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Study on the Green Innovation Efficiency of Manufacturing Enterprises under Technological Heterogeneity

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Abstract

In order to reveal the heterogeneity characteristics and internal driving mechanism of green innovation efficiency of Chinese manufacturing enterprises under the "dual carbon" goal, this study breaks through the technical homogeneity assumption of the traditional efficiency evaluation model, and constructs a common frontier SBM-DEA model integrating non-expected output based on the panel data of manufacturing listed companies from 2015 to 2022. The dynamic action path between the technical gap and the management level is identified by the inefficiency decomposition method. The results show that: (1) the average green innovation efficiency of manufacturing enterprises in China is 0.706, with an improvement potential of 29.4%, and the efficiency gradient of low-carbon, medium-carbon, and high-carbon groups decreases, showing a step-by-step decreasing trend of carbon emission intensity and innovation efficiency. (2) The technology gap is the dominant factor in the efficiency loss of the high-carbon group, while the efficiency loss of the low-carbon group is mainly due to management inefficiency. (3) For high-carbon enterprises, strengthening environmental regulation and intellectual property protection will exacerbate their technological catch-up barriers, while industrial upgrading can narrow the frontier gap; In the low- and medium-carbon group, financing constraints inhibit management inefficiency through the backward pressure mechanism, but digital transformation has a negative impact due to resource misallocation, and ESG performance can significantly optimize the management process. This study clarifies the differentiated improvement path of green innovation from the perspective of carbon emission heterogeneity through the common frontier framework, and provides a theoretical basis for formulating collaborative policies for technical support and management intervention.

Keywords

Green Innovation Efficiency; Common Frontier; Influencing Factors.

1. Introduction

Over the forty years since the reform and opening-up, China's manufacturing industry has achieved leapfrog development with an average annual growth rate of 9.2%. In 2022, its value-added reached 31.6 trillion yuan, making China the world's largest manufacturing country. However, this extensive growth model has led to severe environmental externalities. According to data from the International Energy Agency (IEA), China's carbon emissions in 2022 reached 11.4 billion tons (accounting for 30% of global emissions), with per capita emissions of 8.0 tons, and the average annual growth rate of carbon emissions from 2015 to 2022 was 2%, highlighting the carbon reduction challenges of the traditional development model[1]. Faced with the dual pressures of peaking carbon emissions by 2030 and global temperature control, the report of the 20th National Congress of the Communist Party of China clearly proposed the strategic plan to "promote green development and foster harmony between humans and nature," emphasizing "coordinating the efforts in carbon reduction, pollution control, green expansion, and growth," and incorporating "actively and steadily advancing carbon peak and

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carbon neutrality" into the overall layout of ecological civilization construction. During the 14th Five-Year Plan period, China invested over 7 trillion yuan to promote green transformation, yet carbon emissions from manufacturing enterprises show significant regional heterogeneity, with central and western regions facing greater emission reduction pressures due to technological lag. The effectiveness of their green transformation is directly related to the implementation of the "dual carbon" strategy [2,3], making it urgent to overcome technological gaps and efficiency bottlenecks in the green transformation of manufacturing, so that high-quality development can support the construction of Chinese-style modernization.

Scholars have conducted a lot of research on the evaluation and influencing factors of green innovation efficiency from the perspectives of "provincial", "regional" and "industrial" [4-6]. In terms of research methods, stochastic frontier method (SFA) and data envelope analysis method (DEA) are the current mainstream methods. Among them, DEA has become the main analytical tool in this field because it does not require preset production functions and can handle multiple inputs and outputs. However, the assumption of "technical homogeneity" in the traditional DEA model ignores regional factor endowment differences, resulting in systematic bias in efficiency measurement [7]. Therefore, the common frontier theory proposed by O'Donnell et al. (2008) [8] provides a new idea for heterogeneous efficiency assessment by constructing the dual boundary between the group frontier and the common frontier. For example, Zhang Linyu and Hu Xuhua (2024) [9] revealed the group differentiation law of total factor productivity in the manufacturing industry in the east, central and western regions based on the common frontier-MML index. Xiao Renqiao et al. (2018) [10] used the DEA model of heterogeneous parallel network to measure the innovation efficiency of high-tech industries. However, it is worth noting that the existing studies mostly follow the traditional geographical zoning standards in group division, and fail to effectively map with the technical characteristics of carbon emissions, which not only limits the accuracy of identifying the root causes of efficiency loss of enterprises with different carbon intensity, but also makes it difficult to meet the needs of differentiated emission reduction policies. Further analysis shows that the existing literature on influencing factors mainly focuses on the dimensions of institutional environment, technical environment, and enterprise characteristics [11,12], but the synergistic mechanism of internal and external environmental factors has not been systematically investigated. The efficiency of enterprise green innovation is essentially the result of the collaborative evolution of the internal governance structure and the external institutional environment [2]. Specifically, in terms of the external environment, the intensity of environmental regulation, the level of intellectual property protection, the government's scientific and technological support, the degree of industrial structure advancement, and the quality of digital infrastructure construction [11,13-15] have jointly shaped the institutional environment and technical ecology of green innovation in the manufacturing industry. In terms of internal characteristics, key factors such as enterprise size and property rights, digital technology reserves and capital investment intensity, and social responsibility awareness and execution ability [12,16-18] directly affect the efficiency of resource allocation and technology transformation ability of enterprises. Based on this, this paper breaks through the existing research limitations from three levels: at the theoretical level, carbon emission intensity is innovatively replaced by geographical zoning as the group division criterion, and a heterogeneity analysis framework reflecting the gradient characteristics of green innovation technology in the manufacturing industry is constructed; At the methodological level, the non-desired output SBM model and the common frontier theory are integrated, and the efficiency loss paths of high-carbon, medium-carbon, and low-carbon groups are systematically identified through the decomposition of technology gap ratios and inefficiency values. At the policy level, based on the data of listed manufacturing companies from 2015 to 2022, this paper discusses the differentiated impact of internal and external influencing factors on efficiency loss, provides a scientific basis for formulating classified guidance emission reduction policies, and provides a new analytical perspective for solving the carbon emission dilemma.

2. Research Design

2.1. Research Methods

2.1.1. Common Frontier - SBM-DEA Model

Under the drive of the "dual carbon" strategy, manufacturing enterprises, as microeconomic entities, have green innovation capabilities that are key engines for resolving the paradox between scale expansion and environmental constraints [19]. The technology gap theory points out that differences in energy consumption structure, industrial base, and innovation factor endowments across regions will lead to systematic stratification of the production technology frontier [20]. Ignoring the above heterogeneity and measuring green innovation efficiency using a homogeneous production boundary will underestimate results due to a "technological reference bias." Therefore, this study proposes a carbon emission intensity-oriented grouping framework to avoid the limitations of traditional geographic grouping. By indirectly measuring corporate carbon emission intensity through the ratio of carbon emissions to main business revenue, Chinese manufacturing enterprises are classified into three groups: high-carbon, medium-carbon, and low-carbon. First, the input-output data of evaluation units under the high-carbon, medium-carbon, and low-carbon groups are respectively included in their respective technology sets, denoted as $T^{(q)}$, $q = 1,2,3$, i.e., $T^q = \{(x, y): x \geq 0, y \geq 0;\ x \text{ can produce } y \text{ in group } q\}$, where q represents the high, medium, and low-carbon groups. Suppose that at time t (t=1,2,...,8), enterprises in province j have m inputs $x_j = (x_{1j}, x_{2j}, \dots \dots, x_{mj}) \in R_+^m$ and s outputs $y_j = (y_{1j}, y_{2j}, \dots \dots, y_{mj}) \in R_+^s$ (where green innovation output y can be further divided into desired output y_j^g and undesired output y_j^b). The production possibility set $P^q(x)$ of the q-th group is $P^q(x) = \{y: (x, y) \in T^q\}$, with the upper bound sup $P^q(x)$ defined as the frontier of group q. Therefore, the production technology set of DMUs under the common frontier can be expressed as: $T = T^{(1)} \cup T^{(2)} \cup T^{(3)}$, see Figure 1.

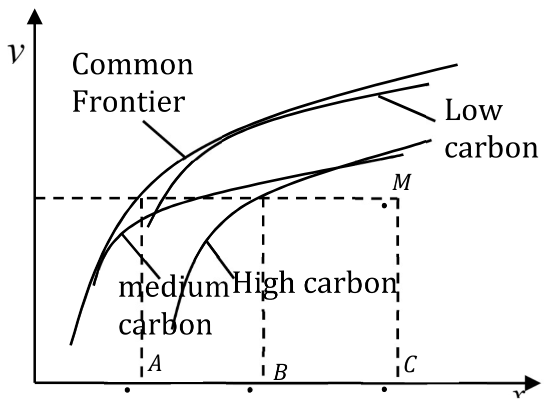

Figure 1. Common Frontier and Group Frontier

On this basis, by constructing a non-parametric joint frontier and distance function, the green innovation efficiency TEq under the frontier of group is solved through the following linear programming, with the specific calculation method shown in equation (1).

$$TE^q\left(x_{i0}, y_{r0}^g, y_{p0}^b\right) = \min \tau = k - \frac{1}{m} \sum_{i=1}^{m} \frac{s_i^-}{x_{i0}}$$

$$s.t.1 = k + \frac{1}{s_1+s_2}\left(\sum_{r=1}^{s_1}\frac{s_r^g}{y_{r0}^g} + \sum_{p=1}^{s_2}\frac{s_p^b}{y_{p0}^b}\right)$$
$$kx_{i0} = \sum_{j=1}^{n}\lambda_j x_{ij} + s_i^- \tag{1}$$
$$ky_{r_0}^g = \sum_{j=1}^{n}\lambda_j y_{jj}^g - s_r^g$$
$$ky_{p0}^b = \sum_{j=1}^{n}\lambda_j y_{pj}^b + s_p^b$$
$$\lambda_j \geq 0, j = 1,2,\cdots,n$$
$$k \geq 0, s_i^- \geq 0, s_r^g \geq 0, s_p^b \geq 0$$
$$\left(x_{ij}, y_{rj}^g, y_{pj}^b\right) \in T^q (q = 1,2,3)$$

In the formula, s_i^-， s_r^g and s_p^b are the slack variables corresponding to input x_{ij}, desired output yrjb, and undesired outputy_{rj}^b, respectively; m， s_1 and s_2 are the numbers of indicators for decision unit inputs, desired outputs, and undesired outputs, respectively; k is a variable, and λ_j is the weight multiplier.

2.1.2. Inefficiency Decomposition

The Technology Gap Ratio (TGR) measures the gap in optimal technology between a group and the national enterprises. Numerically, it is equal to the ratio of efficiency under the common frontier to efficiency under the group frontier. That is: $0 \leq TGR^q(x,y) = D^q(x,y)/D(x,y) = TE(x,y)/TE^q(x,y) \leq 1$. Based on different sources of green innovation efficiency loss, it can be decomposed, with the specific formula as follows:

$$\begin{gathered} TEI = 1 - TE = TGRI + MI \\ TGRI = TE^q \times (1 - TGR^q) = TE^q - TE \\ MI = 1 - TE^q \end{gathered} \tag{2}$$

TGRI (Technology Gap Inefficiency) arises from differences in production technology conditions among different groups, and this exogenous efficiency loss is mainly influenced by external environmental factors; in contrast, MI (Management Inefficiency) is an endogenous efficiency loss caused by internal decision-making errors or poor management within the enterprise, and its causes are mostly related to internal organizational operations [21].

2.2. Selection of Indicators and Data Sources

2.2.1. Selection of Input-Output Indicators

This study is based on a multi-input, multi-output efficiency evaluation framework and constructs a three-dimensional input system that includes human resources, capital, and production: human resource input is represented by the number of R&D personnel in the enterprise; capital input is calculated using the perpetual inventory method to measure R&D capital stock; production input is represented by the net value of fixed assets and deflated using the fixed asset investment price index. Expected outputs include green technological innovation and economic performance, measured respectively by the number of green invention patent applications and the main business revenue adjusted by the industrial product ex-factory price index; the undesired output indicator, referring to the study by Chapple et al. (2013)[22], is the enterprise's carbon dioxide emissions, which are approximately estimated based on industry energy consumption.

2.2.2. Selection of Influencing Factor Variables

The formation of corporate green innovation efficiency is influenced by both the external institutional environment and internal governance structure. In terms of external environmental constraints, the government shapes the external ecosystem for corporate green technology breakthroughs and innovation transformation through measures such as setting environmental regulatory standards, enhancing intellectual property protection, increasing technological support through government funding, promoting the upgrading of industrial structures, fostering a regional innovation atmosphere, and improving digital infrastructure [11,13-15]. Internally, factors such as corporate characteristics, capital, technology, and social responsibility [12,16-18] form the foundation for manufacturing enterprises to achieve green innovation efficiency. Enterprise size and ownership determine resource allocation capacity and governance orientation; digital technology reserves and capital investment reflect the strategic emphasis on technological innovation; while awareness of social responsibility reflects the management's recognition of and ability to implement sustainable development concepts. Additionally, through the interplay between proactive commitments and passive compliance in environmental management, it reveals the dynamic adjustment mechanisms of enterprises in green innovation activities under environmental pressure. The detailed analysis is as follows:

In terms of the external environment. (1) Environmental regulation. Strict environmental regulations can break through the lock-in effect of traditional technologies, promote the diffusion of clean technologies, and narrow the technology gap by forcing enterprises to increase investment in green R&D [11]. However, Xiao et al. (2024) [23] pointed out that the cost of compliance with environmental regulations may crowd out enterprises' innovation resources, especially in traditional industries, which can easily lead to the short-term behavior of "compliance over innovation", which can exacerbate technological lag. Therefore, there is still debate about the impact of environmental regulation on the inefficiencies of the technology gap. (2) Intellectual property protection. Moderate protection incentivizes R&D investment by guaranteeing innovation benefits, but excessive protection may lead to a "technology lock-in" effect [13]. This study argues that in the field of green technology, patent barriers may lead to low-carbon technologies being locked in a few enterprises, hindering the unification of technical standards and the rapid development of green technologies, and further exacerbating the widening of the technology gap. (3) Government science and technology support. R&D subsidies and the cultivation of innovative entities can significantly improve the efficiency of technological innovation, but due to the "Matthew effect", government scientific and technological resources tend to favor technology-leading enterprises, while small and medium-sized enterprises are difficult to obtain equal support due to qualification thresholds, leading to the solidification of technology gradient [24]. The impact of government science and technology support needs to be further tested. (4) Industrial structure upgrading. Huang et al. (2024) [25] showed that industrial structure upgrading has a significant positive driving effect on green innovation efficiency through economic growth, talent agglomeration, and digital transformation. This paper argues that industrial structure upgrading and technology gap play a negative role in regulating the situation. (5) Innovative atmosphere. The innovation atmosphere is the foundation for building an open and inclusive innovation ecosystem, providing basic conditions for technological innovation to share knowledge, integrate resources, and share risks, and stimulate innovation capabilities [26]. This study suggests that the scope of innovation is negatively correlated with the technology gap. (6) Digital infrastructure. Zhao Xing (2022) [15] argues that digital infrastructure significantly promotes technological innovation by optimizing resource allocation and expanding technology spillover, and this study argues that digital infrastructure and technology gap play a negative moderating role.

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Table 1. Variable Description

Type	Indicator	Definition	Symbol
External environmental variables	Environmental regulation	Investment in Industrial Pollution Control / Regional GDP	ER
	Intellectual property protection	Technology Market Transaction Volume/GDP	IPP
	Government technological support	Proportion of government funding in the internal R&D expenditure of industrial enterprises in each region	GSTS
	Industrial structure upgrading	Output value of the tertiary industry / Output value of the secondary industry	ISU
	Innovative atmosphere	Number of industrial enterprises with R&D activities / Total number of industrial enterprises in each region	IA
	Digital infrastructure	Number of Internet broadband access ports per capita in each region	DI
Internal structure variable	Business scale	Natural logarithm of year-end total assets	FS
	Property rights nature	State-owned enterprises take 1, non-state-owned enterprises take 0	ON
	Financing constraints	WW Index	FC
	Digital Transformation	The proportion of the year-end intangible assets related to digital technology to the total intangible assets as disclosed in the notes to the company's financial statements	DT
	ESG performance	Huazheng ESG Rating Index	ESG
	Executives' Environmental Awareness	Using text analysis to analyze the annual reports of listed companies, selecting keywords based on three dimensions: awareness of green competitive advantage, awareness of corporate social responsibility, and perception of external environmental pressures.	EEA

In terms of internal structure: ① Enterprise size. Ma Wenbin et al. (2024) [27] believe that the size of large enterprises can constrain innovation efficiency, as complex management layers weaken responsiveness to innovation. However, factors such as economies of scale, market influence, risk-bearing capacity, and the need for international cooperation collectively give large enterprises an advantage in improving green innovation efficiency. Therefore, the impact of enterprise size still requires further verification. ② Ownership nature. State-owned enterprises have significant advantages in acquiring resources through policy support, which is conducive to innovation [12]. However, the lack of incentives and institutional constraints under public ownership can lead to insufficient innovation motivation, resulting in lower efficiency compared to non-state-owned enterprises. The effect of ownership nature needs further testing. ③ Financing constraints. Research by Zeng Yuan et al. (2024) [17] shows that financing constraints significantly inhibit R&D investment, forcing enterprises to reduce the scale of innovation. This study considers financing constraints to be positively correlated with management inefficiency. ④ Digital transformation. Although digitalization can promote knowledge flow and collaborative innovation, blind investment may crowd out R&D resources [28]. The impact of digital transformation on management inefficiency requires further examination. ⑤ ESG performance. Good ESG performance helps enhance organizational legitimacy, thereby gaining the trust and support of government regulatory agencies, alleviating resource constraints, and acquiring key resources such as government subsidies [29], which is conducive to promoting corporate green innovation activities. This study considers ESG performance to be negatively correlated with management inefficiency. ⑥ Executives' environmental awareness. Upper echelons theory indicates that the management team's interpretation of green innovation is not objectively neutral but is influenced by their values, knowledge structure, and risk preferences. Executives with strong environmental awareness will view the "dual carbon" policy as a technological upgrading opportunity and actively increase green R&D investment [30]. However, this paper argues that compared to traditional innovation, green innovation involves higher investment, greater risk, and higher R&D uncertainty, so executives' environmental awareness may further exacerbate management inefficiency. The specific variables are shown in Table 1.

2.2.3. Data Sources and Processing

This study's data come from the China Statistical Yearbook, China Science and Technology Statistics Yearbook, and the CSMAR database. Missing data were handled using linear interpolation, and the Tibet region was excluded. Based on A-share manufacturing companies data from 2015 to 2022, ST/PT companies, delisted companies, and companies listed in the current year were excluded. After removing samples with missing data, standardization was performed.

3. Empirical Analysis

3.1. Analysis of Differences in Green Innovation Efficiency Among Manufacturing Enterprises with Different Carbon Emissions

From the perspective of technological heterogeneity among different carbon emission manufacturing enterprises, this paper uses the common frontier theory and the SBM model including non-expected output to measure the green innovation efficiency of manufacturing enterprises in 30 provinces in China from 2015 to 2022, and analyzes the TGR value of green innovation and its technology gap of manufacturing enterprises under different carbon emission groups, as shown in Table 2 and Figure 2.

It can be seen from Table 2 that the average green innovation efficiency of national manufacturing enterprises under the common frontier is 0.706, and there is room for improvement of 29.4%, while the green innovation efficiency of the three major groups of manufacturing enterprises decreases in low-carbon, medium-carbon and high-carbon in turn, showing a stepwise decrease of "carbon emission intensity-innovation efficiency". It is worth noting that the average green innovation efficiency of national manufacturing enterprises under the cluster frontier can reach 0.818, which is 15.9% higher than the common frontier level. The possible reason is that when low-tech groups (e.g., high-carbon groups) are benchmarked against a common frontier, their distance from the optimal production boundary is explicitly explicit, and the cluster frontier only reflects the relative efficiency within the group, resulting in inflated efficiency estimates.

From the group level, the average green innovation efficiency of China's high-carbon, medium-carbon and low-carbon group manufacturing enterprises is 0.676, 0.703 and 0.739 respectively, corresponding to 32.4%, 29.7% and 26.1% of the corresponding improvement space, and the low-carbon group occupies the leading position. The national green innovation efficiency showed a trend of "fluctuation decline - stage rebound - shock convergence", from 0.778 in 2015 to 0.692 in 2022, with a cumulative decrease of 11.1%. This trend is driven by both policy shocks and economic cycles: the strategic adjustment of "Made in China 2025" from 2015 to 2016 caused a lag in the clearance of production capacity in the high-carbon group, and its efficiency decrease of -12.7% was significantly higher than that of the low- and medium-carbon group, confirming the "policy adaptation period effect"; From 2016 to 2017, the deepening of supply-side reform promoted the efficiency of the high-carbon group to rebound by 4.2%, but the rebound was weaker than that of the low-carbon group, reflecting its technical rigidity constraints. In the early days of the epidemic from 2019 to 2021, green investment bucked the trend and drove the efficiency of the high-carbon group to rebound by 2.8%, but in 2022, the tightening of epidemic prevention policies led to another decline of 5.1%, highlighting the vulnerability of the high-carbon group's ability to resist risks.

Table 2. Green Innovation Efficiency of Manufacturing Enterprises under Two Frontiers (2015-2022)

Type	Province	Common Frontier					Group Frontline			
		2015	2019	2022	Mean	Ranking	2015	2019	2022	Mean
Low-carbon Emission Regional Manufacturing Enterprises	Beijing	0.870	0.777	0.730	0.798	1	0.892	0.829	0.783	0.854
	Tianjin	0.855	0.716	0.750	0.751	8	0.880	0.762	0.791	0.801
	Shanghai	0.787	0.714	0.692	0.731	11	0.817	0.761	0.719	0.778
	Fujian	0.856	0.768	0.741	0.787	3	0.888	0.831	0.776	0.843
	Shandong	0.764	0.697	0.676	0.708	15	0.779	0.724	0.700	0.744
	Guangdong	0.858	0.766	0.742	0.788	2	0.885	0.811	0.775	0.839
	Guangxi	0.784	0.687	0.672	0.714	13	0.801	0.687	0.684	0.743
	Hainan	0.800	0.717	0.729	0.740	10	0.831	0.765	0.784	0.789
	Chongqing	0.739	0.648	0.659	0.682	20	0.777	0.677	0.741	0.747
	Shaanxi	0.686	0.731	0.712	0.691	17	0.708	0.741	0.717	0.748
	Mean	0.800	0.722	0.710	0.739	(1)	0.826	0.759	0.747	0.789
Medium Carbon Emission Regional Manufacturing Enterprises	Hebei	0.772	0.661	0.667	0.697	16	0.820	0.775	0.727	0.766
	Jilin	0.864	0.741	0.689	0.770	5	0.901	0.809	0.766	0.831
	Heilongjiang	0.823	0.734	0.705	0.749	9	0.872	0.792	0.776	0.803
	Jiangsu	0.846	0.751	0.722	0.771	4	0.884	0.820	0.791	0.828
	Zhejiang	0.768	0.690	0.678	0.709	14	0.816	0.785	0.736	0.777
	Jiangxi	0.724	0.667	0.666	0.681	21	0.790	0.781	0.742	0.761
	Henan	0.713	0.649	0.627	0.666	26	0.777	0.767	0.682	0.747
	Hubei	0.731	0.648	0.641	0.669	23	0.790	0.765	0.709	0.743
	Sichuan	0.629	0.678	0.680	0.666	25	0.733	0.74	0.741	0.751
	Guizhou	0.681	0.641	0.610	0.651	27	0.748	0.741	0.671	0.718
	Mean	0.755	0.689	0.669	0.703	(2)	0.813	0.781	0.734	0.773
High Carbon Emission Region Manufacturing Enterprises	Shanxi	0.788	0.709	0.677	0.720	12	0.941	0.906	0.897	0.909
	Inner Mongolia	0.617	0.583	0.557	0.577	30	0.794	0.780	0.752	0.775
	Liaoning	0.774	0.782	0.723	0.759	7	0.914	0.935	0.924	0.928
	Anhui	0.701	0.667	0.646	0.668	24	0.907	0.912	0.917	0.916
	Hunan	0.738	0.673	0.671	0.687	19	0.923	0.929	0.934	0.926
	Yunnan	0.751	0.748	0.767	0.761	6	0.899	0.919	0.915	0.917
	Gansu	0.658	0.626	0.603	0.618	28	0.853	0.837	0.888	0.845
	Qinghai	0.564	0.637	0.755	0.612	29	0.782	0.958	0.989	0.883
	Ningxia	0.720	0.685	0.684	0.691	18	0.853	0.944	0.941	0.924
	Xinjiang	0.668	0.693	0.678	0.671	22	0.840	0.922	0.940	0.895
	Mean	0.698	0.681	0.676	0.676	(3)	0.871	0.904	0.910	0.892
	National	0.751	0.696	0.685	0.706		0.836	0.815	0.797	0.818

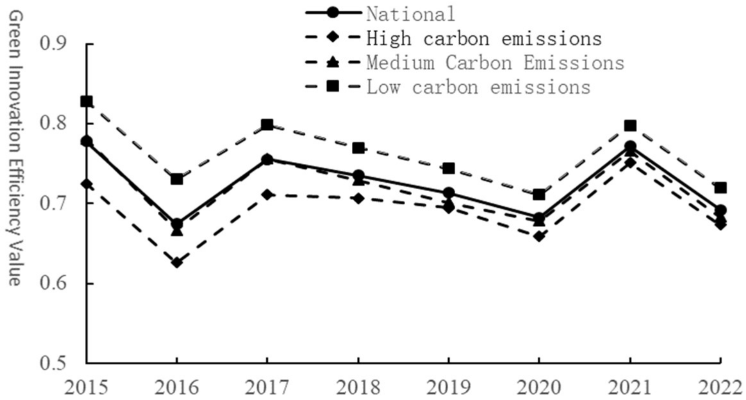

Figure 2. Changes in Green Innovation Efficiency Nationwide and in the Three Major Groups

At the provincial level, Beijing ranks first in the country with an efficiency value of 0.798, thanks to its scientific and technological innovation resources and favorable policy environment as a national political and cultural center, as well as the talent and knowledge support provided by many universities and scientific research institutions. The following provinces of Guangdong and Fujian have promoted the rapid development of green industries by relying on their developed economic and scientific and technological innovation capabilities. Jiangsu and Jilin provinces have shown strong momentum in promoting industrial structure optimization and green technology innovation, and have become the core pillars of China's carbon emission group manufacturing enterprises. In contrast, the average green innovation efficiency of many provinces does not reach the national average, mainly distributed in medium and high carbon emission groups, including Liaoning, Anhui, Hunan, Yunnan, Gansu, Qinghai, Ningxia, Xinjiang, Hebei and other places. Manufacturing enterprises in these provinces usually face greater economic development pressure and environmental governance tasks, and there may be a certain lag in green innovation.

3.2. Comparison of Green Innovation Efficiency and Technology Gaps among Manufacturing Enterprises with Different Carbon Emission Levels

Based on an analysis of the technology gap ratio (TGR) under a common frontier theoretical framework, Table 3 shows that the mean TGR values for the high-carbon, medium-carbon, and low-carbon groups are 0.756, 0.911, and 0.941, respectively, with standard deviations decreasing in sequence. The Kruskal-Wallis test results (Chi-squared=15.260,P < 0.000) confirm a statistically significant stratification of technology gaps among the three groups.

Table 3. Proportion of Technology Gaps in China's Three Major Groups of Manufacturing Enterprises and Test of Their Group Differences

Group	Maximum	Minimum	Mean	Standard deviation
Low carbon	0.969	0.893	0.941	0.024
Medium carbon	0.990	0.780	0.911	0.064
High carbon	0.829	0.689	0.756	0.044
Kruskal-Wallis test	Chi-squared=15.260 P<0.000***			

The dynamic analysis of the technological gap between groups (Figure 3) shows that the technology gap between low- and high-carbon manufacturing enterprises remains persistently high, hovering around 0.2, while the gap between medium- and high-carbon enterprises has converged with fluctuations. Notably, the technology gap between low- and medium-carbon manufacturing enterprises shows a periodic inversion: especially in 2017 and 2021, even

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appearing as negative. Possible reasons include: in 2017, the impact of the "Made in China 2025" policy and the upgrading of technological standards forced traditional industries in the medium-carbon group to transform, leading to a short-term efficiency boost; in 2021, pandemic disruptions affected low-carbon export-oriented economies due to global supply chain breaks, interrupting R&D cooperation and shrinking international market demand, while the medium-carbon group leveraged the resilience of the domestic market to achieve efficiency surpassing the low-carbon group.

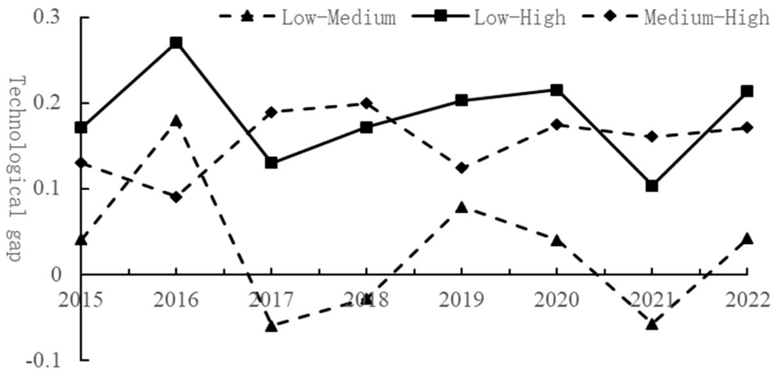

Figure 3. Technical Gaps Among the Three Major Groups of Manufacturing Companies

3.3. Decomposition of Green Innovation Inefficiency Values of Manufacturing Enterprises Across Different Carbon Emission Groups

In order to determine the true source of efficiency loss, this study uses the aforementioned formula (2) to decompose it from two dimensions: 'technology' and 'management.' The average management inefficiency is 0.182, and the average technical gap inefficiency is 0.111. The 30 provinces are divided into four categories (see Figure 4) in order to identify pathways for improving the green innovation efficiency of manufacturing enterprises in each province.

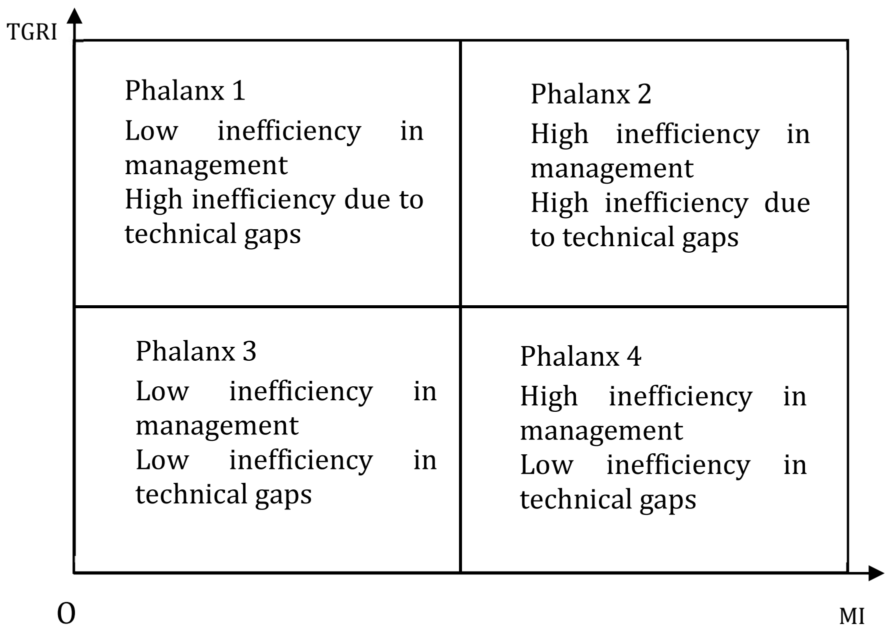

Figure 4. Two-dimensional decomposition of green innovation efficiency losses in manufacturing enterprises across provinces in China

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According to the above definitions, the 30 provinces are divided into four quadrants (see Table 4). Quadrant 1 covers nine central and western provinces and border regions, including Shanxi, Liaoning, and Anhui. These provinces have relatively well-established management systems but lag behind in technological capabilities, making it imperative to build cross-regional technology collaborative innovation mechanisms. Quadrant 2 includes only Inner Mongolia, which faces the dual challenges of 'coarse management and technological gaps.' It needs both internal improvement and external support to achieve balanced development between management optimization and technological catch-up. Quadrant 3 focuses on five developed eastern regions, including Beijing, Jiangsu, and Guangdong, showcasing high efficiency in both management and technology, serving as a model for manufacturing enterprises in other provinces. Quadrant 4 covers 15 provinces, including Hebei, Zhejiang, and Shandong, mainly located in the eastern industrial belt and central manufacturing base. These provinces reveal deep-seated contradictions between internal management capabilities and green innovation levels during the process of scale expansion. Further improvement in their management level will be a key focus for the future.

Table 4. Classification of Strategies for Improving Green Innovation Efficiency in Manufacturing Enterprises Across Provinces in China

Phalanx Type	Region
1 MI with low TGRI and high	Shanxi, Liaoning, Anhui, Hunan, Yunnan, Gansu, Qinghai, Ningxia, Xinjiang
2 High MI, High TGRI	Inner Mongolia
3 Low MI, Low TGRI	Jilin, Jiangsu, Beijing, Fujian, Guangdong
4 High MI, low TGRI	Hebei, Heilongjiang, Zhejiang, Jiangxi, Henan, Hubei, Sichuan, Guizhou, Tianjin, Shanghai, Shandong, Guangxi, Hainan, Chongqing, Shaanxi

From a dynamic perspective, observing Figure 5(a), it can be seen that between 2015 and 2022, management inefficiency in manufacturing enterprises nationwide consistently accounted for 60%-65% of the total efficiency loss, indicating that the structural conflict between traditional management models and the demand for green innovation has become entrenched, making it the main obstacle to improving green innovation efficiency across the country. Further analysis of Figures 5(b), 5(c), and 5(d) reveals that low-carbon emission manufacturing enterprises maintained a relatively low level of technology gap inefficiency throughout the observation period, while management inefficiency consistently exceeded 75%, indicating the importance of optimizing internal management to improve efficiency. The inefficiency values of medium-carbon emission manufacturing enterprises fluctuated significantly; notably, during the intensified environmental inspections in 2018, management inefficiency rose to 87%, and under the 'dual restriction' policy in 2021, it climbed again to 85%, highlighting their vulnerability to policy shocks and indicating considerable room for optimization in management and operations while striving to reduce the technology gap. In contrast, high-carbon emission manufacturing enterprises are trapped in a technical lock-in dilemma, with the proportion rising from 64.5% in 2015 to 71.2% in 2022 (an average annual growth rate of 1.7%), reflecting that these enterprises are experiencing an increasing technology gap when facing environmental pressures.

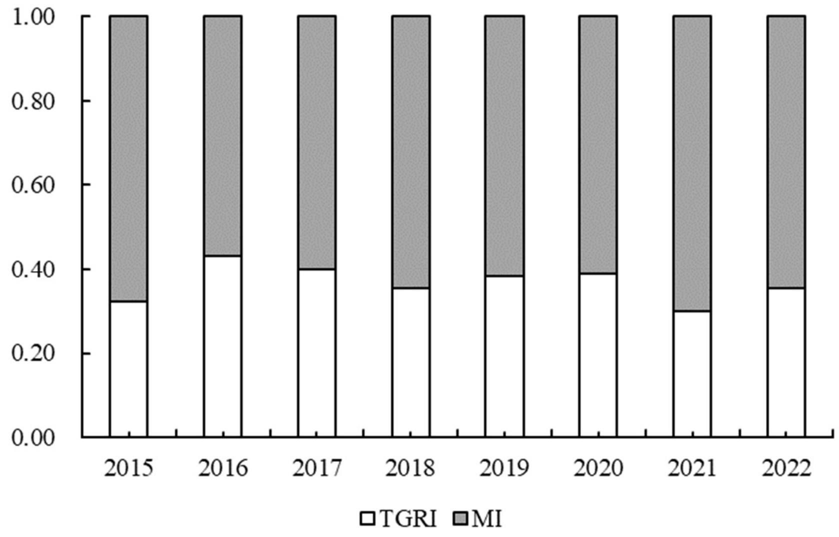

Figure 5(a). Proportion of Inefficiency Decomposition of National Manufacturing Enterprises

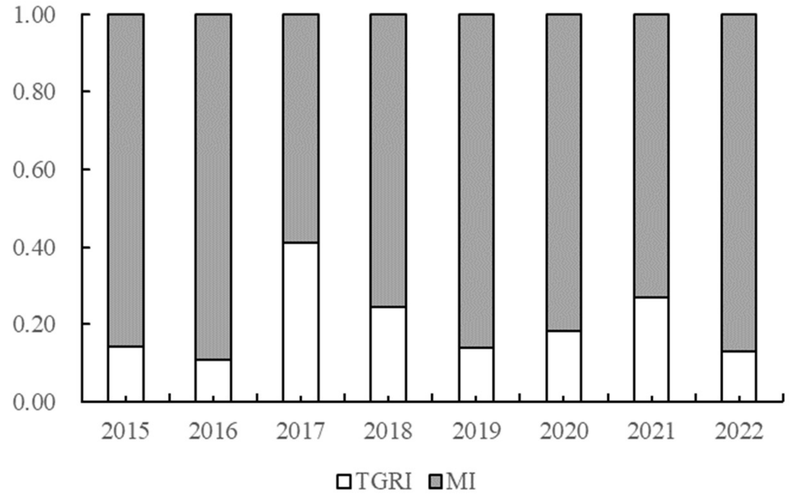

Figure 5(b). Proportion of Inefficiency Value Decomposition for Low-Carbon Emission Manufacturing Enterprises

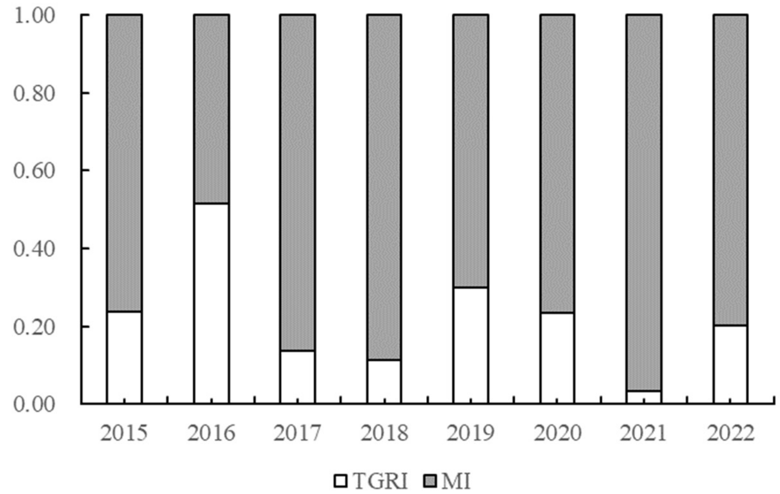

Figure 5(c). Proportion of inefficiency decomposition in medium carbon-emission manufacturing enterprises

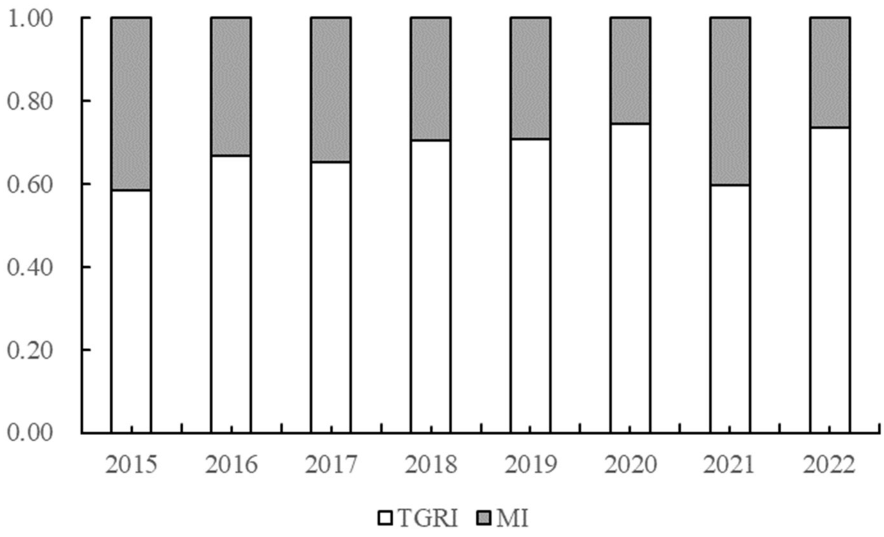

Figure 5(d). Proportion of inefficiency decomposition in high carbon-emission manufacturing enterprises

3.4. Analysis of Factors Affecting the Inefficiency of Green Innovation in Manufacturing Enterprises across Different Carbon Emission Groups

In response to the heterogeneous characteristics of efficiency losses caused by differences in carbon emission gradients, a sub-sample econometric model is constructed for mechanism analysis, revealing significant differences between technological gaps in high-carbon-emission manufacturing and management deficiencies in medium- and low-carbon-emission manufacturing. Using the technological gap inefficiency (TGRI) of high-carbon-emission manufacturing enterprises and the management inefficiency (MI) of medium- and low-carbon-emission manufacturing enterprises from 2015 to 2022 as the dependent variables, and various influencing factors as the independent variables, the panel regression model is constructed as follows:

$$TGRI_{\mathrm{it}} = \alpha_0 + \alpha_1 ER_{it} + \alpha_2 IPP_{it} + \alpha_3 IA_{it} + \alpha_4 ISU_{it} + \alpha_5 GSTS_{it} + \alpha_6 DI_{it} + v_t + \varepsilon_{it} \tag{3}$$

$$MI_{\mathrm{jt}} = \beta_0 + \beta_1 ON_{jt} + \beta_2 FS_{jt} + \beta_3 FS_{jt} + \beta_4 DT_{jt} + \beta_5 ESG_{jt} + \beta_6 EEA_{jt} + v_t + \varepsilon_{jt} \tag{4}$$

Here, i = 1, 2, ..., 10 represents manufacturing enterprises in high carbon emission regions, j = 1, 2, ..., 661 represents manufacturing enterprises in medium-low carbon emission regions, and t = 1, 2, ..., 8 represents the different years from 2015 to 2022; $\alpha0$ and $\beta0$ are constants, and $\alpha1\sim\alpha6$, $\beta1\sim\beta6$ are coefficients to be estimated. vt represents year fixed effects, and εit and εjt are random disturbance terms. Tables 5 and 6 respectively present the differentiated measurement models for technological gap inefficiency of high carbon emission manufacturing enterprises and management inefficiency of medium-low carbon emission manufacturing enterprises. Columns 2 to 4 show the regression results based on two-way fixed effects, random effects, and Tobit models, respectively. Regarding model selection, based on the Hausman test, the high-carbon group ($p>0.10$) uses the random effects model, while the medium-low carbon group ($p<0.10$) uses two-way fixed effects. To enhance robustness, column 5 uses the system GMM method for estimation, applying one-step GMM for the high-carbon group to reduce small sample bias, and two-step GMM for the medium-low carbon group to improve heteroskedasticity robustness. The validity test of the instrumental variables shows that for all models, AR(1) is less than 0.10 and meets the significance level, while AR(2), Sargan, and

Hansen are all greater than 0.10, thus failing to reject the null hypothesis, indicating that the instrumental variables are valid and there is no over-identification problem. The significance and direction of the GMM estimated coefficients did not change significantly compared to other models, and the following explanations are based on the GMM estimation results.

Table 5. Regression Results of Factors Affecting the Technological Gap Inefficiency Values of High Carbon Emission Manufacturing Enterprises

Variable	Technological Gap Inefficiency (High-Carbon Areas)			
	Fixed effects	Random effects	Panel Tobit	System GMM
Lag period inefficiency value				0.642*** (0.098)
ER	2.960 (2.055)	2.331 (1.877)	2.136 (1.711)	3.321* (1.800)
IPP	1.665*** (0.620)	1.426*** (0.564)	1.359*** (0.516)	1.121*** (0.428)
GSTS	-0.048 (0.147)	0.022 (0.118)	0.044 (0.106)	0.074 (0.069)
ISU	-0.010* (0.053)	-0.087* (0.048)	-0.086** (0.043)	-0.067* (0.040)
IA	-0.083 (0.136)	-0.031 (0.121)	0.014 (0.110)	-0.017 (0.073)
DI	0.213** (0.080)	0.149** (0.070)	0.127* (0.069)	-0.027 (0.044)
Constant	0.206** (0.081)	0.198*** (0.072)	0.199*** (0.064)	0.187** (0.077)
Model test value	F=11.220 R^2=0.719 N=80	Wald=149.390 R^2=0.715 N=80	Wald=171.570 Log =165.963 N=80	AR(1)=0.002 AR(2)=0.968 N=70 Sargan =0.154

From Table 5, it can be seen that the lag period inefficiency coefficient of the technology gap is 0.642 and is significant at the 1% level, indicating that the formation of the technology gap of manufacturing enterprises in high-carbon emission areas is a long-term accumulation process. The environmental regulation coefficient is 3.321 and significant at the 10% level, which is consistent with the conclusion of Xiao Yanfei et al. (2024) [23], confirming the applicability of the "Porter hypothesis" in high-carbon areas. The coefficient of intellectual property protection at the test level of 1% is significantly positive, which means that excessive intellectual property protection restricts the technology sharing and dissemination of manufacturing enterprises in high-emission areas, which is not conducive to technology absorption, leading to the formation of a "patent wall", thus widening the technology gap. It is worth noting that industrial structure upgrading has a negative effect on the technology gap, which can effectively promote the growth of green innovation by optimizing the allocation of factors [31], limiting the further expansion of the technology gap. However, the innovation atmosphere, digital infrastructure and government science and technology support are not significant, reflecting the particularity of manufacturing enterprises in high-carbon areas to catch up with technology, and their technological change relies more on policy pressure rather than inclusive innovation environment or digital penetration, and government science and technology subsidies are often intercepted by leading enterprises, failing to effectively make up for the technological gap.

In terms of managing inefficiency values, the specific analysis is as follows:

Table 6. Regression Results of Factors Affecting Management Inefficiency in Low- and Medium-Carbon Emission Manufacturing Enterprises

Variable	Management inefficiency value (medium-low carbon regions)			
	Fixed effects	Random effects	Panel Tobit	System GMM
Lag period inefficiency value				1.011*** (0.262)
FS	0.033*** (0.003)	0.036*** (0.003)	0.036*** (0.003)	0.009 (0.012)
ON	0.004 (0.009)	0.002 (0.006)	0.002 (0.006)	0.012 (0.036)
FC	-0.049* (0.026)	-0.112*** (0.012)	-0.113*** (0.012)	-0.151*** (0.044)
DT	0.001 (0.002)	0.005*** (0.002)	0.005*** (0.002)	0.011** (0.061)
ESG	-0.002 (0.002)	-0.002 (0.002)	-0.002 (0.002)	-0.013* (0.008)
EEA	0.031* (0.019)	0.039*** (0.015)	0.039*** (0.015)	0.337*** (0.061)
Constant	-0.750*** (0.125)	-1.058*** (0.066)	-1.060*** (0.066)	-1.060 (0.390)
Model test value	F=78.810 R^2=0.182 N=5288	Wald=647.680 R^2=0.108 N=5288	Wald=645.580 Log=5489.474 N=5288	AR(1)=0.000 AR(2)=0.109 N=4627 Hansen=0.560

From the regression results in Table 6, it can be seen that the lag period inefficiency coefficient of management ineffectiveness is 1.011 and is significant at the level of 1%, indicating that management inefficiency has strong persistence. Contrary to the conclusion of Zeng Yuan et al. (2024) [17], the possible explanation is that financing constraints force enterprises to control the use of capital resources more strictly, thereby improving management efficiency. The digital transformation coefficient is positive and significant at the 5% level, which is similar to the conclusion of Tavassoli et al. (2018) [28]. Digital transformation should theoretically reduce inefficiencies by optimizing processes, but the results show that it actually increases inefficiencies, which may stem from the high cost of digital transformation overshadowing long-term benefits and increasing management burdens. ESG performance has a negative effect on management ineffectiveness, indicating that the better the ESG performance, the lower the management inefficiency. This is consistent with theoretical expectations, and ESG practices may promote the optimal allocation of resources and improve corporate innovation output by improving internal governance and external reputation. The coefficient of the 1% test level of environmental protection awareness of executives is significantly positive, and the improvement of environmental protection awareness of executives increases management inefficiency, which is contrary to the conclusion of Xu Jianzhong (2017) [30], and may reflect that environmental protection investment increases management complexity or cost. Some scholars believe that technological innovation requires a certain scale effect [32], but the larger the scale of the enterprise, the worse the management level may be, and the state-owned enterprises have significant resource acquisition, which is not a natural lack of innovation motivation [12].

4. Conclusion and Policy Recommendations

This study classifies manufacturing enterprises in various provinces into high-carbon, medium-carbon, and low-carbon groups based on their carbon emission characteristics. A non-desired output common frontier SBM-DEA model is constructed to measure the green innovation efficiency of manufacturing enterprises from 2015 to 2022. It also analyzes the technological gaps among the groups and systematically examines the main factors affecting technological gaps and managerial inefficiencies from the dimensions of external environment and internal management. The study finds: (1) Under the common frontier, low-carbon emission manufacturing enterprises have the highest green innovation efficiency, with an average of 0.739, while high-carbon emission enterprises have the lowest efficiency, averaging 0.676, below the national average of 0.706, indicating substantial potential for enhancement in green innovation among high-carbon manufacturing enterprises. During the study period, overall efficiency shows a declining trend. (2) The Kruskal-Wallis test indicates significant differences in the proportion of technological gaps among different carbon emission groups. The technological gaps of medium and low-carbon groups show a fluctuating trend, while the gaps between low and high-carbon groups, and between medium and high-carbon groups, are relatively stable. (3) Efficiency loss in the high-carbon group mainly stems from technological gaps, with the proportion of TGRI continuously increasing, reflecting technological path dependence and the challenges of low-carbon transformation; in contrast, managerial inefficiency dominates in medium and low-carbon groups, showing significant fluctuations especially under the impact of the pandemic, exposing weaknesses in internal governance and resource allocation. (4) Environmental regulation and intellectual property protection exacerbate technological gaps in high-carbon groups, while industrial structure upgrading can reduce these gaps; managerial inefficiency in medium and low-carbon groups is driven by financing constraints, forcing improvements in efficiency, but digital transformation increases management burdens, ESG performance optimizes governance, and executives' environmental awareness complicates management.

At present, innovation-driven development in various regions of China has made significant progress, but manufacturing enterprises still face practical issues such as widening technological gaps and low levels of internal management in green innovation. Based on this, this study puts forward the following policy recommendations:

(1) Differentiated technological support and industrial structure upgrading. To address the significant technological gaps in high-carbon-emission manufacturing enterprises, a gradient technology collaborative innovation mechanism should be established. The government can set up special funds for green technologies in high-carbon industries, focusing on supporting disruptive technological research and development, such as hydrogen-based steelmaking and carbon capture, while promoting deep collaboration among industry, universities, and research institutions. At the same time, policies to strengthen industrial structure upgrading should be implemented, using tax incentives to guide high-carbon enterprises toward low-carbon industrial chains, breaking the dependence on traditional technological pathways. A cross-regional technology-sharing platform should be established to promote technology spillovers from leading enterprises and avoid the 'patent wall' effect caused by excessive intellectual property protection.

(2) Improving management effectiveness and guiding digital transformation. For low- and medium-carbon emission enterprises that mainly experience efficiency losses due to management deficiencies, it is necessary to implement an ESG governance capability enhancement program, integrate environmental and social governance into the corporate evaluation system, and incentivize management optimization through green finance benefits (such as loan interest rates linked to ESG performance). Establish a risk compensation

mechanism for digital transformation, provide 30%-50% financial subsidies for digital investment by small and medium-sized enterprises, and build regional industrial Internet platforms to reduce transformation costs. Improve the executive green leadership training system to mitigate management complexity caused by a surge in environmental investments through courses on environmental awareness and risk management.

(3) Dynamic environmental regulation and the construction of an innovation ecosystem. Optimize the combination of environmental policy tools and implement a "pressure-support" dual regulation for high-carbon enterprises: strictly enforce the carbon emission quota trading system to drive technological upgrades, while providing tax rebates for pollution control investments to enterprises that meet the standards. In terms of innovation, establish regional green technology innovation alliances, integrating R&D resources from universities, research institutes, and enterprises under government leadership to build a common technology research pool. Strengthen equalized investment in digital infrastructure, with a focus on increasing 5G base station and industrial internet coverage in central and western regions to over 90%, narrowing the regional digital divide. Establish a green technology standards mutual recognition system to promote the rapid nationwide diffusion and application of low-carbon technologies.

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