ISSN: 2688-9323

Research on Green Efficiency of Enterprises based on DEA-Malmquist Index Method

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Abstract

Using the DEA Malmquist index analysis method, panel data from 30 provinces and cities in China from 2166 to 2020 were selected to explore the specific changes in green total factor productivity in the region. And based on this, analyze the regional differences among its provinces. The results indicate that there are regional differences in green total factor productivity within each province, but they are not significant. However, from 2019 to 2020, green total factor productivity showed a downward trend. The conclusion is that in order to further promote the sustainable development of the economy in various provinces in China, it is necessary to increase the progress rate of green technology, thereby improving green total factor productivity, and balancing the efficiency of economic growth and environmental issues.

Keywords

Green Total Factor Productivity; DEA Malmquist; Green Innovation.

1. Introduction

The report of the 19th National Congress of the Communist Party of China highlighted that China's economy has achieved rapid and stable growth, making significant contributions to global economic development. Meanwhile, the awareness and initiative in implementing green development concepts for ecological civilization construction have markedly strengthened, with environmental protection awareness becoming increasingly prominent. However, many enterprises still implement technological innovation projects while neglecting environmental protection and sustainable development, ultimately paying a heavy price. The primary obstacle to green sustainable development lies in low efficiency of innovation investment and output, coupled with insufficient motivation and enthusiasm among enterprises. Green sustainable innovation requires substantial capital investment in green product R&D, environmental protection, and sustainable development. For consumers, the fundamental expectation is to obtain maximum benefits at the lowest cost, which necessitates that enterprises produce goods meeting consumers' physical and mental health needs. This demands improvements in production equipment, increased R&D investment, and enhanced production technologies. Overall, the high cost of green sustainable innovation underscores the need to measure the development level of green economy across provinces and propose corresponding policy measures and recommendations. Green Total Factor Productivity (GTFP), as a key indicator for evaluating the coordinated development of economy and environment, has garnered significant academic attention. Current research primarily focuses on national and regional levels. Therefore, this study calculates GTFP using panel data from industrial enterprises above designated size in 30 provinces, analyzes regional distribution disparities, and proposes strategies and recommendations to promote green development.

ISSN: 2688-9323

2. Literature Review

2.1. Research on Total Factor Productivity

As early as the 18th century, Adam Smith, a pioneer of classical economics, emphasized the importance of labor productivity in economic growth in his work "The Wealth of Nations." Smith believed that through specialized division of labor and technological progress, particularly the application of mechanization, labor productivity could be significantly improved[1]. However, he also pointed out the issue of diminishing marginal returns to factors-meaning that as inputs increase, the additional output generated per additional unit of input gradually decreases, thereby limiting the potential for economic growth. Over the following centuries, with the continuous development of industrialization and technological innovation, productivity theory was further refined and expanded. In the mid-20th century, scholars began employing more precise and complex mathematical tools to measure and analyze productivity. Among these, the Data Envelopment Analysis (DEA) method proposed by Farrel (1957) became a significant milestone[2]. DEA is a non-parametric technique used to measure relative efficiency in production processes. It evaluates the relative efficiency of different decision-making units (such as companies or regions) by constructing a production possibility frontier that includes best practices and assessing their distance from this frontier. Subsequently, Charnes, Cooper, and Rhodes developed the CCR model based on Farrel's work, a DEA model grounded in the assumption of constant returns to scale[3]. Later, Banker, Charnes, and Cooper introduced the BCC model, which incorporated the assumption of variable returns to scale, making the analysis more flexible and closer to real-world production processes. The emergence of these models has made the measurement of Total Factor Productivity (TFP) more precise and scientific, providing economists with powerful tools to study productivity changes and their contributions to economic growth[4]. Over time, an increasing number of economists have begun to employ modern mathematical analysis methods to study TFP. They not only focus on quantitative measurements of productivity but also explore various factors influencing productivity changes, such as technological innovation, human capital accumulation, and institutional changes[5]. These studies have not only deepened our understanding of economic growth mechanisms but also provided policymakers with a basis for formulating policies to promote economic growth[6]. Therefore, productivity theory has become an indispensable part of modern economic research, holding significant theoretical and practical implications for understanding and driving economic development[7].

2.2. Research on Green Total Factor Productivity (TFP)

To date, the academic community has developed four primary measurement approaches for green TFP: the algebraic index method, Solow residual method, stochastic frontier production function method, and data envelopment analysis (DEA). These methodologies have reached a high level of maturity. From a research perspective, some scholars examine TFP growth at the industrial and sectoral levels, while others apply the DEA-Malmquist index to analyze industrial TFP. Chen Wenxin and Pan Yu conducted a DEA-Malmquist-based study on the overall TFP of China's logistics industry across major provinces under low-carbon constraints. Their findings revealed potential for improvement in all input factors and a sustained growth trend in sectoral TFP. The DEA-Malmquist method's functional setup facilitates multi-output scenarios. Existing empirical analyses of green TFP predominantly focus on national, inter-provincial, and specific economic regions, with limited research at the municipal and county levels. Given the simplicity and price-insensitivity of the Malmquist index method, it demonstrates relative advantages over other index-based approaches. Building on this foundation, this paper employs the DEA-Malmquist method to analyze green TFP across 30 Chinese provinces and municipalities, investigating constrained TFP and its influencing factors.

ISSN: 2688-9323

3. Construction of Evaluation Model for Green and Sustainable Innovation Efficiency of Enterprises

3.1. Model Overview

3.1.1. Traditional Data Envelopment Analysis (DEA)

Data Envelopment Analysis (DEA) is a widely used non-parametric method for evaluating production efficiency. This approach constructs production frontier boundaries through linear combinations of known production units, comparing actual input-output efficiency curves with optimal allocation curves on the frontier to reflect relative effectiveness among units. The first model is the Constant Returns to Scale (CRS) DEA model, also known as the CCR model. This model assumes all decision-making units operate at optimal scale, but in reality, factors like unfair competition, economic conditions, and policy changes may prevent some units from reaching optimal scale, making this model inherently flawed. The second model is the Variable Returns to Scale (VRS) DEA model, specifically the BCC model (Banker, 1984). The total factor productivity (TFP) index derived from this model equals the product of comprehensive technical efficiency (TE) and technological progress index. Comprehensive technical efficiency (TE) can be further decomposed into pure technical efficiency (PTE) and scale efficiency (SE), meaning TFP equals the product of PTE and SE. Here, pure technical efficiency reflects the internal management and technological capabilities of China's green enterprises after excluding scale returns, while scale efficiency indicates the optimization level of operational scale in these enterprises.

3.1.2. The Malmquist Index Model.

The DEA model measures the efficiency of different enterprises at a fixed point in time, characterized by cross-sectional data and classified as a static evaluation method. Therefore, this study employs the Malmquist index to examine the trends in provincial green total factor productivity (TFP). The Malmquist productivity index was first introduced by Caves et al. in 1982 and later expanded by Fare et al. The Malmquist TFP indicator enables dynamic analysis of productivity changes, with the model as follows:

$$M_t^{t+1} = \frac{D_0^t(x^{t+1}, y^{t+1})}{D_0^t(x^t, y^t)} \left[\frac{D_0^t(x^{t+1}, y^{t+1})}{D_0^{t+1}(x^{t+1}, y^{t+1})} \times \frac{D_0^t(x^t, y^t)}{D_0^{t+1}(x^t, y^t)} \right]^{\frac{1}{2}} = EFFCG \times TECH$$

$$TFPCH = EFFCH \times TECH = PECH \times SECH \times TECH$$

Here, xt denotes the input vector of the decision-making unit in period t, and yt represents its output vector in period t. The Malmquist index measures the dynamic change in green total factor productivity (TFP) from period t to period t+1. A value of M>1 indicates an improvement in TFP, while M<1 suggests a decline. The first ratio in the equation reflects the change in technical efficiency (EFFCH): EFFCH>1 signifies enhanced technical efficiency, whereas EFFCH<1 indicates reduced efficiency. The second ratio measures technological progress capacity (TECH): TECH>1 denotes technological innovation or advancement, while TECH<1 suggests relatively slow progress.

(1) Input Indicators

The input indicators primarily include labor input, capital investment, technological input, and energy consumption. Labor serves as a crucial production factor. For labor input, the number of employees in production sectors at the end of the year is selected based on data published by the National Bureau of Statistics. Regarding capital investment, the total value of fixed assets in enterprises reflects technological capital accumulation, which forms the foundation for improving production efficiency and quality. Therefore, the total value of fixed assets in large enterprises is selected. For energy consumption, the total energy consumption in production sectors is chosen.

(2) Output Indicators

The selection of output indicators involves analysis from two perspectives: expected output and unintended output. Expected output refers to the maximum profit each enterprise aims to achieve, while unintended output denotes the non-economic efficiency output that accompanies achieving expected output. For expected output indicators, industrial added value above designated size is primarily selected. For unintended output indicators, industrial three wastes (including sulfur dioxide emissions, wastewater discharge, and solid waste discharge) are mainly chosen.

(3) Data Sources

Considering the authenticity and completeness of the currently collected data, to ensure the accuracy of the research findings, the sample includes 30 provinces in China, with the observation period spanning 2016-2020. The key provinces include: (1) Beijing Municipality, (2) Tianjin Municipality, (3) Hebei Province, (4) Shanxi Province, (5) Inner Mongolia Autonomous Region, (6) Liaoning Province, (7) Jilin Province, (8) Heilongjiang Province, (9) Shanghai Municipality, (10) Jiangsu Province, (11) Zhejiang Province, (12) Anhui Province, (13) Fujian Province, (14) Jiangxi Province, (15) Shandong Province, (16) Henan Province, (17) Hubei Province, (18) Hunan Province, (19) Guangdong Province, (20) Guangxi Zhuang Autonomous Region, (21) Hainan Province, (22) Chongqing Municipality, (23) Sichuan Province, (24) Guizhou Province, (25) Yunnan Province, (26) Shaanxi Province, (27) Gansu Province, (28) Qinghai Province, (29) Ningxia Hui Autonomous Region, (30) Xinjiang Uygur Autonomous Region. Using the DEAP2.1 software, the green Malmquist index for each prefecture-level city in Zhejiang Province was estimated based on the collected data.

Table 1. Input-output indicators

primary indicator	secondary indicator	tertiary indicator
put into	capital input	Number of employees in the production department at the end of the year (people)
	technology input	Total value of fixed assets (in billions of yuan)
	energy input	Total energy consumption of production department (10,000 tons)
expected output	value added	Industrial added value (billion yuan)
unintended output	sulfur dioxide	Industrial sulfur dioxide (tons)
	wastewater discharge	Industrial wastewater discharge (10,000 tons)
	solid waste discharge	Solid waste emissions (tons)

3.1.3. Descriptive Statistics

Table 2 reveals that while capital investment exhibits a relatively high average value, its large standard deviation underscores significant regional disparities. Although technology investment averages lower than capital investment, the margin is narrow yet substantial, with a smaller standard deviation indicating relatively uniform levels across regions. Energy consumption investment maintains moderate average values and standard deviations, reflecting moderate regional variations. The average value of industrial added value demonstrates overall profitability in industrial production, while its standard deviation highlights uneven profit distribution. Environmental indicators such as sulfur dioxide emissions, wastewater discharge, and solid waste output reveal that pollution issues may be more severe in certain regions.

Table 2. Descriptive Analysis

	Obs	Mean	Std	Max	Min
capital input	150	1422618	1778564	9596959	71867
technology input	150	14456.66	10894.97	57287.17	1090.45
energy input	150	2836.145	1673.929	7194.8	37.67
value added	150	9770.882	9004.206	39353.9	482.5
sulfur dioxide	150	159615.7	124034	663871	880
wastewater discharge	150	68985.91	56251.63	223566.8	6461.259
solid waste discharge	150	125.27.18	10997.21	46366.9	330.45

3.1.4. Empirical Results Analysis

Table 3. Malmquist Index and Its Decomposition

year	effch	techch	pech	sech	tfpch
2016-2017	1.008	1.073	1.007	1.001	1.082
2017-2018	0.991	1.105	1.004	0.988	1.096
2018-2019	1.021	0.999	1.017	1.004	1.020
2019-2020	0.974	0.961	0.984	0.991	0.936
mean value	0.999	1.033	1.003	0.996	0.936

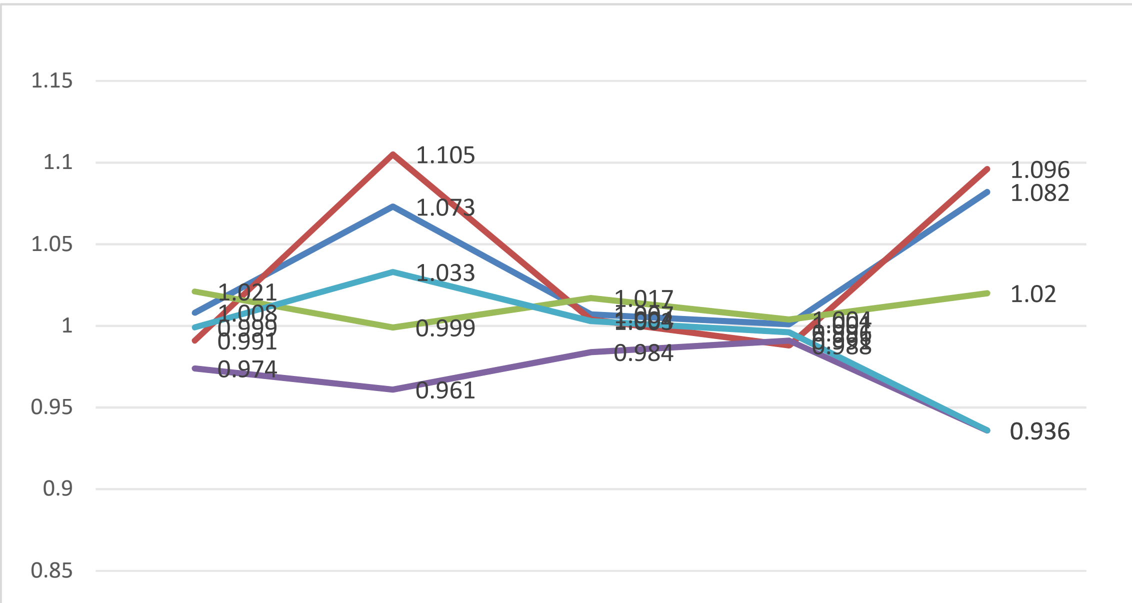

Figure 1. Malmquist index and its decomposition

To examine the dynamic changes in China's provincial-level green total factor productivity (Tfpch) and better reflect its efficiency characteristics, this section employs the DEA-Malmquist index method to calculate the green Tfpch and its decomposition indicators-technical efficiency growth (Effch) and technological progress growth (Techch)-for the sample period 2016-2020, as shown in Table 3 and Figure 1. The overall temporal trends reveal that the growth indicators of Tfpch and technical efficiency follow similar trajectories, with China's green Tfpch demonstrating robust growth during the sample period. Overall, China's green Tfpch exhibits a

ISSN: 2688-9323

fluctuating yet generally positive trend. In 2017, it reached 1.082, marking a high-quality development milestone. However, between 2017 and 2018, the efficiency saw a minor increase, likely due to 2016 being China's inaugural year of green finance. The initial formation of this financial system attracted numerous enterprises into the sector, driving unprecedented high-quality development in 2017. By 2019, as technologies matured, infrastructure improved, and requirements escalated, the green market became more sophisticated while imposing higher demands on enterprises in this field, leading to a temporary decline in China's green efficiency. During the 2019-2020 period, Total Factor Productivity (TFPCH) declined to 0.936, significantly lower than in previous years, with all indicators showing marked declines. The particularly low TFPCH of 0.936 highlighted a substantial reduction in production performance. In summary, despite some technological advancements during this period, overall production efficiency suffered from declining pure technical efficiency and scale efficiency, leading to a downward trend in total factor productivity. This decline may be attributed to the severe global economic impact of the COVID-19 pandemic that began in late 2019. Lockdown measures and economic slowdown caused unprecedented challenges for many industries, directly affecting production efficiency and output levels. Transportation and logistics restrictions disrupted supply chains, impacting raw material availability and product distribution in production sectors. The widespread adoption of remote work and online collaboration during the pandemic posed new management challenges, potentially affecting pure technical efficiency (PECH). Additionally, stricter environmental protection policies and regulations implemented during this period increased compliance costs for businesses, partially suppressing production activities, especially in heavily polluting industrial sectors.

Based on the above, to further explore regional disparities in green finance efficiency across China, this study categorizes the DEA-Malmquist model test results of 30 provincial samples over five years by region, with findings presented in Table 4. Significant differences in total factor productivity (TFP) are observed across regions. On average, TFP reached 1.031 during the study period, indicating overall productivity improvement. However, this progress was uneven. Regions like Qinghai achieved a TFP of 1.208, demonstrating notable productivity gains likely due to successful technological innovations or optimized resource allocation. In contrast, Liaoning and Xinjiang recorded TFP values of 0.899 and 0.894 respectively, suggesting productivity declines that require further analysis and improvement measures. Technological progress (Techch) generally positively impacts TFP, with most regions having Techch indices above 1, indicating technological innovation as a key driver. However, pure technical efficiency (Pech) and scale efficiency (Sech) approaching 1 suggest relative stability in technology and scale without significant efficiency losses. The TFP analysis reveals regional productivity imbalances, highlighting the importance of identifying and promoting successful practices in high-efficiency regions while formulating improvement measures for low-efficiency areas. Meanwhile, the average comprehensive technical efficiency (effch) of 0.999, approaching 1, indicates that regional efficiency remained relatively stable during the study period. However, this does not mean all regions showed no significant changes. For instance, Jilin and Qinghai regions achieved technical progress (techch) of 1.035 and 1.208 respectively, far exceeding the average, demonstrating substantial advancements in technological innovation. Through comparative analysis of regional indicators, we can identify both outstanding performers and areas requiring improvement. Regions with above-average efficiency can analyze their success factors and share best practices, while those below average need to conduct in-depth problem analysis and implement targeted improvement measures. Although most regions have reached high levels of production efficiency and technological advancement, certain areas still require further enhancements in productivity, technical capabilities, and optimized production scales.

ISSN: 2688-9323

Table 4. Malmquist Index and Its Decomposition

area	effch	techch	pech	sech	tfpch
1	1	1.181	1	1	1.181
2	1.01	1.117	1.014	0.997	1.128
3	0.976	1.092	1	0.976	1.065
4	0.959	1.082	1	0.959	1.038
5	1	1.003	1	1	1.003
6	0.996	0.903	1	0.996	0.899
7	1.09	1.035	1.092	0.998	1.128
8	1.02	1.052	1.02	1.001	1.073
9	1	1.031	1	1	1.031
10	1	1.015	1	1	1.015
11	1	1.032	1	1	1.032
12	0.978	0.999	0.987	0.991	0.977
13	1	1.008	1	1	1.008
14	1	0.935	1	1	0.935
15	1.001	1.086	1	1.001	1.087
16	1.015	1.091	1.015	1.001	1.108
17	0.997	1.058	0.989	1.008	1.055
18	1	1.031	1	1	1.031
19	1	0.996	1	1	0.996
20	1	0.99	1	1	0.99
21	0.988	1.043	1	0.988	1.031
22	1.022	1.044	1.024	0.998	1.067
23	0.978	1.102	0.994	0.984	1.078
24	1	0.952	1	1	0.952
25	0.998	1.026	1	0.998	1.023
26	0.987	1.116	0.993	0.994	1.102
27	0.997	0.977	0.997	1	0.974
28	1	1.208	1	1	1.208
29	1	0.914	1	1	0.914
30	0.952	0.938	0.971	0.981	0.894
mean	0.999	1.033	1.003	0.996	1.031

Note: The regional figures are the same as those in the source above.

Table 5. Green Total Factor Productivity Ranking of Chinese Provinces from 2016 to 2020

ranking	area	tfpch	ranking	area	tfpch
1	28	1.208	16	18	1.031
2	1	1.181	17	21	1.031
3	2	1.128	18	mean	1.031
4	7	1.128	19	25	1.023
5	16	1.108	20	10	1.015
6	26	1.102	21	13	1.008
7	15	1.087	22	5	1.003
8	23	1.078	23	19	0.996
9	8	1.073	24	20	0.99
10	22	1.067	25	12	0.977
11	3	1.065	26	27	0.974
12	17	1.055	27	24	0.952
13	4	1.038	13	4	1.038
14	11	1.032	14	11	1.032
15	9	1.031	15	9	1.031
			31	30	0.894

Table 6. Ranking of Comprehensive Technical Efficiency of Chinese Provinces from 2016 to 2020

area	tfpch	ranking	area	tfpch	ranking
1	1.09	7	16	0.997	27
2	1.015	16	17	0.988	21
3	1.022	22	18	1	24
4	1	28	19	0.952	30
5	1	1	20	0.978	23
6	1	13	21	1.02	2
7	1	14	22	0.965	3
8	1.001	5	23	1.038	4
9	1	9	24	1.02	8
10	1	19	25	0.996	6
11	1	18	26	0.978	12
12	1	20	27	0.997	11
13	0.997	17	28	1.001	15
14	0.987	26	29	1	10
15	0.998	25	30	1	29

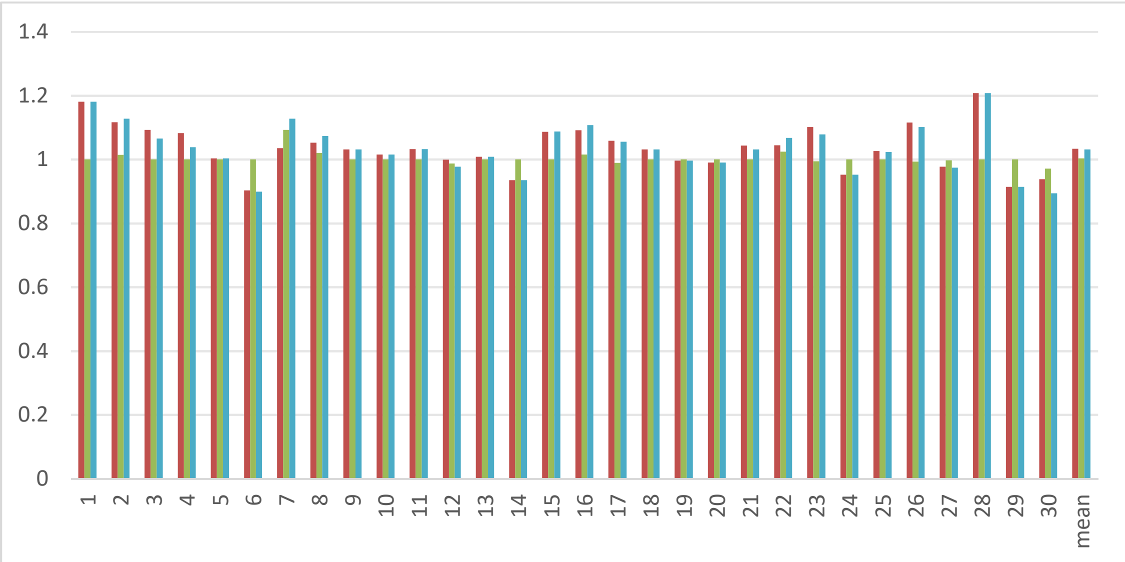

Figure 2. Decomposition of Green Total Factor Productivity in the Region

4. Conclusion and Implications

This study incorporates green total factor productivity (TFP) into the economic development analysis framework, employing the DEA-Malmquist method, which proves relatively effective. However, the research has certain limitations: the DEA method inherently struggles with measurement errors and extreme value sensitivity, requiring further exploration in future studies. From an exponential decomposition perspective, technological progress emerges as the core driver of green TFP growth, while scale efficiency only shows negligible effects in specific provinces. Meanwhile, declining technical efficiency has constrained green TFP expansion. Therefore, regions should enhance factor utilization and scale efficiency while adopting advanced technologies and talent, prioritize pollution control at source, and strengthen environmental protection. Only by leveraging market mechanisms to synchronize technological advancement, resource efficiency, and innovation can the eastern regions achieve sustainable green economic development. Some regions exhibit erratic TFP growth and unstable technical efficiency fluctuations, indicating immature intensive production models that still follow the outdated high-input, low-output development path. This suggests that future progress should focus on upgrading production technologies, optimizing industrial structures, and implementing rational measures to reduce urbanization-related emissions. Provinces should now clearly recognize the importance of green TFP in their development strategies. Green total factor productivity (TFP) is not merely an isolated metric for assessing environmental governance. It exhibits spatial agglomeration and technology spillover effects, where environmental technology upgrades enhance green factor contributions while simultaneously driving economic growth. Provinces and municipalities should proactively and systematically adjust industrial structures. Given regional disparities in economic development levels, each province's pillar industries and growth drivers differ, necessitating differentiated environmental policies tailored to specific regions and developmental stages. In areas with persistent industrial pollution, command-and-control environmental policies should be substantially implemented. This requires improving the environmental institutional framework, strengthening enforcement mechanisms, clarifying reward-punishment boundaries, and enhancing environmental supervision efficiency

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