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Research Article

Research on the Nonlinear Impact of Environmental Regulation on the Efficiency of China's Regional Green Economy: Insights from the PSTR Model

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This paper uses the super-efficiency SBM model to measure the green economic efficiency considering undesired output and analyzes the spatial distribution difference of green economic efficiency; secondly, the nonlinear panel threshold model is used to empirically study the nonlinear relationship between environmental regulations and green economic efficiency, and further analyzed the threshold effect of environmental regulations on the efficiency of green economy and concluded as follows. (1) The green economy efficiency index in the eastern region is mostly more significant than 1, and the green economy efficiency in most provinces in the eastern region has improved. These provinces have higher regional production levels and less environmental pollution. The green economy efficiency of the central region is second only to the eastern region. The green economy efficiency of provinces in the western region except Chongqing is less than 1, indicating that these provinces have insufficient regional production, severe environmental pollution, or extensive resource depletion. (2) The impact of environmental regulations on the efficiency of the green economy presents an inverted "U" shape, with a threshold of 0.5128 for environmental regulations. The impact of the industrial structure on the efficiency of the green economy changes from inhibition to promotion after crossing the threshold of the intensity of environmental regulation, and the degree of opening to the outside world has a complementary effect on the efficiency of the green economy. The impact of urbanization on the efficiency of the green economy changes from promotion to suppression after surpassing the threshold of the intensity of environmental regulations.

1. Introduction

After the industrial revolution, with the development of heavy chemical industries, more and more resource constraints and environmental pollution problems began to emerge. People had to start paying attention to the economic growth costs of resource constraints and environmental pollution and realized that "pollution first, then governance" thinking is no longer suitable for the requirements of sustainable development. For sustainable development, it is necessary to develop a green economy [1, 2]. The government work report of the 18th National Congress of the Communist Party of China pointed out that facing the severe ecological environment, and we must vigorously promote green development, circular development, and low-carbon development. We must adhere to the vital concept of the green economy. The report of the 19th National Congress of the Communist Party of China also pointed out that it is necessary to establish the concept of a green economy and at the same time establish a long-term mechanism for environmental management and control in order to achieve a win-win situation for economic development and environmental protection. The long-term consumption of resources and energy and the deterioration of the ecological environment have been the price of rapid economic growth, and the conversion rate of input to output in the green economy is low [3]. Environmental materials as public goods are prone to "tragedy of the commons" under the "dilemma

of collective action" in economics. Therefore, in the face of the "dilemma" of economic growth and improvement of the ecological environment, how to improve the efficiency of the green economy, make full use of the advantages of resource endowments to promote economic growth while avoiding environmental pollution, and then promote the development of green economy and realize the realization of the new era Economic health and sustainable development are of great significance. Among them, the term "green economy efficiency", which has evolved from the concept of "green development" and is highly representative, has increasingly become a hot topic for scholars. The efficiency of the green economy is different from the traditional economy that ignores resources and environmental costs. Growth performance indicators are also different from environmental performance indicators that bias the evaluation of micro-objects and environmental efficiency indicators that only take economic and environmental benefits into account but are a comprehensive economic efficiency indicator based on resource and environmental constraints [4, 5].

At present, China's economy has shifted from a high-speed growth stage to a high-quality development stage. The improvement of green economy efficiency to promote high-quality development is an inevitable requirement for maintaining sustained and healthy economic development. However, China's economic development has continued to be based on the industrial model of "high input, high consumption, and high emissions" for a long time. Large-scale environmental pollution has brought severe losses to China's economy and threatened the healthy lives of residents. In order to effectively curb environmental pollution, governments at all levels have intensified their efforts to control environmental pollution. However, many regions have encountered unreasonable governance phenomena like year-end surprises and blind imitations to complete the control targets. The particularity and rationality of governance lack a factual basis for judgment, and the academic community also lacks in-depth research on the relationship between environmental regulations and green economic efficiency. Therefore, how to solve China's environmental pollution problems and improve the efficiency of China's green economy through effective environmental regulations is a problem that current scholars and policymakers need to pay attention to [6].

At present, there are still considerable controversies in the academic circles about the impact of environmental regulations on economic efficiency. The key to the "Porter Hypothesis" lies in the magnitude of the innovation compensation effect; that is, only when the innovation compensation effect is favorable will environmental regulations positively impact economic efficiency. As there is still considerable controversy on this issue, this article intends to conduct an empirical analysis, using panel data from 30 provinces (municipalities and autonomous regions) in China to test whether the impact of environmental regulations on green economy efficiency is promoted or inhibited? The higher the environmental regulation, the greater the impact on the efficiency of the green economy, or is there an "inflection point"? Since the implementation of environmental regulation policies may have a lag effect, this article will use environmental regulation as the core explanatory variable to construct a panel model that includes the quadratic term of environmental regulation to test the nonlinear impact of environmental regulation on the efficiency green economy.

The main contributions of this paper are (1) use the Super SBM-DEA model to measure the efficiency of the green economy. Existing studies mainly use the SBM-DEA model to measure the efficiency of the green economy, but the results obtained by the SBM-DEA model cannot compare the efficiency of effective units with an efficacy value equal to 1, and Tobit has to be used in subsequent measurement tests. The model is empirically tested and analyzed, but the Tobit model is a restricted model that reflects limited information. This paper uses the Super SBM-DEA model not only to effectively explain the difference between the regions where the efficiency value is equal to 1 under the SBM-DEA model but also because the efficiency value obtained is not limited by the value of 1. Using the panel data model can reflect more information. Test the nonlinear characteristics of environmental regulations on green economic efficiency. Considering that the implementation of environmental regulation policies is likely to have nonlinear characteristics in the impact of green economy efficiency, this paper uses the square term of environmental regulation to test the nonlinear relationship between environmental regulation and green economy efficiency, which is a valuable supplement to existing research.

2. Literature Review

2.1. Evaluation of Green Economy Efficiency. The main methods for measuring the efficiency of the green economy include data envelopment analysis (DEA), total factor productivity, and stochastic frontier analysis (SFA). The DEA method is a nonparametric method used to evaluate the relative effectiveness of the same type of multi-input and multi-output decision-making unit (DMU) because it does not need to pre-set the specific parameters and form of the production equation, so it is widely used to measure the efficiency of various decision-making units of the same type, the DEA method is widely used in industry, city, region, and global productivity and efficiency evaluation research.

2.1.1. Traditional DEA Method and Improvement. The traditional DEA method is a nonparametric deterministic production frontier method, which measures the technical efficiency of the production unit. The DEA method is widely used because it can handle multiple inputs and multiple outputs. For example, Lv [7] used the DEA model to measure the green economic efficiency of various cities in Guangdong Province from 2011 to 2018 and explore the influencing factors of green economic efficiency. Yang and Hu [8] used the DEA model to measure the green economic efficiency of 29 provinces and municipalities in China and conducted a convergence test on the differences in green economic efficiency growth in various regions. Wang et al.

[9] selected DEA-BCC and DEA Malmquist models to conduct empirical measurement and comparative study on the spatial and temporal differentiation of China's green economy efficiency. Charnes et al. [10] believe that the DEA method can reasonably evaluate the efficiency value in researching Chinese urban economic development problems. Zhang et al. [11] used the DEA model to study agricultural production efficiency to fully understand the regional agricultural development trend and its impact on economic development. However, the problem is that the impact of environmental factors on output is not considered.

In recent years, the DEA method has experienced development from the shallower to the deeper. The idea of evaluating efficiency in the initial DEA model is to use the minor input to produce the most output. However, in actual production activities, by-products such as environmental pollution are also included in the output, so producing as much output as possible means more pollution will be produced, and by-products such as pollution must be reduced to achieve the purpose of economic efficiency improvement. Therefore, the initial DEA method is inconsistent with the original intention of the efficiency evaluation. Lin [12] pointed out that the lack of market pricing for environmental pollution or environmental policies related to pollution taxes makes it challenging to include environmental pollution in production costs. Fare and Pasurka [13] proposed a hyperbolic nonlinear programming method, that is, to reduce the undesired output, the expected output must be reduced. However, because the solution is too complicated, the application is greatly restricted. Chen [14] pointed out that many pieces of literature initially introduced pollution emissions as inputs into the production function, but as scholars deepened their understanding of environmental pollution, scholars believed that environmental pollution should be regarded as output rather than input. However, scholars have not realized the negative externality of pollution but treated it as ordinary output, so the measured productivity is still biased until Chambers et al. [15] and Chung et al. [16] proposed that pollution should be an undesired output with negative externalities, at this time, the restrictive effect of environmental pollution on economic development was discovered for the first time. Since then, Färe et al. [17] and Boyd et al. [18] apply pollution as an undesired output in the article.

2.1.2. Application of Super-Efficiency SBM Model. When measuring efficiency, the traditional DEA model will obtain a situation where the efficiency of many decision-making units is one at the same time; that is, multiple decision-making units result from complete efficiency. At this time, these fully effective decision-making units cannot be compared and ranked efficiently. In response to this problem, Tone [19] proposed the Super-SBM model. The Super-SBM model is based on the modified slack variable so that the efficiency value of the decision-making unit is not restricted by the [0, 1] interval and can reasonably evaluate the efficiency and ranking of those decision-making units with an efficiency value of 1. Qian and Liu [20] used the super-efficiency SBM model to measure the static level and dynamic changes of the green economic efficiency of various provinces in China. Ban and Yuan [21] introduced the undesired output super-efficiency SBM model to measure the efficiency of China's interprovincial green economy from 1991 to 2013 and then introduced a spatial panel model to study the spatial impact mechanism of green economic efficiency in eight regions. Ren and Yao [22] used the SBM model, including undesired output, to measure the eco-efficiency of 30 provinces and cities in China and compared the differences in eco-efficiency in different regions.

Similarly, because the effective decision-making units can be further sorted, the super-efficiency DEA method has a wide range of applications in ordering decision-making units. Li and Cheng [23] used the SBM model to measure environmental efficiency considering undesired output, and the results showed that environmental factors significantly reduced the regional efficiency level. Li and Tao [24] used the SBM directional distance function and Luenberger productivity index to measure the green total factor productivity of the manufacturing industry. Li et al. [25] used the SBM efficiency measurement model considering undesired output and combined it with the ML productivity index to measure subsectors green total factor productivity. On this basis, Li et al. [26] proposed the Super SBM-DEA model that considers undesired output. Based on the research of Tone and Li et al., this paper uses the Super SBM-DEA model of undesired output to measure the efficiency of the green economy.

2.2. The Impact of Environmental Regulations on the Efficiency of the Green Economy. Scholars at home and abroad have studied the different effects of environmental regulations on the efficiency of the green economy and summarized them into three types:

(1) Follow the cost theory. A group of scholars began to think about the factors that affect economic growth. Among them, a large number of studies have been carried out on the impact of environmental systems on the industry's total factor productivity and economic growth. They believe that the formulation of environmental policies has significantly increased the production costs of enterprises, resulting in a decline in corporate benefits. Conrad and Wastl [27] said that the benefits of technology investment are less than the cost of environmental regulations. The benefits cannot offset the costs, environmental regulations are challenging to achieve results, and environmental regulations are abandoned. Wang [28] believed that the government has not adequately designed environmental regulations, leading to noncooperative games between the government and enterprises. Zhao et al. [29] and Zhang [30] pointed out that China's environmental regulations have a cost effect on trade competition, which will reduce the production efficiency of enterprises and increase costs, which is not conducive to international competition. Gollop and Robert [31] measured and

analyzed the impact of sulfur dioxide emission restrictions on the productivity growth rate of the power industry during the 1973–1979 business cycle and found that emission regulations led to a significant increase in the cost of power generation. Subsequently, Gray [32] used the data of 450 manufacturing industries in the United States to calculate the total factor productivity. He also believed that government supervision and environmental regulation increased the environmental cost of enterprise products to a certain extent, resulting in a decrease in the manufacturing industry's productivity. Since then, "following the cost theory" has been continuously verified in empirical studies that select different research methods, research angles, and research objects. Zhao [33] believes that environmental protection policies require companies to pay related costs for the environmental pollution and waste of resources and energy caused by them, which has led to an increase in corporate environmental costs, and environmental cost management has therefore become the focus of corporate attention.

(2) A win-win situation for environmental regulation and economic efficiency. Zhang et al. [34] explored China's environmental regulation performance system, severe environmental system strategy, and changing the turning point of the Kuznets arc. With industrial structure adjustments, it can change the country's high energy consumption per unit of output and achieve a win-win situation; Poter [35] proposed that although environmental regulation will increase the cost of enterprises, it will also stimulate technological innovation of enterprises, thereby enhancing the competitiveness of enterprises. Therefore, it is believed that well-designed and well-executed environmental supervision is beneficial to the environment and the company. Ambec et al. [36] examined the fundamental theoretical basis and empirical evidence of Porter's hypothesis and believed that environmental regulation does exist by stimulating enterprises to carry out technological innovation and enhancing the overall competitiveness of enterprises. Albrizio et al. [37] used the new Schumpeter productivity model to construct a dynamic environmental policy stringency index (EPS) that changes with industry pollution levels and technological progress and finds that the tightening environmental policies and the short-term growth of industrial productivity in technologically advanced countries related. Zhao [38] analyzed the impact of environmental regulations on industrial, technological innovation and found that environmental regulations have a significant positive effect on R&D expenditures and the number of patent applications that lag three phases, indicating that environmental regulations have a particular effect on technological innovation in the medium and long term. The incentive effect of the "Porter Hypothesis" confirms the applicability in China. Li and Mu [39] found that the benefits of environmental regulations have exceeded the costs, and China has entered the stage of "innovation compensation effects." Research is to ensure that environmental regulations are found to promote environmental and economic coordination under long-term conditions. Technological innovation acts as a bridge internally, making the benefits more significant than the required costs, which will eventually improve the efficiency of the green economy.

(3) The relationship between environmental regulations and economic efficiency is uncertain. The difference in the timing of environmental regulation will lead to the uncertainty of environmental regulation on economic efficiency. Zhang et al. [40] used a spatial measurement model to analyze the impact of environmental regulation and other related factors on the efficiency of the green economy. There is an inverted U-shaped relationship between environmental regulations and green economic efficiency. Qi and Chen [41] found that the intensity of environmental regulations in China's eastern, central, and western regions has increased sequentially, while the green economy efficiency growth rate has decreased sequentially. Overall, the Chinese green economy efficiency shows an inverted U-shaped trend with the strengthening of environmental regulations. After exceeding the 0.5995 intensity threshold of environmental regulations, the impact of environmental regulations on green economy efficiency has changed from promotion to inhibition. Song et al. [42] used a panel model to test the impact of environmental regulations on green economic efficiency. The analysis results show that there is an inverted U-shaped relationship between environmental regulations and green economic efficiency. The impact of environmental regulations on the efficiency of green economy is to promote first and then suppress. Gong [43] uses the panel threshold model to analyze the impact of different types of environmental regulations on the efficiency of the green economy. The results show that the impact of environmental regulations on green economy efficiency is time lag and nonlinear characteristics; there is a single threshold for environmental regulations lagging in the first phase. When environmental regulations cross this threshold, the promotion effect of environmental regulations on green economic efficiency is weakened; different types of environmental regulations have different threshold effects on green economic efficiency. There is heterogeneity in regions and periods. Huang and Pomegranate [44]

found that administrative environmental regulations and green economic efficiency have an inverted "U"-shaped relationship, and market-based environmental regulations have a significant role in promoting green economic efficiency. Participatory environmental regulations have an inhibitory effect on the efficiency of the green economy.

To sum up, due to the different research methods, environmental regulation and economic efficiency research results also have inconsistent conclusions such as promotion, inhibition, or uncertainty. The previous literature mostly used linear models to estimate the impact of environmental regulations on economic efficiency, and the conclusions reached also support strengthening the intensity of environmental regulations. Nevertheless, it is worth thinking about whether the more significant the intensity of environmental regulation, the higher the efficiency of the green economy? There are differences in resource endowments, economic development levels, and industrial structures in various regions in China, and there may be nonlinearity between environmental regulations and green economic efficiency. If a linear estimation model is used, the estimation of the impact of environmental regulations on the efficiency of the green economy may be biased. Although some scholars use the quadratic curve method to try to introduce the quadratic term of the explanatory variable for testing to explore the nonlinear relationship between environmental regulations and economic efficiency, they still face the following problems: there may be a correlation between the explanatory variable and its quadratic term, which will affect the estimation results; the second is that the quadratic curve method limits the "U" or inverted "U" shape on both sides of the inflection point to obey a symmetrical distribution. At present, panel threshold estimation methods have gradually received attention when testing the nonlinear relationship between environmental regulations and economic efficiency. However, the ordinary threshold regression model is discrete near the threshold, and it is difficult to analyze the changes near the threshold intuitively. The panel smoothing threshold regression model circumvents the limitations of these models well and is a reasonable method to study the nonlinear characteristics between variables. Based on this, this paper uses the super-efficiency SBM model to measure the green economic efficiency considering undesired output and analyzes the spatial distribution difference of green economic efficiency; second, the nonlinear panel threshold model is used to empirically study the nonlinear relationship between environmental regulations and green economic efficiency, and further analyze the threshold effect of nonenvironmental regulations in various regions on the efficiency of green economy, trying to find the optimal intensity of environmental regulations to improve the efficiency of green economy, in order to provide a basis for formulating environmental regulatory policies with appropriate intensity in different regions.

3. Method

3.1. SBM Model Construction and Variable Selection

3.1.1. SBM Model Construction. The DEA model is widely used in the measurement of economic efficiency. Tone [45] established a DEA model that considers undesired output called the SBM-DEA model.

3.1.1.1. Basic DEA Model for Dealing with Undesired Output. The basic DEA model for dealing with undesired outputs often produces undesired outputs, such as pollution, in the actual production process. The negative externalities of undesired output will have a negative impact on economic efficiency. Tone [46] proposed the SBM-DEA method to deal with the undesired output. Its basic model is as follows: consider each province as a production decision-making unit. Each decision-making unit has three types of input and output: input expected output and undesired output, denoted by $x \in R^m, y^g \in R^{s_1}$, and $y^b \in R^{s_2}$, respectively. Define X, Y^g, and y^b as the following matrix:

$$\begin{aligned} X &= [x_1, x_2, \ldots, x_n] \in R^{m\times n}, \\ Y^g &= [y_1^g, y_2^g, \ldots, y_n^g] \in R^{s_1\times n}, \\ Y^b &= [y_1^b, y_2^b, \ldots, y_n^b] \in R^{s_2\times n}. \end{aligned} \tag{1}$$

Hypothesis 1. $X > 0$, $Y^g > 0$ and $Y^b > 0$. The production possibility set P is defined as $P = \{(x, y^g, y^b) | x \geq X\lambda, y^g \leq Y^g, y^b \geq Y^b\lambda, \lambda > 0\}$.

$\lambda \in R^n$ is the weight vector. The three inequalities of production possibility concentration indicate that when the actual input level is greater than or equal to the boundary investment level, the actual expected output is less than or equal to the boundary expected output, and the actual undesired output is greater than or equal to the undesired boundary output. Tone adjusted Tone's model to obtain an SBM model of undesired output:

$$\rho^* = \min \frac{1 - (1/m)\sum_{i=1}^{m} s_i^- / x_{i0}}{1 + (1/s_1 + s_2)\left(\sum_{r=1}^{s_1} s_r^g / y_{r0}^g + \sum_{r=1}^{s_2} s_r^b / y_{r0}^b\right)}$$

$$\text{s.t.} \begin{cases} x_0 = X\lambda + s^-, \\ y_0^g = Y^g\lambda - s^g, \\ y_0^b = Y^b\lambda + s^b, \\ s^- \geq 0, s^g \geq 0, s^b \geq 0, \lambda \geq 0. \end{cases} \tag{2}$$

Among them, $s^- \in R^m$ and $s^b \in R^{s_2}$ represent the excess of input and undesired output, respectively, and $s^g \in R^{s_1}$ represents the insufficient expected output.

3.1.1.2. DEA Model for Super-Efficient Handling of Undesired Output. In efficiency measurement, the basic DEA model to deal with undesired output often encounters a situation where many decision-making units are 1 simultaneously,

significantly limiting the comparison and ranking of decision-making units with the same efficiency as 1. Therefore, Tone proposed the Super SBM-DEA model. On this basis, Li et al. proposed the Super SBM-DEA model to deal with the undesired output. The advantage of this model is that the efficiency value is not affected by [0, 1]; the limit of the interval can be a good evaluation of the efficiency and ranking of those decision-making units whose efficiency values are all 1. The improved model is as follows:

$$\rho^* = \min \frac{(1/m)\sum_{i=1}^{m} \overline{x_i}/x_{i0}}{(1/s_1+s_2)\left(\sum_{r=1}^{s_1} \overline{y_r^g}/y_{r0}^g + \sum_{r=1}^{s_2} \overline{y_r^b}/y_{r0}^b\right)},$$

$$\text{s.t.}\begin{cases} \overline{x} \geq \sum_{j=1}^{n} \lambda_j x_j, \\ \overline{y^g} \leq \sum_{j=1}^{n} \lambda_j y_j^b, \\ \overline{y^b} \leq \sum_{j=1}^{n} \lambda_j y_j^b, \\ \overline{x} \geq x_0, \overline{y^g} \leq y_0^g, \overline{y^b} \geq y_0^b, \lambda \geq 0. \end{cases} \tag{3}$$

The objective function ρ^* is larger, the greater the efficiency. In the calculation, if the sum reaches 1, it means variable returns to scale (VRS); otherwise, it means constant returns to scale (CRS).

3.1.2. Variable Selection. The selection of indicators directly affects the reliability of the efficiency value. Green economic efficiency is the comprehensive economic efficiency after comprehensively considering the input of production factors, resource consumption, and environmental costs. The input and output variables that need to be considered to calculate the green economic efficiency are as follows and are shown in Table 1.

3.1.2.1. Input Elements. According to the production function, labor and capital input are the primary inputs of production factors, and energy consumption is one of the primary sources of undesired output. Therefore, labor, capital, and energy are used as input factors. The number of employees expresses labor input at the end of the year; capital input is expressed by actual capital stock, measured according to the perpetual inventory method, and converted to a constant price in 2008 using the fixed asset investment index by region. The physical capital stock and depreciation rate at the beginning of the period are referenced. The research of Zhang et al. [47] gave the 2008 provincial physical capital stock data and an estimated depreciation rate of 9.6%; energy consumption data are measured by the total energy consumption of each region.

3.1.2.2. Expected Output. The more commonly used expected output includes the gross domestic product, regional gross product, and industrial added value. This study selects GDP as the expected output and uses 2008 as the base period to deflate the consumer price index of each region.

Table 1: Green economic efficiency measurement indicators.

Index	Variable	Variable description
Input index	Labor input	Employed population by region
	Capital input	Capital stock
	Energy input	Total energy consumption
Expected output	Economic output	Regional GDP
Undesired output	Wastewater	Industrial wastewater discharge
	Exhaust	Industrial waste gas emissions
	Solid waste	Industrial solid waste discharge

3.1.2.3. Unexpected Output. The more commonly used undesired outputs include industrial "three wastes" emissions, sulfur dioxide emissions, chemical oxygen demand COD, and carbon dioxide emissions. Exhaust gas emissions and industrial solid waste emissions are regarded as undesired output.

The input and output factors data are derived from the 2008–2020 China Statistical Yearbook, China Energy Statistical Yearbook, and China Environment Statistical Yearbook. Due to the lack of data in Tibet, and given the availability of data, this study selected 30 provinces, autonomous regions, and municipalities in mainland China from 2008 to 2020, excluding Tibet, as samples to measure the efficiency of the green economy.

3.2. Construction of Panel Smoothing Threshold Regression Model and Variable Selection

3.2.1. Construction of Panel Smoothing Threshold Regression Model. Considering that the sample data of the indicators selected in this paper are all annual panel data, it is challenging to meet the higher requirements of the available time series model for the data sample length. Therefore, this paper chooses the panel smoothing threshold regression (PSTR) model proposed by Gonzalez et al. [48]. The relevant parameters in the model can achieve smooth conversion with the change of the transfer function value, so it can not only effectively reflect the dynamics and heterogeneity of each cross-sectional unit of the panel data. More importantly, the correlation regression coefficients of the model can achieve smooth transitions between multiple zoning systems, which avoids the sudden change of zoning systems and skillfully describes the complex nonlinear impact dynamics that may exist between variables. This model is the development and expansion of the PTR and STAR models. In the PSTR model, as the value of the transfer function changes, the model transitions smoothly between the two mechanisms. This shows that the different values of the conversion variables can achieve continuous changes in the transfer function and

make the changes between the high and low systems continuous. The most basic two-system PSTR model form is as follows:

$$y_{it} = \mu_i + \beta_0' x_{it} + \beta_1' x_{it} g(q_{it}; \gamma, c) + \mu_{it}, \quad i = 1, 2, \ldots, N,\ t = 1, 2, \ldots, T. \tag{4}$$

Among them, N represents the number of individuals in the cross section of the selected data, and T represents the period of the data. y_{it} is a scalar and can also be regarded as a numeric value. x_{it} is a k-dimensional exogenous vector, which takes different values at different time nodes. μ_i and μ_{it} represent the individual fixed effects and calculated residuals, respectively. q_{it} is an observation variable, which is transformed by the conversion function $g(q_{it}; \gamma, c)$. As its continuous function, the value range is [0, 1]. The regression coefficient of β_0 or $\beta_0 + \beta_1$ changes with the value of the transfer function. The most used transfer function is generally the logistic function:

$$g(q_{it}; \gamma, c) = \left\{ 1 + \exp\left[-\gamma \prod_{j=1}^{m} \left(q_{it} - c_j \right) \right] \right\}^{-1}, \quad \gamma > 0, c_1 \le c_2 \le \cdots c_m. \tag{5}$$

Among them, $c = (c_1, c_2, \ldots, c_m)'$ is the m-dimensional vector of the position parameter, and the slope parameter γ determines the speed and smoothness of the mechanism conversion. For the recognition of the model, the conditions of $\gamma > 0$, $c_1 \le c_2 \le \cdots c_m$ are defined. The model is divided into high and low systems according to the change of the transfer function value. When $m = 1$, the model contains only one position parameter. When the transfer function value is the lower limit 0, the model is in the low system, and when the transfer function is the upper limit 1, the model is in the high system. $g(q_{it}; \gamma, c)$ changes continuously with the change of q_{it} in the interval from 0 to 1. When the value of q_{it} is the position parameter c, the transfer function value is 0.5, thus realizing the model with the position parameter as the center of symmetry mechanism conversion. In the process of conversion between high and low systems, the coefficients of the parameters will be smoothly converted from β_0 to $\beta_0 + \beta_1$.

When the number of positional parameters is more than one, for example, when the model contains two positional parameters: $g = 1$ corresponds to the external mechanism of the model. When the conversion variable is the sum of the two positional parameters, the model is in the intermediate mechanism, and g reaches the minimum value.

For $m > 1$, such as $m = 2$, if the value of the conversion function is 1, it means that the model is in the external mechanism; when $q_{it} = c_1 + c_2$, the conversion function takes the minimum value and is in the intermediate mechanism. At this time, $\gamma \longrightarrow \infty$, model (4), is transformed into a three-system threshold model. So under normal circumstances, when $m > 1$, $\gamma \longrightarrow \infty$, the model still has two different systems; when m is any value, if $q_{it} = c$ or $\gamma \longrightarrow 0$, $g(q_{it}; \gamma, c)$ takes the value 0.5, PSTR becomes a basic linear fixed-effects model. Analyze the settings of models (4) and (5). When the individual i and time t are constantly changing, the PSTR model also changes accordingly with the conversion variable. The dependent variable y_{it} has its nonlinear smoothing between different mechanisms. The function of conversion, the in-depth discussion shows that if q_{it} is the lag term of the dependent variable y_{it}, then the model (4) has a specific name—the self-excitation, smooth conversion model. If q_{it} is not the dependent variable in the model (5), the variable selection should reflect the nonlinear transformation of the cross-sectional unit. The PSTR model of the two systems is expanded to obtain the following multisystem panel smooth conversion model:

$$y_{it} = \mu_i + \beta_0' x_{it} + \sum_{j=1}^{r} \beta_1' x_{it} g\left(q_{it}^{(j)}; \gamma, c \right) + \mu_{it}. \tag{6}$$

Among them, the conversion function $g(q_{it}^{(j)}; \gamma, c)$ $j = 1, \ldots, r$ is the logistic function form shown in equation (5). Model (6) is a generalization of the PTR model. If $m = 1$, $q_{it}^{(j)} q_{it,} \gamma_j \longrightarrow \infty$. And $j = 1, \ldots, r$, model (6) is the panel threshold model of the $(r + 1)$ system. Therefore, the model is also regarded as a multibody panel threshold regression model and has a generalization. Of course, the two-system model with $r = 1$, $m = 1$, or $m = 2$ is widely used. This model plays a vital role in model estimation, especially in the test of nonuniform heterogeneity.

3.2.2. Selection and Processing of Variables

3.2.2.1. The Explained Variable. Based on the research of Sun et al. [49] and Liu et al. [50] on the influencing factors of green economy efficiency, this paper selects green economy efficiency (denoted as GEE) as the explained variable in the empirical study and adopts the SBM model to calculate the result.

3.2.2.2. Explanatory Variables and Threshold Variables. Selecting the intensity of environmental regulation (denoted as ERI) as the core explanatory variable and threshold variable, the vital sign of green economic efficiency different from traditional economic efficiency is to consider environmental factors. The economic and social activities of human production and life will inevitably have a massive impact on the environment. Reducing or resolving the effect of economic activities on the environment is an important issue to be explored in the efficiency of the green economy. In terms of environmental protection, the government plays a vital role. The government's attitude and policies can dominate the effect of environmental protection, especially in China. Therefore, this article expresses the intensity of environmental regulation by the proportion of investment in the treatment of industrial pollution in the GDP of the year.

3.2.2.3. Control Variables. industrial structure (ES): the improvement of green development is often accompanied by a higher level and more optimized industrial structure. Regardless of a country or a region, the contribution of the tertiary industry to economic growth is a measure of

harmless and high-quality economic development. Therefore, the ratio of the tertiary industry to GDP is chosen to express the industrial structure.

Urbanization level (UR): the development of urbanization is usually accompanied by large-scale factor flow, industrial changes, and the reallocation of resources. The agglomeration, dispersion, and redistribution of these factors will inevitably have an impact on green development. Therefore, urbanization is classified as one of the factors influencing green economy efficiency; this article describes the urbanization process by the proportion of permanent urban residents in the local population at the end of the year.

Openness to the outside world (FDI): expressed as the proportion of total foreign investment in GDP. The introduction of foreign people in business has brought technology spillover effects and management experience to a certain extent, which will help improve the efficiency of the green economy. However, at the same time, it may also cause environmental problems, and the region has become a "pollution paradise".

4. Results

4.1. China's Regional Green Economy Efficiency Measurement Results. Using DEAP2.1 software, substituting the determined input and output indicators into the model, the results are shown in Table 2.

It can be seen from Table 2 that from 2008 to 2020, the green economy efficiency index in the eastern region is mostly more significant than 1, indicating that the green economy efficiency of most provinces in the eastern region has improved. These provinces have higher regional production levels and less environmental pollution. The green economy efficiency index of the central region is second only to the eastern region. The green economy efficiency index of the western region except Chongqing is less than 1, indicating that these provinces have problems of insufficient regional production, severe environmental pollution, or extensive resource depletion. Judging from the increase in the green economy efficiency index in 2015 and 2006, most provinces showed a rapid increase in the green economy efficiency index. Among them, the regions with a more considerable increase were Zhejiang, Shanghai, Chongqing, and Beijing; a few of them, the provinces showed that the growth rate of the green economy efficiency index was in a downward trend, and the regions with a more considerable decline were Xinjiang, Hebei, Shanxi, and Hubei in order. The reason is that the rapid economic development of Zhejiang, Shanghai, Chongqing, and Beijing has led to a faster increase in the efficiency of the green economy.

In contrast, the severe environmental pollution in Xinjiang, Hebei, Shanxi, and Hubei has led to a decline in the growth rate of the green economy efficiency index. This is consistent with the research conclusions of scholars Qi and Chen [41] and Meng and Shao [51] on the whole, and the efficiency of a regional green economy is generally strong in the east and weak in the west. Inconsistent with previous studies, this article's regional dynamic panel data further distinguish the green economic efficiency of different regions, providing crucial theoretical support for implementing the "Regional Industrial Green Transformation and Upgrading Program" and formulating targeted policies.

4.2. Nonlinear Estimation Results. With reference to the research of Gonzalez et al. [48] and Fouquau et al. [52] on panel smoothing threshold regression (PSTR) models, in this paper, before estimating, first of all, the model should be tested for cross-sectional heterogeneity, that is, "nonlinear" test. If there is no heterogeneity, the model is proved suitable for estimation in a linear framework; if there is the heterogeneity, it is more reasonable to use the PSTR model to estimate. Second, it is necessary to estimate the parameters, generally using the nonlinear least square method. Finally, the model needs to be tested for residual heterogeneity, that is, the "remaining nonlinearity" test; the purpose is to investigate whether the nonlinear model has fully described all the zoning transformations.

4.2.1. Test of PSTR Model. This paper uses Wald Tests, Fisher Tests, and LRT Tests to test the model's cross-sectional heterogeneity (linearity test) and residual heterogeneity test (nonlinearity test). The results show (see Table 3) that regardless of the number of location parameters $m = 1$ or $m = 2$, at the 5% significance level, the null hypothesis of "the model is linear" is rejected, that is, the efficiency of green economy and the intensity of environmental regulation is a significant nonlinear relationship between the industrial structure and the degree of opening to the outside world. That is to say, it is reasonable to use the Panel Smoothing Threshold Regression (PSTR) model to study the relationship between environmental regulations and green economic efficiency by making environmental regulations as threshold variables. In the test of residual heterogeneity, we found that in the two cases of $m = 1$ and $m = 2$, none of the three tests can reject the null hypothesis of "the number of transfer functions is 1", indicating the optimal transfer function of the model number is 1. Combining further thinking with AIC and BIC values, it is found that the result of $m = 2$ is better than $m = 1$. Therefore, this model's number of optimal transfer functions is 1, and the number of optimal positional parameters is 2.

4.3. Analysis of Model Parameter Estimation Results. When $r = 1$ and $m = 2$, we perform nonlinear least-squares estimation on the model. The estimation results show (see Table 4) that the variables are all significant at the 10% significance level. The impact of environmental regulations on the efficiency of the green economy is nonlinear, and its threshold is $c = 0.5128$. When the intensity of environmental regulation is lower than 0.5128, the transfer function $g(q_{it}; \gamma, c) \longrightarrow 0$, and the coefficient of influence of environmental regulation on the efficiency of the green economy is 3.9843. Every time the intensity of environmental regulation increases by 0.01, the efficiency of the green economy increases by 0.3984; When the intensity of environmental regulations reaches 0.5128, the transfer function

Table 2: Calculation results of regional green economy efficiency.

Region		2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	Mean
Eastern	Beijing	1.223	1.246	1.457	1.981	2.223	2.312	2.414	2.778	3.013	3.235	3.567	3.764	3.965	2.552
	Tianjin	0.766	0.769	0.802	0.812	0.839	0.842	0.849	0.816	1.021	1.121	1.242	1.132	1.493	0.962
	Hebei	0.312	0.354	0.379	0.599	0.727	0.833	0.867	0.878	0.898	0.909	0.919	0.922	0.937	0.733
	Liaoning	0.365	0.366	0.387	0.396	0.425	0.456	0.464	0.478	0.494	0.549	0.675	0.783	0.829	0.513
	Shanghai	1.131	1.156	1.190	1.424	1.541	1.765	1.989	2.156	2.345	2.657	2.768	2.987	3.543	2.050
	Jiangsu	0.855	0.876	0.887	0.921	0.933	0.956	1.017	1.234	1.451	1.656	1.768	1.892	1.917	1.259
	Zhejiang	0.776	0.835	0.895	0.923	0.986	1.122	1.324	1.564	1.764	1.982	2.236	2.476	2.781	1.513
	Fujian	0.778	0.798	0.836	0.879	0.946	0.968	0.997	1.147	1.255	1.356	1.459	1.556	1.754	1.133
	Shandong	0.769	0.783	0.798	0.816	0.838	0.892	0.916	0.934	0.967	0.981	1.065	1.097	1.121	0.921
	Guangdong	0.903	0.927	0.987	1.033	1.139	1.232	1.333	1.437	1.449	1.478	1.504	1.558	1.663	1.280
	Hainan	0.813	0.834	0.879	0.887	0.898	0.921	0.998	1.163	1.268	1.366	1.471	1.474	1.479	1.112
Central	Shanxi	0.419	0.426	0.437	0.487	0.566	0.678	0.748	0.756	0.768	0.777	0.789	0.797	0.809	0.651
	Jilin	0.515	0.536	0.567	0.589	0.651	0.683	0.761	0.782	0.865	0.967	1.157	1.272	1.477	0.832
	Heilongjiang	0.633	0.662	0.689	0.731	0.835	0.934	0.996	1.038	1.082	1.248	1.351	1.455	1.563	1.017
	Anhui	0.755	0.787	0.838	0.894	0.935	0.974	0.989	1.158	1.162	1.173	1.245	1.346	1.452	1.054
	Jiangxi	0.401	0.511	0.526	0.531	0.552	0.573	0.585	0.599	0.612	0.634	0.666	0.687	0.721	0.584
	Henan	0.566	0.578	0.598	0.615	0.629	0.649	0.676	0.723	0.725	0.728	0.786	0.867	0.943	0.699
	Hubei	0.506	0.518	0.544	0.567	0.578	0.76	0.58	0.583	0.589	0.597	0.599	0.605	0.614	0.588
	Hunan	0.767	0.778	0.789	0.797	0.806	0.813	0.833	0.857	0.879	0.893	0.903	0.934	0.984	0.849
Western	Neimenggu	0.311	0.305	0.346	0.354	0.365	0.401	0.455	0.458	0.467	0.476	0.489	0.509	0.519	0.420
	Guangxi	0.474	0.478	0.489	0.495	0.499	0.509	0.512	0.533	0.542	0.556	0.568	0.587	0.593	0.526
	Chongqing	0.512	0.549	0.587	0.655	0.775	0.833	0.942	1.054	1.392	1.543	1.665	1.779	1.924	1.093
	Sichuan	0.513	0.516	0.526	0.554	0.566	0.578	0.588	0.596	0.599	0.612	0.619	0.637	0.649	0.581
	Guizhou	0.347	0.348	0.351	0.359	0.365	0.367	0.377	0.386	0.393	0.425	0.436	0.447	0.465	0.390
	Yunnan	0.512	0.515	0.519	0.524	0.526	0.538	0.546	0.557	0.567	0.572	0.583	0.597	0.617	0.552
	Shaanxi	0.687	0.693	0.703	0.726	0.732	0.778	0.792	0.828	0.844	0.857	0.879	0.894	0.923	0.795
	Gansu	0.221	0.218	0.223	0.229	0.239	0.244	0.258	0.273	0.299	0.313	0.338	0.349	0.367	0.275
	Qinghai	0.328	0.332	0.345	0.351	0.354	0.364	0.373	0.385	0.389	0.394	0.399	0.416	0.424	0.373
	Ningxia	0.265	0.271	0.276	0.288	0.296	0.307	0.309	0.313	0.328	0.334	0.343	0.357	0.367	0.312
	Xinjiang	0.378	0.389	0.394	0.399	0.403	0.424	0.425	0.427	0.436	0.446	0.458	0.461	0.473	0.424
National mean		0.593	0.612	0.641	0.694	0.739	0.790	0.830	0.896	0.962	1.028	1.098	1.155	1.246	0.868

Table 3: Cross-sectional heterogeneity test and residual heterogeneity test of the panel smoothing threshold regression model.

Test type	Assumptions	Statistics value	$m=1$	$m=2$
Cross-sectional heterogeneity test	H0 : $r=0$	LM	9.034 (0.024)	11.652 (0.017)
		LMF	2.983 (0.016)	2.184 (0.002)
	Hi : $r \geq 1$	LRT	10.032 (0.003)	13.617 (0.003)
Residual heterogeneity test	H0 : $r=0$	LM	1.367 (0.673)	1.926 (0.238)
		LMF	0.593 (0.348)	0.253 (0.524)
	Hi : $r \geq 2$	LRT	1.573 (0.763)	1.766 (0.291)
		AIC	2.66	2.66
		BIC	2.97	2.93

Note. *P*-value in brackets.

$g(q_{it};\gamma,c) = 0.5$, and the coefficient of the impact of environmental regulations on green economy efficiency is 0.810 (3.9845–6.3490 × 0.5). At this time, every time the intensity of environmental regulation increases by 0.01, the green economy efficiency increases by 0.0810; when the intensity of environmental regulation is more remarkable than 0.5128, the transfer function $g(q_{it};\gamma,c) = 0.5$, the impact of environmental regulations on the efficiency of the green economy coefficient becomes −2.3645 (3.9845–6.3490). Every time the intensity of environmental regulations increases by 0.01, the efficiency of the green economy will decrease by 0.0265. It can be seen that when the intensity of environmental regulations is low, strengthening environmental regulations will have a positive impact on the efficiency of the green economy. If environmental regulations continue to be strengthened at the initial stage of implementation of environmental regulations, it will be conducive to improve green economy efficiency. However, as the intensity of environmental regulations increases, the impact coefficient shows a downward trend until a negative value. Therefore,

Table 4: Parameter estimation results of panel smoothing threshold regression model.

Variable name	Linear part	Nonlinear part
ERI	3.9845**	−6.3490***
ES	−3.1238*	5.9981***
UR	2.4938***	−7.2239***
FDI	4.6732***	−18.3469***
Location parameter		0.6129
Smoothing parameter		17362

Note. ***, **, and * represent the significance level of 1%, 5%, and 10%, respectively.

the impact of environmental regulations on the efficiency of the green economy presents an inverted U-shaped relationship that first rises and then falls, which is consistent with the results of existing research. Consistent with existing research results of Feng and Wang [53] and Song et al. [42], it shows that there is uncertainty in the impact of environmental regulations on the efficiency of the green economy. However, other studies have not investigated the nonlinear effects of environmental regulations. This article provides substantial empirical evidence for scientifically judging the current intensity of environmental regulations in different regions and exploring the optimal regulatory intensity interval. However, some scholars believe that there is no U-shaped relationship between the two. For example, Gong and Zhang's [54] research shows that the intensity of China's environmental regulation and the spatial evolution of green economy efficiency are positively correlated. The main reason may be the research method differences adopted by the scholar. The further analysis of the intensity threshold of environmental regulations in this paper is different from previous studies.

From the perspective of the relationship between the green economy efficiency and the industrial structure of the control variables, the variable coefficient of the linear part is −3.1238, which is significant at the level of 10%. However, when the intensity of environmental regulation crosses the threshold, the variable coefficient becomes 2.8743 (−3.1238 + 5.9981). The increase in the ratio of the tertiary industry will promote the improvement of green economic efficiency. In the initial stage of the development of the tertiary industry, the real economy is the source of the creation of the national economy. As the ratio of the tertiary industry continues to rise, the proportion of the virtual economy will continue to rise. The virtual economy will continue to squeeze the real economy, making the real economy unable to support the national economic development of the green economy declines inefficiently. When the ratio of the tertiary industry reaches a critical value, the development of the tertiary industry is relatively mature, which will drive the rapid development of the national economy and promote the efficiency of the green economy. Most scholars have obtained similar results. For example, scholars Ye et al. [55], Peng et al. [56], and Li and Su [57] all believe that industrial structure has a negative impact on the efficiency of the green economy. It is believed that the industrial development model with high-energy consumption and high pollution has inhibited green development, and the transformation of industrial growth mode from "driven by capital and labor factors" to "driven by technological innovation" should be actively encouraged to realize its green transformation.

From the perspective of the relationship between the efficiency of the green economy and the degree of openness of the control variables, the variables of the linear part and the nonlinear part are both significant at the level of 1%, and the coefficient of the linear part is positive, indicating that the strengthening of the degree of openness will benefit Chinese green economy. The improvement of economic efficiency is consistent with existing research. However, the coefficient of the nonlinear part is negative and significant, indicating that when the intensity of environmental regulation exceeds the threshold, relying too much on foreign trade will inhibit the improvement of green economy efficiency, which is further than existing research.

The reasons may be first, under the background of the international division of labor, foreign-funded enterprises use China's cost advantages to transfer high-polluting industries to China. The fierce competition in attracting investment in various regions will prompt them to ignore the environmental protection requirements of foreign investment in pursuit of the scale of investment, which verifies the foregoing. Deng and Xu [58] also pointed out that the "pollution refuge hypothesis" that China has attracted is pollution-intensive primarily industries. Currently, foreign direct investment's negative environmental spillover effect dominates; the second is China's influence on foreign-funded enterprises. The advanced technology has limited digestion and absorption capacity, failed to be effectively transformed and utilized and reinnovated, and foreign capital transfer to my country may be the backward technology eliminated by the country. Hence, the technology spillover effect brought by foreign direct investment has a long-term role in improving the efficiency of the Chinese green economy. Research on the relationship between the degree of opening up to the outside world and the efficiency of the regional green economy has significant differences. Some scholars believe that foreign direct investment positively impacts the host country's green economy [59–61]. Some scholars hold the opposite view and support the "pollution refuge" hypothesis [62–64]. In response to the above differences, some scholars believe that foreign investors directly impact the investment on the efficiency of the green economy is heterogeneous, and there are different influence relationships due to different factors such as the level of economic development, openness, and human capital levels in the regions where foreign capital flows. The difference between these articles is the study of nonlinear characteristics, and different conclusions are drawn in the linear and nonlinear regions. This is what distinguishes this article from other scholars, and it is also an exploration of this article from a new perspective, which has the value of innovation.

From the perspective of the relationship between green economy efficiency and the degree of urbanization of the control variable, the linear part and the nonlinear part of the

variables are both significant at the level of 1%. The coefficient of the linear part is a positive significant promotion effect. The development of Chinese new urbanization has played an essential role in stimulating domestic consumer demand and promoting the transformation of economic structure. The economic benefits brought by it have exceeded the resource and environmental problems brought about by urbanization. However, the coefficient of the nonlinear part is negative and more significant than the linear part, indicating that when the intensity of environmental regulations exceeds the threshold, excessive reliance on urbanization will inhibit the improvement of green economy efficiency. The reason is that the scale of urbanization's continuous expansion and dense population have caused more pollution, which has led to a decline in the efficiency of the green economy. Urbanization reflects the excessive expansion of capital [65], which only emphasizes the increase in area, ignoring the coordination of the functions of urban land, resulting in the reduction of public green space, the overall low efficiency of land use, and energy waste. There is a significant nonlinear relationship between urbanization and regional green economy efficiency. This conclusion shows that although the population is shifting to nonagricultural industries under the current policy conditions, it is mainly concentrated in high-polluting industries such as manufacturing and construction. This phenomenon is consistent with the research of Gao and Xie [66]. However, with improved employees' quality and professional skills, employment will be concentrated in the relatively environmentally friendly modern service industry, thus changing this situation.

5. Conclusion

This paper uses the super-efficiency SBM model to measure the green economic efficiency considering undesired output and analyzes the spatial distribution difference of green economic efficiency; second, the nonlinear panel threshold model is used to empirically study the nonlinear relationship between environmental regulation and green economic efficiency, and further analyzing the threshold effect of nonenvironmental regulations in various regions on the efficiency of green economy, the conclusions are as follows.

(1) The green economy efficiency index in the eastern region is mainly greater than 1, and the green economy efficiency in most provinces in the eastern region has improved. These provinces have higher regional production levels and less environmental pollution. The green economy efficiency index of the central region is second only to the eastern region. The green economy efficiency index of the western region except Shaanxi is less than 1, indicating that these provinces have problems of insufficient regional production, severe environmental pollution, or significant resource depletion.

(2) The analysis of the threshold of environmental regulations shows that the impact of environmental regulations on the efficiency of the green economy presents an inverted "U" shape, and there is a threshold of 0.5128 for environmental regulations. In addition, the impact of the industrial structure on the efficiency of the green economy changes from inhibition to promotion after crossing the threshold of the intensity of environmental regulation, and the degree of opening to the outside world has a complementary effect on the efficiency of the green economy. The impact of urbanization on the efficiency of the green economy changes from promotion to suppression after surpassing the threshold of the intensity of environmental regulations. Therefore, the government should pay attention to the province's current environmental regulation intensity when formulating relevant policies to improve the efficiency of the green economy. If the province's environmental regulation intensity is less than 0.5128, the government should appropriately strengthen environmental regulation, control the ratio of the tertiary industry, and develop foreign trade. In order to improve the efficiency of the green economy in the region, if the region's environmental regulations are more significant than 0.5128, the government should appropriately weaken the intensity of environmental regulations, develop the tertiary industry, and control foreign trade to promote the improvement of the region's green economy efficiency.

(3) It can be seen from the numerical values and thresholds of the intensity of environmental regulations that most provinces in the eastern region have not crossed the threshold of the intensity of environmental regulations. About 1/2 of the provinces in the central region have crossed the threshold of most provinces in the region that have already crossed this threshold. Therefore, to effectively improve the efficiency of the green economy in various provinces, the government should take differentiated improvement measures for different regions. Specifically, while ensuring the strength of existing environmental regulations, the eastern region should accelerate economic development through the development of foreign trade to increase the efficiency of the green economy; the central region should adopt appropriate environmental regulations and vigorously develop the economy; the western region should face the transfer of polluting industries that should appropriately increase the intensity of environmental regulations, increase the development of the tertiary industry, and appropriately control the expansion of foreign trade.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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