Pol. J. Environ. Stud. Vol. XX, No. X (XXXX), 1-9

DOI: *10.15244/pjoes/211966* ONLINE PUBLICATION DATE: 2025-12-03

Original Research

What Drives the Improvement of Carbon Emission Efficiency of Chinese Cities?

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Received:7 August 2025

Accepted: 12 October 2025

Abstract

A comprehensive evaluation of carbon emission efficiency (CEE) and identification of paths to improve it are crucial for achieving sustainable development goals, yet existing studies have limitations. This study employs the super-efficiency SBM model to measure the CEE of 284 Chinese cities from 2003 to 2022 and uses qualitative comparative analysis to examine the driving paths for improving CEE. The study finds that: (1) from the perspective of CEE measurement results, China's CEE shows a U-shaped trend from 2003 to 2022; (2) regarding the influencing factors of CEE, high CEE is not driven by a single factor but by the combined effect of multiple factors, and the study identifies three functional paths: the energy efficiency and industrial structure-driven path, the energy efficiency and population density-driven path, and the energy efficiency, industrial structure, and population density-driven path. This study provides new insights for the government to implement targeted policies to promote the improvement of CEE.

Keywords: carbon emission efficiency (CEE), super-efficiency SBM model, qualitative comparative analysis

Introduction

The United Nations Framework Convention on Climate Change (UNFCCC) emphasizes that countries must reduce greenhouse gas emissions, such as carbon dioxide, to combat climate change. Given its status as a manufacturing powerhouse and its population of 1.4 billion, China plays a crucial role in global efforts to reduce emissions. According to the Global Energy Review 2025, released by the International Energy Agency (IEA) in March 2025, global carbon dioxide (CO_2) emissions reached 37.8 billion tons in 2024, with China accounting for 12.6 billion tons – nearly one-third of the global total. In response to the UNFCCC, China made a solemn pledge in 2020 to achieve a carbon peak by 2030 and carbon neutrality by 2060. However, a fundamental challenge remains: fossil fuels are still China's primary energy source. This makes it difficult to achieve the "dual carbon" goals within the set timeframe. Therefore, measuring China's Carbon Emission Efficiency (CEE), exploring the spatial evolution patterns and influencing factors of CEE, and identifying pathways to improve CEE are of vital importance. These efforts are crucial not only

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for China but also for the world in achieving sustainable development goals.

Existing research on CEE covers the following aspects: first, regarding its connotation, CEE refers to promoting socio-economic development with the minimum possible inputs of capital, labor, and energy while emitting a certain amount of carbon [1]; second, in terms of measurement, some studies use a single indicator to measure CEE, such as the ratio of GDP to carbon emissions, but this approach fails to fully capture CEE [2]. Most existing studies adopt the traditional Data Envelopment Analysis (DEA) model to measure CEE from the input-output perspective, yet such studies generally have obvious limitations. On the one hand, they fail to fully consider the impact of undesirable outputs and lack horizontal comparative analysis of effective Decision-Making Units (DMUs) [3]. On the other hand, when processing input and output variables, the traditional DEA method cannot incorporate "slack variables" into its calculations [4, 5], while the super-efficiency SBM model can effectively address the problems faced by existing literature in CEE measurement. Third, concerning influencing factors, some studies focus on the impact of macro-policies on CEE: Du et al. (2023) [6] examined the impact of the energy quota trading pilot on the CEE of 275 prefecture-level cities in China from 2006 to 2020; Liu et al. (2024) [7] focused on the impact of the information consumption city policy on urban CEE; Lu et al. (2025) [8] studied the impact of innovation-driven industrial clusters on urban carbon emission efficiency; Peng and Gao (2025) [9] explored the impact of new energy demonstration city pilots and energy consumption right trading system pilots on urban carbon emission efficiency; and Shen et al. (2025) [10] focused on how the marketization of data factors affects urban carbon emission efficiency, while another group of studies focuses on the impact of non-policy factors: Xiao et al. (2023) [11] conducted a comprehensive analysis of factors influencing CEE using the Tobit model and found that the level of urbanization, foreign trade, and the proportion of renewable energy effectively improve CEE; Xing et al. (2023) [12] adopted the machine-learning random forest method to explore differences in CEE-influencing factors across different cities and regions; Wu et al. (2025) [13] explored the impact of green finance; Du et al. (2025) [14] identified the nonlinear impact of the digital economy on CEE; Feng et al. (2025) [15] studied the relationship between the digitalization of the rural economy and CEE; and Li et al. (2025) [16] examined the impact of urban form.

The TOE framework is a comprehensive, context-based model that analyzes how technological, organizational, and environmental factors interact. Indeed, its broad applicability has earned it recognition as a near-universal model. Urban carbon emission efficiency is shaped by the interplay of these three factors: technological breakthroughs hinge on organizational support, organizations require a conducive environment, and environmental gains depend on both innovation and institutional reform. Thus, the TOE framework offers a robust theoretical lens for improving urban carbon emission efficiency. Given its versatility, the framework has been widely adopted across disciplines. For instance, Abed (2020) [17] used it to examine SMEs' adoption of social commerce, Ullah et al. (2021) [18] applied it to risk identification in sustainable smart-city governance, Al-Khatib (2023) [19] explored generative AI adoption, Chittipaka et al. (2023) [20] studied blockchain uptake in supply chains, Zhang et al. (2024) [21] investigated drivers of high-quality development, and Wang et al. (2024) proposed carbon-reduction strategies.

Existing literature has certain limitations in the following aspects. First, it covers a relatively short time span for CEE measurement, and the data used is relatively outdated. Second, there are certain flaws in the measurement methods for urban CEE adopted in existing literature. Third, studies on the influencing factors of CEE only rely on traditional analytical methods, which fail to address the issues of endogeneity or omitted variables. Although some studies adopt machine learning methods to tackle endogeneity, they can only identify the nonlinear effects of individual variables and cannot recognize the interaction effects between factors. In view of this, based on measuring the CEE of 284 Chinese cities from 2003 to 2022, this study adopts the QCA model to identify the interaction effects between various factors, which is more in line with real-world logic.

The contributions of this paper are as follows: First, this study employs the super-efficiency SBM model to measure the CEE of 284 cities in China from 2003 to 2022. This approach not only addresses the limitations of existing literature but also extends the research time span for CEE measurement. Second, previous literature has inadequately discussed the interactions among multiple factors affecting CEE, with fragmented analyses of influencing factors. This paper innovatively adopts the TOE analytical framework as the theoretical basis for improving carbon emission efficiency. Taking 284 cities in China as cases, it employs the QCA method to explore the interactive effects of technological, organizational, and environmental factors on CEE, thereby providing references for developing countries to enhance carbon emission efficiency and achieve sustainable development.

The second part introduces the material and methods; the third part presents the results, and the fourth part is the discussion; the fifth part is the conclusion.

Materials and Methods

Indicator System

The evaluation indicators of CEE are divided into three categories: inputs, desired outputs, and undesired outputs. Input indicators include the number of employees in units at the end of the year, fixed capital stock (actual investment amount, with 2003 as the base period), and energy consumption (calculated using nighttime light data [12]); the desired output is the real GDP with 2003 as the base period; and the undesired output is CO_2 emissions (from the Emissions Database for Global Atmospheric Research (EDGAR V8.0) [22]).

Super-SBM Model

After Kaoru (2021) [23] pioneered the SBM model that takes into account undesired outputs, the academic community has made in-depth improvements to it. Subsequently, Zhang et al. (2017) [24] further expanded and constructed the Super-SBM model that considers undesired outputs, which has promoted research progress in this field. The Super-SBM model that takes into account undesired outputs is used to calculate CEE [25].

QCA Method

Traditional quantitative data analysis methods focus on estimating the "net effect" of conditional variables on outcome variables, adhering to the principles of causal symmetry and consistent causal effects. However, they are constrained by assumptions of linearity and additivity. In reality, the determinants of CEE are diverse and interdependent. The Qualitative Comparative Analysis (QCA) approach, rooted in a holistic and configurational perspective, emphasizes "multiple concurrent causal relationships" across cases, enabling more effective explanations of management practice issues. By leveraging configurational thinking, QCA can uncover the complex mechanisms of interaction, matching, and symbiotic collaboration among factors influencing CEE. Given that all variables designed in this paper are continuous, the method of fuzzy-set qualitative comparative analysis (fsQCA) is utilized. This paper innovatively adopts the TOE framework as its theoretical basis and selects antecedent variables from the perspectives of technology, organization, and environment. Factors at the technological level include green innovation and energy efficiency; factors at the organizational level are human capital, industrial structure, and government intervention; and at the environmental level, they are the level of economic development and population density.

Data

The data used in this paper are derived from the China City Statistical Yearbook, China Energy Statistical Yearbook, China Environment Yearbook, and statistical yearbooks of various provinces and cities. The nighttime light data are sourced from the National Earth System Science Data Center (https://www.geodata.cn). The carbon dioxide data are obtained from the Emissions Database for Global Atmospheric Research (EDGAR) (https://edgar.jrc.ec.europa.eu).

Results

Analysis of Changes in CEE Results

Fig. 1 shows the changes in the average CEE at the national level and across the eastern, central, and western regions of China from 2003 to 2022. At the national level, it presents a U-shaped variation

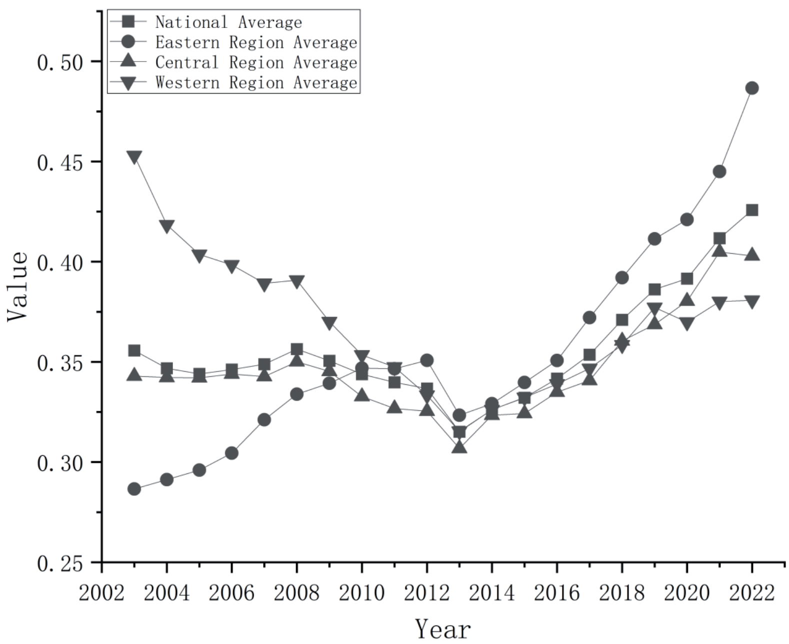

Fig. 1. Results of the CCE.

trend, and Zhang (2023) also found the U-shaped variation pattern of CEE in Chinese cities from 2009 to 2020 [26]. In the early stage of development, the GDP-oriented development model came at the cost of high carbon emissions, which greatly reduced CEE; however, after the Chinese government put forward the concept of green development, it began to attach importance to the coordinated development of environmental protection and the economy, which significantly improved CEE. From a regional perspective, the eastern region has shown a consistent upward trend in CEE, while the central and western regions have exhibited a U-shaped trend, which may be related to the spatial pattern of China's industrial development. From 2003 to 2012, China's industrial spatial pattern underwent significant changes: the industrial proportion of the central region increased from 13.10% to 19.5%, that of the western region rose from 10.59% to 13.87%, and that of the eastern region decreased from 68.1% to 57.86%, with a large number of heavy-polluting and labor-intensive enterprises transferring from the eastern region to the central and western regions simultaneously [27]. Therefore, from 2003 to 2012, CEE in the central and western regions kept declining, while that in the eastern region kept rising. After 2013, China began to advocate sustainable development, and all regions started to attach importance to environmental protection and emission reduction, which promoted the improvement of CEE, with CEE in the eastern region being significantly higher than that in the central and western regions.

Configuration Path of CEE

Driver Selection

The TOE framework is essentially a comprehensive analytical system built based on application scenarios. It focuses on exploring the impacts of various elements covered by the three dimensions of technology, organization, and environment. In fact, the TOE framework has an extremely broad scope of application and serves as a universal model [28]. This paper innovatively explores the paths to improve carbon emission efficiency based on the TOE framework, focusing on the technological, organizational, and environmental factors that influence carbon emission efficiency.

Technical factors pertain to the capacity for technology utilization and innovation, primarily encompassing green innovation (X1) and energy efficiency (X2). Green innovation is conducive to the improvement of CEE [29], which is measured by the number of urban green patent applications. Enhancing energy efficiency can reduce carbon emissions and thereby promote the improvement of CEE [30], which is measured by the ratio of urban real GDP to energy consumption.

Organizational factors relate to human capital (X3), industrial structure (X4), and government intervention associated with technological development and application. The evolution of the human capital structure can spur technological improvement and industrial optimization, thereby enhancing CEE [31], which is measured by the number of students in urban institutions of higher learning. The optimization of the industrial structure, such as reducing high-energy-consuming and high-pollution industries, eliminating backward production capacity, and guiding resources like capital and labor to flow toward more productive and environmentally friendly industries, can boost regional energy efficiency [32], which is evaluated by the proportion of the tertiary industry in GDP. Government intervention (X5) can enhance CEE, such as through the improvement of internet infrastructure [33], which is measured by the proportion of local general public financial budget expenditure to GDP.

Environmental factors refer to the external environment influencing technological application, mainly including the economic development level (X6) and population density (X7). As the economy develops, regional CEE gradually improves, driven by technological advancements [34], which is measured by regional real GDP (with 2003 as the base period). Cities with high population density can achieve economies of scale due to agglomeration effects [35]. These economies of scale can enhance factor productivity, thereby promoting the efficient use of energy and resulting in an improvement in CEE [36], which is measured by the ratio of urban population to urban area.

Variable Calibration and Necessity Analysis

Direct calibration was used to calibrate the data. Following Wu and Xie (2025) [28], the 25^{th}, 50^{th}, and 75^{th} percentiles were adopted as the calibration points for full non-membership, crossover, and full membership, respectively. For variables with a calibrated value of 0.5, 0.501 was substituted for these values to avoid affecting the analysis results, and the calibrated results are presented in Table 1. In Table 1, the consistency level of each variable is less than 0.9, which indicates that there is no single factor contributing to high CEE and no necessary condition for high CEE.

Sufficiency Analysis

The study focuses on the realization paths of high Y. Following the approach of Wu and Xie (2025) [28], the case frequency was set to 2, the raw consistency threshold to 0.8, and the PRI threshold to 0.75. Using R software, the intermediate solution and simple solution were obtained, and core conditional variables were derived based on the two solutions. Table 1 shows that high Y is influenced by three configurational paths. The overall consistency is 0.875, indicating that 87.5% of cities following these configurations achieve high CEE. Specifically:

Table 1. All results required to be reported for QCA.

Variable name	Full subordination	Intersection (50%)	Non-subordination	High Y				High Y		
	-75%		-25%	Consistency	Coverage	Adjusted Distance for Inter-group Consistency	Adjusted Distance for Intra-group Consistency	S1	S2	S3
X1	228	63	15	0.503	0.519	0.62	0.508	⊗	⊗	
~X1				0.588	0.563	0.471	0.61			
X2	58.785	34.579	21.322	0.7	0.704	0.216	0.44	●	●	●
~X2				0.403	0.395	0.36	0.644			
X3	0.915	0.571	0.352	0.472	0.474	0.317	0.61	⊗		⊗
~X3				0.614	0.603	0.231	0.61			
X4	0.461	0.39	0.333	0.562	0.562	0.476	0.457	●	⊗	●
~X4				0.529	0.521	0.476	0.576			
X5	7.542	3.186	1.309	0.443	0.454	0.418	0.661	⊗	⊗	⊗
~X5				0.651	0.627	0.255	0.661			
X6	55321.188	31191.212	16306.912	0.565	0.569	0.582	0.474	⊗	⊗	•
~X6				0.53	0.52	0.519	0.627			
X7	641.793	380.023	198.93	0.525	0.531	0.183	0.576		●	●
~X7				0.569	0.555	0.159	0.61			
Y	0.404	0.331	0.272							
Consistency								0.881	0.895	0.875
PRI								0.813	0.824	0.799
Raw Coverage								0.091	0.108	0.085
Unique coverage								0.043	0.068	0.049
Adjusted Distance for Inter - group Consistency								0.048	0.062	0.111
Adjusted Distance for Intra-group Consistency								0.288	0.305	0.254
Overall consistency								0.875		
Overall PRI								0.814		
Overall coverage								0.207		

Note: ● and ⊗ represent the presence or absence of the core condition, • and ⊗ represent the presence or absence of the edge condition (only present in the intermediate solution), and blanks indicate that the condition is dispensable for the outcome. This paper actually adopts the dynamic QCA method, and the unpresented tests and results can be obtained by contacting the corresponding author.

Energy Efficiency and Industrial Structure-Driven Type (S1). A consistency level of 0.881 and a raw coverage of 0.091 are achieved by this driving way, both within reasonable ranges. S1 indicates that high energy efficiency and a high-level industrial structure as core conditions can achieve high Y. On the one hand, the optimization of the industrial structure – such as reducing high-energy-consuming and high-pollution industries, eliminating backward production capacity, and guiding resources like capital and labor to more productive and environmentally friendly industries – can promote regional energy efficiency improvement [32]. On the other hand, the efficient use of energy in a region also relies on the support of a reasonable industrial structure [37]. A sound industrial structure and high energy efficiency mutually promote and develop together, achieving a "1+1>2" effect to better enhance CEE.

Energy Efficiency and Population Density-Driven Type (S2). The consistency level of this driving way is 0.895, while its raw coverage is 0.108, both within reasonable ranges. S2 shows that high energy efficiency and high population density as core conditions can achieve high CEE. On the one hand, according to the Brand law, cities with high population density have economies of scale due to agglomeration effects [35]. Economies of scale can improve factor productivity, thereby promoting the effective use of energy and enhancing energy efficiency [36]. On the other hand, improved energy efficiency better meets urban energy demands, attracting more people to cities and increasing urban population density [38]. The economies of scale brought by high population density increase economic output, while high energy efficiency reduces adverse outputs such as carbon dioxide emissions, thus improving urban CEE.

Energy Efficiency, Industrial Structure, and Population Density-Driven Type (S3). This driving way features a consistency level of 0.875, coupled with a raw coverage of 0.085, both within reasonable ranges. S3 indicates that high energy efficiency, high population density, and a high-level industrial structure as core conditions can achieve high Y. Under high population density, urban residents' pursuit of a high-quality life promotes the continuous upgrading of the industrial structure, while industrial structure optimization requires the support of more high-tech talents (i.e., high population density) [38]. Energy efficiency, industrial structure, and population density drive and influence each other, jointly promoting the improvement of CEE.

Robustness Test

This study employed three methods for robustness tests: changing the original consistency threshold to 0.85, increasing the PRI threshold to 0.8, and raising the case frequency to 3. The configuration results remained unchanged across all these adjustments, demonstrating that the results of this study are robust.

Discussion

This paper makes several key contributions that merit discussion in relation to existing literature. First, it extends the time span for measuring the carbon emission efficiency (CEE) of Chinese cities. By using nighttime light data to invert urban energy consumption as an input variable for CEE calculation [12], this study provides longer and more updated CEE estimates for Chinese cities. Existing literature, constrained by urban total electricity consumption indicators, has not achieved such an extended time span. For instance, Du et al. (2025) [4] measured CEE for 267 Chinese cities from 2006 to 2020; Chen et al. (2023) [5] covered 283 cities from 2006 to 2019; and Chai et al. (2023) [39] assessed 278 cities from 2003 to 2017. Most previous studies have adopted traditional DEA methods or single-indicator methods, while this study exhibits consistency with the aforementioned research in terms of CEE change trends during overlapping years. This fully verifies the robustness of the results of this study. The reason for not conducting a numerical comparison is that the adopted indicators and data sources differ, precluding direct comparison. On this basis, this study uses the super-efficiency SBM model to measure CEE, which not only overcomes the shortcomings of previous CEE measurement methods but also extends the measurement period to 2022, providing a timely update to CEE research. This makes the measurement results more in line with China's green development practices and more practically significant. The decision to start the research period from 2003 is based on considerations of the comparability of the research period and data availability. This study only uses 284 cities as the research objects for the following reasons: first, existing studies on CEE basically cover 280 cities, which allows the results of this study to be compared with those in existing literature; second, the selection of cities is based on data availability requirements.

Second, this study takes the lead in introducing the Technology-Organization-Environment (TOE) framework into CEE research and proposes that three categories of factors – technology, organization, and environment – jointly influence urban CEE. Combined with Qualitative Comparative Analysis (QCA), this methodological approach addresses the endogeneity or omitted variable issues that exist in traditional econometric models [11, 40]. The study identifies three configurational paths driving high CEE: the energy efficiency and industrial structure-driven path, the energy efficiency and population density-driven path, and the energy efficiency, industrial structure, and population density-driven path. From the composition of these three driving factor combinations, it can be seen that energy efficiency serves as the "foundation, core, and essential condition" for improving CEE, which reveals the core role of energy efficiency and is consistent with the findings of Tao et al. (2024) [37]

and Pasten and Santamarina (2012) [38]. Industrial structure and population density, however, need to synergize with energy efficiency in a differentiated manner based on regional characteristics and initial endowments to promote CEE improvement. This provides new insights and references for the Chinese government to grasp the core conditions while formulating targeted and differentiated policies. For instance, the western region – with its relatively weak industrial foundation and insufficient population agglomeration – can adopt the energy efficiency and population density-driven path; the central region – characterized by moderate industrial structure and population size – can use the energy efficiency and industrial structure-driven path; and the eastern region – boasting a relatively sound industrial structure and concentrated population size – can leverage the path driven by the three factors (energy efficiency, industrial structure, and population density) to give full play to the role of each factor and create a multiplier effect.

Third, different from the consistently improving trend of CEE reported in previous literature [4, 5, 39], this study identifies the U-shaped variation pattern of China's CEE and explains this pattern from three perspectives: economic structure transformation, policy changes, and technological progress. From the perspective of economic structure, in the early stage, China's economic structure was mainly driven by energy-intensive industries, which led to a continuous decline in China's CEE; in the later stage, however, the economic growth model shifted to a low-energy-consumption and sustainable one, thereby boosting China's CEE [26]. For the central and western regions, in the early stage, they undertook the transfer of heavy industries from the eastern region and promoted economic growth at the expense of the environment; in the later stage, the central and western regions also gradually embarked on industrial transformation and upgrading, and their economic growth model moved toward green and low-carbon development, thus forming the U-shaped variation trend of CEE [27]. In terms of policy changes, in the early stage, the central government took economic growth as the assessment target for local governments, and local officials pursued impressive GDP growth by developing the economy at the cost of the environment, resulting in a decline in CEE; when the central government's assessment mechanism shifted to sustainable development, local officials began to focus on the coordinated development of environmental protection and the economy [41]. Regarding technological progress, technological advancement plays a key role in improving energy efficiency [42]. In the early stage, China's economic growth relied excessively on heavy industries with low green technology levels, leading to low energy efficiency; as energy efficiency is the core and essential condition affecting CEE, this situation significantly reduced the CEE level. However, with the continuous improvement of China's technological level, energy efficiency has been steadily enhanced, which has led to the continuous improvement of CEE.

Conclusions

This study employs the super-efficiency SBM model to measure the CEE of 284 Chinese cities from 2003 to 2022. On this basis, it innovatively incorporates these factors into the TOE analytical framework, takes 284 Chinese cities as cases, and uses the QCA method to explore the impact of interactions between these factors on CEE as well as their temporal changes. The main conclusions are as follows:

1. From the perspective of CEE measurement results, China's CEE exhibited a U-shaped change from 2003 to 2022.

2. Regarding the influencing factors of CEE, high CEE is not driven by a single factor but by the combined effect of multiple factors. This paper identifies three action paths: energy efficiency and industrial structure-driven, energy efficiency and population density-driven, and energy efficiency, industrial structure, and population density-driven. The relevant results remain robust after a series of robustness tests.

Policy Implication

The policy recommendations are as follows:

1. Accelerate the optimization of the regional energy structure. The layout of large-scale clean energy bases should be expedited in the western region, which is rich in energy resources, and the construction of cross-regional energy transmission channels should be supported. "Special subsidies for energy efficiency transformation" should be implemented for traditional high-energy-consuming enterprises in the eastern and central areas, with key support for equipment upgrading in industries such as coal power and steel to reduce energy consumption per unit of output.

2. Accelerate industrial upgrading. The eastern region should focus on developing low-carbon industries such as high-end manufacturing and modern services, and orderly guide high-energy-consuming industries to concentrate in advanced coastal manufacturing bases. When undertaking industrial transfer, the central and western regions should strictly implement the pollutant emission double substitution system, and lay out green manufacturing demonstration parks in areas with suitable conditions.

3. Implement city-specific policies. For cities driven by energy efficiency and industrial structure, focus on supporting energy-saving technology R&D and industrial structure optimization. For cities driven by energy efficiency and population density, build satellite cities to alleviate population pressure and improve the matching degree of resources and the environment. For cities driven by multiple factors, pilot comprehensive emission reduction policies in the eastern region first

and then promote adaptable experiences to the central and western regions.

Limitations

This paper still has certain limitations. First, the research accuracy can be further improved. For example, county-level data in China could be used. Second, in terms of selecting influencing factors, this paper should incorporate as many factors as possible and use machine learning methods to identify the most important ones, so as to obtain more reasonable results. Third, due to data availability constraints, this study only focuses on regional analysis, with insufficient research on other dimensions. For instance, there is a lack of research on aspects such as the consistency of government roles and market effectiveness. Future studies could consider conducting multi-angle analyses to make the research more comprehensive. Fourth, limited by the inadequacy of urban-level data in China, the research period of this paper only extends to 2022, which results in a lack of cutting-edge relevance in the study.

Acknowledgments

The authors declare that no funds, grants, or other support were received during the preparation of this manuscript.

Conflict of Interest

The authors declare no conflict of interest.

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