The synergy between CO2 emission reduction and air pollution control in urban China under scale-oriented strategy: A perspective of efficiency

Yilin Su[1, *], Jie Jiang[1], Hang Wu[1]

[1]School of Nanjing University of Science and Technology, Nanjing, China

* Corresponding Author Email: a11061044292022@163.com

Abstract. At present, energy shortages and air pollution are of increasing concern worldwide. During the "14th Five-Year Plan" period, China will more firmly implement the green development strategy. In order to explore the synergistic emission reduction effects of urban greenhouse gases and air pollutants under different strategies, this paper takes 30 major cities in China from 2011 to 2019 as the research object, and analyses the input-output performance of 30 cities under the scale-oriented strategy. The empirical results show that most large cities in China are still in a state of low efficiency and insufficient growth momentum.

Keywords: Energy efficiency; Scale-oriented strategy; Data envelopment analysis.

1. Introduction

Global warming caused by CO2 (carbon dioxide) and air pollutants produced by human activities has attracted more and more attention and discussion. China put forward the goals of carbon peak and carbon neutrality at the United Nations General Assembly in 2020, which brought new opportunities and challenges for China's energy conservation and emission reduction.

In order to better tackle with global warming and climate change, it is necessary to scientifically and systematically explore China's energy utilization efficiency and CO2 emission reduction efficiency. DEA (Data Envelopment Analysis) has long been widely used as a method to assess environmental performance. Most previous literature has included CO2 as the only undesirable output, while only a few have included other pollutants such as sulfur dioxide and nitrogen dioxide in the scope of measurement. However, they ignore the synergistic benefits of reducing CO2 and air pollutants. In general, CO2 will be produced together with air pollutants and manifest itself as a reduction in emissions reductions at the same time. Therefore, once CO2 emissions are reduced, air pollutants did also, that we called it synergistic effect. This paper adds a new air pollution equivalent indicator and incorporates it together with CO2 emissions into the SBM (Slacks-based measure) model, which is an extension of DEA to describe synergies between them.

In addition, most studies assess environmental performance from a company, industry, and provincial perspective. See Toshiyuki Sueyoshi and Mika Goto (2012) comparing Japanese electric power companies to manufacturing companies under natural and managed disposal. Fei and Lin (2016) explored the CO2 emission efficiency of China's agricultural sector over the period 2001-2012. Li Ke and Lin Boqiang (2015) measured the CO2 emission energy efficiency performance of 30 provinces in China. This paper uses cities as decision-making units (DMUs) and measures the emission reduction efficiency of them. Therefore, this paper makes policy recommendations based on an assessment of the emission reduction efficiency of 30 major cities under scale-oriented strategy.

2. Literature review

First, regarding the measurement of environmental performance, existing research can be divided into static and dynamic levels. At the static level, many scholars have done quite a bit of research. Fare et al. (1989) proposed the concept of weak disposability of undesirable outputs, incorporated pollutants (also known as "undesirable outputs") into efficiency measurement models, and constructed environmental production techniques. Since then, this method has been recognized and widely used by the academic community. Matheus et al. (2022) use stochastic frontier analysis to measure economic efficiency performance in Latin America and the Caribbean. Liu et al. (2022) constructed a comprehensive measurement system of agricultural total factor productivity based on the data envelopment analysis model, and evaluated the agricultural total factor productivity of 30 provinces in China in 2018.

At the dynamic level, the productivity index method is the most commonly used method. Wang et al. (2016) constructed a carbon productivity index based on the Lunenberg productivity index to measure and decompose changes in carbon productivity in 37 major carbon countries and regions from 1995 to 2009. In addition, the Manquist Productivity Index and the Manquist-Lunenberg Productivity Index can also be used to dynamically assess environmental performance.

Under the framework of static and dynamic environmental production technology analysis, some studies also introduce different emission reduction strategies to analyze and compare the performance of decision-making units. Toshiyuki Sueyoshi and Mika Goto (2011) introduced the environmental production technology framework into the efficiency evaluation system of Japan's power industry and manufacturing industry. They also used DEA method to investigate the relationship among energy consumption, economic development and environmental protection of Japanese prefectures under different emission reduction strategies, and theoretically extended the role of DEA model in environmental assessment according to this.

The studies on measurement methods in the above literature are complete enough, but they are lacking at the urban level. Therefore, the contribution of this paper may lie in the following two points: First, focusing on the urban level helps to distinguish individual differences between cities. Secondly, focus on synergistic emission reduction efficiency to provide reference for future research.

3. The research methods

3.1. Product technology framework

After collecting some city-level data for this model, a traditional product technology framework is constructed, and the output-input model is used to describe how DMUs affect GDP, reduce carbon dioxide and urban greenhouse gases by adjusting input variables such as capital, total energy consumption, labor, etc.

Under the product technology framework, we use scale-oriented strategy to simulate the emission reduction situation of different city governments at the input side. And, observe output variables, including GDP (Y), CO2 (C) and air pollutants (AP).

The scale-oriented strategy can also be called as natural disposability, we can follow the work by Fanyi Meng et al (2021). Consider a produce process, which has N decision-making units and all use three input variable including labor (L), capital (K) and energy(E), the desirable output is GDP (Y) and the undesirable outputs are carbon dioxide and air pollutants (AP). Thus, the product technology S can be described as follows:

S = {(K; L; E; Y; C; AP): (K; L;) can produce (Y; C; LA)}

Natural disposability implies diminish input variables to reduce output undesirable variables, that is, the scale-oriented strategy. However, it may cause desirable output decreasing. Therefore, we constructed the corresponding DEA model according to this production technology framework to measure the efficiency indexes of the emission reduction strategy in different cities.

The innovation of this production technology framework lies in the fact that we focus on the city level, explore the efficiency of strategy through the coordinated control of air pollutants, and also help to comprehensively consider the compatibility of the whole city with emission reduction strategies.

3.2. Emissions performance under the scale-oriented strategy

In order to put production technology S into practice, we adopted Tone’s slack-Based Measures (SBMT) (Meng et al., 2021) to consider a scale-oriented strategy.

We consider establishing the model under the scale-oriented strategy by using SBMT for a system with m energy inputs, n non-energy inputs and i outputs as follows: λ_k denotes that the intensity levels at which the production activities are conducted by the kth DMU. x_{nk}, e_{mk} represents the non-energy and energy inputs that the kth DMU uses to produce the y_{ik}—desirable outputs and b_k, c_k—undesirable outputs incorporate CO2 and air pollutants, respectively.

$$\text{Model}(1) \qquad \min \cdot \rho = \frac{1 - \frac{1}{M+N}\left(\sum_{m=1}^{M} \frac{s_m^-}{e_{m0}} + \sum_{n=1}^{N} \frac{s_n^-}{x_{n0}}\right)}{1 + \frac{1}{I+2}\left(\sum_{i=1}^{I} \frac{d_i^+}{y_{i0}} + \frac{c^-}{c_0} + \frac{b^-}{b_0}\right)}$$
$$\begin{aligned} \text{subject to} \cdot & \sum_{k=1}^{K} y_{ik}\lambda_k - d_i^+ = y_{i0}, i = 1, \ldots, I \\ \cdot & \sum_{k=1}^{K} x_{nk}\lambda_k + s_n^- = x_{n0}, n = 1, \ldots, N \\ \cdot & \sum_{k=1}^{K} e_{mk}\lambda_k + s_m^- = e_{m0}, m = 1, \ldots, M \\ \cdot\cdot & \sum_{k=1}^{K} c_k\lambda_k + c^- = c_0, \sum_{k=1}^{K} b_k\lambda_k + b^- = b_0 \\ \cdot & \lambda_k, d_i^+, s_m^-, s_n^-, b^-, c^- \geq 0 \end{aligned} \tag{1}$$

Here, ρ, range 0 to 1, is the stationary static efficiency indicator that measures the efficiency of each DMU. ρ equal to 1 represents the DMU has already been optimal in some aspects that it cannot be replaced. By contrast, if ρ equal to 0, that implies the DMU has poorest performance in some aspects and lag behind other DMUs.

4. Empirical studies

4.1. CO2 and air pollutants emissions performance in different cities

Table 1. The mean and slope of the objective function of each city from 2011 to 2019 under natural disposal

Dmus	Average Value	Increasing Rate
Beijing	0.61	0.090
Tianjin	0.22	0.016
Shijiazhuang	0.28	0.005
Taiyuan	0.16	0.011
Huhehaote	0.27	0.042
Shenyang	0.32	0.001
Changchun	0.27	0.023
Ha'erbin	0.38	0.061
Shanghai	0.57	0.085
Nanjing	0.29	0.011
Hangzhou	0.46	0.049
Hefei	0.30	0.029
Fuzhou	0.33	0.022
Nanchang	0.37	0.025
Jinan	0.32	0.019
Zhengzhou	0.42	0.033
Wuhan	0.32	0.028
Changsha	0.78	0.081
Guangzhou	0.68	0.093
Nanning	0.32	0.025
Haikou	0.79	0.052
Chongqing	0.22	0.021
Chengdu	0.49	0.038
Guiyang	0.26	0.033

Kunming	0.25	0.025
Xi'an	0.60	0.073
Lanzhou	0.18	0.010
Xining	0.18	0.004
Yinchuan	0.13	0.007
Wulumuqi	0.21	0.010
Average	0.37	0.034

In order to explore the input-output efficiency of different cities under scale-oriented strategy, we calculate the average ρ and slope of the city-wide mean for each city from 2011 to 2019 in Model 1, as shown in Table 1. As can be seen from Table 1, the efficiency of all cities is improving, among which Shanghai, Xi'an, Guangzhou and Changsha are growing faster, and Xining, Yinchuan, Shenyang and other cities are growing slower. The objective function ρ reflects the input-output efficiency of the city in that year, combined with the undesired output of carbon dioxide and air pollutants, which can also reflect the city's emission reduction level. The results show that Shanghai, Xi'an, Guangzhou and other cities have effectively narrowed their improvement space in the past 9 years of development. It means that the growth strategy of these cities in 9 years are significantly better than other cities, which is of reference significance

4.2. CO2 and air pollutants emissions performance vary over time

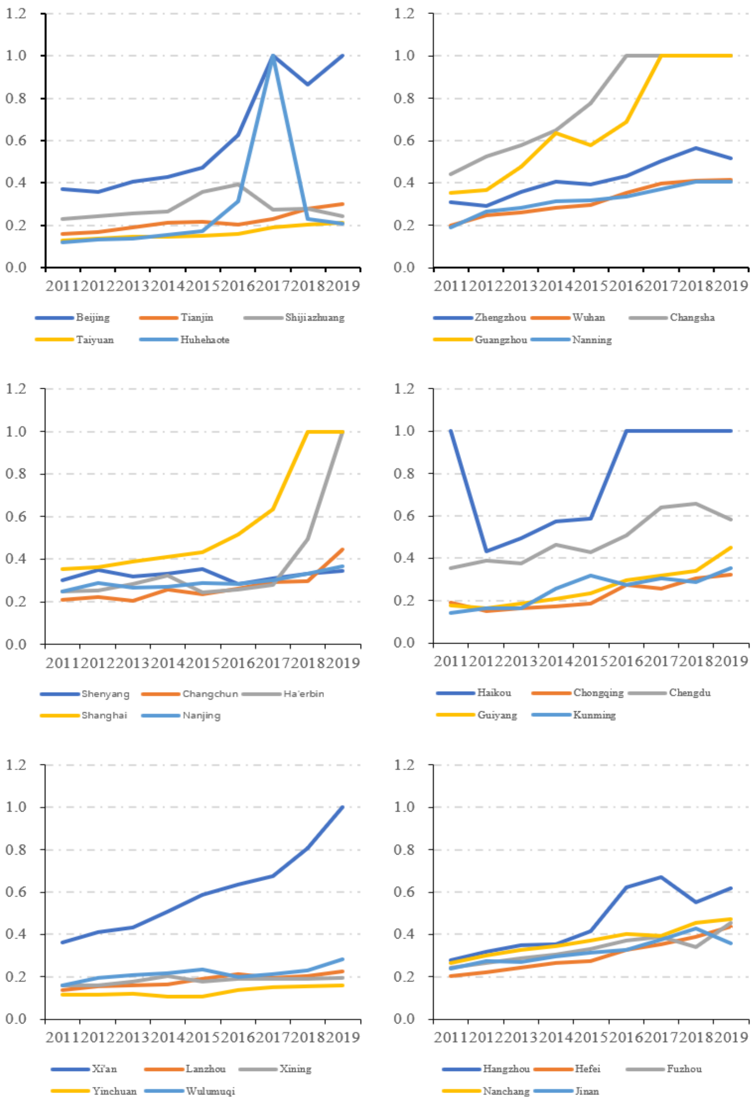

Figure 1. mean value and slope of objective function of each city from 2011 to 2019

Fig 1. shows the mean and slope of the objective function of each city from 2011 to 2019 under scale-oriented strategy. Among them, cities in the upper right corner, such as Guangzhou and Changsha, have higher average functions and faster growth, while cities in the lower left corner have low both. In cities that have significantly improved their efficiency in 9 years, changes in their inputs can be used as a reference for other cities to improve.

First of all, we can find that 30 cities are distributed in the first and third quadrants, and only one or two cities deviate from the first and third quadrants, which also indicates that China's major provincial capitals have a relatively "extreme" situation, either in high efficiency while the growth momentum is sufficient, or in the low efficiency at the same time growth momentum is insufficient, which may also be those cities in the double-low position into the "poverty cycle", so that their efficiency is at a low level in the long term compared to those cities in the double-high position. It is not conducive to the coordinated control of urban greenhouse gases and air pollutants. Secondly, the number of cities in the third quadrant is relatively large, while the number of cities in the first quadrant is few, which also shows that the current urban emission reduction development in China is not balanced, and only a few cities can use their own emission reduction strategies to achieve coordinated emission reduction. According to the above findings, it is proved that China needs to focus more on those cities in double-low positions, let more emission reduction resources be invested in these cities, and improve their growth momentum to improve their emission reduction efficiency.

5. Conclusions

From the above empirical research results and findings, we can draw two conclusions.

First, under the scale-oriented strategy, most cities have poor emission reduction performance and low efficiency, indicating that the simple reduction of investment to curb or reduce carbon emissions and pollutant emissions is not suitable for all cities. Different urban policy makers should find a balance between reduced inputs and economic growth, depending on the circumstances of their cities. Or other ways to reduce emissions of greenhouse gases and air pollutants without reducing economic output.

Second, in the empirical process, we also found that there is a certain synergy between carbon emission reduction and air pollutant emission reduction. This has certain practical significance, which can help decision-makers consider the mutual promotion of emission reduction between the two when formulating emission reduction strategies, so as to formulate more low-cost and efficient emission reduction strategies.

References

[1] Emrouznejad A, Yang G. CO2 emissions reduction of Chinese light manufacturing industries: A novel RAM-based global Malmquist–Luenberger productivity index [J]. Energy Policy, 2016, 96: 397-410.

[2] Färe Rolf, Njinkeu Dominique. Computing returns to scale under alternative models [J]. Economics Letters, 1989, 30(1).

[3] Fei R, Lin B. Technology gap and CO2 emission reduction potential by technical efficiency measures: A meta-frontier modeling for the Chinese agricultural sector [J]. Ecological Indicators, 2017, 73: 653-661.

[4] Guo X D, Zhu L, Fan Y, et al. Evaluation of potential reductions in carbon emissions in Chinese provinces based on environmental DEA [J]. Energy Policy, 2011, 39(5): 2352-2360.

[5] Koengkan Matheus, Fuinhas José Alberto, Kazemzadeh Emad, Osmani Fariba, Alavijeh Nooshin Karimi, Auza Anna, Teixeira Mônica. Measuring the economic efficiency performance in Latin American and Caribbean countries: An empirical evidence from stochastic production frontier and data envelopment analysis [J]. International Economics,2022,169.

[6] Li J, Cheng Z. Study on total-factor carbon emission efficiency of China’s manufacturing industry when considering technology heterogeneity [J]. Journal of Cleaner Production, 2020, 260: 121021.

[7] Li K, Lin B. Metafroniter energy efficiency with CO2 emissions and its convergence analysis for China [J]. Energy Economics, 2015, 48: 230-241.

[8] Liu Shuai, Lei Pengfei, Li Xing, Li Yafei. A nonseparable undesirable output modified three-stage data envelopment analysis application for evaluation of agricultural green total factor productivity in China. [J]. The Science of the total environment, 2022, 838(P1).

[9] Melle Agathe Stenger, Agathe Stenger. A remark on the definition of the Färe–Lovell measure for infeasible production vectors: implication for the Luenberger productivity indicator [J]. International Journal of Production Economics,2017,184.

[10] Meng F, Su B, Thomson E, et al. Measuring China's regional energy and carbon emission efficiency with DEA models: A survey [J]. Applied Energy, 2016, 183: 1-21.

[11] Meng F, Su B, Wang Q. Meta-frontier-based assessment on carbon emission performance considering different mitigation strategies: Evidence from China's manufacturing sectors [J]. Journal of Cleaner Production, 2021, 289: 125662.

[12] Miao Zhuang, Zhang Yuechi, Liu Sicen, Chen Xiaodong, Baležentis Tomas. Heterogeneous strategy and performance decomposition: Energy-economy-environment nexus in the light of natural & managerial disposability [J]. Environmental Impact Assessment Review, 2022, 95.

[13] Nirmalkumar Singh Moirangthem, Barnali Nag. Developing a Framework of Regional Competitiveness Using Macro and Microeconomic Factors and Evaluating Sources of Change in Regional Competitiveness in India Using Malmquist Productivity Index [J]. International Journal of Global Business and Competitiveness, 2020, 15 (prepublish).

[14] Sharp J A, Meng W, Liu W. A modified slacks-based measure model for data envelopment analysis with 'natural'negative outputs and inputs [J]. Journal of the Operational Research Society, 2007, 58(12): 1672-1677.

[15] Sueyoshi Toshiyuki, Goto Mika. Weak and strong disposability vs. natural and managerial disposability in DEA environmental assessment: Comparison between Japanese electric power industry and manufacturing industries [J]. Energy Economics, 2011, 34(3).

[16] Sueyoshi Toshiyuki, Goto Mika. DEA radial and non-radial models for unified efficiency under natural and managerial disposability: Theoretical extension by strong complementary slackness conditions [J]. Energy Economics, 2011, 34(3).

[17] Sueyoshi T, Goto M. Environmental assessment by DEA radial measurement: US coal-fired power plants in ISO (Independent System Operator) and RTO (Regional Transmission Organization) [J]. Energy Economics, 2012, 34(3): 663-676.

[18] Sueyoshi T, Goto M. Returns to scale and damages to scale under natural and managerial disposability: Strategy, efficiency and competitiveness of petroleum firms [J]. Energy economics, 2012, 34(3): 645-662.

[19] Sueyoshi T, Goto M. Undesirable congestion under natural disposability and desirable congestion under managerial disposability in US electric power industry measured by DEA environmental assessment [J]. Energy Economics, 2016, 55: 173-188.

[20] Wang J, Wang S, Li S, et al. Evaluating the energy-environment efficiency and its determinants in Guangdong using a slack-based measure with environmental undesirable outputs and panel data model [J]. Science of the Total Environment, 2019, 663: 878-888.