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Received: February 09, 2022; Accepted: March 08, 2022

Cooperation and competition among urban agglomerations in environmental efficiency measurement: A cross-efficiency approach

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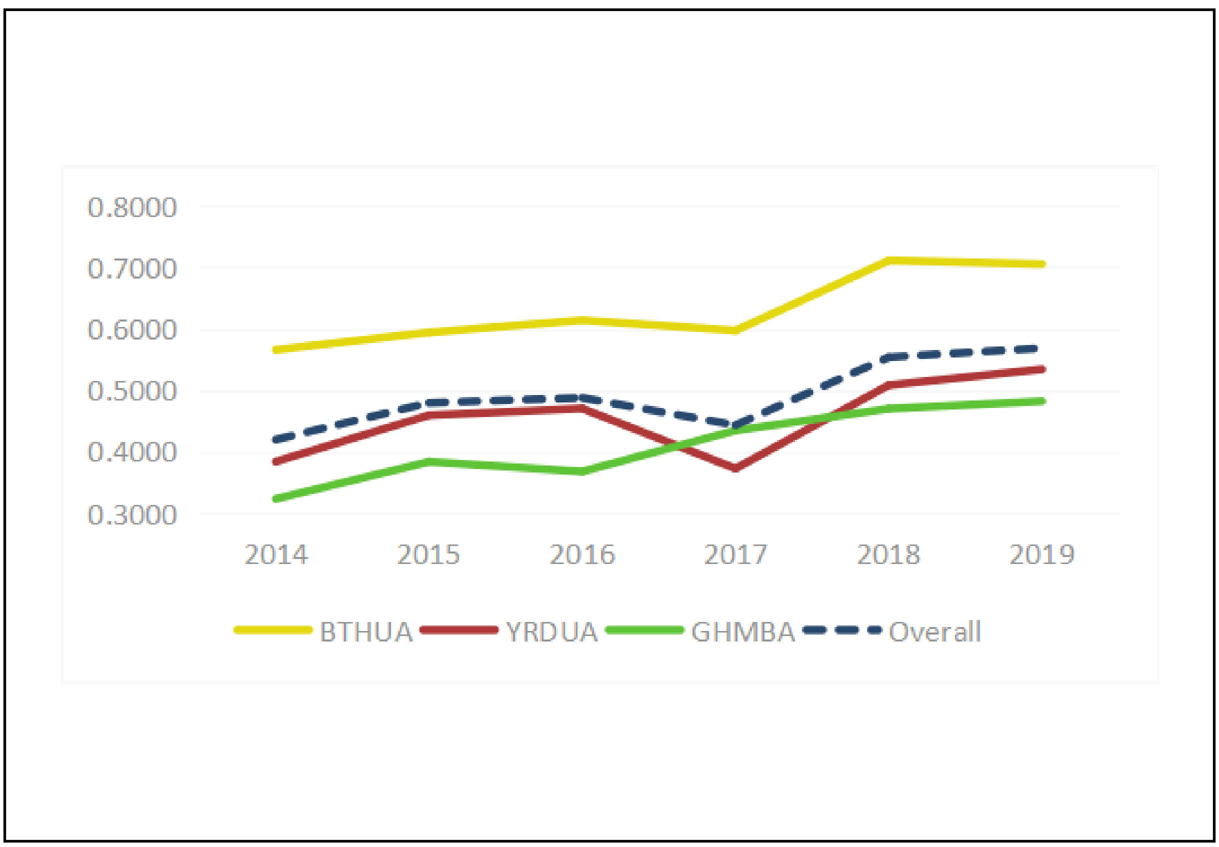
Graphical abstract



Environmental efficiency results for cities within three Chinese urban agglomerations.

Public summary

■ This paper analyzes the regional environmental efficiency by using the data of China's urban agglomerations.

■ This paper considers the cooperation and competition relationship among cities in environmental efficiency measurement.

■ A cross efficiency model is constructed based on the cooperation and competition relationship with considering the performance of undesirable output.

Citation: Liang X X, Zhou Z X. Cooperation and competition among urban agglomerations in environmental efficiency measurement: A cross-efficiency approach. *JUSTC*, **2022**, 52(4): 3. DOI: 10.52396/JUSTC-2022-0028

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Cite This: *JUSTC*, **2022**, 52(4): 3 (10pp)   Read Online

Abstract: Environmental efficiency has become a key indicator in describing the capacity of regional resource utilization with consideration of the negative externality to nature. Notably, with the development of urban agglomerations all over the world, the role and strategy of efficiency measurement for cities should be reorganized to deal with the complex relationships among cities based on urban agglomerations. In this paper, we construct a set of data envelopment analysis (DEA) models based on a peer-evaluation mode with consideration to the cooperative relationships among cities within the same urban agglomeration together with the competitive relationships between different urban agglomerations. Then, this paper we analyze the environmental efficiency of 48 Chinese mainland cities belonging to the Beijing-Tianjin-Hebei Urban Agglomeration (BTHUA), Yangtze River Delta Urban Agglomerations (YRDUA), and Guangdong-Hong Kong-Macao Greater Bay Area (GHMGBA). This was accomplished during 2014 to 2019 by using four inputs, two desirable outputs, and two undesirable outputs. The results of efficiency scores indicate that the environmental efficiency trend increased during the time series from 2014 to 2019 while the difference on environmental efficiency among different cities and urban agglomerations are significant. The BTHUA is the best performing urban agglomeration with much higher environmental efficiency scores in all the years. Besides, this paper selected 11 influencing factors based on three different angles to analyze the internal and external environments to environmental efficiency scores for providing further inspiration to managers.

Keywords: environmental efficiency; cross-efficiency model; urban agglomeration; competition and cooperation

CLC number: F291   **Document code:** A

1 Introduction

As a symbol of the modern world, urbanization has quickly increased during recent decades. The process of urbanization promotes economic growth and causes increasingly serious environmental problems in cities, such as air pollution[1]. Urban areas consume 67% to 76% of the energy and emit 71% to 76% of the CO_2[2]. The urbanization process is irreversible, and it will drive the sustained growth of urban populations and pollution emissions in the future. Therefore, increasing resource utilization efficiency is considered an effective way to resolve environmental problems in urban areas.

In recent decades, China has gained remarkable achievements in urbanization. The national urbanization rate exceeded 60% in 2019. In the new “National Urbanization Plan(2014-2020),” urban agglomeration was identified as a national policy in China, and it is considered an effective way to increase the efficiency of resource utilization and urban competitiveness. More than ten national urban agglomerations have been planned in recent years to cover more than 200 of China’s cities in the future. The Beijing-Tianjin-Hebei Urban Agglomeration(BTHUA), Yangtze River Delta Urban Agglomeration(YRDUA), and Guangdong-Hong Kong-Macao Greater Bay Area(GHMGBA) are the largest and earliest urban agglomerations in China. They include 40 main cities that cover about 30% of the population and contribute more than 40% of the gross domestic product(GDP) in China. The cooperation within urban agglomerations and the competition among them will improve local efficiency in resource utilization and environmental protection.

Data envelopment analysis(DEA) was proposed by Charnes, Cooper, and Rhodes(CCR)[3] in 1978 and is considered an effective method to calculate efficiency scores based on linear programming techniques widely applied in many fields. Scholars have also used DEA to evaluate a region’s operational efficiency on a global scale[4]. In fact, because the problem of environmental pollution is increasingly serious, consideration of undesirable outputs has been inserted into the DEA model to calculate the environmental efficiency score. However, dilemmas remain about the efficiency scores calculated with the traditional DEA model because all the efficiency scores are obtained based on a self-evaluation mode. Sexton et al.[5] proposed the cross-efficiency DEA model based on peer-evaluation, which provides more objective and identifiable efficiency scores for all decision-making units(DMUs). In order to resolve the problem of the non-uniqueness of the weight sets in the classic cross-efficiency model, scholars have introduced advanced cross-efficiency models based on different strategies, such as the benevolent strategy based on cooperation assumptions and the aggressive strategy based on competitive assumptions. However, the relationship between different cities in China should be a symbiotic one that includes competition and cooperation rather than pure competition or cooperation[6].

To provide more accurate and objective environmental efficiency scores for China's cities, we considered urban agglomeration construction. This paper constructs a set of cross-efficiency models based on the symbiotic relationships of competition and cooperation, considering undesirable outputs.

As for the rest of this paper, Section 2 presents a review of the related literature. Next, Section 3 is our construction of a cross-efficiency model based on the symbiotic relationship between competition and cooperation. In Section 4, we introduce our sample of 48 cities within the three largest urban agglomerations. We calculated the environmental efficiency scores using the cross-efficiency model and analyzed the factors that influence the environmental efficiency score using the Tobit model. Finally, Section 5 presents the conclusions and managerial implications for improving the local environmental efficiency.

2 Literature review

2.1 Studies on evaluating local environmental efficiency

Many scholars focus on analyzing local environmental efficiency by using an input–output methodology. The DEA method is the most popular model to compute environmental efficiency because of its capacity to deal with multiple inputs and outputs[7]. Using linear programming, a DEA model can handle multiple variables—including desirable and undesirable output—with techniques that are very easy to compose and solve. Increasingly advanced DEA models are being constructed to measure local environmental efficiency scores. For example, the directional distance function (DDF), slack-based measure(SBM), and cross-efficiency models are constructed to provide more reasonable results for decision-making units while considering the characteristics of regions under evaluation[8].

Using the basic DEA approach, regional environmental efficiency measurements are a popular research topic worldwide. Some research analyzes the environmental efficiency of countries, considering factors such as energy efficiency[8, 9]; manufacturing sector environmental efficiency[10]; and electric power industry environmental efficiency[11] in Organisation for Economic Co-Operation and Development(OECD) countries in various years. Empirical studies have also been completed to measure the environmental efficiency of Asia-Pacific Economic Cooperation(APEC) economies[12]; developing countries[13]; and other selected countries. Regional environmental performance measurement based on the DEA model is also an important research topic. For example, Honma and Hu[14] computed the regional total-factor energy efficiency of 47 prefectures in Japan; moreover, Ozkara and Atak[15] investigated energy consumption efficiency considering environmental influences for 20 regions in Turkey.

Many studies have utilized the DEA approach to evaluate the regional environmental efficiency affected by unbalanced development in China. As Sueyoshi et al.[16] concluded, most of these studies have analyzed China's environmental performance from a provincial perspective. Some studies use time-series data to analyze the dynamic efficiency scores and trends for multiple years.

For example, Wu et al.[17] measured the environmental efficiency of 28 Chinese provinces from 1997 to 2008. Another characteristic of previous research is that many advanced models are constructed to calculate China's regional performance more accurately, such as a Shannon-DEA approach[18] to determine weights with more information. The basic Malmquist DEA models[6] measure the efficiency during multiple time series. Also, two-stage DEA approaches[19, 20] open the "black boxes" of regional production and DEA window analysis evaluates dynamic efficiency[21]. The zero-sum game DEA model considers a fixed number of input or output variables[22].

Performance studies that only consider particular cities are insufficient, even when the number of corresponding studies has increased over time[23]. Long et al.[24] measured the environmental efficiency of 268 of China's cities after the Beijing Olympic Games. Zhou et al.[21] utilized the DEA approach to calculate the dynamic performance of air pollution measures in Chinese cities; additionally, Zhang et al.[25] used DEA methods to evaluate the environmental efficiency scores of 197 Chinese cities. A few studies analyze the regional environmental efficiency considering a single urban agglomeration, such as the YRDUA[26, 27] and the BTHUA[28]. However, no published studies analyze the regional environmental efficiency considering the competition and cooperation within urban agglomerations.

2.2 Methods for calculating cross-efficiency

Traditional DEA methods are constructed based on self-evaluation, which labels the DMUs as efficient or inefficient, with no ability to distinguish between the efficient ones. The self-evaluation also provides many efficiency results based on unreasonable weights. Sexton et al.[5] constructed a cross-efficiency DEA model based on peer-evaluation to improve the differentiation and ranking of efficient DMUs[29]. The cross-efficiency DEA model is considered a more objective way to calculate efficiency scores and is widely applied in all kinds of fields.

However, the cross-efficiency results based on the originally proposed approach are not unique. Doyle and Green[30] incorporate secondary targets to provide unique efficiency scores based on different strategies, such as the benevolent(aggressive) model to maximize(minimize) other DMUs' scores. Different strategies are considered to construct advanced cross-efficiency models and are used to provide different kinds of efficiency scores. Wang and Chin[31] compared the results of different cross-efficiency models and constructed some alternative models. Yang et al.[32] proposed a cross-efficiency model based on interval data to provide reasonable efficiency scores and full ranking order with considering acceptability from under evaluated DMUs. Tsai et al.[33] pointed out that competitive and cooperative relationships simultaneously exist under some conditions and constructed a new cross-efficiency model for such situations. Liang et al.[34]

DOI: 10.52396/JUSTC-2022-0028
JUSTC, **2022**, 52(4): 3

proposed a cross-efficiency model incorporating game theory based on cooperative relationships among DMUs. So, cross-efficiency models are widely utilized in reality for attaining objective efficiency scores and full ranking order.

3 Methodologies

3.1 DEA model based on self-evaluation mode

Assume n DMUs consume m inputs to produce s desirable outputs and t undesirable outputs. The ith input, rth desirable output, and pth undesirable output of DMU_j $(j=1,2,\cdots,n)$ are denoted by $x_{ij}\,(1=1,2,\cdots,m)$; $y_{rj}\,(r=1,2,\cdots,s)$; and y^b_{tj} $(t=1,2,\cdots,p)$ respectively. Accordingly, we can transform undesirable outputs into desirable outputs using a linear data transformation to calculate the environmental efficiency score. For a focal DMU_d, its environmental efficiency score based on self-evaluation is obtained from the following linear program:

$$\left.\begin{aligned}
&\max E_{dd}=\sum_{r=1}^{s}\mu_{rd}y_{rd}+\sum_{t=1}^{p}v_{td}\bar{y}_{td}\\
&\text{s.t.}\sum_{i=1}^{m}\omega_{id}x_{ij}-\sum_{r=1}^{s}\mu_{rd}y_{rj}-\sum_{t=1}^{p}v_{td}\bar{y}_{tj}\geqslant 0,j=1,2,\cdots,n\\
&\sum_{i=1}^{m}\omega_{id}x_{ij}=1\\
&\omega_{id}\geqslant 0,i=1,2,\cdots,m\\
&\mu_{rd}\geqslant 0,r=1,2,\cdots,s\\
&v_{td}\geqslant 0,p=1,2,\cdots,p
\end{aligned}\right\}\qquad(1)$$

In model (1), the optimal results $\omega^*_{1d},\cdots,\omega^*_{md},\mu^*_{1d},\cdots,\mu^*_{sd}$, $v^*_{1d},\cdots,\mu^*_{td}$ represent the weights determined by DMU_d to maximize its efficiency score. The E_{dd} indicates the efficiency score of DMU_d is based on self-evaluation; moreover, DMU_d is efficient if and only if E_{dd}=1. Then, the optimal weights of DMU_d can be used to calculate the cross-efficiency score of another DMU_j based on peer evaluation:

$$E_{dj}=\frac{\sum_{r=1}^{s}\mu^*_{rd}y_{rj}+\sum_{t=1}^{p}v^*_{td}\bar{y}_{tj}}{\sum_{i=1}^{m}\omega^*_{id}x_{ij}},d,j=1,2,\cdots,n\qquad(2)$$

DMU_j attains its cross-efficiency score based on the weight set determined by another DMU_d. The cross-efficiency method has advantages over the traditional DEA model, providing more objective efficiency results and typically providing a fuller ranking order. However, the optimal weights for computing the cross-efficiency score may not be unique, thereby resulting in multiple cross-efficiency values and rankings for any DMU.

3.2 Cross-efficiency model considering the cooperative relationship among DMUs

Doyle and Green[30] introduced the benevolent cross-efficiency model to calculate the efficiency score for DMUs considering a cooperative relationship among DMUs. In this model, each DMU chooses the weight set that maximizes the efficiency scores of other DMUs while maintaining its own optimal score. The efficiency value of DMU_d is defined as E_{dj} and the weight choice keeps the self-evaluated efficiency value E_{dd} of DMU_d unchanged. The cross-efficiency score can be obtained from the following model:

$$\left.\begin{aligned}
&\max\sum_{j=1}^{n}E_{dj}=\sum_{j=1}^{n}\sum_{r=1}^{s}\mu^d_{rj}y_{rj}+\sum_{j=1,j}\neq d^n\sum_{t=1}^{p}v^d_{tj}y^b_{tj}\\
&\text{s.t.}\ \sum_{i=1}^{m}\omega^d_{ij}x_{il}-\sum_{r=1}^{s}\mu^d_{rj}y_{rl}-\sum_{t=1}^{p}v^d_{tj}y_{tl}\geqslant 0,l=1,2,\cdots,n\\
&\sum_{j=1,j\neq d}^{n}\sum_{i=1}^{m}\omega^d_{ij}x_{ij}=1\\
&E_{dd}\times\sum_{i=1}^{m}\omega^d_{ij}x_{id}-\sum_{r=1}^{s}\mu^d_{rj}y_{rd}-\sum_{t=1}^{p}v^d_{tj}y_{td}\leqslant 0\\
&\omega^d_{ij}\geqslant 0,i=1,2,\cdots,m\\
&\mu^d_{rj}\geqslant 0,r=1,2,\cdots,s\\
&v^d_{tj}\geqslant 0,t=1,2,\cdots,p
\end{aligned}\right\}\qquad(3)$$

In model (3), the cross-efficiency score for DMU_j based on a cooperative relationship among DMUs is scaled by the average value of all results based on peer-evaluation: $\overline{E_j}=\frac{1}{n}\sum_{d=1}^{n}E_{dj},\ (j=1,2,\cdots,n)$.

3.3 Evaluation model considering the competitive and cooperative relationships among DMUs

The previous model only considers the situation where all DMUs have cooperative relationships, while in reality, some DMUs have competitive relationships and others have cooperative relationships. In this study, we use the competition and cooperation cross-efficiency model proposed by Tsai et al.[33] to measure the environmental efficiency of cities in China’s city groups. We assume that cities within the same agglomeration are cooperative and cities in other city groups are competitive. The resulting model is as follows:

$$\left.\begin{aligned}
&\min\sum_{j\in\Omega_1}\delta_{dj}+\sum_{j\in\Omega_2}-\varepsilon_{dj}\\
&\text{s.t.}\sum_{i=1}^{m}\omega_{id}x_{ij}-\sum_{i=1}^{m}\mu_{rd}y_{ij}-\sum_{t=1}^{p}v_{td}y^b_{tj}\geqslant 0,j=1,2,\cdots,n\\
&\sum_{i=1}^{s}\mu_{rd}y_{rj}+\sum_{t=1}^{p}v_{td}y^b_{tj}-\sum_{i=1}^{m}\omega_{id}x_{ij}+\delta_{dj}=0,j\in\Omega_1\ \ (a)\\
&\sum_{i=1}^{s}\omega_{id}x_{ij}-\sum_{r=1}^{m}\mu_{rd}y_{rj}-\sum_{t=1}^{p}v_{td}y^b_{tj}-\varepsilon_{dj}=0,j\in\Omega_2\ (b)\\
&\sum_{i=1}^{m}\omega_{id}x_{id}=1\\
&\sum_{r=1}^{s}\mu_{rd}y_{rd}+\sum_{t=1}^{p}v_{td}y^b_{td}=E_{dd}\\
&0\leqslant\delta_{dj}\leqslant 1,\varepsilon_{dj}=0,\quad j\in\Omega_1\\
&0\leqslant\varepsilon_{dj}\leqslant 1,\delta_{dj}=0,\quad j\in\Omega_2\\
&\omega_{id}\geqslant 0,i=1,2,\cdots,m\\
&\mu_{rd}\geqslant 0,r=1,2,\cdots,s\\
&v_{td}\geqslant 0,t=1,2,\cdots,p
\end{aligned}\right\}\qquad(4)$$

In model (4), Ω_1 denotes the set of DMUs that cooperate with DMU_d, while Ω_2 denotes the set of DMUs that compete with DMU_d. Two deviation variables $\delta_j\ (0\leqslant\delta_j\leqslant 1)$ and $\varepsilon_j\ (0\leqslant\varepsilon_j\leqslant 1)$ are introduced to simultaneously maximize the

DOI: 10.52396/JUSTC-2022-0028
JUSTC, 2022, 52(4): 3

efficiency scores of cooperating DMUs and minimize the efficiency scores of competing DMUs. We obtained the cross-efficiency score for each DMU_j considering both cooperative and competitive relationships as

$$\tilde{E}_j = \frac{1}{n}\sum_{d=1}^{n}(E_{dj}+\delta_{dj}-\varepsilon_{dj})\ (d=1,2,\cdots,n) \tag{5}$$

The optimal results calculated by programming (5) could describe the cross efficiency score of DMU_j with considering the different relationships among cities.

3.4 Analysis model of the factors that influence the city's environmental efficiency valuealue

The environmental efficiency score based on the DEA model above is calculated by considering the direct input and output variables while ignoring the influence of the many indirect factors. This study adopts the Tobit model to analyze such factors that influence a city's environmental efficiency value.

$$\tilde{E}_j^* = \beta_k Z_{kj} + \mu_j, \quad j = 1,2,\cdots,n \tag{6}$$

Here, $\tilde{E}_j^*$ is the latent variable, $Z_{kj}$is the kth independent variable vector for DMU_j, $\beta_k$is the correlation coefficient vector for the kth independent variable, and $\mu_j$is the error term. The relationship between the observed variable $\tilde{E}_j$ and the latent variable $\tilde{E}_j^*$is

$$\tilde{E}_j = \begin{cases} \tilde{E}_j^*, & \tilde{E}_j^* > 0 \\ 0, & \tilde{E}_j^* \leqslant 0 \end{cases} \tag{7}$$

4 Performance measurement

4.1 Description of samples and variables

Because of the data availability and different developments of Chinese urban agglomerations, our empirical study considers 48 mainland Chinese cities from three major Chinese urban agglomerations. That includes 13 cities from the BTHUA, 26 cities from the YRDUA, and 9 cities from the GHMGBA.

Following the studies reviewed above, this paper selects the following eight input and output variables to scale environmental efficiency. Specifically, for water consumption (IWC): The total water consumption by the industrial sector in each city(100 million cubic meters); Industrial current assets(ICA): The total current assets for all the industrial companies enterprises above a designated size in each city(billion Yuan); Number of full-time staff(NFS): The total number of full-time staff employed in the industrial sector in each city(thousands of persons); Industrial electricity consumption (IEC): The electricity consumed by the industrial sector in each city(billion KWh); GDP: The GDP generated by secondary industry in each city (in billion Yuan); proportion of GDP in secondary industry(PSI): The share of GDP in secondary industry in the total GDP for each city; Wastewater(WW): The total amount of wastewater discharged from the industrial section of each city(in millions of tons); sulfur dioxide emission(SO_2): the total amount of SO_2 emitted from the section of each city(tons). Given this, Table 1 provides the statistical description of the input and output variables for all 48 cities from 2014 to 2019.

4.2 Efficiency measurement based on self-evaluation approach

In this section, we calculated the environmental efficiency scores for all 48 cities based on the traditional CCR and cross-efficiency models. First, we used the classic CCR model to evaluate the efficiency score of all cities from 2014 to 2019; the results are described in Table 2.

Generally, the efficiency shows an increasing trend from 2014 to 2019 while the average efficiency score increased from 0.6691 in 2014 to 0.7900 in 2019, which infers that the development of urban agglomerations improves the environmental efficiency of resource utilization. As such, there are obvious differences in the environmental efficiency scores among urban agglomerations. The average environmental efficiency scores of the BTHUA are the highest every year, while the GHMGBA performs poorly with the lowest efficiency scores.

By using the traditional CCR model, we cannot attain sufficient information to analyze the environmental efficiency of China's urban agglomerations. These efficiency scores are relatively high because of the self-evaluation mode which can divide all DMUs into efficient and inefficient but cannot provide a full ranking order for all DMUs in general. Specifically, using the traditional CCR model, at least ten cities are considered efficient in all six years. Moreover, the efficiency scores obtained by the classic CCR model are not objective or acceptable enough because each city only considers the preferred weights for variables that can maximize its efficiency score.

4.3 Efficiency calculation based on the cross-efficiency model

As will be presented in this section, we utilized the newly presented cross-efficiency model to calculate the environmental efficiency score for cities in three major agglomerations while considering the cooperation within an agglomeration and the competition between agglomerations. In this regard, the efficiency scores are shown in Table 3. Principally, no city is recognized as environmentally efficient by all cities in the cross-evaluation because the maximum values are al-

Table 1. Statistics for variables of 48 Chinese cities from 2014 to 2019.

	IWC	ICA	NFS	IEC	GDP	PSI	WW	SO_2
Average	7.15	508.68	664.94	26.32	648.68	44.93	106.78	27415.82
Min	0.01	20.93	32.71	0.86	32.38	16.16	4.86	978
Max	37.44	2856.86	2805.88	156.96	3815.6	65.72	605.06	214723
S.D	8.66	576.65	635	24.52	730.32	8.3	93.16	30389.47

DOI: 10.52396/JUSTC-2022-0028
JUSTC, **2022**, 52(4): 3

Table 2. Description of efficiency scores based on the CCR model.

		2014	2015	2016	2017	2018	2019
Overall	Number of efficient	13	13	12	12	11	13
	Max	1	1	1	1	1	1
	Min	0.2998	0.3318	0.3523	0.2031	0.3994	0.3978
	Average	0.6991	0.7233	0.7392	0.6955	0.774	0.79
BTHUA	Number of efficient	7	5	5	6	4	4
	Max	1	1	1	1	1	1
	Min	0.5733	0.5685	0.6306	0.5753	0.679	0.6705
	Average	0.9109	0.8801	0.8945	0.9278	0.92	0.8739
YRDUA	Number of efficient	5	6	5	2	4	6
	Max	1	1	1	1	1	1
	Min	0.2998	0.3318	0.3632	0.2031	0.4374	0.434
	Average	0.6543	0.7028	0.7268	0.5879	0.7472	0.7833
GHMGBA	Number of efficient	1	1	1	2	2	2
	Max	1	1	1	1	1	1
	Min	0.3661	0.3851	0.3523	0.4827	0.3994	0.3978
	Average	0.541	0.5711	0.5666	0.6844	0.6539	0.6966

Table 3. Environmental efficiency scores based on cross-efficiency.

		2014	2015	2016	2017	2018	2019
Overall	Max	0.8719	0.9205	0.9494	0.886	0.9161	0.9393
	Min	0.4229	0.4802	0.4889	0.4401	0.5511	0.5693
	Average	0.175	0.209	0.2073	0.1574	0.2825	0.2846
BTHUA	Max	0.8719	0.9205	0.9494	0.8221	0.9161	0.9393
	Min	0.3327	0.4037	0.4432	0.389	0.533	0.507
	Average	0.5645	0.5971	0.62	0.6058	0.721	0.7095
YRDUA	Max	0.7581	0.7587	0.7966	0.886	0.8421	0.7608
	Min	0.1978	0.2469	0.2647	0.1574	0.3052	0.3089
	Average	0.3837	0.4591	0.4702	0.3724	0.5082	0.5339
GHMGBA	Max	0.6366	0.778	0.6279	0.661	0.7346	0.8289
	Min	0.175	0.209	0.2073	0.3184	0.2825	0.2846
	Average	0.3231	0.3833	0.3675	0.4342	0.4698	0.482

ways lower than 1. From another point of view, all the cities have space to improve their performance by decreasing input (undesirable output) or increasing desirable output. The results of the cross-efficiency analysis also show an increasing trend during 2014 to 2019, where the average efficiency scores keep increasing in all years considered, except for a slight decrease in 2017.

Fig.1 shows the trends for average efficiency scores during the six years for all three agglomerations. The average efficiency of the BTHUA is much higher than that of the YRDUA and GHMGBA, while the performance of the YRDUA is better than the GHMGBA in all years except for 2017. So, the dominance of the BTHUA might be explained by the development time as the BTHUA was one of the first agglomerations and has had more than seven years of development.

Moreover, the high environmental efficiency score of the BTHUA possibly resulted from the strict environmental regulation based on the "Beijing-Tianjin-Hebei regional integration" since 2014.

Fig.2 shows the box plot for efficiency scores from 2014 to 2019, where all the cities are marked in different colors according to their agglomerations. Generally, the efficiency scores have obvious variations during different years caused by the double change in variable values and weight sets. The highest efficiency score (0.9494) was obtained by Cangzhou in 2016, while the lowest efficiency score is only 0.1574 (Suzhou in 2017). The changes of individual cities during different years are also significant; for example, the efficiency score of Hengshui increases from 0.5600 in 2014 to 0.9393 in 2019. The changing range of the efficiency score in the GHMGBA (in the color green) is smaller than that of the BTHUA and YRDUA; also, some agglomerations' effi-

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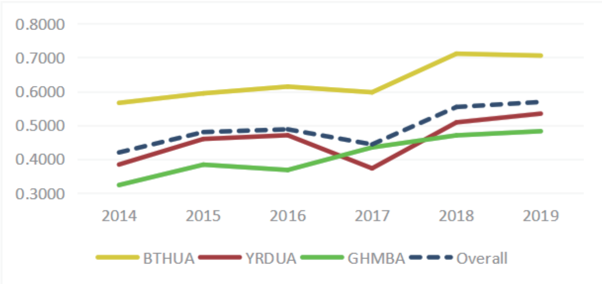

Fig. 1. Average cross-efficiency scores for three agglomerations.

ciency are relatively low except for Guangzhou and Zhaoqing.

To uncover the role of spatial distribution in environmental performance, we discuss the efficiency scores of cities with considering the location of cities. First, the northern cities perform better than the southern cities, and the environmental efficiencies of the BTHUA cities are better than the cities in the other agglomerations. In northern China, the environmental regulation is much stricter because of the lack of water resources and the fragile condition of the air. There are significant differences between coastal and inland cities' environmental performance in all three agglomerations; notably, this might be caused by the development of industry caused by the continuous growth of exports in coastal cities during recent years. Furthermore, the environmental efficiency for different cities has obvious spatial continuity. For example, Suzhou and Dongguan are China's most famous manufacturing bases, and their efficiency scores trigger spillover effects in adjacent cities.

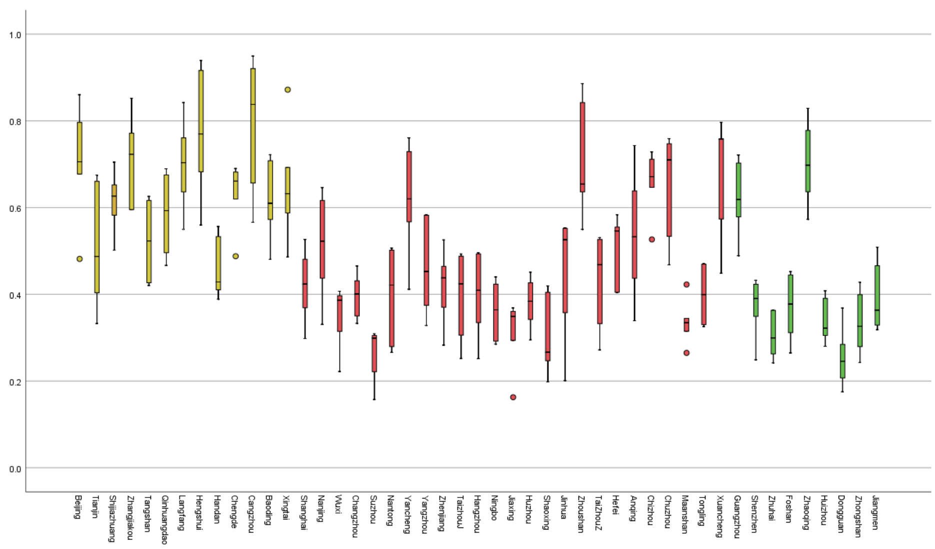

Fig. 2. Box plot for all the cities during from 2014 to 2019.

The differences in efficiency results are based on different DEA models, as shown in Table 4 by using the data from 2019. The efficiency score and ranking orders based on the traditional CCR model are shown in columns 3 and 4. In contrast, the results based on arbitrary and newly constructed cross-efficiency models are illustrated in the last four columns. The classic CCR model cannot give different efficiency scores for all cities as it divides all cities into efficient (13 of 48) and inefficient (35 of 48). Using CCR, both the efficiency scores and ranking orders are calculated using the self-evaluation mode. As such, the efficiency scores are lower and more discriminating using the peer-evaluation model.

For comparison, in Table 4, we list the efficiency results of cross-efficiency models based on both arbitrary and cooperation and competition strategies. The two cross-efficiency models provide a full ranking order and more objective efficiency scores for all cities. The efficiency scores and ranking orders should change considering the cooperation and competition relationship in model (4). For example, Beijing ranks fourth based on the arbitrary cross-efficiency model, while it ranks second when using the cooperation and competition cross-efficiency model. The efficiency scores also change in different directions by applying the newly presented model; in particular, some cities gain higher efficiency scores, such as Beijing, Chizhou, and Shenzhen, while other cities' efficiency scores decrease, such as Qinhuangdao, Nantong, and Zhaoqing. Based on the strategy of getting stronger practical significance by fully considering the relationship among cities, the newly presented model provides more reasonable efficiency results that could help managers design excellent development models for agglomerations.

4.4 Analysis of factors that influence environmental efficiency

The above analyses show the efficiency results for cities in three major agglomerations. Next, we discuss the internal and external environments of the environmental efficiency score of cities by considering the influence factors from three different angles. Based on the above analysis and data availability, this paper selects the 11 influence factors shown in Table 5.

In this section, we present a consideration of the environmental efficiency as an independent variable and construct the following Tobit regression equation to analyze how the 11 selected influencing factors affect efficiency scores.

DOI: 10.52396/JUSTC-2022-0028
JUSTC, **2022**, 52(4): 3

Table 4. Efficiency scores and ranking orders based on different models in 2019.

	City	CCR		Arbitrary cross-efficiency		Model (4)	
		Efficiency score	Rank	Efficiency score	Rank	Efficiency score	Rank
BTHUA	Beijing	1	1	0.8442	4	0.8602	2
	Tianjin	0.6705	35	0.5121	30	0.507	29
	Shijiazhuang	0.7311	29	0.5777	20	0.5826	19
	Zhangjiakou	1	1	0.8576	3	0.8521	3
	Tangshan	0.8837	20	0.607	19	0.6258	18
	Qinhuangdao	0.9086	17	0.7006	13	0.6895	13
	Langfang	1	1	0.7867	7	0.7608	6
	Hengshui	1	1	0.9027	1	0.9393	1
	Handan	0.6843	34	0.5511	23	0.5563	21
	Chengde	0.8068	24	0.6667	15	0.6736	14
	Cangzhou	1	1	0.8154	5	0.8279	5
	Baoding	0.9575	15	0.7193	11	0.722	11
	Xingtai	0.8449	22	0.6172	18	0.6267	17
YRDUA	Shanghai	0.7621	26	0.53	26	0.5266	25
	Nanjing	0.9078	18	0.6572	16	0.6461	16
	Wuxi	0.6053	38	0.3981	42	0.3967	42
	Changzhou	0.7607	27	0.4647	34	0.4654	33
	Suzhou	0.434	46	0.3134	46	0.3089	46
	Nantong	0.8087	23	0.5373	25	0.5019	30
	Yancheng	1	1	0.7702	10	0.7608	7
	Yangzhou	0.8953	19	0.6201	17	0.5823	20
	Zhenjiang	0.8754	21	0.5268	28	0.5255	27
	Taizhou J	0.689	33	0.5166	29	0.4879	32
	Hangzhou	0.7004	32	0.5034	31	0.4958	31
	Ningbo	0.573	40	0.4424	37	0.4402	37
	Jiaxing	0.4664	45	0.3626	45	0.3606	45
	Huzhou	0.5558	43	0.46	36	0.4511	36
	Shaoxing	0.6005	39	0.4385	38	0.4194	40
	Jinhua	0.7511	28	0.5669	22	0.5532	23
	Zhoushan	1	1	0.6844	14	0.6675	15
	Taizhou Z	0.7223	30	0.5479	24	0.5307	24
	Hefei	0.7917	25	0.576	21	0.5549	22
	Anqing	1	1	0.787	6	0.7431	10
	Chizhou	1	1	0.4877	33	0.5266	26
	Chuzhou	0.9692	14	0.7848	8	0.759	8
	Maanshan	0.7136	31	0.4269	40	0.4227	39
	Tongling	1	1	0.494	32	0.4643	34
	Xuancheng	1	1	0.781	9	0.7569	9
GHMGBA	Guangzhou	1	1	0.7176	12	0.7028	12
	Shenzhen	0.5658	41	0.418	41	0.4231	38
	Zhuhai	0.9383	16	0.3682	44	0.3631	44
	Foshan	0.6088	37	0.4643	35	0.4524	35
	Zhaoqing	1	1	0.8667	2	0.8289	4
	Huizhou	0.5458	44	0.4274	39	0.4082	41
	Dongguan	0.3978	47	0.2966	47	0.2846	47
	Zhongshan	0.5649	42	0.3894	43	0.3665	43
	Jiangmen	0.648	36	0.5298	27	0.5087	28

DOI: 10.52396/JUSTC-2022-0028
JUSTC, **2022**, 52(4): 3

Table 5. Variable descriptions of influencing factors.

	Variable	Symbol	Unit
Social factors	Total Urban Population	TUP	Ten thousand people
	Number of Local Colleges	NLC	-
	Number of College Students	NCS	Person
	Number of Industrial Enterprises Above Scale	NIE	ton
	Average Annual Salary	AAS	Yuan
Natural factors	Coastal City (yes or no)	CC	-
	Total Quantity of Water Resource	TWS	100 Million M^3
Urban factors	Agglomeration	AGG	-
	Planned Urban Land-use Area	PUL	Square kilometer
	Density of Drainage Pipe	DDP	Kilometer/Square kilometer
	Density of Water Supply Pipe	DWP	Kilometer/Square kilometer

$$EE_{it} = \beta_0 + \beta_1\mathrm{TUP}_{it} + \beta_2\mathrm{NLC}_{it} + \beta_3\mathrm{NCS}_{it} + \beta_4\mathrm{NSE}_{it} + \beta_5\mathrm{AAS}_{it} + \beta_6\mathrm{CC}_{it} + \beta_7\mathrm{TWS}_{it} + \beta_8\mathrm{AGG}_{it} + \beta_9\mathrm{PUL}_{it} + \beta_{10}\mathrm{DDP}_{it} + \beta_{11}\mathrm{DWP}_{it} + \varepsilon_{it} \quad (8)$$

In the above model (8), the independent variable *GE* represents the environmental efficiency score for city *i* in year *t*, β_0 is a constant term, and $\beta_1, \cdots, \beta_{11}$ are the regression parameters for the 11 dependent variables, while ε_{it} is a random error term. The data about influencing factors are selected from the *China Urban Statistical Yearbook* and *Regional Water Resources Bulletin* from 2014 to 2020. The software STATA 11 is used to calculate the Tobit regression model.

In Table 6, columns *A* and *B* indicate the regression results with or without considering individual effects, respectively. From the results in column Ⅰ, we can find that: ① all the social influencing factors significantly impact the environmental efficiency score, among which total population(TUP), large industrial enterprises(NIE), and income(AAS) have an impact at a 1% significance level; ② the impact from all natural influencing factors are not significant; ③ some of the urban factors significantly impact the environmental efficiency score. Based on the panel data in this paper, we also calculate the regression results considering the individual effect and illustrate the results in column Ⅱ. By comparing the results in columns Ⅰ and Ⅱ, we find that these two regression models provide the same influence directions for factors with different significance.

We discuss the regression analysis results with individual effects as follows:

(Ⅰ) TUP is an important social resource in urban development, indicating the quality of potential human resources in

Table 6. Tobit model regression analysis results.

	Variable	A (with)	B (without)
	Constant	0.434*** (6.95)	0.394*** (3.82)
Social factors	TUP	$8.40\times E^{-5}$*** (5.94)	$6.00\times E^{-5}$*** (2.87)
	NLC	$-1.78\times E^{-3}$** (−2.54)	$-7.00\times E^{-4}$ (−1.30)
	NCS	$1.32\times E^{-7}$* (1.70)	$3.10\times E^{-8}$ (0.30)
	NIE	$-3.76\times E^{-5}$*** (−10.17)	$-2.67\times E^{-5}$*** (−3.43)
	AAS	$2.97\times E^{-6}$*** (6.92)	$3.48\times E^{-6}$*** (8.36)
Natural factors	CC	$-4.00\times E^{-3}$ (−0.23)	$-6.00\times E^{-3}$ (−0.17)
	TWS	$1.80\times E^{-8}$ (0.83)	$5.50\times E^{-8}$* (1.84)
Urban factors	AGG	$-4.10\times E^{-2}$** (−2.22)	$-6.4\times E^{-2}$* (−1.78)
	PUL	$4.10\times E^{-6}$*** (3.03)	$4.3\times E^{-6}$* (1.81)
	DDP	$-1.00\times E^{-3}$ (−0.77)	$-2.3\times E^{-3}$** (−2.09)
	DWP	$-2.60\times E^{-3}$* (−1.74)	$-6.00\times E^{-4}$ (−0.49)
	Individual effect	No	Yes
	No. of Cities	48	48
	Observations	288	288

Note: ***, **, and * represent the significance levels of 1%, 5%, and 10%, respectively.

DOI: 10.52396/JUSTC-2022-0028
JUSTC, **2022**, 52(4): 3

all industrial sectors. The TUP has a significant positive relationship with environmental efficiency; notably, a city can improve its environmental efficiency by $6.00\times E^{-5}$ for every 10000 people added to its population. The people's income, AAS, is also an important indicator of local human resources that has a significant positive correlation with environmental efficiency.

(Ⅱ) Although the development of the higher education institutions is recognized as a key force to promote regional innovation, the influence of NLC and NCS on environmental efficiency score is not significant. This probably results from the human mobility among different cities in China as higher education students cultivated by one city might be attracted by other cities because of a higher AAS.

(Ⅲ) NIE indicates the number of large industrial enterprises and negatively correlates with the environmental efficiency score. The number of NIE could reflect the industry's position in the regional economy. Based on the regression results, we can conclude that cities with more large industrial enterprises have lower environmental efficiency scores by consuming more resources or emitting more pollution.

(Ⅳ) Natural factors do not have a powerful impact on environmental efficiency as expected because the influence from CC is not significant. At the same time, the positive correlation of water resource(TWS) is only significant at the 10% level. With the development of urbanization, the importance of natural factors is declining. City managers should pay more attention to forming advantages based on social factors and urban infrastructure construction rather than more deeply mining natural resources. The significant relationship with drainage pipe(DDP) could also confirm that result.

(Ⅴ) The relationship between urban characteristics and environmental efficiency score is significant in cities belonging to agglomerations. Cities from different agglomerations attain significantly different environmental efficiency scores, which infers differences in the overall development strategy for these three agglomerations in China. Moreover, the cities' urban surface area, represented by variable PUL, also positively impacts environmental efficiency.

5 Conclusions

In recent years, environmental efficiency has attracted increasing attention because of its usefulness for analyzing regional development using a DEA approach. After the high-speed construction of China's urban agglomerations, the individual cities are no longer independent production systems. We need to consider the complex relationships among cities, such as cooperation within an agglomeration and competition between agglomerations. This paper constructs a set of cross-efficiency models based on a cooperation and competition strategy to characterize the relationships among cities under urban agglomeration. By comparing the new models' results with those obtained by the classic model, we see that the new cross-efficiency model provides more discriminative efficiency scores and achieves a full ranking order. As a new strategy to construct secondary goal programming, our cross-efficiency model's efficiency scores and ranking order differ from those of the traditional cross-efficiency model.

This paper analyzes the environmental efficiency in three major China agglomerations in an empirical study including 48 cities from 2014 to 2019, selecting four inputs, two desirable outputs, and two undesirable outputs as variables. The efficiency results show increasing trends in all three agglomerations during the time under evaluation. Generally, the BTHUA performs better than YRDUA and GHMGBA, attaining higher average efficiency scores in all six years. We found some distribution characteristics of the environmental efficiency scores. For example, cities in the north perform better. The local environmental efficiency score has spillover effects in adjacent areas in the south. Therefore, we constructed a Tobit regression model to study 11 key influencing factors from three angles to discover environmental efficiency scores' internal and external bases. The regression results show that four indicators—namely TUP, AAS, TWS, and city area(PUL)—have significant positive impacts on environmental efficiency. In comparison, three indicators, namely NIE, agglomeration (AGG), and DDP have significant negative impacts.

The environmental efficiency of cities in urban agglomerations are analyzed in this paper by constructing a set of cross-efficiency models based on the assumption of competition and cooperation. Owing to the limitation of data and development processes of urban agglomerations, this paper only measured 48 mainland cities in three agglomerations. In the future, we intend to extend this study by expanding research samples. Besides, this paper assumes the competitive and cooperative relationship among cities in agglomerations without an analysis of the influences of urban agglomeration development to individual cities. So, a further study could focus on analyzing the influence of urban agglomeration development on different cities.

Acknowledgements

This research was supported by the National Natural Science Foundation of China (72071066, 72188101).

Conflict of interest

The authors declare that they have no conflict of interest.

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DOI: 10.52396/JUSTC-2022-0028
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