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Evaluation of Green Transformation Efficiency in Manufacturing Industry based on Super Efficient SBM-ML Model

Abstract. Introduction*. The manufacturing sector is a vital driver of high-quality economic development and plays a crucial role in promoting comprehensive green economic and social transformation.*

Purpose*. Promoting the green transformation and upgrading of the manufacturing industry is essential for achieving high-quality economic development and accelerating the sector's continuous growth.*

Results*. This paper uses provincial panel data from 2011 to 2023 and the SBM-GML index model to evaluate the efficiency of China's green transformation and development in manufacturing. The paper also uses kernel density estimation methods to depict the evolution of these trends over time.*

Conclusions*. To improve the efficiency of the manufacturing industry's green transformation and development, the paper suggests improving the level of green technology innovation, strengthening policy guidance and supervision, and enhancing talent training for manufacturing transformation.*

Keywords*: Super Efficiency SBM-ML Model; Kernel Density Estimation; Green Transformation of Manufacturing Industry*

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Оцінка ефективності «зеленої» трансформації обробної промисловості на основі надефективної моделі SBM-ML

Анотація. *Обробна промисловість є важливим двигуном сприяння високоякісному розвитку національної економіки та відіграє важливу роль у просуванні комплексної зеленої трансформації економічного та соціального розвитку. Сприяння «зеленої» трансформації та модернізації обробної промисловості є не лише неминучою вимогою для досягнення якісного економічного розвитку, а й неминучим вибором для прискорення сталого розвитку обробної промисловості. У цій статті вибрано провінційні панельні дані за період з 2011 по 2023 рік, використовується модель індексу SBM-GML для оцінки ефективності розвитку обробної промисловості Китаю, а також використовується метод оцінки густини ядер для опису тенденції її динамічної еволюції.*

Ключові слова: *надефективна модель SBM-ML; оцінка щільності ядра; "Зелена" трансформація обробної промисловості*

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Formulation of the problem. As the global climate governance system undergoes profound changes and technological innovation continues to advance, green and low-carbon development has become a strategic advantage in international industrial competition and an inevitable trend in global economic transformation. As a major manufacturing country, China's green transformation impacts not only its domestic "dual carbon" goals, but also significantly influences the global green and low-carbon development landscape. This transformation involves integrating environmental protection, resource conservation, and ecological friendliness into every aspect of production, including technological innovation, management optimization, and industrial restructuring. It is crucial to evaluate the efficiency of this complex transformation process, identify efficiency differences among regions, industries, and enterprises, and understand the factors influencing these differences. This information is essential for formulating precise and effective green transformation policies, optimizing resource allocation, and enhancing overall competitiveness. Establishing a more scientific, comprehensive, and dynamic framework for efficiency evaluation analysis can provide robust empirical support for the green transformation of China's manufacturing sector. This framework offers the government a scientific basis and decision-making reference for formulating targeted policies for the green transformation of manufacturing and helps enterprises optimize resource allocation and improve production methods. Thus, it promotes the high-quality, sustainable green transformation and upgrading of the manufacturing industry.

Research Methods. The Super-Efficiency Slack-Based Measure (SBM) Model is a Data Envelopment Analysis (DEA) method designed to assess technical efficiency and provide improvement guidance. Tone K developed it through gradual refinement to address the limitation of basic DEA models, which have an efficiency value ceiling of 1. This makes it impossible to compare the efficiency levels of different decision-making units. The Super-Efficiency SBM Model builds on traditional DEA by incorporating slack variables, which represent potential improvements in resources and outputs. The model considers differences in resource allocation among units and their potential for improvement, offering more accurate and reasonable efficiency assessments and improvement recommendations. In the context of green transformation and development in manufacturing, input variables are fundamental to output outcomes, and this paper employs an input-oriented super-efficiency SBM model. Under variable returns to scale, there are n decision-making units (DMUs), denoted as DMUj (j=1,2,...,n). Each DMU has m inputs xi (i=1,2,...,n) and q outputs yr (r=1,2,...,q). The super-efficiency model for the k-th DMU from an input perspective is as follows:

$$\min \rho = 1 + \frac{1}{m}\sum_{i=1}^{m}\frac{s_i^-}{x_{i,k}} \tag{1}$$

$$s.t.\begin{cases} \sum_{j=1, j\neq k}^{n} x_{ij}\lambda_j - s_i^- \leq x_{ik} \\ \sum_{j=1, j\neq k}^{n} y_{rj}\lambda_j \geq y_{rk} \\ \lambda, s^-, s^+ \geq 0 \\ i = 1,2,\ldots m; r = 1,2,\ldots q; j = 1,2,\ldots; (j \neq k) \end{cases} \tag{2}$$

The Malmquist index measures economic and production efficiency and is used to evaluate changes in production efficiency between two time periods or groups. It measures the change in total factor productivity (TFP) of a unit or industry between two time points or groups. According to its calculation method, if the Malmquist index of a unit or industry is greater than one, it indicates an increase in production efficiency. Conversely, if it is less than one, it indicates a decrease. When the Malmquist index equals 1, production efficiency remains unchanged. The formula for the Malmquist index is as follows:

$$ML^{t+1} = \frac{D^{t+1}(x^{t+1}, y^{t+1})}{D^{t+1}(x^t, y^t)} \tag{3}$$

D is the technical distance function for a specific period, and t and t+1 periods will show different levels of technology. At the same time, considering the error that may be generated by randomly selecting reference points, it is usually set as the geometric average of M t and Mt+1 in the calculation of Malmquist productivity index, as shown below:

$$TFP = M(x^{t+1}, y^{t+1}, x^t, y^t) = \left[\frac{D^t(x^{t+1}, y^{t+1})}{D^t(x^t, y^t)} * \frac{D^{t+1}(x^{t+1}, y^{t+1})}{D^{t+1}(x^t, y^t)}\right]^{\frac{1}{2}} \tag{4}$$

To explore the evolving characteristics of green development in China's manufacturing sector, this paper employs a non-parametric kernel density estimation method to analyze the spatiotemporal dynamic evolution of spatial distribution. It aims to plot the kernel density curve of the green transformation and development in manufacturing, thereby analyzing the spatiotemporal evolution characteristics of this transformation. Assuming that random variables X_1,X_2,X_3,.......X_nare independent and identically distributed, with X1's density function f(x) being unknown, the kernel density estimation formula can be expressed as:

$$f(x) = \frac{1}{Nh}\sum_{i=1}^{N} K\left(\frac{X_i - x}{h}\right) \tag{5}$$

N is the number of samples; h is the bandwidth; Xi is the independent and identically distributed observation value; X is the mean; K (·) is the kernel function, which satisfiesK≥0, $\int_{-\infty}^{+\infty} K(X)\,dx=1$

Gaussian kernel function is adopted, and the expression is as follows:

$$K(x) = \frac{1}{\sqrt{2\pi}}\exp\left(-\frac{x^2}{2}\right) \tag{6}$$

Based on the above calculation method, a further constructed evaluation index system is developed to measure the green transformation and development level of China's manufacturing industry. This system adheres to the principles of scientificity, comprehensiveness, operability, comparability, and quantification. It also makes appropriate adjustments and measurements according to specific conditions to ensure the scientificity and accuracy of the evaluation results.

Table 1 **Evaluation index system of green transformation development level in manufacturing industry**

Primary indicators	Secondary indicators	Measures of achievement
Input indicators	capital input	Stock of fixed capital
	energy consumption	Total industrial energy consumption
	Labor input	Number of people employed in manufacturing
Expected output indicators	Economic output	Value added of the secondary industry
Non-expected output indicators	environmental pollution	Carbon dioxide emissions
		Industrial wastewater discharge
		Industrial sulfur dioxide emissions
		General industrial solid waste

The data mainly come from the China Energy Statistical Yearbook, the China Statistical Yearbook, the China Labor Statistical Yearbook, and the China Environmental Statistical Yearbook. Some missing values were filled using the interpolation method.

Formulation of research goals. This study uses the super-efficiency SBM-GML index model to accurately assess the green transformation efficiency of China's manufacturing sector. Unlike traditional efficiency models, it uses the super-efficiency SBM model to differentiate and quantify the relative efficiency levels of manufacturing enterprises or regions that have reached the efficiency frontier, identifying true efficiency leaders. The study also considers unintended outputs generated during the green transformation of the manufacturing industry. It addresses these undesirable output indicators through the SBM model, providing a more accurate reflection of the true efficiency outcomes of the green transformation. This approach avoids overestimating efficiency by neglecting pollution issues. Integrating the ML index allows the study to accurately gauge the effectiveness of green transformation at various points in time for manufacturing enterprises. This enables the study to dynamically track and measure evolving trends and convergence of green transformation efficiency over time, effectively revealing dynamic patterns of improvement or decline in the manufacturing sector's green transformation efficiency.

Outline of the main research material. Using the super efficiency SBM model of non-desired output with formula (1)-(4), the green development level of China's manufacturing industry from 2011 to 2023 is measured by green total factor productivity, and the specific calculation results are shown in the figure below:

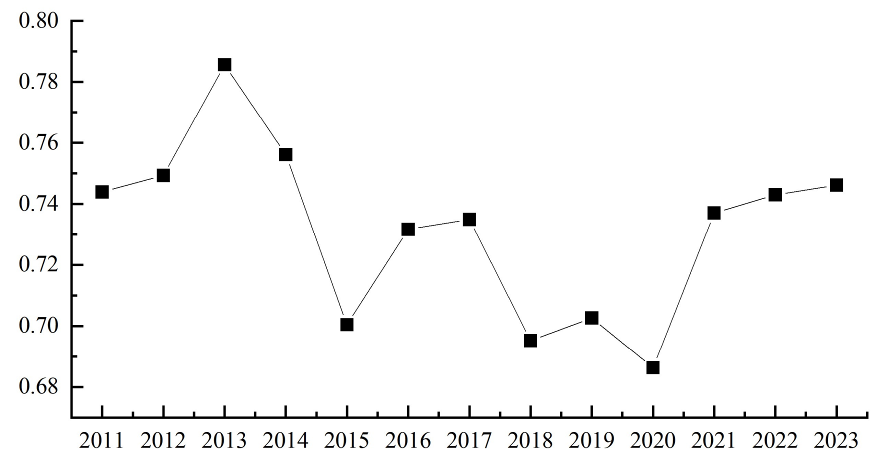

Figure 1 **– Trend of green development level of China's manufacturing industry from 2011 to 2023**
Source: Calculated by Matlab Software

As shown in Figure 1, China's manufacturing industry experienced fluctuating levels of green development from 2011 to 2023. Specifically, from 2011 to 2013, the level remained relatively stable despite significant fluctuations, indicating an upward trend. This indicates that, during this period, the manufacturing sector was making slow progress in its green transformation and had not yet established clear growth momentum. After

2015, China's green development level began to rise significantly, reaching approximately 0.73 by 2017. This improvement was likely due to the implementation of environmental protection policies and green development strategies at the national level, promoting the manufacturing industry's transformation towards greener practices. There was a slight decline in 2018, but the level rebounded in 2019. It reached its lowest point in 2020 due to the impact of the pandemic, which restricted the manufacturing sector's development and led to a lower growth rate in green development. Since 2022, the level has slowly risen, primarily due to national green development policies, technological innovation, and market demand. This demonstrates China's significant progress in promoting the green transformation of the manufacturing industry. Overall, China's manufacturing industry's green development level has fluctuated upward over the past decade, reflecting the guiding role of national policies such as industrial green and low-carbon transformation and green development. These policies have helped promote the manufacturing industry in a direction that is greener and lower-carbon.

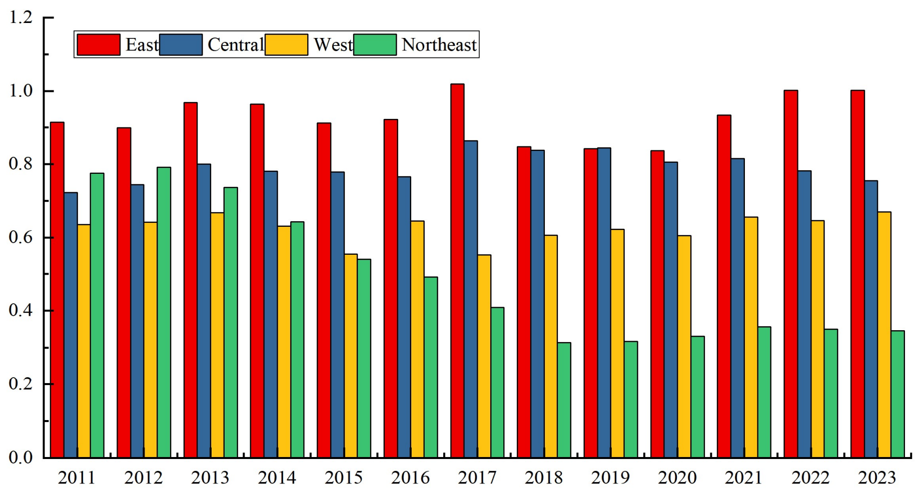

Figure 2 **Green development level of manufacturing industry in four regions from 2011 to 2023**

Source: Calculated by Matlab Software

As shown in Figure 2, the trend of green development in manufacturing has steadily increased across the four regions from 2011 to 2023. The eastern region is leading the green transformation and development of manufacturing overall, though differences remain among the four regions. Before 2020, the green development levels of manufacturing in the eastern, central, western, and northeastern regions were all rising, with the eastern region showing notably higher growth rates than the other regions. This is mainly due to the eastern region's strong economic foundation and well-developed industrial chains, which provide a solid economic base for the green transformation of manufacturing enterprises. Meanwhile, the central region also showed a growth trend, but its growth rate was slower than that of the eastern region. This is primarily because the central region has more traditional industries, making it more challenging to transition to green development. In contrast, the western region has significant green development potential due to its mountainous terrain, abundant natural resources, and national policy support, which provide favorable conditions for manufacturing enterprises to undergo green transformation. However, the northeastern region has experienced significant fluctuations in its green development level because it is dominated by heavy industry and has a single industrial structure, which makes it difficult for enterprises to achieve green transformation. Following the onset of the global pandemic, the green transformation and development levels of manufacturing in the four regions have fluctuated significantly. These fluctuations are driven by the national "dual carbon" goals, which have made green development an inevitable choice for achieving sustainable business growth. To further study the dynamic changes in green transformation efficiency in China's manufacturing industry, the Malmquist index was calculated using MATLAB software to analyze the changes in the total factor productivity of manufacturing enterprises in 30 provinces from 2011 to 2023. The changes in comprehensive technical efficiency and technological progress rate were then decomposed. The specific results are shown in the following table.

To further study the trend of the dynamic changes in green transformation efficiency in China's manufacturing industry, the Malmquist index was calculated using MATLAB software. This analysis obtained the changes in the dynamic efficiency (total factor productivity) of manufacturing enterprises in 30 provinces from 2011 to

2023. The changes in comprehensive technical efficiency and the technological progress rate were then decomposed. The specific results are shown in the following table.

Table 1 **Efficiency of green transformation and decomposition changes in manufacturing industry from 2011 to 2023**

Year	MI	EC	TC
2011-2012	1.0802	1.0122	1.0701
2012-2013	1.0136	1.0704	0.9526
2013-2014	1.0241	0.9563	1.0724
2014-2015	0.9422	0.9177	1.0285
2015-2016	1.2152	1.0380	1.1789
2016-2017	1.0756	1.0420	1.0472
2017-2018	1.0703	0.9829	1.0933
2018-2019	1.1627	1.0082	1.1545
2019-2020	1.1649	1.0025	1.1758
2010-2021	0.9072	1.1131	0.8365
2021-2022	1.2687	1.0315	1.2467
2022-2023	0.7216	1.0105	0.7164
Average	1.0539	1.0155	1.0477

Data source: Matlab calculation

As shown in Table 1, total factor productivity (TFP) in the green transformation of the manufacturing industry has fluctuated slowly, decreasing from 1.0802 in 2011 to 0.7216 in 2023. The average TFP was 1.0539 between 2011 and 2023, with nine years exceeding 1. However, the TFP was below 1 during 2014–2015, 2010–2021, and 2022–2023, at 0.9422, 0.9072, and 0.7216, respectively. These results suggest a declining trend in the efficiency of the manufacturing industry's green transformation. This decline may be due to economic downturns, intensified market competition, and the impact of the COVD-19 pandemic on the industry's green transformation efforts. The TFP decomposition results indicate that the average values for comprehensive technical efficiency and the technological progress rate were 1.0155 and 1.0477, respectively. Comprehensive technical efficiency exhibited an upward spiral trend from 2011 to 2023, while the technological progress rate remained above 1 throughout this period except for the years 2012–2013, 2010–2021, and 2022–2023, when it fell below 1. These findings underscore the pivotal role of technological innovation in the green transformation of the manufacturing industry, highlighting the critical importance of technological progress in enhancing the efficiency of this transformation.

To explore the dynamic evolution of China's manufacturing industry's green transformation development level, the kernel density estimation method (5)–(6) was used to create a three-dimensional kernel density map of the entire country, as shown in the following figure.

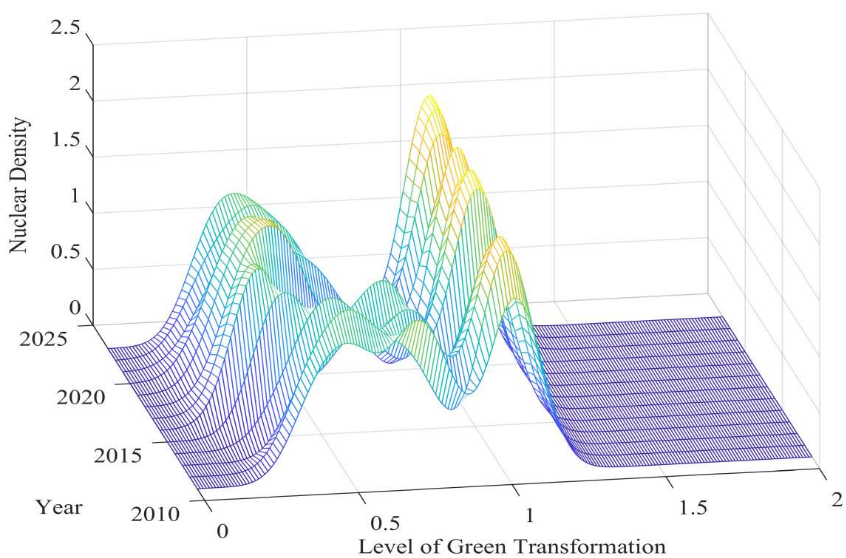

Figure 3 **Kernel density map of green development level of the national manufacturing industry from 2011 to 2023**

Source: Drawn by Matlab Software

As shown in Figure 3, the level of green transformation and development in China's manufacturing sector has fluctuated over time. It initially rose, then declined, and finally rose again. By 2023, a left-trailing phenomenon was evident, likely due to the impact of the pandemic, which reduced the level of green development in the sector. Additionally, the presence of multiple peaks indicates significant differences in green development levels across different regions in China. These differences are primarily due to variations in economic development levels and green technology innovation, resulting in a multi-polar distribution of green transformation and development in the manufacturing sector.

Conclusion. In the context of green development in manufacturing, green transformation has become an essential choice for achieving sustainable business growth. However, the ultra-efficient SBM-ML model, using data from 2011 to 2023, was employed to measure the level of green transformation in China's manufacturing sector. This revealed low efficiency during the transformation process. To improve the efficiency of green transformation in manufacturing, this paper offers the following recommendations:

First, increase the level of green technology innovation. Green technology innovation is the core driving force for improving the efficiency of green transformation in manufacturing. Increasing investment in green technology innovation allows the manufacturing industry to adopt advanced, environmentally friendly production processes and equipment, reducing energy consumption and emissions. The government must increase investment in green technology research and development, establish special scientific research funds, and encourage collaboration between universities, research institutions, and enterprises to address green technology challenges collectively. Second, manufacturing companies should actively introduce advanced foreign green manufacturing technologies, strengthen their internal R&D teams, and continuously develop green products with independent intellectual property rights. They should also build technical exchange platforms with other enterprises to promote technology sharing and cooperation, avoid redundant R&D efforts, and improve the overall efficiency of technological innovation.

Second, improve policy guidance and supervision. Effective policy oversight provides institutional support for the orderly green transformation of the manufacturing sector. The government is continuously improving and formulating relevant preferential policies. These policies include implementing green tax incentives for manufacturing production, encouraging the adoption of green production processes and equipment, and offering tax reductions. Additionally, a robust green manufacturing certification system has been established to certify products from enterprises that meet green standards. This system increases consumer recognition of green products, stimulates market demand, and guides manufacturing companies to accelerate their green transformation and upgrading.

Third, enhance the cultivation of talent for manufacturing transformation. Talent cultivation is essential for improving the efficiency of the green transition in manufacturing. To achieve this, companies must strengthen their collaboration with universities and vocational schools, intensify the training and education of talent for the green transformation and upgrading of manufacturing, and nurture professionals who are proficient in technology and management. Additionally, a comprehensive training system should be established to regularly provide employees with knowledge and skills in green production, thereby enhancing their proficiency. Furthermore, the government should encourage the recruitment of outstanding talent by setting up a green talent reward fund to continuously attract top-tier professionals from abroad.

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