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Pathways for Green Transformation in the Manufacturing Sector under the Dual-Carbon Goals: An Empirical Analysis of the Steel and Chemical Industries in Jiangsu Province

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ABSTRACT

Under the strategic framework of China's dual-carbon goals, the manufacturing sector—being a major source of energy consumption and carbon emissions—faces increasing pressure to improve the efficiency of its green transformation. Jiangsu Province, as a leading manufacturing region, hosts large-scale high-energy-consuming industries, making it imperative to assess efficiency scientifically to identify transformation gaps and design differentiated pathways. This study focuses on three representative sectors: chemical raw materials and chemical products manufacturing, ferrous metal smelting and rolling, and non-ferrous metal smelting and rolling. Using cross-sectional data from 2023, a "two-input–one-output" framework is applied, with total assets and average employment as inputs and operating revenue as output. Efficiency is measured via DEA models (CCR and BCC), and a robustness check based on labor-only input is conducted. The results show that efficiency varies significantly across sectors. Ferrous and non-ferrous metal industries generally lie on the DEA frontier, while the chemical sector exhibits low efficiency and considerable input redundancy. The inefficiency in the chemical sector is mainly attributable to technical and managerial limitations rather than scale constraints. Efficiency sensitivity differs by input perspective: the chemical sector's disadvantage is more pronounced in labor terms, whereas the non-ferrous metal sector relies on the capital–labor combination effect. Accordingly, green transformation pathways should be sector-specific: the chemical sector should prioritize process optimization and technological innovation, while the ferrous and non-ferrous metal sectors should focus on deep decarbonization

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technologies and input-structure optimization while sustaining high efficiency. This study contributes by empirically revealing the efficiency heterogeneity of high-energy-consuming industries under dual-carbon constraints, clarifying the sources of inefficiency, and providing an evidence-based reference for policy-making, enterprise-level green transformation, and targeted financial support.

1. Introduction

The intensification of global climate change and increasing resource and environmental constraints have made green and low-carbon transformation a widely recognized consensus and policy focus internationally. The United Nations Paris Agreement explicitly calls for limiting the global average temperature rise to well below 2°C, while pursuing efforts to cap it at 1.5°C. Achieving this target poses profound challenges to national economic development models and energy utilization patterns, and has catalyzed a global research agenda on carbon reduction pathways, energy structure optimization, and industrial upgrading (Cheng et al., 2023). In this context, China proposed its "carbon peaking and carbon neutrality" strategy in 2020, aiming to reach peak carbon emissions before 2030 and achieve carbon neutrality by 2060. This commitment not only represents China's contribution to global climate governance but also serves as an intrinsic requirement for promoting high-quality economic and social development.

As the sector with the highest concentration of energy consumption and carbon emissions, the efficiency of green transformation in the manufacturing industry is directly linked to the achievement of the dual-carbon goals (Zhang et al., 2023). Within China's manufacturing landscape, Jiangsu Province has long ranked among the top regions, with large industrial scale and high total energy consumption and carbon emissions. Although Jiangsu has made certain progress in green development and emission reduction in recent years, high-energy-consuming and high-emission industries continue to face substantial decarbonization pressure, making the task of green transformation formidable (Chen et al., 2021).

Among these industries, chemical raw materials and chemical products manufacturing exhibits significant environmental pressure due to long industrial chains and complex emission types; ferrous metal smelting and rolling, as a typical foundational industry, is characterized by high energy consumption and emissions, making it a key area for industrial low-carbon governance; non-ferrous metal smelting and rolling possesses certain advantages in capital and output efficiency but still faces challenges in deep decarbonization (Zheng et al., 2022). Although all three sectors are high-carbon-emitting industries, they differ markedly in transformation pathways, efficiency levels, and constraint mechanisms, highlighting the need for systematic efficiency assessment and pathway design.

Against this backdrop, the present study offers dual contributions. Theoretically, it integrates frameworks from industrial economics and environmental economics and applies data envelopment analysis (DEA) to measure and compare the green transformation efficiency of high-energy-consuming industries, enriching the efficiency evaluation system for manufacturing sector green transformation. Practically, it empirically examines the utilization efficiency of capital and labor inputs across typical high-energy-consuming industries in Jiangsu, providing differentiated low-carbon transformation pathway recommendations. This not only supports enterprises in optimizing production factor allocation and green upgrading but also informs government policy-making for sector-specific green finance and decarbonization strategies.

Based on this rationale, this study addresses the following key questions: What is the level of green transformation efficiency in Jiangsu's manufacturing sector under the dual-carbon goals? What efficiency differences exist among the chemical, ferrous metal, and non-ferrous metal industries? Are inefficiencies primarily driven by scale constraints or by technical and managerial factors? How can differentiated green transformation pathways be designed accordingly? To answer these questions, this study adopts a mixed quantitative and qualitative research approach. Quantitatively, using 2023 industry statistics, DEA models (including CCR and BCC models, supplemented by single-factor robustness checks) are employed to measure and compare industry green transformation efficiency. Qualitatively, the study systematically analyzes industry transformation pathways by considering policy context, industry characteristics, and green development practices, thereby providing targeted policy recommendations and pathway optimization strategies.

2. Literature Review

2.1 Theoretical Foundations and Research Framework

Research on green transformation in the manufacturing sector is generally situated within the broader context of sustainable development and the low-carbon economy, with the central issue being how to achieve a dynamic balance between economic growth and environmental constraints. At the theoretical level, green total factor productivity (GTFP), energy efficiency, and the Environmental Kuznets Curve (EKC) constitute the primary analytical frameworks. GTFP comprehensively reflects overall economic efficiency after accounting for resource consumption and environmental emissions, and characterizes the interactions among technological progress, factor inputs, and environmental constraints (Cai & Ye, 2020). Studies on energy efficiency focus on maintaining economic output growth while reducing energy consumption and pollutant emissions, aligning closely with the high-energy-consuming nature of manufacturing. The EKC theory further elucidates the nonlinear relationship between environmental pollution and economic development, suggesting that pollutant emissions may follow an inverted U-shaped trajectory as the economy grows.

In terms of mechanism explanation, the Porter Hypothesis provides important theoretical support for green transformation. Empirical evidence shows that reasonable and stringent environmental regulations do not undermine corporate competitiveness; instead, they can incentivize firms to pursue green technological innovation, generating an “innovation compensation” effect that improves efficiency over the long term (Liu et al., 2022). Within this logic, environmental regulation, market incentives, and technological progress are regarded as three pillars driving green growth, and their positive interaction facilitates a dynamic balance between efficiency improvement and innovation in the manufacturing sector (Cheng et al., 2023).

2.2 Industry-Level Green Transformation Pathways

At the practical level, high-carbon industries such as steel and chemicals represent both the focal points and the major challenges of global manufacturing green transformation. International studies indicate that low-carbon pathways in the steel industry primarily focus on short-process technologies and raw material substitution. For example, scrap steel recycling and electric arc furnace (EAF) steelmaking are widely considered effective approaches to reducing carbon intensity, while advanced technologies such as hydrogen-based ironmaking and carbon capture, utilization, and storage (CCUS) represent deep decarbonization strategies (Sun et al., 2021; Jin et al., 2023). In the chemical industry, emphasis is placed on production process optimization and raw material substitution, achieving simultaneous reductions in energy consumption and emissions through green process development, renewable feedstock utilization, and clean production systems (Dandotiya et al., 2023). In these industries, technological advancement and policy incentives act as complementary mechanisms, jointly driving low-carbon transformation.

Domestic research closely aligns with China’s dual-carbon strategic goals, emphasizing the coordinated advancement of carbon peaking, carbon neutrality, and high-quality development. At the macro level, scholars focus on industrial structure optimization, region-specific emission reductions, and the enhancement of local governance capacity (Yang et al., 2021). At the industry level, steel and chemical sectors remain research hotspots. Studies on the steel industry primarily address energy efficiency improvement, process optimization, and CCUS application demonstrations, including short-process steelmaking, process intensification, and green electricity substitution. Research on the chemical sector emphasizes green feedstock substitution and process intensification, covering the development of green catalysts, establishment of recycling systems, and minimization of hazardous waste (Ma et al., 2020). Comparative studies generally conclude that low-carbon transformation in the steel industry relies more on process and operational optimization, whereas in the chemical industry it depends on raw material substitution and process innovation, highlighting the complexity and sector-specific nature of transformation pathways.

2.3 Methodological Applications and Research Progress

In terms of research methods, efficiency measurement has become a crucial tool in studies of green transformation. Data Envelopment Analysis (DEA), super-efficiency Slack-Based Measure (SBM) models, and the Malmquist index are widely applied for both static and dynamic assessments of green efficiency. These methods can simultaneously account for multiple inputs and outputs, including undesirable outputs, thereby providing a more accurate depiction of green performance in the manufacturing sector (Zhao et al., 2022). Among them, the DEA-SBM model is frequently employed in carbon emission efficiency studies due to its adaptability to undesirable outputs, revealing differences in green efficiency across regions and industries as well as their dynamic evolution (Cai & Ye, 2020). The Malmquist index, by decomposing efficiency changes over time, distinguishes the contributions of technological progress and technical efficiency, offering a valuable tool for analyzing the dynamic evolution of green transformation.

Meanwhile, the Stochastic Frontier Analysis (SFA) method has also been applied in green efficiency research. Its advantage lies in identifying the sources of efficiency loss and revealing how institutional environments, technological levels, and factor allocation differentially affect efficiency (Liu et al., 2022). Supported by these methods, green total factor productivity (GTFP) has gradually become a key indicator for evaluating industrial structure optimization and emission reduction performance. Overall, the diversification of methodologies has significantly advanced research on green transformation, enabling scholars to uncover spatial-temporal variations and evolutionary patterns of manufacturing sector green efficiency from multiple perspectives.

2.4 Research Gaps and Study Positioning

Despite the accumulation of substantial literature, several gaps remain. First, contextualized studies at the region–industry level are relatively limited, and cross-industry systematic comparisons are scarce, resulting in insufficient understanding of the heterogeneity of green transformation pathways across industries. Second, the integration of efficiency measurement methods with industry practices remains insufficient; some studies overemphasize model calculations while neglecting alignment with practical emission reduction technologies and policy instruments, thereby weakening the policy relevance of their conclusions. Third, although the "regulation–innovation–performance" transmission mechanism has been explored to some extent, how local governments, industry associations, and enterprises collaboratively deploy policy tools to promote green transformation remains largely empirically untested (Zhang et al., 2022).

To address these gaps, this study focuses on Jiangsu Province—a major manufacturing hub in China—selecting the steel and chemical industries as the primary cases, with the non-ferrous metal sector as a reference. Methodologically, it combines DEA-based efficiency measurement with industry practice analysis, revealing differences in green transformation efficiency across industries while enhancing the robustness of conclusions through sensitivity checks. The study aims to contribute to region–industry contextualized analysis, cross-industry comparison, and the integration of methodology with practice, providing empirical support and policy insights for the green transformation of high-carbon industries in China.

3. Research Methods

3.1 Data Source

All data employed in this study are obtained from the Jiangsu Statistical Yearbook 2024, which is compiled and published by the Jiangsu Provincial Bureau of Statistics. The yearbook provides comprehensive and authoritative statistical information on the province' s economic and social development. For the purposes of this research, we extracted industry-level indicators related to the manufacturing sector, including energy consumption, fixed asset investment, labor input, and industrial output. These variables constitute the core dataset for evaluating the efficiency of green transformation. All figures and tables presented in the results section are derived from empirical modeling and analysis based on this dataset.

3.2 Model Selection and Theoretical Foundation

Under the dual-carbon constraints, the green transformation of the manufacturing sector hinges on improving the coordinated efficiency of factor inputs and outputs, particularly energy, capital, and labor. A central methodological challenge is how to rigorously assess the relative efficiency of industries in resource utilization and output generation. Efficiency evaluation methods are generally divided into parametric and non-parametric approaches. The former specifies a functional form of production and is prone to bias from model misspecification, while the latter does not require prior assumptions about the production function and instead constructs the efficiency frontier directly from observed data. This makes non-parametric methods particularly suitable for multi-indicator efficiency analysis at the industry level.

Among non-parametric methods, Data Envelopment Analysis (DEA) has been widely applied in studies of green development and industrial efficiency because it can simultaneously handle multiple inputs and outputs and delineate the production possibility frontier through linear programming. Given that green transformation emphasizes "minimizing inputs for a given output level," this study employs an input-oriented DEA model to measure the relative efficiency of industries in terms of energy, capital, and labor inputs. Let the j-th decision-making unit (DMU) have an input vector $x_j = (x_{1j}, x_{2j}, \dots, x_{mj})^{\top}$ and an output vector $y_j = (y_{1j}, y_{2j}, \dots, y_{sj})^{\top}$. Under the CCR model, the efficiency evaluation problem for the o-th DMU can be expressed as:

$$\min_{\theta,\lambda} \theta \tag{1}$$

$$\text{s.t.} \sum_{j=1}^{n} \lambda_j x_{ij} \le \theta x_{io}, \quad i = 1, \dots, m \tag{2}$$

$$\sum_{j=1}^{n} \lambda_j y_{rj} \geq y_{ro}, \quad r = 1, \ldots, s \tag{3}$$

$$\lambda_j \geq 0, \quad j = 1, \ldots, n \tag{4}$$

where θ represents the efficiency score and λj denotes the weight variables. When θ = 1 and all constraints are satisfied, the DMU lies on the efficiency frontier; otherwise, it exhibits varying degrees of efficiency loss.

To further distinguish technical efficiency from scale efficiency, this study introduces a convexity constraint in the BCC model—building on the CCR model assumption of constant returns to scale (CRS)—to capture variable returns to scale (VRS) conditions. The objective function is consistent with that of the CCR model, but the constraints are more stringent:

$$\sum_{j=1}^{n} \lambda_j = 1 \tag{5}$$

By comparing efficiency results from the CCR and BCC models, overall efficiency can be decomposed into pure technical efficiency and scale efficiency, thereby revealing the extent to which industries' green transformation is constrained by technological versus scale limitations.

3.3 Indicator Selection and Variable Construction

Based on data provided by the *Jiangsu Industrial Statistics Yearbook* and the characteristics of green transformation in manufacturing, this study constructs input and output indicators according to the principles of availability, representativeness, and relevance. For inputs, "total assets" and "average employment" are selected as proxies for capital and labor factors at the industry level. Total assets reflect the industry's capital stock and fixed investment scale, while average employment captures the level of labor input; together, they provide a comprehensive depiction of resource allocation across industries. For outputs, "operating revenue" is chosen as a representative indicator of economic output, reflecting both market creation capacity and, indirectly, the efficiency of resource utilization.

Accordingly, the structure of the DEA model can be formalized as:

$$X = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \end{bmatrix}, \quad Y = \begin{bmatrix} y_{11} & y_{12} & \cdots & y_{1n} \end{bmatrix} \tag{6}$$

where the input matrix X includes total assets and average employment, and the output matrix Y comprises operating revenue.

Regarding industry selection, this study focuses on typical high-energy-consuming and high-emission sectors within Jiangsu's manufacturing industry. The primary industries examined are "ferrous metal smelting and rolling" (i.e., steel industry) and "chemical raw materials and chemical products manufacturing" (i.e., chemical industry), with "non-ferrous metal smelting and rolling" serving as a reference to enhance comparability in efficiency measurement. These industries are prominent contributors to energy consumption and carbon emissions, and exhibit certain differences in transformation pathways, providing empirical support for analyzing both the commonalities and heterogeneities of green transformation in Jiangsu's manufacturing sector.

3.4 Empirical Procedure and Robustness Design

The empirical procedure begins by treating industries as decision-making units (DMUs), constructing DEA models, and calculating industry efficiency scores under both constant returns to scale (CRS) and variable returns to scale (VRS) assumptions. By comparing CCR efficiency with BCC efficiency, the scale effects on industry efficiency can be further analyzed, revealing the extent of scale constraints and potential for optimization in different sectors' green transformation.

To ensure the robustness of the empirical results, a sensitivity test is designed. Specifically, the input indicator system is adjusted to retain only "average employment" as a single input, the DEA model is rerun, and the efficiency results are compared with those obtained under the original "two-input–one-output" framework. The testing logic can be simplified as:

$$\theta^{(1)} = f\left(X^{(2)}, Y\right), \quad \theta^{(2)} = f\left(X^{(1)}, Y\right) \qquad (7)$$

where $\theta^{(1)}$ represents efficiency results under the dual-input system, and $\theta^{(2)}$ represents efficiency results under single labor input. If the efficiency rankings and relative differences remain largely consistent across both scenarios, the study's conclusions can be considered robust.

In summary, the empirical design follows a logical path of "model selection → indicator construction → efficiency measurement → robustness check," which not only reveals the current status and disparities of green transformation efficiency in the steel and chemical industries but also enhances the scientific rigor and credibility of the findings through methodological validation.

4. Results

4.1 Baseline Efficiency Measurement

To evaluate the green transformation efficiency of typical high-energy-consuming industries in Jiangsu Province under the dual-carbon constraints, industries were treated as decision-making units (DMUs) and assessed using an input-oriented DEA model. Inputs included "total assets" (100 million CNY) and "average employment" (10,000 persons), while "operating revenue" (100 million CNY) was used as the output. Efficiency scores under constant returns to scale (CRS) and variable returns to scale (VRS) assumptions are presented in Table 1.

Table 1. Green Transformation Efficiency of Industries (Two Inputs–One Output)

Industry	Total Assets (100 million CNY)	Average Employment (10,000 persons)	Operating Revenue (100 million CNY)	CCR (CRS) Efficiency	BCC (VRS) Efficiency

Chemical Raw Materials and Chemical Products Manufacturing	10,699.54	30.98	9,384.61	0.5611	0.5687
Ferrous Metal Smelting and Rolling	9,256.30	21.44	12,721.05	1.0000	1.0000
Non-ferrous Metal Smelting and Rolling	2,938.15	13.05	6,074.06	1.0000	1.0000

As shown in Table 1, the efficiency scores of ferrous (steel) and non-ferrous metal smelting and rolling industries are equal to 1 under both the CCR and BCC models (θ = 1), indicating that these two sectors lie on the DEA frontier based on the input-output framework employed in this study. There is no significant input redundancy or output insufficiency, and they can be considered the efficiency frontier within the sample.

By contrast, the chemical raw materials and products manufacturing industry exhibits a CCR efficiency of 0.5611 (BCC efficiency = 0.5687), far below 1. For an input-oriented DEA model, θ = 0.5611 can be interpreted as follows: while maintaining the current output level, total inputs in this industry could theoretically be reduced to approximately 56.11% (a reduction of 43.89%) to reach the efficiency frontier. This indicates substantial input redundancy or insufficient output. The small difference between CCR and BCC scores for the chemical industry (CCR/BCC ≈ 0.987) suggests that scale efficiency is nearly 1, implying that the low efficiency is primarily attributable to technical or managerial factors—such as process level, workflow management, or limited green innovation—rather than scale constraints.

To visually present these results, Figures 1 and 2 illustrate the efficiency distribution of each industry under the CCR and BCC assumptions, respectively.

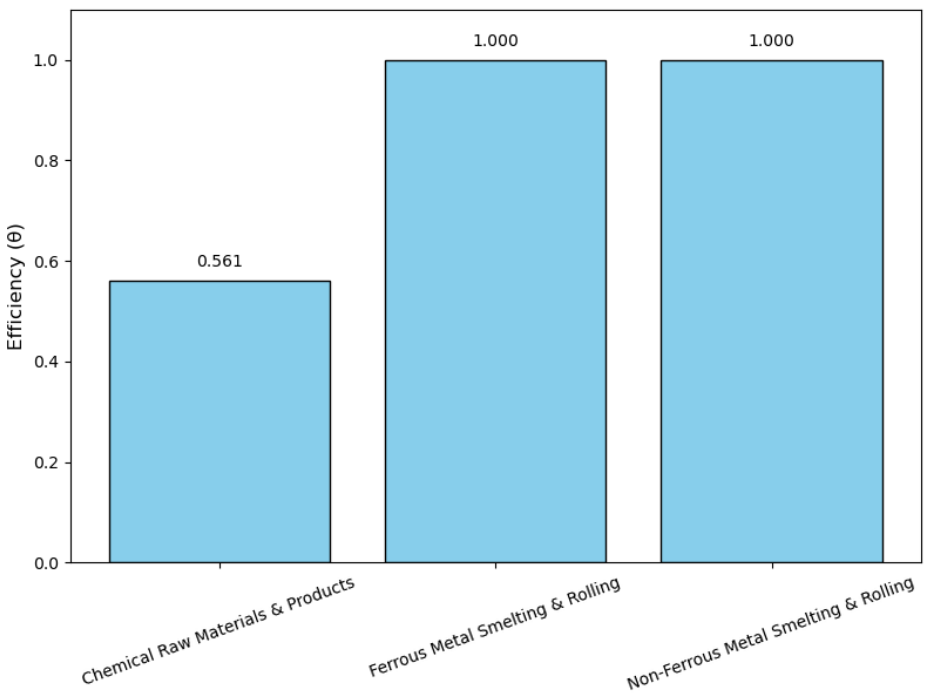

Figure 1. CCR (CRS) Efficiency Results: Two Inputs–One Output

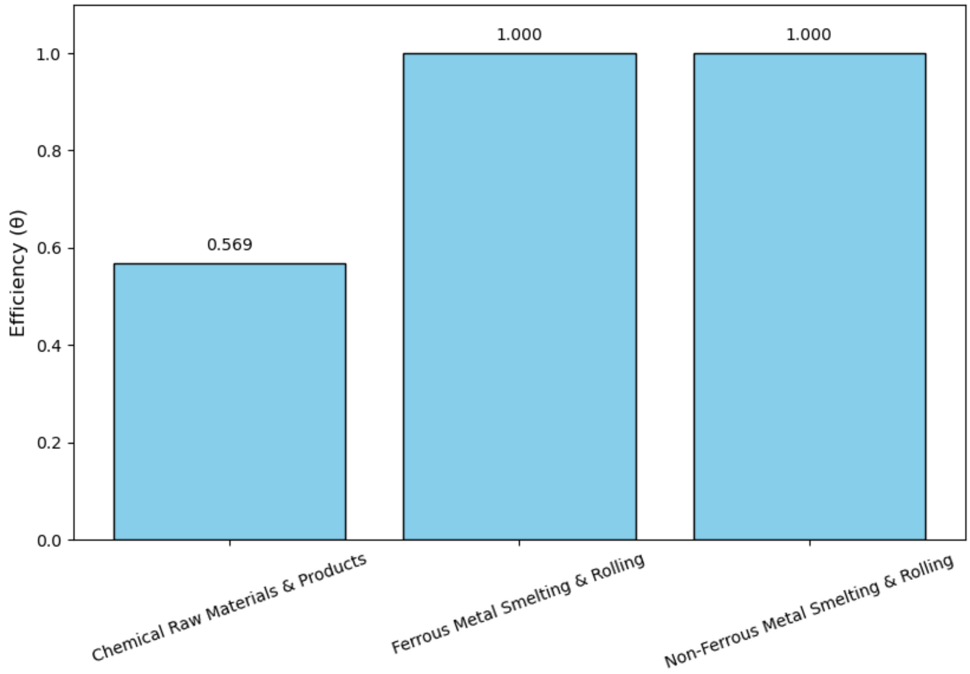

Figure 2. BCC (VRS) Efficiency Results: Two Inputs–One Output

Figure 1 shows that under the CRS assumption, ferrous and non-ferrous metal smelting and rolling industries achieve full efficiency (efficiency = 1), while the chemical raw materials and products manufacturing industry scores only about 0.561, lagging behind the other two sectors. This indicates considerable input waste or output insufficiency in the chemical industry under the context where overall production scale is linked to output, and its resource allocation efficiency does not reach the frontier level.

Figure 2 presents the VRS-based efficiency results. The ferrous and non-ferrous metal industries maintain full efficiency (efficiency = 1), further confirming their high factor utilization and output efficiency in green transformation. The chemical industry's efficiency shows a slight increase (from 0.561 to 0.569), but overall remains low. This suggests that even after accounting for potential scale inefficiencies, the low efficiency in the chemical sector is still driven by internal management, process technology, or insufficient green innovation, rather than scale limitations.

Overall, the results from both figures consistently indicate that the steel and non-ferrous metal smelting industries are on the efficiency frontier and remain relatively stable in the green transformation process, whereas the chemical industry exhibits efficiency disadvantages. This disparity highlights differences in green transformation pathways across industries and provides direct empirical evidence to inform subsequent policy recommendations.

4.2 Robustness Check

To further verify the robustness of the results and more intuitively illustrate inter-industry efficiency differences, two visualization tools were employed: radar charts and 3D efficiency frontier surfaces.

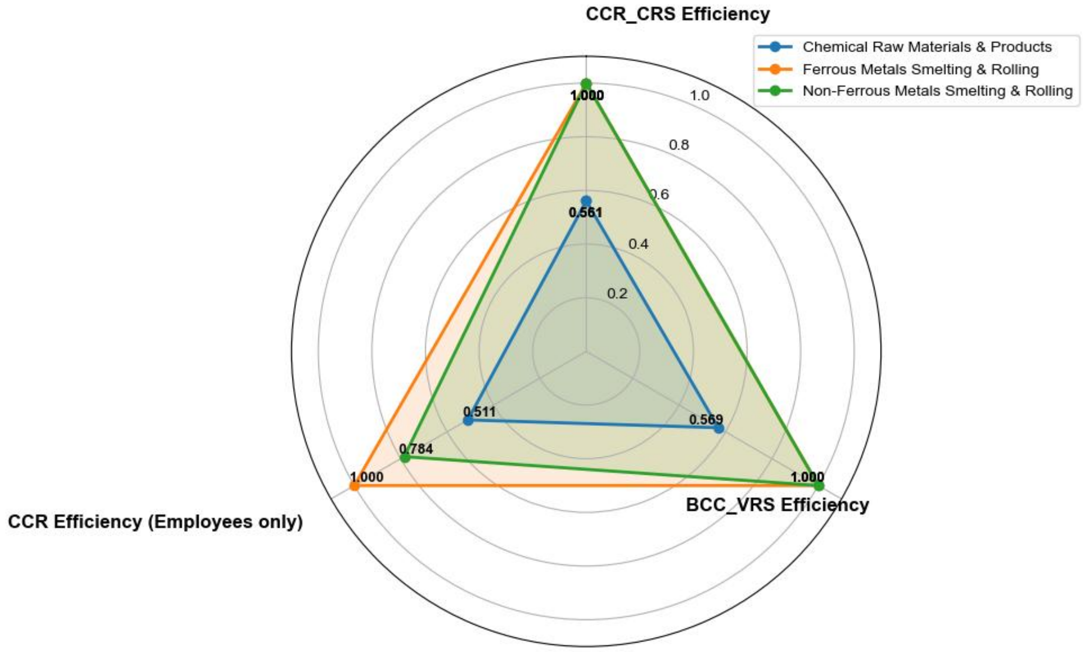

Figure 3. Radar Chart of Industry Green Transformation Efficiency (Comparison of CCR, BCC, and Single Labor Input)

The radar chart in Figure 3 visually compares the performance of each industry across different efficiency measures. The chemical raw materials and chemical products manufacturing industry exhibits generally low efficiency: CCR–CRS efficiency is 0.561, BCC–VRS efficiency is 0.569, and under the single-input (labor) scenario, efficiency further decreases to 0.511, highlighting its notable inefficiency. In contrast, ferrous metal smelting and rolling maintains full efficiency ($\theta = 1.000$) across all three dimensions, indicating optimal utilization of both labor and capital. The non-ferrous metal smelting and rolling industry reaches the frontier under the two-input scenario, but efficiency drops to 0.784 under the single labor input, suggesting that its efficiency relies on a reasonable combination of capital and labor.

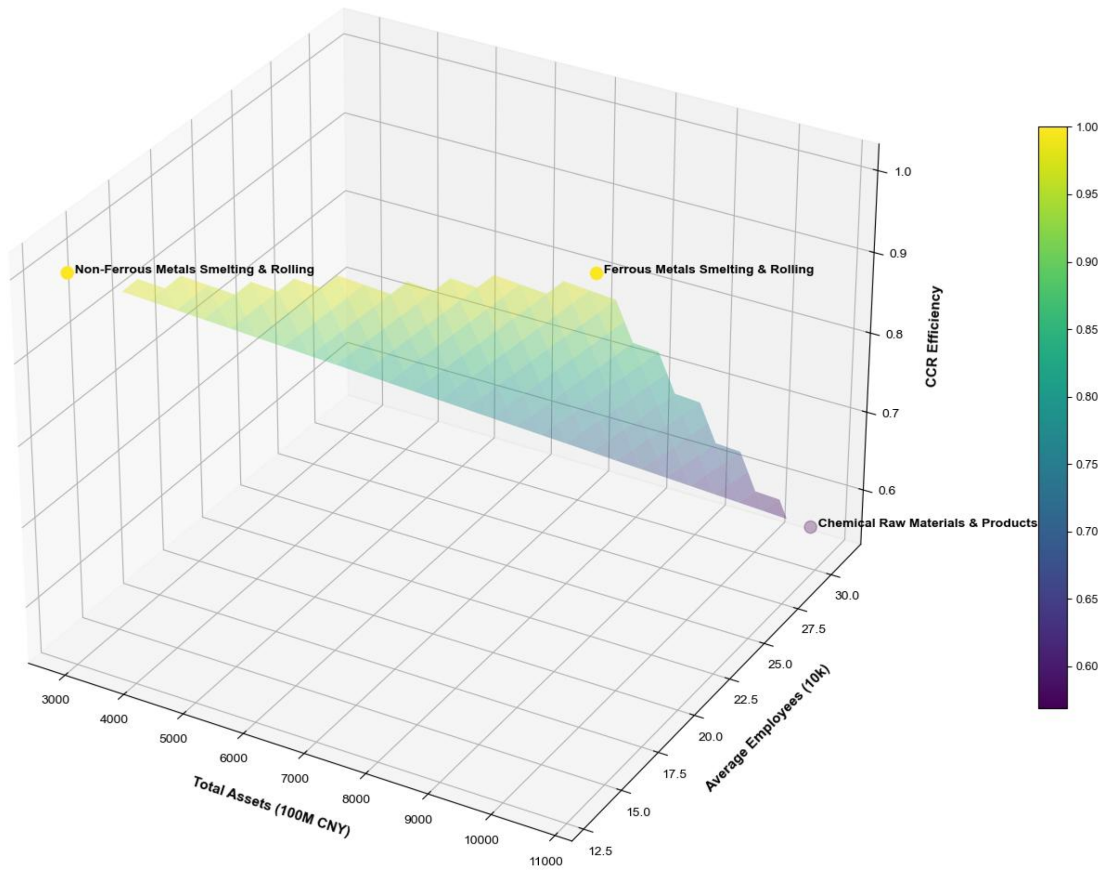

Figure 4. 3D Distribution and Efficiency Frontier Surface of Industry Green Transformation (CCR Model)

In Figure 4 (3D distribution and efficiency frontier based on CCR efficiency), the x- and y-axes represent total assets (100 million CNY) and average employment (10,000 persons), respectively, while the z-axis shows CCR (CRS) efficiency. Point colors are scaled by BCC (VRS) efficiency. Using griddata interpolation, the CCR efficiency of the three observed points is smoothed over the asset–labor plane to generate a semi-transparent surface, visually illustrating the spatial distribution of efficiency values with respect to the two inputs.

Combining with the specific values in Table 1: the chemical industry (total assets = 10,699.54, employment = 30.98) has CCR = 0.561 and BCC = 0.569; ferrous metal (total assets = 9,256.30, employment = 21.44) and non-ferrous metal (total assets = 2,938.15, employment = 13.05) industries both have CCR and BCC efficiencies of 1.000. In the 3D plot, the steel and non-ferrous metal points are positioned at the CCR = 1 level (the observed "efficient" points), while the chemical industry lies well below this height ($z \approx 0.561$), fully consistent with Table 1 values. This indicates that the former two industries form the DEA efficiency frontier in the sample and input-output framework, whereas the chemical industry exhibits a significant efficiency gap.

It should be noted that the plotted surface is an interpolated approximation of the three observed CCR values, not the DEA frontier strictly derived from linear programming. Due to the limited sample size (three points), the interpolated surface provides a qualitative visualization and may produce boundary artifacts or local undulations; thus, it should be interpreted as a visual aid rather than a quantitative proof. Quantitatively, the DEA frontier remains represented by the θ values in Table 1. Based on this understanding, the key insights from Figure 4 are: (1) ferrous and non-ferrous metals reach the observed sample efficiency frontier under the applied input-output framework; (2) the chemical industry's CCR ≈ 0.561 (BCC ≈ 0.569) is substantially below 1, indicating a notable inefficiency primarily due to technical or managerial factors rather than scale effects. This reinforces the conclusion drawn from the CCR and BCC comparison.

Overall, these visualizations further strengthen the reliability of the baseline results: ferrous and non-ferrous metal smelting and rolling industries lie on the efficiency frontier and exhibit high resource allocation efficiency, whereas the chemical industry clearly lags, with inefficiency consistently demonstrated across different metrics and visual checks.

4.3 Result Analysis

Synthesizing the baseline measurements and robustness checks yields several insights:

(1) The ferrous metal smelting and rolling industry exhibits the highest efficiency, indicating a relatively balanced performance in energy conservation, emission reduction, and output creation. Its future green transformation efforts should focus on deep decarbonization and technological breakthroughs. (2) The chemical raw materials and products manufacturing industry shows significantly lower efficiency, highlighting substantial room for improvement in green processes, technological innovation, and factor allocation. Future efforts should prioritize raw material substitution, clean processes, and circular utilization to enhance input efficiency. (3) The non-ferrous metal smelting and rolling industry maintains generally high efficiency; however, the radar chart indicates sensitivity to input structure, suggesting that optimizing the match between capital and labor is critical to prevent efficiency decline during transformation.

In summary, under the dual-carbon constraints, significant inter-industry differences in green transformation efficiency exist within Jiangsu's manufacturing sector. The chemical industry remains a bottleneck and should be a priority for policy support and technological innovation, while the steel and non-ferrous metal sectors, despite high efficiency, still need to explore pathways for deeper decarbonization.

5. Conclusions and Recommendations

5.1 Conclusions

Based on DEA (input-oriented, with assets and average employment as inputs and operating revenue as output) empirical measurements for 2023 cross-sectional data of three representative high-energy-consuming industries in Jiangsu Province—namely, chemical raw materials and chemical products manufacturing, ferrous metal smelting and rolling, and non-ferrous metal smelting and rolling—the main conclusions of this study are as follows:

Significant inter-industry efficiency differences. Under the "two-input, one-output" framework, ferrous and non-ferrous metal smelting and rolling industries are located on the DEA frontier in both CCR and BCC models ($\theta = 1$), indicating a relatively balanced combination of capital and labor inputs and output generation, with no significant input redundancy. In contrast, the chemical industry exhibits significantly lower efficiency (CCR $\theta \approx 0.561$, BCC $\theta \approx 0.569$), suggesting substantial input redundancy or output insufficiency. From an input-oriented perspective, the industry could reduce overall inputs by approximately 43.9% to reach the sample frontier.

Low efficiency is not primarily caused by scale issues. The minimal difference between CCR and BCC efficiency values in the chemical industry indicates scale efficiency is close to 1; thus, returns to scale are not the main driver of its inefficiency. This implies that the industry's low efficiency mainly stems from technical, process, or managerial shortcomings rather than simple mismatches in production capacity.

Sensitivity to input specification varies across industries. Robustness checks using only average employment as input show that ferrous metals maintain frontier efficiency ($\theta = 1$) from a labor perspective; chemical industry efficiency further declines ($\theta \approx 0.511$), highlighting its disadvantage under labor-intensive conditions; non-ferrous metals see a significant drop in efficiency (from 1.000 to 0.7845), indicating strong dependence on the capital–labor combination.

Policy and technological pathways require differentiation. The three industries exhibit significant heterogeneity in green transformation performance and constraint mechanisms. The chemical industry should prioritize technological upgrades and process optimization, focusing on managerial and process innovation. Ferrous and non-ferrous metals, despite overall high efficiency, still need to pursue deep decarbonization technologies and optimize input structures to avoid the "high-efficiency but high-carbon" trap.

In summary, under the dual-carbon targets, Jiangsu's manufacturing sector is not uniformly deficient: some industries have achieved relatively reasonable input-output configurations, while others (notably the chemical industry) face significant efficiency gaps, requiring coordinated efforts in technology, management, finance, and policy.

5.2 Recommendations

Based on the above conclusions, the following recommendations are proposed from multiple perspectives, including government, industry associations, enterprises, financial mechanisms, and research institutions.

Government level: Implement differentiated policy mixes to avoid "one-size-fits-all" management. For the chemical industry, provide fiscal subsidies, tax incentives, and green funds to support process upgrades and green technology adoption. For the steel and non-ferrous metal sectors, promote demonstrations of deep decarbonization technologies such as hydrogen metallurgy, electric furnace substitution, and CCUS to maintain both efficiency and emission reduction. Additionally, improve green regulation and performance assessment systems by incorporating carbon intensity and energy consumption into evaluation metrics, linking them with fiscal support and credit conditions to form dynamic incentives. Cross-regional industrial collaboration and industrial park energy complementarity can further enhance systemic resource utilization efficiency.

Industry and association level: Develop low-carbon roadmaps specifying short-, medium-, and long-term green transformation targets, and promote experience replication through standardization and demonstration projects. Establish collaborative platforms for industrial chain coordination and green process demonstration, particularly in the chemical industry to strengthen raw material substitution and circular utilization. Enhance management and frontline workforce green production capabilities through vocational training and knowledge dissemination.

Enterprise level: Chemical industry firms should prioritize energy efficiency improvement and process optimization, conduct energy audits, and implement ISO 50001 energy management systems. Accelerate the adoption of green raw materials, by-product recycling, and clean processes to reduce input waste and emission intensity. Non-ferrous metal firms should optimize capital–labor matching through digitalization, automation, and intelligent manufacturing to prevent efficiency decline due to factor misallocation. Steel and non-ferrous metal enterprises should invest in deep decarbonization technologies and low-carbon pilot projects to avoid path dependence of “high efficiency but high carbon.”

Financial and market mechanisms: Use green credit, green bonds, and carbon finance products to lower transformation costs, and link credit and insurance mechanisms to energy efficiency and emission reduction performance to guide resource allocation. Carbon markets should further improve price discovery, provide clear economic incentives for emission reduction, and implement transitional arrangements to buffer short-term shocks.

5.3 Research Limitations and Future Directions

Although the findings of this study are informative, several limitations exist:

The indicator system is incomplete, omitting undesirable outputs such as energy consumption and carbon emissions. Future research could apply Malmquist indices or similar methods to study the dynamic evolution of carbon efficiency.

The study focuses on the industry level and does not cover heterogeneity at the enterprise or sub-industry level. Future research could use more granular data to enhance DEA discriminative power and provide more precise policy recommendations.

This study is based on static cross-sectional analysis. Future work could integrate policy shocks and market factors, employing quasi-experimental methods to identify causal effects of different policy instruments on green transformation efficiency.

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