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Environmental regulation, technology density, and green technology innovation efficiency

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ABSTRACT

From the perspective of the innovation value chain, this study divides the innovation efficiency of green technology into two stages: R&D efficiency and achievement transformation efficiency. Technology density is introduced as a threshold variable to examine the influence of environmental regulation on the efficiency of green technology innovation at both stages. The findings reveal that China's overall green technology innovation efficiency (GTIE) is improving. R&D efficiency initially declined, then increased, while the efficiency of achievement transformation experienced a three-stage pattern: rise-fall-rise. The GTIE distribution across the two stages progressively increases from the northwest to the southeast, resulting in a concentrated, contiguous "line-shaped" and "block-shaped" pattern. High-efficiency areas are primarily found in the eastern coastal regions. Nationally, Environmental regulation and R&D efficiency share an inverted U-shaped relationship, with a double threshold effect of technology density. Environmental regulation does not significantly affect achievement transformation efficiency, but there is a single threshold effect due to technology density.

1. Introduction

Since the reform and opening, China's economy has been proliferating, and the per capita GNP has increased from the initial $165 to the present $12,551. In 1978, China's Gross Domestic Product (GDP) accounted for 1.74 % of the world's economy, and by 2021, it accounted for more than 18 %, with an average annual increase of 0.378 % [1]. However, in China's rapid economic growth, ecological and environmental problems caused by the single-minded pursuit of rapid economic development have gradually become evident. For example, environmental pollution continues to worsen, and the depletion of finite energy sources and the destruction of ecological habitats have become increasingly severe [2,3]. In 2010, China became the world's second-largest economy, and the economic growth rate began to slow down gradually. The economic development mode also shifted from a high-speed development mode to a high-quality one [4]. The economic, environmental, and social problems brought about by the traditional development mode have garnered significant attention from the state. The National Development and Reform Commission pointed out in the "Guiding Opinions on Building a Market-Oriented Green Technological Innovation System" that green technological innovation plays an essential role in the new round of the global industrial revolution and scientific and technological competition. As China's economic system of green, low-carbon, and recycling development continues to take shape [5], green technological innovation has become a major driving force

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for China's economic and social development.

Regarding the relationship between the environment, economy, and innovation, traditional economic theory maintains that the cost of environmental pollution caused by enterprises during the development process is not factored into the total cost of production. This omission can potentially lead to the problem of "market failure" [6]. According to this theory, the government must exert control by implementing environmental regulations. However, increasing the environmental regulation level will also raise enterprises' investment in pollution control. This, in turn, can displace the funds that should be allocated to scientific and technological innovation activities, thus diminishing the level of innovation output by enterprises and resulting in the "crowding out effect" [7]. In contrast, Porter's hypothesis offers a different perspective [8]. He contends that moderate environmental regulation can stimulate green technological innovation within enterprises. In other words, there exists a reasonable range for environmental regulation that can offset the additional costs incurred by its implementation, thereby giving rise to the "innovation compensation effect."

The "Porter's hypothesis" proposal has garnered considerable attention within the academic community, leading scholars to explore the relationship between environmental regulation and green technological innovation from various perspectives. This exploration has primarily resulted in the formation of three main viewpoints. Support for Porter's Hypothesis: Scholars such as Yang et al. advocate for Porter's hypothesis, asserting that reasonable environmental regulation policies not only stimulate enterprise green technological innovation but also bolster the sales profits of companies [9]. This compensation effect can offset the costs incurred by businesses due to pollution control and ultimately enhance their overall competitiveness. The research findings of Feng et al. similarly corroborate this perspective [10]. Inhibition of Green Technological Innovation: Another viewpoint suggests that environmental regulation can inhibit green technological innovation. Scholars like Brunner Meier & Cohen and Barbera & McConnell argue that environmental regulation increases the costs associated with pollution control, leading to a "crowding out effect" on existing R&D investments by enterprises. This, in turn, hampers their ability to innovate in the green technology sector [11,12]. Non-linear Relationship: A third perspective posits that the relationship between environmental regulation and green technological innovation is non-linear. Alpay et al. and Albrizio et al. have discovered that the impact of environmental regulation on green technological innovation varies across industries and regions, resulting in various non-linear relationships [13,14]. A systematic conclusion is needed for studies investigating the connection between environmental legislation and green technology innovation, as is evident from a survey of the available literature. On top of that, it has the following flaws that need fixing: First. "Porter's hypothesis" and traditional economic theories have thoroughly studied green technology innovation and environmental control. Additional research is needed to uncover the inner workings of the green technology innovation process. Second, most studies on green technology innovation have concentrated on determining criteria such as the amount of environmental legislation and pollution control. Green technical innovation can be hindered by internal factors that are typically ignored.

This paper's primary innovations and potential contributions can be outlined as follows. First, recognizing that green technological innovation comprises a series of sub-processes encompassing research and development, manufacturing, and sales, this study dissects the green technological innovation process into two distinct stages: R&D and achievement transformation. It examines the impact of environmental regulation on green technological innovation at various stages, treating each stage as a separate entity. Second, prior investigations have often overlooked the influence of internal factors on green technology innovation. In contrast, this paper introduces the technology density index as an internal determinant of green technology innovation. It employs a threshold model to rigorously evaluate the effects of technology density on green technology innovation. Third, this paper conducts a region-specific analysis of China, differentiating the eastern, central, and western regions to investigate variations in the impact of environmental regulations on green technological innovation across these distinct geographic areas.

The rest of the paper is organized as follows: Section 2 describes the mechanism of environmental regulation on green technology innovation and the moderating role of technology intensity on environmental regulation. Section 3 explains the selection of research indicators, data sources, and the research model. Section 4 analyzes the measurement results and spatial differences in green technology innovation efficiency. Section 5 presents an empirical analysis and discusses the results of green technology innovation efficiency. Section 6 summarizes the conclusions of this study and provides some policy recommendations.

2. Theoretical basis and research hypothesis

2.1. Environmental regulation's impact on GTIE

According to relevant theories, the impact of environmental regulation on green technological innovation includes both the "innovation compensation effect" and the "compliance cost effect" [15]. The "innovation compensation effect" refers to the willingness of enterprises to increase investment in scientific and technological innovation to improve production efficiency and reduce pollution emissions at the source [16]. The "compliance cost effect" refers to the willingness of enterprises to invest more in pollution control costs to reduce pollution emissions at the end of the pollution process [17]. In the short term, environmental regulation will cause problems such as increasing enterprise costs and crowding out R&D funds, thus inhibiting green technology innovation. Additionally, based on the threshold theory, Dai et al. believe that the increase in production costs of large enterprises and the increase in government "rent-seeking" incentives will reduce their scale and financial advantages, resulting in a negative impact of environmental regulation on green technological innovation [18]. In the long run, enterprises will be forced to bear higher environmental governance costs with the continuous implementation and strengthening of environmental regulation policies. When these costs exceed the cost of enterprise innovation, companies will increase their investment in scientific research and innovation, leading to a revolution in production technology and promoting the enhancement of green technological innovation.

The impact of environmental regulation on green technological innovation results from the trade-off between the "innovation compensation effect" and the "compliance cost effect." The relationship between these two factors is illustrated in Fig. 1. Faced with varying levels of environmental regulation, enterprises will make trade-offs based on their own "cost-benefit" optimization. Depending on the circumstances, companies may reduce capital investment in innovation and increase pollution control costs to meet environmental standards or intensify scientific and technological innovation to enhance corporate profits, meeting the financial demands of pollution control capital needs. The effect of environmental regulation on green technological innovation varies with the intensity of environmental regulation. Wang et al. analyzed enterprise data and found a U-shaped relationship between environmental regulation and green technological innovation [19]. Du et al., using city data, discovered an inverted U-shaped relationship between environmental regulation and green technological innovation [2]. Lv et al., Zhang et al., Xie et al., and other researchers have examined this issue and concluded that a nonlinear relationship exists between environmental regulation and green technology innovation [20–22].

However, previous studies have often treated the innovation process as a "black box," neglecting innovation's internal structure and operational mechanisms. Green technology innovation involves multiple factor inputs, including intermediate inputs, intermediate outputs, and additional inputs, as well as multiple innovation stages. Drawing upon the theory of the "innovation value chain" proposed by Hansen and building on the research findings of Zhang & Wang [23] and Nikbakht et al. [24], this paper divides the process of green technological innovation into two stages: R&D and achievement transformation. This approach helps unveil the "black box" of innovation, facilitating a deep analysis of the inner mechanisms of the green technology innovation process. The R&D stage encompasses the process from the initial resource input to the generation of technological innovation results. In contrast, the transformation stage pertains to further marketizing and applying technological innovation results. Environmental regulatory policies can influence both the initial resource input and product marketization within the green technological innovation process, subsequently affecting the R&D and achievement transformation stages. Since the initial resource input and product marketization are two distinct behaviors, the impact of environmental regulation on R&D and achievement transformation may also differ. Based on this, this paper proposes the first and second research hypotheses.

H1. There exists a nonlinear relationship between the impact of environmental regulation on two-stage green technology innovation.

H2. There is heterogeneity in the impact of environmental regulation on R&D and achievement transformation.

2.2. The moderating effect based on technological density

Most of the existing literature concerning the impact of environmental regulation on green technological innovation is predicated on the assumption that green technological innovation in a region is primarily determined by external factors such as the level of economic development, the intensity of environmental regulation, and investment in R&D. Less consideration is given to factors inherent to the industry. In reality, the industrial characteristics of a region also play a significant role in green technological innovation, influencing the region's development potential and industry expectations to some extent [25]. Technology density, as one of the industrial characteristics of a region, is closely linked to green technological innovation. On a micro level, enterprises with higher technological density possess greater innovation power and more enormous innovation potential. When the government implements appropriate environmental regulation policies, it promotes the enhancement of green technological innovation. Conversely, enterprises with lower technological density are constrained by limited innovation space and capacity. When environmental regulation becomes more stringent, their production levels may struggle to meet the required environmental standards, eventually putting them at risk of closure [26]. On a macro level, environmental regulation can impact green technological innovation only when a region's technological density has reached a certain threshold. In regions with relatively underdeveloped technological levels, high-intensity environmental regulation might harm green technological innovation. In regions with advanced technological development, environmental regulation positively affects green technological innovation [27]. Therefore, this paper proposes the third research hypothesis:

H3. There exists a "technology density" threshold for environmental regulation's impact on the green technological innovation.

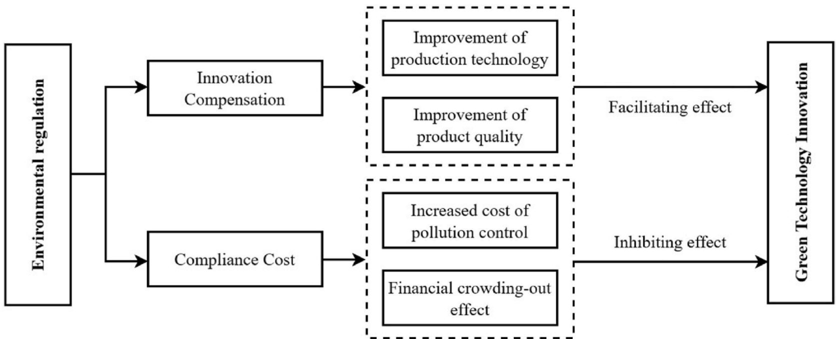


Fig. 1. Path of environmental regulation on green technology innovation.

3. Research design

3.1. Data

3.1.1. Explained variable

Concerning the selection of green technology innovation efficiency indicators, the research findings of Zhu et al. [28] and Miao et al. [29] lead to dividing green technology innovation efficiency into R&D efficiency (Y1) and achievement transformation efficiency (Y2). For the input index of the R&D stage, the full-time equivalent of R&D personnel signifies the level of human capital input, while internal R&D expenditure indicates capital input. Following the methodology of Kichikawa et al. [30] Furthermore, R&D internal funding expenditure is adjusted using the R&D price index with 2010 as the base period, and stock processing is carried out using the perpetual inventory method. The R&D price index is 0.25 times the producer index and 0.75 times the consumer price index.

Green technology innovation intermediate outputs mainly encompass papers, patents, monographs, and other forms. In this study, the total number of patent applications, the number of authorized invention patents, and the number of new product development projects are selected as representative output indicators for the technology R&D stage. These intermediate variables can function as input indicators for the results transformation stage. The additional inputs in the transformation stage primarily comprise the cost of introducing technology, purchasing domestic technology, and total industrial energy consumption. These are chosen because industrial enterprises, as the main contributors to innovation, have a significant role in green technology innovation activities.

Regarding output indicators in the transformation stage, green technology innovation output elements mainly consist of economic and non-desired output. This paper uses new product sales revenue to represent economic output. As for non-desired output, the study employs industrial wastewater emissions, industrial solid waste emissions, and industrial smoke (dust) emissions. These three indicators reflect the direct environmental impact caused by excessive resource consumption, an irrational industrial structure, and haphazard production methods during the innovation process.

3.1.2. Explanatory variable

The explanatory variable is environmental regulation (*ER*). Environmental regulation policy tools can generally be elaborated from two perspectives: income indicators and expenditure indicators [31,32]. One is the environmental regulation income index, which measures the final income of environmental regulation from the perspective of the environmental governance effect. Reducing environmental pollution emissions can improve the control effect, usually measured by the number of specific (multiple) pollutants emissions. The second is the environmental regulation expenditure index, which measures environmental regulation efforts from the economic expenditure perspective. As the economic expenditure on pollution control, the higher the investment in pollution control, the greater the economic effort in environmental regulation. It is usually expressed as the proportion of environmental pollution control costs to GDP.

3.1.3. Threshold variable

Technology Intensity (TE) is calculated as the product of the ratio of R&D expenditures and the ratio of R&D personnel. The proportion of R&D expenditure is defined as the share of R&D expenditure in GDP. In contrast, the proportion of R&D personnel is

Table 1
Indicators system.

Index type	Evaluating index	Variable	Unit
Technology R&D investment index	Capital investment	R&D internal expenditure	million yuan
	Human input	R&D personnel full-time equivalent	person
Technology R&D output index and Achievement transformation input index	Intermediate output	total number of patent applications	piece
		invention patent authorization quantity	piece
		number of new product development projects	piece
	Additional investment	introduction of technical costs	million yuan
		buy domestic technology costs	million yuan
		total industrial energy consumption	ten thousand tons of standard coal
Achievement transformation output index	Economic output	new product sales revenue	million yuan
	Unexpected output	industrial wastewater discharge	million tons
		industrial solid waste emissions	million tons
		industrial smoke (powder) dust emissions	million tons
Explanatory variable	Environmental regulation	environmental pollution control costs/GDP	%
Threshold variable	Technology density	proportion of R&D expenditure × proportion of R&D personnel	NA
Control variable	Information technology level	number of Internet users	person
	Opening-up degree	total import and export of products/GDP	%
	Industrial structure	the secondary industry added value/GDP	%
	Human resources	the number of students in colleges and universities	million people

defined as the share of the total number of R&D personnel in the total number of employed people. The level of green technology innovation shows a positive correlation with technology intensity. Higher technology intensity signifies that the R&D sector has invested more R&D expenditure and human capital in the innovation process, consequently exerting a more significant influence on green technology innovation.

3.1.4. Control variable

(1) Information technology (*IT*). This paper uses the total number of Internet users in the region to represent the level of information technology [33]. (2) Opening-up (*OPEN*). In this paper, the opening-up degree is measured by the ratio of total imports and exports of products to GDP. (3) Industrial structure (*INS*). This paper selects the proportion of the secondary industry's added value in GDP to represent the industrial structure. (4) Human resources (HR). The endogenous growth theory believes that the accumulation of human capital can significantly impact scientific and technological innovation [34]. This paper selects the number of students in colleges and universities to measure the level of human resources.

This study spans the period from 2010 to 2020 and investigates the mechanism through which environmental regulation impacts the efficiency of green technology innovation across the two stages within this timeframe. The sample data are sourced from the "China Statistical Yearbook," "China City Statistical Yearbook," "China Science and Technology Statistical Yearbook," and the EPS database. The specific indicators used in this study are summarized in Table 1.

3.2. Super efficiency SBM model based on the undesirable output

The super-efficiency SBM model [35,36] effectively addresses the shortcomings of traditional DEA and SBM models by comprehensively accounting for the impact of input and output slack variables on efficiency levels. Furthermore, the super-efficient model distinguishes effective DMUs, while the SBM model can assess ineffective DMUs. The super-efficient SBM accurately measures the input-output efficiency of DMUs and simultaneously facilitates comparisons among multiple effective DMUs. Therefore, this paper constructs a super-efficient SBM model based on non-expected outputs, assuming that the green technology innovation efficiency of n DMUs is being assessed. In this context, the efficiency expression of each DMU is as follows:

$$\min \rho = \frac{1 + \frac{1}{m}\sum_{i=1}^{m}\left(\frac{S_i^-}{x_{ik}}\right)}{1 - \frac{1}{q_1 + q_2}\left(\sum_{r=1}^{q_1}\frac{S_r^+}{y_{rk}} + \sum_{t=1}^{q_2}\frac{S_t^-}{b_{tk}}\right)}$$

$$s.t.\begin{cases} x_{ik} \geq \sum_{j=1, j\neq k}^{n} x_{ij}\lambda_j - S_i^- \\ y_{rk} \geq \sum_{j=1, j\neq k}^{n} y_{rj}\lambda_j + S_r^+ \\ b_{tk} \geq \sum_{j=1, j\neq k}^{n} b_{tj}\lambda_j - S_t^- \\ 1 - \frac{1}{q_1 + q_2}\left(\sum_{r=1}^{q_1}\frac{S_r^+}{y_{rk}} + \sum_{t=1}^{q_2}\frac{S_t^-}{b_{tk}}\right) > 0 \\ \lambda_i \geq 0, S_i^- \geq 0, S_r^+ \geq 0, S_t^- \geq 0 \end{cases} \tag{1}$$

In Equation (1), ρ is the green technology innovation efficiency value. k is the measured DMU. λ_j is the weight of each DMU. Each DMU has m input indicators: x_i ($i = 1, 2 \ldots$, m), q_1 desired output indicator: y_r ($r = 1,2 \ldots, q_1$), q_2 non-desired output indicators: b_t (t = 1,2 …, q_2). S_i^-、 S_r^+、 S_t^- denotes the slack variables for input x_i, desired output y_r and undesired output b_t, respectively.

3.3. Econometric model

This paper constructs two-panel models to explore the impact of environmental regulation on R&D efficiency and the efficiency of achievement transformation. Equation (2) examines the effect of environmental regulation on R&D efficiency. Where i denotes the province and t denotes the year. *Y1* is the explained variable, indicating R&D efficiency; *ER* is the core explanatory variable, indicating environmental regulation. X represents the control variable. *C* is a constant term; β denotes the parameter to be estimated. V_i represents the individual effect, λ_i denotes the time effect, and ε_{it} represents the random error term. Equation (3) examines the effect of environmental regulation on the efficiency of achievement transformation. Y2 is the explained variable, indicating the efficiency of achievement transformation. The meaning of other variables remains unchanged.

$$Y1_{it} = C + \beta_1 ER_{it} + \beta_2 ER_{it}^2 + \beta_3 X_{it} + V_i + \lambda_t + \varepsilon_{it} \tag{2}$$

$$Y2_{it} = C + \beta_1 ER_{it} + \beta_2 ER_{it}^2 + \beta_3 X_{it} + V_i + \lambda_t + \varepsilon_{it} \tag{3}$$

It is found that the effect of environmental regulation on GTIE may be affected by technology density. Therefore, this paper draws on the panel threshold model proposed by Hansen to examine the impact of environmental regulation on R&D efficiency and the efficiency of achievement transformation under the constraints of technology density [37]. (1)In Equations (4) and (5), i represents the province and t represents the time. *Y1* and *Y2* have explained variables that represent the R&D efficiency and the efficiency of achievement transformation. *ER* is the core explanatory variable, indicating environmental regulation; *TE* represents the technology density; τ is the threshold estimate; *I (.)* is the indicator function, $\sum_{j=1}^{n} \alpha_j X_{it}^j$ is other control variables, and μ_{it} is the random error term.

$$Y1_{it} = B_1 + \alpha_1 ER_{it} I(TE \le \tau) + \alpha_2 ER_{it} I(TE \ge \tau) + \sum_{j=1}^{n} \alpha_j X_{it}^j + \mu_{it} \tag{4}$$

$$Y2_{it} = B_1 + \alpha_1 ER_{it} I(TE \le \tau) + \alpha_2 ER_{it} I(TE \ge \tau) + \sum_{j=1}^{n} \alpha_j X_{it}^j + \mu_{it} \tag{5}$$

4. GTIE's spatiotemporal evolution characteristics analysis

4.1. GTIE analysis

The average values of R&D efficiency and achievement transformation efficiency for each province are presented in Table 2. From a national perspective, the two-stage GTIE is generally low, with averages of 0.530 and 0.628, respectively, leaving ample room for development and improvement. The efficiency of achievement transformation significantly surpasses R&D efficiency, making it the primary driver for GTIE improvement. While local governments have enhanced their efforts to protect the ecological environment and the phenomenon of resource wastage has gradually improved, resource utilization efficiency still needs to improve due to the influence of traditional development models and technological constraints. From a regional perspective, the R&D and achievement transformation efficiency in the eastern, central, and western regions are 0.687 and 0.858, 0.522 and 0.535, and 0.379 and 0.466, respectively. The eastern region holds the highest R&D and achievement transformation efficiency, while the western region has the lowest.

To further analyze the differences between GTIE, according to the average value of R&D efficiency and achievement transformation efficiency in each province, the different types of green technology innovation are divided into four quadrants with 0.50 and 0.60 as the boundary. The first quadrant represents the high R&D-high transformation type, the second quadrant represents the low R&D-high transformation type, the third quadrant represents the low R&D-low transformation type, and the fourth quadrant represents the high R&D-low transformation type. The distribution of GTIE in the four quadrants at different stages of each province is demonstrated in Fig. 2.

The provinces in the first quadrant's R&D efficiency and achievement transformation efficiency belong to the nationally leading level, mainly including Beijing, Guangdong, Shanghai, and other provinces. Relying on the international market environment and advanced technical level, these provinces have inherent advantages in developing green technology innovation, which guarantees efficient R&D and achievement transformation. The provinces in the second quadrant, primarily Shandong, Xinjiang, Hebei, and others, are increasingly significant in the achievement transformation stage. In the stage of green technology innovation, these provinces can convert scientific research achievements into market economy value to the greatest extent; however, their initial resources, such as talent and funds, need to be improved, and their R&D capacity needs to be stronger. The R&D and achievement

Table 2
The average efficiency of two-stage green technology innovation in China's provinces.

Province	R&D efficiency	Achievement transformation efficiency	Province	R&D efficiency	Achievement transformation efficiency
Beijing	0.816	1.044	Henan	0.556	0.577
Tianjin	0.746	0.836	Hubei	0.631	0.594
Hebei	0.437	0.648	Hunan	0.523	0.531
Shanghai	0.814	1.031	Central mean	0.522	0.535
Jiangsu	0.781	0.843	Inner Mongolia	0.305	0.355
Zhejiang	0.749	0.880	Guangxi	0.276	0.393
Fujian	0.695	0.815	Sichuan	0.608	0.554
Shandong	0.482	0.765	Chongqing	0.654	0.618
Guangdong	0.865	1.112	Guizhou	0.507	0.513
Hainan	0.684	0.855	Yunnan	0.221	0.308
Liaoning	0.487	0.607	Shaanxi	0.518	0.547
Eastern mean	0.687	0.858	Gansu	0.306	0.614
Jilin	0.357	0.397	Qinghai	0.196	0.266
Heilongjiang	0.435	0.416	Ningxia	0.241	0.346
Shanxi	0.477	0.621	Xinjiang	0.335	0.611
Anhui	0.614	0.581	Western mean	0.379	0.466
Jiangxi	0.583	0.562	National mean	0.530	0.628

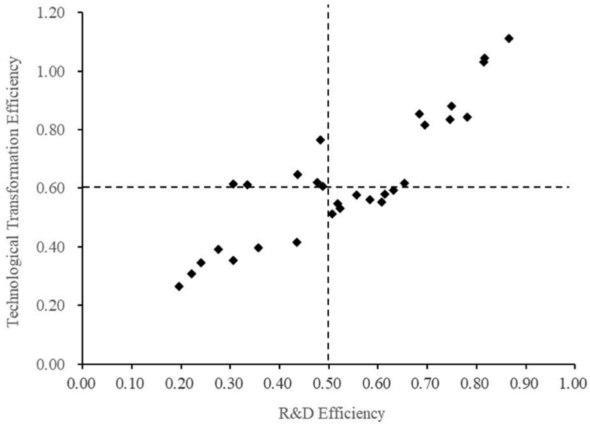


Fig. 2. Quadrant distribution of R&D efficiency and achievement transformation efficiency in each province.

transformation efficiency of the third quadrant provinces are low, including Yunnan, Jilin, Guangxi, and other provinces, mainly distributed in the northeast and western regions. These provinces' degree of economic development could be higher, and the loss of scientific and technological talent is severe. The lack of investment in R&D contributes to inefficient R&D. The provinces in the fourth quadrant are more prominent in the R&D stage, and the efficiency of achievement transformation is low, mainly including Sichuan, Hubei, Anhui, and others. In the initial phase of green technological innovation, these provinces can better convert scientific research resources into patents and paper achievements. However, their capacity to convert scientific research successes into economic value must be more assertive.

4.2. GTIE time series variation characteristics

The super efficiency SBM model calculates the R&D efficiency and achievement transformation efficiency of green technology innovation in 30 provinces in China. The specific results of the time trend chart are displayed in Fig. 3. From 2010 to 2020, achievement transformation efficiency was higher than R&D efficiency, oscillating between 0.65 and 0.75 and exhibiting a 'rise-recession-rise' pattern. Although R&D efficiency is slightly lower than achievement transformation efficiency, it has always maintained a constant growth state. Since 2013, its growth rate has accelerated dramatically, producing a catch-up trend for achievement transformation efficiency. This result demonstrates that although green technology innovation has constantly increased, it is still modest, and innovative resource allocation must be further streamlined.

4.3. GTIE spatial series variation characteristics

Spatial distribution maps of R&D efficiency and achievement transformation efficiency for 2010, 2013, 2017, and 2020 are created using ArcGIS 10.2 software. The natural breakpoint method divides the R&D and achievement transformation efficiency into four tiers. The levels, from least to most efficient, are low, lower, higher, and high. Fig. 4(a–d) and 5(a-d) depict the specific outcomes.

From the R&D stage perspective (Fig. 4a, b, 4c and 4d), R&D efficiency in 2010 displayed a distribution that gradually increased from northwest to southeast. High-efficiency areas are primarily distributed along the southeast coast and the Beijing-Tianjin-Hebei region, with higher-efficiency areas concentrated mainly in North China and South China. Lower-efficiency areas are primarily

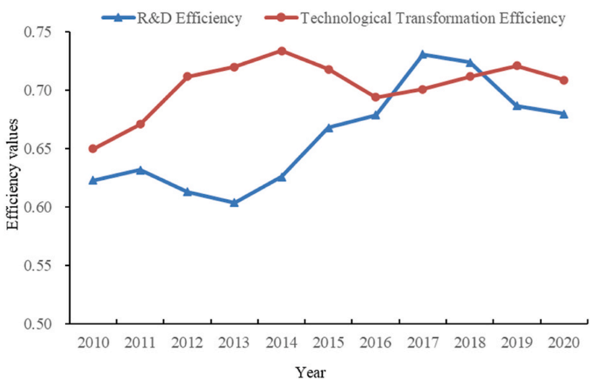
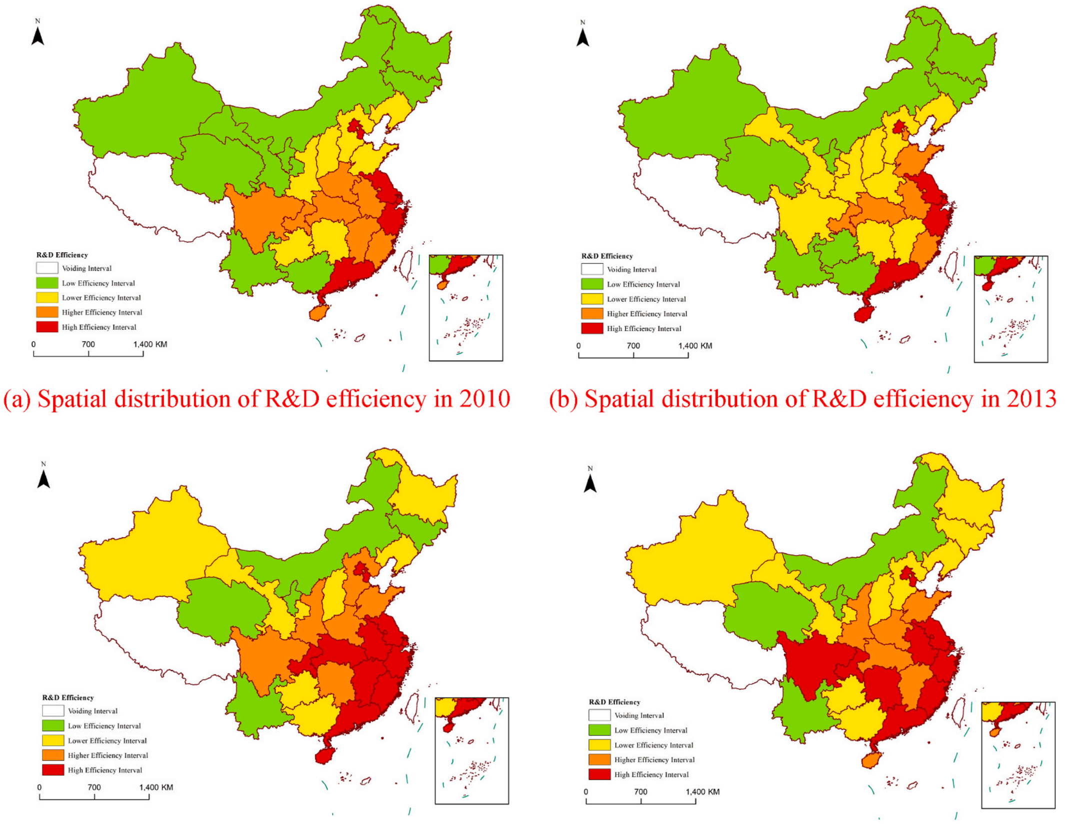


Fig. 3. National GTIE trend.



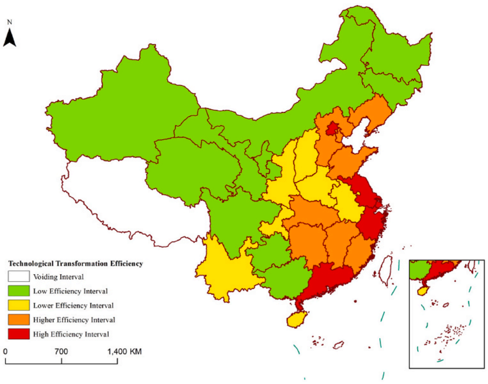
(a) Spatial distribution of R&D efficiency in 2010 (b) Spatial distribution of R&D efficiency in 2013

(c) Spatial distribution of R&D efficiency in 2017 (d) Spatial distribution of R&D efficiency in 2020

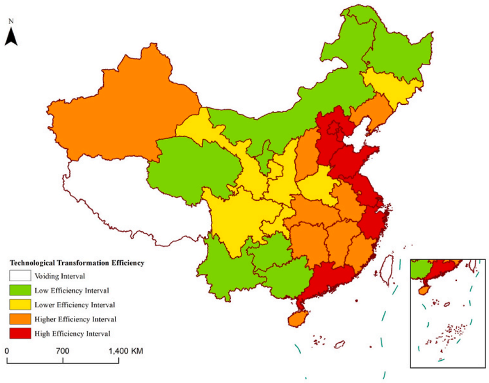
Fig. 4. Spatial distribution pattern of R&D efficiency.

found in the "Liaoning-Hebei-Shanxi-Shaanxi" chain. By 2020, the "ladder" feature of the spatial distribution of R&D efficiency was further emphasized, characterized by a concentrated and contiguous "line" and "block" distribution. High-efficiency areas remained concentrated in the coastal areas, while the scope of the lower-efficiency areas expanded further. The difference in the southwest region was the most pronounced, encompassing almost all efficiency zones. Beijing, Guangdong, Zhejiang, and other provinces remained in the high-efficiency area throughout the study period. Compared to 2010, provinces like Chongqing, Sichuan, and Anhui joined the high-efficiency area, while Xinjiang, Gansu, Heilongjiang, and others exited the low-efficiency area. The provinces with lower efficiency and higher efficiency witnessed relatively stable changes, accounting for approximately 60 %. From 2010 to 2020, the overall level of R&D efficiency increased, with steady growth in the eastern region and the central and western regions gradually moving towards balanced development. However, the polarization of R&D efficiency between the eastern and western regions persists.

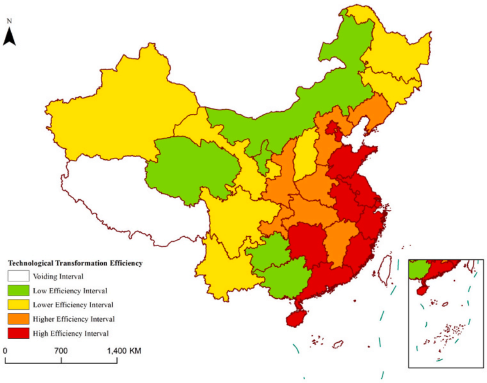
From the achievement transformation stage perspective (Fig. 5a, b, 5c and 5d), the efficiency of achievement transformation in 2010 still exhibited a gradual increase from the northwest to the southeast. The high-efficiency areas are primarily distributed along the southeast coast and in Beijing. The higher-efficiency areas are mainly concentrated around the Bohai Rim and South China. The lower-efficiency areas are mainly found in provinces such as Shanxi, Shaanxi, and Anhui. The low-efficiency areas are concentrated in the northeast, northwest, and southwest regions. With economic development, the efficiency of achievement transformation in 2020 was primarily characterized by densely populated regions 'block' distribution features. The high-efficiency areas remained concentrated in the coastal regions, and the complex terrain in the southwest formed various efficiency areas. Throughout the research period, Beijing, Zhejiang, Guangdong, and other provinces consistently held top national positions, achieving a "double high" in R&D efficiency and achievement transformation efficiency. Compared to 2010, the efficiency of achievement transformation in provinces such as Shandong, Anhui, and Hubei increased rapidly, with a significant rise in the proportion of high-efficiency areas. The efficiency of achievement transformation improved to varying degrees in provinces like Sichuan, Jilin, and Hebei, mainly in higher-efficiency areas. Provinces like Inner Mongolia, Qinghai, and Guangxi remained in low-efficiency areas. These provinces are affected by factors like geographical location and economic conditions. The input and output of scientific innovation are not balanced, and the two-stage innovation link needs to be coordinated, resulting in weak innovation and achievement transformation capabilities. From 2010 to 2020, the efficiency of achievement transformation developed significantly, and the expansion of high-efficiency areas in the eastern region led to improvements in the central and western regions.



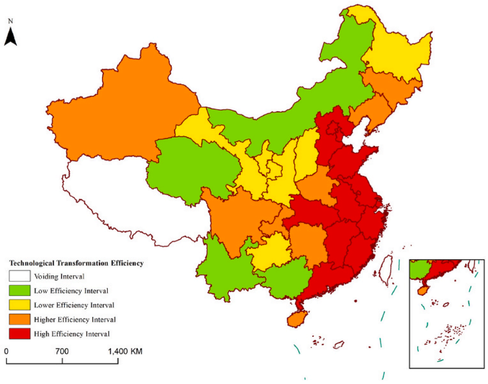
(a) Spatial distribution of achievement transformation efficiency in 2010



(b) Spatial distribution of achievement transformation efficiency in 2013



(c) Spatial distribution of achievement transformation efficiency in 2017



(d) Spatial distribution of achievement transformation efficiency in 2020

Fig. 5. Spatial distribution pattern of achievement transformation efficiency.

5. Results and discussion

5.1. Data stationarity test

This paper employs the ADF-Fisher, IPS, and LLC methods to test whether there is a panel unit root to ensure the stability of panel data. The test results indicate that all panel data have good stability, as displayed in Table 3. Based on this, this paper will further analyze the impact of environmental regulation on two-stage GTIE.

Table 3
Panel unit root test results.

Variable	ADF-Fisher	IPS	LLC
Y1	204.425***	−17.651***	−37.642***
Y2	162.571***	−8.327***	−54.351***
ER	129.347***	−60.248***	−75.809***
TE	84.233***	−11.456***	−23.847***
IT	108.482**	−3.615***	−40.278***
OPEN	217.579***	−38.974***	−7.410***
INS	276.863***	−45.113***	−80.594***
HR	95.418***	−21.035***	−10.372**

Note: ***, **, and * represent the adoption of 1 %, 5 %, and 10 % significance levels, respectively, the same as below.

5.2. The mechanism of environmental regulation on GTIE

5.2.1. Baseline regression

First, the general linear model is used to analyze the impact of environmental regulation on GTIE at the national level. The Hausman test results reject the null hypothesis at the 5 % level, so the fixed effect model is used for further research. The specific results are demonstrated in Table 4, models A1 and A2.

In the R&D stage, the primary coefficient of environmental regulation is 1.094, and the number of secondary terms is −2.802. The coefficients of environmental regulation and its square term pass the significance test at the 1 % level, indicating that the impact of environmental regulation on R&D efficiency is an inverted “U” type, which confirms H1 of this paper. In the control variables, the impact of informatization level, openness, and human capital on R&D efficiency is positive, and all pass the significance test at the 1 % level. The coefficient of industrial structure is −1.556, and the impact on R&D efficiency is negative. The reason may be that when environmental regulation is low, enterprises are more willing to trade in environmental pollution for economic benefits. When environmental regulation is gradually strengthened, businesses’ production and sales revenue scale will be impacted. Enterprises will boost their investment in R&D to improve resource utilization efficiency and innovation efficiency to sustain their original income. At this time, environmental regulation has a “compensating effect” on developing green innovations. With increasingly stringent environmental regulations, the benefits brought by enterprises through R&D cannot compensate for the cost of pollution control. At this time, enterprises may choose to go to an area with a low level of environmental regulation to “escape pollution,” eventually decreasing R&D efficiency. Therefore, with the change in environmental regulation from weak to strong, the impact of environmental regulation on R&D efficiency shows an inverted “U” trend of increasing first and then decreasing.

In the stage of achievement transformation, the first-order coefficient of environmental regulation is −2.034, and the second-order coefficient is 1.056. Neither passed the significance test, confirming this paper’s second hypothesis (H2). Among the control variables, the influence of the level of information technology and degree of openness on the efficiency of achievement transformation is positive. It passes the significance test at the 1 % level. However, the industrial structure and human resources must still pass the significance test. This outcome may be because moderate environmental regulation can assist enterprises in improving innovation efficiency to secure profits earlier, compensating for the additional costs of environmental governance. The R&D stage primarily influences further transforming R&D achievements into productivity. When environmental regulation is within a specific limit, increasing environmental costs could impose a substantial burden on enterprises, making it challenging to realize the marketization of R&D achievements further.

5.2.2. Threshold regression

The above research verifies that there is a nonlinear relationship between environmental regulation and two-stage GTIE. To further analyze the impact of environmental regulation on green technology innovation at different stages, this paper uses technology density as a threshold variable to explore whether environmental regulation has a threshold effect on two-stage GTIE. First, the bootstrap method is employed to estimate the F statistic and P value to determine the number of specific thresholds, as demonstrated in Table 5.

The regression results (Table 6) show that with increasing technology density, environmental regulation has a nonlinear relationship with GTIE. In the R&D stage, when the technology density is lower than 0.148, the regression coefficient of environmental regulation is −0.554. This indicates that when the technology density is low, the impact of environmental regulation on R&D is negative. This may be because China’s economic development is unbalanced, and it is difficult for funds and infrastructure to meet the development requirements at this stage. At this time, if the government implements strong environmental regulations, it will often lead to enterprises occupying a large number of R&D costs and hindering the improvement of R&D efficiency. When the technology density is between 0.148 and 0.430, the regression coefficient of environmental regulation is 1.267. This result shows that with the improvement of the economic development level and the increase in technology density, the current environmental regulation level will have a “compensation effect” on technological innovation and promote the improvement of technological innovation. When the technology density is higher than 0.430, the regression coefficient of environmental regulation is 2.092, which indicates that when the technology density crosses the second threshold, the promotion effect of environmental regulation on R&D efficiency is further

Table 4
Regression results of the national linear model.

Variable	R&D stage		Achievement transformation stage	
	Linear model A1	t-value	Linear model A2	t-value
IT	0.742***	3.46	0.320***	3.58
OPEN	0.061***	8.31	0.020***	4.82
INS	−1.556**	−2.35	2.015	0.76
HR	0.013***	4.70	−0.008	−1.35
ER	1.094***	3.78	−2.034	−1.12
ER^2	−2.802***	−4.68	1.056	0.32
C	1.247***	6.32	0.813***	5.50
Time fixed effect	Yes		Yes	
Individual fixed effect	Yes		Yes	
R^2	0.786		0.740	

Note: ***, **, and * represent the adoption of 1 %, 5 %, and 10 % significance levels, respectively, the same as below.

Table 5
The existence test and threshold estimation of the threshold effect of environmental regulation on GTIE.

Variable	Model	Estimated value	F value	P value	95 % confidence interval	BS times
R&D stage	Single threshold	0.148	17.354	0.000	[0.145 , 0.207]	300
	Double threshold	0.430	13.285	0.020	[0.430 , 0.536]	300
	Triple threshold		25.604	0.750	[0.615 , 0.738]	300
Achievement transformation stage	Single threshold	0.235	8.017	0.000	[0.230 , 0.285]	300
	Double threshold		17.018	0.350	[0.340 , 0.881]	300
	Triple threshold		34.329	0.460	[0.975 , 1.145]	300

Table 6
Threshold regression results of environmental regulation on GTIE.

Variable	R&D stage		Achievement transformation stage	
	Threshold regression B1	t-value	Threshold regression B2	t-value
IT	0.247***	6.44	0.185***	3.71
OPEN	0.075***	4.58	0.070**	2.27
INS	−0.181	−0.65	0.129***	6.43
HR	0.013***	5.33	0.011	1.42
ER_1	−0.554***	−4.18	−0.330***	−4.58
ER_2	1.267***	5.48	−0.105**	−2.06
ER_3	2.092**	2.43		
F	75.39		57.36	
R^2	0.765		0.684	

Note: ER_1 to ER_3 represent the coefficients of environmental regulation in different threshold intervals, the same as below.

enhanced. In the achievement transformation stage, environmental regulation hurts the efficiency of achievement transformation.

When the technology density is less than 0.235, the regression coefficient of environmental regulation is −0.330; when the technical density is more significant than 0.235, the regression coefficient is −0.105. This result indicates that environmental regulation will hinder the transformation of achievements. The possible reason is that, on the one hand, due to the low entry threshold for patent inventions in China, patent inventions occupy a large number of R&D funds, but the practicality of inventions needs to be improved. On the other hand, because the achievement transformation stage fails to achieve good docking with the first stage, the conversion rate of patent achievements needs to be increased, which hinders the improvement of achievement transformation efficiency. This result verifies H3 in this paper.

5.3. Robustness test and endogeneity test

5.3.1. Robustness test

To ensure the authenticity and reliability of the conclusion, this paper draws on the practice of Bao and Chai [38]. Moreover, it conducts a robustness test on the general linear and panel threshold regression models. The specific practices are as follows: ① For the general linear model, the one-period lag of environmental regulation is used as a new core explanatory variable for the robustness test. The results are displayed in models A3 and A4 in Table 7 ② For the panel threshold regression model; the environmental regulation revenue index is used to replace the environmental regulation expenditure index for the regression test. The results are displayed in models B3 and B4 in Table 8. The above robustness test results demonstrate that under the adjustment of technology density, the regression outcomes of environmental regulation on two-stage GTIE change less than the original model, indicating that the empirical research conclusions of this paper have certain robustness.

Table 7
Regression results of the national linear model.

Variable	R&D stage		Achievement transformation stage	
	Robustness test A3	t-value	Robustness test A4	t-value
IT	0.535***	2.95	0.135**	2.57
OPEN	0.058*	1.79	0.032***	5.27
INS	−0.824**	−2.05	1.012*	1.82
HR	0.027***	5.18	−0.004	−1.03
ER	1.531***	10.24	−1.644	−1.27
ER^2	−2.356**	−2.13	0.848	1.33
C	0.364***	4.21	1.446***	6.77
Time fixed effect	Yes		Yes	
Individual fixed effect	Yes		Yes	
R^2	0.632		0.682	

Table 8
Threshold regression results of environmental regulation on GTIE.

Variable	R&D stage		Achievement transformation stage	
	Robustness test B3	t-value	Robustness test B4	t-value
IT	0.359***	8.48	0.114***	4.58
OPEN	0.104**	2.30	0.102***	5.61
INS	−0.130	−1.04	0.207**	2.39
HR	0.036***	4.15	0.084	0.65
ER_1	−0.382**	−2.16	−0.482**	−2.47
ER_2	0.944***	2.87	−0.141**	−2.16
ER_3	1.830***	3.04		
F	62.21		49.87	
R^2	0.732		0.656	

5.3.2. Endogeneity test

To prevent model estimation errors resulting from endogeneity problems, this paper employs the 2SLS method for re-estimation. Drawing from Laura's study [39], the air circulation coefficient (Air) is the chosen instrumental variable. Initially, ArcGIS 10.2 software is utilized to transform meteorological raster data into useable data, after which each grid's air circulation data is computed. The air circulation coefficient exhibits a strong association with environmental regulation intensity. When the air circulation coefficient is low, air pollutants, such as PM2.5, smoke (dust), and other contaminants, have difficulty dispersing. Consequently, environmental regulation within the city becomes more stringent. Since the city's natural environment primarily determines the air circulation coefficient and lacks a direct link with green technology innovation, it meets the criteria for instrumental variable usage.

When utilizing the air circulation coefficient as an instrumental variable for analysis, the estimation results are presented in Table 9. In both Columns (1) and (3), the F-statistics exceed 10, and the instrumental variables exhibit significant results at the 1 % level. This suggests the absence of weak instrumental variables, confirming the validity of the chosen instrumental variables. The regression results in Columns (2) and (4) demonstrate that environmental regulation significantly contributes to the efficiency of green technology innovation, affirming the robustness of the benchmark regression results.

5.4. Heterogeneity analysis

There is a "gradient difference" in the level of economic development and R&D in China's eastern, central, and western regions, leading to a specific regional heterogeneity of environmental regulation on GTIE. Moreover, as an increasing number of nations join the Belt and Road economic circle, the intensification of international investment cooperation may have new effects on GTIE. Consequently, this research investigates the effect of environmental regulation on GTIE under varying conditions of technology density in the eastern, central, and western areas.

In the R&D stage, the eastern and central regions passed the double threshold test, while the western region passed the single threshold test. The regression results are shown in Table 10. When the technology density is less than 0.375 for the eastern region, the regression coefficient of environmental regulation is 0.214. When the technical density ranges from 0.375 to 0.850, the regression coefficient is 0.330. When the technical density exceeds 0.850, the regression coefficient is 0.581. All of these passed the significance test. This suggests that environmental regulation positively impacts R&D efficiency, and its influence gradually increases with technology density. In the central region, when the technology density is less than 0.130, the regression coefficient of environmental regulation is −0.186. When the technical density lies between 0.130 and 0.445, the regression coefficient is 0.301. When the technical density surpasses 0.445, the regression coefficient is 0.226. All of these passed the significance test. This demonstrates that when the technology density in the central region is low, environmental regulation impedes R&D efficiency. However, as technology density increases, the positive effect of environmental regulation on R&D efficiency gradually emerges. The reason might be that the central region's technological and industrial bases are relatively weak, and economic development is slow, which has not significantly promoted R&D efficiency. As the economic foundation and technological level continue to improve, R&D efficiency will increase

Table 9
2SLS regression results.

	(1)	(2)	(3)	(4)
	ER	Y1	ER	Y2
Air	0.543*** (6.92)		0.319*** (4.32)	
ER		1.247*** (9.17)		−1.014 (1.24)
Control variable	Yes	Yes	Yes	Yes
Time fixed effect	Yes	Yes	Yes	Yes
Individual fixed effect	Yes	Yes	Yes	Yes
F	1220.47	68.12	1846.58	93.25
R^2	0.41	0.23	0.39	0.17

Table 10
Threshold regression results of environmental regulation on R&D efficiency.

Variable	Eastern Region	Central Region	Western region
IT	0.239***	0.442***	0.316***
	(3.04)	(5.25)	(8.24)
OPEN	0.051***	−0.021	−0.057
	(7.14)	(-0.75)	(-3.24)
INS	−0.015**	−0.017***	−0.008***
	(-2.16)	(-1.51)	(-4.91)
HR	0.085*	0.022***	0.028***
	(1.81)	(11.32)	(6.30)
TE threshold in the interval	≤0.375	≤0.130	≤0.055
ER_1	0.214***	−0.186***	−0.307**
	(3.06)	(-4.70)	(2.06)
TE threshold in the interval	(0.375,0.850]	(0.130,0.445]	(0.055,0.105]
ER_2	0.330***	0.301***	0.008
	(2.87)	(13.06)	(1.60)
TE threshold in the interval	> 0.850	> 0.445	
ER_3	0.581***	0.226**	
	(4.20)	(2.10)	
F	89.41	74.06	51.30
R^2	0.823	0.782	0.696

correspondingly. In the Western region, where the technology level and innovation capability are limited and the technology density is relatively low, environmental regulation significantly impacts R&D efficiency.

The eastern, central, and western regions all passed the single threshold test at the achievement transformation stage. The regression results are displayed in Table 11. In the eastern region, the impact of technology density on the achievement transformation stage is minimal, and the regression coefficient of environmental regulation does not pass the significance test. In the central region, when the technology density is less than 0.120, the coefficient of environmental regulation is −0.048. However, when the technical density exceeds 0.120, the regression coefficient is 0.174. Both coefficients passed the significance test. This suggests that as technology density increases in the central region, environmental regulation initially hinders and then promotes the efficiency of achievement transformation. In the western region, when the technology density is less than 0.076, the regression coefficient of environmental regulation is 0.340. However, when the technical density exceeds 0.076, the regression coefficient is −0.022. Both coefficients passed the significance test. This demonstrates that a low technology density in the western region can help enterprises improve the efficiency of achievement transformation, allowing them to earn profits earlier to offset pollution control costs. However, as the technology density increases, enterprises are more inclined to invest in R&D, leading to decreased efficiency of achievement transformation.

6. Conclusions and future prospects

6.1. Conclusions and recommendations

This paper takes 30 provinces in China as the research object and studies the spatial and temporal evolution characteristics and influencing factors of GTIE in China from the perspective of the innovation value chain. First, the super efficiency SBM model considering undesired output is used to calculate the two-stage GTIE of each province in China, namely, R&D efficiency and achievement transformation efficiency, and the spatial and temporal evolution process of R&D efficiency and achievement transformation efficiency is analyzed by ArcGIS 10.2 software. Then, the spatial econometric model is selected to analyze the impact of environmental regulation on the two-stage GTIE. The main conclusions are: (1) From 2010 to 2020, China's two-stage GTIE was generally low. Although the average R&D efficiency is lower than the efficiency of achievement transformation, it can maintain a stable growth trend. The efficiency of achievement transformation shows a trend of "rise-decline-rise." (2) There are significant spatial heterogeneity characteristics in China's two-stage GTIE, and R&D efficiency and achievement transformation efficiency gradually increase from northwest to southeast. The high efficiency is mainly concentrated in the eastern coastal areas, showing the distribution characteristics of "line" and "block." (3). Only when the technology density reaches a particular threshold value can environmental regulation significantly impact GTIE. At the national level, environmental regulation and R&D efficiency have a double threshold effect on technology density. Environmental regulation has a single threshold effect on the efficiency of achievement transformation. At the regional level, in the R&D stage, the eastern and central regions passed the double threshold test, and the western region passed the single threshold test. The eastern, central, and western regions all passed the single threshold test at the achievement transformation stage.

Based on the above conclusions, we propose several recommendations for improving the efficiency of green technology innovation in China: First, in the eastern region, environmental regulations should be intensified reasonably. Increasing the stringency of environmental regulations can encourage enterprises to reduce pollutant emissions and enhance their pollutant treatment capabilities gradually. Furthermore, due to the rising pollution control costs, enterprises can be compelled to increase investments in scientific and technological research and development to boost green technological innovation. Second, flexible environmental regulatory policies

Table 11
Threshold regression results of environmental regulation on achievement transformation efficiency.

Variable	Eastern Region	Central Region	Western Region
IT	0.134***	0.113***	0.096***
	(5.42)	(6.75)	(11.30)
OPEN	0.301***	0.081	0.0052
	(6.77)	(0.66)	(1.25)
INS	0.035	0.117***	0.338
	(1.46)	(7.32)	(0.71)
HR	0.0042*	0.0032	0.0024*
	(1.90)	(1.54)	(1.70)
TE threshold in the interval	≤0.231	≤0.120	≤0.076
ER_1	0.318	−0.048**	0.340**
	(0.76)	(-2.21)	(2.08)
TE threshold in the interval	> 0.231	> 0.120	> 0.076
ER_2	0.470	0.174***	−0.022***
	(1.04)	(13.58)	(-10.52)
F	36.30	28.49	45.32
R^2	0.711	0.662	0.738

should be adopted in the central and western regions. As shown in the previous section's analysis, the efficiency of green technology innovation could be lower in provinces with lower technological levels and weaker economic development, which drags down the national average efficiency. Given the significant economic disparities between the central and western regions, different strategies and measures should be applied when formulating environmental regulation policies, especially for small and medium-sized enterprises. The government can adopt a standardized approach to address pollution emissions. Third, the government should gradually increase incentives for environmental regulation and guide enterprises to approach environmental regulation correctly. This can be achieved by offering tax rebates and R&D expense subsidies. Additionally, the government should provide robust legal safeguards to attract enterprise investment through policy advantages and stimulate industrial and technological clustering, thereby promoting green technological innovation in less developed provinces.

6.2. Research gaps and prospects

While this paper delves into the detailed impact of environmental regulation on green technology innovation, it still possesses certain limitations. In future research, we can expand our investigation into two aspects: First, China's environmental regulation policy remains in a developmental stage without establishing a unified, expansive market. Moreover, data continuity and completeness scarcity have resulted in insufficient research at the prefectural-level city level. In the future, we can extend our focus to national cities, contributing to developing more scientifically formulated environmental policies.

Secondly, in this paper, only the technology density indicator was considered among the internal influencing factors of green technology innovation, though several other influential elements exist. Hence, future research will encompass a more comprehensive array of influencing factors to ensure the objectivity and precision of our research conclusions.

Ethics declarations

This study did not need an ethics committee's review and/or approval because permission was acquired to gather the raw data.

Data availability statement

The study's data has not yet been deposited into a publicly available repository. However, the data supporting the findings are accessible upon reasonable request from the corresponding author.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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