandong, Jiangsu, Shanghai, and Guangdong are comparatively high. Therefore, relations between production and environment can be handled well in those areas, which results in high CUO coefficients. Production capacities in the areas of Inner Mongolia and Tibet are so low that there is little pollution there. Hence, they have high CUO coefficients and belong to the category of provinces without production congestion. Although the areas of Liaoning, Jilin, Guangxi, Zhejiang, and Qinghai are located on the production frontier, their environmental protection efficiencies are not high, which places them in the category of provinces with severe production congestion. Generally, other provinces with little production congestion are located in central and southern China, resulting from weak awareness of environmental protection in many medium and small enterprises there. These conclusions are consistent with the reality in China.

[2] **National Bureau of Statistics of China and Ministry of Environmental Protection of China.** 2011. *China Environmental Statistical Yearbook*. Beijing: China Statistics Press.



Source: Made by authors of this article.

Figure 2 Distribution of Provinces in China with Different Levels of Production Congestion

In this study, we construct a CUO coefficient measurement model as follows:

$$CUO_{it} = \alpha_0 + \alpha_1 TFP_{it} + \alpha_2 DDF_{it} + \alpha_3 PF_{it} + \alpha_4 DDF_{it} / TFP_{it} + \alpha_5 RD_{it} + \varepsilon. \tag{8}$$

In Equation (8), CUO refers to the coefficient of the congestion effect; TFP refers to total factor productivity; DDF refers to a green technology progress rate; PF refers to pollutant emission treatment fees; DDF/TFP refers to pollution intensity; RD refers to research and development intensity; i refers to province or city; and t refers to time.

TFP represents productive technological change. We use a DEA–Malmquist method for our calculation. As per the Solow model, capital stock and year-end employment quantity are selected as input indexes for each province or city and industrial added value is selected as the output index. DDF represents technological change considering environmental factors. As per the directional distance function put forward by Färe and Grosskopf (2010), we set up a Malmquist–Luenberger productivity function, which makes it possible to measure technological change. Different from the selection of TFP indexes, the quantity of wastewater treatment facilities is added as an input index and wastewater discharge quantity is added as an undesirable output index. PF expresses the production cost of each industrial sector. The ratio of costs for the treatment of waste gas, wastewater, and solid waste pollutants in each province or city to the total income of each province or city is taken as an index of pollutant emissions treatment fees to measure the cost configuration between production and pollutant emissions treatment in each province or city. We use DDF/TFP to represent the functions of energy-savings and emissions reduction technology on production. The higher the DDF/TFP is, the stronger are the features of energy savings and emissions reduction. Hence, this index can be used to represent pollutant emissions intensity. The RD index is represented by comparing the research and development expenses of each province or city stated in each year's China Scientific Statistical Yearbook with the gross production value of a certain industry in the province or city. Data used in this model come from the China Statistical Yearbook, China Scientific Statistical Yearbook, China Environmental Statistical Yearbook, and China Industrial Statistical Yearbook for each year of 2001 to 2014. We analyze 14 years of data for 30 areas during the period 2000 to 2013. The estimation results of the empirical tests are shown in Table 3.

Table 3 Model Analysis about Technological Change and "Congestion"

Index	OLS estimation	FE	RE	Differential GMM	Systematic GMM
C	0.154*** (3.264)	0.102*** (11.544)	0.101*** (12.547)	0.188*** (14.111)	0.194*** (13.741)
TFP	0.412 (1.255)	0.248 (1.259)	0.224 (1.236)	0.142 (1.278)	0.166 (1.500)
DDF	0.037* (1.741)	0.212* (1.898)	0.049* (2.005)	0.065* (1.968)	0.064* (1.992)
PF	0.013* (2.201)	0.052* (2.317)	0.039* (2.141)	0.034 (1.105)	0.042 (1.640)
DDF/TFP	0.062*** (5.480)	0.071*** (4.578)	0.074*** (4.850)	0.068*** (3.841)	0.070*** (3.741)
RD	0.002** (2.690)	0.003** (2.680)	0.002*** (3.261)	0.004** (2.419)	0.004** (2.470)
Time fixed effect	*yes*	*yes*	*yes*	*yes*	*yes*
R^2	0.957	0.966	0.974	0.679	0.630
AR(2) test value				0.374	0.317
P-value				0.808	0.817
Hansen test value				9.154	9.547
P-value				1.000	1.000
Sargan test				74.256***	81.189***

Note: *, **, *** respectively refers to passing tests at 10%, 5% and 1% significance level; FE and RE respectively refers to fixed effect model and random effect model; null hypothesis of AR(2) test is that second-order lag is effective. If accepted, GMM model can be true; null hypothesis of Hansen test is that excessive identification is effective.

Source: Calculated through programming by EViews7.0.

From Table 3 we can see that productive technological change can relieve the level of congestion but the effects are not obvious. However, energy-savings and emissions reduction technological change can strongly relieve the congestion phenomenon and the estimation coefficient passes the test at the 10% significance level. We establish that the pollutant emissions intensity index can significantly enhance the ability to relieve the congestion phenomenon and the significance level of the estimation coefficient is more than 1%. Fitting the results about the ratio of pollutant emissions treatment fees and research and development intensity are comparatively significant and pass the test at the 10% significance level. This indicates that an increase of pollutant emissions treatment fees would stimulate each area to improve its rate of equipment utilization or resource allocation efficiency; in addition, an increase of research and development intensity would stimulate technological change, and regardless of productive technological change or energy-savings emissions reduction technological change, both would relieve the congestion phenomenon. Moreover, research and development intensity could more effectively alleviate the losses of production efficiency resulting from congestion than technological change.

4. Conclusions

This study reviewed relevant existing literature about environmental efficiency evaluation based on DEA and quantitative analysis of the production congestion phenomenon. Previously, undesirable outputs were taken as inputs to calculate classical efficiency values. Thereafter, constraints were changed to analyze production efficiencies under equivalent undesirable outputs and degrees of reducing undesirable outputs under equivalent input conditions. Then, a CUO coefficient that considers both production congestion and undesirable outputs was put forward, which improved the accuracy of environmental efficiency evaluation. In this study, we collected data from Chinese provinces and cities during 2000 to 2013 to conduct an overall evaluation using DTC theory to combine technological change and the congestion phenomenon.

The production congestion phenomenon has been ignored in most previous environmental efficiency evaluations, although undesirable outputs were inevitable in production processes. There are not only strong incidence relations between undesirable outputs and desirable outputs, but the production congestion phenomenon exists also between outputs and between outputs and inputs. Such a congestion phenomenon has interfered strongly with the estimation results based on traditional DEA models. By using the new DEA model constructed in this study, which simultaneously considers both the production congestion phenomenon and undesirable outputs, the degree of production congestion of DMUs can be analyzed quantitatively so as to improve the accuracy and reliability of the model estimation.

Judging from the analysis on the influences of technological change on the congestion degree, the effects of productive technological change on improving the congestion degree are not significant while energy-savings and emissions reduction technological change can do better to improve resource utilization efficiency and relieve congestion conditions. If energy-savings and emissions reduction technological change could dominate overall technological change, then the production congestion phenomenon would improve surely and significantly. Conditions that stimulate energy-savings and emissions reduction technological change include not only an increase of research and development inputs, but also, more importantly, an increase of pollutant emissions treatment fees that make enterprises choose the best solutions under strong environmental regulations. In that case, the efficiency of energy savings and emissions reduction would improve significantly and the congestion phenomenon would be relieved.

During our research, we noticed that production congestion exists widely in reality, making relations among inputs, desirable outputs, and undesirable outputs more complicated. Although this study developed a new model and quantitatively described the relations among inputs and outputs, there is further work to be done. Widespread congestion phenomena have existed for a long time in production and how to reduce pollution maximally remains a problem for yet further study. In future research, we should reevaluate those DMUs that are efficient in production but not for the environment in order to reveal their problems and find solutions. In addition, we should introduce a network analysis method to detail pollution control processes in enterprises in order to provide complicated decision-making processes with data support.

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