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RESEARCH ARTICLE

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Efficiency evaluation of government investment for air pollution control in city clusters: A case from the Beijing–Tianjin–Hebei areas in China

Abstract Air pollution poses a significant threat to human health, particularly in urban areas with high levels of industrial activities. In China, the government plays a crucial role in managing air quality through the Air Pollution Prevention and Control Action Plan. The government provides direct financial support and guides the investment direction of social funds to improve air quality. While government investment has led to improvements in air quality across China, concerns remain regarding the efficiency of such large-scale investments. To address this concern, we conducted a study using a three-stage data envelopment analysis (DEA)-Malmquist model to assess the efficiency of government investment in improving air quality in China. Our analysis revealed regional disparities and annual dynamic changes. Specifically, we focused on the Beijing–Tianjin–Hebei areas as a case study, as the investment primarily targeted industrial activities in urban areas with the goal of improving living conditions for urban residents. The results demonstrate significant differences in investment efficiency between regions. Beijing exhibits relatively high investment efficiency, while cities in Hebei Province require improvement. We identified scale inefficiency, which refers to the ratio of air pollutant reduction to financial investment, as the main factor contributing to regional disparities. However, we found that increasing the total investment scale can help mitigate this effect. Furthermore, our study observed positive but fluctuating annual changes in investment efficiency within this city cluster from 2014 to 2018. Investment-combined technical efficiency, which represents the investment strategy, is the main obstacle to improving yearly investment efficiency. Therefore, in addition to promoting investment strategies at the individual city level, it is crucial to enhance coordination and cooperation among cities to improve the investment efficiency of the entire city cluster. Evaluating the efficiency of government investment and understanding its influencing factors can guide future investment measures and directions. This knowledge can also support policymaking for other projects involving substantial investments.

Keywords investment efficiency, government investment, air pollution control, three-stage DEA-Malmquist model

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1 Introduction

Air pollution poses a significant threat to the health of urban residents. Industrial cities contribute significantly to air pollution through the release of waste gases and toxic chemicals from industrial production (Sun et al., 2019a). China, as the world's largest manufacturing and industrial nation, emits massive amounts of pollutants into the atmosphere, leading to increased risks of diseases and premature death (Dong, 2019). In 2013, the average concentration of $PM_{2.5}$ was 58 μg/m^3 (Liu et al., 2021), which exceeded the safe standards of global air quality guidelines by 1060% (WHO, 2021), resulting in 123525 premature deaths from cardiovascular disease and 39165 premature deaths from respiratory disease (Cui et al., 2022).

To address the issue of air pollution, the Chinese government implemented the 2013 Air Pollution Prevention and Control Action Plan (Yu et al., 2022), which has effectively improved air quality in China. Fiscal finances have played a vital role in this atmospheric control effort (Gramkow and Anger-Kraavi, 2018). Rationalizing government investments has improved the efficacy of air pollution control and facilitated sustainable fiscal distribution across the country. Since 2013, the Chinese government has allocated 179.95 billion yuan to air pollution prevention and special control funds. This substantial investment has resulted in 64.3% of Chinese cities meeting air quality standards in 2021, a significant increase from 4.1% in 2013.

Research on government investment in air pollution control has become a prominent issue, as it guides future investment measures and directions. Improving government investment efficiency is crucial for the sustainable development of atmospheric management (Florea et al., 2021). Scholars have employed panel data (Xu, 2019; Cheng et al., 2020) to measure investment efficiency in air pollution control and have suggested the need to improve the efficiency of national investments (Yu and Lin, 2018; Sun et al., 2019b). Studies have also reported investment redundancies (Guo et al., 2018). Inefficient and redundant investments necessitate the optimization of the current allocation of financial investment in air quality control. To investigate the factors influencing air pollution control, scholars have conducted research on the effects of fiscal policy (Halkos and Paizanos, 2016; Akbar et al., 2021), foreign direct investment (Akbar et al., 2021), and taxation (Hu et al., 2019) on pollutant emissions. A consensus has emerged that fiscal policy tools are more reliable in controlling air pollution by reducing emissions.

Existing studies have limitations that may result in biased conclusions. While the Chinese government allocates fiscal funds to cities separately, most previous studies rely on provincial panel data, which fail to identify the reasons for investment inefficiency and offer targeted investment recommendations. Given that this research focuses on an economic model with diverse inputs and outputs, the use of the nonparametric data envelopment analysis (DEA) model (Charnes et al., 1978; Banker et al., 1984) would be more appropriate, as it does not require assumptions of a particular functional form and is useful for uncovering relationships that other methods might overlook (Han and Wei, 2002; Halkos and Argyropoulou, 2021). Scholars have utilized the DEA model to appraise environmental investment efficiency (Zhang et al., 2019; Cheng et al., 2020; He et al., 2023). However, previous studies on environmental investments have overlooked macroenvironmental factors, which may lead to an unrealistic estimation of the efficiency value of environmental investments. In particular, disparities in economic and social progress across cities in China could impact fiscal investment efficiency due to significant regional variations. Another drawback of the DEA model is its inability to determine efficiency changes over successive years, limiting the creation of annual investment strategies.

To address these research gaps, we constructed a three-stage DEA-Malmquist model to assess fiscal investment efficiency in air pollution control. The three-stage DEA model, initially proposed by Fried et al. (1999) and later expanded by Fried et al. (2002), considers environmental factors and random noise and has been widely utilized in various domains, including water pollution (Chen et al., 2022), healthcare (Liu et al., 2022), municipal waste (Ye et al., 2022), banking (Mei et al., 2014), transportation (Song et al., 2020), and carbon emissions (Liu and Liu, 2016). Additionally, we utilized the DEA-Malmquist index (Färe et al., 1992; 1994) to estimate the changes in efficiency over time. The DEA-Malmquist combines the DEA approach with the Malmquist productivity index to assess efficiency and productivity changes over time. By integrating these two methodologies, DEA-Malmquist allows for the evaluation of dynamic changes, captures technological progress, and enables the simultaneous analysis of efficiency and productivity variations. Specifically, we utilized municipal panel data from the Beijing–Tianjin–Hebei areas (referred to as the BTH region hereafter), a city cluster with severe air pollution, as a case study. We assessed the investment efficiency of local governments in this region at the city level and analyzed the annual dynamic changes in efficiency from 2014 to 2018. Our research aims to evaluate the efficiency of fiscal investment by municipal governments in air pollution control within the framework of the Air Pollution Prevention and Control Action Plan policy, investigate the factors influencing investment efficiency in municipal governments, and suggest appropriate investment strategies. The outcomes can provide guidance to the Chinese government in making informed decisions regarding future air pollution prevention and control investments.

The remainder of this paper is organized as follows. Section 2 presents our three-stage DEA-Malmquist model to evaluate the efficiency of government investment in air pollution control. Section 3 discusses the empirical results of the evaluation of government investment efficiency in the BTH region between 2014 and 2018. Section 4 provides potential options for improving the efficiency of government investment. Finally, Section 5 concludes the paper.

2 Materials and methods

2.1 Three-stage DEA-Malmquist model

This study constructs a three-stage DEA-Malmquist model to calculate the efficiency of financial investment and its annual dynamic changes. This method eliminates the influence of environmental factors and random interference on efficiency evaluation and improves the objectivity and accuracy of the calculation results. Figure 1 shows the framework of the three-stage DEA-Malmquist model constructed for this study.

2.1.1 Stage 1: Conventional DEA-BCC model

The DEA model is used to evaluate the relative efficiency values of different decision units within the same period, which represents static efficiency. When selecting a DEA model, one must choose between input-oriented or output-oriented approaches and consider the assumption of constant returns to scale using the Charnes, Cooper, and Rhodes model or variable returns to scale using the Banker, Charnes, and Cooper (BCC) model (Daraio and Simar, 2007; Cooper et al., 2011). The input-oriented approach aims to minimize inputs while assuming constant outputs, whereas the output-oriented approach aims to optimize outputs while assuming constant inputs. The choice between input and output orientation depends on whether input conservation or output augmentation is more crucial (Daraio and Simar, 2007).

In the context of government investments in air pollution control, the objective is to optimize the allocation of input variables to maximize investment efficiency. This calls for selecting an input-oriented model. Additionally, we propose that the returns to scale can vary based on the assessment of input–output indicators, indicating that the investment input variables do not necessarily vary proportionally with the pollution output variables. Hence, we have chosen the input-oriented BCC model.

It is important to note that the model assesses the relative efficiency of air pollution control investments made by municipal governments, representing the efficiency of investment for the current year. This value is not significantly influenced by historical pollution levels. Therefore, an investment can be deemed inefficient even if a city has relatively good air quality. Conversely, the investment efficiency of a city can be evaluated as high even if it has

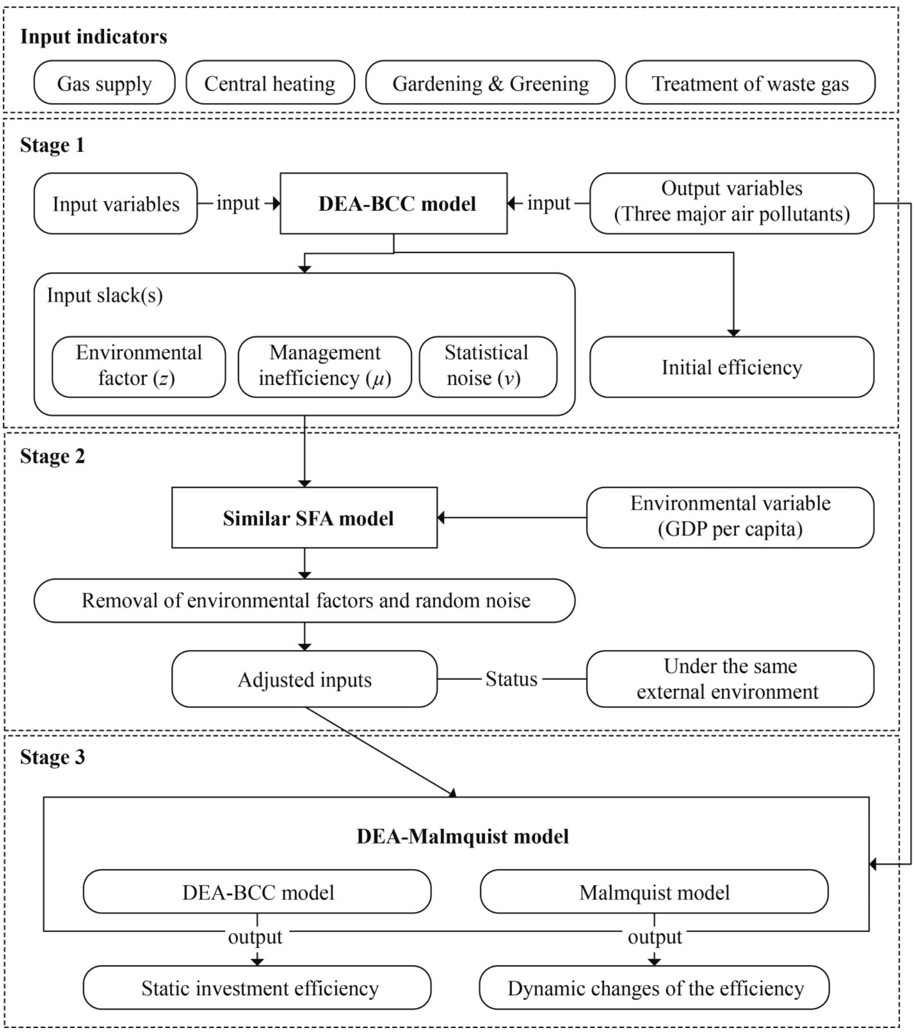

Fig. 1 Framework of the three-stage DEA-Malmquist model.

a history of significant air pollution problems.

The DEA model requires a set of input and output variables, as well as a set of decision-making units (DMUs). For any DMU, the duality model of input-oriented DEA-BCC is shown in Eq. (1).

$$\min \theta - \varepsilon(\hat{e}^{\mathrm{T}} S^- + e^{\mathrm{T}} S^+)$$

$$s.t. \begin{cases} \sum_{j=1}^{n} X_j \lambda_j + S^- = \theta X_0 \\ \sum_{j=1}^{n} Y_j \lambda_j - S^+ = Y_0 \\ \lambda_j \geqslant 0,\ S^-,\ S^+ \geqslant 0 \end{cases}, \tag{1}$$

where θ represents the efficiency value, ε is the optimal non-Archimedean epsilon, e represents units matrix, λ_j represents weight coefficient, n denotes the number of the DMUs, S^- and S^+ denote slack variables for the input and output indicators, respectively, and X_0 and Y_0 are the input and output matrices, respectively, composed of all DMUs. Only when the efficiency value $\theta = 1$ and the slack variables $S^- = 0$, $S^+ = 0$, can the DMU be called efficient; otherwise, it is inefficient, implying that it has potential for improvement.

This stage calculates the initial efficiency and slack variables of the input variables using DEAP 2.1. The efficiency value calculated by the BCC model is the comprehensive technical efficiency (TE), which can be further decomposed into scale efficiency (SE) and pure technical efficiency (PTE). These are related as shown in Eq. (2).

$$TE = SE \times PTE. \tag{2}$$

TE refers to the efficiency value that comprehensively considers PTE and SE and represents the comprehensive management ability of regional government investment in air pollution control. PTE refers to the production efficiency of the DMU under the influence of management and technology with certain inputs, which in the text is the efficiency of government investment. SE refers to production efficiency due to the scale factor of the investment, reflecting the difference between the actual scale and the optimal production scale. This study relates to changes in air pollutants when the scale of government investment is expanded.

2.1.2 Stage 2: Similar stochastic frontier analysis for input adjustment

The investment situation and air pollutant concentration are closely related to regional production and operational activities, particularly economic development and industrial production. Therefore, investment efficiency calculation is inevitably influenced by the external environment, which leads to the possibility of bias. By dividing management inefficiencies, environmental factors, and random noise, a similar stochastic frontier analysis (SFA) regression can be used to provide proper weighting for efficiency evaluations. Thus, we used this model to remove environmental factors and statistical noise. Based on Fried et al. (2002) and the first-stage model, a similar SFA regression function based on the input orientation was constructed, as shown in Eq. (3).

$$S_{ni} = f(Z_{ni};\ \beta_i) + \nu_{ni} + \mu_{ni},\ n = 1,\ 2,\ ...,\ N,\ i = 1,\ 2,\ ...,\ I, \tag{3}$$

where S_{ni} denotes the slack of the input variable i for the DMU n. There are several regression equations for several input variables, including X_i. $f(Z_{ni};\ \beta_i) = \sum(\beta_i Z_{ni}) + C_i$ indicates the effect of environmental factors on the slack variables, where Z_{ni} represents environmental variables i for DMU n, β_i is the coefficient of the environmental variables, and C_i is regression coefficient. $\nu_{ni} + \mu_{ni}$ refers to the mixed error term, where ν_{ni} is a stochastic error term with a distribution of $\nu \sim N(0,\ \sigma_\nu^2)$ and μ_{ni} is a management inefficiency term with a distribution of $\mu \sim N^+(0,\ \sigma_\mu^2)$. When the likelihood ratio (LR) test rejects the null hypothesis that there is an inefficiency term, ordinary least squares (OLS) can be used to eliminate random interference without considering environmental factors. At this stage, the estimated value of C, β, σ^2, γ was obtained using Frontier 4.1 software (regression results are shown in Appendix A in the Supporting Materials).

An estimate of management inefficiency $E[\mu_{ni} \mid \nu_{ni} + \mu_{ni}]$ is separated using Eq. (4) following the methods proposed by Jondrow et al. (1982), Luo (2012), and Chen et al. (2014).

$$E(\mu|\varepsilon) = \sigma_* \left[\frac{\phi(\lambda\varepsilon/\sigma)}{\Phi(\lambda\varepsilon/\sigma)} + \frac{\lambda\varepsilon}{\sigma} \right], \tag{4}$$

where $\sigma_* = \sigma_\mu \sigma_\nu / \sigma$, $\sigma = \sqrt{\sigma_\mu^2 + \sigma_\nu^2}$, $\lambda = \sigma_\mu / \sigma_\nu$, $\sigma_\mu^2 = \sigma^2\gamma$, $\varepsilon = \nu + \mu$. ϕ and Φ are the distribution and density functions, respectively, of the standard normal distribution. Equation (5) is used to separate the random error terms.

$$E[\nu_{ni} \mid \nu_{ni} + \mu_{ni}] = S_{ni} - f(Z_{ni};\ \beta_i) - E[\mu_{ni} \mid \nu_{ni} + \mu_{ni}]. \tag{5}$$

A similar SFA model can eliminate the influence of environmental and random factors on the efficiency value and adjust DMUs in the same external environment. The adjustment formula is given by Eq. (6).

$$X_{ni}^* = X_{ni} + \left[\max\left(f\left(Z_{ni};\ \hat{\beta}_i\right)\right) - f\left(Z_{ni};\ \hat{\beta}_i\right)\right] + [\max(\nu_{ni}) - \nu_{ni}], \quad i = 1,\ 2,\ ...,\ I,\ \ n = 1,\ 2,\ ...,\ N, \tag{6}$$

where X_{ni}^* and X_{ni} are the adjusted and original input values i for DMU n, respectively, and $\hat{\beta}_i$ denotes the estimated value of the environmental variable. The subsequent parts of this stage calculate the values using Microsoft Excel.

2.1.3 Stage 3: Improved DEA-Malmquist model

The third stage involves inputting the adjusted input variables from the second stage and the original output variables into the first-stage DEA model and the Malmquist index to calculate the annual investment efficiency and yearly dynamic efficiency changes with the aid of DEAP 2.1 software. The DEA-Malmquist index comprises total factor productivity (TFPch), combined technical efficiency (Effch), and technological progress efficiency (TEch), as demonstrated in Eq. (7).

$$TFPch = Effch \times TEch. \tag{7}$$

TFPch, in this study, refers to the additional production efficiency achieved by maintaining a constant level of production factors, excluding government investment capital and labor. It captures the efficiency change resulting from factors such as technological development, economies of scale, and technological levels. TFPch values greater than 1 indicate an increase in productivity, TFPch equals to 1 represents constant productivity, and TFPch values less than 1 indicate decreased productivity.

Effch, the technical efficiency change index, measures the relative degree of technical efficiency change between two consecutive periods, often referred to as the "catch-up effect" (Liu and Liang, 2010). It explores the rate of change in government resource allocation efficiency. Effch values greater than 1 indicate that the DMU is closer to the production frontier in period $t + 1$ compared to period t, indicating an increase in the relative investment level. Effch equals to 1 suggests a constant investment level, while Effch values less than 1 imply a decrease in the investment level.

TEch, also known as the technological change index, measures the level of technological advancement in the production frontier over two consecutive periods, commonly referred to as the "frontier moving effect" (Liu and Liang, 2010). It represents the rate of change in technical development within the government investment sector over two consecutive years. TEch values greater than 1 signify technological progress, TEch values equal to 1 indicate technological invariance, and TEch values less than 1 denote technological decline.

2.2 Data sources

The data sources for this study include the *China Statistical Yearbook*, *China Statistical Yearbook on Environment*, *China Environmental Yearbook*, *China Urban Statistical Yearbook*, *China Urban Construction Yearbook*, and regional statistical yearbooks. The study focuses on 19 cities in the BTH region (details provided in Appendix B in the Supporting Materials), which provided data on investment in air pollution control and atmospheric pollution levels between 2014 and 2018 as the DMUs (95 DMUs).

It is worth noting that the Air Pollution Prevention and Control Action Plan, initiated in 2013, consisted of ten measures that were implemented over a period of five years (2013–2017). National policy changes can result in variations in the investment environment, such as investment objectives, investment structure, and investment agents. To ensure a consistent and stable external policy environment for evaluating investment efficiency using DEA, we chose the study period as 2014–2018, which is the second year after the implementation of fiscal funds.

The 19 cities selected for this study are representative of the critical environmental cities in the studied area and are part of BTH region air pollution transmission channel. These cities, namely, Beijing; Tianjin; Shijiazhuang, Tangshan, Handan, Baoding; Taiyuan, Yangquan, Changzhi; Hohhot, Baotou, Chifeng; Jinan, Zibo, Jining; Zhengzhou, Kaifeng, Anyang, Jiaozuo, correspond to Beijing, Tianjin, Hebei, Shanxi, Inner Mongolia Autonomous Region, Shandong, and Henan, respectively.

2.3 Indicators

Four input indicators, three output indicators, and one environmental variable were selected based on the literature (Xu, 2019) and Chinese government investment, as shown in Table 1.

Input indicators. The input index in this study represents government investment in air pollution control. Based on the summary of environmental pollution control investment in the *China Statistical Yearbook on Environment*, fiscal expenditure for air pollution control consists of three components: Investment in urban environment infrastructure facilities, Investment in treatment of industrial pollution sources, and Environmental Protection Investment in the environmental protection acceptance projects in the year. Under atmospheric management, Investment in urban environment infrastructure facilities includes Gas supply, Central heating, and Gardening & Greening. Investment in the treatment of industrial pollution sources involves the Treatment of waste gas. However, there is no separate section on atmospheric management in the Environmental Protection Investment in the environmental protection acceptance projects in the year. Therefore, we selected four input indicators: Gas supply, Central heating, Gardening & Greening, and Treatment of waste gas. These indicators were chosen based on data availability and their relevance to air pollution control.

It is important to note that during the data collection process, a small number of zero values were encountered for the input indicators. The DEA model requires positive data, which necessitates processing of these values. The dimensionless method is the most widely used and effective approach for processing such data, as it does not alter the meaning of the data or the final result. In this study, the data were transformed to a dimensionless interval using a

Table 1 Assessment index system for government investment efficiency of air pollution control

Tier 1 indicators	Secondary indicators	Variables	Variable type	Unit
Urban environment infrastructure facilities	Gas supply	Investment amount of gas	Input	yuan
	Central heating	Investment amount of centralized heating	Input	yuan
	Gardening & Greening	Investment amount of landscaping	Input	yuan
Treatment of industrial pollution sources	Treatment of waste gas	Investment amount of treatment of waste gas	Input	yuan
Major atmospheric pollutants	Sulphur dioxide	Inverse of the average SO_2 concentration	Output	$m^3/\mu g$
	Nitrogen oxides	Inverse of the average NO_2 concentration	Output	$m^3/\mu g$
	Smoke (dust)	Inverse of the average $PM_{2.5}$ concentration	Output	$m^3/\mu g$
Environmental effects	Gross domestic product (GDP), Population	GDP per capita	Environmental variable	yuan

mapping technique (Mei et al., 2014), as shown in Eq. (8).

$$Y_{i,j} = 0.1 + 0.9\frac{X_{i,j} - X^i_{\min}}{X^i_{\max} - X^i_{\min}}, \tag{8}$$

where $X_{i,j}$ is the original variable, $Y_{i,j}$ is the processed variable, $X^i_{\min} = \min(X_{i1}, X_{i2}, ..., X_{ij})$, and $X^i_{\max} = \max(X_{i1}, X_{i2}, ..., X_{ij})$. i denotes the number of DMUs, $i = 1, 2, ..., 19$; j represents the number of periods, $j = 1, 2, ..., 5$.

Output indicators. Pollutant emissions directly reflect the effects of government investment, with the ultimate goal of reducing atmospheric pollutant concentrations. Since 2013, the dominant atmospheric pollutants in BTH region are Sulphur Dioxide, Nitrogen Oxides, Soot and Dust (Feng et al., 2014; Wang et al., 2014). For this reason, this study selected the annual average urban concentrations of SO_2 ($\mu g/m^3$), NO_2 ($\mu g/m^3$), and fine particulate matter ($PM_{2.5}$ ($\mu g/m^3$)) as output indicators. Two reasons underpinned the selection of the average air pollutant data. First, China recognized air quality control as a matter of administrative area management, and using average data to represent urban air quality was consistent with this method of oversight. Second, China has adopted a three-tier decentralized fiscal policy at the Central–Provincial–Municipal level, assessing the efficiency of government investment in air pollution on a city-by-city basis. The DEA model necessitates a direct relationship between the output indicator value and efficiency, meaning that the higher the value, the more efficient the process. However, when measuring atmospheric pollutants, the inverse relationship is true, and the lower the concentration of pollutants is, the higher the efficiency level. Consequently, the inverse of the average annual concentration of pollutants was employed as an output variable.

Environment variables. This study selected GDP per capita (yuan) as the environmental variable in the three-stage DEA model. Previous studies have highlighted the urban population and GDP as significant factors that affect industrial pollution emissions and government investment (Liu et al., 2015; Wen and Zhang, 2020). Economic imbalances may result in environmental injuries. Hence, we selected GDP per capita as the environmental variable to eliminate the impact of demographic and economic factors on the findings.

3 Results

3.1 Government investment and air pollutants in 19 cities

Figure 2 illustrates the government's investment in urban air control, including Gas supply, Central heating, Treatment of waste gas, and Gardening & Greening, along with the reduction rates of three air pollutants ($PM_{2.5}$, SO_2, and NO_2). Over the course of five years, the Chinese government invested 363 billion yuan in the BTH region. It is worth noting that Beijing accounted for a significant portion of the financial investment in air pollution control, representing 38.2% of the total investment. Conversely, Yangquan had the lowest investment, accounting for only 0.5% of the total. There were also notable differences in the amount of money invested across different components. Gardening & Greening investment had the highest ratio, comprising 48% of the total investment, while Gas supply investment had the lowest ratio at 10.8%.

The concentrations of $PM_{2.5}$, SO_2, and NO_2 exhibited significant improvements from 2014 to 2018, with reductions of 31% (28.3 $\mu g/m^3$), 63% (38.9 $\mu g/m^3$), and 9% (5.5 $\mu g/m^3$), respectively. The Air Pollution Prevention and Control Action Plan policy set a target of a 25% reduction in $PM_{2.5}$ concentration within five years for the BTH region (source: gov.cn/zwgk/2013-09/12/content_2486773.htm). However, this standard was not met in Hohhot, Jiaozuo, Yangquan, Taiyuan, Changzhi, Kaifeng, and Anyang. Additionally, the results revealed that the most significant reduction occurred in SO_2 concentrations over the five-year period. On the other hand, the reduction in NO_2 concentrations was relatively small, and its concentrations increased in Taiyuan, Chifeng, and Yangquan. The government's investment in atmospheric management has yielded positive outcomes in this region; however, urban air pollution still persists.

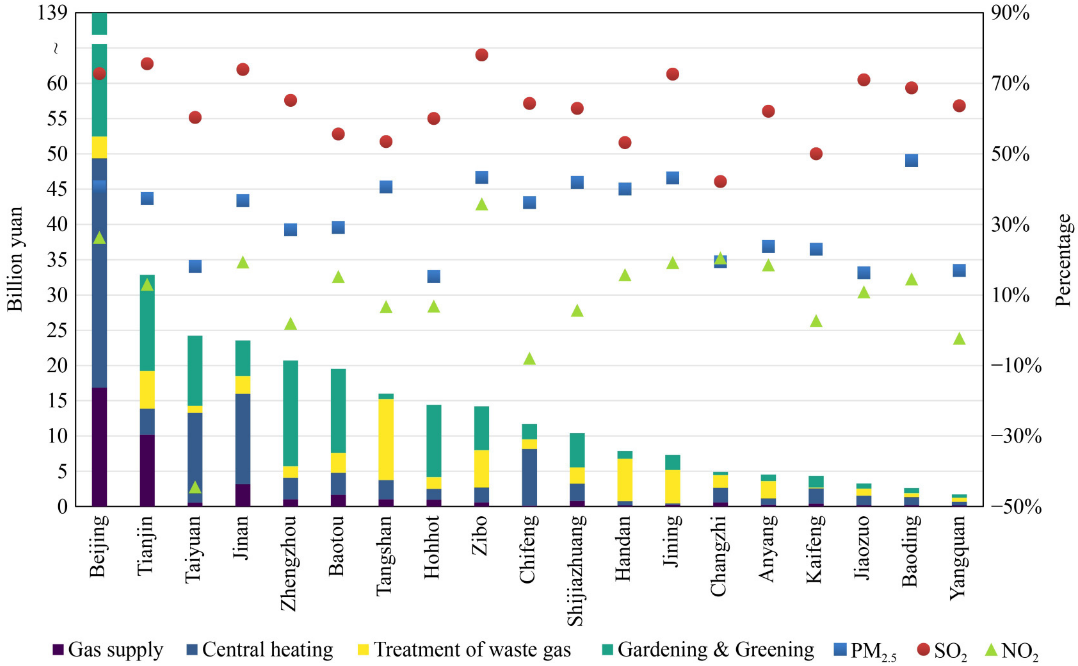

Fig. 2 Government investment and primary air pollutants reduction rate (2014–2018).

3.2 Government investment efficiency in air pollution control of 19 cities

China employs a three-tiered fiscal management system, encompassing Central, Provincial, and Municipal levels. This research assesses the efficiency of governmental investments in air pollution control, considering these distinct management structures at the overall, provincial, and municipal tiers. The overarching findings furnish a broad perspective on the subject area, while insights derived from provincial data hold practical significance for provincial administration and national fiscal distribution. Further, the analysis of urban efficiency underscores the investment capacities of individual municipalities in air pollution control.

3.2.1 Overall government investment efficiency

Regarding the overall government investment efficiency, Fig. 3 presents a summary of the annual average efficiency of government investments in air pollution control, which exhibited fluctuating increases in overall investment efficiency from 2014 to 2018. The overall combined TE was calculated to be 0.901, representing the comprehensive investment efficiency that encompasses various aspects, such as the ability to allocate funds and the efficiency of fund utilization. TE increased from 0.863 in 2014 to 0.921 in 2018, indicating an improvement in efficiency over the study period. However, it is important to note that investment efficiency remained below the optimal level, as indicated by an efficiency value less than 1 (ineffective DEA).

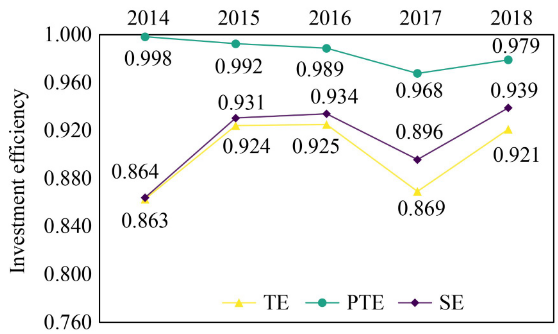

Fig. 3 Overall investment efficiency summary in air pollution control (2014–2018).

The overall TE is influenced by PTE (0.985) and SE (0.913). PTE represents the investment efficiency resulting from factors such as management and technology, while SE refers to the investment efficiency derived from the influence of investment-scale factors. Notably, the trend in SE exhibited fluctuating upward movements, similar to the trend in TE, indicating an increase in SE. However, PTE followed a fluctuating downward trend over the five-year period, implying a decrease in investment management capacity and technology level.

From 2014 to 2018, scale inefficiency emerged as the primary factor influencing low investment efficiency. By combining Eq. (2) with the observed efficiency trends, we found that the impact of SE on overall TE was stronger, indicating a significant influence of SE on TE. To quantify the relationship and determine the specific impact level, we conducted a correlation analysis of the three efficiency values across the 19 cities. The correlation coefficient between TE and SE (0.97) was higher than the correlation coefficient between TE and PTE (0.56). This indicates that low investment efficiency was primarily affected by SE, which was 41% higher than PTE over the five-year period. Notably, with the exception of Beijing in 2017, all other regions experienced increasing returns to scale from 2014 to 2018. This implies that the reduction in pollutant concentrations surpassed the proportional increase in investment elements within those regions.

3.2.2 Provincial investment efficiency

Figure 4(a) shows a summary of government investment efficiency at province-level in the studied cities in 2014–2018. Beijing ranked first in terms of investment efficiency at 0.994. The cities in Hebei Province had the lowest investment efficiency at 0.776. The PTE and SE of this region are 0.988 and 0.925, respectively, which are 2.6% and 12.8% lower than the average, respectively. Therefore, we can conclude that scale inefficiency led to low investment efficiency in Hebei Province from 2014–2018.

Figure 4(b) shows the investment efficiency of air pollution control in the BTH region from 2014–2018, indicating significant inter-province differences and slight intra-province differences. To explore the degree of efficiency difference, we introduced a variation coefficient to compare the magnitude of dispersion. A difference of less than 10% was considered slight. The mean efficiency difference among the provinces was 10%, indicating significant inter-province differences. We also calculated the degree of difference among cities within different provinces and found that the intra-provincial difference was only 6%. This implies slight intra-provincial differences.

3.2.3 Urban investment efficiency

Figure 5(a) illustrates the 5-year average efficiency of each city. Hohhot and Chifeng in Inner Mongolia and Kaifeng in Henan Province ranked first in investment efficiency every year, which suggests that they reached DEA effectiveness with TE, PTE, and SE efficiencies of 1. Shijiazhuang had the lowest efficiency, 20% lower than the city average. Its PTE and SE were 7.6% and 13.3% below the mean, respectively, resulting in DEA ineffectiveness. The results demonstrate an improvement in government investment efficiency in most cities, excluding Hohhot, Chifeng, and Kaifeng. However, SE needs improvement in Zhengzhou, Beijing, Jiaozuo, Yangquan, Jining, and Taiyuan. In addition, both SE and PTE need to be improved for the remaining cities.

Figures 5(b)–5(d) display the annual efficiency differences for cities concerning combined TE, SE, and PTE from 2014–2018. The scattered distribution of the TE values of government investment in cities indicates a gap in investment efficiency among cities in the BTH region. The point distribution of SE values was denser in 2018 than in 2014, showing a narrowing gap over the five years. The gap in PTE values between cities was small but broadened in 2017. Furthermore, we calculated the coefficients of variation to accurately describe the degree of variation among cities. The outcomes demonstrate that the overall investment efficiency difference tended to fluctuate downward across the five years, dropping by 5.8% but still high (11%). This illustrates the persistence of disparities in investment efficiency among cities during 2014–2018.

The disparity in SE was found to be the primary factor contributing to the variation in investment efficiency among cities. Although SE increased over the five-year period, the average coefficient of variation for PTE was less than 4%. This indicates that the differences in PTE among cities were relatively insignificant. On the other hand, although the coefficient of variation for SE slightly decreased, its average value remained above 10%. This suggests that the substantial differences in SE among cities contribute to the significant gap in investment efficiency.

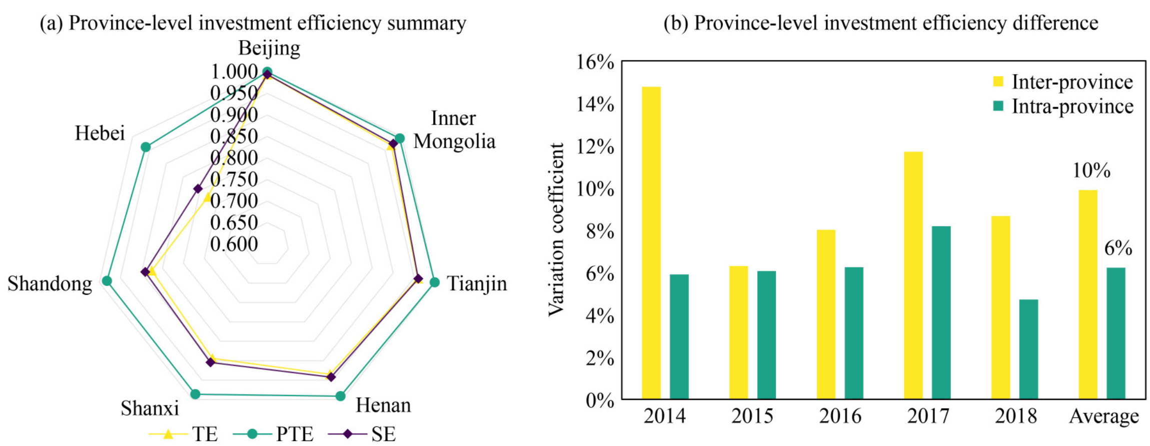

Fig. 4 Province-level investment efficiency in air pollution control and efficiency difference (2014–2018).

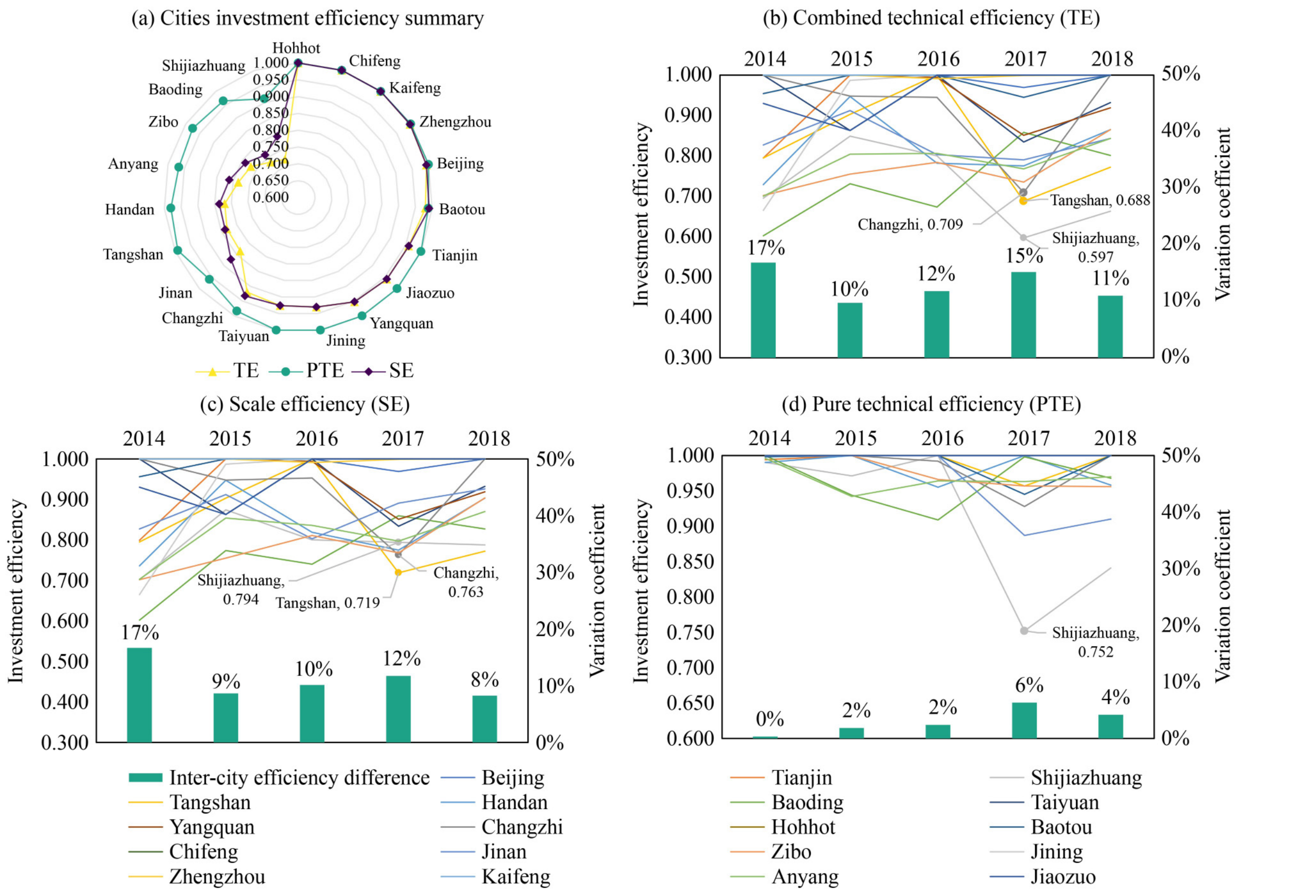

Fig. 5 Urban investment efficiency in air pollution control and efficiency difference (2014–2018).

Notably, there was a significant decline in SE in 2017, leading to an overall decrease in investment efficiency. By examining the efficiency change ratios, we found that the decline in investment efficiency in 2017 was mainly driven by decreases in Shijiazhuang, Tangshan, and Changzhi, which accounted for 70.8% of the overall decline. In Shijiazhuang, the TE, PTE, and SE values were 0.597, 0.752, and 0.794, respectively, representing decreases of 19.2%, 62.2%, and 0.8% compared to the previous year. Tangshan experienced decreases of 10.8% in PTE and 38.7% in SE, while in Changzhi, the PTE and SE decreased by 16.0% and 26.1%, respectively. Overall, the decrease in investment efficiency in 2017 was primarily due to lower PTE in Shijiazhuang and lower SE in Tangshan and Changzhi.

Regarding returns to scale, most relatively inefficient cities exhibited increasing returns to scale in investment, indicating that increased investment was beneficial. In contrast, Beijing experienced decreasing returns to scale in investment in 2017, while the majority of relatively inefficient cities witnessed increasing returns. It is important to note that the model does not specify the returns to scale value for cities that achieve optimum relative efficiency, such as Hohhot, Chifeng, and Kaifeng. Increasing returns to scale suggest that when investment expands, the improvement in air quality surpasses the proportional increase in investment size, leading to a higher marginal return on investment.

3.3 Annual efficiency changes in government investment in air pollution control of 19 cities

The results show that the average overall comprehensive investment efficiency (TFPch) change rate increased by 37.9% between 2014 and 2015. The cumulative growth rate (TFPch cumulative multiplier) reached 3.617, indicating that the comprehensive efficiency of government investment increased significantly over the five-year period. The Effch and TEch increased by 1.9% and 35.4%, respectively, representing the progress in investment management ability and the advances and innovation of investment technology, respectively. It is inferred that technological progress in investment mainly influenced the improvement in integrated investment efficiency. Furthermore, we performed a correlation analysis of the three efficiency change rate indices for 19 cities to determine the specific impact level. The correlation coefficient between TFPch and TEch was 0.91, which was higher than that between TFPch and Effch (0.17). This demonstrates that the change rate of investment efficiency was affected by technological progress 74% more than investment efficiency progress over the five years.

Figure 6 shows the TFPch index of the 19 cities to analyze the rate of change in investment efficiency for different years. From 2014 to 2015, the TFPch of the 19 cities was greater than two, representing rapid growth. In 2015–2016, the TFPch fold was generally below "$y = 1$", meaning that the change rate decreased. From 2016 to 2017, the TFPch line was generally within the range of "$y = 1$" and "$y = 2$", indicating an increase in 2017. In 2017–2018, they were stable around "$y = 1$" except for Beijing (3.957), which indicates stability in investment efficiency. In summary, the yearly changes in investment efficiency experienced yearly fluctuations, with positive trends from 2014–2018.

4 Discussion

This study introduces innovative methods to improve investment strategies for cities by analyzing the efficiency of municipal government investment in air pollution prevention and control during the 2014–2018 period. The study sheds light on the investment challenges faced by city governments under the Chinese government investment model and recommends regional cooperative investment in air pollution prevention and control.

During the 2014–2018 period, Hohhot, Chifeng, and Kaifeng achieved optimal investment efficiency by prioritizing desulfurization, denitrification, dust removal, and controlling urban dust. Chifeng became the first city in Inner Mongolia, with over a million people meeting the $PM_{2.5}$ standards through efficient management of industrial pollution, while Kaifeng successfully reduced coal combustion-induced air pollution by implementing "coal to electricity" clean heating projects. Under certain conditions, such as similar pollution sources, climatic environments, and industrial structures, policy migration is possible, enabling cities with similar conditions to collaborate or learn from each other.

The study revealed significant intercity and interprovincial differences in government investment efficiency among the 19 cities during 2014–2018, with minor intraprovincial variation. Investment efficiency improved across the 19 cities over the study period, and the degree of difference among cities decreased. The primary reason for the difference in efficiency was attributed to variations

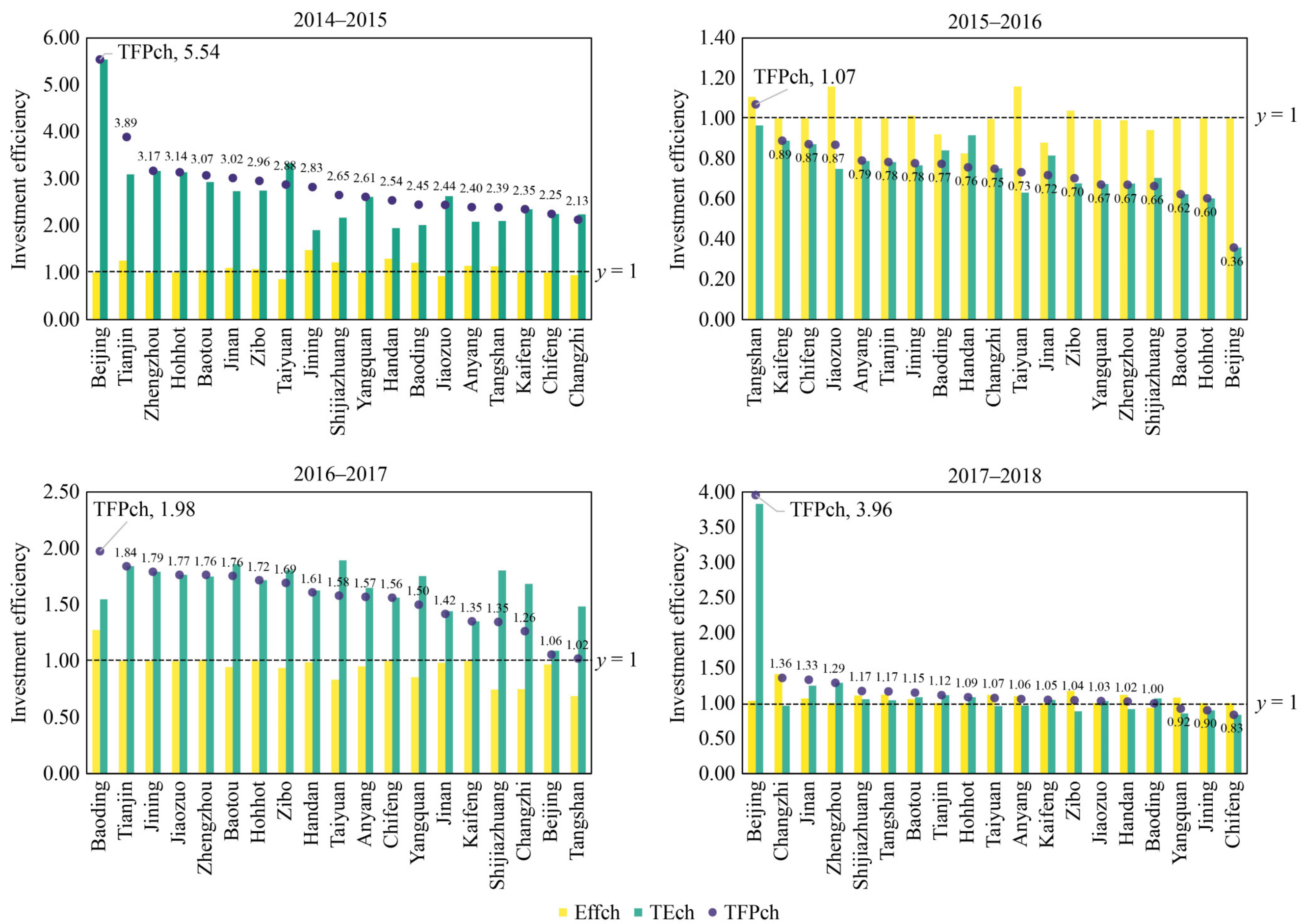

Fig. 6 TFPch index of 19 cities (2014–2018).

in SE among cities. Understanding the factors that influence investment efficiency and the underlying mechanisms is crucial in addressing how to invest efficiently. Based on the results, three recommendations are offered for government investment strategies.

First, increasing government investment in air pollution control to improve its effectiveness should be considered. From 2014 to 2018, the Chinese government provided a substantial amount of financial support for atmospheric pollution control in BTH cities, which led to remarkable results. Nevertheless, some cities experienced an ongoing increase in pollutant levels that did not meet the required standards, indicating suboptimal efficiency in investment planning across the region. Scale ineffectiveness, which comprises inadequate investment and unreasonable investment allocation, was the main factor contributing to this nonoptimal efficiency. The average annual proportion of GDP invested in environmental protection between 2014 and 2018 was 1.25%. However, the World Bank (1997) concluded that the environment deteriorates when the proportion of GDP invested in environmental protection is less than 1.5%. Despite fluctuating and rising environmental investment in recent years, its share of GDP has declined by 1%. China's increased economic strength has not been accompanied by a parallel increase in environmental protection investment, which poses a serious threat to air pollution and other ecological problems. Thus, expanding financial investment in air control is essential. Additionally, the proportion of pollutant improvement increased compared to the proportion of investment scale, thereby indicating that expanding government investments in air control could lead to more effective air quality improvement. In addition to direct investment, the government should consider expanding investment in energy conservation and emission reduction, technological progress, and industrial restructuring to rationalize the distribution of financial investment. Furthermore, the government should mobilize multiple parties to participate in air pollution control investments and promote collaborative investment by society as a whole.

Second, the government should enhance its management of investments in air pollution control and maintain technological progress. The study reveals that the primary reason for the increase in government investment efficiency across 19 cities between 2014 and 2018 was the increase in investment technological progress (35.4%). This indicates the development of technological progress and innovation in terms of government investment factors and assets. Unfortunately, the level of organizational investment management increased by only 1.9%. The organization and management of investment include both the technological capacity of investment management and the scale and factor allocation of investment. The government needs to improve investment patterns and enhance the investment evaluation process to promote investment efficiency in atmospheric management. Additionally, by improving the integrity of the investment chain, resource allocation capacity, and regeneration efficiency of cities, the government can increase the marginal efficiency of investment and the level of investment scale economies. In addition to enhancing its investment management capacity and technology, the studied area can achieve clean air by enhancing the allocation of government investments in energy, industrial, and transportation structures.

Finally, the government must strengthen investment cooperation among cities in various provinces within the BTH region, eliminate interprovincial barriers, and reallocate funds for efficient management. Current administrative regions are divided by provinces, which is inconsistent with atmospheric transmission channels and can lead to unreasonable allocations. Each year, provinces allocate fiscal funds based on city importance and the severity of air pollution to meet environmental performance regulations. However, owing to variations in economic conditions and atmospheric pollution levels, provinces implement different air control fund allocation programs that can cause significant inter-province efficiency differences in government investment, as seen in Hebei and Shanxi. Interestingly, cities with low investment efficiency, including Shijiazhuang, Baoding, Handan, and Tangshan in Hebei Province, Zibo and Jinan in Shandong Province, and Anyang in Henan Province, were in the inner circle of the BTH atmospheric transmission region and on multiple provincial border lines. Baoding in Hebei Province, for example, had 12% higher $PM_{2.5}$ pollution than Anyang in Henan, but the investment was just about half of that given to Anyang, which ranked first in funding for air pollution control despite being in the middle of the air pollution level in Henan. Similarly, although Handan in Hebei was heavily polluted compared with Zibo in Shandong, it received less investment. This unreasonable investment allocation intensifies the overall low investment efficiency. In the next phase, the government should redefine its investment strategy from a regional perspective and reallocate the fiscal fund management area under the BTH atmospheric transmission corridor. Special funds for atmospheric control could be uniformly allocated to the middle region and redistributed, considering each city's economic conditions and pollution situation.

This model was subject to certain assumptions. Climatic factors, such as annual precipitation and wind speed, can impact air quality, which in turn may reduce the accuracy of investment efficiency results. Therefore, this model is suitable for city clusters with similar climatic conditions. The BTH region has a temperate monsoon climate with a low occurrence of drought and a high incidence of severe winter haze. The findings of this study were not significantly affected by climate variables.

5 Conclusions

Following the termination of the Air Pollution Prevention and Control Action Plan, this study set out to assess the effectiveness of municipal investments in curbing air pollution and the factors influencing them. The research offers insights into enhancing investment efficiency in municipal-level air pollution control via national financial resource allocation and ensuring sustainable investment. The input-oriented three-stage DEA-Malmquist model was employed to analyze government investment efficiency and year-over-year efficiency changes among 19 cities in the BTH region. The findings reveal a marked improvement in investment efficiency over the past five years, largely due to technological advancements in financial investment. While government investments between 2014 and 2018 notably ameliorated the atmosphere, they yielded low overall government investment efficiency due to imperfect SE. Areas of low efficiency were predominantly found at the interprovincial junction within the inner circle of the BTH region. Additionally, it was found that enhancing investment management capacity is essential. Expanding the investment scale is necessary for bolstering investment efficiency and management capacity and fostering yearly efficiency improvement. Significantly, the research determined that discrepancies in intercity investment efficiency were more substantial than interprovincial efficiency differences. A restricted allocation of resources was observed in high pollution regions with low investment, leading to an overall low efficiency of government investment in air pollution control across the BTH region. To refine the regional air pollution control investment initiative, a shift from the traditional province-centric investment model to a collaborative investment model with cities as cooperative units is recommended. This could potentially increase the effectiveness of investment and promote more equitable resource distribution.

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Competing Interests The authors declare that they have no competing interests.

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