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Research on Environmental Performance Measurement and Influencing Factors of Key Cities in China Based on Super-Efficiency SBM-Tobit Model

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Abstract: In recent years, China has experienced significant economic growth and some degree of environmental pollution control. However, achieving a perfect balance between the environment and economic development remains a challenge. In order to seek solutions to this issue and promote the sustainable development of cities, this paper starts from the urban level, which is relatively lacking in existing research. Based on the panel data of urban indicators from 2013 to 2021, it quantifies the environmental performance of key cities using the slack-based measure (SBM) model of super-efficiency based on a non-expected output. Furthermore, it utilizes the Tobit panel regression model suitable for limited dependent variables to analyze the impact of driving factors on the environmental performance of key cities, and it further explores the reasons for the loss of urban environmental performance from the dual perspectives of inputs and outputs. The research findings indicate the following. (1) The average environmental performance of 30 key cities has shown an increasing trend but has not yet reached a valid state. The cities' environmental performance rises in the range of [0.444, 0.821], indicating that there is room for improvement in urban environmental management. (2) Cities in the northeastern region of China have lagged behind the eastern, central, and western regions in terms of environmental performance over this nine-year period, and the redundancy of undesirable outputs is partly responsible for this decline. (3) The large proportion of the secondary industry, the number of vehicles on the road, and the population density have a significantly negative impact on urban environmental performance, while the per capita regional GDP and urban maintenance and construction funds make a positive difference. These research findings provide a scientific basis and valuable insights into urban environment performance enhancement and can serve as a reference for areas in need of balanced development between the urban environment and economic growth.

Keywords: urban environmental performance; super-efficiency SBM model of undesirable output; spatial pattern; Tobit model; driving factors

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1. Introduction

As the economy exhibits rapid growth and people's living standards are improved, the generation of environmental loads has become an issue, hindering the sustainable development of cities. Human activities generate pollutants such as waste gas, waste water, and solid waste, which have compromised the environmental quality of cities. This has resulted in various environmental problems that threaten people's health. Air pollution, especially the problem of fine particulate matter, $PM_{2.5}$, has become a key and challenging issue in urban environmental management due to its diverse types and complex composition [1–3]. $PM_{2.5}$ can persist in the air without dispersing and possesses a large specific surface area

that attracts a significant amount of pollutants. It can enter the human body through the respiratory system, taking a toll on human health and even leading to death [4–6]. Economic development often comes at the cost of high energy consumption [7], creating an imbalance between the environment and economic development. Achieving sustainable development between the environment and the economy is a widely discussed topic. Therefore, it is necessary to adopt scientific methods to quantify the environmental management levels of cities, thereby proposing corresponding environmental protection policies to improve the urban environmental quality, achieve balanced development between the environment and the economy, and promote urban sustainable development.

In response to the imbalance between the environment and the economy, there have been international efforts to address this issue through the establishment of environmental management standards. The International Organization for Standardization (ISO) has introduced a series of such standards, which offer organizations a set of environmental performance indicators to assess and evaluate their environmental performance based on reliable information. The term "environmental performance evaluation" was formalized in 2000 to describe this practice. Recognizing the unique national conditions of different countries, China conducted its first environmental performance evaluation in 2005, drawing inspiration from international standards. Environmental performance evaluation serves as a crucial tool in measuring and managing environmental performance. It is an essential prerequisite in carrying out environmental management work and forms an integral part of the urban environmental management process. Researchers have widely embraced environmental performance evaluation, applying it in various industries. For example, Biagetti et al. utilized this approach to study the sustainable development of the animal husbandry industry and assess the environmental impact of dairy production [8]. Furthermore, Guo et al. explored the field of water environment governance through environmental performance evaluation, examining the efficacy of environmental protection policies and opening up new possibilities for water environment governance in other regions [9]. Ye et al. focused on atmospheric environment governance, employing the pressure–state–response (PSR) model to construct a performance evaluation system for Anhui Province. They conducted a comparative analysis of governance in different regions using the entropy method and put forward targeted solutions [10]. In a similar vein, Liu et al. applied environmental performance evaluation to the Beijing–Tianjin–Hebei region's atmospheric environment governance. They evaluated the governance from 2010 to 2019 using a comprehensive evaluation index model and the DPSIR model. Additionally, they explored the factors influencing the performance index of atmospheric environment governance, aiming to enhance pollution control in the region [11]. Opazo-Basáez et al. evaluated the impact of green technology innovation on organizational and environmental performance [12]. Ernst Andersen et al. applied environmental performance at the architectural level, analyzing the environmental performance of timber structures [13]. To gauge the level of urban environmental management and assess the environmental quality, this paper employs environmental performance evaluation at the city level. The objective is to analyze the current state of environmental management in key cities, identify shortcomings, and propose solutions.

Methods for the evaluation of environmental performance abound, with data envelopment analysis (DEA) now widely used in measuring environmental performance [14]. It is a non-parametric research method that evaluates multiple input and multiple output indicators [15–17]. DEA models, including the CCR and BCC models, are radial models without any requirements for weights, providing significant advantages in efficiency measurement. In many cases, multiple output indicators not only include desirable outputs but also undesirable outputs. In urban environmental performance measurement, undesirable outputs such as exhaust gases, wastewater, and noise generated due to human activities are inevitably included. Traditional DEA models do not consider undesirable outputs and cannot account for the impact of potential slack variables, resulting in biased environmental performance measurement results. Therefore, they are not applicable for the study of urban

environmental performance measurement with undesirable outputs included. To address the limitations of DEA models, Tone Kaoru proposed the slack-based measure (SBM) model in 2001 [18], which addresses the issue of traditional radial DEA models that do not include undesirable outputs and slack variables in efficiency measurement [19,20]. However, there are limitations to the SBM model, such as its inability to compare the efficiency of decision-making units (DMUs) effectively [21], with the efficiency measurement results of DMUs all being 1. In order to address this limitation, this study proposes a method that combines the undesirable output SBM model with the undesirable output super-efficiency SBM model to measure urban environmental performance. The super-efficiency SBM model, introduced by Tone Kaoru as an extension of the original SBM model, has been utilized by Pan et al. to examine the spatio-temporal characteristics and driving factors of land use efficiency in the three northeastern provinces using the super-efficiency SBM-Tobit model [22]. Li et al. have also applied the super-efficiency SBM-ESDA and Tobit models to evaluate the green innovation efficiency of the manufacturing industry in the Yangtze River Economic Belt and analyze its spatio-temporal differences [23]. Furthermore, Zhang et al. have computed the provincial-level pollution reduction and carbon reduction efficiency in China based on the super-efficiency SBM-Tobit model and panel data from 2010 to 2019 [24]. Lotfi et al. used the SBM model to address the issue of adverse outputs in the wheat industry [25]. Nyangchak utilized the super-efficiency SBM model to analyze the efficiency of renewable energy in China [26]. While the super-efficiency SBM model has found extensive use in efficiency measurement research across various fields, its application to the measurement of urban environmental performance remains limited. However, due to its ability to address the inefficiency ranking and comparison issue while correcting the slack variables of inefficient decision-making units, it proves to be suitable for the study of urban environmental performance in this paper [27]. Existing studies mostly focus on analysis at the provincial level, and the models used are not innovative enough, resulting in a lack of focus on the environmental performance of key cities. This paper fills this gap by using the super-efficiency SBM model to analyze the environmental performance and driving factors of key cities, which is of certain positive significance for urban sustainable development.

There are various factors at play in the changes in urban environmental performance. Therefore, it is crucial to not only analyze the internal indicators of environmental performance but also explore the external factors that drive these changes. With the purpose of optimizing urban environmental performance, this study integrates the internal indicators and external factors that impact urban environmental performance to identify the main reasons behind better performance and the coordinated development of the urban environment and economy. The imbalance between the ecological environment and economic development has brought ecological protection and governance to the fore for a long time in China. President Xi Jinping has emphasized that economic development should not come at the expense of ecological destruction, as the ecological environment itself is a vital part of the economy, and ecological development contributes to productivity development. This statement underscores the dialectical relationship between ecological protection and economic development. To achieve a sustainable future, economic growth and environmental protection should be combined, and we should make coordinated efforts towards them. A green development mode and lifestyle must be embraced, with a focus on translating environmental benefits into economic benefits. The objectives of this study are as follows: (1) to quantify the environmental performance of key cities, (2) to analyze the spatio-temporal evolution characteristics of environmental performance measurement in these cities, and (3) to explore the driving factors influencing urban environmental performance. The findings from this research on environmental performance measurement in key cities can provide valuable insights for related studies and analyses in other regions, ultimately facilitating the balanced development of the urban environment and economy.

2. Research Data and Methods

2.1. Data Source and Processing

2.1.1. Selection of Indicator System

Urban environmental performance serves as a crucial metric in evaluating the coordinated progress of the urban environment and economy, revealing a city's level of environmental management. To gauge urban environmental performance, multiple facets must be taken into account. Wang conducted a study on the cities in the Yangtze River Delta, employing the undesirable output data envelopment analysis model to assess environmental efficiency based on capital, manpower, resources, economic development, and pollutants [28]. Similarly, Shi's research from 2005 to 2013 focused on Chinese cities' environmental performance, emphasizing manpower, capital stock, total social water consumption, energy consumption, and pollutant emissions [29]. The rapid urbanization process encompasses not only the depletion of natural resources but also the treatment of human-induced environmental pollution. This study comprehensively considered the representativeness, coverage, and accessibility of indicator data. We selected four municipalities directly under the central government and 26 provincial capital cities in China as the research objects to conduct urban environmental performance assessments. Provincial capital cities often possess more resources and policy preferences, providing strong support for their economic development, and they play a significant role in regional economic development. Starting the evaluation system reform from these prefecture-level cities and directly governed municipalities could better promote the continuous progress of environmental performance assessments in China. This study selected 4 municipalities directly under the central government and 26 provincial capital cities as decision-making units (DMU), with Lhasa City excluded due to data unavailability. The research period spanned 2013 to 2021, aligning with the improved data availability regarding $PM_{2.5}$ statistics in China since 2013 (China started to track these data in 2012 but has improved the statistics since 2013). Panel data from 2013 to 2021 were utilized to measure the urban environmental performance of 30 key cities in China from various perspectives, including capital, labor, natural resources, economic development, environmental quality, environmental pollution, and pollution control. The urban environmental performance index system of key cities and the data sources for each index are detailed in Table 1. All data used in this study were publicly released by the Chinese government's statistical departments and authorities. In the event of any missing statistical data, the linear interpolation method was used to fill the gaps.

Table 1. Indicator system and data sources.

Category	Primary Indicator	Secondary Indicator	Indicator Type	Data Source
Input indicators	Capital	Local general public budget expenditure (10,000 yuan)	Input	China City Statistical Yearbook
	Labor	Number of employees in human resources, water conservancy, environment and public facility management industry	Input	China City Statistical Yearbook
	Natural resources	Built-up area (km^2)	Input	China City Statistical Yearbook
		Water supply (10,000 m^3)	Input	Statistical Yearbook of Prefecture-Level Cities
		Total energy consumption (10,000 tons of standard coal)	Input	Statistical Yearbook of Prefecture-Level Cities

Table 1. *Cont.*

Category	Primary Indicator	Secondary Indicator	Indicator Type	Data Source
Output indicators	Economic development	Per capita GDP (yuan)	Desirable output	China City Statistical Yearbook
	Environmental quality	Proportion of days with air quality reaching or better than the secondary standard (%)	Desirable output	China City Statistical Yearbook
		Greening coverage rate of built-up area (%)	Desirable output	China City Statistical Yearbook
	Environmental pollution	$PM_{2.5}$ annual average concentration ($\mu g/m^3$)	Undesirable output	China City Statistical Yearbook
		Annual average concentration of NO_2 ($\mu g/m^3$)	Undesirable output	China City Statistical Yearbook
		Annual average concentration of SO_2 ($\mu g/m^3$)	Undesirable output	China City Statistical Yearbook
		Road traffic noise (DB)	Undesirable output	China City Statistical Yearbook
	Pollution control	Sewage treatment rate (%)	Desirable output	China City Statistical Yearbook
		Comprehensive utilization rate of general industrial solid waste (%)	Desirable output	China City Statistical Yearbook
		Harmless treatment rate of domestic waste (%)	Desirable output	China City Statistical Yearbook

2.1.2. Selection of Driving Factors

There are many factors at play in environmental performance, sparking ongoing debates. Different scholars draw different conclusions based on their selected indicators. Chen et al. [30] identified the economic scale, international trade, technological progress, industrial structure, and regional characteristics as influencing factors and proposed policy recommendations to reduce pollution emissions and enhance the urban environmental efficiency based on their empirical analysis results. Zeng et al. [31] explored the driving factors of urban environmental efficiency and drew empirical conclusions by considering the economic scale, innovation ability, industrial structure, and environmental regulation. Wang [28], when studying the factors that influenced the environmental performance of the Yangtze River Delta urban agglomeration, selected the economic scale, technological innovation, industrial structure, car ownership, population density, and foreign capital dependence. The research results provide a theoretical reference and empirical support for regional governments to improve their environmental performance. Liang et al. [32] delved into the influencing factors of water resource efficiency in the western region, considering the industrial structure, economic development, urbanization level, technological innovation, natural factors, environmental regulations, and foreign direct investment. Their research is of great significance for the sustainable development of water resources in the region. These findings underline the multifactorial nature of environmental performance and the need for further exploration to discern the factors' relative significance, as not all factors are equally significant. Urban environmental performance is not only sensitive to the internal input–output indicators but also to the external environment. This article explores the impact of the industrial structure, economic scale, scientific and technological expenditure, educational expenditure, urban maintenance and construction funds, quantity of cars on the road, and population density on urban environmental performance. It provides reliable countermeasures to improve the urban environmental performance based on an empirical analysis and offers theoretical support for municipal government decisions. The driving factor data used in this article are drawn from authoritative sources such as the China City Statistical Yearbook and the Statistical Yearbook of Prefecture-Level Cities.

2.2. Research Methods

2.2.1. Super-Efficiency Slack-Based Measure (SBM) Model

The data envelopment analysis (DEA) model examines efficiency based on the input–output. It leverages linear programming to determine the relative efficiency without considering undesirable outputs. Therefore, Weng, Yang, and others included undesirable outputs as input indicators in the DEA model to evaluate the environmental performance of regions [33,34]. Although this approach meets the requirement of minimal input in the DEA model, it might lead to imprecise results. The DEA models comprise the BCC and CCR models [35], both of which are radial DEA efficiency evaluation models, allowing proportional changes in all inputs or outputs. However, in cases of excessive inputs or insufficient outputs, i.e., the presence of a non-zero slack for inputs or outputs, improvements in slack are not reflected in the efficiency measurement [36]. Consequently, the use of the DEA model often overestimates the efficiency. Taking this into consideration, Tone proposed the undesirable output slack-based measure (SBM) model in 2001 [37,38]. Compared to the DEA model, this model not only avoids the bias caused by radial and angular measurements but also accounts for the influence of undesirable outputs in the production process, better capturing the essence of efficiency evaluation. The SBM model is a non-parametric modeling method that evaluates efficiency by comparing the input and output data of DMUs with an ideal "best practice frontier". It can handle non-desirable outputs, a feature not present in other DEA models. A key characteristic of the SBM model is its ability to directly incorporate slack variables into the objective function. This helps to address slack issues in the input–output data, such as underutilized resources in actual production processes, thereby identifying the factors leading to low efficiency values. For instance, researchers analyzing the efficiency of green energy across various provinces in China used the SBM model to determine efficiency values for each province and pinpoint the underlying causes of the low efficiency, proposing corresponding policy solutions [39].

However, when evaluating the undesirable output SBM model, multiple decision-making units frequently have efficiency values of 1, making it challenging to rank and differentiate these efficient DMUs [40,41]. In this case, the undesirable output super-efficiency SBM model is useful. Tone introduced the undesirable output super-efficiency SBM model in 2002 [42]; this is a non-radial model that avoids overlooking certain aspects of the input or output, as radial models do. It can only handle situations where the efficiency value is 1 in the undesirable output SBM model. For cases where the efficiency value is less than 1, the efficiency measurement results of the undesirable output super-efficiency model are all displayed as 1. Hence, this study combines the undesirable output SBM model with the undesirable output super-efficiency SBM model to analyze the environmental performance levels of 30 key cities in China from 2013 to 2021. By integrating these two models, we can gain better insights into and compare the efficiency situation among decision-making units and provide valuable insights for their enhancement.

Suppose that there are n decision-making units, each consisting of three elements: inputs, desirable outputs, and undesirable outputs (pollutants generated from human activities), denoted as X, Y, and Z vectors, respectively, with $X > 0, Y > 0, Z > 0$. The evaluation of the undesirable output SBM model formula for a DMU (x_0, y_0, z_0) is as outlined below:

$$\begin{aligned}
\rho = min \frac{1 - \frac{1}{m}\sum_{i=1}^{m} \frac{s_i^x}{x_{io}^t}}{1 + \frac{1}{s_1+s_2}\left(\sum_{k=1}^{s_1} \frac{s_k^y}{y_{ko}} + \sum_{l=1}^{s_2} \frac{s_l^z}{z_{lo}}\right)} \\
x_{io} = \sum_{j=1}^{n} \lambda_j x_j + s_i^x, \forall i \\
y_{ko} = \sum_{j=1}^{n} \lambda_j y_j - s_k^y, \forall k \\
z_{lo} = \sum_{j=1}^{n} \lambda_j z_j + s_l^z, \forall l \\
s_i^x \geq 0, s_k^y \geq 0, s_l^z \geq 0, \lambda_j \geq 0, \forall i, j, k, l
\end{aligned} \tag{1}$$

where $s^x \in R^m$, $s^z \in R^{s2}$ represents the surplus of inputs and undesirable outputs, respectively; $s^y \in R^{s1}$ indicates the shortfall in desirable outputs. ρ indicates the efficiency value of the DMU; $m, s1, s2$ indicate the number of inputs, desirable outputs, and undesirable outputs, respectively. When $\rho = 1$, it indicates that the efficiency value of the DMU is valid. When $\rho < 1$, it implies that the efficiency value of the DMU is invalid and there is room for improvement. No weights or dimensionless data processing are involved in this model analysis.

The evaluation of the undesirable output super-efficiency SBM model formula for a decision-making unit or DMU (x_0, y_0, z_0) is as follows:

$$\begin{aligned}
\rho = min \frac{1 + \frac{1}{m}\sum_{i=1}^{m} \frac{s_i^x}{x_{io}^t}}{1 - \frac{1}{s_1+s_2}\left(\sum_{k=1}^{s_1} \frac{s_k^y}{y_{ko}} + \sum_{l=1}^{s_2} \frac{s_l^z}{z_{lo}}\right)} \\
x_{io} \geq \sum_{j=1,\neq 0}^{n} \lambda_j x_j - s_i^x, \forall i \\
y_{ko} \leq \sum_{j=1,\neq 0}^{n} \lambda_j y_j + s_k^y, \forall k \\
z_{lo} \geq \sum_{j=1,\neq 0}^{n} \lambda_j z_j - s_l^z, \forall l \\
1 - \frac{1}{s_1+s_2}\left(\sum_{k=1}^{s_1} \frac{s_k^y}{y_{ko}} + \sum_{i=1}^{s_2} \frac{s_l^z}{z_{lo}}\right) > 0 \\
s_i^x \geq 0, s_k^y \geq 0, s_l^z \geq 0, \lambda_j \geq 0, \forall i, j, k, l
\end{aligned} \tag{2}$$

where the efficiency value calculated by the super-efficiency SBM model of undesirable outputs $\rho \geq 1$. No weights or dimensionless data processing are involved in this model analysis.

From the perspective of the input–output, this study establishes an index system to evaluate the performance of urban environments. It integrates the undesirable output SBM model and the undesirable output super-efficiency SBM model to analyze the efficiency values of 30 decision-making units, including 26 provincial capital cities and 4 municipalities directly under the Central Government of China. This analysis can expose redundancies in decision-making units and propose improvement strategies to address insufficient urban management, thus fostering the balanced development of the urban environment and economy.

2.2.2. Tobit Panel Regression Model

Ordinary least squares (OLS) is a type of linear regression model that can be used to handle data with a continuous dependent variable. However, in some cases, the values of the dependent variable are often constrained, resulting in left censoring or right censoring or being limited within a specific range. Therefore, the results obtained using the OLS model will be biased and not accurate enough. To address the challenges posed by constrained or censored data, it is necessary to utilize a more suitable model for regression analysis. The Tobit panel regression model is a linear regression model used to analyze the impact of independent variables on a censored dependent variable (the dependent variable in this context is constrained within the interval [0, 2]). The Tobit panel regression model, first proposed by James Tobin in 1958, is suitable for situations where the value of the dependent variable is censored [43]. Su Shuai and others [44] applied the Tobit model to the green economic efficiency with constraints on the dependent variable's value, and they verified the influence of environmental regulations on China's green economic efficiency. In the study of Wang and others [45], the range of the dependent variable was limited to the interval [0, 1], so the Tobit regression model was used for the analysis of the factors influencing the energy efficiency. Ji and others [46] employed Tobit regression to study the Chinese resource tax, exploring the driving factors behind its performance. In addition, the Tobit panel regression model with constraints in the dependent variables is now widely used in the field of economics. This study takes the results of urban environmental performance measurement as the dependent variable, which is constrained within the range of [0, 2], belonging to censored data. Therefore, this study adopts a Tobit panel regression model based on the maximum likelihood estimation (MLE) method to analyze the driving factors. The formula for the Tobit regression model is shown below:

$$y_i = \begin{cases} y_i^* = \beta x_i + u_i \,, & y_i^* > 0 \\ 0 & , \; y_i^* \le 0 \end{cases} \tag{3}$$

where x_i, y_i represent independent and dependent variables, respectively; β is the coefficient vector; and error term u_i is independent and subject to a normal distribution, $u_i \sim N(0, \sigma^2)$. The descriptive statistics of the corresponding explanatory variables are presented in Table 2 below.

Table 2. Descriptive statistics of influencing factors of urban environmental performance (2013–2021).

Variable	Unit	Obs	Mean	Std. Dev.	Min	Max
Proportion of secondary industry (x1)	%	270	37.553	9.059	15.05	55.96
Per capita gross regional product (x2)	10,000 yuan	270	91,431.4	31,631.29	37,691	185,338
Science and technology expenditure (x3)	10,000 yuan	270	599,512.1	923,998.9	8284	4,494,463
Education expenditure (x4)	10,000 yuan	270	2,222,192	2,334,873	234,735	11,478,293
Capital expenditure for urban maintenance and construction (x5)	10,000 yuan	270	2,998,042	4,285,550	3735	36,741,708
Number of vehicles on the road (x6)	Vehicles	270	21,977.52	17,973.71	1756	102,679
Population density (X7)	Persons/km^2	270	15,869.18	6574.946	4652	46.230

Abbreviations: observed value (Obs), standard deviation (Std. Dev.), minimum (Min), maximum (Max).

(1) The industrial structure consists of the primary industry, the secondary industry, and the tertiary industry. The primary industry includes agricultural, forestry, animal husbandry, and fishing activities. The secondary industry mainly comprises industrial enterprises, which can burden the city with their pollution emissions. The tertiary industry refers to industries outside of the primary and secondary sectors—primarily the service industry. Therefore, this study focuses on the secondary industry as the influencing factor for urban environmental performance.

(2) The economic scale plays a role in urban economic development. The per capita regional GDP can reflect the economic status of a region and the standard of living of

its residents. Thus, this study analyzes the influencing factors using the per capita regional GDP.

(3) The selection of scientific and technological expenditure and educational expenditure is based on the understanding that advances in science and technology and higher education levels contribute to the rapid development of cities.

(4) Investing in the maintenance of the urban infrastructure plays a vital role in enhancing the quality of the urban environment. As the number of cars in operation increases, so does the emission of harmful pollutants from car exhaust. The population density of a city has a dual impact on its development. Therefore, it is crucial to consider factors such as the allocation of funds for urban maintenance and construction, the number of cars on the road, and the population density when assessing the environmental performance of a city.

3. Results

3.1. Analysis of Environmental Performance Measurement of Key Chinese Cities from 2013 to 2021

Using a combination of the undesirable output SBM model and the undesirable output super-efficiency SBM model, the environmental performance of 30 major cities in China from 2013 to 2021 was measured. The overall environmental performance value of these cities was determined by taking the arithmetic mean, and the results are presented in Table 3.

(1) Overall analysis of the environmental performance of the 30 key cities: The measurement results regarding the environmental performance from 2013 to 2021 indicated an overall upward trend. The efficiency of the environmental performance in these cities showed an increase over the studied time period (Table 4). The range of change in environmental performance was [0.444, 0.821], suggesting that the environmental management level in these cities was continually improved. However, as the efficiency value $\rho < 1$, it suggests that the cities' environmental performance was invalid, and they still require considerable effort to optimize the coordination between the environment and the economy. In this sense, the 30 key cities still have room to enhance their environmental management capabilities. Figure 1 illustrates that the overall mean of the environmental performance in the key cities declined from 2013 to 2015 and then began to rise in 2016. The decline can be attributed to air pollution, frequent smoggy days, and the public's growing awareness of the harmful effects of fine particulate matter $PM_{2.5}$ on human health and the importance of environmental well-being in recent years. Aware of the negative impact of $PM_{2.5}$, China started the comprehensive monitoring of $PM_{2.5}$ in various regions in 2012, and it was not until 2013 that data on $PM_{2.5}$ were comprehensively collected in various regions. Furthermore, in 2013, the State Council issued the "Action Plan for Prevention and Control of Air Pollution" and launched strong measures against air pollution to improve the overall air quality in the country. The year 2015 marked a turning point for urban environmental performance, as it coincided with the launch of the "Belt and Road" initiative, contributing to the strong economic development of China. With increased efforts to control air pollution, the environmental performance of the 30 key cities improved. In 2011, China categorized its economic regions into four areas: the eastern, central, western, and northeastern regions. Although the overall environmental performance in the 30 key cities from 2013 to 2021 showed an increase, a regional analysis reveals that the northeastern region consistently lagged behind the others, with an environmental performance range of [0.248, 0.342], even lower than the overall average of the 30 cities.

(2) The changes over time in the environmental performance of the 30 key cities from 2013 to 2021: Out of these 30 cities, 14 displayed a fluctuating upward trend in environmental performance (Figure 2), indicating an overall improvement in the urban environmental conditions as China strengthened its efforts in environmental protection. In 2017 and 2021, Kunming reached a valid state, achieving a balance between the urban environmental economy and governance, while Hohhot consistently maintained a high level of environmental performance throughout the period. Beijing, Taiyuan, Guangzhou,

and Urumqi experienced significant fluctuations in their environmental performance levels (Figure 3). Beijing saw a sharp decline in 2017 but gradually recovered from 2017 to 2021 through joint efforts and the implementation of the "Beijing–Tianjin–Hebei and Surrounding Areas Atmospheric Pollution Control Action Plan", which restricted or suspended the production of heavily polluting enterprises. Taiyuan initially had low environmental performance due to its extensive coal use and abundant industrial enterprises but recovered over time. Guangzhou and Urumqi showed a "U-shaped" improvement, with high environmental performance in 2013 due to lower investments. The remaining 12 key cities demonstrated stability in their environmental performance (Figure 4), indicating consistent environmental management practices. Xining and Haikou reached valid environmental performance over the 9-year period, as these two prefecture-level cities had lower undesirable outputs and excellent atmospheric environments. Yinchuan achieved valid performance every year except for 2017, when it also maintained a high level of environmental performance. Guiyang, Nanning, Wuhan, Harbin, Changchun, Chongqing, Tianjin, Shenyang, and Jinan showed stable environmental performance within a specific range of [0.08, 0.62].

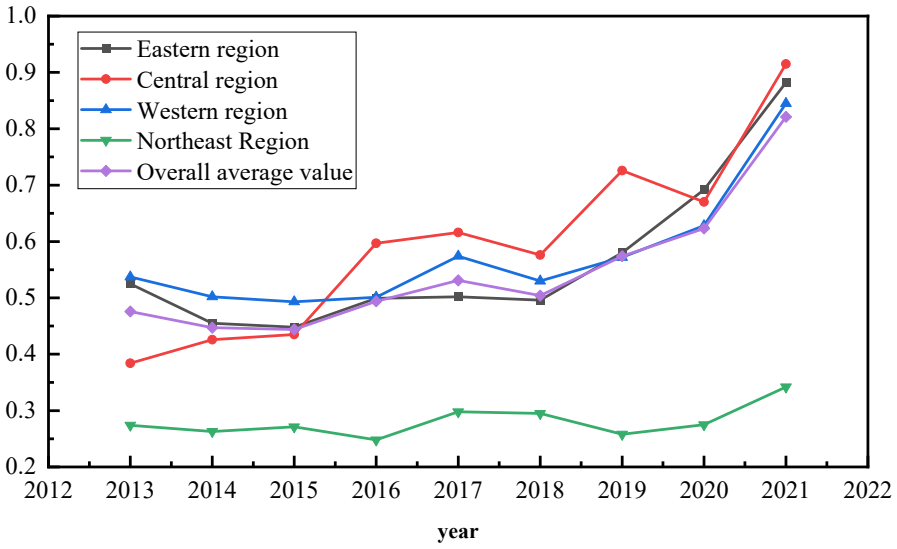


Figure 1. Changes in urban environmental performance over the years.

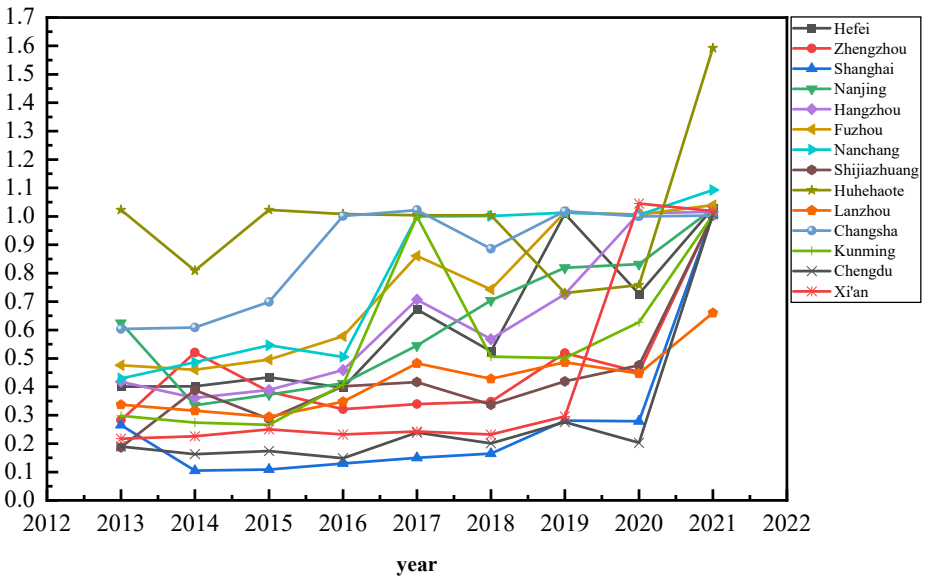


Figure 2. Environmental performance of 14 key cities in a fluctuating upward state.

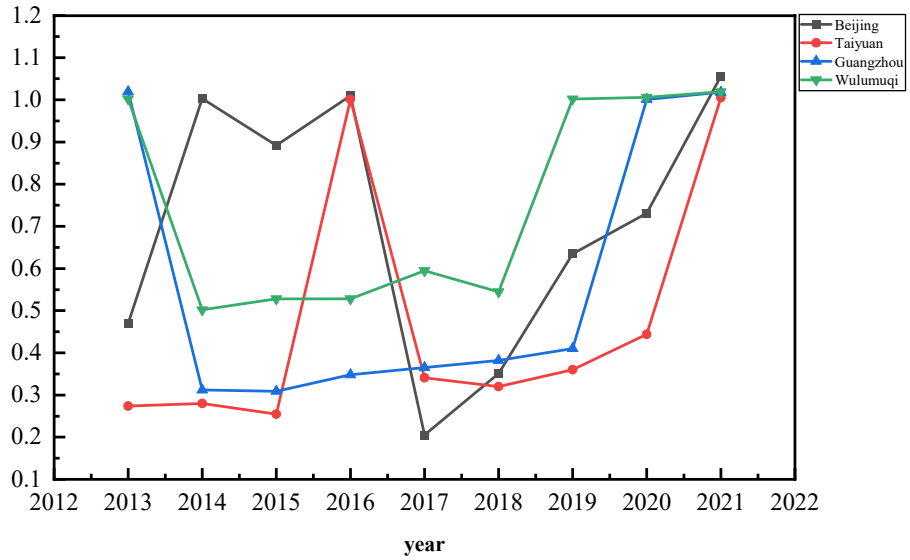


Figure 3. Significant changes in environmental performance of four key cities.

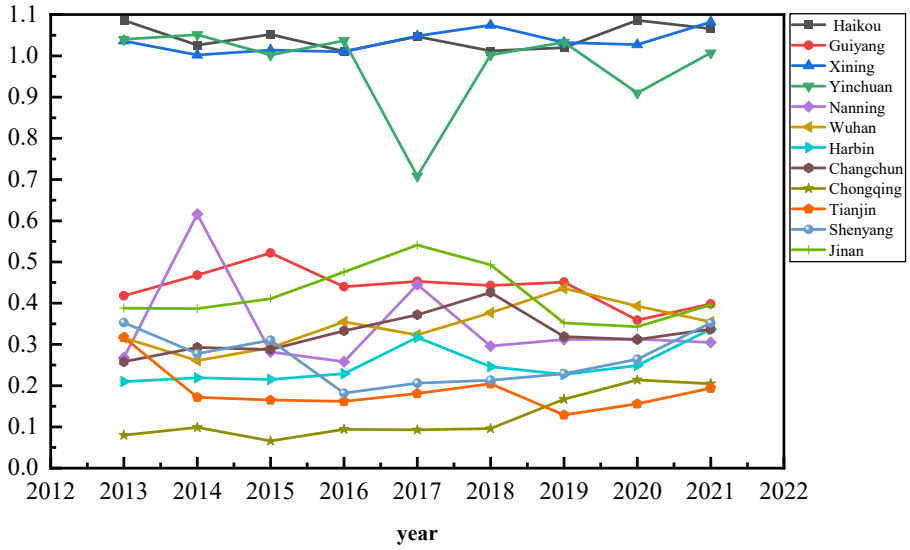


Figure 4. Environmental performance of 12 key cities tending towards stability.

Table 3. Measurement results of urban environmental performance (2013–2021).

Region	2013	2014	2015	2016	2017	2018	2019	2020	2021	Mean Value
Beijing	0.470	1.003	0.892	1.010	0.205	0.351	0.635	0.731	1.056	0.706
Tianjin	0.317	0.172	0.165	0.162	0.181	0.205	0.129	0.156	0.194	0.187
Shijiazhuang	0.187	0.388	0.287	0.402	0.417	0.337	0.419	0.476	1.002	0.435
Taiyuan	0.274	0.280	0.255	1.001	0.341	0.320	0.360	0.444	1.005	0.476
Hohhot	1.023	0.809	1.023	1.008	1.004	1.004	0.730	0.758	1.592	0.995
Shenyang	0.353	0.278	0.310	0.182	0.206	0.213	0.229	0.264	0.352	0.265
Changchun	0.258	0.293	0.288	0.333	0.372	0.426	0.319	0.312	0.337	0.326
Harbin	0.210	0.219	0.215	0.229	0.317	0.246	0.227	0.249	0.337	0.250
Shanghai	0.265	0.105	0.109	0.130	0.150	0.165	0.281	0.279	1.007	0.277
Nanjing	0.625	0.335	0.373	0.412	0.545	0.704	0.819	0.832	1.027	0.630
Hangzhou	0.418	0.361	0.389	0.459	0.707	0.568	0.726	1.011	1.016	0.628
Hefei	0.401	0.402	0.433	0.397	0.672	0.525	1.009	0.727	1.029	0.622
Fuzhou	0.476	0.460	0.496	0.578	0.861	0.743	1.014	1.007	1.039	0.741

Table 3. *Cont.*

Region	2013	2014	2015	2016	2017	2018	2019	2020	2021	Mean Value
Nanchang	0.429	0.486	0.546	0.505	1.000	1.001	1.013	1.005	1.093	0.787
Jinan	0.388	0.387	0.411	0.476	0.541	0.493	0.352	0.343	0.396	0.421
Zhengzhou	0.283	0.521	0.383	0.321	0.339	0.348	0.519	0.452	1.005	0.463
Wuhan	0.316	0.261	0.292	0.355	0.323	0.377	0.436	0.393	0.355	0.345
Changsha	0.604	0.609	0.699	1.001	1.022	0.886	1.018	1.000	1.003	0.871
Guangzhou	1.019	0.312	0.309	0.348	0.365	0.382	0.410	1.001	1.018	0.574
Nanning	0.268	0.616	0.282	0.258	0.445	0.296	0.312	0.313	0.305	0.344
Haikou	1.086	1.026	1.052	1.011	1.047	1.012	1.020	1.086	1.066	1.045
Chongqing	0.080	0.099	0.066	0.094	0.093	0.096	0.167	0.214	0.205	0.124
Chengdu	0.190	0.163	0.174	0.149	0.239	0.201	0.276	0.203	1.007	0.289
Guiyang	0.418	0.468	0.522	0.440	0.453	0.443	0.451	0.359	0.398	0.439
Kunming	0.298	0.274	0.266	0.408	1.000	0.506	0.501	0.627	1.005	0.543
Xi'an	0.217	0.226	0.250	0.232	0.243	0.232	0.296	1.045	1.019	0.418
Lanzhou	0.337	0.316	0.294	0.348	0.483	0.428	0.486	0.447	0.660	0.422
Xining	1.036	1.002	1.014	1.010	1.048	1.074	1.032	1.027	1.082	1.036
Yinchuan	1.040	1.051	1.002	1.037	0.708	1.002	1.033	0.910	1.007	0.977
Urumqi	1.002	0.502	0.528	0.528	0.595	0.545	1.002	1.006	1.019	0.748
Eastern region	0.525	0.455	0.448	0.499	0.502	0.496	0.580	0.692	0.882	0.564
Central region	0.384	0.426	0.435	0.597	0.616	0.576	0.726	0.670	0.915	0.594
Western region	0.537	0.502	0.493	0.501	0.574	0.530	0.572	0.628	0.845	0.576
Northeast China	0.274	0.263	0.271	0.248	0.298	0.295	0.258	0.275	0.342	0.281
Overall mean	0.476	0.447	0.444	0.494	0.531	0.504	0.574	0.623	0.821	0.546

Table 4. Valid rates of environmental performance measurement of 30 key cities.

	2013	2014	2015	2016	2017	2018	2019	2020	2021
Valid rate of urban performance	20	13.3	13.3	16.7	16.7	16.7	26.7	30	66.7
Invalid rate of urban performance	80	86.7	86.7	83.3	83.3	83.3	73.3	70	33.3

3.2. Spatial Distribution Characteristics of Environmental Performance in Key Cities

To visually depict the spatial heterogeneity of the environmental performance among different prefecture-level cities, we selected 2013, 2017, and 2021 as time nodes and used GIS 10.8.1 software to visualize and analyze the environmental performance measurement results of the 30 key cities, as shown in Figure 5. This paper expands the provincial capital city areas of each province to the provincial area to make the results more explicit and facilitate a spatial comparative analysis.

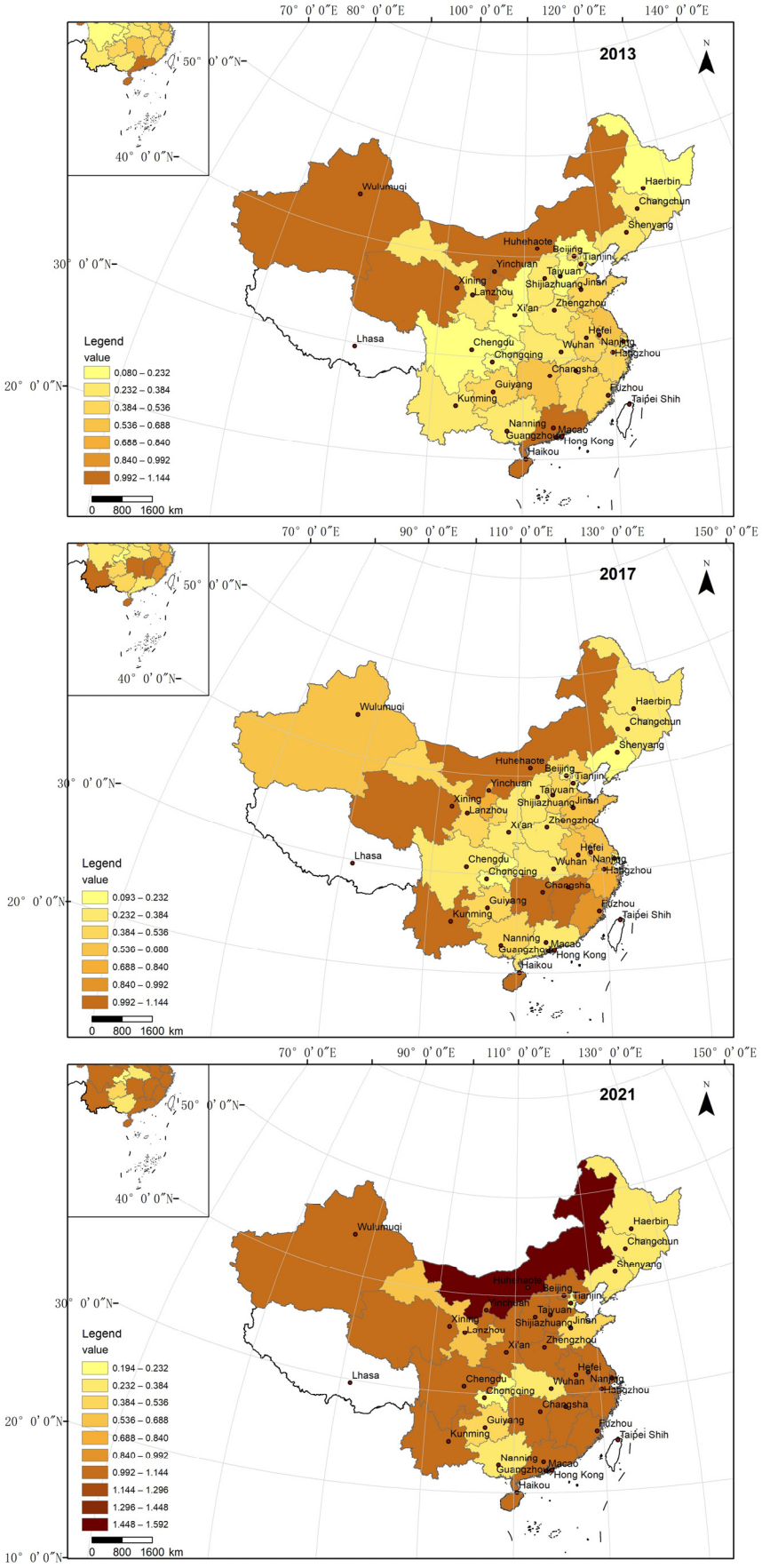


Figure 5. Spatial distribution characteristics of urban environmental performance.

By comparing the spatial patterns of the environmental performance of the 30 key cities in 2013, 2017, and 2021, it is evident that the color depth (a darker color represents higher environmental performance) increased over the years, indicating an improvement in urban environmental performance and more balanced development between the environment and economy. The 30 key cities were categorized into the western, eastern, central, and northeastern regions. It was observed that, in 2013, the western region outperformed the others regarding the overall environmental performance, while the central region performed the best in 2017 and 2021. On the other hand, the northeastern region consistently had the poorest environmental performance in 2013, 2017, and 2021. The northeastern region, as an industrial hub in China, is home to a large proportion of heavy industrial and pollution-intensive enterprises, with an unbalanced industrial structure, resulting in escalating energy consumption [47,48] and substantial emissions of pollutants such as smoke, dust, and organic compounds, imposing a considerable environmental burden, deteriorating ecological functions, and disrupting ecosystem services (ESs). Beyond resource depletion and pollution generation, it also has severely hindered the harmonious development of the environment and economy in the region. Consequently, the urban environmental performance of the northeastern region was consistently ranked the lowest among the four regions. Enhancing the urban environmental performance in the northeastern region necessitates the prioritization of environmental governance, entailing the implementation of scientific measures to mitigate pollutant emissions and elevate the region's urban management standards.

4. Discussion

4.1. Analysis of Influence Mechanism of Driving Factors

The driving factors of urban environmental performance are empirically analyzed using the econometric regression software STATA17, and the variables are logarithmically processed to eliminate the impact of dimensionless differences. The results of the empirical analysis are shown in Table 5.

Table 5. Tobit panel model regression results of driving factors.

Variable	Coefficient	Std. Err.	Z-Value	*p*-Value
X1 (Proportion of secondary industry)	−2.996 ***	0.084	−3.550	0.000
X2 (Per capita gross regional product)	0.557 ***	0.086	6.460	0.000
X3 (Science and technology expenditure)	−0.021	0.039	−0.540	0.592
X4 (Education expenditure)	−0.020	0.074	−0.270	0.789
X5 (Capital expenditure for urban maintenance and construction)	0.044 **	0.015	2.960	0.003
X6 (Number of vehicles on the road)	−0.281 ***	0.063	−4.470	0.000
X7 (Population density)	−0.136 *	0.997	3.260	0.056
_cons	2.177 *	1.282	−1.700	0.090
Prob>= chibar2	0.000	0.000	0.000	0.000

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Abbreviations: standard error (Std. Err.).

Through the empirical analysis results, it is concluded that five of the seven driving factors selected in this paper are significant, and the other two are not significant. The impact of the science and technology expenditure and education expenditure on urban environmental performance is not significant, indicating that there is no direct impact relationship between the science and technology expenditure and education expenditure and urban environmental performance, and their impact on urban environmental performance is too limited to be noticed.

(1) The impact of the secondary industry is significant, with a negative effect on urban environmental performance when it accounts for 1%. The secondary industry is

primarily composed of the industrial sector, which is an important contributor to the GDP and the primary cause of environmental pollution. Industrial enterprises, known for their "high energy consumption, high emissions, and high pollution", have a detrimental impact on the environment. The various pollutants produced during their production processes are especially harmful to the atmosphere, upsetting the balance between the urban environment and the economy. Consequently, the northeastern region, as the industrial base of the country, has maintained low levels of urban environmental performance due to the imbalanced industrial structure.

(2) The per capita gross regional product is significant when it reaches 1%, with a significant, positive impact on urban environmental performance. This metric mirrors the degree of economic growth and the living standards of the people in the region. An increase in the per capita gross regional product signifies an enhancement in people's quality of life and improvements in their environmental awareness and literacy, thereby fostering more balanced regional development between the environment and economy and elevating the cities' environmental governance standards.

(3) When 5% of the funds are allocated to urban maintenance and construction, the result passes the significance test and shows a significant, positive impact on urban environmental performance. These funds are primarily utilized for the maintenance and improvement of urban public utilities and facilities. The maintenance of urban public facilities can drive urban development and enhance the living standards of residents. Increasing the number of designated trash cans in urban public areas can greatly alleviate the burden on the environment, boost waste reuse, and raise the standard of urban environmental performance, contributing to the creation of a livable and aesthetically pleasing city.

(4) When the number of vehicles on the road reaches 1%, the result passes the significance test and displays a significant, negative impact on urban environmental performance. While cars provide convenience and efficiency in transportation, the extensive emissions from their exhaust contribute to worse atmospheric pollution. Key pollutants such as CO, NO_X, CO_2, SO_X, $PM_{2.5}$, and solid particulate matter lead to photochemical smog. Moreover, the extensive use of cars generates environmental noise, affecting people's work, study, and sleep quality, thereby diminishing visibility and urban environmental performance.

(5) A population density of 10% is significant and has a negative impact on urban environmental performance. As cities undergo rapid urbanization, there is a shift in the population from rural to urban areas, resulting in a sharp increase in the population density in some developed cities. Although this increase can bolster urban economic development, it also poses challenges and difficulties for cities. A high population density not only adds to the environmental burden on cities but also places economic pressure on the residents, hindering the improvement of the urban environmental performance.

4.2. Analysis of Urban Environmental Performance Loss

When the DMU is valid ($\rho \geq 1$), it implies that the input–output ratio of the DMU is optimized on the common production frontier without a slack. Conversely, when the DMU is invalid ($\rho < 1$), it indicates that the input–output ratio of the city has not yet reached optimization, leaving room for improvement. The slack results obtained from the undesirable output SBM model and the undesirable output super-efficiency SBM model can indicate the input–output gap in achieving environmental performance optimization in invalid cities. If the slack value of the input item is >0, it implies an excess of inputs and calls for input reduction. Similarly, if the slack value of the undesirable output item is >0, it suggests a need to reduce the undesirable outputs of the city (Table 6). Table 6 reveals that the loss in urban environmental performance is a combination of both input indicators and undesirable indicators. The redundancy of input indicators and excessive undesirable outputs are the primary internal factors contributing to the decline in urban environmental performance.

Table 6. Redundancy analysis of inputs and undesirable outputs in eastern, central, western, and northeastern regions.

Region	Year	Input				Undesirable Output				
		Local General Public Budget Expenditure (10,000 Yuan)	**Employees in Human Resources, Water Conservancy, Environment and Public Facility Management Industry (Persons)**	**Built-Up Area (km^2)**	**Water Supply (10,000 m^3)**	**Total Energy Consumption (10,000 Tons of Standard Coal)**	**$PM_{2.5}$ Annual Average Concentration (μ g/m^3)**	**Annual Average Concentration of NO_2 (μ g/m^3)**	**Annual Average Concentration of SO_2 (μ g/m^3)**	**Road Traffic Noise (DB)**
Eastern Region	2013	6,724,349.609	20,945.853	167.917	62,142.543	3132.617	42.489	20.426	30.527	0.000
	2017	16,685,511.532	28,402.524	357.254	85,695.633	3654.886	14.368	14.898	5.054	0.000
	2021	2,644,296.435	17,005.175	128.114	28,210.445	1087.454	1.749	1.816	0.389	0.000
	Mean value	11,151,204.741	23,173.030	266.470	68,709.102	3165.425	18.684	13.632	9.447	0.000
Central Region	2013	2,706,387.735	6589.077	147.189	32,640.595	2403.534	59.212	25.916	34.084	0.000
	2017	3,211,508.892	8896.783	110.208	29,262.728	2059.333	16.757	16.456	8.190	0.000
	2021	1,969,034.067	5203.784	87.272	15,321.464	595.337	0.514	1.911	0.000	0.000
	Mean value	3,376,754.265	8145.371	122.284	27,752.297	1796.410	24.134	14.501	11.206	0.000
Western Region	2013	4,814,098.009	11,142.465	207.206	20,552.418	1242.184	29.167	17.426	15.932	0.106
	2017	5,952,610.233	12,346.665	247.166	28,747.804	1539.176	18.116	18.004	3.764	0.000
	2021	4,638,367.093	3184.852	153.600	20,474.193	1024.994	1.794	4.297	1.244	0.000
	Mean value	5,990,270.435	10,380.748	234.932	27,461.074	1389.354	16.528	15.418	6.156	0.028
Northeastern Region	2013	4,330,010.150	24,292.772	237.199	18,441.425	1592.846	52.255	30.435	52.207	0.000
	2017	5,223,011.404	20,500.321	274.273	22,375.142	3578.614	28.189	22.684	21.519	0.000
	2021	6,581,260.087	6216.638	340.123	25,480.276	3653.368	9.621	10.427	4.580	0.000
	Mean value	5,967,657.691	17,831.956	296.810	24,054.854	2913.346	28.778	21.918	24.770	0.266

Note: The mean value in the table refers to the period from 2013 to 2021.

The annual loss in urban environmental performance: From 2013 to 2021, the eastern, central, western, and northeastern regions experienced a steady increase in urban environmental performance. Table 6 illustrates a gradual decrease in the undesirable outputs of these four key regions during the same period, indicating a strong connection between the decline in urban environmental performance prior to 2021 and the redundancy of undesirable outputs. The changes in undesirable output suggest that the "Air Pollution Control Action Plan" issued by the State Council in 2013 and subsequent environmental protection policies have produced positive outcomes. As a result, the urban environmental performance of the four key regions has improved year after year.

The spatial loss of urban environmental performance in different regions: The spatial distribution results of the urban environmental performance in the eastern, central, western, and northeastern regions are described in Section 3.2, showing that the western region achieved the best overall environmental performance in 2013, while the central region outperformed the others in 2017 and 2021. On the other hand, the northeastern region consistently performed the worst from 2013 to 2021. Based on this finding, an analysis using the slack value of the input–output revealed that road traffic noise had a limited impact on the urban environmental performance, with a low redundancy value among the undesirable outputs. However, the redundancy value of the remaining undesirable outputs in the northeastern region, such as the annual average concentrations of $PM_{2.5}$, SO_2, and NO_2, was consistently the highest. Among the input items, the total energy consumption in the northeastern region was also relatively high, mainly due to the consumption of electricity, coal, and oil, which contributed to the undesirable outputs. Therefore, the comprehensive consideration of the slack value of the input–output helps to identify the primary internal factors leading to the poor urban environmental performance in the northeastern region. To address this issue, it is imperative to reduce the redundancy of input items and put in place appropriate policies aimed at improving the environment and reducing excessive undesirable outputs, ultimately moving towards the goal of creating beautiful cities.

5. Conclusions

5.1. Research Conclusions

This study combines the SBM model and the super-efficiency SBM model to measure and compare the environmental performance of 30 key cities in China. The Tobit panel regression model has also been used to delve into the factors influencing urban environmental performance. The following conclusions are drawn: despite the invalid average environmental performance of the 30 cities from 2013 to 2021, there was a gradual improvement over the 9-year period, moving closer to validity. In 2021, 66.7% of the 30 key cities achieved valid environmental performance, representing a 44.7% increase compared to 2013. Conversely, the proportion of invalid cities decreased by 46.7% compared to 2013, indicating a significant improvement in environmental governance. The northeastern region had poorer environmental performance and lagged behind other regions due to high levels of industrial emissions, but it has considerable potential for improvement. The proportion of the secondary industry negatively affected the urban environmental performance, leading to more undesirable output emissions. The number of vehicles on the road and the population density also had a negative impact on urban environmental performance, burdening the urban environment. On the other hand, an increase in the per capita regional GDP and urban maintenance and construction fund expenditure had a promotional effect on urban environmental performance, contributing to the balanced development of the environment and the economy.

5.2. Policy Recommendations

(1) Restructuring industries: It is recommended to encourage the coordinated development of various industries, with a focus on expanding the tertiary industry (service industry) while reducing the proportion of the secondary industry to optimize the

industrial structure. In line with the "14th Five-Year Plan", efforts should be made to reduce undesirable outputs while enhancing the digital economy and intelligent equipment development. For the industrial base in the northeastern region, it is advisable to accelerate the transformation of the secondary industry, harness the power of scientific and technological approaches to mitigate structural conflicts, phase out outdated and highly energy-consuming industrial enterprises, and achieve the high-quality development of the environment and the economy.

(2) Advancing energy conservation and carbon reduction: Given the substantial amount of exhaust emissions from vehicles that add the atmospheric environmental burden, it is essential to encourage low-carbon and eco-friendly travel practices, increase urban maintenance and construction funds, and optimize the allocation and maintenance of shared bicycles and electric vehicles. The promotion of new energy vehicles brings multiple benefits, including energy conservation, reduced greenhouse gas and atmospheric pollution emissions, and progress in renewable energy. These efforts contribute to improved air quality, climate change mitigation, and a faster transition to a green economy.

(3) Strengthening regional cooperation: Enhancing regional cooperation mechanisms is essential for the effective allocation and synergistic utilization of diverse regional resources. It facilitates the exchange of knowledge, science, and technology, particularly in the fields of environmental protection and clean energy. Environmental issues extend beyond individual regions, and problems in one region may have ripple effects in neighboring areas and beyond. By working together across regions, we can develop and implement strategies that drive society towards sustainability.

(4) Reinforcing government regulation: It is advisable for environmental authorities to closely supervise and exert reasonable pressure on industrial enterprises that exceed the emission standards and conduct regular inspections of polluting enterprises. Industrial enterprises should conduct environmental performance assessments in a timely manner, identify areas for improvement, and devise solutions. In response to the existing environmental pollution, the government should disclose environmental quality information to the public, enhance the transparency of environmental governance and public participation awareness, encourage public engagement in environmental protection through education and awareness campaigns, and foster sustainable development.

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