Environmental Efficiency Assessment of the Chinese Industrial Sector Considering Policymakers' Preferences: A Two-Stage Network SBM-DEA Approach

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Abstract: Efficiency improvements in the industrial sector are critical to the sustainable development of China's economy and the reduction of greenhouse gas (GHG) emissions. This paper extends the environmental efficiency analysis from a "black box" to a network structure, where the industrial sector is divided into industrial production and pollution treatment stages. Under the framework of cooperative game, a slack-based two-stage network DEA model considering the preferences of policymakers is introduced and the environmental efficiency of 30 provincial industrial sectors in China is evaluated for the period 2007-2015. The findings suggest that environmental efficiency is strongly influenced by policymakers' preferences and exhibits divergent effects at the regional and provincial levels. Specifically, under either weight distribution, the eastern region has the highest total efficiency, followed by the central and western regions. Inter-regional efficiency differences are mainly due to differences in the pollution treatment stage. At the provincial level, the heterogeneous effect of policymakers' preferences can be grouped into four categories. Finally, the level of coordinated development of industrial production and environmental protection in China's provinces is low, and the industrial green transformation needs to be continuously promoted.

1 INTRODUCTION

Over the past decades, the industrial sector has exhibited tremendous rapid growth and has become the primary driving force of China's economic development. However, the industrial expansion mode fueled by fossil energy has also brought about unprecedented environmental degradation (Shao et al. 2019). Moreover, as the world's largest emitter of GHG since 2006, China is under huge pressure to reduce emissions worldwide, and the industrial sector is the key to achieving these goals. Recently, President Xi Jinping has officially announced that China will spare no effort to reach peak carbon by 2030 and carbon neutrality by 2060. This task is more challenging than expected because China is still undergoing rapid industrialization and urbanization, which means that the demand for energy consumption will continue to increase for a long time (Guo et al. 2021). Therefore, a more suitable option for China is to improve environmental efficiency through technological progress and to reconcile economic growth with environmental protection.

Generally, industrial system can be divided into two interrelated stages, the production stage and the treatment stage, respectively. Weighting methods for subsystems are often used to capture the preferences of policymakers. Specifically, a higher weighting of the first stage implies that policymakers place more importance on economic growth and vice versa for environmental protection. Current studies usually assume that policymakers give equal importance to industrial production and pollution treatment, and therefore adopt a simple equal-weight distribution for the subsystem (Iftikhar et al. 2018). However, the equal weight assignment ignores the potential trade-off between economic growth and environmental protection among regions, which is inconsistent with practice and may yield misleading results. Thus, this paper attempts to fill this gap and

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make contributions in the following aspects. Firstly, a slack-based two-stage network model that considers the internal structure is proposed to provide more accurate results. Compared with traditional CCR-based models, which assume proportional changes in inputs or outputs, the slack-based DEA model is non-radial and can directly deal with input excess and output shortfall (Tone and Tsutsui 2009). Secondly, this paper attempts to set different weights for each stage to examine the impact of various preferences of policymakers on environmental efficiency.

The remainder of this paper is organized as follows. Section 2 describes a slack-based two-stage network DEA model based on the cooperative game framework. The results and discussions are presented in Section 3. Eventually, conclusions and policy implications are provided.

2 METHODOLOGY

2.1 Slack-based Two-Stage Network DEA Model

Suppose there are n DMUs, and in the first stage, the observed data on the input, desirable output and undesirable output vectors can be denoted as $X^p = (X^p{}_{1,j}...X^p{}_{i,j}...X^p{}_{mp,j}) \geq 0$, $Y^p = (Y^p{}_{1,j}...Y^p{}_{i,j}...Y^p{}_{sp,j}) \geq 0$ and $Z = (Z^p{}_{1,j}...Z^p{}_{i,j}...Z^p{}_{h,j}) \geq 0$. The outputs Z generated in the first stage are used as inputs for the second stage. Besides, there's an external input vector denoted by $X^t = (X^t{}_{1,j}...X^t{}_{i,j}...X^t{}_{mt,j})$ putting into the pollution treatment stage. The final product is represented by $Y^t = (Y^t{}_{1,j}...Y^t{}_{i,j}...Y^t{}_{st,j})$.

This paper builds on Iftikhar et al. (2018) by assuming that all variables are freely disposable. Besides, undesirable outputs in this paper are treated directly as inputs based on Hailu and Veeman (2001). All models presented in this paper are based on the SBM method proposed by Tone (2001), which has been widely used in many studies associated with energy and environmental efficiency measurements.

2.2 Environmental Efficiency Measurement Based on the Cooperative Game Framework

Referring to the seminal work of Liang et al. (2006), the environmental efficiency of the two-stage structure is calculated based on the cooperative game framework. In this approach, the total efficiency is first optimized, while the efficiency of the subsystem is derived as a offspring from the optimal solution that maximizes the efficiency of the system. The model based on the SBM approach under variable returns to scale (VRS) and free linkage assumptions is as follows.

$$\theta = \min \frac{w_p \cdot \left(1 - \frac{1}{m_p + \mathrm{h}}\left(\sum_{i=1}^{m_p} \frac{s_i^{p-}}{x_{i0}^p} + \sum_{\mathrm{k}=1}^{h} \frac{s_k^{zp-}}{z_{k0}}\right)\right) + w_t \cdot \left(1 - \frac{1}{m_t + h}\left(\sum_{i=1}^{m_t} \frac{s_i^{t-}}{x_{i0}^t} + \sum_{k=1}^{h} \frac{s_k^{zt-}}{z_{k0}}\right)\right)}{w_p \cdot \left(1 + \frac{1}{s_p}\sum_{r=1}^{s_p} \frac{s_r^{p+}}{y_{ro}^p}\right) + w_t \cdot \left(1 + \frac{1}{s_{\mathrm{t}}}\sum_{r=1}^{s_{tt}} \frac{s_r^{t+}}{y_{ro}^t}\right)} \tag{1}$$

$$s.t.\begin{cases} \sum_{j=1}^{n}\lambda_j^p \cdot x_{ij}^p + s_i^{p-} = x_{i0}^p, i = 1,...m_p \\ \sum_{j=1}^{n}\lambda_j^p \cdot y_{rj}^p - s_r^{p+} = y_{r0}^p, r = 1,...s_p \\ \sum_{j=1}^{n}\lambda_j^p \cdot z_{kj} + s_k^{zp-} = z_{k0}, k = 1,...\mathrm{h} \\ \lambda_j^p \geq 0, \sum_{j=1}^{n}\lambda_j^p = 1, \ \ j = 1,...n, \\ s_r^{p+} \geq 0, r = 1,...s_p, \ \ s_i^{p-} \geq 0, i = 1,...m_p, \ s_k^{zp-} \geq 0, k = 1,...\mathrm{h} \\ \sum_{j=1}^{n}\lambda_j^t \cdot x_{ij}^t + s_i^{t-} = x_{i0}^t, i = 1,...m_t \\ \sum_{j=1}^{n}\lambda_j^t \cdot z_{kj} + s_k^{zt-} = z_{k0}, k = 1,...\mathrm{h} \\ \sum_{j=1}^{n}\lambda_j^p \cdot y_{rj}^t - s_r^{t+} = y_{r0}^t, r = 1,...s_t \\ \lambda_j^t \geq 0, \sum_{j=1}^{n}\lambda_j^t = 1, \ \ j = 1,...n, \\ s_i^{t-} \geq 0, i = 1,...m_t, \ \ s_k^{\mathrm{z}t-} \geq 0, k = 1,...h, \ s_r^{t+} \geq 0, r = 1,...s_t \\ \sum_{j=1}^{n}\lambda_j^p \cdot z_{kj} - \sum_{j=1}^{n}\lambda_j^t \cdot z_{kj} = 0, k = 1,...\mathrm{h} \end{cases} \tag{2}$$

Where s_i^{p-}, s_r^{p+} and s_k^{zp-} are slacks of inputs, outputs, and undesirable outputs in production stage, respectively. s_i^{t-}, $s_k^{\mathrm{z}t+}$ and s_b^{ut-} are slacks of inputs, intermediate variables, and undesirable outputs in treatment stage, respectively. Besides, λ_j^p and λ_j^{t} are intensity variable for production and treatment stage, respectively. w_p and w_t are the weights of individual stages with respect to its importance, which satisfy the constraints: $w_p + w_t = 1$. Based on the total efficiency, the production efficiency and the treatment efficiency can be defined as θ^p and θ^t.

The efficiency of production stage:

$$\theta^p = \frac{\left(1 - \frac{1}{m_p + \mathrm{h}}\left(\sum_{i=1}^{m_p} \frac{s_i^{p-}}{x_{i0}^p} + \sum_{\mathrm{k}=1}^{h} \frac{s_k^{z-}}{z_{k0}}\right)\right)}{1 + \frac{1}{s_p}\sum_{r=1}^{s_p} \frac{s_r^{p+}}{y_{r0}}} \tag{3}$$

The efficiency of treatment stage:

$$\theta^t = \frac{1-\frac{1}{m_t+h}\left(\sum_{i=1}^{m_t}\frac{s_i^{t-}}{x_{i0}^t}+\sum_{k=1}^{h}\frac{s_k^{z-}}{z_{k0}}\right)}{1+\frac{1}{s_t}\left(\sum_{r=1}^{s_t}\frac{s_i^{t+}}{y_{r0}^t}\right)} \qquad (4)$$

2.3 Variables and Data

2.3.1 Input-Output Variables

Figure 1 illustrates the operational mechanism of the two-stage network DEA model for industrial system. X_1 denotes the input variables of industrial production, including labor, capital, and energy. The desirable output produced in this stage is represented by Y_1, while undesirable outputs are represented by U_1. The efficiency of this sub-stage is called total factor productivity (PE). These undesirable outputs from the first stage are also inputs to the second stage and are referred to as intermediate products. In the pollution treatment stage, intermediate products U_1 and exogenous inputs represented by X_2 are converted to desirable outputs represented by Y_2. The efficiency of this sub-stage is called the pollution treatment efficiency (TE). The total efficiency is calculated by considering these two stages and is called environmental efficiency (EE).

Based on data availability, this paper uses data from 2007-2015 for 30 Chinese provinces (except Hong Kong, Macao, Taiwan and Tibet) to measure environmental efficiency. The three inputs to the industrial production subsystem are *labor*, *capital*, and *energy*. *Labor* is calculated by the average number of industrial employees per year. *Capital* is estimated using the Perpetual Inventory Method (PIM). *Energy* is measured as total energy consumption, all of which is converted to 10,000 tons of coal equivalent (tce). Gross industrial output is chosen as a proxy for desirable output and deflated by the Producer Price Index (PPI) in constant 2003 prices. The undesirable outputs are industrial SO_2 and smoke emissions, which represent emissions from industrial processes that are not treated in any way. In the second stage, the inputs consist of two components: first, exogenous inputs, such as investments in industrial waste gas treatment; and second, undesirable outputs generated in the first stage. The desirable outputs are SO_2 removal and smoke removal, indicating the effectiveness of the pollution treatment. The variables are described in detail in Table 1.

Table 1: Description of the variables.

Variables		Unit	Data source
Industrial production subsystem			
Input(X_1)	Labor	Ten thousand	CSY
	Capital	Hundred million	CSY
	Energy	Ten thousand tce	CESY
Desirable output (Y_1)	Gross industrial output	Hundred million	CIESY
Undesirable output(U_1)	Industrial SO_2 emission	Ten thousand tons	CSY, CEY, CCSY
(Intermediate output)	Industrial smoke emission	Ten thousand tons	CSY, CEY
Pollution treatment subsystem			
Input(X_2)	Investments in industrial waste gas treatment	Hundred million	CESY
Desirable output (Y_2)	Industrial SO_2 removal	Ten thousand tons	CSY, CCSY
	Industrial smoke removal	Ten thousand tons	CSY, CEY, CCSY

Note: CSY denotes China Statistical Yearbook; CEY denotes China Environmental Yearbook; CESY denotes China Energy Statistical Yearbook; CIESY denotes China Industry Economy Statistical Yearbook; CCSY denotes China City Statistical Yearbook; CESY denotes China Environmental Statistics Yearbook.

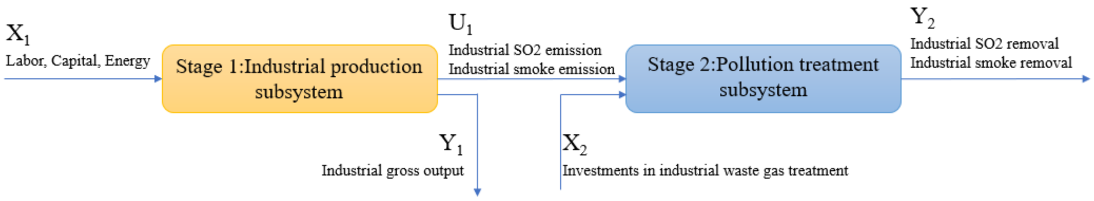

Figure 1: Two-stage system of industrial production and environmental treatment.

2.3.2 Sub-Stage Weight Indicator

Referring to Bian et al. (2015), this paper uses the ratio of energy conservation and environmental protection expenditure to total fiscal expenditure to capture policymakers' preferences. Specifically, let

E denote the annual amount of regional spending on energy conservation and environmental protection, and P denote the amount of regional spending to support production and construction. Thus, $W_p = P/(E+P)$, and accordingly W_t= 1- W_p. The results show that the weights assigned by local governments to the production and treatment stages are relatively stable from 2007 to 2015, with W_p ranging from 0.876 to 0.898 and W_t ranging from 0.102 to 0.124. The sub-stage weight indicator is described in detail in Table 2.

Table 2: The sub-stage weight indicator.

	2007	2008	2009	2010	2011	2012	2013	2014	2015
W_p	0.880	0.876	0.880	0.876	0.898	0.896	0.894	0.897	0.893
Wt	0.120	0.124	0.120	0.124	0.102	0.104	0.106	0.103	0.107

3 RESULTS AND DISCUSSIONS

3.1 The Impact of Policymakers' Preferences on Environmental Efficiency

3.1.1 Regional Heterogeneity Analysis

Referring to Wu et al. (2016), policymakers' preferences are distinguished by the weights assigned to each subsystem, and simply assume that W_p is between 0.1 and 0.9. As shown in Table 3, the total efficiency (EE) keeps increasing from 0.673 to 0.738 with the increase of W_p, and the pollution treatment efficiency (TE) is also on the rise with a growth rate of approximately 37.97%, which far exceeds the growth of EE. Total factor efficiency (PE), on the other hand, shows the opposite direction. Notably, there is an inflection point in the contribution of sub-stages to the total efficiency, with TE becoming the primary driver of EE when W_p>0.6. This finding suggests that environmental efficiency is strongly affected by policymakers' preferences. In addition, significant regional differences are found in the impact of policymakers' preferences. Under either weight distribution, the eastern region has the highest environmental efficiency, followed by the central and western regions. The differences in total efficiency between regions are mainly due to differences in the efficiency of the treatment stages.

Table 3: The impact of policymakers' preferences on environmental efficiency.

Region	W_p	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
East	EE	0.757	0.759	0.760	0.762	0.763	0.765	0.766	0.768	0.771
	PE	0.975	0.951	0.928	0.901	0.876	0.852	0.831	0.810	0.791
	TE	0.773	0.791	0.810	0.832	0.856	0.883	0.909	0.939	0.969
Central	EE	0.630	0.637	0.645	0.655	0.665	0.677	0.690	0.706	0.724
	PE	0.973	0.947	0.920	0.894	0.864	0.839	0.814	0.790	0.766
	TE	0.646	0.672	0.699	0.729	0.767	0.802	0.843	0.889	0.942
West	EE	0.620	0.626	0.634	0.644	0.655	0.667	0.681	0.698	0.717
	PE	0.970	0.939	0.910	0.880	0.853	0.828	0.804	0.781	0.758
	TE	0.638	0.664	0.692	0.725	0.759	0.798	0.839	0.888	0.942
Total Sample	EE	0.673	0.677	0.683	0.690	0.697	0.705	0.715	0.726	0.738
	PE	0.973	0.945	0.919	0.891	0.865	0.839	0.816	0.794	0.772
	TE	0.690	0.712	0.737	0.765	0.797	0.830	0.866	0.907	0.952

Note: EE denotes overall efficiency, PE denotes total factor efficiency, TE denotes pollution treatment efficiency.

3.1.2 Provincial Heterogeneity Analysis

Heterogeneous effects of policymakers' preferences on provincial environmental efficiency can be classified into four categories. The first category indicates that the efficiency is not influenced by policymakers' preferences, such as Beijing, Jiangsu, Jiangxi, Shandong, Guangdong, Hainan, and Gansu. The second category refers to the fact that the more priority is given to production stage, the lower the total efficiency. That is, in order to maximize total efficiency, more emphasis needs to be placed on pollution control rather than industrial production. The third category indicates that total efficiency increases with higher production weights, suggesting the need to focus on the production side to increase green total factor productivity. The last category demonstrates that there is a turning point in the effect of policymakers' preferences, exhibiting an inverted U-shaped trend. The total efficiency rises first with the increase of W_p, and then decreases after reaching the turning point. The efficiency of such provinces peaks in a given combination of weights. For instance, the optimal combination of weights for W_p and W_t in Tianjin in 2015 is (0.8,0.2). Similarly, the combination for Shanghai in 2015 is (0.8,0.2), Hubei is (0.2,0.8), and Guizhou is (0.6,0.4).

3.2 Evaluation of the Coordination of Industrial Development

This section uses the sub-stage weight indicators in subsection 2.3.2 to calculate the environmental efficiency of the industrial sector in each province of China from 2007-2015. The relative ranking of environmental efficiency is used to represent the degree of coordinated industrial development in each province. All provinces are divided into four categories based on their ranking, such as highly coordinated, moderately coordinated, uncoordinated and highly uncoordinated. To capture the dynamic trend, we further divide the period into 2007-2010 and 2012-2015; the former belongs to the 11th Five-Year Plan and the latter belongs to the 12th Five-Year Plan. As shown in Table 4, China's provinces have a relatively low level of industrial coordination development, with a deteriorating trend during the 12th Five-Year Plan. Nearly half of the provinces face a critical imbalance between industrial development and environmental protection, most of which are central and western provinces. Only six provinces, including Beijing, Shandong, Jiangxi, Guangdong, Hainan, and Shanghai, have achieved coordinated development of industrial production and environmental protection, while Xinjiang, Sichuan, and Liaoning continue to suffer from a mismatch between industrial production and pollution control. In contrast, provinces such as Henan, Jiangsu, Hunan, Tianjin, Hubei and Yunnan have made great progress in the coordinated development of production and environmental protection.

Table 4: The level of coordinated industrial development in China's provinces.

East	2015 EE	Category		Central	2015 EE	Category		West	2015 EE	Category	
		2007-10	2012-15			2007-10	2012-15			2007-10	2012-15
Beijing	1.00	1	1	Shanxi	0.36	1	3	IMongolia	0.25	2	3
Tianjin	0.45	4	3	Jilin	0.52	3	4	Guangxi	0.42	2	4
Hebei	0.34	3	4	HLjiang	0.35	2	4	Chongqing	0.59	1	2
Liaoning	0.42	4	4	Anhui	0.67	2	3	Sichuan	0.63	3	3
Shanghai	0.58	2	2	Jiangxi	1.00	1	1	Guizhou	0.34	2	4
Jiangsu	1.00	2	1	Henan	0.98	2	1	Yunnan	0.91	4	1
Zhejiang	0.65	2	3	Hubei	0.56	4	3	Shaanxi	0.49	3	4
Fujian	0.58	2	3	Hunan	0.89	3	2	Gansu	1.00	1	3
Shandong	1.00	1	1					Qinghai	0.40	1	2
Guangdong	1.00	1	1					Ningxia	0.25	2	4
Hainan	1.00	1	1					Xinjiang	0.41	3	3
Average	0.73	0.78	0.76	Average	0.67	0.73	0.70	Average	0.52	0.76	0.63

Note: HLjiang is short for Heilongjiang; IMongolia is short for Inner Mongolia. "1,2,3,4" represents highly coordinated, moderately coordinated, uncoordinated and highly uncoordinated, respectively.

4 CONCLUSION AND POLICY IMPLICATIONS

This study investigates the impact of policymakers' preferences on environmental efficiency based on a two-stage network DEA model. Afterwards, we evaluate the coordination of industrial development for each province in China. The conclusions and corresponding policy implications are presented below.

Firstly, environmental efficiency is strongly influenced by policymakers' preferences. Under either weight distribution, the eastern region has the highest environmental efficiency, followed by the central and western regions. The differences in total efficiency between regions are mainly due to differences in the efficiency of the treatment stages.

At the provincial level, the heterogeneous effects of policymakers' preferences can be grouped into four categories. Thus, every effort should be made to avoid a one-size-fits-all policy and take full account of the actual situation in different regions.

Secondly, China's provinces have a relatively low level of industrial coordination development, with a deteriorating trend during the 12th Five-Year Plan. Nearly half of the provinces face a critical imbalance between production and environmental protection, most of which are central and western provinces. In the future, China needs to continue its efforts on the industrial green transformation and promote to shift to a low-emission, efficiency-driven mode.

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