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Evaluation of Green Technology Innovation Efficiency, Regional Differences and Influencing Factors of Industrial Enterprises in China: Based on a Two-Stage Perspective

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Abstract: The symposium on industrial green and low-carbon development held by the Ministry of Industry and Information Technology in January 2024 emphasized the need to steadily promote carbon reduction in the industrial sector, and improving the efficiency of green technology innovation in industrial enterprises has important practical significance in promoting their green transformation and upgrading. Therefore, this article uses inter-provincial panel data from 2005 to 2022, and constructs super efficiency EBM model, ML index model, Dagum Gini coefficient model, and spatial Durbin model to measure, decompose, analyze the sources of differences and influencing factors in the two-stage efficiency of industrial enterprises. The results show that the efficiency of technology research and development is higher than the efficiency of technology transformation, and the efficiency level of each stage is directly proportional to the economic development level of the region. The scale efficiency level of each stage remains stable at 0.9 or above, and the low pure efficiency is an important reason for the significantly low efficiency. The efficiency level of each stage shows an increasing trend from 2005 to 2022, and the efficiency level of each stage in the eastern region is higher than that of other regions. The efficiency level of China's research and development stage shows a good development trend, but there is insufficient coordination between technological efficiency and technological progress in the transformation stage, and there are significant bottlenecks in the technological progress index. The differences in efficiency levels between different stages mainly come from the differences in efficiency levels between regions, with more significant differences between the eastern region and other regions. The industrial structure and market competitiveness have a significant promoting effect on efficiency levels, while environmental regulations have a significant inhibitory effect on efficiency levels.

Keywords: Green technology innovation efficiency; Super-efficient EBM-ML model; Dagum Gini coefficient model; Spatial Durbin model

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1. Introduction

The report of the 20th Party Congress clearly puts forward that by 2035, a new type of industrialization will be basically realized, which is defined as "industrialization + informatization + intelligentization + greenization". In January 2024, the Ministry of Industry and Information Technology held a symposium on the green and low-carbon development of industry to comprehensively promote the deployment of industrial green and low-carbon development. The meeting highlighted the necessity to steadily promote carbon emission reduction in the industrial sector, vigorously support green and low-carbon industries, help traditional industries realize green upgrading, and accelerate the pace of synergies between pollution reduction and carbon reduction. New quality productivity is a living force that can promote scientific and technological innovation, integrate and utilize factor resources, and cultivate new advantages in industrial competition, which is spawned by revolutionary breakthroughs in technology, innovative allocation of production factors, and in-depth transformation and upgrading of industries.

Since September 2023, General Secretary Xi Jinping has repeatedly emphasized the need to focus on integrating scientific and technological innovation resources, leading the development of strategic emerging industries, and promoting the in-depth transformation and upgrading of industries, so as to accelerate the formation of new quality productivity. Against the background of an industrial value added of 30.1% of GDP in 2024, new industrialization remains the main battleground for new quality productivity. Therefore, research on the efficiency of green technological innovation of industrial enterprises is of great significance in boosting the transformation and upgrading of China's industrial enterprises to green and low-carbon.

In existing studies, efficiency measurement methods mainly use frontier analysis. The frontier analysis method contains the parametric method represented by stochastic frontier analysis (SFA) and the nonparametric method represented by data envelopment analysis (DEA), which derives a variety of improved models such as SBM and EBM. Additionally, research targets measured by efficiency are abundant, Liu *et al.* used three-stage DEA to study the innovation efficiency of state-level high-tech industrial development zones in Sichuan and Chongqing regions [1]. Liang *et al.* used DEA Models to measure the Efficiency of New Urbanization and Logistics Industry in Three Provinces and One City in the Yangtze River Delta Region [2]. Tang measured the Circulation Efficiency of the Distribution Industry in 30 Provinces, Regions and Municipalities in China with DEA-Malmquist Indexes [3]. Liu analyzed the financing efficiency of listed companies in the textile industry with the SBM-Malmquist index model [4].

Regarding the object of green technology innovation efficiency measurement, scholars mostly focus on the regional, industry and enterprise levels. At the regional level, many scholars have measured the green technology efficiency value of industrial enterprises in 30 provinces in China [5-8]. Yuan and Dong evaluated the industrial green technology innovation efficiency of the provinces in the Yellow River Basin by using the super-efficiency EBM model, and explored the sources of regional efficiency differences through the Dagum Gini coefficient [9]. Huang *et al.* used a two-stage global network SBM-DEA model to measure the efficiency of green technology innovation in agriculture [10]. Cao and Su used the super-efficient SBM-DEA model to measure the efficiency of green technology innovation in 30 provinces in China [11]. Hou used the super-efficient SBM-DEA model to measure the innovation efficiency of green transportation technology in 16 cities of Chengdu-Chongqing city cluster from 2001 to 2020 [12]. At the industry level, Yu *et al.* measured the technological innovation efficiency of high-tech industries by using a non-radial SBM model [13]. Chen measured the green technology innovation efficiency of China's manufacturing industry by using the super-efficiency SBM model, and categorized it into three categories based on the change trend [14]. At the enterprise level, Lv and Ma measured the green technology innovation efficiency by using the SFA method based on a sample of 801 observations from A-share listed industrial enterprises in China [15]. Wang *et al.* measured the green technology innovation efficiency of new energy enterprises with the SBM model [16]. Zou used a three-stage DEA model to measure the green technology innovation efficiency of industrial listed companies in Shanghai and Shenzhen main boards [17].

In the study of influencing factors, Fang found that factors such as environmental regulation, external technology, and industry scale are the key factors affecting the efficiency of green technological innovation in China's heavily polluted industries, among which the impact of over-reliance on external technology and policy uncertainty on industrial green technological innovation is negative [18]. He and Cai found that the level of green economy development, government support, enterprise revenue, and foreign investment positively affect the efficiency of green technology innovation of industrial enterprises in 27 cities in the Yangtze River Delta [19]. Yan *et al.* found that the degree of openness to the outside world, science and technology innovation environment has a significant positive impact on the efficiency of industrial green technology innovation in 11 provinces and municipalities of the Yangtze River Economic Belt, the industrial structure has a significant negative impact on the efficiency, the dependence on foreign investment, the market competition environment also has a negative impact on the efficiency, but not significant [20].

The existing literature on the efficiency of green technology innovation is also rich, but there is still much room for expansion as follows:

(1) In terms of research methodology, the EBM mixed distance function model is used to make up for the shortcomings of the radial and non-radial models in the measurement of input-output variables;
(2) Focusing on the spatial imbalance of green technology innovation efficiency, the Dagum Gini coefficient is utilized to reveal the source of regional efficiency differences and to solve the problem of cross overlap between groups;
(3) From a research perspective, spatial econometric models are employed to analyze the impact of various factors on pure green technological innovation at different stages to provide a reference for innovation-driven and green transformation policies.

Based on this, the article uses inter-provincial panel data from 2005–2022 to measure, decompose, analyze the sources of differences and influencing factors of efficiency in stages by constructing the super-efficiency EBM model, ML index model, Dagum coefficient model, and spatial Durbin model, its research value can be explored from both theoretical and practical perspectives. Theoretically, this multi-model integrated analytical framework enriches the quantitative research methodology within the field. Moreover, by precisely identifying key efficiency determinants using long-term inter-provincial data, it provides new empirical evidence for green technological innovation efficiency studies. Practically, the findings offer actionable pathways for industrial enterprises to advance green transformation through existing technological innovation. They also furnish robust empirical support for policymakers seeking to optimize regional green innovation resource allocation and facilitate industrial upgrading.

This paper is structured into five sections following a logical sequence of "background-methodology-analysis-conclusions" as listed:

(1) The introduction clarifies the research significance, reviews existing findings, and delineates the innovative direction;
(2) It details the research methodology, indicator system, and data processing;
(3) It measures efficiency across R&D and transformation stages, analyzing efficiency variations and regional

disparities;

(4) It examines influencing factors through regression, robustness, and heterogeneity analyses;

(5) It summarizes conclusions and proposes policy recommendations.

2. Research methods and data processing

2.1.Research methodology

2.1.1.Super-efficient EBM model

The article measures efficiency using a super-efficient EBM model with **Equation (1)**.

$$K^* = \min_{\theta,\eta,\lambda,s^-,s^+} \frac{\theta + \varepsilon_x \sum_{i=1}^{m} \frac{W_i^- S_i^-}{x_{io}}}{\eta - \varepsilon_y \sum_{r=1}^{s} \frac{w_r^+ s_r^+}{y_{ro}} - \varepsilon_b \sum_{q=1}^{p} \frac{w_q^{b-} s_q^{b-}}{b_{qo}}} \tag{1}$$

$$s.t.\begin{cases} \sum_{t=1}^{T}\sum_{j=1,j\neq 0}^{n} x_{ij}^t \lambda_j^t - s_i^- \leq \theta x_{io}, i = 1,2,\ldots,m \\ \sum_{t=1}^{T}\sum_{j=1,j\neq 0}^{n} y_{ij}^t \lambda_j^t - s_i^+ \geq \eta y_{r0}, r = 1,2,\ldots,s \\ \sum_{t=1}^{T}\sum_{j=1,j\neq 0}^{n} b_{ij}^t \lambda_j^t - s_q^{b-} \leq \eta b_{q0}, q = 1,2,\ldots,p \\ \sum_{t=1}^{T}\sum_{j=1,j\neq 0}^{n} \lambda_j^t = 1 \\ \lambda \geq 0, s_i^- \geq 0, s_i^+ \geq 0, s_q^{b-} \geq 0 \end{cases}$$

Where k^* is the optimal efficiency value, $(w_i^-, w_r^+, w_a^{b-}, s_i^-, s_r^+, s_a^{b-}, m, s, p)$ are the input element, expected outputs, weights for non-expected outputs, non-zero relaxation measures and indicators, respectively; θ is the radial conditional efficiency values; η is the output expansion ratio; ε is key parameters, indicating the degree of combination of radial and non-radial, the value range is 0~1.

2.1.2. Dagum Gini coefficient model

The Dagum Gini coefficient is used to measure the degree of geospatial imbalance [21]. The formulas for total Gini coefficient (G), intra-group Gini coefficient (G_{jj}), inter-group Gini coefficient (G_{jh}), intra-group contribution (G_w), inter-group contribution (G_{nb}) and hypervariable density contribution (G_t) are as follows:

$$G = \frac{\sum_{j=1}^{k}\sum_{h=1}^{k}\sum_{i=1}^{nj}\sum_{r=1}^{nk}|y_{ji}-y_{hr}|}{2n^2\bar{y}}, G_{jj} = \frac{\frac{1}{2\bar{y_j}}\sum_{i=1}^{nj}\sum_{r=1}^{nj}|y_{ji}-y_{jr}|}{n_j^2}, G_{jh} = \frac{\sum_{i=1}^{nj}\sum_{r=1}^{nj}|y_{ji}-y_{hr}|}{n_j n_h(\bar{y_j}-\bar{y_h})} \tag{2}$$

$$G_w = \sum_{j=1}^{k} G_{jj} p_j s_j, G_{nb} = \sum_{j=2}^{k}\sum_{h=1}^{j-1} G_{jh} D_{jh}(p_j s_h + p_h s_j), G_t = \sum_{j=2}^{k}\sum_{h=1}^{j-1} G_{jh}(p_j s_h + p_h s_j)(1 - D_{jh}) \tag{3}$$

Where (n,k) represent the number of provinces and regions that is studied; $(\bar{y}, \bar{y}_i(\overline{y_h}), y_{ji}(y_{hr}))$ are the level of efficiency of i(r) industrial firms in each province, within j(h) region and j(h) region. $p_i = n_i|n, s_i = n_i\bar{y}|n\bar{y}, D_{jh} = m_{jh} - n_{jh}/m_{jh} + n_{jh}$ represents the relative impact between regions.

2.1.3. Malmquist-Luenberger exponential model

The Malmquist-Luenberger productivity index model is able to decompose the efficiency change into two components, technical progress and efficiency improvement, as follows [22]:

$$ML_t^{t+1} = EC * TC = \sqrt{\frac{D_G^t(x^t,y^t,b^t)}{D_G^t(x^{t+1},y^{t+1},b^{t+1})} \times \frac{D_G^{t+1}(x^{t+1},y^{t+1},b^{t+1})}{D_G^{t+1}(x^t,y^t,b^t)}} \tag{4}$$

$$EC = \frac{\frac{D_{t+1}^G\left(x^{t+1},y^{t+1},b^{t+1}\right)}{D_t^G(x^t,y^t,b^t)}}{\sqrt{D_t^G(x^{t+1},y^{t+1},b^{t+1})/D_t^G(x^t,y^t,b^t) \times D_{t+1}^G(x^{t+1},y^{t+1},b^{t+1})/D_{t+1}^G(x^t,y^t,b^t)}}$$

$$TC = \sqrt{\frac{D_t^G(x^{t+1},y^{t+1},b^{t+1})}{D_{t+1}^G(x^{t+1},y^{t+1},b^{t+1})} \times \frac{D_t^G(x^t,y^t,b^t)}{D_{t+1}^G(x^t,y^t,b^t)}}$$

Where $D_t^G(x^t,y^t,b^t)$ represents the generalized distance function that takes into account the non-expected output of b^t,(x^t,y^t) is the vector of inputs and the vector of desired outputs in period t. When there is no non-desired output, i.e., when $b_t = b_{t+1} = 0$, the ML index degenerates into the M index. EC refers to the index of change in technical efficiency, and TC refers to the index of change in technical progress.

2.2. Selection of indicators and data sources

2.2.1. Selection of indicators

As shown in **Table 1**, carbon dioxide and the environmental pollution index of “three industrial wastes” calculated by entropy value method are used as non-expected outputs to measure the green technology innovation efficiency of industrial enterprises and then analyzed and researched. For the robustness test, the four pollutants are re-measured and empirically analyzed for efficiency as non-expected outputs.

Table 1. Green technology innovation efficiency index system of industrial enterprises

Phase	Indicator type	Indicator name	Indicator unit
Technology development phase	Input	RD personnel	(Person)
		RD expenditure	RD internal expenditure stock (RMB 10,000)
		New product development expenditure	New product development expenditure balance (RMB 10,000)
		Total costs for technology introduction, etc.	Total accumulated expenses for technology introduction, etc. (RMB 10,000)
	Intermediate input	Number of patent applications	Piece
		Number of valid invention patents	Piece
		New product development project	Item
Results conversion phase	Energy input	Total energy consumption	10,000 tons of standard coal
	Expected output	New product sales revenue	Deflated by the industrial producer price index (10,000 yuan)
	Unexpected output	Industrial wastewater	10,000 tons
		Industrial sulfur dioxide	10,000 tons
		Industrial solid waste generation	10,000 tons
		Industrial carbon dioxide	10,000 tons
		Industrial waste pollution index	-

2.2.2. Data sources

The article utilizes panel data from 30 provinces and cities outside of Hong Kong, Macao, Taiwan, and Tibet of China's state-owned industrial enterprises from 2005–2022 to develop the analysis. The data for the article are mainly from the EPS data platform, China Science and Technology Statistical Yearbook, China Environmental Statistical Yearbook, China Statistical Yearbook, China Carbon Accounting Database, National Bureau of Statistics and provincial statistical yearbooks.

In order to eliminate the effect of inflation and the cumulative effect of the funds, the funds are deflated by the research and development price index for the base period of 2005 and then calculated by using the perpetual inventory method. The methodology for the R&D price index is: R&D price index = 0.55*consumer price index + 0.45*fixed asset investment price index. The perpetual inventory method calculates the stock as follows: $K_{it} = (1 - \delta)K_{it-1}+I_{it}$. Where $K_{it}K_{it-1}$ are the capital stock of province i in year t and t-1, respectively. δ denotes the capital depreciation rate, which is set to be 20.8%, and I_{it} denotes the actual internal expenditure of funds in province i in year t. According to the formula: $K_{i0} = I_{i0}/(g + \delta)$ calculating the capital stock in the base period [23–26].

3. Measuring and analyzing green technology innovation efficiency of Chinese industrial enterprises

3.1. Measuring the efficiency of green technology innovation

Based on the index system constructed in the previous article, the article uses IDEA Ultra software to measure the green technology innovation efficiency of industrial enterprises in each province of China from 2005 to 2022.

3.1.1. Analysis of technological innovation efficiency in the R&D stage

As shown in **Table 2**, the average values of total green technology R&D efficiency, pure green technology R&D efficiency and scale efficiency of industrial enterprises are 0.848, 0.920 and 0.922 respectively. At the provincial level, seven of the top ten rankings for total technology R&D efficiency are in the east, two in the center, and one in the west. Among the ten provinces and cities ranked lower, six are in the west, two in the northeast, one in the center, and one in the east, indicating the spatial imbalance in the efficiency of green technology R&D in various regions of China. Scale efficiency is low in Guizhou, Gansu, Qinghai, Ningxia, Xinjiang and Hainan, especially in Qinghai and Hainan. The pure technology R&D efficiency levels in Hainan and Qinghai are 1.002 and 0.926 respectively, but the corresponding scale efficiencies are 0.798 and 0.773 respectively, with a serious mismatch between pure technology R&D efficiency and scale efficiency. Hainan, due to its relatively remote geographical location, making enterprises face certain difficulties in the expansion of off-island markets, to a certain extent, constraints on the scale of the efficiency of technology research and development in Hainan.

In addition, the relatively late start of Hainan's industry and the insufficient capacity of the industrial system and industrial support will also make it impossible to realize the economies of scale of technological research and development through large-scale industrialization. At the regional level, the technical efficiency of East continues to have the highest level. In terms of longitudinal evolutionary trends, all regions showed a more pronounced and consistent upward trend in technology R&D efficiency over the study period, as shown in **Figure 1**.

Table 2. Green technology R&D innovation efficiency of industrial enterprises

Province	Efficiency of scale	Pure technical R&D efficiency	Overall technical R&D efficiency	Ranking
Beijing	0.952	0.956	0.911	3
Tianjin	0.947	0.945	0.894	7
Hebei	0.935	0.901	0.843	17
Shanghai	0.977	0.923	0.902	6
Jiangsu	0.974	0.934	0.91	4
Zhejiang	0.968	0.948	0.918	2
Fujian	0.94	0.905	0.852	14
Shandong	0.969	0.921	0.893	8
Guangdong	0.968	0.982	0.951	1
Hainan	0.798	1.002	0.798	24
Shanxi	0.914	0.87	0.797	25
Anhui	0.941	0.959	0.903	5
Jiangxi	0.925	0.9	0.834	20
Henan	0.931	0.913	0.851	16
Hubei	0.938	0.92	0.864	12
Hunan	0.927	0.937	0.87	10
Liaoning	0.961	0.887	0.853	13
Jilin	0.941	0.865	0.816	23
Heilongjiang	0.914	0.901	0.825	22
Inner Mongolia	0.893	0.857	0.767	29
Guangxi	0.928	0.899	0.835	19
Chongqing	0.943	0.917	0.866	11
Sichuan	0.929	0.956	0.888	9
Guizhou	0.886	0.948	0.841	18
Yunnan	0.898	0.923	0.829	21
Shanxi	0.924	0.922	0.852	15
Gansu	0.882	0.903	0.795	26
Qinghai	0.773	0.926	0.715	30
Ningxia	0.842	0.939	0.79	27
Xinjiang	0.874	0.899	0.785	28
Eastern Region	0.943	0.942	0.887	
Central region	0.929	0.917	0.853	
Western Region	0.888	0.917	0.815	
Northeast Region	0.939	0.884	0.831	
National level	0.920	0.922	0.848	

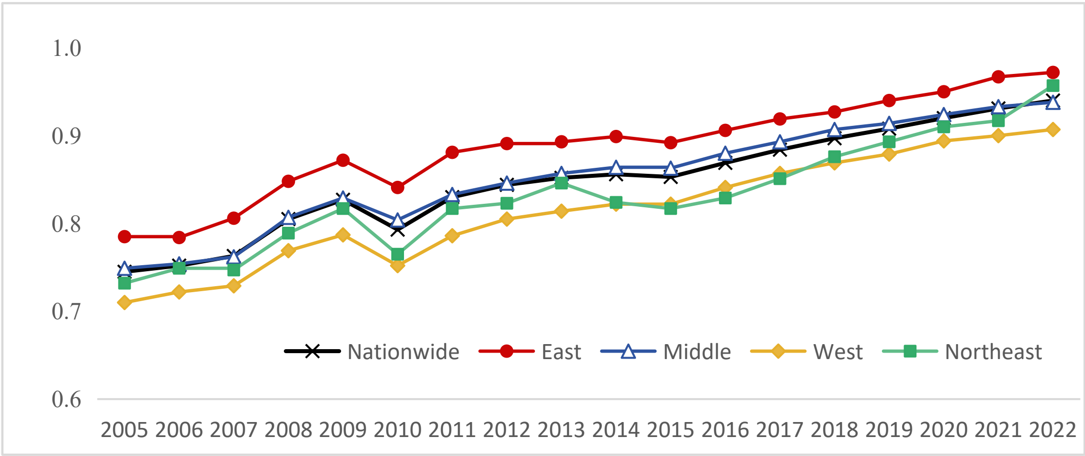

Figure 1. Trends in technology R&D efficiency by region.

3.1.2. Analysis of the efficiency of technological innovation at the transformation stage

As shown in **Table 3**, the average values of technology conversion efficiency, pure technology conversion efficiency and scale efficiency are 0.689, 0.752 and 0.920 respectively. The conversion efficiency is much lower than the efficiency of technology research and development, mainly caused by the low efficiency of pure technology conversion, and the value of conversion efficiency in each region from east to west shows a decreasing trend. At the provincial level, in the top ten regions ranked in terms of technology transformation efficiency, only the east accounted for eight, with the remaining two being Jilin Province in the northeast and Chongqing in the west, and among the bottom ten regions, the west accounted for eight, with the other two being Shanxi in the center and Heilongjiang in the northeast. The eastern part of the country continues to have significant advantages in technology transformation, but among them, Shanghai, Jiangsu, Zhejiang, Shandong and Guangdong are the five lowest ranked regions in terms of scale efficiency, which may be due to the fact that the eastern part of the country is rich in innovation resources, such as talents, scientific research institutes, and outstanding enterprises, which makes the resources dispersed.

In addition, the diversified and individualized market demands in developed regions make it difficult to achieve large-scale standardized production for technology transformation. At the regional level, the scale efficiencies of the central, western and northeastern regions are equal and slightly higher than those of the eastern region, but the pure technical transformation efficiencies of all three are significantly lower than those of the eastern region, with the largest difference between the pure technical transformation efficiencies of the eastern region and those of the western region. Compared with the eastern region, the western region's degree of opening up to the outside world, market development are relatively weak, information is relatively closed, access to cutting-edge technology and market information channels are limited, and there are few opportunities for international cooperation and exchanges, which hinders the transformation of technology.

The longitudinal evolution trend shows that the conversion efficiency in the eastern region remains high and oscillating, much higher than in the other regions, as shown in **Figure 2**. As of 2022, the Northeast's technology conversion efficiency has bounced back to exceed the national average and even surpassed that of the Central region. In recent years, Northeast China has accelerated the transformation of traditional industries into high-end, intelligent and green industries, and built growth points around strategic emerging industries, which provides a broad application prospect for technology transformation.

Table 3. Green technology transformation and innovation efficiency of industrial enterprises

Province	Efficiency of scale	Pure technical R&D efficiency	Overall technical R&D efficiency	Ranking
Beijing	0.94	0.874	0.822	1
Tianjin	0.905	0.897	0.811	3
Hebei	0.917	0.716	0.657	20
Shanghai	0.868	0.941	0.816	2
Jiangsu	0.891	0.863	0.768	7
Zhejiang	0.882	0.885	0.779	5
Fujian	0.929	0.804	0.748	10
Shandong	0.883	0.821	0.725	11
Guangdong	0.861	0.881	0.755	9
Hainan	0.934	0.841	0.781	4
Shanxi	0.94	0.660	0.621	22
Anhui	0.936	0.769	0.72	12
Jiangxi	0.937	0.750	0.7	15
Henan	0.922	0.734	0.677	17
Hubei	0.917	0.774	0.71	13
Hunan	0.918	0.772	0.708	14
Liaoning	0.917	0.745	0.684	16
Jilin	0.918	0.849	0.778	6
Heilongjiang	0.938	0.651	0.608	24
Inner Mongolia	0.931	0.662	0.614	23
Guangxi	0.946	0.711	0.672	18
Chongqing	0.922	0.823	0.76	8
Sichuan	0.927	0.716	0.665	19
Guizhou	0.952	0.607	0.577	28
Yunnan	0.951	0.631	0.600	25
Shanxi	0.95	0.666	0.633	21
Gansu	0.935	0.642	0.594	26
Qinghai	0.857	0.66	0.561	29
Ningxia	0.937	0.629	0.585	27
Xinjiang	0.93	0.579	0.536	30
Eastern Region	0.901	0.852	0.766	
Central region	0.928	0.743	0.689	
Western Region	0.931	0.666	0.618	
Northeast Region	0.925	0.748	0.690	
National level	0.920	0.752	0.689	

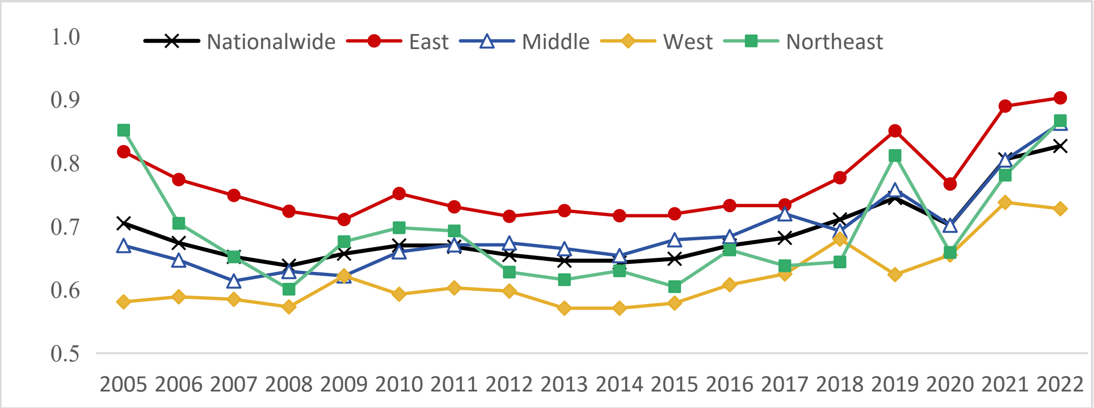

Figure 2. Trends in technology transfer efficiency by region.

3.2. Malmquist-Luenberger index analysis

The efficiency level was measured and analyzed in the previous section, and the ML index in this section is able to decompose the efficiency change into two parts: technological progress and efficiency improvement, which helps to clarify whether the increase in the efficiency of green technological innovation is originated from the improvement of the technological level or the improvement of the efficiency of resource utilization and other efficiency in the production process, so as to analyze the intrinsic mechanism of the efficiency change in a more in-depth manner.

3.2.1. Malmquist-Luenberger index analysis of the R&D phase

As shown in **Figure 3**, the ML index and technical progress index of the 30 provinces in the R&D stage are all greater than 1, and the efficiency change index and technical progress index are all distributed below the ML index, indicating that the relationship between technical efficiency and technical progress is coordinated in all regions in the R&D stage, and the overall development of China's green technology R&D efficiency is good.

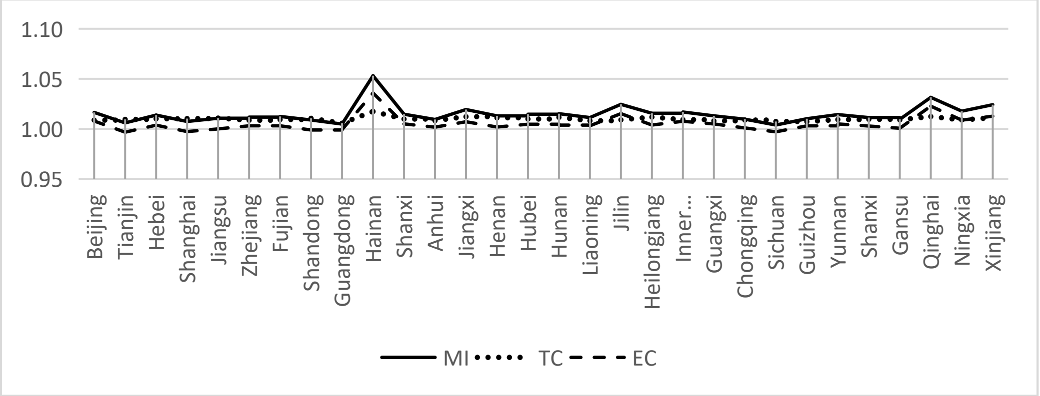

Figure 3. ML index decomposition of technology R&D efficiency in each province.

3.2.2. Dynamic analysis of the Malmquist-Luenberger index at the transformation stage

As shown in **Figure 4**, there are 18 provinces with ML indexes less than 1 at the transformation stage, of which 13 provinces, including Hebei, Fujian, Shanxi, and Jiangxi, are caused by the technical regression index less than 1. Hainan is caused by the technical efficiency index less than 1, mainly caused by the decline of technical efficiency, and Tianjin, Shanghai, and Jilin are caused by both the technical efficiency index and the technical progress index less than 1, caused by the combination of technological regression and the decline of technical efficiency. The technical efficiency index is higher than the technical progress index in most regions, and the gap between the technical efficiency index and the technical progress index is more significant in the central, western and northeastern regions.

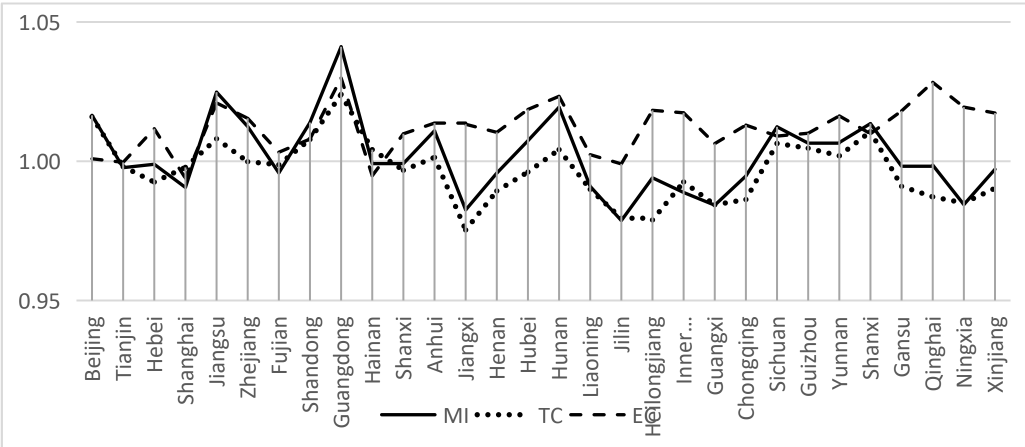

Figure 4. ML index decomposition of the efficiency of technological transformation in each province.

3.3. Decomposition of regional differences in green technology innovation efficiency

This section calculates and decomposes the regional differences in green technology innovation efficiency, R&D efficiency and transformation efficiency of industrial enterprises in 30 provinces of China from 2005 to 2022 by applying the Dagum Gini coefficient decomposition method through stata software.

3.3.1. Decomposition of regional differences in green technology R&D efficiency

As shown in **Table 4**, the total Gini coefficient shows a decreasing trend, which is from 0.053 to 0.023, and the efficiency differences within and between regions also show a decreasing trend, The degree of spatial differentiation of efficiency within the four regions is West > East > Center > Northeast, and differences in efficiency are the greatest between the eastern and western regions. The average contribution of interregional efficiency differences in the R&D phase (57.278%) remains much larger than the average contribution of intraregional differences (23.722%) and the average contribution of hypervariable density differences (19.002%).

Table 4. Gini coefficient and decomposition of green technology R&D efficiency in industrial enterprises

Year	Gini coefficient	Contribution		
		Gw	Gnb	Gt
2005	0.053	25.525	43.880	30.637
2006	0.060	25.830	31.533	42.637
2007	0.054	25.327	43.591	31.082
2008	0.044	24.434	50.710	24.856
2009	0.042	24.469	56.166	19.365
2010	0.045	24.658	57.574	17.768
2011	0.043	24.319	61.309	14.372
2012	0.039	24.659	59.631	15.709

Table 4 (Continued)

Year	Gini coefficient	Contribution		
		Gw	Gnb	Gt
2013	0.035	24.529	60.331	15.140
2014	0.037	24.064	57.799	18.137
2015	0.036	24.445	55.685	19.870
2016	0.033	23.819	57.277	18.904
2017	0.029	23.024	58.883	18.093
2018	0.026	23.100	60.437	16.463
2019	0.024	22.827	65.667	11.505
2020	0.021	21.872	68.249	9.880
2021	0.023	20.581	71.277	8.142
2022	0.023	19.519	71.007	9.474
Mean	0.037	23.722	57.278	19.002

3.3.2. Decomposition of regional differences in green technology transfer efficiency

As shown in **Table 5**, the average value of the total Gini coefficient, the average value of the Gini coefficient within each region and the average value of the Gini coefficient between regions are significantly larger in the technology transformation stage than in the R&D stage. The degree of spatial differentiation within each region is presented as Northeast > West > East > Center. The differences in the efficiency of technology transfer are the largest between the East and the West. Differences in conversion efficiency mainly come from inter-region, and the average contribution of inter-regional differences to the total differences even reaches 64.773%, which is much higher than the average contribution of intra-region (20.335%) and the average contribution of hypervariable density (14.897%).

Table 5. Gini coefficient and decomposition of green technology transformation efficiency of industrial enterprises

Year	Gini coefficient	Contribution		
		Gw	Gnb	Gt
2005	0.113	18.115	75.064	6.821
2006	0.097	20.636	66.422	12.942
2007	0.083	20.406	69.856	9.738
2008	0.076	16.940	71.101	11.958
2009	0.066	22.808	48.829	28.363
2010	0.079	17.691	70.058	12.251
2011	0.073	21.730	61.050	17.220
2012	0.070	22.278	60.068	17.653
2013	0.074	18.214	74.593	7.193
2014	0.074	19.292	70.471	10.237
2015	0.078	18.946	66.460	14.594

Table 5 (Continued)

Year	Gini coefficient	Contribution		
		Gw	Gnb	Gt
2016	0.071	21.110	61.037	17.853
2017	0.067	20.830	58.156	21.105
2018	0.060	24.855	58.646	16.499
2019	0.095	16.817	74.702	8.481
2020	0.064	22.674	57.723	19.603
2021	0.075	23.456	57.925	18.619
2022	0.077	19.234	63.744	17.022
Mean	0.077	20.335	64.773	14.897

4. Research on the influencing factors of green technology innovation efficiency of Chinese industrial enterprises

4.1. Variable selection

The government is the one who formulates and implements environmental protection policies, green development strategies and technical standards, the enterprise is the direct implementer of green technological innovation, and the market is an important testing ground for green technological innovation, and the three constitute a dynamic innovation ecosystem. Therefore, this paper researches the influencing factors of pure green technology innovation efficiency of industrial enterprises from these three aspects, and the specific indicators selected are shown in **Table 6**.

Table 6. Impact factors and their measurement indicators

Symbol	Variable	Variable measure	Unit
RDPI	Human resource investment	The ratio of personnel in R&D institutions of large-scale industrial enterprises to the number of R&D institutions in large-scale industrial enterprises	person/ individual
RDI	Research and development expenditure	The proportion of internal expenditure on R&D funding above the specified standard in total industrial output value	%
SC	Company size	The ratio of total assets of large-scale industrial enterprises to the number of large-scale industrial enterprises	Ten thousand yuan per unit
GOV	Government support	Proportion of government funds in internal R&D expenditure of industrial enterprises above designated size	%
ST	Degree of nationalization	Main business income of state-owned and state-controlled industrial enterprises / Main business income of large-scale industrial enterprises within the region	%
ER	Environmental Regulation	Industrial pollution control investment as a percentage of GDP	%
MC	Market competitiveness	Number of industrial enterprises above designated size Take the logarithm	Individual
RDC	R&D competitiveness	Number of large-scale industrial enterprises with R&D institutions / Number of large-scale industrial enterprises with R&D activities	%
FDI	Foreign investment	Foreign direct investment as a percentage of GDP	%
IS	Industrial structure	Secondary industry GDP as a percentage of GDP	%
EL	Level of education	The proportion of undergraduate students enrolled in regular higher education institutions relative to the region's permanent resident population at year-end	%

4.2. Model construction

The general form of the Spatial Durbin Model (SDM) is as follows:

$$y_{it} = \alpha + \rho W_{ij} y_{it} + \beta x_{it} + \lambda W_{ij} x_{it} + \mu_i + v_t + w_{it} \tag{5}$$

Where α is constant term , (ρ,λ) are the spatial lag term coefficients, β is the coefficient of the explanatory variable, W_{ij} is spatial weighting matrix, the text refers to the spatial geographic distance square matrix and the spatial geographic distance matrix, ($\rho W_{ij} y_{it}$,$\lambda W_{ij} x_{it}$) represent the spatial lag term of the explained and explanatory variables, (μ_i,v_t,w_{it}) represent the individual, time fixed effects, and error terms, respectively.

4.3. Model checking

As shown in **Table 7**, the Moran's index test is significant at the 10% level, indicating that the non-spatial panel model regression results are not sufficiently reflective of the true state of the economy. The p-value of SEM test, robust SEM test, SAR test, and robust SAR test in the LM test is less than 0.1, indicating that both models are applicable. The LR model test p-value is less than 0.1 and the spatial Durbin model outperforms the spatial error model and the spatial lag model. Furthermore, the *P*-value in the LR time-individual fixed effects test was less than 0.1, and it was more reasonable to choose two-way fixed effects. The p-value in the Wald test is less than 0.1, confirming that the spatial Durbin model does not degenerate into a spatial lag and spatial error model.

Table 7. Green technology innovation efficiency spatial measurement model selection test

Spatial model testing	Research and development phase		Transformation stage	
	Value	*P*-Value	Value	*P*-Value
Moran's I	6.748	0.000	6.640	0.000
Lagrange multiplier	39.870	0.000	38.552	0.000
Robust Lagrange multiplier	10.910	0.001	12.700	0.000
Lagrange multiplier	82.640	0.000	26.252	0.000
Robust Lagrange multiplier	53.680	0.000	0.400	0.527
LR=SDM/SAR	88.480	0.000	41.29	0.000
LR=SDM/SEM	88.680	0.000	38.77	0.000
LR-both/time	62.190	0.000	253.51	0.000
LR-both/ind	378.640	0.000	48.71	0.000
Wald-SDM/SAR	153.610	0.000	26.53	0.005
Wald-SDM/SEM	164.720	0.000	26.85	0.005

4.4. Regression analysis

Through the above model test, the article used the spatial Durbin model with double fixed effects to analyze the various factors affecting the efficiency of green pure technological innovation of industrial enterprises in China, and the results are shown in **Table 8**.

The coefficients of human resource input (RDPI) at the stage of technology R&D and W*RDPI are 0.092 and 0.220, respectively, and both are significant at the 5% test level, indicating that the input of human resources at the stage of technology R&D not only promotes technology R&D in the region, but also promotes technology

R&D in neighboring regions. At the stage of technological transformation, the input of human resources has a non-significant facilitating effect on the region, but a very significant inhibiting effect on neighboring regions. The investment of human resources in the region may lead to the gathering of talents, promote knowledge sharing and cooperation, optimize resource allocation, and make technological innovation and transformation more efficient. Human resource inputs from neighboring regions often compete with resource allocations in their own regions, which may lead to brain drain and competition for resources, thereby inhibiting the efficiency of neighboring regions. While human resource investment in the region improves technological R&D and innovation capabilities, this knowledge and experience tends to spill over to neighboring regions through channels such as cooperation, exchanges, and industry conferences, leading to technological R&D and innovation in neighboring regions.

R&D capital investment (RDI) has an inhibitory effect on technological R&D in the region at the R&D stage, but has a significant role in promoting technological R&D in neighboring regions at the 1% test level. Local R&D funding may inhibit local technological R&D due to allocation imbalance and path dependence, while at the same time positively promoting technological R&D in neighboring regions due to the local innovation environment that attracts attention and cooperation from them. The promotion effect of R&D capital investment on technology transformation in the region and the inhibition effect on technology transformation in neighboring regions are not obvious at the transformation stage.

The coefficient of firm size (SC) in the R&D stage is -0.144, which is significant at the 5% test level, indicating that firm size has a significant inhibitory effect on the efficiency of technological research and development, while the effect of firm size on the efficiency of technological transformation is not significant. Large firms have a certain dominant position in the market by virtue of their existing technological advantages and product lines, which may lead to a weakening of competitive pressures in the industry, and lack pressure in innovation. Enterprise size has a significant inhibitory effect on the efficiency of both technological R&D and technological transformation in neighboring regions, and this inhibitory effect suggests that in the process of enterprise development due to the monopoly effect of the market, restricted technological diffusion, or competition for talents, the development of local enterprises will have a weakening effect on the development of enterprises in neighboring regions.

The effect of government support (GOV) on technology R&D efficiency and technology transfer efficiency is insignificant and it is significant at 5% level for neighboring regions. Due to the cooperation synergy effect, enterprises in neighboring regions are more likely to form cooperation with enterprises in their own regions and take advantage of their own technological resources, government support, etc. to realize the improvement of the efficiency of technological research and development and technological transformation.

The degree of nationalization (ST) and the efficiency of technological R&D and technological transformation are significant at the 1% and 5% levels with coefficients of 0.209 and 0.480, respectively. The degree of nationalization inhibits the level of technological innovation efficiency and the efficiency of technological research and development of industrial firms in neighboring regions. Although there are some long-term institutional barriers to state-owned enterprises, state-owned enterprises have a large number of key laboratories, technology centers, talent centers, etc., which still play a leading role in innovation.

The coefficients of environmental regulation (ER) at different stages are -0.098, -0.091 and are significant at 1%, 1% and 5% test levels, respectively, indicating that environmental regulation has a significant inhibitory effect on the efficiency of both the R&D stage and the transformation stage. Environmental regulation has a negative spillover effect, and it has a significant inhibitory effect on the efficiency of technology R&D in neighboring regions and a non-significant effect on the promotion of transformation efficiency in neighboring regions. It can be seen that environmental regulation mainly manifests in increasing compliance costs for firms, which can have a depressing effect on the development and transformation of technology. In addition, strict environmental regulatory policies in the province and city will force enterprises with high pollution levels and more difficult transformation and upgrading to move their industries to neighboring provinces and cities where environmental control is easier, adding to the pressure of local environmental pollution.

The relationship between the degree of market competition (MC) and the efficiency of technological development is not significant, and the relationship with the efficiency of technological transformation is significant at the 1% level with coefficients of 0.200 and 0.169, respectively. The coefficients of W*MC for the R&D stage and the technology conversion stage are -2.354 and -1.499, respectively, and both are significant at the 1% test level. The degree of competition in the market can motivate firms to continuously improve the efficiency of technological transformation, neighboring regions may inhibit technological R&D and transformation due to over-concentration of resources or shifting of competitive pressures.

R&D competitiveness (RDC) has a significant positive contribution to technology R&D efficiency with a coefficient of 0.073 and the coefficient is significant at 5% level, while R&D Competitiveness and the technology transformation efficiency are insignificant. There is a positive spatial spillover effect of local competitiveness in technology R&D, but the effect on the efficiency of technology R&D and technology transformation in neighboring regions is not significant, with coefficients of -0.156 and -0.051, respectively.

Foreign investment (FDI) does not play a significant role in the region's technology R&D and technology transformation efficiency, but the coefficient of FDI and technology transformation efficiency is 0.246, which is significant at the 10% level, indicating that the technology and management model of foreign enterprises can positively influence neighboring regions through the relationship of human capital flow and supply chain.

The coefficients of industrial structure (IS) in the R&D and transformation stages are 0.235 and 0.133 respectively, and are significant at the 5% and 1% levels, indicating that an increase in the share of value added of the secondary industry in GDP can promote the efficiency of technological research and development and the efficiency of technological transformation. The rapid development of the secondary industry often requires technological advances and innovations to enhance competitiveness, prompting firms to engage in green technological innovations to meet regulatory and market requirements for the environment. This demand drives the rapid development of green technologies. IS can have a positive spillover effect, significantly contributing to technology development and technology transformation in neighboring regions.

The coefficient of education level (EL) at the R&D stage is 0.259 significant at the 1% level, and the coefficient of W*EL is not significant, indicating that the development of education in the region can effectively lead to the improvement of the quality of workers in the region. The coefficient of EL at the stage of transformation is -0.499, which is significant at the 1% level, and the coefficient of W*EL is -0.027, which has a non-significant effect, and the level of education has an inhibitory effect on the efficiency of technological transformation in the region and neighboring regions. Highly educated R&D personnel may be more inclined to theoretical innovation research, neglecting practical application transformation, commercial application transformation thus inhibiting the efficiency of technology transformation.

Table 8. Spatial Durbin regression results

Variable name	PTEC1		PTEC2	
	Main	Wx	Main	Wx
RDPI	0.092** -2.116	0.220** -2.236	0.031 -0.682	-0.271*** -2.596
RDI	-0.117 -1.449	0.600*** -3.138	0.130 -1.531	-0.172 -0.856
SC	-0.144** -2.075	-0.667*** -4.662	0.008 -0.113	-0.293* -1.956
GOV	0.012 -0.32	0.217** -2.334	-0.006 -0.151	-0.215** -2.198
ST	0.209** -2.234	-0.875*** -4.111	0.480*** -4.874	0.081 -0.356
ER	-0.098*** -2.840	-0.352*** -3.466	-0.091** -2.498	0.085 -0.799
MC	0.200 -0.918	-2.354*** -4.980	1.690*** -7.376	-1.499*** -2.946
RDC	0.073** -2.237	-0.156 -1.495	0.024 -0.683	-0.051 -0.464
FDI	0.047 -0.952	0.109 -0.911	0.010 -0.191	0.246* -1.946
IS	0.235*** -4.141	0.113 -0.893	0.133** -2.201	0.492*** -3.796
EL	0.259** -2.157	-0.088 -0.287	-0.499*** -3.940	-0.027 -0.082

4.5. Robustness analysis

The article adopts two methods to conduct robustness tests on the pure efficiency values of the R&D stage and the transformation stage respectively to ensure the credibility of the empirical results, as shown in **Table 9**. The two methods are as follows:

(1) Replacing weights: The previous article used a spatial geographic distance square matrix for the empirical study, this article replaces the matrix with a spatial geographic distance matrix for the empirical study again and finds that the sign and significance of the data remain consistent, indicating that the results are robust;

(2) Replacing measures of efficiency: In the previous paper, the environmental pollution indexes of industrial carbon dioxide and "industrial three wastes" were used as non-expected outputs in the efficiency measurement, but here the non-expected outputs are replaced by "industrial three wastes" and industrial pollution to conduct empirical analysis after re-measuring the efficiency, and it is found that the sign and significance of the data are still the same as that of the data and the results are robust.

Table 9. Robustness test of pure green technology innovation efficiency

Variable name	Research and development phase				Transformation stage			
	Replace weights		Replacing measures of efficiency		Replace weights		Replacing measures of efficiency	
	Main	Wx	Main	Wx	Main	Wx	Main	Wx
RDPI	0.083* -1.912	0.622** -2.442	0.092** -2.116	0.220** -2.236	0.014 -0.299	-0.544** -1.963	0.044 -1.051	-0.232** -2.414
RDI	-0.069 -0.878	2.396*** -4.793	-0.117 -1.449	0.600*** -3.138	0.103 -1.199	-0.088 -0.163	0.087 -1.112	-0.069 -0.373
SC	-0.170** -2.520	-1.515*** -4.063	-0.144** -2.075	-0.667*** -4.662	-0.015 -0.200	-0.766* -1.893	-0.026 -0.386	-0.225 -1.633
GOV	0.011 -0.29	0.731*** -2.859	0.012 -0.32	0.217** -2.334	-0.019 -0.438	-0.547** -1.984	-0.006 -0.149	-0.163* -1.810
ST	0.193** -2.086	-2.151*** -3.759	0.209** -2.234	-0.875*** -4.111	0.502*** -5.013	0.507 -0.814	0.452*** -4.986	0.072 -0.348
ER	-0.114*** -3.264	-1.041*** -4.117	-0.098*** -2.840	-0.352*** -3.466	-0.080** -2.114	0.236 -0.865	-0.085** -2.530	-0.014 -0.145
MC	0.116 -0.55	-5.428*** -4.617	0.200 -0.918	-2.354*** -4.980	1.549*** -6.775	-3.201** -2.481	1.507*** -7.156	-1.425*** -3.059
RDC	0.018 -0.527	-1.150*** -3.869	0.073** -2.237	-0.156 -1.495	0.017 -0.466	-0.128 -0.397	0.010 -0.315	-0.093 -0.915
FDI	0.085* -1.674	0.191 -0.563	0.047 -0.952	0.109 -0.911	0.048 -0.865	0.832** -2.257	0.066 -1.378	0.243** -2.088
IS	0.238*** -4.214	0.482* -1.66	0.235*** -4.141	0.113 -0.893	0.143** -2.321	1.345*** -4.357	0.155*** -2.77	0.607*** -5.052
EL	0.270** -2.274	-0.046 -0.051	0.259** -2.157	-0.088 -0.287	-0.476*** -3.691	-0.074 -0.076	-0.367*** -3.146	-0.166 -0.557

4.6. Heterogeneity analysis

The 30 provinces in China were divided into four regions, East, Central, West and Northeast, and were empirically demonstrated with the spatial Durbin regression model respectively, and the analysis results are shown in **Table 10**.

R&D personnel and industry structure in the eastern region contribute significantly to the efficiency of technological R&D, while firm size inhibits the efficiency of technological R&D at the 1% level. In the transformation phase, both R&D expenditure and industry structure contribute significantly to the level of efficiency. R&D expenditure, government support, and the degree of R&D competition in the central region are all unfavorable to the improvement of R&D efficiency, and the factors that play a significant role in contributing to the improvement are the degree of market competition and the level of education. The degree of R&D competition may lead to fragmentation of resources and manpower, hindering the efficiency of technology development. In contrast, none of the influencing factors at the transformation stage had a significant effect on the level of efficiency. Human resource investment and education level in the western region contribute significantly to the efficiency of technological R&D, and R&D expenditure and industrial structure play a significant inhibitory role.

Government support, the degree of nationalization, and the degree of market competition can significantly promote the transformation of technology, while environmental regulations and the degree of R&D competition can hinder the transformation of technological achievements. Environmental regulation requires firms to comply with relevant environmental standards, which often requires firms to consider issues such as the cost of pollution control associated with the use of technology, and may lead to relatively less transformation of innovations for commercialization. Foreign investment, education level, degree of nationalization and environmental regulation all have a significant effect on R&D efficiency in the Northeast at the 1% level, with the first two being promotional and the latter two being inhibitory.

In the transformation stage, the investment of R&D personnel and the degree of R&D competition will inhibit the transformation of technological achievements, while the degree of nationalization, the degree of market competition and industrial restructuring will significantly promote the transformation of technology. Traditional industries in the northeast region account for a large proportion of the overall transformation and upgrading is slow, its slow economic development and high-quality talent loss make the overall quality of RD personnel to reduce, thus inhibiting the level of regional transformation efficiency level, and the improvement of the market environment can effectively promote the commercialization of technological achievements.

Table 10. Spatial heterogeneity regression results

Variable name	Eastern region		Central region		Western region		Northeast region	
	PTEC1	PTEC2	PTEC1	PTEC2	PTEC1	PTEC2	PTEC1	PTEC2
RDPI	0.103*	0.235	0.086	0.154	0.183**	0.080	0.122	-0.787***
	-1.749	-1.217	-1.259	-1.408	-2.181	-0.867	-1.125	-2.843
RDI	0.244	1.148***	-0.265**	0.003	-0.599***	0.052	0.287	-0.623
	-1.586	-3.479	-2.489	-0.017	-5.207	-0.408	-1.367	-1.192
SC	-0.499***	-0.305	-0.341	0.413	0.019	-0.022	-0.328	0.434
	-3.661	-1.141	-1.623	-1.076	-0.099	-0.103	-0.736	-0.371
GOV	0.047	-0.006	-0.127**	0.023	0.053	0.194**	-0.024	0.146
	-1.035	-0.029	-2.452	-0.289	-0.665	-2.211	-0.362	-0.86
ST	-0.124	0.139	0.193	-0.048	0.206	0.366*	-1.019***	0.947**
	-1.113	-0.292	-1.226	-0.15	-1.078	-1.741	-4.618	-2.034
ER	-0.054	-0.1	-0.026	0.195	-0.079	-0.115*	-0.200***	0.16
	-1.159	-0.453	-0.364	-1.58	-1.306	-1.713	-2.752	-0.989
MC	0.25	-1.685	0.596**	0.531	-0.175	1.195***	-0.538	3.219**
	-0.655	-0.949	-2.497	-1.645	-0.433	-2.672	-0.938	-2.148
RDC	-0.025	0.267	-0.176**	-0.045	0.075	-0.368***	-0.176	-0.934***
	-0.542	-0.993	-2.44	-0.411	-0.831	-3.737	-1.621	-3.162
FDI	-0.023	-0.272	-0.075	-0.025	-0.041	0.037	0.417***	0.499
	-0.342	-1.18	-1.134	-0.262	-0.505	-0.42	-3.191	-1.577
IS	0.451***	2.358***	-0.093	-0.195	-0.286**	-0.003	0.158	3.469***
	-2.724	-4.941	-1.063	-0.836	-2.39	-0.025	-0.518	-4.333
EL	-0.421	-0.173	1.093***	-0.451	0.438**	-0.098	1.301***	0.634
	-1.336	-0.174	-4.115	-0.959	-2.033	-0.412	-4.006	-0.83

5. Conclusions and policy implications

The article used the panel data of 30 provinces and cities in China from 2005 to 2022 to measure, decompose and analyze regional differences in green technology R&D efficiency and transformation efficiency of industrial enterprises in China by using the super-efficiency EBM model, the ML index model and the Dagum Gini coefficient model, then the article analyzed the influencing factors of pure efficiency at each stage by using the spatial Durbin model, and robustness and heterogeneity analyses were also performed, the conclusions are as follows.

Through the efficiency measurement and analysis, it is found that:

(1) Technology R&D efficiency > technology transformation efficiency, and the level of efficiency at each stage is directly proportional to the level of economic development of the region; Scale efficiency stabilized above 0.9 at all stages, and low levels of pure efficiency contributed to low levels of total efficiency.

In view of the fact that the efficiency of technology transformation is much lower than the efficiency of technology research and development, and there are bottlenecks in technological progress at the transformation stage, it is necessary to strengthen the collaborative research and development and innovation of industry-university-research, and at the same time, to focus more on the breaking down of barriers to technological transformation. Through the establishment of "R&D-pilot-industrialization" whole chain docking mechanism, enterprises are encouraged to join colleges and universities, research institutes to form industrial innovation alliances, set up special funds for technology transformation, and focus on supporting the construction of pilot platforms in new quality productivity areas such as artificial intelligence, Internet of Things, and green manufacturing. Implementing the system of "revealing a list of commanders", focusing on necklace technologies, such as high-end chips and industrial software, and improving the transformation efficiency through market-oriented projects. Optimize the allocation of resources at the transformation stage and use digital tools (e.g., industrial Internet) to monitor the process of technology transformation in real time, reduce the mismatch of resources, and improve the efficiency of pure technology (e.g., management efficiency);

(2) The level of efficiency in all phases tends to increase from 2005–2022, with the Eastern region having a higher level of efficiency in all phases than the other regions; China's overall stage and R&D stage efficiency levels show good development, but there is insufficient coordination between technical efficiency and technological progress at the transformation stage, and there are significant bottlenecks in technological progress. Differences in the level of efficiency at each stage come mainly from differences in the level of efficiency between regions, with more pronounced differences between the eastern region and the other regions.

Based on the fact that the efficiency level in the eastern region is much higher than that in other regions, i.e., the problem of imbalance in efficiency levels among regions, efforts should be made to promote the balanced development of regions. In the eastern region, relying on the advantages of R&D and transformation, focusing on the development of the "R&D headquarters + transformation base" model, exporting technological achievements to the central and western regions, and establishing a cross-regional benefit-sharing mechanism (e.g., technology shareholding, tax revenue sharing). Central, western and northeastern regions, undertake the transfer of technology from the east, build regional technology trading markets, and reduce the cost of transformation. Establishing an "Eastern-Western and Northeastern China Technology Transfer Fund" to support the transformation of research and development results from the east in the central, western, northern and eastern China; and establishing an "enclave economy" model, for example, by constructing industrial parks in the East in the Central and Western China, so as to achieve complementarity of resources. Promoting the twinning of city clusters such as Beijing-

Tianjin-Hebei, the Yangtze River Delta, and the Guangdong-Hong Kong-Macao Greater Bay Area with central and western provinces to reduce regional disparities through the division of labor in industrial chains and the sharing of innovation resources.

Through analysis of influencing factors, it was found that at the national level, the degree of nationalization and industrial structure contribute significantly to the level of efficiency, environmental regulation plays a significant inhibitory role in the level of efficiency, and human resource investment, R&D competitiveness, and market competitiveness have a significant role in the efficiency of the R&D stage only, and the former two play a significant contributing role, while the latter plays an inhibitory role. The level of education plays a significant role in promoting the efficiency of the R&D stage and a significant inhibiting role in the efficiency of the transformation stage.

Based on the results of the regression analysis, it is necessary to promote the transformation of state-owned enterprises into innovative subjects, encourage central enterprises and state-owned enterprises to take the lead in forming innovation consortiums, and give play to the positive effect of the degree of nationalization on efficiency through the introduction of market-based assessment mechanisms, such as the proportion of R&D investment and the effectiveness of the transformation of the linkage between the salary. We also need to pull industrial structural adjustment with new quality productivity, accelerate the deep integration of "intelligent manufacturing + industrial Internet", such as guiding enterprises to use cloud computing and empowering them with intelligence, relying on low-cost SaaS platforms and intelligent decision-making systems to improve production and management efficiency, building a national industrial big data platform, promoting cross-regional and cross-industry data sharing, and narrowing the regional efficiency gap and reshape the pattern of industrial development with new quality productivity. Besides, formulating "industrial green technology innovation roadmap", such as giving low-carbon technology research and development tax breaks, improving the carbon emissions trading market mechanism, turning environmental regulatory pressure into innovation momentum, forcing enterprises to upgrade technology is still an urgent task. In addition, Through the "New Quality Productivity Talent Special Program", focusing on cultivating "R&D + Transformation" composite interdisciplinary talents, as well as lowering the threshold of entry, strengthening intellectual property protection and other ways to consolidate the foundation of applied talents and amplify the degree of competition in the market to promote efficiency is also very important.

At the level of regional heterogeneity, each influencing factor has a different effect on the level of efficiency at each stage in the East-Central-West and Northeast regions. Based on the results of the analysis of regional heterogeneity, it is necessary to optimize the allocation of regional resources and unleash new quality productivity dynamics. In the eastern region, we will continue to consolidate our advantages in human resources and industrial structure, and attract global innovation factors through the "talent + capital + technology" integration model.

In the central region, direct government intervention should be reduced, and market vitality should be stimulated through the liberalization of industry access, the cultivation of specialized small and medium-sized enterprises, and other competitive policies that expand the autonomous decision-making power of enterprises. In response to problems such as inefficient utilization of R&D funds, a digital platform is used to fine-tune the management of funds and to regularly track the effectiveness of the use of funds. The western region should balance environmental regulation and efficiency improvement, develop green technologies such as photovoltaic, wind power and energy storage, and turn environmental pressure into low-carbon industrial advantages. The government can strengthen special subsidies and green finance to guide enterprises to adopt cleaner production technologies. Strengthening human resources development, implementing the "Western Talent Return Program", and relying on the Chengdu-Chongqing, Xi'an and other urban agglomerations to create a regional talent plateau. In the Northeast, foreign investment and cooperation should be expanded by taking advantage of geographic location, introducing advanced technology and management experience, and activating the dynamics of market competition. Optimizing the talent policy to curb the problem of "manpower loss", such as through school-enterprise cooperation to train industrial workers, relying on the transformation of old industrial bases demonstration zones, to promote the deep integration of traditional industries and digital technology, such as steel, equipment manufacturing intelligent transformation.

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