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Original Research

Environmental Issues for Cities in China: SO_2 Emissions and Population Distribution

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Abstract

In this paper we establish a number of environmental indices to rate the green efficiency of cities in China, while at the same time using them to discuss two problems in China: emissions of sulfur dioxide (SO_2) and population distribution. The indices used in this paper have never been implemented in the literature. From them, we can understand the level of environmental protection in China and be better equipped to improve the country's environmental pollution. We also use macroeconomic data in this paper, and draw valuable conclusions. The data cover 1998 to 2003. All nominal variables are transformed into real variables based on 1998 price levels using the GDP deflator. To the best of our knowledge, China's eastern cities have the most prosperous economies in China. However, their overall green efficiency value is inferior to that of the central cities. We further find that no city has a population that exceeds the optimal population target value. This is an astonishing finding. The eastern cities' emissions of SO_2 are the highest and their additional population capacity is the lowest. The overall performance of the central cities of China is therefore superior to that of the eastern cities. Finally, we also find that the development between the eastern and western areas of China is balanced.

Keywords: green efficiency, environmental index, SO_2, population capacity

Introduction

It is well known that China has recently experienced rapid economic growth, an astonishing economic feat that has been widely acclaimed by other countries. In the past, many countries used their national income to measure their economic development level. However, while this parameter emphasizes economic growth, it ignores the importance of environmental protection. Reports drawn up by China's State Environmental Protection Administration and the National Bureau of Statistics show that pollution in China has resulted in an economic loss of about 61.9 billion USD, or 3.05% of GNP. The relationship between environmental protection and economic development has been unbalanced in China.

Environmental pollution in China is becoming more and more serious. Since many factories are located in large cities, the air pollution in these places can be particularly bad. As for water pollution, polluted rivers and groundwater have affected the quality of drinking water. In addition, the increased population density of the cities has given rise to noise pollution and a lack of green areas. The shifting population in

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China has also adversely affected the development of cities. From 1994 to 2008, the average economic growth rate in China was 10.1%. The rapid economic growth and urbanization have brought much pressure to bear on the development of Chinese cities. Thus we use air pollution, water pollution, noise pollution and green coverage rates to study the development of Chinese cities.

Chang et al. [1] were the first to apply the Data Envelopment Analysis (DEA) method to analyze this issue in Taiwan, but no environmental factor was included among the input and output variables of the DEA model. The concept of including environmental factors in the input and output variables did not appear until Lovell et al. [2]. The main conclusion of that paper was that China and ASEAN (Association of Southeast Asian Nations) had pursued economic growth at the cost of giving up environmental quality. Although everybody knows there is a serious environmental pollution problem in China, nobody has provided an environmental strategy that is based on an environmental index. Hu and Kao [3] use an energy index in the DEA model to analyze the energy-saving targets of 17 APEC countries using energy that is more efficient.

In this paper we treat the environmental factors as input variables and the output variables in the DEA model to analyze China's environmental protection problem. Due to our considering the environmental variables in the DEA model and using them to estimate efficiency values, we refer to such efficiency values as green efficiency values. As for China's environmental issue, we focus on the sulfur dioxide (SO_2) emissions and population. SO_2 is the main cause of acid rain. Recently, one-third of China's land has suffered from rain with annual average pH values below 5.6 [4]. Besides, acid rain in China has seriously affected human health, ecosystems, cultural resources, agriculture, and forestry. Szarek-Łukaszewska [5] has observed the influence of SO_2 on the Niepołomice Forest in southern Poland over a period of 30 years. She finds that atmospheric precipitation has recently become more acidic than in the 1970s. For sustainable development, both in China and globally, SO_2 emissions should be controlled and managed in China. Besides, if the population is excessively dense in a city, then it will give rise to many environmental problems, for example noise pollution, garbage pollution, air pollution, etc. Krzeminska-Flowers et al. [6] take Łódź city in Poland as an example to estimate urban air pollution based on traffic intensity, coal combustion and soil re-suspension. In a similar manner, we structure a number of environmental indices and use them to provide environmental improvement suggestions on SO_2 emissions and population.

We now turn to a review of some of the related literature to explain these issues in detail. Dong et al. [7] study the problems and strategies of industrial transformation in China's resource-based cities using SO_2 emissions, GDP per capita, electricity consumption and water consumption. In this paper, we also use the same variables to study the environmental issue for cities in China.

Li et al. [8] employ principal components analysis to study the urban employment of 35 cities in northeastern China. They divide these 35 cities into "old industrial base cities," "resources-exhausted cities," and "medium-sized and small towns with a low level of development," and conclude that since industrial cities provide much employment, the solution to the employment problems in Northeast China should be viewed in the context of the industrial cities.

Zhang and Yang [9] take Shenzhen, a coastal city in southern China, as an example to estimate the eco-efficiency of the urban material metabolism according to the development laws of the Environmental Kuznets Curve. The variables that they use include the volume of industrial SO_2 emissions, the annual turnover of permanent population, the volume of industrial wastewater and so on. They find that the main ways of improving the eco-efficiency of the urban material metabolism include increasing resources and environmental efficiencies and establishing a recycling chain for the reuse of water resources. Similarly, Huang [10] studies the material metabolism in Taipei through the use of a dynamic method.

Chang et al. [1] apply the proposed DEA model in Färe et al. [11] to evaluate output efficiency and productivity change in Taiwan's 23 counties. Their goal is to determine whether the relative change in regional development in Taiwan's 23 administrative regions has moved forwards or backwards between 1983 and 1990. Lovell et al. [2] use two kinds of air pollution emissions (carbides and nitrides) to compute the respective performances of OECD and non-OECD countries. They observe that there is not a significant difference in the ranking of relative efficiency values among the different countries. Färe et al. [12] take the amount of CO_2 emissions, the amount of suspended particles and per capita national income as the output variables, while including the total labor force and total capital stock as the input variables. They apply the DEA model to assess the environmental efficiency values of 24 OECD countries from 1971 to 1999.

Färe et al. [13] use the emission amounts of sulfide dioxide, nitride oxide, volatile organic compounds, and carbon nitride as output variables, while using the total labor force and total capital stock in the American manufacturing industry as input variables. They then use the Malmquist Productivity Index to estimate the American manufacturing industry's productivity. The data period extends from 1974 to 1986. Hu et al. [14] apply the emissions of SO_2 in each area of China as a proxy variable. They find that, if the environmental factor is not considered in the model, the productivity and performance in eastern China is deemed to have been better than that in western China for the past ten years. If the environmental factors are considered in the model, then the rankings of productivity and performance do not change, but there are large differences in the values of productivity and performance after the environmental factors are considered. This implies that the economy and environment in eastern China have deteriorated.

Table 1. Location distributions of China's 44 cities.

Area	Provinces (Municipalities)	City name
Eastern	Beijing, Tianjin, Shanghai Anking, Hebei, Shandong, Jiangsu, Zhejiang, Fujian, Guangdong, Guangxi, Hainan	Beijing, Tianjin, Shanghai Shi Jiazhuang, Tang Shan, Handan, Xingtai, Baoding, Cangzhou, Shenyang, Xuzhou, Nantong, Yancheng, Hangzhou, Wenzhou, Quanzhou, Qingdao, Yantai, Ji'ning, Linyi, Guangzhou, Zhanjiang, Maoming
Central	Heilongjiang, Jilin, Neimeng, Shanxi, Henan, Anhui, Hubei, Hunan, Jiangxi	Changchun, Harbin, Anking, Fuyang, Liuan, Ganzhou, Zhengzhou, Luo Yang, Shangqi, Nanyang, Xinyang, Wuhan, Jingzhou, Huanggang, Hengyang, Shaoyang
Western	Xinjiang, Qinghai, Gansu, Shaanxi, Ningxia, Yunnan, Sichuan, Guizhou	Chongqing, Chengdu, Nanchong, Zunyi, Xi'an

Lo et al. [15] use the emissions of CO_2 as an environmental variable. CO_2 is a good that is not wanted in the manufacturing process, and if it is treated as an output variable, it will then be referred to as an undesirable output. They find that the productivity growths of China and ASEAN significantly deteriorate after the environmental factor is taken into consideration in the model. On the contrary, the productivity growths of Taiwan, Japan, and South Korea are found to improve after taking into consideration the environmental factors in the model. This implies that China and ASEAN pursue economic growth at the cost of giving up environmental quality.

Materials and Methods

Information on Sample Data

The sample used in this study comprises 44 Chinese cities that are ranked based on the sizes of their respective populations. The location distributions of the 44 cities are shown in Table 1. All data are annual data, and are obtained from the *China City Statistics Yearbook*. If there are any deficiencies in the sample data, we can make up for the lack by consulting the "National Bureau of Statistics of China" or each province's statistics homepage in China. We use panel data from 1998 to 2003.

Data Envelopment Analysis Method

This research applies data envelopment analysis to compute municipal efficiency and target the values of outputs and inputs. The aim is to find the most efficient cities in China, and then to draw a line to link these regions. This line is called the production frontier. Using the production frontier as a standard, if cities are not located on the production frontier, then they are inefficient. The distance from the production frontier to the locations of the inefficient cities represents inefficiency. Finally, we use linear programming to compute the inefficient cities' efficiency values and their improvement directions.

Farrell [16] pioneered the taking of multiple inputs and multiple outputs to compute an efficiency value. This method was built upon by Charnes et al. [17], who used linear programming to obtain city production frontiers which were then used to compute efficiency values. This method is referred to as the DEA method. Because they assumed that the production process exhibited constant returns to scale, their model was also referred to as the CCR model.

While Charnes, Cooper, and Rhodes provided a constant returns-to-scale (CRS) model [17], Banker et al. [18] instead assumed variable returns to scale (VRS). In the input-oriented CRS DEA model, we assume that there are data on K inputs and M outputs for each of the N firms. For the i-th city, these are represented by the column vectors x_i and y_i. The K×N input matrix X and the M×N output matrix Y represent the data for all N firms. The output-oriented CRS DEA model then solves the following linear programming problem for city i in each year:

$$\begin{aligned} &\max_{\phi,\lambda} \ \phi \\ &\text{s.t. } -\phi y_i + Y\lambda \leq 0 \\ &\quad x_i - X\lambda \geq 0 \\ &\quad \lambda \geq 0 \end{aligned} \tag{1}$$

...where $\phi = 1/\theta \geq 1$, and θ is defined as overall technical efficiency (OTE).

The value of θ is used as the efficiency score for the i-th firm that satisfies $0 \leq \theta \leq 1$. The value of unity indicates a point on the frontier and hence a technically efficient firm, according to Farrell's definition [16]. The DEA problem in equation 1 takes the i-th firm and then seeks to radially contract the input vector, x_i, as much as possible, while still remaining within the feasible input set. The inner-boundary of this set determined by the observed data points is a piecewise linear iso-quant. The radial contraction of the input vector, x_i, produces the projected point ($X\lambda$, $Y\lambda$) on the frontier of this technology. This projected point is a linear combination of these observed data points. The constraints in equation 1 confirm that this projected point cannot lie outside the feasible set. To illustrate the efficiency measurement, for example,

Table 2. Table of the correlation coefficients of input and output variables.

	y_1	y_2	y_3	y_4	y_5	x_1	x_2	x_3	x_4	x_5
y_1	1.000									
y_2	0.300	1.000								
y_3	0.298	0.049	1.000							
y_4	0.855	0.119	0.230	1.000						
y_5	0.163	0.197	0.146	0.138	1.000					
x_1	0.606	0.335	0.002	0.583	0.039	1.000				
x_2	0.699	0.082	0.224	0.637	0.189	0.463	1.000			
x_3	0.775	0.209	0.184	0.620	0.147	0.595	0.631	1.000		
x_4	0.887	0.365	0.192	0.862	0.126	0.780	0.642	0.768	1.000	
x_5	0.027	0.043	0.057	0.063	0.211	0.084	0.072	0.039	0.002	1.000

Fig. 1 interprets C and D as being the efficient firms which define the frontier such that A and B are inefficient firms. Farrell's measure of overall technical efficiency [16] explains that the respective efficiencies of firms A and B are $\overline{OA'}/\overline{OA}$ and $\overline{OB'}/\overline{OB}$, respectively.

U Mann-Whitney Test

Brockett and Golany [19] first applied the U Mann-Whitney Test to the DEA efficiency ranking test. The U Mann-Whitney Test is used to determine whether two populations have the same medians, whether the two samples come from the same population, or if the two populations have the same variances.

The basic assumptions of the U Mann-Whitney Test are:

(1) the two populations have a continuous distribution, and they have the same shape;

(2) the two samples are random with sizes n_1 and n_2, respectively.

When we use this, we mix the two samples first, and then the samples are ranked from the smallest value to the largest one. The ranking sums of the two samples are W_1 and W_2, respectively. The symbol U_1 indicates that the number of the second sample's observation values is smaller than those of the first observation, and the symbol U_2 denotes that the number of the first sample's observation values is smaller than that of the second observation values:

$$U_1 = n_1 n_2 + [n_1(n_1 + 1) / 2] - W_1,$$
$$U_2 = n_1 n_2 + [n_2(n_2 + 1) / 2] - W_2 \qquad (2)$$

We take the minimized value between U_1 and U_2 as the statistics' U value. If both n_1 and n_2 are smaller or equal to the critical value of 8, or one of them lies between the critical values of 9 and 20, then we can make a decision based on the U Mann-Whitney Test.

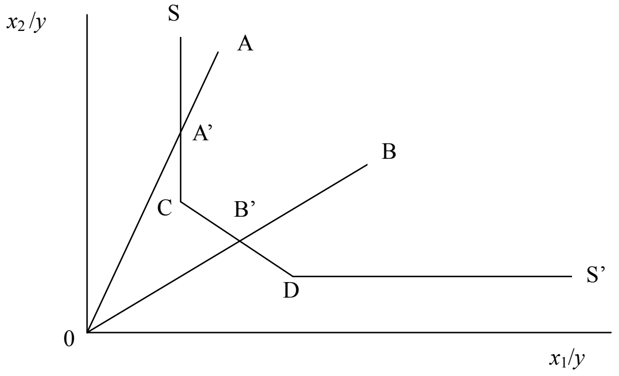

Fig. 1. Efficiency measurement in the CRS DEA model.

Empirical Analysis

In this study we apply the two-stage analysis method to analyze the issue of green efficiency [19]. In the first stage, we use the DEA method to compute the efficiency values of Chinese cities. In the second stage, the U Mann-Whitney Test is applied to check whether there is an efficiency value difference that exists among China's eastern cities, central cities, and western cities.

Choice of Input and Output Variables

Traditionally, GDP, total labor force, and total capital stocks have been chosen to serve as the independent variables. Because we use the environmental variables to compute the performance of Chinese cities in this study, we refer to the previous literature to understand which variables are usually chosen and added as environmental variables in the model so as to explain how the environmental variables influence the performances of Chinese cities. In this model the output variables include the annual real income of a city (y_1), population (y_2), the proportion of

Table 3. The descriptive statistics of inputs and outputs.

	Unit	Mean value	Standard deviation	Maximum value	Minimum value
y_1	1,000 USD	14,722,658.259	16,200,118.075	128,061,849.249	56,625.601
y_2	1,000 people	8,392.800	3,799.000	31,301.000	5,967.300
y_3	%	78.060	23.660	100.000	0.000
y_4	%	0.820	1.310	10.200	0.000
y_5	%	30.100	7.210	57.850	14.090
x_1	1,000 people	1,119.400	1,398.800	7,720.700	220.900
x_2	1,000 USD	812,829.900	1,761,403.100	12,596,480.300	53.800
x_3	1,000 USD	1,517,349.200	4,623,493.841	44,736,502.308	15,818.619
x_4	1,000 KW/hr	6,964,453.400	10,956,257.100	74,597,000.000	149,130.000
x_5	ton	66.980	131.090	887.800	0.000

industrial wastewater treated to standard (y_3), the proportion of environmental noise reduced to standard (y_4), and the green coverage rate in the developed area (y_5). The input variables include total employees (x_1), the utilization of foreign capital (x_2), the total financial expenditure of the local government (x_3), electricity consumption (x_4), and total emissions of SO_2 (x_5).

There are four environmental variables within these variables: the proportion of industrial waste water treated to standard, the proportion of environmental noise reduced to standard, the green coverage rate in the developed area, and total SO_2 emissions. Each environmental variable is defined as follows:

(1) the proportion of industrial wastewater treated to standard = (the amount of industrial wastewater reach to discharge standards / total amount of industrial waste water discharged) × 100%;
(2) the proportion of environmental noise reduced to standard = (area size of environmental noise reach to standards / total area size) × 100%; and
(3) the green coverage rate in the developed area = (vertically projected area of green area / total area size) × 100%.

On the other hand, the annual real income of the city (y_1), the utilization of foreign capital (x_2), the total financial expenditure of the local government (x_3), and all variables are changed to real variables by taking the 1998 GDP deflator as a base period.

Table 2 shows that all correlation coefficients of input and output variables are positive. This implies that the amount of output should not decrease when any amount of input increases. Hence, the input and output variables meet the iso-tonicity condition.

Table 3 shows the descriptive statistics of the input and output variables. It shows that each standard deviation of the input and output variables is large. For example, the standard deviation of the annual real income of a city is 16,200,118.075, the standard deviation of the utilization of foreign capital is 1,761,403.100, the standard deviation of the total financial expenditure of the local government is 4,623,493.841, and the standard deviation of total SO_2 emissions is 131.090. These findings imply that there are large differences among Chinese cities.

Green Efficiency Analysis

Table 4 presents the overall efficiency values of the 44 cities during the six-year period. However, the overall efficiency values in the model are estimated using the macroeconomic variables and environmental variables. Thus, we define the overall efficiency values in the model as the "green efficiency values". According to the difference in geographic location, we separate the 44 cities of China into three sub-areas: the eastern, central, and western areas [20, 21]. (The notations E, C, and W in Table 4 represent the eastern, central, and western cities, respectively.)

Table 4 shows that the green efficiency values for 11 cities equal 1 from 1998 to 2003. We refer to the ranking of the 11 cities' competitiveness in the "2004 Report on Competitiveness on Chinese cities" and observe that Nantong's competitiveness is ranked 48^{th}, which is shown as Nantong (48). The competitiveness of the other cities is as follows: Hangzhou (5), Fuyang, Liuan, Quanzhou (40), Ganzhou, Zhengzhou (50), Shangqi, Huanggang, Maoming (88), and Nanchong (159). However, only the ranking of Hangzhou's competitiveness is similar to that of the big cities such as Beijing and Shanghai. The competitiveness of the other cities is inferior to that of the big cities. Of the 11 cities, 4 cities are located in the east, 6 cities are located in the central area, and 1 city is located in the west.

The percentages of the cities' green efficiency values equal to 1 are 17.4%, 37.5%, and 20% for the eastern, central, and western cities, respectively. The central cities have a high average overall green efficiency value of 0.94. However, the average overall green efficiency value for eastern cities is 0.89, and the average overall green efficiency value in western cities is 0.88. The rankings of the average overall green efficiency values for the cities from high to low are ordered as follows: central, eastern, and western. However, this result goes against the general intuition. To our knowledge, if a city has a prosperous economy, then it has a high efficiency value.

According to this concept, the three sub-areas' efficiency values should be ranked as follows: eastern, central, and western. A reasonable explanation is that, because our model includes economic and environmental variables, we can explain this result from the phases of the economy and environment in the following way: although there is good economic performance in the eastern cities, excessive economic development hurts the environment. On the contrary, although there is bad economic performance in the western cities, the undeveloped economy induces a good and consistent environment, while the central cities maintain a development balance with regard to the economy and environment. The average green efficiency value of Beijing is the worst among the three largest cities of China, namely Shanghai, Beijing and Guangzhou. The reason is that because Beijing served as the major city for the 2008 Olympic Games, many construction projects have been ongoing there. Thus, the construction projects have resulted in environmental pollution that has caused the green efficiency value of Beijing to drop. The numbers of cities where the green efficiency value hits 1 exhibit an increasing trend from 1998 to 2002. However, there is a slight decrease in 2003.

Results and Discussion

In this subsection, we turn to discuss the improved space for emissions of SO_2 and the city's population and population adjustments in Chinese cities. Finally, we perform a U Mann-Whitney Test to check the robustness of the results.

Improved Space for Environmental Variables

We can use the model in this paper to obtain the optimal values of the inputs and outputs for each city in each year. This is helpful for understanding which environmental variable has an improved space by comparing the real efficiency value with the targeted efficiency value.

Total Emissions of SO_2

The improved space in regard to the total emissions of SO_2 is defined as follows:

The improved space on the total emissions of:

$$SO_2 = 1 - (\text{the target value of the emission amount} / \text{the real value of the emission amount}) \geq 0 \quad (3).$$

This index is established by Hu [11]. An index value equal to zero indicates that there is no improved space in the total emissions of SO_2. At this time, the total emission of SO_2 reaches its optimal value. The larger the index value is, the more improved the space will be. We use this index to compute the improved space in the total emissions of SO_2 and obtain results as shown in the following table: In Table 5 the total emissions of SO_2 in Shenyang, Jingzhou, and Xi'an did not reach the emission standard for at least four years in the data period, and in some specific years, some cities' total emissions of SO_2 exceeded the optimal value: for example, Cangzhou in 2000, Handan in 1998 and 1999, Linyi in 1999, Qingdao in 1998, Tang Shan in 1999, Xingtai in 1998 and 2000, and Anking in 1998 and 2001. However, these seven cities exhibited a good performance in 2002 and 2003. This implies that China's government asked these six cities to manage and control their total emissions of SO_2. There are 21 cities that achieved the optimal value of the total emissions of SO_2 in the data period.

In January 1998 the State Council of the People's Republic of China promulgated the regulations on acid rain control areas and SO_2 pollution control areas. In the "Outline of National Economic and Societal Development," it clearly stated that the total emissions of SO_2 in the acid rain control areas in 2005 would be 20% lower than in 2000. This announcement has become one of the country's major environmental protection projects. Table 5 shows that 12 cities did not achieve the emission standard for SO_2 in 1998 and 1999. However, the number of cities which did not achieve the emission standard, decreased to 4 in 2002 and 2003. This implies that the emissions of SO_2 have been controlled. More specifically, all cities in eastern China achieved the emission standard in 2003.

In Table 5 the average values of the improved space in the total emissions of SO_2 are 6.98, 5.92, and 4.71 for the eastern, central, and western cities, respectively. It shows that the largest improved space is in the east and the smallest improved space is in the west. This result meets China's economic development situation.

We use "City" as a decision-making unit (DMU) and conclude that the improved space of emissions of SO_2 in the eastern cities is larger than that in the western cities. However, Hu [20] uses "province" as a DMU and concludes that the improved space of emissions of SO_2 in the western area is larger than that in the eastern area. By combining the conclusions of Hu [20] and this paper, this implies that the main emissions of SO_2 in the eastern area come from large cities, and the main emissions of SO_2 in the western area come from small cities. Thus, there should be a different policy to manage and control the emissions of SO_2 between the eastern and western areas. In other words, China's government should manage and control large cities' emissions of SO_2 in the eastern area, and manage and control small cities' emissions of SO_2 in the western area. This finding also implies that there is the development of a balance between the eastern and the western areas of China.

Table 4. Overall green efficiency values of 44 cities in China (E = eastern, C = central, W = western).

City name	Area	1998	1999	2000	2001	2002	2003	Average
Baoding	E	0.74	0.65	0.85	1.00	1.00	0.85	0.85
Beijing	E	0.60	0.52	0.72	0.93	0.35	0.69	0.63
Cangzhou	E	0.87	0.85	0.86	1.00	1.00	1.00	0.93
Guangzhou	E	1.00	0.98	1.00	1.00	0.90	0.92	0.97
Handan	E	0.61	0.68	0.52	0.66	0.84	1.00	0.72
Hangzhou	E	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Ji'ning	E	0.84	0.93	0.94	0.76	1.00	1.00	0.91
Linyi	E	0.93	0.75	1.00	1.00	1.00	1.00	0.95
Maoming	E	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Nantong	E	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Qingdao	E	0.40	0.68	0.74	0.81	0.89	0.91	0.74
Quanzhou	E	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Shanghai	E	0.63	0.81	0.87	1.00	0.87	0.81	0.83
Shenyang	E	0.62	0.47	0.75	0.90	0.86	0.95	0.76
Shi Jiazhuang	E	0.61	0.55	1.00	0.82	0.87	0.75	0.77
Tang Shan	E	0.64	0.63	0.76	0.91	1.00	0.90	0.81
Tianjin	E	0.61	0.62	0.77	1.00	0.74	1.00	0.79
Wenzhou	E	1.00	0.89	1.00	1.00	1.00	1.00	0.98
Xingtai	E	0.70	1.00	0.91	1.00	1.00	1.00	0.93
Xuzhou	E	0.89	1.00	1.00	0.97	1.00	1.00	0.98
Yancheng	E	1.00	0.93	1.00	1.00	1.00	1.00	0.99
Yantai	E	0.74	1.00	1.00	1.00	1.00	1.00	0.96
Zhanjiang	E	0.69	0.98	0.98	1.00	0.94	1.00	0.93
Anking	C	0.91	1.00	0.95	0.89	1.00	1.00	0.96
Changchun	C	0.80	0.57	1.00	1.00	0.87	1.00	0.87
Fuyang	C	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Ganzhou	C	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Harbin	C	0.42	0.21	0.63	0.77	0.96	0.99	0.66
Hengyang	C	0.93	0.97	1.00	1.00	1.00	0.77	0.95
Huanggang	C	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Jingzhou	C	0.68	0.79	0.73	0.76	1.00	1.00	0.83
Liuan	C	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Luo Yang	C	1.00	0.97	1.00	1.00	1.00	1.00	0.99
Nanyang	C	0.68	0.86	1.00	1.00	1.00	0.80	0.89
Shangqi	C	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Shaoyang	C	0.93	0.89	1.00	1.00	1.00	1.00	0.97
Wuhan	C	1.00	1.00	1.00	0.97	0.60	0.59	0.86
Xinyang	C	0.99	1.00	1.00	1.00	1.00	0.94	0.99
Zhengzhou	C	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Chongqing	W	0.58	1.00	0.77	0.89	0.92	0.68	0.81
Chengdu	W	0.81	1.00	1.00	1.00	1.00	1.00	0.97
Nanchong	W	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Xi'an	W	0.69	0.89	0.67	0.59	0.61	0.46	0.65
Zunyi	W	1.00	1.00	0.90	1.00	1.00	1.00	0.98
Average	E	0.79	0.82	0.90	0.95	0.92	0.95	0.89
	C	0.90	0.89	0.96	0.96	0.96	0.94	0.94
	W	0.82	0.98	0.87	0.90	0.91	0.83	0.88

Table 5. The improved space on total emissions of SO_2 (%).

City name	Area	1998	1999	2000	2001	2002	2003	Average
Baoding	E	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Beijing	E	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Cangzhou	E	0.00	14.68	89.25	0.00	0.00	0.00	17.32
Guangzhou	E	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Handan	E	89.40	91.75	0.00	0.00	0.00	0.00	30.19
Hangzhou	E	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Ji'ning	E	0.00	0.00	0.00	31.36	0.00	0.00	5.23
Linyi	E	0.00	79.27	0.00	0.00	0.00	0.00	13.21
Maoming	E	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Nantong	E	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Qingdao	E	84.13	30.71	0.00	0.00	0.00	0.00	19.14
Quanzhou	E	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Shanghai	E	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Shenyang	E	15.13	42.99	20.52	10.07	13.78	0.00	17.08
Shi Jiazhuang	E	11.74	0.00	0.00	0.00	0.00	0.00	1.96
Tang Shan	E	77.29	0.00	0.00	0.00	0.00	0.00	12.88
Tianjin	E	7.03	8.23	0.00	0.00	0.00	0.00	2.54
Wenzhou	E	0.00	50.29	0.00	0.00	0.00	0.00	8.38
Xingtai	E	96.26	0.00	94.35	0.00	0.00	0.00	31.77
Xuzhou	E	2.66	0.00	0.00	0.00	0.00	0.00	0.44
Yancheng	E	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Yantai	E	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Zhanjiang	E	0.00	0.00	0.00	0.00	2.54	0.00	0.42
Anking	C	75.99	0.00	0.00	95.63	0.00	0.00	28.60
Changchun	C	20.18	22.16	0.00	0.00	0.00	0.00	7.06
Fuyang	C	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Ganzhou	C	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Harbin	C	0.00	86.78	0.00	12.52	0.00	0.00	16.55
Hengyang	C	0.00	0.78	0.00	0.00	0.00	21.23	3.67
Huanggang	C	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Jingzhou	C	28.79	20.39	23.28	23.82	0.00	0.00	16.05
Liuan	C	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Luo Yang	C	0.00	32.23	0.00	0.00	0.00	0.00	5.37
Nanyang	C	0.00	0.00	0.00	0.00	0.00	23.68	3.95
Shangqi	C	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Shaoyang	C	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Wuhan	C	0.00	0.00	0.00	0.00	38.71	38.37	12.85
Xinyang	C	0.00	0.00	0.00	0.00	0.00	3.59	0.60
Zhengzhou	C	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Chengdu	W	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Chongqing	W	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Nanchong	W	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Xi'an	W	9.59	0.00	30.63	26.80	20.63	53.53	23.53
Zunyi	W	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Average	E	16.68	13.82	8.87	1.80	0.71	0	6.98
	C	7.81	10.15	1.46	8.25	2.42	5.43	5.92
	W	1.92	0	6.13	5.36	4.13	10.71	4.71

Table 6. Population adjustment ratio of China's 44 cities (%).

City name	Area	1998	1999	2000	2001	2002	2003	Average
Baoding	E	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Beijing	E	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Cangzhou	E	0.00	21.02	7.38	0.00	0.00	0.00	4.73
Guangzhou	E	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Handan	E	7.31	31.67	0.00	0.00	0.00	0.00	6.50
Hangzhou	E	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Ji'ning	E	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Linyi	E	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Maoming	E	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Nantong	E	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Qingdao	E	7.99	0.22	0.00	0.00	0.00	0.00	1.37
Quanzhou	E	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Shanghai	E	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Shenyang	E	48.67	8.28	0.00	33.95	23.11	0.00	19.00
Shi Jiazhuang	E	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Tang Shan	E	16.43	0.00	0.00	0.00	0.00	0.00	2.74
Tianjin	E	14.83	0.00	0.00	0.00	0.00	0.00	2.47
Wenzhou	E	0.00	0.80	0.00	0.00	0.00	0.00	0.13
Xingtai	E	2.64	0.00	12.53	0.00	0.00	0.00	2.53
Xuzhou	E	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Yancheng	E	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Yantai	E	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Zhanjiang	E	0.00	0.00	0.00	0.00	8.01	0.00	1.34
Anking	C	32.04	0.00	0.00	26.11	0.00	0.00	9.69
Changchun	C	40.18	41.24	0.00	0.00	0.00	0.00	13.57
Fuyang	C	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Ganzhou	C	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Harbin	C	0.00	0.00	0.00	8.69	0.00	0.00	1.45
Hengyang	C	0.00	8.66	0.00	0.00	0.00	5.07	2.29
Huanggang	C	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Jingzhou	C	12.07	14.81	18.96	18.38	0.00	0.00	10.70
Liuan	C	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Luo Yang	C	0.00	19.81	0.00	0.00	0.00	0.00	3.30
Nanyang	C	0.00	0.00	0.00	0.00	0.00	3.31	0.55
Shangqi	C	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Shaoyang	C	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Wuhan	C	0.00	0.00	0.00	0.00	0.00	4.33	0.72
Xinyang	C	0.00	0.00	0.00	0.00	0.00	13.90	2.32
Zhengzhou	C	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Chengdu	W	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Chongqing	W	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Nanchong	W	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Xi'an	W	32.40	0.00	0.08	18.31	0.00	28.14	13.16
Zunyi	W	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Average	E	4.26	2.70	0.87	1.48	1.35	0.00	1.77
	C	5.27	5.28	1.19	3.32	0.00	1.66	2.79
	W	6.48	0.00	0.02	3.66	0.00	5.63	2.63

The City's Population and Population Adjustment

We next use this model to calculate each city's population target value. By comparing the population target value with the real population value, we can understand whether the city has achieved the optimal population level.

We need to define two indices: a difference value and a population adjustment ratio. The former is defined as the population target value minus the real population value; the latter is defined as (the difference value/ the real population value) × 100%. If the population adjustment ratio equals zero, then it means that the real population value is equal to the population target value. In other words, the population has achieved optimal value. If the population adjustment ratio is larger (smaller) than zero, then it means that the population target value is larger (smaller) than the real population value. It indicates that the city can (not) accommodate any additional population. We use the population adjustment ratio to calculate the population index and obtain results presented in Table 6.

Table 6 shows that no city's population is over the population target value. This result is astonishing to us. A possible reason is that because the environment of each of the cities exhibited a great improvement and the environmental improvement induced each city's capacity to increase, there is no city's population that exceeds the population target value. Many cities have become saturated in terms of their populations. Shanghai, Beijing, and Quanzhou are the three largest cities in China and all are characterized by this. On the other hand, the average values of the population adjustment ratio for the eastern, central, and western cities are 1.77, 2.79 and 2.63, respectively. This suggests that the eastern cities can accept the amount of migrated population as the lowest among these three areas. In the case of the 44l observations, 23 cities belong to the east. Of all eastern cities, 14 are saturated and as a percentage this is over 50%.

Generally speaking, if the proportion of urban population is more than 30%, then the growth of urban population will be more rapid. In 1998, China's proportion of urban population was 30.4%. This implies that China's population is moving more rapidly toward the eastern cities. Because many people continuously moved into eastern cities from 1998 to 2003, there has been a decreasing trend in the average value of the eastern cities' population adjustment ratio from 1998 to 2003. On the contrary, because the population of the western cities migrated to the eastern and central cities, the western cities' population adjustment ratio average value was as high as 5.63 in 2003. Specifically, Xi'an among the western cities had a high average value of its population adjustment ratio in 1998, 2000, 2001 and 2003. This implies that Xi'an faces a serious problem in terms of its population brain drain.

An unbalanced population distribution not only induces a bad influence on economic growth, but also increases environmental pollution. In this regard, China's government should encourage the rural population to seek jobs in neighboring cities. Shenyang is a heavy industrial city in eastern China that has the highest average population adjustment ratio of all eastern cities. This implies that Shenyang can accommodate the largest amount of immigrated population among all eastern cities. Thus, China's government can encourage the rural population of Shenyang's neighboring cities to migrate to those cities. After doing this, China's government should continuously take note of environmental protection and environmental management when large numbers of people flow into the city.

For the average population adjustment ratio, the three sub-areas' average values from high to low are 2.79 for central cities, 2.63 for western cities, and 1.77 for eastern cities. This implies that the central cities can accommodate the largest influx of population. Although the western cities have an unpolluted environment, they can accommodate the smallest influx of population. The reason for this is that their undeveloped economy means that this area cannot sustain too many people.

U Mann-Whitney Test

Among the three segregated sub-areas, the eastern area is a coastal one and is also highly developed. The western area is undeveloped in China. The situation of the central area is between that of the other two areas. We have maintained above that the three sub-areas' average overall green efficiency values from best to worst in that order are those for the central cities, the eastern cities, and the western cities. In this section we want to test whether there is a significant difference in the average overall green efficiency values in the three sub-areas.

We now compare the overall green efficiency values among the three sub-areas. We implement a computer program for the U Mann-Whitney Test (http://eatworms.swmed.edu/~leon/~stats/utest.html) to determine whether there is a significant difference in the average overall green efficiency value in the three sub-areas. We use the one-side P value as a critical point. Table 7 shows the results from the U Mann-Whitney Test.

Table 7. U Mann-Whitney test on China's 3 sub-areas.

	Eastern and central cities	Central and western cities	Western and eastern cities
n_1	253	176	55
n_2	176	55	253
U statistics	26471.5	5456.5	7341.5
P-value (one-side)	0.000395***	0.07633*	0.260923

* The significance level is 90%;
*** The significance level is 99%.

The results show that there is a significant difference between the eastern area's overall efficiency value and the central area's overall efficiency value. Similarly, the central area's and the western area's overall efficiency values are also significantly different. However, there is no significant difference between the eastern area's overall efficiency value and the western area's overall efficiency value. The results imply that:

(1) In terms of the aspect of economic development or environmental protection, eastern cities are superior to central cities. Similarly, the central cities' economic development or environmental protection is superior to that for the western cities.

(2) Although the eastern cities' economic development is superior to the western cities' economic development, the eastern cities' environmental pollution is inferior to the western cities' environmental pollution. This is because the eastern cities have sacrificed their environmental quality to develop their economies.

However, western China is a lagging area in terms of economic development. Thus, the environment can be maintained. Hence, the eastern cities' overall efficiency value and the western cities' overall efficiency value do not exhibit any significant indifference.

Conclusions

Although China has been characterized by a prosperous economic development and high economic growth rates in each year, the country has sacrificed its natural and ecological environment. Based on the concept of sustainable development, China is aware of the importance of environmental protection. We therefore use macroeconomic data to estimate the overall green efficiency values of 44 cities in China. We also use two indices – the improved space in the total emissions of SO_2 and the population adjustment ratio – to discuss two problems in the cities: SO_2 emissions and population.

Generally speaking, we believe that an economically prosperous city should have a higher efficiency value. However, when we use green efficiency to estimate a city's performance, we find that an economically prosperous city does not necessarily have a higher green efficiency value. For example, eastern China is the most prosperous of the three sub-areas. However, the eastern cities' overall green efficiency value is inferior to the central cities' overall green efficiency value. This is because eastern China has sacrificed its environment for economic development.

One kind of greenhouse gas is SO_2, for which the emission standard has been stipulated in the Kyoto Protocol. Moreover, China has begun to control and manage its emissions of SO_2 so as to prevent acid rain. From the index of the improved space on the total emissions of SO_2, the more prosperous an area is, the more emissions of SO_2 there will be. In other words, the rankings in the different regions in terms of the SO_2 emissions from high to low are the eastern, central, and western groupings of cities. This result meets China's economic development situation. By combining the conclusions of Hu [20] and this paper, we suggest that China's government should manage and control large cities' emissions of SO_2 in the eastern area, and manage and control small cities' emissions of SO_2 in the western area. This finding also implies that there is a more balanced distribution of population developing between the eastern and western areas of China.

There is a seriously unbalanced population distribution in China. Most of China's population is in the east. The lowest density of population of China is in the west. The unbalanced population distribution not only has a negative influence on economic development, but it also accelerates environmental pollution. To improve the situation regarding the population distribution, the Chinese government should encourage the rural population to seek employment in neighboring cities. However, before doing this, the Chinese government should consider the cities' population capacity. We have an astonishing finding in this paper that no city's population exceeds the population target value. A possible reason for this is that a city's population capacity increases after the city's environment has improved. In terms of the population capacity of these three sub-areas, the central cities can accommodate the largest immigrant population. Although the western cities have an unpolluted environment, they can accommodate only the smallest influx of population. The reason for this is that their undeveloped economies cannot sustain many people.

Because the three sub-areas have different average overall green efficiency values, we use the Mann-Whitney U Test to examine whether there is a significant difference in these areas. The average overall green efficiency value of the eastern cities is superior to that of the central cities. The reason is that the eastern cities are located in the coastal and plain regions of China. There are many international businesses and industries based there. Thus, advanced technologies and high-tech employees have moved toward this area from the central area. There is an obvious difference in average overall green efficiency values between eastern and central cities. This also induces eastern cities to have the highest emissions of SO_2 and the lowest population capacity. The same result is seen in the central and western cities. Although the western cities are far away from the eastern cities and it is difficult for interaction to take place between technology and employees, the western cities have an unpolluted environment. Therefore, the difference in the average overall green efficiency values between eastern cities and western cities is not significant.

It is valuable discussing whether China's environmental protection has achieved international standards. It has been suggested that China be compared with those countries whose economic development experiences are similar to its own. This method is helpful for realizing whether the development of Chinese cities meets the global trend and whether China's environmental protection conforms to international standards.

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