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Research on Industry Differentiation and Driving Factors of Green Innovation Efficiency in China

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Abstract

Green innovation is the core force driving the green and low-carbon development of industry, and its efficiency performance is related to the success or failure of enterprise transformation. Based on the data of 40 industry segments in China, a three stage DEA model is used to analyze the industry differentiation characteristics and driving factors of green innovation efficiency in China's industry. The results show that the overall efficiency of green innovation in China's industry is 0.519, with nearly 50% room for improvement. The efficiency loss is mainly attributed to the low pure technical efficiency. The efficiency of the industry is characterized by unbalanced development, with the efficiency of the hydropower supply industry performing better, while the efficiency of the mining industry performing worst; Resource and labor intensive industries are "depressions" of industrial efficiency, while capital intensive industries have better efficiency. The analysis of influencing factors shows that the overall external environment promotes industry efficiency, and the lack of internal management is the key reason for restricting efficiency improvement. Further research has found that the former can adjust the degree of nationalization and increase policy support to improve innovation efficiency, while the latter mainly restricts the exertion of innovation scale effects.

Keywords

Industry differences; Green innovation efficiency; Environmental promotion; Inadequate management

1. Introduction

Green and low-carbon development is a crucial trend in industrial economic growth. Confronted with increasingly stringent resource and environmental constraints, industrial enterprises must accelerate green innovation and enhance the efficiency of innovation resource utilization [1]. The 20th National Congress of the Communist Party of China regards scientific and technological innovation as the foundation and key to solving all problems. The Ministry of Industry and Information Technology has explicitly identified "efficiency first, innovation-driven" as a principle in the "14th Five-Year Plan" for industrial green development. In recent years, China's investment in industrial innovation resources has continuously increased, yet the corresponding improvements in resource and environmental outcomes have not been significant [2]. How to improve green innovation efficiency has become critical for enterprises to overcome resource and environmental constraints and achieve high-quality development. At the same time, China's industrial system is comprehensive, with differences across industries in terms of market environments, technological composition, etc. [3-4], indicating that pathways for efficiency improvement vary by industry, and policy formulation cannot adopt a one-size-fits-all approach. Under these circumstances, scientifically measuring the green innovation efficiency of China's industrial sectors, clarifying inter-industry differences, characteristics of efficiency loss, and key paths for efficiency improvement, is of great significance for precisely formulating industry-specific green innovation policies and promoting the green development of China's industry.

Green innovation is an important means for enterprises to comply with environmental policies and shape competitive advantages in the market, encompassing multidimensional values in economic, resource, and environmental aspects [5]. There are various interpretations and expressions regarding its connotation. The Ministry of Science and Technology of China defines green innovation as "developing emerging technologies aimed at reducing consumption, pollution, and ecological degradation, and promoting harmony between humans and nature" [6]. The academic community uses this concept more broadly, considering that any process involving product manufacturing, process improvement, technological innovation, and organizational management arrangements that incorporate resource conservation and ecological enhancement should fall within the scope of green innovation [7]. Regarding green innovation efficiency, both practitioners and scholars consistently emphasize achieving greater output value—including economic, environmental, and resource value—with fewer innovation inputs [8-9].

In terms of measuring and evaluating green innovation efficiency, studies generally construct evaluation index systems that include green patents or pollution outputs to assess green innovation efficiency across different spatial scales or geographical units, predominantly using DEA or SFA methods [10]. Research at the national or regional level mainly focuses on provincial innovation systems, analyzing differences and dynamic evolution characteristics of green innovation efficiency across provinces or regions. Relevant studies indicate significant spatial autocorrelation and uneven development in China's industrial green innovation efficiency [11]. At the city level, research primarily examines urban agglomerations such as the Yangtze River Delta [10], Beijing-Tianjin-Hebei [12], and Guangdong-Hong Kong-Macao [13], or national central cities [14], investigating urban differences and agglomeration characteristics of green innovation efficiency. These studies suggest that urban green innovation efficiency exhibits “club convergence” characteristics, with coexisting “spillover effects” and “polarization effects” [12]. Research at the industrial or sectoral level is relatively scarce, mainly concentrating on high-tech industries or specific manufacturing sectors. For example, Li et al. [15] found that China’s heavily polluting industries exhibit a pattern of being “innovative but not green.”

Some studies also explore pathways for efficiency improvement, examining the influencing factors and mechanisms of green innovation efficiency from multiple perspectives. A number of scholars focus on micro-level enterprise characteristics such as organizational structure, knowledge level, and management capabilities, emphasizing the critical impact of firms’ intrinsic attributes or behavioral factors on green innovation efficiency. For instance, Jia et al. [16] argue that due to bounded rationality and inertia in innovative thinking, enterprises often struggle to abandon traditional technological innovation models, resulting in insufficient motivation for green innovation and low efficiency. Ye et al. [17] show that enhancing firms’ knowledge absorption capacity or shifting their innovation modes can improve green innovation efficiency. Other scholars emphasize external environmental factors such as macro policies, market conditions, and industrial characteristics, verifying the significant effects of environmental regulation [3], foreign investment [9], industrial agglomeration [18], technology transfer [19], and industry-university-research collaboration [20], advocating for government intervention in corporate innovation activities.

The above research provides ideological and methodological guidance for our study, yet there remains room for improvement. First, most studies adopt regional or urban perspectives, overlooking differences across industrial sectors. Although some scholars have analyzed green innovation efficiency at the industry level, their focus remains limited to specific industries or sectors, lacking a detailed examination at the overall industrial level. Second, the selection of efficiency evaluation indicators often neglects key climate impact metrics, failing to fully reflect the practical requirements of industrial green and low-carbon development. Based on this, by constructing a three-stage DEA model that incorporates climate impacts, this study analyzes the sectoral differentiation characteristics of green innovation efficiency across China’s industries at the overall industrial level. It compares the differential impacts of enterprise management factors and external environmental variables, aiming to identify the true sources of efficiency loss in industrial green innovation and provide a basis for formulating differentiated industry-specific green innovation policies.

2. Methods, Variables, and Data

2.1. Methods

This study employs the classic Undesirable Three-Stage Data Envelopment Analysis

(DEA) model. This model can measure innovation efficiency while providing results on the influence of environmental variables, managerial factors, and stochastic disturbances. The specific model construction and calculation methodology refer to the research by Fried et al. [21] and Zhang et al. [22] The core logic of the model construction is divided into three stages: First, the initial efficiency scores for each Decision-Making Unit (DMU) are calculated using a Slacks-Based Measure (SBM) model that incorporates undesirable outputs, yielding comprehensive efficiency values and input-output slack variables. Second, using these slack variables as the dependent variables, a Stochastic Frontier Analysis (SFA) model is constructed to quantify the influence of various environmental factors and random noise. Subsequently, all DMUs are adjusted to operate under identical environmental conditions and luck levels through a reverse adjustment procedure. Finally, the adjusted input-output data are used to run the DEA model again for efficiency analysis, thereby obtaining more accurate genuine green innovation efficiency values that reflect only managerial inefficiency. This method can effectively pinpoint the sources of efficiency loss, providing a clearer basis for policy analysis.

2.2. Variable Definitions and Descriptive Statistics

Environmental variables refer to factors that may affect efficiency but are beyond the control of the sample units. Drawing on existing research, this paper selects five environmental variables from the perspectives of the macro-development environment and industry characteristics. a) Industry-University-Research Collaboration: As a key factor in accelerating the translation of knowledge into productivity, it is measured by the proportion of expenditure to universities and research institutions in the industry's total external R&D spending. b) State-Owned Share: The influence of "ownership discrimination" on green technology innovation efficiency cannot be ignored. It is represented by the proportion of state-owned and state-controlled enterprises in the industry's total operating revenue. c) Foreign Direct Investment (FDI): The impact of FDI-induced pollution transfer and technology flow on host countries' innovation efficiency is complex. It is measured by the proportion of foreign capital in the industry's total capital. d) Environmental Regulation: Effective environmental instruments can promote green innovation efficiency. It is represented by the operating costs of waste gas and wastewater treatment facilities per unit of output value. e) Government Support: Government support plays a significant guiding role in promoting corporate green innovation behavior and enhancing innovation capacity. It is measured by the proportion of government funds in the R&D expenditure.

2.3. Industry Selection and Data Description

As DEA evaluation results represent relative efficiency, and the influence of technological progress cannot be effectively eliminated, cross-year efficiency results for the same decision-making units lack practical comparability. This makes cross-sectional data analysis more accurate. Furthermore, following Cao et al. [11], a one-period lag is applied to the output indicators. Accordingly, cross-sectional data for 40 Chinese industrial sectors in 2022-2023 were collected. All data are sourced from the China Statistical Yearbook and the China Energy Statistical Yearbook.

Additionally, to examine the heterogeneity of industrial green innovation efficiency across sectors, the analysis primarily adopts the factor intensity classification as a starting point, exploring efficiency differences among resource-intensive, labor-intensive, and capital- or technology-intensive industries. Given that factor intensity typically changes very slowly and remains highly stable in the short term, this study draws on the classification results from Cheng et al. [24] to group the industrial sectors, as shown in Table 1.

Table 1. Industrial Sector Grouping Based on Factor Intensity

Resource-Intensive Industries	Labor-Intensive Industries	Capital- or Technology-Intensive Industries
A1. Mining and Washing of Coal	B1. Mining of Ferrous Metal Ores	C1. Manufacture of Cultural, Educational, Arts, Crafts, Sports, and Entertainment Goods
A2. Extraction of Petroleum and Natural Gas	B2. Mining of Non-ferrous Metal Ores	C2. Processing of Petroleum, Coal, and Other Fuels
A3. Processing of Agricultural Products	B3. Mining and Processing of Non-metal Ores	C3. Manufacture of Raw Chemical Materials and Chemical Products
A4. Manufacture of Food Products	B4. Mining Support Activities	C4. Manufacture of Medicines
A5. Manufacture of Liquor, Beverages, and Refined Tea	B5. Manufacture of Textiles	C5. Manufacture of Chemical Fibers
A6. Manufacture of Tobacco Products	B6. Manufacture of Textile Wearing Apparel and Clothing	C6. Smelting and Pressing of Ferrous Metals
A7. Processing of Timber, Manufacture of Wood, Bamboo, Rattan, Palm, and Straw Products	B7. Manufacture of Leather, Fur, Feather, and Related Products and Footwear	C7. Smelting and Pressing of Non-ferrous Metals
A8. Production and Supply of Electric Power and Heat Power	B8. Manufacture of Furniture	C8. Manufacture of General-Purpose Machinery
A9. Production and Supply of Gas	B9. Manufacture of Paper and Paper Products	C9. Manufacture of Special-Purpose Machinery
A10. Production and Supply of Water	B10. Printing and Reproduction of Recording Media	C10. Manufacture of Automobiles
	B11. Manufacture of Rubber and Plastics Products	C11. Manufacture of Railway, Shipbuilding, Aerospace, and Other Transport Equipment
	B12. Manufacture of Non-metallic Mineral Products	C12. Manufacture of Electrical Machinery and Apparatus
	B13. Manufacture of Metal Products	C13. Manufacture of Computers, Communication, and Other Electronic Equipment
	B14. Other Manufacturing	C14. Manufacture of Measuring Instruments and Machinery
	B15. Comprehensive Utilization of Waste Resources	
	B16. Repair of Metal Products, Machinery, and Equipment	

3. Empirical Results and Analysis

3.1. Results of the First-Stage Estimation

The green innovation efficiency of each industry was calculated using a DEA model accounting for undesirable outputs, with the results presented in Table 2.

Overall, the mean green innovation efficiency across all Chinese industries in 2023 was 0.519, indicating significant efficiency loss. The average pure technical efficiency (0.664) was lower than the average scale efficiency (0.781), suggesting that the primary reason for the overall low industrial efficiency lies in substantial pure technical efficiency losses. Therefore, more efforts are needed in the future to improve pure technical efficiency. At the sectoral level, 14 industries, accounting for 35% of the total, achieved a comprehensive efficiency score of 1. These include fuel processing and electronic equipment manufacturing, which are characterized by their typical capital- and technology-intensive nature. The remaining industries all exhibited considerable efficiency losses. Further observations of industry-specific efficiency characteristics are as follows:

First, examining broad industry categories, the average comprehensive green innovation efficiency for Mining (0.112) was lower than the overall industrial average (0.519), which in turn was lower than that for Manufacturing (0.571). The average efficiency for Public Utilities like Electricity and Water Production and Supply (0.791) was the highest. This pattern is closely related to industry organizational characteristics and technological foundations. Specifically, compared to mining or manufacturing, public utilities such as electricity and water supply often possess natural monopoly attributes. Their high market concentration greatly amplifies economies of scale in production and helps firms overcome industrial organization barriers to technology supply, thereby achieving higher levels of green technology provision efficiency. Although mining also involves extracting natural resources, it retains the typical features of traditional heavy industry, characterized by significant dependence on and consumption of energy. Coupled with low adoption rates of modern management practices and insufficient sectoral technological accumulation, the mining industry struggles to effectively break away from traditional innovation paths, constraining improvements in innovation efficiency.

Second, analyzing industries by factor intensity, the average comprehensive efficiency for both Resource-intensive industries (0.429) and Labor-intensive industries (0.385) was considerably lower than the overall industrial average, jointly constituting the "lowlands" of green innovation efficiency within China's industrial sector. Decomposing the efficiency scores reveals that low pure technical efficiency is the main source of efficiency loss for both groups, underscoring an urgent need for changes focused on enhancing pure technical efficiency. The average comprehensive efficiency for Capital-intensive industries performed relatively well, with limited room for improvement. The reasons are twofold: On one hand, as labor and raw material costs rise, the contribution of labor and resource inputs to output growth gradually weakens, while the contribution of capital inputs becomes more pronounced. This results in better efficiency performance for capital-intensive industries, which utilize more capital under similar conditions. On the other hand, while talent is a prerequisite for green innovation, high labor mobility makes it difficult for labor-intensive industries to accumulate human capital through "learning by doing" [25]. Furthermore, the generally superficial nature of industry-university-research collaboration and the lack of competitive compensation levels in these sectors exacerbate the disadvantage in human capital accumulation, thereby constraining their innovation efficiency.

Table 2. Measurement Results of Green Innovation Efficiency for Industrial Sub-sectors

Industry Type	No.	CE	PTE	SE	No.	CE	PTE	SE
Resource-Intensive Industries	A1	0.055	0.065	0.842	A7	0.180	0.266	0.678
	A2	0.098	0.108	0.910	A8	0.176	0.228	0.771
	A3	0.180	0.266	0.678	A9	0.197	0.234	0.843
	A4	0.176	0.228	0.771	A10	1	1	1
	A5	0.197	0.234	0.843	Mean	0.429	0.512	0.837
	A6	1	1	1				
Labor-Intensive Industries	B1	0.128	1	0.128	B10	0.576	0.579	0.996
	B2	0.101	0.228	0.442	B12	0.412	0.427	0.963
	B3	0.117	0.447	0.261	B12	0.220	0.335	0.656
	B4	0.170	1	0.170	B13	0.393	0.435	0.903
	B5	0.187	0.280	0.670	B14	0.389	0.432	0.899
	B6	0.364	0.371	0.981	B15	0.097	0.999	0.097
	B7	0.342	0.348	0.984	B16	1	1	1
	B8	1	1	1	Mean	0.358	0.577	0.676
	B9	0.227	0.345	0.657				
Capital-Intensive Industries	C1	1	1	1	C9	1	1	1
	C2	1	1	1	C10	1	1	1
	C3	0.171	0.307	0.558	C11	0.736	0.752	0.979
	C4	0.344	0.344	0.999	C12	1	1	1
	C5	0.259	1	0.259	C13	1	1	1
	C6	1	1	1	C14	1	1	1
	C7	0.230	0.815	0.282	Mean	0.767	0.873	0.863
	C8	1	1	1				

Note: CE, PTE, and SE represent Comprehensive Efficiency, Pure Technical Efficiency, and Scale Efficiency, respectively.

3.2. Second-Stage Input-Output Adjustment

The influence of environmental variables and stochastic factors on the slack variables of first-stage inputs and undesirable outputs was analyzed using Frontier 4.1 software. The results are presented in Table 3. The large absolute value of the log-likelihood function, along with the significant LR statistics and most of the estimated coefficients, indicates that the data and variable selection satisfy the application assumptions of the SFA model. Environmental variables, such as Industry-University-Research (I-U-R) Collaboration, have a significant impact on industrial green innovation efficiency. The γ values for all slack variables are significantly close to or equal to 1, suggesting that within the composite error term, managerial factors dominate, while the influence of random noise is negligible. Comparing the effects of different environmental variables, a negative coefficient indicates that increasing the environmental variable reduces input waste or decreases undesirable outputs, thereby improving green innovation efficiency.

Table 3. SFA Estimation Results of Environmental Variables on Innovation Slack Variables.

Variable	R&D Personnel Slack	R&D Funding Slack	Energy Input Slack	CO_2 Emission Slack	COD Emission Slack	SO_2 Emission Slack
Constant	-4.47E+04*** (49.988)	-251.035*** (1.000)	42.266*** (9.055)	-331.372*** (1.000)	-3.79E+04*** (1.085)	-2.05E+05*** (1.000)
I-U-R Collaboration	-4.39E+03*** (101.565)	-2.248*** (0.487)	-1.273*** (0.1706)	-3.791*** (0.0842)	-360.465*** (42.8641)	-2.12E+03*** (1.000)
State-Owned Share	152.487 (196.532)	1.148* (0.687)	0.423*** (0.047)	-0.355724	-126.772*** (52.560)	-1332.313*** (1.000)
Foreign Direct Investment	-22.441 (242.146)	0.128 (0.928)	0.258*** (0.078)	-2.161*** (0.294)	526.526*** (9.582)	2706.204*** (1.021)
Environmental Regulation	-33.962 (164.959)	0.030 (0.904)	0.507*** (0.009)	1.808* (1.006)	165.300*** (14.457)	1385.053*** (1.000)
Policy Support	-721.066*** (251.832)	-4.0243*** (0.950)	-1.439*** (0.164)	-2.621*** (0.866)	-343.657*** (16.6973)	-978.580*** (1.000)
σ^2	1.13E+09*** (1.000)	2.36E+04*** (1.000)	2.19E+04*** (1.003)	1.78E+05*** (1.000)	2.37E+09*** (1.000)	7.34E+10*** (1.236)
γ	0.998*** (0.017)	1.000*** (0.030)	1.000*** (0.001)	1.000*** (0.001)	1.000*** (0.002)	1.000*** (0.266)
Log-Likelihood	-446.813	-230.16	-219.516	-263.735	-460.618	-529.412
LR Statistic	16.657***	18.850***	37.790***	33.780***	18.555***	19.587***

Note: Figures in parentheses are standard errors. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

I-U-R Collaboration Variable. The coefficients for the I-U-R collaboration variable are all significantly negative, indicating that strengthening I-U-R collaboration will promote industrial green innovation efficiency. The primary reason is that I-U-R collaboration can integrate heterogeneous resources from different innovation actors, transcend the organizational boundaries between knowledge production and application, lower the threshold for knowledge comprehension, and simultaneously improve the efficiency of knowledge absorption and utilization. This accelerates the transformation of green technologies into productive forces, thereby enhancing enterprise green innovation efficiency.

State-Owned Share Variable. The influence of the state-owned share variable is positive on input slacks but negative on undesirable output slacks. This suggests that increasing the state-owned share may exacerbate the wasteful use of innovation resources, yet it helps mitigate climate impacts and pollution damage. The reason is related to the dual economic and political attributes characteristic of state-owned enterprises (SOEs). On one hand, compared to the 'credit discrimination' faced by non-public enterprises, SOEs operate under relatively relaxed credit constraints. This often leads to a lack of motivation for independent innovation and resource-intensive management within the state-owned sector, resulting in inefficient use of innovation resources. On the other hand, the distinct political attribute means SOEs typically bear greater environmental protection responsibilities. Coupled with stringent environmental inspections and performance evaluations, this prompts enterprises to pay more attention to environmental remediation, especially end-of-pipe pollution control. Therefore, the impact of increasing the state-owned share on green innovation efficiency is complex. The net effect depends on whether the "improvement effect" on climate impact and pollution damage can offset the accompanying "deterioration effect" of increased waste in innovation resource inputs.

Foreign Direct Investment (FDI) Variable. The results for FDI support the "Pollution Haven Hypothesis" [21]. This can be explained by the industrial gradient transfer theory and green technology barrier theory. Although FDI facilitates international industrial transfer and technology flows, for host countries, especially less developed ones, it often entails taking on more energy-intensive, low-efficiency labor- or resource-intensive industries, thereby exacerbating pollution and resource depletion in the host country. Simultaneously, facing severe green trade barriers, the technology flows induced by FDI primarily belong to the realm of traditional innovation rather than emerging green technologies. This can easily solidify the technological imitation path for domestic firms and dampen their enthusiasm for independent innovation, ultimately hindering the improvement of green innovation efficiency.

Environmental Regulation Variable. This study uses "the sum of operating costs for waste gas and wastewater treatment facilities per unit of output value" to represent environmental regulation. The significantly positive regression coefficient indicates that, at the current stage, further increasing expenditure on pollution control facility operations is detrimental to green innovation efficiency. There is an urgent need for enterprises to shift from end-of-pipe pollution control to source innovation. This is because operating costs for pollution control facilities, as necessary expenses for end-of-pipe environmental management, generally affect innovation efficiency through two channels: "innovation compensation" and "cost compliance." Against the backdrop of overall declining corporate profitability, additional end-of-pipe control expenditures significantly amplify the "cost compliance effect," crowding out resources originally allocated for innovation R&D or new product commercialization. This negative impact outweighs the potential positive "innovation compensation" effect, thereby hindering improvements in green innovation efficiency.

Policy Support Variable. The coefficients for the policy support variable are all significantly positive, indicating that strengthening policy support will comprehensively promote industrial green innovation efficiency. The reason is likely that, constrained by the externalities and high risks associated with green innovation, enterprises often lack the intrinsic motivation for independent innovation. Necessary policy support can, to some extent, compensate for this deficiency by reducing innovation uncertainty and risks, setting a clear direction for green innovation, and guiding enterprises to focus on innovation efficiency.

3.3. Third Stage: Analysis of Adjusted Green Innovation Efficiency in Industrial Sectors

Efficiency evaluation was conducted again using the adjusted data to obtain the green innovation management efficiency for each sector. The results are presented in Table 4.

Comparing Table 2 and Table 4, after removing the effects of environmental variables and stochastic factors, China's industrial green innovation efficiency has noticeably decreased. The mean comprehensive efficiency across all sectors dropped from 0.519 to 0.367. This indicates that, overall, the external environment has a favorable impact on industrial green innovation efficiency, and inefficiencies in internal enterprise management are the underlying cause of innovation efficiency loss. Examining the efficiency decomposition results, the adjusted means for pure technical efficiency and scale efficiency are 0.614 and 0.598, respectively. This suggests that the primary source of inefficiency within enterprises is low scale efficiency. At the sectoral level, the number of sectors achieving DEA efficiency decreased from 14 to 7 after adjustment, including sectors such as tobacco manufacturing, furniture manufacturing, and gas supply. Further observations on the adjusted sectoral heterogeneity characteristics are as follows: oa

Table 4. Efficiency Evaluation Results for Adjusted Industrial Subsectors.

Industry Type	No.	CE	PTE	SE	No.	CE	PTE	SE
Resource-Intensive Industries	A1	0.074	0.209	0.355	A7	0.242	1.000	0.242
	A2	0.161	0.500	0.323	A8	1	1	1
	A3	0.216	0.310	0.697	A9	0.176	1	0.176
	A4	0.204	0.371	0.550	A10	0.072	0.993	0.073
	A5	0.177	0.360	0.492	Mean	0.261	0.674	0.419
	A6	0.287	1	0.287				
Labor-Intensive Industries	B1	0.058	1	0.058	B10	0.204	0.504	0.404
	B2	0.093	1	0.093	B12	0.356	0.461	0.771
	B3	0.029	0.128	0.227	B12	0.318	0.382	0.833
	B4	0.032	0.065	0.487	B13	0.426	0.518	0.823
	B5	0.256	0.381	0.672	B14	0.126	0.298	0.422
	B6	0.154	0.337	0.457	B15	0.025	0.042	0.581
	B7	0.144	0.393	0.366	B16	0.088	0.387	0.227
	B8	0.193	0.339	0.570	Mean	0.173	0.414	0.480
	B9	0.276	0.395	0.697				
Capital-Intensive Industries	C1	0.277	0.486	0.569	C9	1	1	1
	C2	0.564	1	0.564	C10	1	1	1
	C3	0.330	0.360	0.918	C11	0.515	1	0.515
	C4	0.351	0.559	0.628	C12	1	1	1
	C5	0.200	0.284	0.702	C13	1	1	1
	C6	1	1	1	C14	0.358	0.488	0.734
	C7	1	1	1	Mean	0.664	0.798	0.810
	C8	0.705	1	0.705				

Note: CE, PTE, and SE represent Comprehensive Efficiency, Pure Technical Efficiency, and Scale Efficiency, respectively.

From the perspective of broad industry categories, the innovation efficiency performance of the Mining sector remains significantly lower than the overall industry average, with its comprehensive efficiency (CE) decreasing from 0.112 before adjustment to 0.075. The innovation efficiency of the Manufacturing sector and the Public Utilities sector (e.g., electricity and water production and supply) continues to outperform the overall industry average. Their respective CE values decreased from 0.571 and 0.791 before adjustment to 0.419 and 0.416. Further analysis reveals that the efficiency loss in the Manufacturing sector primarily stems from low pure technical efficiency (PTE), whereas the efficiency loss in other industry categories is mainly due to low scale efficiency (SE). This implies that the former should focus on overcoming challenges related to low-technology application, while the latter should better leverage economies of scale.

Examining industries by factor intensity, after adjustment, the average CE for resource-intensive, labor-intensive, and capital-intensive industries all declined. However, the ranking of their efficiency performance remains unchanged: capital-intensive industries > overall industry average > resource-intensive industries > labor-intensive industries. Among them, managerial inefficiency in resource-intensive industries is primarily attributed to significant SE losses. The root cause of managerial inefficiency in labor-intensive industries continues to be low PTE. For capital-intensive industries, the decomposed efficiency values are relatively close, indicating limited room for improvement.

4. Conclusions and Implications

Green innovation serves as the core driving force for promoting green and low-carbon development in industry, with its efficiency being crucial to the success of industrial transformation. Based on cross-sectional data from 40 Chinese industrial sectors for 2022-2023, this study employs a three-stage DEA model to analyze the sectoral differentiation characteristics and influencing factors of China's industrial green innovation efficiency. The main conclusions and implications are as follows.

Firstly, overall, the average green innovation efficiency of China's industry is 0.519, with efficiency losses primarily attributable to low pure technical efficiency. Secondly, sectoral analysis reveals heterogeneous and uneven development patterns in efficiency across different industries. The innovation efficiency performance ranks as follows: Public Utilities such as Electric Power > Manufacturing > Mining; and Capital-intensive industries > Overall industry average > Resource-intensive industries > Labor-intensive industries. Thirdly, analysis of influencing factors indicates that insufficient internal enterprise management is a key constraint on efficiency improvement. External environmental variables, on the whole, promote industrial green innovation efficiency, while the impact of stochastic disturbances is minimal and negligible. Notably, the effects of different environmental variables show subtle variations: increasing the state-owned share brings improvements in climate impact and pollution reduction but also leads to greater waste in innovation resource use; results for Foreign Direct Investment support the "Pollution Haven Hypothesis"; at the current stage, further increasing pollution control facility operating costs is detrimental to efficiency improvement, necessitating a shift from end-of-pipe treatment to source innovation for enterprises; and strengthening policy support promotes innovation efficiency. Fourthly, pathways for improving managerial efficiency differ across sectors. Manufacturing or labor-intensive industries should focus on overcoming low-technology application challenges, while other sectors should emphasize leveraging economies of scale.

Accordingly, the following policy implications are derived. First, green innovation is a practical choice for industrial enterprises to achieve low-carbon and green development. However, overall innovation efficiency across sectors remains relatively low, requiring concerted efforts from multiple stakeholders to enhance it in the future. Second, the performance, causes of loss, and improvement paths for green innovation efficiency vary significantly across different industrial sectors. Policy formulation must comprehensively consider the characteristics of each industry and develop differentiated green innovation policies. Third, as the creator and maintainer of the policy environment and market innovation climate, the government should further enhance the role of policy regulation in promoting green innovation efficiency, particularly by guiding and stimulating the endogenous motivation for enterprises to improve managerial efficiency. Fourth, as the primary responsible entity for green innovation production, enterprises themselves bear the most fundamental responsibility for efficiency losses due to insufficient internal management. They must focus on and improve their management capabilities, appropriately increase capital intensity, and strive to realize economies of scale.

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