Industrial and Environmental Governance Efficiency in China's Urban Areas

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Industrial efficiency is important for the development of regional economic policies. Based on a network data envelopment analysis (DEA) methodology which considered undesirable outputs and links between sub-processes, we studied the overall industrial efficiency, pollution governance efficiency and industrial production efficiency of China's largest five urban agglomerations (Beijing-Tianjin-Hebei, Yangtze River Delta, Middle Reaches of Yangtze River, Pearl River Delta, and Chengdu-Chongqing) during 2000-2014. Our results show that:

1) The overall industrial efficiency grows in a wave form. Yangtze River Delta and Beijing-Tianjin-Hebei occupy the highest two positions in overall industrial efficiency. Environmental governance in Pearl River Delta is the most effective. Both overall industrial efficiency and environmental governance efficiency in Chengdu-Chongqing are at the lowest position.
2) The poor efficiency of environmental pollution governance is the key factor that limits the industrial efficiency of the five urban agglomerations. The sources of the inefficiencies of the pollution governance sub-process are the inefficiencies of desirable outputs.

Increasing the efficiency and technical levels of industrial pollution treatment is an important measure to improve the ecological environment of urban areas and the overall industry efficiency, which will ultimately promote more sustainable urban economic and environmental development.

INTRODUCTION

According to the Eleventh Five Year Plan of National Economic and Social Development of China (March 2006), urban agglomerations are the primary form of urbanization and have a leading role in promoting inter-regional cooperation. It was proposed in the 2010 China Development Report that three mega agglomerations, namely Beijing-Tianjin-Hebei, Yangtze River Delta and Pearl River Delta, would be given development priority. The Middle Reaches of the Yangtze River and Chengdu-Chongqing agglomerations were also approved by the State Council of China in April 2015 and April 2016, respectively. So far, there are five major urban agglomerations. Statistics indicate that between 2000 and 2014, the total gross regional product (GRP) of the top five urban agglomerations (TFUA) has increased to 5.9 trillion renminbi (RMB) yuan, growing at an annual average rate of 1.3% and accounting for 53% of China's GDP in 2014. This indicates that the TFUA are increasingly important for economic growth and development.

The rapid expansion of urban agglomerations has led to a series of unsustainable problems including urban resource shortages and environmental pollution. By the end of 2014, the amount of three types of industrial waste discharge from 91 cities in the TFUA were 9.4, 0.055 and 0.045 billion tons, respectively, accounting for 48.3%, 34.6% and 36.4% of China's total emissions. The total investment by the TFUA for industrial pollution treatment has increased 38.8% from 46.7 billion in 2000 to 64.9 billion RMB yuan in 2014. As leaders of Chinese economic growth, there are questions relating to industrial efficiency and environmental impacts. What is the level of the TFUA's overall industrial efficiency? How are laws of environmental governance efficiency evolving. What are the main sources of inefficiency? These questions need to be considered and analyzed. Their solutions reflect the practical significance of our study and are provided in this chapter.

Literature Review

The concept of efficiency comes from physics and can be traced to its introduction during the first industrial revolution. Färe et al. in 1989 explored the evaluation of environmental efficiency [1]. Since then, many studies on environmental efficiency emerged and different types of evaluation models and methods were introduced [2]. These included total factor productivity (TFP), the environmental performance index (EEI), life cycle assessments (LCA), stochastic frontier analysis (SFA), data envelopment analysis (DEA), sustainable value (SV), among others [3-8]. The DEA is a nonparametric method of operations research often used to estimate production frontiers and to empirically assess the efficiency of decision making systems. This widely used analysis methodology requires neither uniform index dimensions nor advance determination of indicator weights, and handles multi-inputs and outputs flexibly [9]. To clarify the development tract of DEA efficiency evaluation, Table 1 compares common DEA models.

Traditional DEA methodologies (i.e., the early Chames, Cooper and Rhodes model and its extensions) fail to consider undesirable outputs in the study of environmental efficiency; therefore, the results tend to deviate from the actual values. Numerous researchers and analysts have placed undesirable outputs into analytical frameworks to reflect the impact of resource and environmental constraints on industrial efficiency [10-12]. Most of these DEA models were radial and oriented, leaving redundant input and output indicators unanalyzed. To this end, Zhou et al., and Mahdiloo and Saen used a non-radial DEA method to estimate environmental performance [13-14]. Zhao and Song used a four-stage DEA technology to eliminate the external environmental impacts on efficiency values [15]. Shi combined Banker-Charnes-Cooper (BCC) and the stochastic frontier approach (SFA) to propose a three-stage DEA model, determining that scale inefficiency was the dominant factor restraining the control efficiency of industrial wastewater on provincial levels in China [16]. Using the modified three-stages bootstrapped DEA model, Liu et al. determined that governance efficiency in Chinese local governments exhibited a "wavy shape" and deteriorated [17].

Though these studies were non-radial and non-oriented, treating the evaluated systems as "black boxes," they failed to reflect the impact of the intermediate product. The slacks-based measure (SBM)

Table 1. Evolution of DEA model for environmental efficiency evaluation.

Models	*Consider undesirable outputs*	*Radial / Non-radial*	*Oriented / Non-oriented*	*Consider slacks*	*Consider intermediate process*	*Consider links between processes*
Traditional DEA	N	N/A	N/A	N	N	N
Radial DEA	Y	Radial	Oriented	N	N	N
Non-radial DEA	Y	Non-radial	Non-oriented	Y	N	N
Multistage DEA	Y	Non-radial	Non-oriented	Y	N	N
SBM	Y	Non-radial	Non-oriented	Y	Y	N
Network DEA	Y	Non-radial	Non-oriented	Y	Y	Y

approach effectively deals with this problem [18]. Song et al., Hadi-Vencheh et al., and Lan and Chen applied a SBM model to calculate the efficiency of environmental governance [19-21]. Castellet and Molinos-Senante emphasized the significant manpower and energy cost saving potentials in sewage treatment plants through a weighted relaxation measure model [22]. Nevertheless, the links between adjacent production processes were often ignored and underestimated the efficiency of environmental governance [23]. By dividing the whole process of decision making units (DMUs) into several sub-processes, the network DEA method produces more accurate results [24,25]. According to Lozano and Gutiérrez, the network DEA method obtains reliable results due to its higher discrimination capacity compared to one-process DEA methods [26].

Even with identical network structures, there will be a variety of network DEA models with varying conclusions that result from variables evaluated as DMUs and parameter settings (see Table 2). Given the limited data available, the existing network DEA literature mainly focuses on measuring provincial environmental efficiency, failing to distinguish both overall and governance efficiency among urban agglomerations in terms of efficiency level, evolution law, and the main sources of inefficiencies. Understanding this is the theoretical significance of our study.

Models and Indicators: The Network DEA Model

Consider n DMUs, which has K divisions (or sub-processes). In division k of DMU i (DMU_i), β_k desirable outputs $y^k_i = (y_1, y_2, \ldots, y_{\beta k})$ $y^k_i = (y_1, y_2, \ldots, y_{\beta k}) \in R+^{\beta k}$ and y_k γ_k undesirable outputs $b^k_i = (b_1, b_2, \ldots, b_{\Upsilon k}) \in R+^{\Upsilon k}$ are produced by using α_k inputs $x^k_i = (x_1, x_2, \ldots, x_{\alpha k}) \in R_+^{ak}$. $\tau(k,h)$ representing both the intermediate outputs of division k and the intermediate inputs of the division h. The number of intermediate products is represented by $\delta(k,h)$. According to Tone and Tsutui [18], the possible production set of the network DEA $\{(x^k, y^k, b^k, \tau^{(k,h)}\}$ can be described as:

$$x^k \geq \sum^n{}_{t=1} x^k_i \lambda^k_i \,(k=1, 2\ldots K) \qquad y^k \geq \sum^n{}_{t=1} y^k_i \lambda^k_i \,(k=1, 2\ldots K)$$

$$\tau^{(k,h)} = \sum^n{}_{i=1} \tau_t{}^{(k,h)} \lambda^k_t \,(\forall(k,h)) \quad \tau^{(k,h)} = \sum^n{}_{i=1} \tau^{(k,h)}{}_t \lambda^k_t \,(\forall(k,h)) \qquad (1)$$

$$e\lambda^k = 1(\forall k),\ \lambda^k \geq (\forall k)$$

where $e\lambda^k=1(\forall k)$ indicates the variable return scale (VRS).

Table 2.
Representative research of environmental efficiency in China based on DEA.

Models / Methods	*Research object*	*Key points*	*Ref.*
DEA and Conditional Generalized Minimum Variance Method	Environmental pollution control efficiency in Henan province in 2000-2007	There is large redundancy in pollution control investment of Henan, which has a declining scale return.	Guo and Zheng (2009) [27]
Four-stages DEA and Bootstrap-DEA model	Environmental governance efficiency of China in 2010	The overall efficiency of the central and eastern was significantly better than the west, and the western scale efficiency is better.	Zhao and Song (2013) [15]
Network DEA and the two-sided panel Tobit model	Industrial governance efficiency in 1998-2010 in China	Environmental technology efficiency measured by traditional method underestimates the environmental governance efficiency.	Song et al. (2013) [19]
BCC and Tobit model	Environmental governance efficiency of China in 2003-2010	The local government's efficiency is very low; Fiscal decentralization and public awareness have significant negative impact on environmental treatment efficiency.	Zhang and Li (2014) [28]
Three-stage DEA model	Treatment efficiency of industrial water pollution of China in 2012	The Treatment efficiency of industrial water pollution is only 0.682, and the scale inefficiency is the essential element to hinder the improvement of treatment efficiency.	Tone (2001) [29]
ISBM model and ISBM-Luenberger productivity index	Ecological management efficiency in China from 2003 to 2012	The changes in technical progress and scale efficiency were the main driver for China's ecological management TFP changes.	Hou (2015)
Network DEA based on RAM model	Industrial production efficiency and environmental governance efficiency in China from 2001 to 2010	Industrial production efficiency is higher than environmental governance efficiency. The insufficiency and inefficiency of investment in pollution treatment is the main reason that resulting in low environmental governance efficiency.	Wang and Luo (2015) [30]
Super-SBM model	Efficiency of air pollution abatement in China between 2002 and 2011	There are small differences in efficiency of air pollution abatement between provinces.	Lan and Chen (2015) [21]
Modified DEA	Environmental spending efficiency of 29 provinces from China in 2007-2013	There seems more efficiency loss after excluding the exogenous and random factors, and efficiency score appears wave shape in the time period and is being worsen.	Liu et al. (2016) [17]
Super DEA-Malmquist model	Efficiency of industrial air pollution treatment in China during 2006-2013	The overall treatment efficiency of industrial air pollution is not high. Input redundancy and output insufficient exist at the same time in industrial sectors.	Fan and Jiang (2016) [31]

Equation 1 becomes the constant return scale if this constraint is neglected. In addition, there are always two types of links between two divisions. First, the free link (the connection can be disposed freely while maintaining the cohesion between the inputs and outputs) with the equation expressed as:

$$\tau^{(k,h)} \lambda^{h} = \tau^{(k,h)} \lambda^{k} \, (\forall(k,h)) \tag{2}$$

Second, the fixed links (the connections remain unchanged) with the formula expressed as:

$$\tau_{o}^{(k,h)} = \tau^{(k,h)}\lambda^{h}, \ \tau_{o}^{(k,h)} = \tau^{(k,h)}\lambda^{k} \, (\forall(k,h)) \tag{3}$$

where the subscript o means "overall."

In accordance with the majority of relative literature, the free link is considered in the current study. Then, the network DEA model containing undesirable outputs can be formulated as:

$$\theta^{*} = \underset{\lambda^{k},s^{k-}_{\alpha},s^{k+}_{\beta},s^{k-}_{\gamma}}{Min.} \frac{1 - \sum^{k}_{k=1} p_{k}[(1/\alpha_{k}) \sum^{\alpha x}_{\alpha=1} s^{k-}_{\alpha o}/x^{k}_{\alpha o}]}{1 - \sum^{k}_{k=1} p_{k}[1/(\beta_{k} + \gamma_{k})]\sum^{\beta x}_{\beta=1} (s^{k+}_{\beta o}/y^{k}_{\beta o}) + \sum^{yx}_{y=1}(s^{k-}_{yo}/b^{k}_{yo})} \tag{4}$$

$$\begin{aligned}
&x^{k}_{\alpha o} = x^{k}_{\alpha o}\lambda^{k} + s^{k-}_{\alpha o}\\
&y^{k}_{\beta o} = y^{k}_{\beta o}\lambda^{k} - s^{k+}_{\beta o}\\
&b^{k}_{\gamma o} = b^{k}_{\gamma o}\lambda^{k} + s^{k-}_{\gamma o}\\
&ep^{k} = 1, e\lambda^{k} = 1, p^{k} \geq \mathbf{0}, \boldsymbol{\lambda^{k}} \geq \mathbf{0}, s^{k-}_{\alpha o} \geq \mathbf{0}, s^{k+}_{\beta o} \geq \mathbf{0}, s^{k-}_{\gamma o} \geq \mathbf{0} \, (\forall k)
\end{aligned}$$

where $s^{k-}_{\alpha o}$, $s^{k+}_{\beta o}$, $s^{k-}_{\gamma o}$ represent the slack vectors of inputs, desirable outputs and undesirable outputs respectively.

The objective function θ^{*} equals the unit when all of the slack variables are zero, indicating the most effective state of the DMU. The parameter p_{k} is the weight of division k, for the simplest situation, supposing p_{k}=1/K, implying the uniform weights of all divisions.

Further, we have

$$\begin{aligned}
&x^{k} = (x^{k}_{1}, x^{k}_{2}, \ldots, x^{k}_{n}) \in R^{\alpha_{k} xn}\\
&y^{k} = (y^{k}_{1}, y^{k}_{2}, \ldots, y^{k}_{n}) \in R^{\beta_{k} xn}\\
&b^{k} = (b^{k}_{1}, b^{k}_{2}, \ldots, b^{k}_{n}) \in R^{\gamma_{k} xn}
\end{aligned} \tag{5}$$

Equation (4) can be solved by being transformed to linear programming according to Charnes and Cooper [32].

Models and Indicators:
The Decomposition of Industrial Inefficiency

Based on the non-radial and non-oriented network DEA model above, we can obtain the efficiency of the overall industry and the divisions by using the input-output slack as follows:

$$\theta_o = \frac{1 - \sum^{k}_{k=1} p_k[(1/\alpha_k) \sum^{\alpha x}_{\alpha=1} s^{k-*}_{\alpha o}/x^{k}_{\alpha o}]}{1 - \sum^{k}_{k=1} p_k[1/(\beta_k + \gamma_k)]\sum^{\beta k}_{\beta=1} (s^{k+*}_{\beta o}/y^{k}_{\beta o})+\sum^{yx}_{y=1}(s^{k-*}_{yo}/b^{k}_{yo})}$$

$$\theta_o = \frac{1 - (1/\alpha_k) \sum^{\alpha k}_{a=1} (s^{k-*}_{\alpha o}/x^{k}_{\alpha o})}{1 + [1/(\beta_k + \gamma_k)] [\sum^{\beta k}_{\beta=1} (s^{k+*}_{\beta o}/y^{k}_{\beta o}) + \sum^{yx}_{y=1}(s^{k-*}_{yo}/b^{k}_{yo})]} (\forall k) \quad (6)$$

where $s^{k-*}_{\alpha o}, s^{k+*}_{\beta o}, s^{k-*}_{yo}$ represents the optimal solution resulting from Equation (4).

Furthermore, the inefficiency can be decomposed in reference to Cooper et al. [33] as:

Input inefficiency $\theta_x = 1/\alpha_k [\sum^{\alpha k}_{a=1} (x^{k}_{\alpha o}-s^{k-*}_{\alpha o})/ x^{k}_{\alpha o}]$ (7)

Desirable output inefficiency $\theta_y = [1/\beta_k [\sum^{\beta k}_{\beta=1} (y^{k}_{\beta o}+s^{k+*}_{\beta o})/y^{k}_{\beta o}]]^{-1}$ (8)

Undesirable output inefficiency $\theta_b= [1/\gamma_k [\sum^{\gamma k}_{\gamma=1} (b^{k}_{\gamma o}+s^{k-*}_{\gamma o})/b^{k}_{\gamma o}]]^{-1}$ (9)

In Equations (7, 8 and 9), the smaller the value of θ_x, θ_y, θ_b, the lower the efficiency of inputs and outputs. θ_x, θ_y, θ_b will reach the maximum value of 1 when $s^{k-*}_{\alpha o}, s^{k+*}_{\beta o}, s^{k-*}_{yo}$ equals zero, which indicates that the input-output is the most efficient.

Indicators Design

Consider the industrial efficiency of a two-stage production shown in Figure 1.

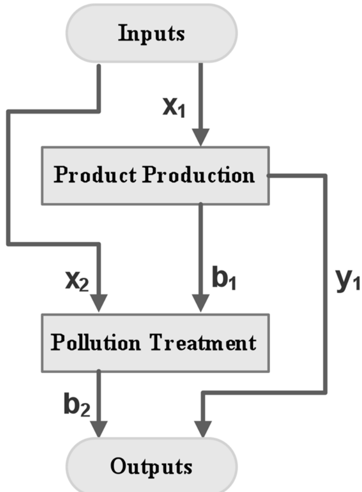


Figure 1. The two-stage industrial process.

In the first sub-process (product production), utilizing the input variables including labor L_p (represented by employment population of industry), capital K (represented by average annual net value of fixed assets, converted to year 2000 constant price according to the price index of fixed assets) and energy E (consumption of industrial energy), we obtain desirable output Y (gross industrial output, converted to year 2000 constant price according to the price index of industrial producer), and undesirable outputs (emissions of industrial wastewater W_p, industrial sulfur dioxide S_c, soot and dust F_p).

In the second sub-process (pollution treatment), input variables contain environmental protection staff L_c (the employment population of water conservancy, environment, and public management as proxy variables), investment in industrial pollution control I, and technology innovation in pollution control T (represented by scientific operating expenditure). Variables I and T were both converted to 2000 constant prices according to the industrial producer's price index. Only desirable outputs such as the amount of industrial wastewater treatment W_c, the removal of industrial sulfur dioxide S_c, the removal of industrial soot and dust F_c, urban green coverage area G_a, and the coverage rate G_r are considered. There is no undesirable output during this process.

As the keystone of this study is the industrial efficiency of 91 prefecture level cities in the TFUA (see Table 3), the industrial data of those cities in 2000-2014 are selected as the research sample. Data are mainly derived

Table 3. List of the 91 prefecture level cities in the TFUA.

Urban Agglomerations	*Cities*
Beijing-Tianjin-Hebei	Beijing, Tianjin, Shijiazhuang, Tangshan, Qinhuangdao, Handan, Xingtai, Baoding, Zhangjiakou, Chengde, Cangzhou, Langfang and Hengshui.
Yangtze River Delta	Shanghai, Nanjing, Wuxi, Xuzhou, Changzhou, Suzhou, Nantong, Lianyungang, Huai'an, Yancheng, Yangzhou, Zhenjiang, Taizhou4, Suqian, Hangzhou, Ningbo, Wenzhou, Jiaxing, Huzhou, Shaoxing, Jinhua, Quzhou, Zhoushan, Taizhou2, Lishui, Hefei, Wuhu, Huainan, Ma'anshan and Chuzhou.
Middle Reaches of Yangtze River	Wuhan, Huangshi, Yichang, Ezhou, Jingmen, Xiaogan, Jingzhou, Huanggang, Xianning, Changsha, Zhuzhou, Xiangtan, Hengyang, Yueyang, Changde, Yiyang, Loudi, Jingdezhen, Jiujiang, Xinyu, Yingtan, Ji'an, Yichun, Fuzhou and Shangrao.
Pearl River Delta	Guangzhou, Shenzhen, Zhuhai, Foshan, Jiangmen, Zhaoqing, Huizhou, Dongguan and Zhongshan.
Chengdu-Chongqing	Chongqing, Chengdu, Zigong, Deyang, Mianyang, Suining, Neijiang, Leshan, Nanchong, Meishan, Guang'an, Dazhou and Ziyang.

from the 2001-2015 *China City Statistical Yearbook*, the *Statistical Yearbook* of each city, and the *Statistical Bulletin of National Economic and Social Development*. Interpolation is used to deal with the missing data. The statistical summary of 15 variables is listed in Table 4.

During 2000-2014, there existed significant differences among the TFUA in gross industrial output, pollution emissions (taking industrial SO_2 emission as an example) and investment in environmental governance (see Figure 2).

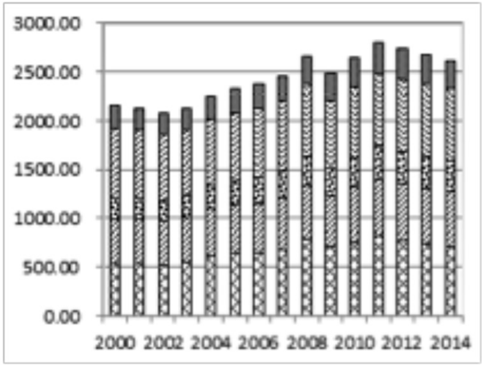
Figure 2 conveys the following:

1) Considering relative levels of industrial production for the TFUA, pollution emissions and environmental governance investment for Beijing-Tianjin-Hebei and Pearl River Delta are ranked highest. Yangtze River Delta is ranked second, and the Middle Reaches of the Yangtze River rank lowest.

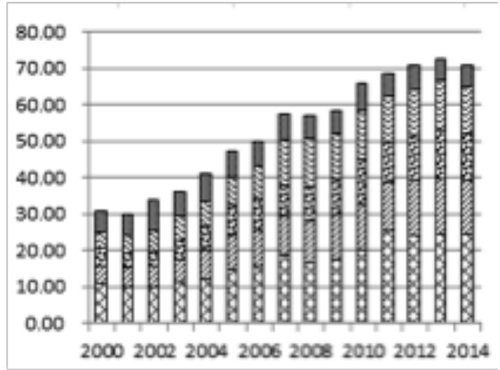
2) From the level of development, the trends of industrial growth and pollution emissions vary. As is shown in Figures 2(a) and 2(b), the gross industrial output between Beijing-Tianjin-Hebei and Pearl River Delta is similar, but industrial SO_2 emissions of the former are much higher than the latter. The growth rate of SO_2 emissions of Middle Reaches of Yangtze River is higher than that of Chengdu-Chongqing, although industrial development of the two agglomerations is similar.

Table 4. The descriptive statistics of input-output variables.

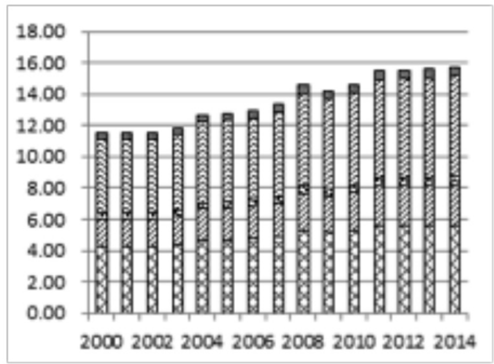
Variables	*Mean*	*Standard Deviation*	*Minimum*	*Maximum*	*Count*
Employment population of industry (10^4 people)	24.8	34.0	1.5	279	1,365
Average annual net value of urban fixed assets (10^8 RMB Yuan)	377.7	638.2	16.5	5,501	1,365
Consumption of industrial energy (10^4 tons)	1,226.1	1709.2	10.4	15,382	1,365
Gross industrial output (10^8 RMB Yuan)	608.8	653.5	52.1	4,716	1,365
Emissions of industrial wastewater (10^4 tons)	12,326.3	13,824.2	232.0	91,260	1,365
Emissions of industrial sulfur dioxide (10^4 tons)	16.1	21.14	0.3	154	1,365
Emissions of industrial soot and dust (10^4 tons)	184.4	766.4	0.2	17,357	1,365
Employment population of water conservancy, environment and public management (10^4 people)	0.9	1.2	0.01	10	1,365
Investment in industrial pollution control (10^8 RMB Yuan)	6.1	17.2	0.02	178	1,365
Scientific operating expenditure (10^4 RMB Yuan)	3,337	1,0291	30	75,101	1,365
Amount of industrial wastewater treatment (10^4 tons)	11,208	12,925	57	88,072	1,365
Removal of industrial sulfur dioxide (10^4 tons)	8.8	16.2	0.0	145.0	1,365
Removal of industrial soot and dust (10^4 tons)	181.0	765.6	0.1	17,353	1,365
Urban green coverage area (ha)	5,872.2	9,204.7	16.0	83,729	1,365
Urban green coverage rate (%)	36.9	9.1	0.4	92.9	1,365



(a) Gross industrial output



(b) Industrial SO_2 emission



(c) Pollution control investment

Figure 2. The changes of industrial output, pollution emissions and pollution control investment of the TFUA (2000-2014).

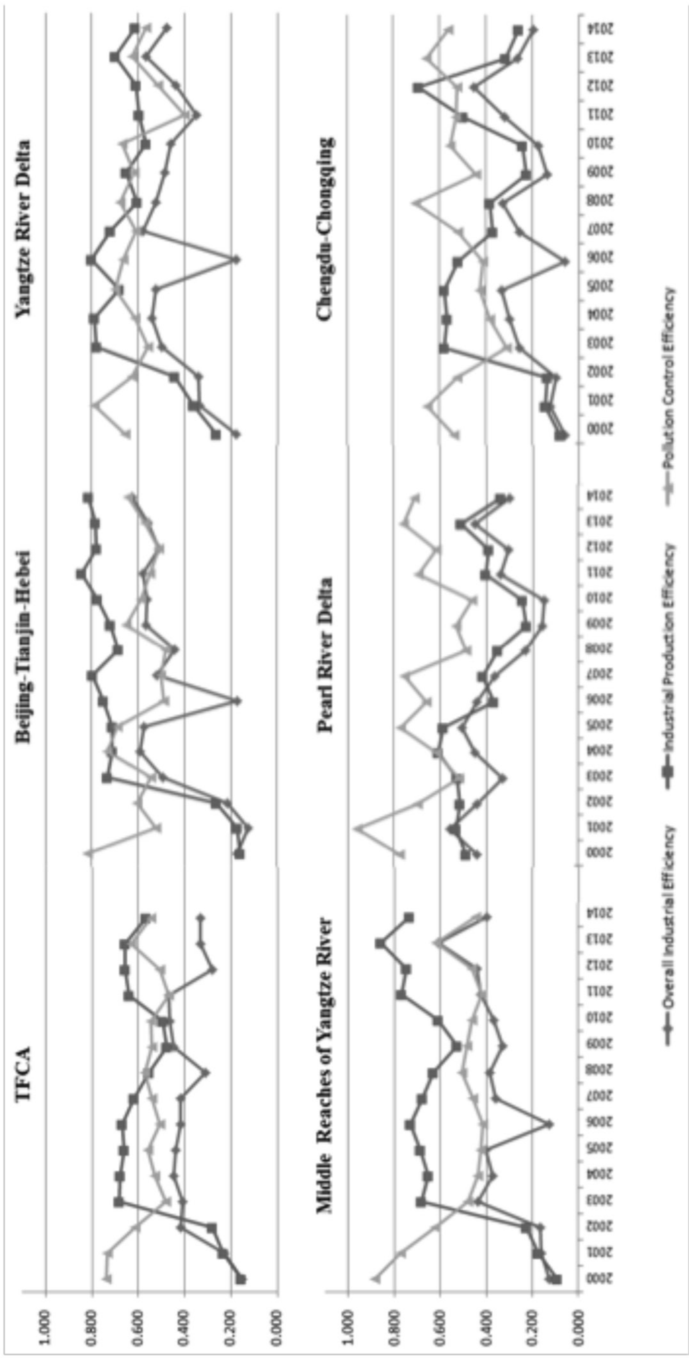


Figure 3. The evolution of industrial efficiency of TFUA and each agglomeration in 2000-2014.

3) The pollution emissions and investment in pollution control were disproportionate. Comparing Figures 2(b) with 2(c), given the comparable investment in environmental treatment, SO_2 emissions in Pearl River Delta were better controlled when compared to Beijing-Tianjin-Hebei. The Middle Reaches of Yangtze River produced similar SO_2 emissions at a much lower cost when compared with Yangtze River Delta and Pearl River Delta.

RESULTS

Temporal Differences in Industrial Efficiency

Considering the temporal dimension, industrial efficiency has evolved across urban agglomerations (see Figure 3). From 2000 to 2014, the total industrial efficiency for the TFUA and each agglomeration fluctuated within a narrow range. The industrial production efficiency showed an increasing trend after rapid development in the previous three years while the pollution control efficiency decreased sharply at first and then gradually flattened. For most of the 15-year period, pollution control efficiency moves between the overall industrial efficiency and industrial production efficiency in the TFUA with the exception of the Pearl River Delta. There the pollution control efficiency is higher than the other two types of efficiencies during almost the entire period.

Spatial Differences in Industrial Efficiency

Considering the spatial dimension, the distribution of industrial efficiency among the agglomerations is also variable (see Figure 4). The Yangtze River Delta has the highest overall efficiency, while Chengdu-Chongqing has the lowest. The rank of industrial production efficiency for five urban agglomerations is similar to that of overall efficiency. Pearl River Delta leads in pollution control efficiency, followed by Yangtze River Delta and Beijing-Tianjin-Hebei. Chengdu-Chongqing ranks lowest in overall industrial efficiency and industrial production efficiency among the TFUA. The industrial efficiency of TFUA is proportionate to their economic development, which is consistent with the conclusions of previous research and shows the reliability of the model described by Equation (4).

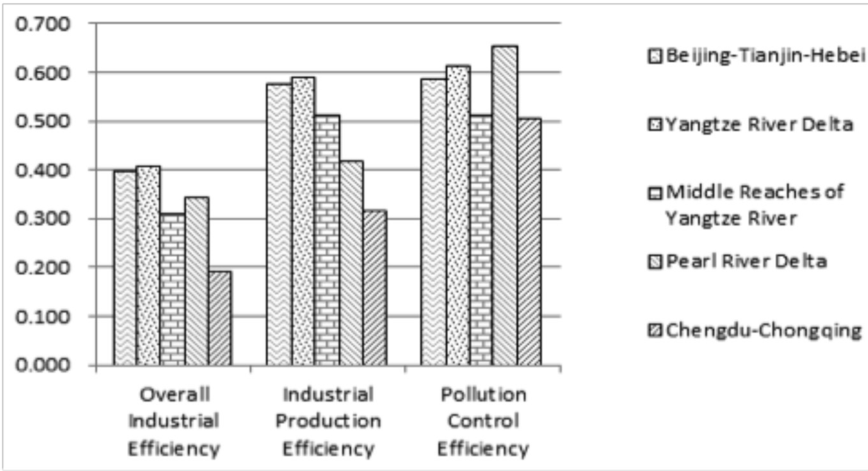


Figure 4.
TFUA industrial and pollution control efficiencies (2000-2014).

The spatial difference of industrial efficiency is reflected not only within each urban agglomeration but among them. Using Yangtze River Delta as an example (see Figure 5), the industrial efficiency for 30 cities in this region can be classified as three gradients.

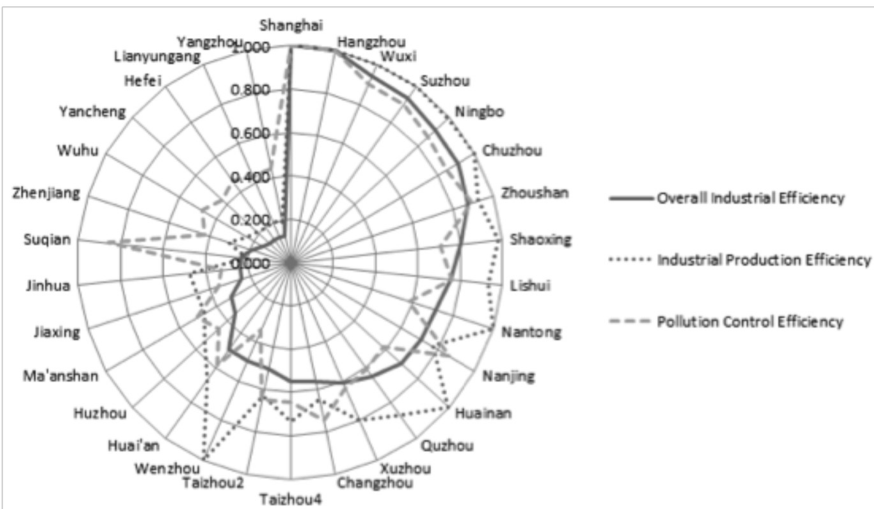


Figure 5. Comparison of industrial efficiency within Yangtze River Delta (2000-2014) decomposition of inefficiency.

Gradient 1—Urban agglomerations with the highest overall and sub-process efficiencies above 0.8 which include Shanghai, Hangzhou, Wuxi, Suzhou, Ningbo, Chuzhou and Zhoushan.

Gradient 2—Urban agglomerations with moderate efficiencies between 0.5 and 0.8 which include 10 cities from Shaoxing to Taizhou 2.

Gradient 3— The remaining urban agglomerations.

The industrial efficiencies and economic levels of these cities are commensurate to a degree. While the industrial production efficiency in Wenzhou is very high, its pollution control efficiency is only 0.341, so it is classified as Gradient 3. Suqian is categorized in Gradient 3 due to its low overall efficiency and industrial production efficiency (only about 0.2), though its pollution control efficiency is high (0.859).

To explore the suppression of industrial efficiency, the decomposition of inefficiency was performed using Equations 7, 8 and 9, and the inefficiency in the overall process and the sub-processes was obtained (see Table 5).

The conclusions derived from the data in Table 5 are interesting. For the industrial production sub-process, undesirable output is most inefficient, indicating that pollution emissions during this stage have not been well controlled. For the pollution control sub-process without undesirable output, input efficiency is much higher than efficiency of desirable output, which suggests that desirable output (i.e., treatment of industrial wastes and urban greening) is inefficient. Finally, affected by the pollution control sub-process, the efficiency of desirable output through the overall industrial process is substantially lower than input efficiency—the lowest among three types of efficiencies. While counterintuitive, this *indicates that inefficiency of pollution control is the driving force for inefficient industrial productivity*.

Further Analysis

By combining Figure 2 with the data from Figures 4 and 5, we can better explain the differences and sources of pollution control efficiency among urban agglomerations. For example, Figure 2 shows that Beijing-Tianjin-Hebei and Pearl River Delta have similar industrial development and environmental investment, while SO_2 emissions in the former region are much higher than those in the latter. Intuitively, the pollution

Table 5. Industrial inefficiency of urban agglomerations (2000-2014).

		TFUA	*Beijing-Tianjin-Hebei*	*Yangtze River Delta*	*Middle Reaches of Yangtze River*	*Pearl River Delta*	*Chengdu-Chongqing*
Industrial production sub-process	Input Inefficiency	0.865	0.882	0.877	0.887	0.763	0.854
	Inefficiency of Desirable Output	0.996	1	0.997	0.993	1	0.993
	Inefficiency of Undesirable Output	0.546	0.644	0.618	0.562	0.495	0.39
Pollution control sub-process	Input Inefficiency	0.814	0.795	0.826	0.848	0.74	0.799
	Inefficiency of Desirable Output	0.31	0.391	0.383	0.283	0.33	0.195
	Inefficiency of Undesirable Output	-	-	-	-	-	-
Overall Industrial Process	Input Inefficiency	0.845	0.845	0.858	0.871	0.763	0.831
	Inefficiency of Desirable Output	0.338	0.422	0.413	0.312	0.356	0.216
	Inefficiency of Undesirable Output	0.546	0.644	0.618	0.562	0.495	0.39

control in Beijing-Tianjin-Hebei should be less efficient compared to the latter, and this is confirmed in Figure 4.

The industrial pollution emissions in the Middle Reaches of Yangtze River are growing faster than those in Chengdu-Chongqing region (see Figure 2). While this would suggest lower pollution control efficiency in the Middle Reaches, it is higher. The reason may be that the inputs such as environmental investment during the pollution control sub-process in Middle Reaches of Yangtze River are less than those in Chengdu-Chongqing agglomeration. The desirable outputs of the Middle Reaches region are higher; both input efficiency and output efficiency are shown in Table 5, and hence resulted in greater pollution control efficiency.

Furthermore, by contrast with Yangtze River Delta and Pearl River Delta, Middle Reaches of Yangtze River show large amounts of SO_2 emissions and very low environmental investment (see Figure 2). It seems that pollution control in this agglomeration should be more efficient, which is proved to be contrary to the evidence (see Figure 4). This may be due to the fact that desirable outputs, such as treatment of industrial wastewater (55.0 million tons) is about half of that in Yangtze River Delta (101.4 million tons) and Pearl River Delta (112.9 million tons). Industrial soot, dust removal and green coverage are much less than the other two regions. This indicates less desirable pollution governance and thus the lower pollution control efficiency.

The empirical results indicate that the efficiency of regional pollution control cannot be accurately modeled by relying solely on either industrial pollution emissions or investments in pollution control. By combining these indicators with desirable outputs and undesirable outputs, more practical environmental decisions are possible.

CONCLUSIONS

In this chapter, the overall industrial process consists of two substages—industrial production and pollution treatment. By using the network DEA model, considering undesirable outputs, and the industrial data of 2000-2014 from the TFUA, the overall industrial efficiency, industrial production efficiency and pollution governance efficiency are estimated. The evolution trends and spatial differences among urban agglomerations are also analyzed. Industrial inefficiency is decomposed and calculated using inefficiencies, desirable output inefficiencies and undesirable output inefficiencies. The primary difference of pollution governance efficiency among urban agglomerations is illustrated.

This study shows that since 2000, the industrial production efficiency of the TFUA has increased remarkably. However, the overall industrial efficiency did not improve substantially due to fluctuations in pollution governance efficiency. Among the TFUA, Beijing-Tianjin-Hebei and Yangtze River Delta were in leading positions in overall industrial efficiency and industrial production efficiency, while Pearl River Delta has the highest pollution treatment efficiency. Meanwhile, all efficiencies in Beijing-Tianjin-Hebei and Middle Reaches of Yangtze

River increased steadily, which varies from the TFUA regions. Generally, there is potential for industrial efficiency to be improved in Middle Reaches of Yangtze River and Chengdu-Chongqing compared with other urban agglomerations.

It was determined by decomposition of inefficiency that input efficiency is always higher than desirable output efficiency, either in the overall process or in the pollution governance sub-process. The desirable output efficiency is lower when insufficient desirable outputs in the pollution governance sub-process offsets the desirable outputs in the industrial production sub-process. *Therefore, raising the level of pollution treatment improves the overall industrial efficiency.*

Due to the constraints of data availability, this study was limited in the selection of industrial input and output indicators. There remain questions that need to be analyzed in-depth. For example, what are the main factors that affect the efficiency of industrial pollution control? During the process of industrial transfer and optimization, how can the synergy of environmental policies within an urban agglomeration or among urban agglomerations be optimized? We plan to focus on these extended problems in our future research.

Note: If there was no special description, all of the mean values mentioned in this chapter use the geometric mean to eliminate the influence of extreme values.

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