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Research Article

Research on the Impact of Environmental Regulation on Total Factor Energy Effect of Logistics Industry from the Perspective of Green Development

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This study uses the super efficiency DEA model to evaluate the logistics industry's total factor energy efficiency in various Chinese provinces, autonomous regions, and municipalities, and examines the relationship between environmental regulations and the total factor energy efficiency. The results show that environmental regulations can help improve the logistics industry's total factor energy efficiency. This study further analyzes the threshold effect of environmental pollution control investment level, quality of labor, and logistics industry development level in environmental regulations on the logistics industry's total factor energy efficiency. The results showed that the level of investment in environmental pollution control in environmental regulations has a significant single threshold effect on logistics industry's total factor energy efficiency. The quality of labor has a significant double threshold effect on environmental regulation's impact on the logistics industry's total factor energy efficiency. Logistics industry development level has a significant double threshold effect on the impact of environmental regulation on logistics industry's total factor energy efficiency.

1. Introduction

Since the industrial revolution, the continuous improvement of social productivity has been accompanied by a large amount of fossil fuel consumption, rapid growth in greenhouse gas emissions, rapid changes in the surface temperature of the Earth, destruction of the ecological cycle system, frequent natural disasters, and severe challenges to human survival and social development [1, 2].

The logistics industry is a composite service industry that integrates warehousing, transportation, information services, and other industries. It is a basic and strategic industry in China's economic development. In recent years, China's policies and regulations have repeatedly mentioned that the logistics industry's current main task is to vigorously develop green logistics and adhere to the main energy-saving principles, emission reduction, green environmental protection, and efficiency improvement. In the context of the new normal, driving steady economic growth through the development of low-carbon green logistics is the only way to develop the logistics industry. Additionally, China has continuously emphasized "accelerating green logistics' development" as an "endogenous power to enhance the high-quality development of logistics," reducing energy consumption and controlling carbon emissions in the logistics industry. According to the "China Energy Statistical Yearbook," the logistics industry's total energy consumption in 2000 was 114.47 million tons of standard coal, accounting for 7.79% of the country's total energy consumption. In 2020, the total energy consumption of the logistics industry was 413.09 million tons of standard coal, accounting for 8.29% of the total energy consumption in China. As one of the major energy consumption industries in China, the logistics industry ranks first in the consumption of refined oil in various industries. More than 90% of gasoline and 60% of diesel in the country are consumed by the logistics industry.

However, reasonable environmental regulations can help logistics companies to achieve maximum benefits given the circumstances of cost constraints, promote technological progress, and ultimately enhance environmental protection and energy efficiency in a win-win situation. The logistics industry's total factor energy efficiency is the endogenous driving force that determines its green development and is an important starting point for improving its green total factor productivity. Improving the logistics industry's total factor energy efficiency is an effective means to alleviate logistics economic activities' environmental impact. Improving the energy efficiency of all factors in the logistics industry will help improve its resource allocation capabilities, which can further promote the Chinese economy's sustainable development and promote the global low-carbon energy transition. While improving the logistics industry's economic efficiency, it will help to improve its energy input efficiency and reduce pollution emissions, which is of great significance to realizing the logistics industry's low-carbon transformation. Therefore, studying environmental regulations' impact on the logistics industry's total factor energy efficiency is of great significance for improving its energy efficiency.

In recent years, scholars have increasingly researched the logistics industry's efficiency. Scholars start from different angles and use DEA methods to analyze deep-seated problems in the logistics industry's development [3]. Wu et al. [4] and Song and Lyu [5] analyzed Chinese logistics enterprises' operational efficiency and Chinese logistics service industry's production efficiency.

While developing the logistics industry, the carbon emissions concept has become something that people cannot ignore. Early scholars systematically analyzed the relationship between carbon emissions and economic development [6–9], and on this basis, the mechanism and principles of carbon emission reduction have been studied [10, 11]. At present, scholars have conducted a lot of research on the emission reduction potential of carbon dioxide; however, most of them are limited to industrial [12, 13], regional carbon emissions, etc. [14, 15]. Additionally, few studies have considered issues such as the analyzing factors that influence the logistics industry's total factor energy and its potential for carbon dioxide emission reduction, by measuring the logistics industry's total factor energy efficiency. It is worth noting that traditional total factor productivity tends to focus on capital, labor, and technology but does not consider energy elements, along with in-depth research, many scholars include energy elements in the total factor productivity analysis framework. In this case, the conceptual connotations of energy efficiency and total factor productivity are consistent. To distinguish it from the total factor productivity that does not include energy factors, this study adopts the total factor energy efficiency concept.

Recently, an increasing number of researchers have conducted research on environmental regulations' impact on the logistics industry's total factor energy efficiency. Environmental regulations' impact on the logistics industry's total factor energy efficiency has two positive and negative interweaving effects. Based on this, scholars have drawn three conclusions. The first category is suppression theory. Knellera and Manderson [16] and Dutta and Narayana [17] proved that environmental regulations have an inhibitory effect on energy efficiency. The second category promotes the theories [18]. Mandal conducted research on the Indian cement industry and analyzed environmental regulations' impact on energy efficiency and determined that environmental regulations can indeed promote energy efficiency [19]. Pan et al. conducted research on China's provincial panel data from 2006 to 2015, and found that environmental regulations regarding command and control can directly promote energy efficiency improvement [20]. In the third category, environmental regulations and the logistics industry's energy efficiency present a "positive U-shaped" relationship [21]. Zhang et al.'s study also demonstrated that environmental regulations and energy efficiency present a "positive U-shaped" relationship, that is, on the left side of the "inflection point," cost effects dominate, and on the right side of the "inflection point," innovation compensation effects play a leading role [22].

By combining relevant literature, we found that many important results have been achieved by studying environmental regulations' impact on energy efficiency, however, no consistent conclusion has been reached so far. There are areas that still merit improvement. First, most existing studies have studied environmental regulations' impact on the logistics industry's total factor productivity. Although some researchers have discussed environmental regulations' impact on the logistics industry's total factor energy efficiency, they have not analyzed the relationship between the two in depth. Second, most existing studies examine environmental regulations' impact on different industries from the industry's perspective, and rarely examine environmental regulations' impact on the logistics industry's total factor energy efficiency from a provincial scale. Third, environmental regulations' impact on the logistics industry's total factor energy efficiency is a complex and dynamic process that is constrained by many factors. Therefore, this study further explores environmental regulations' nonlinear threshold effect on the logistics industry's total factor energy efficiency.

The remaining of this study is organized as follows: Section 2 established the research hypothesis of this paper. Research methods and data collection are shown in Section 3. In Section 4, based on previous research results, we analyzed the relationship between environmental regulation and total factor energy efficiency of the empirical analysis' logistics. Third, we learn from the Hansen threshold model to conduct theoretical analysis and empirical testing on the nonlinear relationship between environmental regulations and of logistics industry's total factor energy efficiency. Conclusions, policy implications, and limitations are shown in Section 5.

2. Mechanism Analysis and Hypothesis

There are certain doubts about environmental regulations' impact on the logistics industry's development, especially its total factor energy efficiency. Environmental regulations can effectively improve environmental quality, however, it hinders the industry's development. This is a problem worthy of discussion. Some studies believe that environmental regulations are positively correlated with the development of related industries, and some studies have shown that there is a significant positive correlation between environmental regulations and corporate competitiveness. Chen and Zhang empirically studied different environmental regulation tools' impact on energy efficiency [23]. Bi et al. used data from China's thermal power industry to analyze environmental regulations' impact on energy efficiency and determined that environmental regulations are conducive to promoting the thermal power industry's energy efficiency [24]. Holmfeld surveyed Danish companies to study the effectiveness of environmental regulations in improving energy efficiency. The results confirmed that the Danish government's environmental permit and ban framework is relatively vague and cannot provide the right direction to promote energy efficiency [25]. Zhang et al. [22] and Zhang et al. [26] used the super efficiency DEA model to analyze 30 Chinese provinces' panel data from 2000 to 2012. The empirical results show that environmental regulations can significantly promote China's total factor energy efficiency. Few studies have examined the relationship between environmental regulations and the logistics industry's total factor energy efficiency. According to existing studies, there are no simple linear relationship between environmental regulations and industrial economic growth. Environmental regulations' impact on industrial economic growth has a threshold effect. Wang et al. reported that environmental regulations' impact on energy efficiency has a threshold effect, with a threshold of 0.0002 [27]. Zhang et al. also showed that with the continuous improvement of environmental regulation intensity, energy efficiency will increase and then decrease [28]. Ye and Wang's study showed that environmental regulations have a significant positive impact on economic efficiency [29]. Liang et al.'s study showed that environmental regulations have a significant positive impact on the total factor productivity growth of the logistics industry in Jiangsu province [30].

The logistics industry's total factor energy efficiency is an important indicator for measuring its green development. The environmental regulations' goal is to achieve both economic growth and environmental quality. Can both environmental regulations and the logistics industry's development be achieved? On this basis, to improve the logistics industry's total factor energy efficiency, environmental regulations' impact on the logistics industry's total factor energy efficiency is discussed from a theoretical perspective. Based on this, we propose Hypothesis 1.

Hypothesis 1. Under the control of other influencing factors, environmental regulations are conducive to improving the logistics industry's total factor energy efficiency

Since environmental regulations' impact on the logistics industry's total factor energy efficiency is a complex and dynamic process, subject to a variety of conditional factors, this study considers the differences in factors such as the level of investment in environmental pollution control, the quality of labor, and the developmental level of the logistics industry, as well as environmental regulations' nonlinear impact on the logistics industry's total factor energy efficiency.

2.1. The Environmental Pollution Control Investment Level (INV). The environmental pollution control investment level (INV) directly reflects the intensity of the government's power to suppress environmental pollution, investments made into urban environmental infrastructure facilities, environmental protection, and environmental protection acceptance projects.

Wu et al. showed that the impact of environmental pollution control investment level on technological innovation expenditure contributes to economic performance. When the investment level in environmental pollution control is too high, the impact of enterprise R&D expenditure on economic performance increases with the increase in investment level in environmental pollution control [31, 32].

Therefore, the threshold effect of environmental pollution control investment level in the environmental regulation affecting the logistics industry's total factor energy efficiency is summarized as follows: (1) the expansion of investment in environmental pollution control is conducive to the improvement of all-factor energy efficiency in the logistics industry, that is, to improve environmental quality, the government should continuously increase the investment scale of environmental pollution control funds relying on clean technology's progress to reduce energy consumption and pollutant emissions, thereby, improving energy efficiency. (2) The investment level of environmental pollution control is further improved, and a reversing mechanism can be formed to promote logistics enterprises' independent innovation, and to realize production methods' upgrading and transformation, and thus, improve the logistics industry' energy efficiency. Logistics companies' pollution source control investment is mainly used to control the terminal emission of pollution. Often, environmental pollution control's performance is relatively weak, and companies usually pay more attention to production and operational capabilities. Thus, Hypothesis 2 is proposed.

Hypothesis 2. Under the control of other influencing factors, environmental regulations' impact on of the logistics industry's total factor energy efficiency has a threshold effect on the level of investment in environmental pollution control.

2.2. Quality of Labor (HUC). The quality of labor refers to the labor force's inherent characteristics and quality in the production process. The quality of labor is closely related to the factor productivity. With economic development, the scarcity of resources has made various economies increasingly committed to improving their productivity and efficiency. According to neoclassical growth theory, economic growth stems from the accumulation of factors as well as from the growth of total factor productivity. As the basic elements that constitute the economic development mode and the source of technological progress, the quality of labor constrains the growth of total factor productivity and is an important factor that explains the difference between regional economic growth and industrial development.

With the logistics industry developing from extensive to intensive, high-quality development, the input of high-quality labor, and specialized knowledge are essential. Lu proves that the quality of workers has a positive impact on the efficiency of the logistics industry [33]. To a certain extent, the quality of workers is closely related to citizens' awareness of environmental protection. People with higher levels of education and knowledge have a clearer understanding of the severity of environmental problems and have a stronger awareness of environmental protection. Pargal and Wheeler mentioned that the higher the per capita income, the higher the residents' requirements for environmental quality, and per capita income is positively related to environmental regulations [34].

Human capital is a necessary condition for the logistics industry to progress. It determines the direction of the upgrades in the logistics industry. The spillover characteristics of human capital can utilize diversified labor, reduce the time cost of technical learning, and provide talent support for the logistics industry's rationalization and advancement, and contribute to internal technology accumulation and continuous technological innovation. In fact, due to differences in education levels and skills, different types of human capital have different technological spillovers, learning capabilities, and innovative potential. As an important carrier that drives technological progress, human capital plays an important role in environmental protection practices. A series of empirical studies have shown that the level of pollution in a region is closely related to the status of local human capital [35]. Companies whose employees are more educated are more inclined to implement environmental standards and increase environmental protection effort. The existence of the "pollution paradise" hypothesis is also inseparable from the human capital supply in the region [36]. Thus, we propose Hypothesis 3.

Hypothesis 3. Under the control of other influencing factors, environmental regulations' impact on the logistics industry's total factor energy efficiency has a threshold effect on the quality of labor.

2.3. Logistics Industry Development Level (LDL). The logistics industry is a modern service industry integrating warehousing, transportation, packaging, circulation processing, and information technology. The industry promotes the development of other related multi-industry linkages and is a booster for economic development. Improving the logistics industry's service level will help improve the logistics industry's total factor energy efficiency. The logistics industry's development level is the core factor in improving logistics efficiency.

The analysis of the threshold effect of the logistics industry's development level in the environmental regulations affecting its total factor energy efficiency is as follows: (1) areas with a high level of development in the logistics industry usually have a good foundation for the development of manufacturing and service industries, or a well-established transportation infrastructure. Enterprises usually have strong resource allocation capabilities, which helps them increase their opening to the outside world and strengthen cooperation with foreign and other companies. Regional communication promotes the exchange of advanced logistics technologies and management methods, vigorously build digital logistics infrastructure, such as the logistics Internet, and use the development of new logistics industries in the fields of digitization, intelligence, and low carbonization. (2) The improvement of the logistics industry's development level will help its specialization and division of labor, continuously promote industrial transformation and upgrading, gradually eliminate some primitive and low-level noncore competitiveness enterprises, and help focus the industry on core competitiveness and sustainable development. To a certain extent, the logistics industry's total factor energy efficiency has improved. Thus, we propose Hypothesis 1.

Hypothesis 4. Under the control of other influencing factors, environmental regulations' impact on the logistics industry's total factor energy efficiency has a threshold effect on the logistics industry's development level.

3. Research Methods and Data Collection

3.1. Model Theory and Construction

3.1.1. DEA Model Application. Data envelopment analysis (DEA) was originally proposed by American scholars Charnes et al. in 1978 as a method to evaluate the relative efficiency of decision making unit (DMU) under the mode of "multi-input multi-output" [37]. There are two DEA models: CCR with constant returns to scale and BCC with variable returns to scale. It uses linear programming mathematical methods to evaluate the relative efficiency of DMUs. When the efficiency value is equal to 1, it means that the DMU is at the production frontier and is efficient. When the efficiency value is less than 1, it means that the DMU is far from the production frontier and is inefficient or weakly effective. Suppose that there are n evaluation objects, each of which is labeled DMU, and each DMU has m inputs and S outputs. Let X_{ij} denote the j-th input of DMU_i and Y_{ij} denote the k-th output of DMU_i. All DMU_i inputs can be expressed as follows:

$$X_i = (X_{i1}, X_{i2}, \ldots, X_{im}), i = 1, 2, \ldots, n. \quad (1)$$

The output of the DMU can be expressed as follows:

$$Y_i = (Y_{i1}, Y_{i2}, \ldots, Y_{is}). \quad (2)$$

Assume that the weight vectors of the input and output indicators are $v = (v_1, v_2, \ldots, v_m)^T$ and $u = (u_1, u_2, \ldots, u_s)^T$, respectively.

The efficiency of the DMU can be expressed as follows:

$$E_i = \frac{u^T Y_i}{v^T X_i}, \tag{3}$$

where v^T denotes the input index weight vector and u^T denotes the output index weight vector. Appropriate selection of weights v and u can make $E_i \leq 1$.

If the i_0-th DMU is evaluated, denoted as DMU_0, where the input is X_0 and the output is Y_0, the CCR-DEA evaluation model of the relative efficiency of the first DMU is as follows:

$$\begin{aligned}&\operatorname{Max} E_0 = \frac{u^T Y_0}{v^T X_0}\\&\text{s.t.}\begin{cases}\dfrac{u^T Y_i}{v^T X_i} \leq 1, i = 1, 2, \ldots, n,\\ u \geq 0, v \geq 0.\end{cases}\end{aligned} \tag{4}$$

Let's turn the above equation into a linear program:

$$\begin{aligned}&\operatorname{Max} \omega^T Y_0\\&\text{s.t.}\begin{cases}\eta^T X_j \geq \omega^T Y_j, j = 1, 2, \ldots, n,\\ \eta^T X_0 = 1,\\ \omega \geq 0, \eta \geq 0.\end{cases}\end{aligned} \tag{5}$$

The dual problem of this linear programming problem is as follows:

$$\begin{aligned}&\operatorname{Min} \theta\\&\text{s.t.}\left\{\sum_{i=1}^{n} X_i\lambda_i \leq \theta X_0, \sum_{i=1}^{n} Y_i\lambda_i \leq Y_0, \lambda_i \geq 0, i = 1, 2, \ldots, n.\right.\end{aligned} \tag{6}$$

If the constraint condition $\sum_{i=1}^{n} \lambda_i = 1$ is added to the CCR-DEA evaluation model, the BCC-DEA evaluation model can be obtained as follows:

$$\begin{aligned}&\operatorname{Min} \theta^{BCC}\\&\text{s.t.}\left\{\sum_{i=1}^{n} X_i\lambda_i \leq \theta^{BCC} X_0, \sum_{i=1}^{n} Y_i\lambda_i \geq Y_0, \sum_{i=1}^{n} \lambda_i = 1, \lambda_i \geq 0, i = 1, 2, \ldots, n.\right.\end{aligned} \tag{7}$$

In 1993, Andersen and Petersen proposed an improved model of CCR model, namely super-efficiency DEA model [38]. It overcomes the defect of the traditional CCR model that multiple DMUs cannot be further evaluated and compared, so that effective DMUs can be further compared and ranked.

The feature of the super efficiency DEA model is that when a DMU is to be evaluated for efficiency, it is excluded first. Therefore, for ineffective DMUs, the input increases proportionally on the basis of constant efficiency values, the increased proportion is recorded as super efficiency, and the measured super efficiency is greater than the efficiency values measured by the traditional DEA model. The higher the super efficiency evaluation value of effective DMU, the higher the relative efficiency.

The basic idea of the super efficiency CCR-DEA model is to make the input and output of the i_0 th DMU be replaced by the linear combination of all other DMU inputs and outputs while excluding the first DMU, while the CCR-DEA model includes this unit when evaluating the i_0 th DMU efficiency. An efficient decision making unit (DMU) can increase its input by a ratio while keeping its efficiency unchanged. Its input increase ratio is its super efficiency evaluation value.

There are two different types of super efficiency DEA models: output-oriented and input-oriented. The pursuit of output-oriented is to maximize the output under the condition that the input level remains unchanged. The input-oriented pursuit is to minimize the input while the output level remains constant. Since this paper aims to analyze how to achieve the optimal total factor energy efficiency of the logistics industry in each region with the least resource consumption and environmental damage, we choose the input-oriented super efficiency DEA model. Traditional DEA models such as CCR and BBC models measure relative efficiency from a radial perspective and do not consider the input and output slack, which tends to lead to high calculation results, affecting its calculations' accuracy. To solve this problem, Tone proposed a slacks-based measure (SBM) model in 2001 [39].

On this basis, this paper combines the super efficiency DEA with the SBM model to improve the bias in the measurement process. The input-oriented super-efficient SBM model is selected to measure the degree of DMU inefficiency that is evaluated from the perspective of input. The programming formula of the super-efficient SBM is only applicable to the effective DMU. For the DMU with efficient SBM, the mathematical form of the input-oriented super-efficient SBM model is as follows:

$$\begin{aligned}&\operatorname{Min} \rho_{SE} = \frac{1/m \sum_{i=1}^{m} x_i/x_{ik}}{1/s \sum_{r=1}^{s} y_r/y_{rk}}\\&\begin{cases}\text{s.t} \displaystyle\sum_{j=1, j\neq k}^{n} x_{ij}\lambda_j \leq \overline{x}; \sum_{j=1, j\neq k}^{n} y_j\lambda_j \geq \overline{y},\\ \displaystyle\sum_{j=1, j\neq k}^{n} x_{ij}\lambda_j + s_i^- = x_{ik}, i = 1.2. \ldots, m,\\ \displaystyle\sum_{j=1, j\neq k}^{n} y_{rj}\lambda_j - s_r^+ = y_{rk}, r = 1, 2, \ldots, s,\\ \overline{x} \geq x_k, \overline{y} \leq y_k, j = 1, 2, \ldots, n(j \neq k),\\ \overline{y} \geq 0, \lambda \geq 0, s_i^- \geq 0, s_r^+ \geq 0,\end{cases}\end{aligned} \tag{8}$$

where ρ_{SE} is the DEA super efficiency value; x and y represent the input and output variables, respectively; $(\overline{x}, \overline{y})$ is the reference point of the decision variable; m and s are the number of input and output indicators, respectively; s_i^- and s_r^+ are the slack variables of input and output; and λ is the weight variable. ① When $\rho_{SE} \geq 1$ and $s_i^- = s_r^+ = 0$, it indicates that DEA is relatively effective; ② when $\rho_{SE} \geq 1$, $s_i^- \neq 0$ or $s_r^+ \neq 0$, it indicates that weak

DEA is effective; ③ when $\rho_{SE} \leq 1$, it indicates that DEA is relatively invalid, which illustrates the need for proper input and output improvements.

3.1.2. Environmental Regulations and the Total Factor Energy Efficiency of the Logistics Industry. To verify Hypothesis 1, this study constructs a measurement model of the relationship between environmental regulation and the logistics industry's total factor energy efficiency:

$$\mathrm{LnLTFEE}_{it} = \alpha_1 + \alpha_2 \mathrm{LnREG}_{it} + \alpha_3 \mathrm{Ln}X_{it} + \delta_i + \varepsilon_{it}, \quad (9)$$

where LTFEE is the logistics industry's total factor energy efficiency, REG is the environmental regulation, X is the control variable, i represents different provinces, t represents different years, δ_i represents regional effects, and ε_{it} represents random interference terms.

3.1.3. Threshold Regression Model and Application. Hansen first proposed a static panel threshold model that can be used to analyze the impact of threshold variables on the explained variables at different stages [40]. The intervals at different stages are described using different regression equations. Each threshold value of the threshold variable is a critical point; according to the number of thresholds, a single threshold or multiple threshold models can be set. Its advantages are that on the one hand, this method does not need to give the form of linear equation, the threshold value and its number are completely and endogenously determined by the sample data, and the threshold value can be estimated. At the same time, it can also carry out the significance test for the endogenous "threshold effect." This method provides a progressive distribution theory to establish confidence intervals for the parameters to be estimated, and a "Bootsrap" method can be used to estimate the statistical significance of the thresholds. This method overcomes the shortcomings of subjectivity and lack of reliable parameter estimation in the "cross product term method" and "group test method." In the case of unknown threshold values, the following threshold regression model is constructed, and in order to avoid heteroscedasticity, all variables are logarithmic.

Firstly, this paper understands the idea of Hansen's single threshold modeling, so as to model the effect of environmental regulation on the total factor energy efficiency of the logistics industry below. The single threshold model is set as follows:

$$Y_{it} = \mu_i + \beta_1 x_{it} I(q_{it} \leq \gamma) + \beta_2 x_{it} I(q_{it} > \gamma) + \varepsilon_{it}, \quad (10)$$

where i represent different areas; t for different years; μ_i is the individual effect; $I(\cdot)$ is the exponential function; γ is threshold value; q_{it} is threshold variable; and ε_{it} is the random disturbance term.

The matrix expression is as follows: $Y_{it} = \mu_i + \beta x_{it}(\gamma) + \varepsilon_{it}$. The within-group average of the matrix expression was performed, and then the within-group average was subtracted to eliminate the influence of individual effect μ_i, and the transformed matrix expression was obtained: $Y^* = \beta x^*(\gamma) + e^*$. The sum of squares of the residuals is $S_1(\gamma) = e^*(\gamma) = Y^*(1 - X^*(\gamma))[X^*(r)X^*(\gamma)]^{-1}X^*(\gamma)r^*$. By finding the threshold optimal estimator γ, $S_1(\gamma)$ is minimized.

Secondly, the significance of the threshold effect and whether the threshold estimate is true were tested. The significance of the threshold effect is mainly measured by constructing the F-statistic, that is, $F_1 = (S_0 - S(\hat{\tau}))\tau^2$. For a single threshold, H_0 represents no threshold value and H_1 presents that there is a threshold value. Both P values and critical values were obtained by applying "Bootsrap" repeated sampling 500 times. If the P value was small enough, H_1 was accepted, which had at least one threshold value, and then continued to test whether there were more thresholds until the P value was not significant. Whether the threshold estimate is true or not generally determines whether the null hypothesis $\tau = \hat{\tau}$ is true, and the likelihood function can be established for estimation test: $LR(\tau) = (S_1(\tau) - S_1(\hat{\tau}))/\tau^2$.

Finally, when the threshold test was completed, the corresponding parameter estimation operation was performed on the model to obtain the coefficient estimates of the corresponding variables. The general threshold model has multiple threshold values, which can be modeled with reference to the double threshold, and the double threshold model can be established as follows:

$$Y_{it} = \mu_i + \beta_1 x_{it} I(q_{it} \leq \gamma) + \beta_2 x_{it} I(q_{it} > \gamma) + \beta_3 x_{it} I(q_{it} > r_2)\varepsilon_{it}. \quad (11)$$

The rest of the procedure is similar to the single threshold.

According to the previous assumption, this paper will draw on the idea of Hansen threshold effect for the study of the nonlinear effect between environmental regulation and total factor energy efficiency of the logistics industry. Since the specific threshold number is unknown, the model is constructed according to the previous modeling idea as follows:

$$\mathrm{LnLTFEE}_{it} = \mu_i + \alpha k_{it} + \beta_1 \mathrm{LnREG}_{it} \times I(q_{it} \leq \gamma_1) + \beta_2 \mathrm{LnREG}_{it} \times I(\gamma_1 < q_{it} < \gamma_2) + \beta_3 \mathrm{LnREG}_{it} \times I(q_{it} \geq \gamma_2) + \beta_4 X_{it} + \varepsilon_{it}, \quad (12)$$

where μ_i is the individual effect; α and β are coefficients; q is the threshold variable, which indicates the level of investment in environmental pollution control, the quality of labor, and the level of development of the logistics industry; γ_1 and γ_2 are waiting for the estimated threshold; $I(\cdot)$ is the exponential function; and ε_{it} is the random disturbance term.

3.2. Variable Description

3.2.1. Logistics Industry's Total Factor Energy Efficiency. To calculate the logistics industry's total factor energy efficiency, this study uses a nonradial data envelopment analysis model—Super-SBM model based on slack variables is used to measure the logistics industry's total factor energy efficiency in 30 Chinese provinces from 2004 to 2020, and then the impact of environmental regulations on the logistics industry's total factor energy efficiency is analyzed. In terms of indicator selection, the number of employees in the logistics industry, fixed asset investment in the logistics industry, and energy consumption are used as input variables. The added value of the logistics industry and freight turnover are the expected output variables and carbon dioxide emissions are the undesired output variables. Due to China's logistics industry's imperfect statistical system, data from transportation, warehousing, and postal industries are used for analysis instead of logistics data. The specific explanation is as follows:

① For the logistics industry's energy consumption, the annual energy consumption data of transportation, warehousing, and postal industries of each province, city, and district from 2004 to 2020 are obtained from the "China Energy Statistical Yearbook." Due to the lack of data in the energy statistical yearbook, the missing statistical data are obtained from the statistical yearbooks of the corresponding missing provinces, cities, and districts (the energy data for Tibet, Hong Kong, Macau, and Taiwan are not available, so these regions are excluded). According to the energy conversion coefficient in the IPCC (Intergovernmental Panel on Climate Change), all energy consumption in the transportation, storage, and postal industries in various regions is converted into standard coal.

② The amount of investment in fixed assets in the logistics industry is based on the amount of investment in fixed assets in the transportation, warehousing, and postal industries in each region as per the "China Statistical Yearbook." First, considering 2003 as the base period, use the fixed asset price index to deflate the fixed asset investment from 2003 to 2020. The depreciation rate of the logistics industry draws on the 12.1% set by Liu and Liu [41], the perpetual inventory method is used to calculate the value of the fixed asset capital stock of the logistics industry from 2004 to 2020.

③ Undesired output. We use carbon dioxide emissions as an indicator for undesired output. Carbon dioxide emissions mainly come from the use of various fuels. Table 1 shows the carbon emission calculation method design of various indicators and coefficients. According to the IPCC Carbon Emission Calculation Guidelines, the calculation formula is as follows:

$$CO_2 = \sum_{i=1}^{8} CO_{2i} = \sum_{i=1}^{8} E_i \times SCC_i \times CEF_i, \qquad (13)$$

where E_i represents the i-th energy consumption, $i = 1, 2, \ldots, 8$; SCC_i represents the conversion factor of primary energy into standard coal; and CEF_i is the carbon emission factor provided by IPCC.

3.2.2. Environmental Regulations' Strength. As this study's core explanatory variable, environmental regulations' intensity is measured by the ratio of the added value of the logistics industry to the energy consumption in each region.

3.2.3. Threshold Variable

① Environmental pollution control investment level (INV): considering the availability of data, we use a measure of the amount of investment intensity that implements environmental regulation of environmental pollution of the logistics industry in the region in China Energy Statistical Yearbook [42], where a larger value indicates a greater implementation intensity of government environmental regulations.

② Qualities of labor (HUC): Educational investment can directly reflect the laborers' quality level and education level and is an important way to improve production efficiency, promote industrial development, and enhance the intensity of environmental regulations. Considering the regional differences between various regions in China, according to China's Population and Employment Statistics Yearbook, this study constructs labor quality indicators based on the education status of the employed population in the logistics industry in each region. The specific calculation formula is as follows:

$$H = \sum \left(\frac{pri}{em} \times 9 + \frac{hig}{em} \times 12 + \frac{col}{em} \times 15 + \frac{uni}{em} \times 16 + \frac{gra}{em} \times 19 \right), \qquad (14)$$

where pri, hig, col, uni, and gra indicate the number of people of the logistics industry with junior high school, high school, junior college, university, and postgraduate qualifications, respectively; em indicates the total number of employees of the logistics industry in each region in the employment population; and 9, 12, 15, 16, and 19 are weights assigned based on years of education.

③ Logistics industry development level (LDL): this study uses the ratio of the added value of the logistics industry in each province to the added value of the tertiary industry in China Statistical Yearbook to measure the development level of the logistics industry in each region.

3.2.4. Control Variable. (1) Economic development level (EDL): in this study, the per capita GDP in China Statistical Yearbook is used to measure the level of economic development in the provinces and to enhance the comparability of data, each province's per capita GDP is based on the actual per capita GDP in 2000. (2) Urbanization level (URB): in this study, the ratio of the provinces' resident population to the

Table 1: Carbon emission calculation method design of various indicators and coefficients.

Fuel type	Coal	Coke	Crude oil	Fuel oil	Gasoline	Kerosene	Diesel	Natural gas
Fold the standard coal coefficient	0.7143	0.9714	1.4286	1.4286	1.4714	1.4714	1.4571	1.33
Carbon emission factor	0.7559	0.855	0.5538	0.5857	0.5921	0.5714	06185	0.4483

Note: SCC data are from China energy statistical yearbook in 2019; CEF data came from the 2006 IPCC.

total population of all the provinces in China Statistical Yearbook is used to measure the level of urbanization. (3) Openness (OPEN): in this study, the total import and export goods in all regions the ratio of GDP in China Statistical Yearbook is used to measure the level of opening. (4) Industrial structure (STR): in this study, the ratio of various provinces and tertiary industries' where industrial GDP in China Tertiary Industry Statistical Yearbook measure different provinces. (5) Infrastructure construction level (IEN): in this study, the ratio of highway mileage to the total population in China Statistical Yearbook is used to measure infrastructure construction.

Table 2: Descriptive statistics of major variables.

Variable	Mean	Std. dev.	Max	Min
LTFEE	0.439	0.265	2.778	0.030
REG	0.979	0.349	3.702	0.234
INV	192.460	137.380	1416.200	0.200
HUC	7.616	1.375	13.259	0.944
LDL	0.131	0.048	1.393	0.003
EDL	36867.802	18529.027	128994.000	4317.000
URB	51.793	11.104	89.600	20.520
OPEN	0.376	0.357	6.569	0.008
STR	0.431	0.063	0.806	0.297
IEN	37.269	20.518	264.995	3.466

3.3. Data Sources. This study selects the panel data of 30 Chinese provinces, municipalities, and autonomous regions from 2004 to 2020 as the sample (considering the availability of data, Tibet, Hong Kong, Macao, and Taiwan are not included). The data are obtained from the "China Statistical Yearbook," "China Energy Statistical Yearbook," "China Tertiary Industry Statistical Yearbook," "China Population and Employment Statistical Yearbook," and annual statistical yearbooks of various regions. Table 2 provides descriptive statistics on the main variables involved in this study.

4. Results and Discussions

4.1. Evaluation Results. During the study period, the provinces with high total factor energy efficiency in China's logistics industry were relatively stable. From 2004 to 2020, the total factor energy efficiency of the logistics industry in Beijing, Tianjin, Hebei, Shanghai, Jiangsu, Zhejiang, and other provinces has been at the leading level in the country. The reason is that these provinces have a good foundation for the development of the logistics industry. Most of the provinces belong to the eastern region with a relatively high level of economic development and have more green development resources for the logistics industry. Although more and more provinces and regions are vigorously promoting the concept of green logistics development, it is difficult to quickly catch up with the leading provinces. This shows that the improvement of the total factor energy efficiency of the logistics industry is a process of gradual accumulation of resources, which requires a certain economic foundation, complete infrastructure, and a foundation for the development of the logistics industry, so as to gradually shape the green development advantages of the logistics industry.

The total factor energy efficiency value of the logistics industry in Guangxi, Guizhou, Qinghai, Ningxia, Gansu, Xinjiang, Inner Mongolia, and other provinces has been below 0.4 for a long time. Although these provinces have increased their GDP growth rates during the study period, the agricultural green production efficiency is low, and there are still serious environmental damage: slow growth of total factor energy efficiency in the logistics industry and resource waste. From the perspective of time dimension, the interprovincial gap in agricultural green production efficiency narrowed slightly after 2010. In 2010, Inner Mongolia had the lowest total factor energy efficiency value in the logistics industry, with a value of 0.03, and the gap with Hebei Province, a high-efficiency province, was 1.64. In 2020, the province with the lowest efficiency value was Inner Mongolia, with a value of 0.137, which was close to that of high-efficiency Beijing. The gap between the two is 1.55. The gap between the highest and lowest efficiency values in 2020 is 0.09 smaller than that in 2012. On the one hand, it reflects the long-term imbalance in the green development of China's interprovincial logistics industry, and on the other hand, it shows that the backward provinces in China's logistics industry have achieved initial success in catching up with the leading provinces, but there is still a lot of room for growth.

The eastern and northeastern regions are far more efficient than the central and western regions. The results are shown in Figure 1. It can be seen that although there are changes in the spatial distribution of logistics industry efficiency in various regions, the changes are small. Most of the areas with high logistics industry efficiency values are concentrated in the eastern coastal areas, followed by the middle and the west. On the one hand, since the country's reform and opening up, many economic development policies have been implemented in the eastern coastal areas, such as the construction of Shanghai Pudong New Area, and the continuous introduction of a large number of professional and technical personnel, which has brought great favorable conditions for the development of the logistics industry. On the one hand, there are many ports in the eastern coastal area, the import and export trade is developed, and the total import and export trade is in the leading

Table 3: Total factor energy efficiency of logistics industry in 30 provinces and regions in China from 2004 to 2020.

Region	2004	2008	2012	2016	2020
Beijing	1.236	1.136	1.276	1.522	1.687
Tianjin	0.478	0.488	1.065	1.117	1.123
Hebei	0.651	0.491	1.686	1.257	0.951
Shanxi	0.21	0.235	0.417	0.456	0.409
Inner Mongolia	0.053	0.032	0.08	0.101	0.137
Liaoning	0.353	0.195	0.391	0.454	0.389
Jilin	0.268	0.21	0.337	0.280	0.263
Heilongjiang	0.182	0.17	0.26	0.251	0.245
Shanghai	0.391	0.448	1.09	1.247	1.393
Jiangsu	0.127	0.265	0.543	1.024	1.158
Zhejiang	0.333	0.714	1.028	1.063	1.062
Anhui	0.19	0.292	0.552	0.614	0.890
Fujian	0.381	0.351	0.466	0.59	0.581
Jiangxi	0.251	0.304	0.583	0.546	0.505
Shandong	0.435	0.577	0.491	0.528	0.496
Henan	0.235	0.524	0.628	0.816	0.859
Hubei	0.101	0.14	0.398	0.393	0.435
Hunan	0.142	0.189	0.45	0.42	0.346
Guangdong	0.399	0.708	1.049	1.159	1.371
Guangxi	0.137	0.207	0.436	0.447	0.399
Hainan	0.097	0.164	0.496	0.385	0.429
Chongqing	0.266	0.373	0.731	0.706	0.794
Sichuan	0.293	0.318	1.014	0.577	0.570
Guizhou	0.147	0.111	0.299	0.301	0.304
Yunnan	0.163	0.073	0.149	0.161	0.161
Shaanxi	0.174	0.192	0.383	0.51	0.497
Gansu	0.243	0.27	0.536	0.362	0.341
Qinghai	0.268	0.172	0.317	0.258	0.259
Ningxia	0.081	0.156	0.394	0.359	0.341
Xinjiang	0.075	0.09	0.245	0.221	0.215

position in my country. Central regions such as Tianjin and Hebei also have the rapid development of the logistics industry due to the port logistics.

In general, during the study period, there were regional differences in the total factor energy efficiency of China's logistics industry. The total factor energy efficiency of the logistics industry in the eastern provinces and the northeastern provinces increased steadily, while the provinces in the central and western regions were still hovering at a low level showing a "central collapse" as a whole. The possible reasons for this phenomenon are as follows: the eastern region is the head region of China's high-quality economic development, has a good foundation for the green development of the logistics industry, and is a pilot area for the logistics industry policy. This shows that the ability to absorb superior resources is the key point for the green development of the logistics industry. Under the implementation of many policies to guide the sustainable development of the logistics industry, the northeast region has accelerated the promotion of the concept of green logistics development, continuously reduced pollutant emissions, and promoted the continuous improvement of the green development level of the logistics industry. The green total factor energy efficiency of the logistics industry in the central region is low. Although there is a slight increase, the overall resource input is high, the output efficiency is low, and the environmental pollution is serious, which continues to widen the gap with the eastern region. The western region is relatively stable, the agricultural green production efficiency value is around 0.3, the green development foundation of the logistics industry is relatively weak, and the potential to support the green and high-quality development of logistics has yet to be released.

4.2. *Environmental Regulations' Effects on the Logistics Industry's Total Factor Energy Efficiency*

4.2.1. Benchmark Regression. This study uses OLS and fixed effects to perform regression testing on the measurement model (1). Table 4 reports the regression estimation results of environmental regulations' impact on the logistics industry's total factor energy efficiency. As shown in Table 4, the explained variables in the first to fourth columns are the logistics industry's total factor energy efficiency. Under different estimation methods and model settings, environmental regulations always account for 5% of the logistics industry's total factor energy efficiency. Alternatively, the positive impact is at the 1% statistical level. According to the results in the fourth column, environmental regulations' regression coefficient is 0.616, which is significant at the 1% level, showing that environmental regulations are beneficial for improving the logistics industry's energy efficiency. Comparing OLS and fixed effects, it is found that the regression coefficients of the different methods are different, but there is a consistent effect overall. Therefore, a single estimation method may lead to deviations in the results, and multiple estimation methods are required for verification to enhance robustness.

4.2.2. Robustness Test. Considering the large differences in the logistics industry's development level between various Chinese regions, this study further examines the relationship between environmental regulations and the logistics industry's total factor energy efficiency at the subregional level. Therefore, this study divides the 30 provinces into eastern, central, and western regions according to the National Bureau of Statistics' classification method. Table 5 shows the regression results of regional environmental regulations' impact on the logistics industry's total factor energy efficiency. The study uses OLS to estimate the model. The regression results show that the environmental regulations of the eastern, central, and western regions and the logistics industry's total factor energy efficiency are significantly and positively correlated at 1%, 5%, and 10% levels, respectively. This conclusion is consistent with the aforementioned results. The conclusion has once again verifies the robustness of the conclusion.

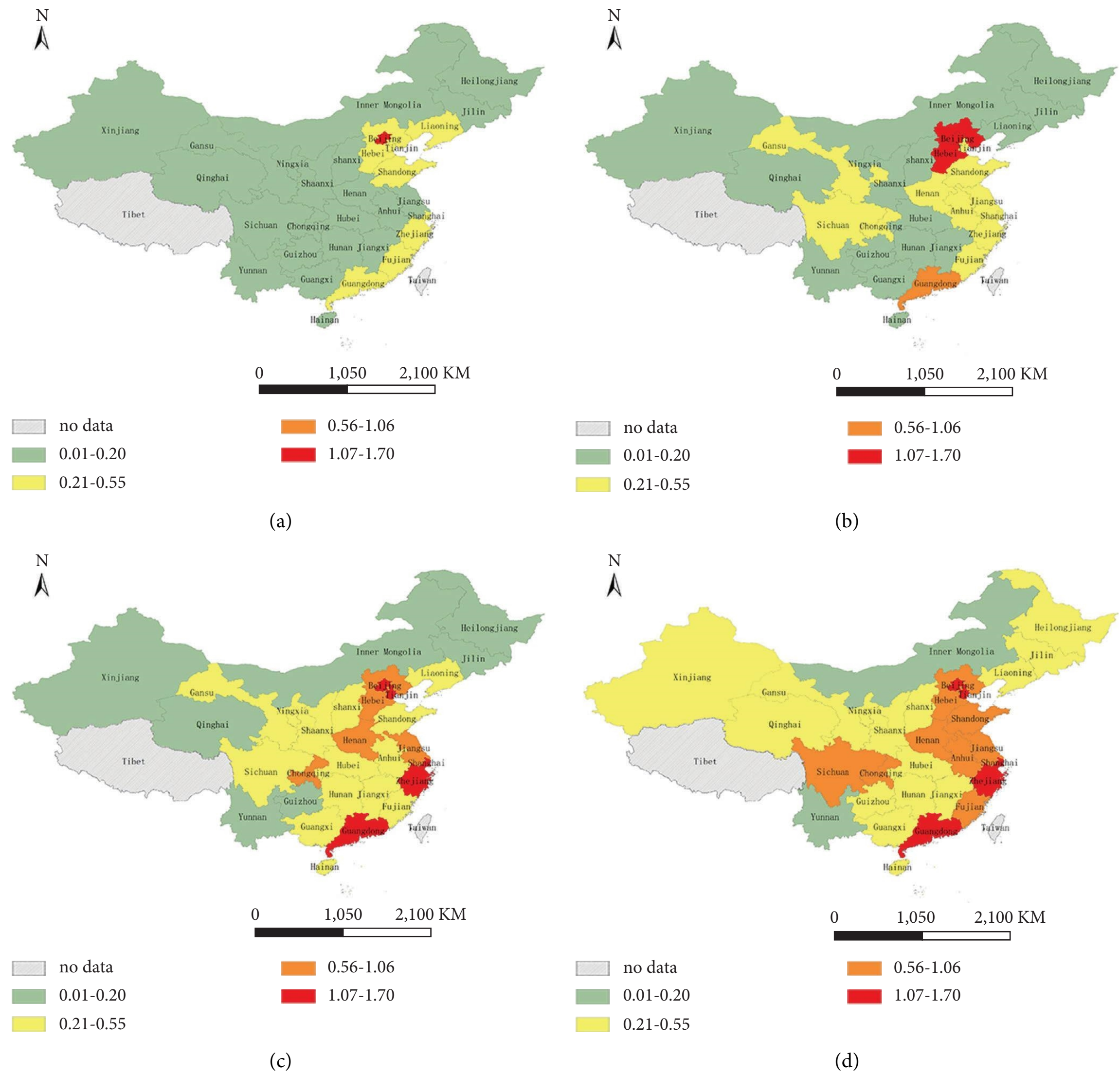

Figure 1: Logistics industry's total factor energy efficiency in 30 regions of China from 2004 to 2020. (a) LTFE in 2004. (b) LTFE in 2009. (c) LTFE in 2014. (d) LTFE in 2020.

Table 4: Regression estimation results of the impact of environmental regulation on logistics industry's total factor energy efficiency.

Variable	LTFEE			
	(1) OLS	(2) OLS	(3) FE	(4) FE
LnREG	0.709*** (0.201)	0.396** (0.263)	0.472*** (0.568)	0.616*** (0.55)
LnEDL		0.619*** (0.017)		0.262** (0.101)
LnURB		0.924 (0.236)		0.248 (1.097)
LnOPEN		0.747* (0.406)		0.524* (0.213)
LnSTR		1.16*** (0.267)		1.574*** (1.186)
LnIEN		0.774* (0.506)		1.271*** (0.472)
con	7.391*** (0.476)	4.889*** (0.776)	5.336*** (0.239)	2.228*** (1.81)
N	450	450	450	450
R^2	0.6940	0.5313	0.2301	0.5660

Note: *** is statistically significant at 1%, ** is statistically significant at 5%, and * is statistically significant at 10%.

Table 5: Impact of environmental regulation on logistics industry's total factor production efficiency in different regions.

Variable	LTFEE					
	The eastern region		The central region		The western region	
LnREG	1.058*** (3.31)	0.253*** (2.58)	2.394*** (3.45)	2.157** (2.38)	2.154** (3.37)	0.728* (1.429)
LnEDL		1.216** (1.34)		0.514 (0.371)		1.778 (0.60)
LnURB		0.791 (0.73)		0.911 (0.97)		1.056 (0.218)
LnOPEN		0.626*** (3.97)		0.364** (2.683)		1.235*** (3.92)
LnSTR		1.212** (1.650)		0.644*** (2.871)		1.57 (0.038)
LnIEN		0.243** (1.964)		0.399** (1.216)		0.687 (0.954)
con	5.644*** (0.16)	6.889*** (1.846)	5.492*** (2.217)	4.403** (1.951)	3.328*** (0.104)	2.987*** (2.523)
N	165	165	120	120	165	165
R^2	0.672	0.779	0.535	0.869	0.517	0.341

Note: *** is statistically significant at 1%, ** is statistically significant at 5%, and * is statistically significant at 10%. In the east, 11 provinces (cities) include Beijing, Tianjin, Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, and Hainan. The central region includes eight provinces, including Shanxi, Jilin, Heilongjiang, Anhui, Jiangxi, Henan, Hubei, and Hunan. The western region includes Inner Mongolia, Guangxi, Chongqing, Sichuan, Guizhou, Yunnan, Shaanxi, Gansu, Qinghai, Ningxia, and Xinjiang 11 provinces (cities, autonomous regions).

4.3. Environmental Regulations' Threshold Effect on the Logistics Industry's Total Factor Energy Efficiency

4.3.1. Stationarity Test of Variables. The premise of testing the threshold regression model is that the threshold variable is a stationary variable. Therefore, this study first conducts a unit root test on the relevant variables in the model. We use the LLC, IPS, and Fisher-ADF tests to test stationarity. According to the results in Table 6, the level series of the explained variables, core explanatory variables, and threshold variables in the model show obvious unevenness; however, the first-order difference series of each variable showed significant stationarity at the 1% and 5% confidence intervals.

4.3.2. Threshold Effect Test. The prerequisite for the threshold level test is that there must be a threshold effect. Therefore, we first test the threshold effect's significance. Second, we estimate the specific threshold value. This study selects the method of Bootstrap repeated self-sampling 500 and obtains the threshold P value, according to the corresponding result, confirming the threshold level and the number of thresholds in turn.

(1) Level of investment in environmental pollution control: according to the results in Table 7, the F statistic and P value of the environmental pollution control investment amount as the threshold variable can be known, and at 10% statistical level, the investment's impact in environmental pollution control on the logistics industry's total factor efficiency has passed the double threshold test, which shows that the impact of environmental pollution control investment level as a threshold variable is verified based on the double threshold effect. According to the results in Table 8, the F statistic of the double threshold of environmental pollution control investment level is not significant, that is, the impact of environmental pollution control investment level on the total factor energy efficiency of the logistics industry has a single threshold effect on the level of logistics development. In Table 8, the first column is the estimated result of the threshold of investment level in environmental pollution control. The results show that when the investment level of environmental pollution control is lower than 5.077, environmental regulations' impact coefficient on the logistics industry's total factor energy efficiency is positive, and it is significant at the 10% statistical level, and the estimated impact coefficient is 0.036. When the investment level of environmental pollution control exceeds 5.077, environmental regulations' impact on the logistics industry's total factor energy efficiency is also positive and significant at the 10% level, and the estimated impact coefficient rises to 0.646. This shows that as the level of investment in environmental pollution control increases, environmental regulations' impact on the logistics industry's total factor energy efficiency also increases. There are two reasons for this: first, when the investment level of environmental pollution control is low, the application of new energy technologies in the logistics industry is insufficient, and there is a lack of tools (such as optimizing transportation routes) to improve transportation efficiency, and the environmental regulations have not given full attention to the logistics industry's overall impact. Second, as the level of investment in environmental pollution control increases, enterprises are encouraged to carry out logistics activities. However, enterprises should accept certain environmental

Table 6: Stationary test of major variables.

Variable	LLC inspection		IPS inspection		Fisher-ADF inspection	
	Horizontal sequence	First difference	Horizontal sequence	First difference	Horizontal sequence	First difference
LnLFEE	−1.833 (0.5497)	−1.127*** (0.0056)	8.675*** (0.0000)	9.953*** (0.0294)	30.5823 (0.2820)	137.9068*** (0.0000)
LnINV	−0.191 (0.4243)	−3.442*** (0.0003)	−0.9171 (0.1795)	3.114*** (0.0000)	84.6759 (0.1970)	93.0724*** (0.004)
LnHUC	−2.569 (0.1560)	5.7949*** (0.0051)	3.8132 (0.9999)	−2.371** (0.0840)	45.7005 (0.1370)	78.4194** (0.0554)
LnLDL	4.924*** (0.0000)	−9.953*** (0.0294)	2.8799 (0.9980)	2.311** (0.0104)	40.7137 (0.0890)	69.1712*** (0.0000)

Note: *** is statistically significant at 1%, ** is statistically significant at 5%, and * is statistically significant at 10%.

Table 7: Threshold effect test of each variable.

Variable	Threshold number	F-value	P-value	Critical value			Threshold value
				1%	5%	10%	
LnINV	A single threshold	38.77**	0.0233	41.7595	33.6488	26.5382	5.0770
	Double threshold	16.75	0.2267	36.0620	28.2542	22.9746	6.3320
LnHUC	A single threshold	21.1**	0.0267	24.6418	19.8401	16.3602	0.5741
	Double threshold	11.17*	0.0633	21.5922	17.0186	13.6411	1.0395
LnLDL	A single threshold	24.87**	0.0300	45.8900	32.8626	25.5656	2.2799
	Double threshold	16.94**	0.0133	38.3564	28.2080	23.9518	2.4179

Note: *** is statistically significant at 1%, ** is statistically significant at 5%, and * is statistically significant at 10%.

Table 8: Regression results statistics of the threshold effect of each variable.

INV (1)		HUC (2)		LDL (3)	
LnEDL	0.238** (0.097)	LnEDL	0.356*** (0.000)	LnEDL	0.195** (0.0977)
LnURB	−0.355 (1.055)	LnURB	0.778 (1.015)	LnURB	0.705** (1.06)
LnOPEN	0.223* (0.209)	LnOPEN	0.085*** (0.000)	LnOPEN	0.083*** (0.000)
LnSTR	0.4331 (1.146)	LnSTR	0.191*** (1.085)	LnSTR	0.469*** (0.000)
LnIEN	0.357** (0.455)	LnIEN	0.008** (0.435)	LnIEN	0.113** (0.4555)
LnREG (LnINV < 5.077)	0.036** (0.603)	LnREG (LnHUC < 1.6799)	0.042*** (0.000)	LnREG (LnLDL < 1.5741)	0.195 (0.782)
LnREG (LnINV ≥ 5.077)	0.646** (0.671)	LnREG (1.6799 ≤ LnHUC ≤ 2.1163)	0.049*** (0.000)	LnREG (1.5741 ≤ LnLDL ≤ 2.0395)	0.311*** (0.586)
		LnREG (LnHUC > 2.1163)	0.15** (0.522)	LnREG (LnLDL > 2.0395)	0.985* (0.947)

Note: *** is statistically significant at 1%, ** is statistically significant at 5%, and * is statistically significant at 10%.

regulations and government supervision for energy conservation and emission reduction. The reward and punishment mechanism jointly promote the optimization of the logistics management system in the industry, forcing enterprises to continuously improve logistics efficiency.

(2) Quality of labor: according to the report results in Table 7, the F statistic and P value of the quality of labor as the threshold variable can be known. The F statistic of the double threshold is significant, while the F statistic of the triple threshold is not significant. The quality of workers has passed the double threshold test on the logistics industry's total factor energy efficiency, which shows that the impact of the quality of labor as a threshold variable is verified based on the double threshold effect. According to the results in the second column of Table 8, when the quality of workers is lower than the threshold value of 2.2799, environmental regulations' impact coefficient on the logistics industry's total factor energy efficiency is 0.042 and is significant at the 1% level. With the gradual improvement of the quality of workers, it enters the second interval with an interval limit of 2.4179, and the promotion of environmental regulations on the total factor energy efficiency of the logistics industry continues to increase, with the

influence coefficient increasing to 0.049; when the quality of workers exceeds 2.4179, environmental regulations' impact coefficient on the logistics industry's total factor energy efficiency is 0.15 and is significant at the 10% statistical level. This shows that the improvement in the quality of workers has improved the promotion effect of environmental regulations on the logistics industry's total factor energy efficiency. The mechanism of action is as follows: first, when the quality of workers in logistics companies is low, workers' environmental awareness and awareness of the government's environmental planning are limited, resulting in a lack of environmental innovation elements and technology development conditions for employees in the logistics industry. The industry's total factor energy efficiency is also low. Second, with the improvement in the quality of workers, the government has strengthened environmental regulations and the social awareness related to environmental protection has increased; thus, workers' productivity can be improved, the logistics industry's operation cost can be reduced, and the logistics industry's total factor energy efficiency can be improved.

(3) Development level of logistics industry: according to the results in Table 7, the double threshold's F statistic of the logistics industry's development level is significant, and the F statistic of the triple threshold is not significant, that is, the impact of the logistics industry's development level on the logistics industry's total factor energy efficiency has passed the double threshold test. In Table 8, the third column is the threshold estimation result for the logistics industry's development level. It shows that when the logistics industry's development level is less than the first threshold value of 0.5741, environmental regulations' impact coefficient on the logistics industry's total factor energy efficiency does not pass the significance level test. When the development level of the logistics industry crosses the first threshold of 0.5741, environmental regulations' regression coefficient is significant at the 1% level, and the estimated impact coefficient is 0.311. When the logistics industry's development level crosses the second threshold of 1.0395, environmental regulations' regression coefficient increases to 0.985 at the 10% level. This shows that an increase in the logistics industry's development level can enhance environmental regulations' positive effect on the logistics industry's total factor energy efficiency. The main reasons are as follows: first, when the logistics industry has a low level of development, logistics companies have limited operating strength, and most of them develop in an extensive mode and lack a balance in resource allocation, green development concepts, service levels, and modern technical means. Second, as the development of the logistics industry continues to improve, the development of new logistics formats accelerate. With the continuous development of new generation information technologies, such as cloud computing, big data, mobile Internet, and the Internet of Things, the traditional logistics industry uses advanced technologies to form new core competitiveness. Moreover, new business forms and new models continue to emerge that helps the logistics industry to reduce costs and increase efficiency. Logistics and manufacturing industries develop in conjunction. By providing transportation services for manufacturing companies, logistics companies can save manufacturing companies' logistics costs while further increasing their revenues and expanding their market shares.

Table 9 shows the passage of the threshold effect of the investment level of environmental pollution control in various regions. In 2004, 26 provinces, municipalities, and autonomous regions including Tianjin did not cross the first threshold of investment in environmental pollution control. Only 4 provinces, municipalities, and autonomous regions including Beijing, Shanghai, Jiangsu, and Zhejiang crossed the first threshold; in 2012, including Jilin, 14 provinces, cities, and autonomous regions including Heilongjiang did not cross the first threshold of investment in environmental pollution control; 16 provinces, cities, and autonomous regions including Beijing and Tianjin crossed the first threshold; 7 provinces, cities, and autonomous regions including Hainan did not cross the first threshold in 2020 The investment level of environmental pollution control is the first threshold value, and 23 provinces, municipalities, and autonomous regions including Beijing and Tianjin have crossed the first threshold. This shows that the level of investment in environmental pollution control in various provinces, municipalities, and autonomous regions across the country is steadily increasing year by year.

Table 10 shows the passing situation of the labor quality threshold effect in various regions. In 2004, 20 provinces, cities, and autonomous regions, including Shanxi, did not cross the first threshold of worker quality, 10 provinces, cities, and autonomous regions, including Beijing and Shanghai, crossed the first threshold of worker quality, and none crossed the second threshold. In 2012, 11 provinces, cities, and autonomous regions, including Hebei and Shanxi, did not cross the first threshold of labour quality, 17 provinces, cities, and autonomous regions, including Tianjin and Jiangsu, crossed the first threshold, and only Beijing and Shanghai crossed the second threshold of labour quality. In 2020, Inner Mongolia, Liaoning, and seven provinces, crossed the second threshold value of the quality of workers; Tianjin and 16 other provinces crossed the first threshold; and, Beijing, Hebei, and seven other provinces crossed the quality of workers and second threshold value. It can be seen that the quality of labor in various provinces, cities, and autonomous regions across the country is generally at a relatively low level.

Table 11 shows the passage of the threshold effect of the logistics industry's development level in each region. In 2004, 19 provinces, municipalities, and autonomous regions,

Table 9: Regional distribution of different threshold values according to the level of investment in environmental pollution control.

Threshold interval	Province distribution at different time points		
	2004	2012	2020
LnREG (LnINV < 5.077)	Tianjin, Hebei, Shanxi, Inner Mongolia, Liaoning, Jilin, Heilongjiang, Anhui, Fujian, Jiangxi, Shandong, Henan, Hubei, Hunan, Guangdong, Guangxi, Hainan, Chongqing, Sichuan, Guizhou, Yunnan, Shaanxi, Gansu, Qinghai, Ningxia, and Xinjiang	Jilin, Heilongjiang, Henan, Hunan, Guangxi, Hainan, Sichuan, Guizhou, Yunnan, Shaanxi, Gansu, Qinghai, Ningxia, and Xinjiang	Jilin, Heilongjiang, Hainan, Yunnan, Gansu, Qinghai, and Ningxia
LnREG (LnINV ≥ 5.077)	Beijing, Shanghai, Jiangsu, and Zhejiang	Beijing, Tianjin, Hebei, Shanxi, Inner Mongolia, Liaoning, Shanghai, Jiangsu, Zhejiang, Anhui, Fujian, Jiangxi, Shandong, Hubei, and Guangdong, Chongqing	Beijing, Tianjin, Hebei, Shanxi, Inner Mongolia, Liaoning, Shanghai, Jiangsu, Zhejiang, Anhui, Fujian, Jiangxi, Shandong, Henan, Hubei, Hunan, Guangdong, Guangxi, Chongqing, Sichuan, Guizhou, Shaanxi, and Xinjiang

Table 10: Regional distribution of different threshold values according to the quality of labors.

Threshold interval	Province distribution at different time points		
	2004	2012	2020
LnREG (LnHUC < 1.6799)	Shanxi, Inner Mongolia, Liaoning, Jilin, Heilongjiang, Anhui, Fujian, Jiangxi, Guangxi, Hainan, Henan, Sichuan, Chongqing, Guizhou, Yunnan, Shaanxi, Gansu, Qinghai, Ningxia, and Xinjiang	Hebei, Shanxi, Inner Mongolia, Liaoning, Jilin, Heilongjiang, Jiangxi, Guangxi, Hainan, Gansu, and Qinghai	Inner Mongolia, Liaoning, Heilongjiang, Jiangxi, Guangxi, Gansu, and Qinghai
LnREG (1.6799 ≤ LnHUC ≤ 2.1163)	Beijing, Tianjin, Hebei, Jiangsu, Shanghai, Zhejiang, Shandong, Hubei, Hunan, and Guangdong	Tianjin, Jiangsu, Zhejiang, Anhui, Fujian, Shandong, Hubei, Hunan, Sichuan, Henan, Guangdong, Chongqing, Guizhou, Yunnan, Shaanxi, Ningxia, and Xinjiang	Tianjin, Shanxi, Jilin, Anhui, Fujian, Shandong, Hubei, Hunan, Hainan, Sichuan, Henan, Guizhou, Yunnan, Shaanxi, Ningxia, and Xinjiang
LnREG (LnHUC > 2.1163)		Beijing and Shanghai	Beijing, Hebei, Shanghai, Jiangsu, Zhejiang, Guangdong, and Chongqing

Table 11: Regional distribution of different threshold values according to the development level of the logistics industry.

Threshold interval	Province distribution at different time points		
	2004	2012	2020
LnREG (LnLDL < 1.5741)	Tianjin, Hebei, Shanxi, Inner Mongolia, Liaoning, Heilongjiang, Anhui, Fujian, Jiangxi, Henan, Hainan, Chongqing, Sichuan, Guizhou, Shaanxi, Gansu, Qinghai, Ningxia, and Xinjiang	Hebei, Inner Mongolia, Guizhou, and Ningxia	
LnREG (1.5741 ≤ LnLDL ≤ 2.0395)	Jilin, Jiangsu, Zhejiang, Shandong, Hubei, Hunan, Guangdong, Guangxi, and Yunnan	Shanxi, Liaoning, Fujian, Jiangxi, Shandong, Guangxi, Hainan, Gansu, Qinghai, and Xinjiang	Hebei, Shanxi, Inner Mongolia, Liaoning, Jiangxi, Hainan, Guizhou, Ningxia, and Xinjiang
LnREG (LnLDL > 2.0395)	Beijing and Shanghai	Beijing, Tianjin, Jilin, Heilongjiang, Shanghai, Jiangsu, Zhejiang, Anhui, Henan, Hubei, Hunan, Guangdong, Chongqing, Sichuan, Yunnan, and Shaanxi	Beijing, Tianjin, Jilin, Heilongjiang, Shanghai, Jiangsu, Zhejiang, Anhui, Fujian, Shandong, Henan, Hubei, Hunan, Guangdong, Guangxi, Chongqing, Sichuan, Yunnan, Shaanxi, Gansu, and Qinghai

including Tianjin, did not cross the first threshold of the logistics industry's development level, including Jilin and Jiangsu's nine provinces and autonomous regions across the first threshold. Beijing and Shanghai alone crossed the second threshold value. In 2012, Hebei, Inner Mongolia, and four other provinces did not cross the level of development of the logistics industry's first threshold value; Shanxi, Liaoning, and 10 other provinces and autonomous regions cross the first threshold; Beijing and Tianjin, including 16 provinces cross the second level of logistics development threshold. In 2020, no province, municipality, or autonomous region has crossed the first threshold of the development level of the logistics industry, including Hebei, Shanxi, and nine provinces and autonomous regions across the logistics industry development level of the second threshold value; Beijing, Tianjin, and 21 other provinces and autonomous regions cross the second level of the development of the logistics industry. The overall development level of the logistics industry in various provinces, municipalities, and autonomous regions across the country is developing rapidly.

5. Conclusions

This paper expounds the relationship between environmental regulation and the logistics industry's total factor energy efficiency through theoretical analysis, and establishes the threshold effect of the investment level of environmental pollution control, the quality of labor, and the logistics industry's development level by empirically analyzing the data of 30 Chinese provinces, municipalities, and autonomous regions from 2004 to 2020. The main conclusions are as follows: (1) environmental regulations are conducive to improving the logistics industry's total factor energy efficiency. (2) The level of investment in environmental pollution control has a significant single threshold effect on environmental regulations' impact on the logistics industry's total factor energy efficiency. When the investment level of environmental pollution control does not exceed the threshold, environmental regulations have no significant impact on the logistics industry's total factor energy efficiency, and when the investment level of environmental pollution control exceeds the threshold, environmental regulations have a significant impact on the total factor energy efficiency of the logistics industry. (3) The quality of labor has a significant double threshold effect on the environmental regulations affecting the logistics industry's total factor energy efficiency. (4) The logistics industry's development level has a significant double threshold effect on the environmental regulations affecting the logistics industry's total factor energy efficiency.

Based on these conclusions, this study recommends the following policy changes: (1) China needs to strengthen the investment and development of green logistics, from the rapid development of logistics to the green, healthy, and high-quality development of logistics, and take the road of intensive development. Furthermore, the government should comprehensively consider the characteristics of the difference in the level of logistics development between regions, and formulate relevant differentiated policies for the logistics industry's development in different regions, the level of infrastructure, the level of investment in environmental pollution control, human capital, and other resources to promote the healthy and sustainable development of regional logistics. Using green logistics' development concepts and models from developed countries or regions, we can minimize the waste of resources and optimize logistics output's efficiency. (2) The government should actively encourage and intervene through environmental regulation tools during the logistics industry's green transformation and development. Therefore, it is necessary to incorporate the construction of an ecological civilization into local governments' performance evaluation. The government should use performance appraisal as a baton to urge local officials to establish an effective environmental regulation system and force local governments to change their governance methods, thereby, avoiding the extensive economic development model that promotes growth through changes in resources and the environment. (3) The government should not use compulsory environmental regulation tools to adopt comprehensive restrictions regarding energy conservation and emission reduction in the logistics industry. To avoid an administrative order causing irreversible production damage to the enterprise, the order should be based on the local government's goals on economic development, resources, and environmental protection. Government departments should systematically guide the logistics industry's green transformation and upgrading.

Although this article has conducted in-depth research on the impact of environmental regulation on the total factor energy efficiency of the logistics industry, and made some progress, this research still has the following shortcomings: (1) Due to the difficulty in obtaining data, the research sample selected in this paper does not include Tibet, Hong Kong, Macao, and Taiwan; there is also a lack of cross-country comparison research with foreign logistics industry. (2) This article only studies the threshold effect of environmental regulation on the total factor energy efficiency of the logistics industry and does not consider other effects.

Data Availability

The data presented in this study are available on request from the corresponding author. The data are not publicly available due to privacy restrictions.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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