

Article

Can Resource Dependency and Corporate Social Responsibility Drive Green Innovation Performance?

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Abstract: As the producers of environmental pollution, it is urgent for enterprises to make up for their lack of environmental responsibility and to realize green transformation and development. At the same time, resource dependence is promoted from the single level of economic growth to the field of green development, which is a field of research and development on resource dependence and broadens the perspective of related research in the academic world. In this paper, we select panel data from 30 regions in China from 2009 to 2022 to validate the research on the impact of resource dependence and corporate social responsibility on green innovation performance. The conclusions are as follows: (1) From 2009 to 2022, the average industrial green innovation performance of the 30 provinces in China was 0.553, with the efficiency values of the eastern, central, and western regions showing a gradual decreasing trend. (2) We found a consistently negative correlation between resource dependency and green innovation performance, confirming the existence of a “resource curse” linking the two. Meanwhile, the regression coefficient of CSR for green innovation performance was positive, confirming the driving effect of the former on the latter. (3) The “resource curse” does not manifest conditionally or have a threshold effect. Instead, we found that it has long-term and persistent characteristics. Meanwhile, the impact of CSR on green innovation performance shows a “reverse N-shaped” double-threshold effect, where CSR can improve green innovation performance only when it reaches a certain threshold value. This paper provides insights to support Chinese enterprises in enhancing their green innovation performance and lays a theoretical foundation for enterprises to fulfill their social responsibility.



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1. Introduction

There are two carbon-related goals to be realized: carbon peaking and carbon neutrality. Carbon peaking means that emissions of greenhouse gases such as carbon dioxide have reached their peak value and are no longer growing, but rather, are gradually declining. Carbon neutral means that the carbon dioxide emitted directly and indirectly by human activities in a certain area within a certain period of time will be offset by an equal absorption of emitted carbon dioxide through tree planting, etc., so as to realize “net zero” carbon dioxide emissions. Simply put, it means that the amount of carbon produced should be reduced or eliminated through certain procedures that can reduce or eliminate the impact on the environment of this carbon in order to realize zero emissions. Enterprises need to continuously reduce carbon emissions to achieve “net zero” and to realize green transformation; enhancing green innovation performance is an important tool to achieve these dual carbon goals [1–3]. Since the reform and opening up of China, China’s economic development model has overly relied on resource factor inputs rather than the improvement of production efficiency, which has led to a series of problems such as resource waste, environmental pollution, and ecological damage. In light of these, protecting the environment while promoting economic development has become important.

In this context, green development has become a common pursuit of all countries and covers the three core connotations of economic growth, resource conservation, and environmental friendliness. Reducing the dependence on resource industries is also regarded as an effective way to change the crude economic growth mode, transform the economic development mode, and enhance green innovation capability. In recent years, green innovation has gradually become a hot topic in the academic and environmental protection fields, attracting increasing attention and research. As the main bodies responsible for environmental protection and innovation, enterprises and their various stakeholders are increasingly concerned about the fulfillment of corporate environmental responsibility. Today, corporate social responsibility is not only a policy requirement but also a positive response to potential market demand. Moreover, considering that the fulfillment of corporate social responsibility can alleviate the overdependence on resource industries to a certain extent, studying the relationship between corporate responsibility and green innovation is of great significance in coordinating the contradictions and conflicts between enterprises and various stakeholders and in promoting the harmonious development of the economy, society, and the environment. However, the existing research is still insufficient on the relationships between corporate responsibility, resource dependence, and green innovation performance [4]. This study aimed to fill that research gap, with a view to providing useful references and bases for enterprises and society to realize sustainable development of the economy and the environment.

Corporate social responsibility concerns not only the market rules and business ethics that companies should follow but also their active contribution to social welfare. By assuming such responsibility, companies can establish solid cooperative relationships with local governments, financial institutions, and other market participants. Currently, there are two distinct viewpoints regarding the relationship between CSR and green innovation. On the one hand, some propose that corporate social responsibility helps to alleviate information asymmetry, thereby reducing negative sentiment among investors [5]. By disclosing more information, companies can establish closer cooperation and communication with stakeholders, thereby promoting research and development innovation. Aligning with this view, Shahzad [6] believes that all types of corporate social responsibility activities have a positive impact on green technological innovation. However, on the other hand, there are also those who believe that corporate social responsibility may be a means of covering up negative news and pursuing self-interests. This viewpoint holds that companies may use social responsibility to smooth the impact of negative news while limiting the quantity and quality of research and development investment, thus having a negative impact on green innovation. For example, Poussing [7] believes that general corporate social responsibility activities cannot effectively promote green technological innovation. Although some pieces in the literature have discussed the impact of CSR on green innovation, there is still a lack of detailed analysis of its underlying mechanisms. As such, there is an urgent need for in-depth research and verification of the effectiveness and implementation path of CSR promoting green innovation. This will not only help us to more fully understand the significance of corporate social responsibility, but also provide guidance for companies on how to better fulfill their social responsibilities and promote green innovation in practice [8,9]. So, does fulfilling their social responsibility cause companies to bear too much of a burden, thus leading to a negative, avoidance attitude when facing environmental governance issues and suppressing corporate green innovation? Or does the company bridge the potential gap between itself and stakeholders in the process of fulfilling social responsibility, deepening the connection and cooperation between the two and enabling the company to obtain innovative resources and promote corporate green innovation? These were the questions at the core of the present study. As China is the largest developing country, setting this study in China for an exploration of the associated relationships was of great significance for producing findings on environmental protection and sustainable development.

Natural resources, as necessary inputs in the material production process, are considered symbols of wealth and growth. However, excessive reliance on resource-based industries may have a negative impact on the green transformation of the economy. Resource dependence mainly refers to an economic growth model that relies on the comparative advantages of regional resources, especially mineral resources, through the extraction of natural resources, primary processing, and the formation of primary products. One of the important reasons why the UK, the US, and other Western countries achieved rapid economic growth and became developed countries is their rich natural resources [10]. However, countries like Venezuela and Nigeria, which also have abundant natural resources, show a complete opposite trend in economic growth. Furthermore, although it is a developed country in Europe, the Netherlands suffered a serious economic crisis in the 1980s due to its overdependence on natural gas exports, which suppressed other industry sectors. This phenomenon is known as the “resource curse”: overdependence on natural resources can hinder the healthy development of the economy [11]. Similarly, while China’s economy has been making great progress, this development has come at the cost of resource consumption, which has brought about many problems, such as ecological damage. These create an urgent need to find a balance between economic growth and environmental protection. Against this backdrop, green development has gradually become the global consensus. This approach emphasizes economic growth while also focusing on resource conservation and environmental friendliness, reducing the dependence on resource industries, and achieving the transformation of economic development methods and the improvement of green innovation performance [12].

The main contributions of this paper are as follows: (1) Scholars have not yet been found to incorporate resource dependence, CSR, and green innovation performance into the same framework of research. This paper investigates the relationship between the three and is a refinement and supplementation of the existing research deficiencies, can enrich the existing theoretical research, and has a certain degree of theoretical significance. (2) Exploring the relationship between CSR and green innovation performance can provide a reference basis for Chinese enterprises to promote green transformation and realize industrial upgrading, helping Chinese enterprises to enhance their core competitiveness in the international arena, which is of strong practical significance. (3) It can provide guidelines for government departments to further coordinate and optimize the work related to enterprise green innovation, which is conducive to the improvement of the enterprise financing environment, and provide policy suggestions for them to enhance their green innovation performance and take the road of high-quality development; thus, it has strong policy significance. (4) It extends resource dependence from the single level of economic growth to the field of green development with the goals of economic growth, resource conservation, and environmental friendliness, which is another field of research and development on resource dependence; thus, it broadens the perspective of related research in the academic world and fills the gaps in the existing research. To that end, corporate social responsibility and resource dependency are incorporated into a holistic research framework with regional green innovation performance development, and we put forward targeted countermeasures that should promote regional green innovation performance. Additionally, policy suggestions are made to suppress the resource curse effect and improve green innovation performance.

2. Literature Review

2.1. Measurement of Green Innovation Performance

In the evaluation of green innovation performance, scholars use stochastic frontier analysis (SFA), factor analysis, and the production function method for their research. For example, Miao et al. [13] used the SFA model to study the impact of green technological innovation on natural resource utilization efficiency; Xiao and Lin [14], based on the industrial sector level, used the SFA model to evaluate innovation efficiency; Li et al. [15] used the SFA method to measure green innovation efficiency; Xiao and Zhang [16] used

an improved SFA model to measure ecological welfare performance under the strong sustainability concept; and Chen [17] used the factor analysis method to evaluate the green innovation performance differences between cities.

Compared with the above research methods, data envelopment analysis (DEA), as a representative of nonparametric methods, has an absolute advantage in efficiency evaluation research of multiple inputs and multiple outputs. Its classic model and extended models have been favored by many scholars. For example, Wu et al. [18] used the DEA method to measure the green innovation efficiency of heavily polluted enterprises and their respective industries, and Du et al. [19] and Fang et al. [20] also adopted the model to measure the green innovation efficiency of industrial enterprises in China. With the deepening of green innovation research, Tone proposed the RAM-SBM model, which considers slack, non-radial, and non-angle variables, overcoming the issue whereby traditional DEA models do not consider slack variables, which impacts their reliability and creates inefficient situations. Gao and Xiao [21] chose the SBM-DEA model to evaluate green technological innovation efficiency. Ren et al. [22], in a study based on the DEA-RAM model, evaluated the green innovation efficiency of the industrial sector. Furthermore, Yi et al. [23], Liu et al. [24], Nie and Qi [25], and Lv et al. [26] all used the SBM-DEA model to calculate the green innovation efficiencies of different enterprises.

2.2. *The Relationship between Corporate Social Responsibility and Green Innovation Performance*

Currently, while scholars have studied the relationship between CSR and green innovation performance, there is considerable controversy. Some scholars believe that corporate social responsibility can significantly promote green innovation. For example, Porter and Vander [27] believe that companies that take the lead in green innovation can greatly improve their market bargaining power, thus helping companies to avoid penalties for environmental damage and to establish a good external image. Chang [28] conducted a survey of manufacturing enterprises in Taiwan, China and found that under the trend of environmental protection, enterprises focusing on the cultivation of a green organizational culture promoted CSR behavior, and proactive CSR behavior helped enterprises invest resources in green technology and product innovation, ultimately promoting corporate green innovation performance. Mbanyele et al. [29] also found that mandatory requirements for corporate social responsibility disclosure helped improve corporate green innovation capabilities. Hao and He [30] found that corporate social responsibility can have a positive promoting effect. Wang and Ning [31] used the PSM-DID method and found that mandatory disclosure of corporate social responsibility information strengthened the legitimacy and normative legitimacy of corporate regulation, thereby promoting corporate green transformation. Hu and Zhang [32] found that under environmental regulations, corporate fulfillment of environmental protection and social responsibility could reduce environmental pollution costs and subsequent environmental compliance costs; increase R&D investment in production and waste treatment processes, gradually forming a green innovation mechanism; and promote corporate green innovation. Yuan and Cao [33] pointed out that corporations undertake social responsibility to improve their green dynamic capabilities, thereby promoting green innovation activities. However, other scholars hold different opinions. For example, Zhang [34], from the perspective of corporate social responsibility reports' information disclosure, proposed that companies do not really want to assume social responsibility, and so they implement "cover-up" activities with hidden purposes, which may inhibit green innovation activities. Furthermore, Isabel et al. [35], according to the resource-based theory, noted that not all social responsibilities create value for companies, with some instead leading to increased corporate costs. They also suggested that the output of innovation activities is characterized by contingency and that corporate social responsibility may not promote innovation performance; the empirical results provided in their paper confirmed these ideas, showing a negative relationship between CSR and innovation activities. Yang et al. [36] divided CSR into internal and

external aspects and found that internal CSR can promote green innovation, while external CSR inhibits green innovation.

2.3. Research on the Relationship between Resource Dependency and Green Innovation Performance

There is little literature about the relationship between resource dependency and green innovation performance, and the studies published to date are mainly focused on the fields of resource dependency and economic growth and technological innovation. Some scholars believe that resource dependency restricts industrial transformation and technological innovation, thereby affecting economic development. Zhang et al. [37] used data from resource-based cities in China to show that resource dependency inhibits the green transformation of cities. Nasiru et al. [38] used the percentage of natural resource rent in GDP to measure the dependence of WAIFEM member countries on natural resources, and they proposed that resource dependency hinders the economic growth of member countries under any circumstances. Hu et al. [39] confirmed that resource dependency inhibits economic growth, and as resource dependency increases, the economy will eventually show negative growth. Cheng et al. [40] started from the perspective of green economic growth and asserted that resource dependency inhibits the growth of China's green economy. Qin et al. [41] showed that resource dependency is prone to breeding corruption and reducing the integrity of the government, thereby having a negative impact on urban green innovation. There are also some scholars who have noted a promoting effect, such as Ahmadov and Borg [42], who believe that natural resource utilization can promote technological progress, which is beneficial to green innovation.

When reviewing the literature on corporate social responsibility, green innovation performance, and resource dependency, through a summary of the core variables, it can be found that there are certain limitations in the related research, but the literature also provides an important basis and ideas for further research. Most of the existing research focuses on the impact of CSR on innovative behavior, while little considers CSR and green innovation performance, and the conclusions that can be drawn are still controversial [34,37]. Meanwhile, there have been fewer empirical analyses of CSR and green innovation performance, and these have been unable to reveal the effect and potential mechanism of the impact of CSR on green innovation performance. At the same time, the research on the "resource curse" proposition is relatively rich at present, but most scholars focus on economic growth [40,41], ignoring the areas of green innovation performance. Against that background, it is important to verify whether the resource curse impacts green innovation performance.

3. Research Hypotheses

3.1. Corporate Social Responsibility and Green Innovation

Corporate social responsibility can alleviate the double external in the process of green innovation. First, from the perspective of stakeholder theory, consumers are the most critical external stakeholders of enterprises, environmental social responsibility is an important part of corporate social responsibility, corporate social responsibility is needed to fulfill environmental protection in order to meet the customer demand for environmental protection, and green innovation is one of the manifestations of consumer demand for environmental protection, so enterprise initiatives to assume social responsibility will help enterprises to carry out green innovation activities [43]. Second, the negative externalization brought to society by the environmental impacts of green innovation and pollution emissions lead to a series of economic, legal, and ethical problems faced by enterprises in the process of green innovation, which cause dissatisfaction among some stakeholders and prevent enterprises from obtaining the resources needed for green innovation through effective interaction with the external environment [44].

However, CSR does not always help to promote corporate green innovation. Agency theory suggests that corporate managers often use social responsibility as a "front" to

allocate their limited resources to their preferred projects or other rent-seeking activities rather than to projects that benefit society. Corporate social responsibility depletes limited resources, affects the quantity and quality of R&D investment, and inhibits innovation output. Han et al. [45] argued that CSR can crowd out the funds needed for corporate R&D activities and thus is not conducive to the improvement of corporate innovation capacity. When the CSR of an enterprise exceeds a certain level, it will not only consume a large amount of the enterprise's resources, but also make the enterprise too dependent on its existing business partnerships, while reducing its sensitivity to discover potential customers and weakening its ability to recognize technological innovation opportunities. In view of those considerations, this paper asserts that it is not the case that the more social responsibility a firm undertakes, the more it helps to promote green innovation and that the relationship between the two may be constrained by the level of CSR; i.e., it may be nonlinear.

In summary, the following hypotheses are proposed:

H1. *Fulfilling corporate social responsibility may promote green innovation in enterprises.*

H2. *There may be a threshold effect on the impact of CSR on green innovation.*

3.2. Resource Dependence and Green Innovation

Resource dependence and green innovation are not simply linear; there may be a resource curse effect in this area, i.e., excessive resource dependence brings about high-intensity resource development; and the resource development activities are mostly spontaneous exploitation without effective environmental protection and pollution control measures. This makes the high-intensity resource development activities bring negative impacts such as ecological damage and environmental pollution. In addition, the negative impacts of environmental pollution and ecological damage often do not manifest themselves immediately, which means the government and enterprises pay little attention to the negative impacts of resource development activities. Driven by their interests, mine owners and other stakeholders continue to expand the scope of resource development activities; with the expanding scope of resource development activities and ecological damage, environmental pollution problems increasingly appear; and the ecological crisis presents serious obstacles to urban development, which also deals a heavy blow to the enhancement of green innovation performance; i.e., the increase in resource development inhibits green innovation performance [41]. Based on these considerations, we developed a third research hypothesis:

H3. *There is a resource curse effect in the area of green innovation performance; i.e., overreliance on resource-based industries may reduce green innovation performance.*

4. Methodology

4.1. Measurement of Green Innovation Performance

4.1.1. Method Selection

A hot topic in current research is efficiency evaluation, which often involves the construction of a comprehensive evaluation system using multiple indicators with a flexible selection of evaluation methods based on the characteristics of the data. In this evaluation system, the allocation of weights is particularly crucial. Existing weight allocation methods are mainly divided into two categories: subjective weighting methods and objective weighting methods. Subjective weighting methods mainly rely on the opinions and experiences of experts or authoritative institutions; an example is the subjective assignment method (AHP). AHP hierarchical analysis is a qualitative and quantitative calculation of the weight of the research method, the use of the two-by-two comparison method, the establishment of the matrix, and the use of the relative size of the number. The larger the number, the more it is weighted as important. Ultimately calculated to obtain the importance of each factor,

the hierarchical analysis method is applicable to more than one level of comprehensive evaluation. Hierarchical analysis is suitable for comprehensive evaluation with multiple levels. It has a greater advantage than the objective weighting method (entropy weighting method) in determining the weights according to the decision maker's intention, but the objectivity is relatively poor and the subjectivity is relatively strong [46]. The other is the entropy value method, which belongs to a kind of objective assignment method, which utilizes the size of the information carried by the data to calculate the weights and obtain more objective indicator weights. Entropy value is a measure of uncertainty. The smaller the entropy, the greater the amount of information carried by the data and the greater the weight; on the contrary, the larger the entropy, the smaller the amount of information and the smaller the weight. The entropy method is widely used in various fields, and it can be calculated for common questionnaire data (cross-section data) or panel data. In practical research, it is usually used in conjunction with other weight calculation methods, such as factor or principal component analysis, to obtain the weight of the factor or principal component—that is, to obtain the weight of the high dimensionality and then use the entropy method to calculate the weight of the specific items. To ensure objectivity and accuracy in the evaluation results, in this study, we chose to adopt an objective weighting method. This approach avoids the potential biases and subjectivity associated with subjective weighting methods, allowing for a more scientific and objective determination of weights through automatic calculations using relevant software. Measurement of performance is currently the main approach, achieved through the stochastic frontier method or the DEA method. The basic assumptions of the SFA model are more complex, with a need to consider the production function and the distribution of the technical inefficiency term of the specific form, which makes further expansion challenging. Because the density function of the synthetic error term ε has a complex form, the corresponding likelihood function is more complex, which introduces a lot of computational difficulties to the parameter estimation, so it is difficult to further analyze the heteroskedasticity and other situations or to perform further model expansion. The main advantages of DEA are that the user does not need to consider the specific form of the production frontier, they need only input and output data; the model easily supports other forms of expansion; and there are dozens of DEA models. In addition, because the model assumptions of SFA are more complex and the input and output data requirements are higher, if the input and output data do not meet the basic assumptions of the model, it is prone to skewness, ultimately leading to computational failure. Therefore, in this study, we chose the data packet Luo method to measure green innovation performance.

Data envelope analysis mainly includes two models, CCR and BCC, but both fail to fully consider the issue of slack variables [47]. The traditional DEA model has obvious shortcomings: the model does not take into account the impact of the respective differences in the changes in inputs and outputs on the efficiency value of the research object and does not take into account whether it is dominated by inputs or outputs. Therefore, later scholars carried out research on the traditional DEA model. Finally, based on the principle of the DEA model, a methodological model that does not need to take into account the differences in the changes in inputs and outputs or preset the dominant direction was put forward; i.e., the SBM model overcame the problems of the differences in the changes in inputs and outputs and the selection of the dominant direction of the traditional DEA model, and the results were relatively more accurate. However, when solving the efficiency value according to the SBM model, the efficiency value of the decision variables is generally less than 1, but at the same time, there are many decision variables in the research object whose efficiency values are all 1, in which case it is impossible to use the efficiency value of the decision variables to judge the efficiency of the research object. In this case, the Super-SBM model, also known as the super-efficiency model, is used, which is a model that allows for further comparison of efficiency values that have already reached the production surface. To comprehensively evaluate efficiency and address the issue of slack variables, in this study, we chose the Super-SBM model. This model not only takes into account undesirable

outputs but also aligns closely with the essence of green innovation performance, making the research targeted and practically significant [48]. The specific principle is as follows: Assume that there are n decision-making units, including m inputs, and r_1 and r_2 are the number of desired and undesired outputs, respectively. The input variables are $x \in R^m$, the desired output is $y^g \in R^{s_1}$, and the undesired output is $y^b \in R^{s_2}$. The matrices X , Y^g , and Y^b are defined as follows:

$$[X] = [x_1, \dots, x_n]^T \in R^{m \times n}, [Y^g] = [y_1^g, \dots, y_n^g]^T \in R^{s_1 \times n}, [Y^b] = [y_1^b, \dots, y_n^b]^T \in R^{s_2 \times n},$$

$$X > 0, Y^g > 0, Y^b > 0$$
(1)

The production possibility set is as follows:

$$p = \{(x, y^g, y) \mid x \geq X\lambda, y^g \leq Y^g\lambda, y^b \geq Y^b\lambda, \lambda \geq 0\}$$
(2)

The SBM model considering an undesired output is shown in Equation (3):

$$SBM \left\{ \begin{array}{l} \min \rho = \frac{1 - \left(\frac{1}{m}\right) \sum_{i=1}^m (W_i^-)}{1 + \left(\frac{1}{s_1 + s_2}\right) \left(\sum_{r=1}^{s_1} \frac{w_r^g}{y_{rk}^g} + \sum_{q=1}^{s_2} \frac{w_q^b}{y_{qk}^b} \right)} \\ s.t. x_{ik} = \sum_{j=1}^n x_{ij} \lambda_j + w_i^-, i = 1, 2, \dots, m, \\ y_{rk}^g = \sum_{j=1}^n y_{rj}^g \lambda_j - w_r^g, r = 1, 2, \dots, s_1, \\ y_{qk}^b = \sum_{j=1}^n y_{qj}^b \lambda_j + w_q^b, q = 1, 2, \dots, s_2, \\ \lambda_j \geq 0, j = 1, 2, \dots, n, \\ w_i^- \geq 0, i = 1, 2, \dots, m, \\ w_r^g \geq 0, r = 1, 2, \dots, s_1, \\ w_q^b \geq 0, q = 1, 2, \dots, s_2 \end{array} \right.$$
(3)

where b , g , and w are the slack variables for inputs, desired outputs, and undesired outputs, respectively. To analyze efficient units, the Super-SBM model is used, defined as in Equation (4):

$$\left\{ \begin{array}{l} \min \rho = \frac{1 - \left(\frac{1}{m}\right) \sum_{i=1}^m \left(\frac{\bar{x}_i}{x_{ik}}\right)}{1 + \left(\frac{1}{s_1 + s_2}\right) \left(\sum_{r=1}^{s_1} \frac{\bar{y}_r^g}{y_{rk}^g} + \sum_{q=1}^{s_2} \frac{\bar{y}_q^b}{y_{qk}^b} \right)} \\ s_i t \bar{x}_i \geq \sum_{j=1, j \neq k}^n x_{ij} \lambda_j, i = 1, 2, \dots, m, \\ \bar{y}_r^g \leq \sum_{j=1, j \neq k}^n y_{rj}^g \lambda_j, r = 1, 2, \dots, s_1, \\ \bar{y}_q^b \geq \sum_{j=1, j \neq k}^n y_{qj}^b \lambda_j + w_q^b, q = 1, 2, \dots, s_2, \\ \lambda_j \geq 0, j = 1, 2, \dots, n, \\ \bar{x}_i \geq x_{ik}, i = 1, 2, \dots, m, \\ \bar{y}_r^g \leq y_{rk}^g, r = 1, 2, \dots, s_1, \\ \bar{y}_q^b \geq y_{qk}^b, q = 1, 2, \dots, s_2 \end{array} \right.$$
(4)

4.1.2. Selection of Input and Output Indicators

Input Indicators

Regarding the input indicators for green innovation performance, existing studies often consider human resources and funding. Based on the research by Zhang and Wang [49],

in this study, we measured the human resource indicator using the full-time equivalent of R&D personnel in large-scale industrial enterprises and the funding indicator using the internal funding expenditure for R&D in large-scale industrial enterprises.

The capital input was measured by three items: internal expenditure for industrial R&D, funding for new product development in the industry, and funding for technology introduction and transformation in the industry. These three types of funding inputs were adjusted according to the industrial producer purchase price index to a constant price based on the year 2000.

The indicator of total energy consumption reflected the degree of energy consumption accompanying activities in a certain region, mainly including the total consumption of primary energy, secondary energy generated from the processing and conversion of primary energy, other fossil energies, new energies, and other renewable energies. The energy input was represented by the energy consumption value per CNY 10,000 of GDP.

Output Indicators

The desired output included new product sales revenue and green patents. The new product sales revenue indicator is a commonly used measure of the degree of product innovation and was, therefore, included in the innovation desired output. Another commonly used indicator to reflect the innovation output is patent numbers. Given that the object of this study's research was green innovation performance, the environmental attributes of the output results needed to be reflected, and green patents were used to represent the green attributes of the output results. The data were classified and sorted according to the applicant's region, and the number of green patent grants for each province was statistically obtained each year. The undesired output mainly consisted of three types of waste emissions, namely, industrial wastewater, industrial waste gas, and industrial solid waste emissions. The inclusion of the undesired output indicator was aimed at examining the green innovation performance after considering environmental protection, and it was also a reflection of the green nature of green innovation performance.

4.2. System GMM Estimation Method

Panel data, i.e., data that track the same set of individuals over time, encompasses both individual samples in the cross-sectional dimension (totaling N samples) and data in the time-series dimension (spanning T periods). In the framework of panel data analysis, if the explanatory variables include their own lagged terms as explanatory factors, such models are called "dynamic panels" [50]. Panel data exhibit significant advantages in addressing the problem of omitted variables and help capture the time-series characteristics of individuals. Because panel data contain information in two dimensions, their sample sizes are usually larger, which helps to improve the accuracy of parameter estimates. Although fixed-effects and random-effects models are commonly used in panel data regression analysis, they have limitations; in particular, they cannot be used to effectively study the dynamic relationships among variables and tend to ignore the inertial effects of individual behavior, which may lead to endogeneity problems. The presence of endogeneity can bias parameter estimates, which, in turn, affects the economic interpretations made on the basis of these parameters [51]. In order to overcome these problems, generalized method of moments (GMM) estimation has been developed; it is more advantageous in dealing with endogeneity and heteroskedasticity than the traditional panel data estimation methods, with parameter estimation results that are more robust and closer to the actual situation.

The system GMM estimation method further improves the estimation efficiency by combining difference and level equations to form a unified system of equations for estimation. However, the use of system GMM estimation requires the fulfillment of specific conditions and the passing of an autocorrelation test and an overidentification test in the empirical tests to ensure that there is no autocorrelation in the difference series of the panel data disturbance terms and that all the factors used as instrumental variables are valid. The model is applicable only when these conditions are met.

The basic regression model for panel data is as follows:

$$y_{it} = \alpha y_{it-1} + \beta X_{it} + \mu_i + \varepsilon_{it} \quad (5)$$

where y_{it} is the explained variable, X_{it} is the explanatory variable, μ_i is the fixed effect, and ε_{it} is residual. The static model generally assumes that the explained variable is on a stable path. In this study, we considered the shortcomings of the static model, so we selected the dynamic GMM (generalized method of moments) model. One of the important advantages of the GMM model is that it can reveal the dynamic changes in the explained variable. To overcome individual fixed effects in Formula (5), we performed a first-order difference on Formula (5) to obtain

$$\Delta y_{it} = \alpha \Delta y_{it-1} + \beta \Delta X_{it} + \Delta \varepsilon_{it} \quad (6)$$

Formula (6) effectively eliminates individual fixed effects. Considering possible bidirectional causality between variables, we further processed the endogeneity that potentially existed between variables by judging the rationality of the instrumental variables and the model setting. The model we established was

$$\ln GIP_{i,t} = \alpha_0 + \gamma_1 \ln GIP_{i,t-1} + \beta_1 \ln CSR_{i,t} + \beta_2 \ln RD_{i,t} + \beta_3 \ln ER_{i,t} + \beta_4 \ln HL_{i,t} + \ln FDI_{i,t} + \ln GOV_{i,t} + \mu_i + \varepsilon_{i,t} \quad (7)$$

where i is provincial regions and t is different periods. GIP is green innovation performance. $GIP_{i,t-1}$ represents the first-order lag of green innovation performance, $CSR_{i,t}$ represents corporate social responsibility, $RD_{i,t}$ represents resource dependency, $ER_{i,t}$ represents environmental regulation, $HL_{i,t}$ represents the human capital level, $FDI_{i,t}$ represents foreign direct investment, and $GOV_{i,t}$ represents government subsidies.

4.3. Threshold Effect Model

Regarding the validation method of nonlinear relationships, the conventional practice in academia is to add square or interaction terms to the model, but this practice is prone to the problem of multicollinearity, which affects the fitting results. The threshold regression method, on the other hand, is able to avoid both the problem of multicollinearity among variables and the subjectivity of the experimenter's grouping based on descriptive statistics. The threshold regression method can accurately reveal the relationships between the explanatory variables and the variations in the explained variables in different groups according to the intrinsic characteristics of the data. In this study, we decided to use the threshold model developed by Hansen (1999) [52] to empirically analyze the relationship between variables, and we estimated the threshold model using the least-squares method. This method does not require setting a nonlinear equation form to determine the threshold and threshold domain through endogenous sample data; therefore, this model can be used to scientifically study the dynamic relationships between variables. This method includes two steps. The first step is to calculate the minimum residual square through the bootstrap method, and based on the minimum residual square, the threshold value γ is obtained. The second step is to use the obtained threshold value γ to estimate the threshold model and the model coefficients. Specifically, the single threshold model can be used as an example to briefly introduce the panel threshold model. Assuming that the theory shows that there should be a single threshold value, the single threshold model is set up as follows (here is the simplest single threshold model, that is, with no control variable group):

$$y_{it} = \beta_1 x_{it} I(q_{it} < \gamma) + \beta_2 x_{it} I(q_{it} \geq \gamma) + e_{it} + \mu_i \quad (8)$$

where y_{it} is the explained variable, x_{it} is the explanatory variable, β is the coefficient vector, e_{it} is the error vector, I is the indicator function, q_{it} is the scalar of the threshold variable, and γ is the threshold value scalar. According to the relationship between the threshold variable q_{it} and the threshold value γ , the model can be changed to a piecewise function form. In the single regression threshold model, the two segmented regression coefficients

are β_1 and β_2 . If $q_{it} < \gamma$, the coefficient of x_{it} is β_1 , and if $q_{it} > \gamma$, the coefficient of x_{it} is β_2 . Only by obtaining the threshold value γ can the ordinary least-squares method be used to estimate the coefficient values of each segment β . The method for the multiple threshold model is the same as that for the single threshold model, which will not be introduced in this paper.

4.4. Variable Selection and Data Sources

4.4.1. Explained Variables

Green innovation performance. The green innovation performance data were measured using the Super-SBM model based on the model selection results in Section 3.1 above, and the results are shown in Table 1.

Table 1. Measurement results of green innovation performance.

	Region	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	Mean
Eastern	Beijing	0.995	1.003	1.015	1.026	1.077	1.119	1.126	1.135	1.164	1.185	1.196	1.201	1.218	1.243	1.122
	Tianjin	0.991	1.092	1.101	1.112	1.125	1.136	1.139	1.142	1.147	1.159	1.216	1.225	1.239	1.264	1.149
	Hebei	0.223	0.232	0.247	0.269	0.226	0.237	0.344	0.357	0.365	0.422	0.558	0.635	0.759	0.769	0.403
	Liaoning	0.299	0.321	0.333	0.341	0.353	0.367	0.405	0.423	0.436	0.457	0.463	0.472	0.481	0.499	0.404
	Shanghai	0.681	0.692	0.721	0.738	0.751	0.768	0.785	0.793	0.821	0.989	1.043	1.097	1.151	1.196	0.873
	Jiangsu	0.415	0.422	0.438	0.441	0.455	0.505	0.523	0.567	0.656	0.743	0.856	0.895	0.966	0.975	0.633
	Zhejiang	0.856	0.894	0.918	0.943	0.968	1.024	1.026	1.035	1.041	1.089	1.112	1.132	1.147	1.163	1.025
	Fujian	0.488	0.518	0.526	0.541	0.616	0.627	0.742	0.745	0.751	0.805	0.821	0.846	0.882	0.927	0.702
	Shandong	0.436	0.442	0.451	0.464	0.471	0.526	0.542	0.593	0.635	0.643	0.657	0.699	0.724	0.758	0.574
	Guangdong	0.681	0.692	0.721	0.738	0.751	0.768	0.785	0.893	0.921	0.989	1.043	1.097	1.151	1.186	0.887
	Hainan	0.289	0.311	0.328	0.341	0.368	0.405	0.428	0.457	0.466	0.483	0.516	0.549	0.582	0.621	0.439
Eastern mean		0.536	0.562	0.578	0.593	0.608	0.636	0.672	0.701	0.724	0.778	0.829	0.865	0.908	0.936	0.709
Central	Shanxi	0.217	0.218	0.226	0.231	0.253	0.266	0.281	0.287	0.322	0.352	0.461	0.482	0.538	0.562	0.335
	Jilin	0.315	0.332	0.326	0.338	0.391	0.416	0.453	0.496	0.513	0.636	0.662	0.697	0.728	0.759	0.504
	Heilongjiang	0.267	0.282	0.297	0.219	0.226	0.237	0.244	0.357	0.365	0.422	0.458	0.535	0.559	0.579	0.361
	Anhui	0.365	0.377	0.485	0.518	0.523	0.541	0.653	0.662	0.671	0.712	0.724	0.738	0.751	0.787	0.608
	Jiangxi	0.323	0.335	0.367	0.412	0.526	0.532	0.544	0.561	0.595	0.674	0.728	0.775	0.813	0.871	0.575
	Henan	0.331	0.339	0.425	0.437	0.448	0.457	0.462	0.573	0.581	0.592	0.606	0.719	0.824	0.834	0.545
	Hubei	0.337	0.348	0.458	0.463	0.514	0.521	0.628	0.632	0.667	0.694	0.712	0.735	0.845	0.865	0.601
	Hunan	0.341	0.355	0.367	0.418	0.524	0.537	0.647	0.627	0.644	0.763	0.776	0.797	0.813	0.829	0.603
Central mean		0.312	0.323	0.369	0.380	0.426	0.438	0.489	0.524	0.545	0.606	0.641	0.685	0.734	0.761	0.517
Western	Neimenggu	0.187	0.193	0.218	0.223	0.234	0.248	0.359	0.362	0.330	0.413	0.522	0.537	0.542	0.598	0.355
	Guangxi	0.334	0.335	0.347	0.345	0.367	0.403	0.411	0.421	0.456	0.513	0.521	0.535	0.542	0.564	0.435
	Chongqing	0.337	0.343	0.356	0.383	0.423	0.448	0.533	0.578	0.585	0.631	0.658	0.677	0.712	0.729	0.528
	Sichuan	0.286	0.315	0.327	0.385	0.397	0.412	0.428	0.433	0.451	0.523	0.532	0.541	0.552	0.564	0.439
	Guizhou	0.203	0.223	0.235	0.333	0.355	0.367	0.412	0.426	0.432	0.424	0.511	0.565	0.604	0.628	0.408
	Yunnan	0.267	0.284	0.327	0.336	0.363	0.435	0.447	0.458	0.467	0.469	0.474	0.487	0.494	0.506	0.415
	Shanxi	0.302	0.313	0.332	0.343	0.352	0.368	0.423	0.434	0.441	0.448	0.532	0.565	0.614	0.562	0.431
	Gansu	0.301	0.316	0.323	0.336	0.343	0.355	0.408	0.424	0.437	0.477	0.485	0.518	0.527	0.536	0.413
	Qinghai	0.302	0.315	0.328	0.338	0.347	0.354	0.416	0.427	0.432	0.471	0.505	0.519	0.523	0.567	0.417
	Ningxia	0.282	0.295	0.311	0.324	0.332	0.411	0.425	0.437	0.442	0.451	0.515	0.529	0.521	0.527	0.414
	Xinjiang	0.321	0.335	0.346	0.358	0.413	0.426	0.437	0.443	0.452	0.456	0.479	0.521	0.525	0.533	0.432
Western mean		0.290	0.304	0.321	0.347	0.364	0.395	0.434	0.449	0.460	0.490	0.526	0.548	0.565	0.576	0.434
National mean		0.379	0.396	0.423	0.440	0.466	0.490	0.532	0.558	0.576	0.624	0.665	0.699	0.736	0.757	0.553

Note: The Region column lists the 30 different regions in China selected, and according to the administrative division of China, the 30 regions are divided into three major regions: east, central, and west. The mean value of the corresponding region was sought, and the data in the table are the values of the green innovation performance of the different regions in the period of 2009–2022.

4.4.2. Explanatory Variables

Corporate social responsibility (CSR). In domestic research, there are several methods for measuring CSR, including the reputation index method, questionnaire survey method, content analysis method, dummy variable method, accounting index method, and charitable donation method. Among them, the reputation index method, which uses the CSR comprehensive score published by Hexun, Runling, and the Chinese Academy of Social Sciences to evaluate corporate social responsibility, is widely used by scholars in China [53]. Due to the subjective nature of CSR measurement indicators, academia has not yet reached a consensus on a uniform measurement method. Accordingly, in this study, we adopted the CSR comprehensive score. This scoring method can effectively combine the actual situations of listed companies in China to evaluate their CSR behavior and is widely accepted by the public.

Resource dependency (RD). Resource industry dependency in this paper refers to the proportion of employees in the mining industry to the total number of employees at the end of the year in each region. This indicator was chosen due to its data availability and relevance, as suggested in the research by Shao et al. (2013) [54].

4.4.3. Control Variables

Environmental regulation (ER). At present, there is no consensus in academia on environmental regulation measurement. Through a review of the relevant literature, we found that scholars' measurements of environmental regulation mainly include the following: (1) emission reduction cost type; (2) emission reduction performance type; (3) government behavior type; and (4) public participation type. Although various indicators have their advantages and disadvantages for measuring environmental regulation, considering that the environmental regulation involved in this study concerned industrial structural upgrading, we adopted an environmental regulation evaluation index using pollution fees, unit pollution emission amounts, and unit industrial pollution control completion investment to measure environmental regulation in multiple dimensions.

Human capital level (HL). Human capital with high-tech knowledge spillover can improve green innovation performance. The higher the level of human capital, the more abundant the green innovation performance results may be. The number of R&D personnel in enterprises is the most intuitive data variable reflecting the input of human capital in enterprises. Therefore, we selected the full-time equivalent of R&D personnel in enterprises to represent human capital.

Foreign direct investment (FDI). The inflow of foreign capital may produce a "pollution halo" effect, bringing advanced foreign technology and stricter environmental governance standards, which are conducive to technological innovation and pollution reduction and ultimately promote the improvement of green innovation performance. However, some scholars believe that foreign capital will produce a "pollution haven" effect. Developed countries have stronger environmental regulations and are more inclined to transfer high-pollution/high-emission enterprises to China, increasing China's environmental burden. Moreover, the inflow of foreign capital may also produce a "crowding-out" effect, causing enterprises to rely overly on foreign technology and lose their ability to innovate independently, ultimately reducing green innovation capabilities. Ultimately, we used the proportion of foreign capital to total capital to represent FDI.

Government subsidies (GOVs) refer to direct and indirect subsidies provided by the government to enterprises, including financial allocations, financial interest subsidies, gratuitous assignment of non-monetary assets, and tax refunds. From the perspective of data availability, we used the amount of government subsidies actually obtained by enterprises in the year under study as our measure and performed logarithmic processing.

5. Results

5.1. Measurement Results of Green Innovation Performance

In this study, we selected the Super-SBM model to measure green innovation performance, and the results are given in Table 1.

In recent years, China has witnessed significant economic growth and development, but this growth has not been evenly distributed across all regions. The eastern region, which has traditionally been the economic hub of the country, has consistently outpaced the central and western regions in terms of various economic indicators. This disparity is clearly reflected in the data presented in Table 1, which compare the average green innovation performance levels of 30 regions in China from 2009 to 2022.

According to the table, the average green innovation performance for the entire country during this period was 0.553. However, when we look at the averages for different regions, it becomes evident that the eastern region significantly surpassed the national average. This is not surprising given the fact that the eastern region is home to many of China's most developed cities and industries. On the other hand, the central and western regions lagged behind, with their average green innovation performance values falling below the national average.

Moreover, the trend in Table 1 indicates a steady decline in efficiency values for the central and western regions. This decline is particularly pronounced in the western region, where efficiency values have dropped significantly over the past decade. This pattern suggests that the resource allocation efficiency in these regions is deteriorating, further widening the gap between the eastern region and the rest of the country.

The reasons for this unbalanced development are numerous and complex. Geographical factors, such as access to natural resources and proximity to major markets, play a crucial role. The eastern region, which is located along China's coastline, enjoys a natural advantage in terms of trade and transportation. This advantage has historically attracted more investment and led to faster economic growth in this region.

5.2. Correlation Analysis and Multicollinearity Test

Correlation analysis serves as a tool to explore the relationships between two or more variables. In the present study, the Pearson correlation coefficient was utilized to determine the strengths and directions of the relationships between the variables. The outcomes of this analysis are summarized in Table 2.

Table 2. Correlation analysis and multicollinearity test results.

Variable	RD	CSR	ER	FDI	HL	GOV
RD	1					
CSR	−0.004	1				
ER	−0.045	0.155	1			
FDI	0.156	0.054	−0.012	1		
HL	0.112	0.087	0.033	0.224	1	
GOV	−0.002	0.167	0.052	0.146	0.198	1
VIF	2.34	1.56	3.44	2.18	1.89	1.90

5.3. Regression Model Selection

The data in this study were short-panel data, and the panel data models were divided into two categories: unobserved-effects models and mixed-regression models. The former was used when there were unobservable individual effects; otherwise, the latter was used. Panel data generally require mixed OLS regression, fixed-effects regression, or random-effects regression. Accordingly, in this study, we applied the F test, LM test, and Hausman test for model selection. The Hausman test is a statistical test used to test the fixed- and random-effects models to determine which is more suitable. In applied empirical research, both are often used to analyze panel data, but the Hausman test can help researchers to

choose the most appropriate model, thus improving the accuracy and credibility of the research results. The corresponding results are presented in Table 3.

Table 3. Regression model selection test results.

Test Method	Statistical Value	<i>p</i> -Value	Reject/Accept
F test	92.82	0.0000	Reject
LM test	324.45	0.0000	Reject
Hausman test	64.23	0.0000	Reject

Table 3 reveals the following: Initially, the models' individual effects were evaluated through the F test, rejecting the null hypothesis. This implied that the fixed-effects model outperformed the OLS mixed model. Subsequently, the models' time effects were assessed via the LM test, which also rejected the null hypothesis. This indicated that the random-effects model was more suitable than the OLS mixed model. Lastly, the Hausman test was applied, strongly rejecting the null hypothesis. This conclusive test suggested that the fixed-effects model was superior to the random-effects model. Based on these findings, the fixed-effects model was employed for regression analysis in this study.

5.4. Regression Results Analysis

In this study, we used the system GMM for the benchmark regression, and the regression results are shown in Table 4.

Table 4. Regression results.

Explanatory Variables	Elasticity Coefficient	<i>p</i> -Value	t-Value
RD	−0.159	0.0000	4.17
CSR	0.167	0.0000	4.55
ER	0.1322	0.0013	3.25
FDI	−0.0367	0.1324	1.01
HL	0.1753	0.0012	4.28
GOV	0.0455	0.0000	2.99
Hansen test		0.2621	
AR(1)		0.0031	
AR(2)		0.2316	

The regression outcomes consistently indicated a negative correlation between resource dependency and green innovation performance that was highly significant. This suggests that excessive reliance on resources hinders the enhancement of local green innovation performance and that, as the degree of dependency increases, the obstructive effect intensifies. The finding confirmed that the resource curse exists between green innovation performance and resource industry dependence. In the literature, Hu and Zhao [55] tested the existence of the resource curse in the coal industry of China's coal-rich provinces and found that it existed among those provinces, whether based on coal resource abundance or dependence. Meanwhile, Zhang [56] found that the phenomenon of the resource curse existed generally in China's regions, with regional comparisons showing a sequence of the central region > western region > eastern region. Additionally, Zhang and Yan [57] found that the resource curse existed at the level of green development efficiency. The present paper verifies the existence of the resource curse effect in the field of green innovation performance, while enriching and expanding the research field on the resource curse. With these findings, hypothesis 3 was verified. It can be seen that in the process of economic development in resource-rich regions, it is necessary to enhance the concept of ecological environmental protection and to explore the green development approach suitable for the particular situation to avoid crowding out the green industry through excessive dependence on the resource industry, which will hamper the green development of the region and produce the resource curse. The resource curse between green innovation performance

and resource industry dependency raises the question of whether their relationship is a simple linear correlation. The study by Shao et al. (2013) [54] demonstrated a distinct inverted U-shaped relationship between economic growth and resource dependency. Such a Kuznets curve leads us to believe that the occurrence of the resource curse is conditional; that is, moderate resource development activities can have a stimulating effect on economic growth in the short term, but once a threshold is exceeded, the “curse” manifests, impeding economic growth.

The regression coefficient for CSR (corporate social responsibility) was found to be 0.167. As such, when considering relevant factors at the corporate level, the significance of CSR for green innovation performance was firmly established. This is consistent with the findings of most scholarly studies. For example, Xiao et al. [58] found that CSR had a significant promotion effect on the green technological innovation of enterprises. Meanwhile, Mou et al. [59] revealed that the fulfillment of CSR can significantly promote the level of green innovation, which is conducive to the green development of the enterprise. The main difference between this paper and the previous scholars’ research is that we adopted a green innovation performance perspective rather than green innovation. We did so because performance better reflects the quality of green innovation. As such, this paper deepens the research in this area, expanding the research field of green innovation and corporate social responsibility. Moreover, our findings on green innovation performance confirmed hypothesis 1. Firstly, we found that through the active fulfillment of social responsibilities, corporate management is able to bridge any gap with stakeholders, fostering mutual understanding and trust. This, in turn, helps to overcome challenges such as funding constraints, technological limitations, and equipment shortages, which often hinder green innovation performance. By addressing these challenges, a solid material foundation is established for the promotion of green initiatives. Secondly, CSR activities involving employees not only boost their organizational identity but also kindle their passion for innovation. As a result, employees become agents of change, driving the green innovation process within the company. In conclusion, CSR plays a pivotal role in green innovation performance by fostering stakeholder relationships, overcoming challenges, and engaging employees as agents of sustainable development. For the company as a whole, proactive CSR creates a positive atmosphere within the organization. For example, companies with strong CSR provide a greater sense of security for employees, helping them navigate the uncertainties that innovation brings. In addition, embracing social responsibilities is key to cultivating a reputable corporate image in the market. This positive image boosts consumers’ confidence in the company’s novel and innovative products, making them more receptive. Furthermore, investors are more inclined to fund the company’s green innovative undertakings due to its positive corporate image.

From the perspective of those who are not market stakeholders, legitimate pressure from the government, the community where the company is located, and the media can compel companies to implement green innovation. Furthermore, companies that actively assume social responsibilities can not only receive government policy subsidies but also gain a good reputation and establish positive social network relationships, making it easier to access various forms of resources. Lastly, companies that actively fulfill their social responsibilities can facilitate a complementary effect between the external knowledge held by stakeholders and the company’s own knowledge, providing technical and knowledge support for corporate green innovation.

5.5. Robustness Test

To ensure the accuracy of the model, we used a replacement model to conduct a robustness test. Because green innovation performance is a restricted variable, using the Tobit model for estimation allowed us to effectively avoid the inconsistency and bias problems that may arise from OLS estimation. The test results are shown in Table 5 below, which indicates that a correlation between the core independent variables still existed and

was significant, consistent with the sign of the regression results above. This proves that the model regression results were robust.

Table 5. Robustness test results.

Explanatory Variables	Elasticity Coefficient	<i>p</i> -Value	T-Value
RD	−0.176	0.0000	3.56
CSR	0.112	0.0000	5.13
ER	0.143	0.0013	3.76
FDI	−0.076	0.2218	0.78
HL	0.1456	0.0012	5.19
GOV	0.0619	0.0000	4.45
Hansen test	0.3897		
AR(1)	0.0012		
AR(2)	0.3189		

5.6. Threshold Effect Results

5.6.1. Threshold Test

In this study, we used the bootstrap method developed by Hansen (1999) and the threshold command developed by Wang and Lu [60] to test the threshold effects of resource dependency and corporate social responsibility, respectively. By using the bootstrap method with 300 samples, the gradual distribution and the *p*-value were derived. The F-statistic and *p*-value are used to judge whether resource dependency and corporate social responsibility have threshold effects on green innovation performance. If there is a threshold effect, the number of thresholds must also be calculated.

In the threshold effect model, resource dependency is both an independent variable and a threshold variable. The test results are given in Table 6. In the single threshold test, the F-statistic was 12.88 and the *p*-value was 0.1452, which were not significant, leading us to accept the hypothesis of no threshold, indicating that resource dependency does not have a single threshold for green innovation performance. In the double threshold test, the F-statistic was 13.54 and the *p*-value was 0.2214, which were not significant, leading us to accept the hypothesis of no threshold, indicating that resource dependency does not have a double threshold for green innovation performance. In the triple threshold test, the F-statistic was 19.05 and the *p*-value was 0.2671, which were not significant, meaning it could not be concluded that resource dependency has a triple threshold for green innovation performance. In Table 6, it can be seen that there is indeed a “resource curse” phenomenon between resource industry dependency and green innovation performance. The fact that resource industry dependency did not pass the threshold effect test does not prove that there is a conditional resource curse phenomenon between the two. We propose that the obstructive effect of resource industry dependency on green innovation performance is long-term and persistent; that is, the resource curse has persistent, long-term characteristics. As such, there is no threshold effect.

Table 6. Threshold test results for resource dependency.

Model	F-Value	<i>p</i> -Value	Result
Single threshold	12.88	0.1452	Reject threshold
Double threshold	13.54	0.2214	Reject threshold
Triple threshold	19.05	0.2671	Reject threshold

The results of the threshold effect test of CSR are presented in Table 7. In the threshold effect model, CSR serves as both an independent variable and a threshold variable. The F-statistic for the single threshold test was 22.56 with a *p*-value of 0.0363, which were significant at the 5% level, indicating the presence of a single threshold for CSR in relation

to green innovation performance. For the double threshold test, the F-statistic was 19.96 with a p -value of 0.0126, also significant at the 5% level, suggesting that there are two thresholds for CSR. In the triple threshold test, the F-statistic was 9.23 with a p -value of 0.1549, which were not significant, thus failing to establish the presence of a triple threshold for CSR. As indicated in Table 8, CSR exhibited a dual threshold effect on green innovation performance, with the thresholds being 0.4215 and 0.4933, respectively. Consequently, the subsequent analysis in this study employed a double threshold regression model.

Table 7. Results of the threshold effect test for corporate social responsibility.

Model	F-Value	p -Value	Result
Single threshold	22.56	0.0363	Accept the presence of a threshold
Double threshold	19.96	0.0126	Accept the presence of a threshold
Triple threshold	9.23	0.1549	Reject the presence of a threshold

Table 8. Estimated threshold values.

Independent Variable	Threshold Variable	Number of Thresholds	Estimated Value
Corporate social responsibility	Corporate social responsibility	Single threshold	0.4215
		Double threshold	0.4933

5.6.2. Threshold Model Regression

According to the above analysis, the single and double thresholds of the corporate social responsibility threshold variable passed the significance test, while the triple threshold did not have significance, indicating that the effective number of thresholds was two. That is, there is a double threshold effect between corporate social responsibility and green innovation performance. The double threshold regression model is as follows (Equation (9)):

$$\begin{aligned} \ln GIP_{i,t} = & \alpha_0 + \alpha_1 CSR_{i,t} \cdot I(CSR_{i,t} \leq \mu_1) + \alpha_2 CSR_{i,t} \cdot I(\mu_1 < CSR_{i,t} \leq \mu_2) + \\ & \alpha_3 CSR_{i,t} \cdot I(CSR_{i,t} > \mu_2) + \sum \alpha_i X_{i,t} + \varepsilon_{i,t} \end{aligned} \quad (9)$$

The threshold effect results of this model, used in a quantitative regression, are shown in Table 9.

Table 9. Threshold effect regression results.

	Elasticity Coefficient	p -Value	t-Value
RD	−0.195	0.0000	5.23
CSR (CSR ≤ 0.4215)	−0.149	0.0000	3.44
CSR (0.4215 < CSR ≤ 0.4933)	0.079	0.0000	2.98
CSR (CSR > 0.4933)	−0.238	0.0000	4.82
ER	0.019	0.0183	2.12
FDI	−0.054	0.1452	1.03
HL	0.166	0.0000	4.47
GOV	0.183	0.0342	2.22

Based on the two CSR threshold values obtained from the threshold effect test, the sample was divided into three groups: low (CSR ≤ 0.4215), moderate (0.4215 < CSR ≤ 0.4933), and excessive CSR (CSR > 0.4933). The threshold regression results (Table 9) show that when enterprises had low CSR (before reaching the first threshold value), the regression coefficient of CSR was −0.149, which was significant at the 1% level. This indicates that CSR has not yet had a positive effect on green innovation performance. The reason may be that when CSR performance is poor, it causes dissatisfaction among stakeholders, leading to tense relationships and damaging the company's reputation. This makes it difficult for the company to obtain various explicit or implicit resources. In other words, external

financing for the company will be difficult to obtain, which is not conducive to the smooth progress of green innovation activities. Therefore, enterprises should fully consider the reasonable demands of all stakeholders, turn the pressure from stakeholders into green innovation power, actively build a productive and stable stakeholder network, establish a positive image of the enterprise, and provide a stable and lasting impetus for the development of green innovation. When enterprises actively assume CSR after reaching the first threshold value, the inhibiting effect of CSR on green innovation performance transforms into a positive promotion, with a regression coefficient of 0.079. This finding indicates that fulfilling CSR helps promote green innovation performance. When the CSR performance of enterprises was excessively good (after reaching the second threshold value), the coefficient of CSR became negative again, significant at the 5% level. This suggests that an overly high level of CSR is not conducive to green innovation performance. The reason may be that when a company's CSR level is too high, it not only occupies funds used for R&D activities but may also become overly reliant on existing customer relationships, reducing its "sense of smell" for potential customers and weakening its ability to identify technological innovation opportunities, thus inhibiting the company's green innovation performance. Overall, the impact of CSR on green innovation performance shows a "reverse N-shaped" double threshold effect, with CSR first inhibiting, then promoting, and finally inhibiting again. In summary, CSR has a positive promoting effect on green innovation performance only when it reaches a certain threshold value. This indicates that the impact of CSR on green innovation performance does not follow a simple linear relationship. This is consistent with the findings of most scholars. For example, Ding [61] showed that there is an inverted U-shaped relationship between CSR and corporate innovation. When a certain critical value is reached, corporate innovation activities will be reduced with an increase in the degree of fulfillment of corporate social responsibility. Too much fulfillment of CSR will, on the one hand, take up a lot of corporate resources and inhibit the development of innovative activities, and on the other hand, it will take up a lot of managers' energy; then, when seeking to maintain the business objectives of the enterprise, managers can focus their limited energy only on improving the financial performance of the enterprise, to the detriment of corporate innovation activities. Thus, hypothesis 2 was verified. In sum, we constructed a threshold regression model to explore the nonlinear impact of corporate social responsibility on green innovation performance, and in doing so, we produced findings that enrich the literature on the economic consequences of corporate social responsibility and the factors affecting green innovation performance.

6. Conclusions and Suggestions

6.1. Conclusions

In this study, we used panel data from 30 regions from 2009 to 2022 to establish an evaluation index system for regional green innovation performance. For the first time, this incorporates corporate social responsibility and resource dependency in a holistic research framework with regional green innovation performance. The conclusions are as follows.

From 2009 to 2022, the average industrial green innovation performance of the 30 provinces in China was 0.553. The eastern region had a higher average value than the national average, while the central and western regions had lower averages than the national average. The efficiency values of the eastern, central, and western regions showed a gradual decreasing trend, indicating a significant gap in resource allocation efficiency between the central and western provinces and the eastern region, and a phenomenon of unbalanced development was prominent.

There was a consistently negative correlation between resource dependency and green innovation performance. Excessive dependence on resources hinders the improvement of local green innovation performance, and as the degree of dependence further increases, its obstructive effect is further enhanced. This confirms the existence of the resource curse between green innovation performance and resource industry dependency. The regression coefficient of corporate social responsibility and green innovation performance

was positive, establishing the role of corporate social responsibility in promoting green innovation performance when considering the relevant factors at the enterprise level.

There is no conditional resource curse phenomenon or threshold effect. Instead, we found that the resource curse has long-term and persistent characteristics. Meanwhile, the impact of CSR on green innovation performance shows a “reverse N-shaped” double threshold effect, with the former having a positive promoting effect on the latter only when it reaches a certain threshold value.

6.2. Suggestions

In enterprises, the management should change its business philosophy, abandon short-sighted thinking, and actively assume corporate social responsibility. It should explore new areas and forms of social responsibility, such as the outstanding performance of leading internet companies in the fight against the COVID-19 pandemic, which has refreshed the public’s traditional perception of private enterprises through a demonstration of the application of their advanced technologies in various areas of people’s lives and livelihoods. Furthermore, by actively assuming social responsibilities and disclosing their CSR in reports, companies can enhance their reputation and image, which is beneficial for their long-term development. In addition, companies should comply with regulations but also innovate in how they fill out disclosure forms of corporate social responsibility to more effectively present their corporate image, and they should continuously consolidate the contractual relationships between the company and relevant stakeholders. For shareholders, they should improve the corporate governance mechanism as well as integrate the fulfillment of corporate social responsibility and green innovation strategy into the compensation and incentives for executives through methods such as new incentive mechanisms for management and strengthening internal audits. By rewarding long-term success and tolerating short-term failures, companies can effectively encourage the disclosure of their CSR and promote corporate innovation, leading to a win-win situation for the economy and the environment.

The government should also improve corporate-social-responsibility-related policies. CSR can bring long-term value to a company’s growth and development, and a comprehensive policy and legal system for CSR can provide a foundation for companies to assume social responsibilities. The government should guide companies to actively disclose their CSR and improve the quality of the reports, encourage companies to actively and continuously assume social responsibilities, and substantially improve the quality of CSR fulfillment. This will create a positive atmosphere for corporate social responsibility, guide companies to actively engage in green technological innovation activities, and achieve a win-win situation for economic and environmental effects.

Additionally, the government should increase its support for environmental protection industry policies to incentivize companies to undergo green transformation and upgrading. These policies can provide resource support for companies so that they can assume social responsibilities, guide companies to implement green innovation strategies, and create a favorable environment for corporate green innovation activities. These policies can also enhance the promoting effect of CSR on green innovation, thereby reducing the negative impact on the environment and achieving sustainable development of the economy and society, supporting the realization of China’s “dual carbon” goal.

Natural resources themselves do not have a negative impact on high-quality economic development. Instead, overreliance on natural resources in resource-based regions leads to a single structured industry, which results in a decline in the ability of resource-dependent regions to resist economic risks. In resource-rich regions, the industrial system formed during economic development, which mainly relies on resources, tends to rely on technological progress, and this is not conducive to improving green growth efficiency, instead forming path dependence. Accordingly, resource-rich regions perform worse than resource-poor regions in terms of green growth efficiency. To avoid the harm caused by industrial system monomerization, the most effective solution is to promote the optimization and

upgrading of the industrial structure and reduce dependence on resource-based industries. For resource-dependent regions, the proportion of resource-based industries should be reasonably controlled, the fixed-asset investment in mining industries should be reduced, the access threshold for resource-based industries should be raised, and quota mining should be implemented. The technological content of resource-based industries should be improved, technological transformation and the introduction of related high technologies should be accelerated, production efficiency should be increased, and the destruction and pollution of the environment during the development and utilization of resources should be reduced. Resource-based industrial clusters should also be formed to achieve regional cooperation advantages, bring greater benefits, and promote coordinated regional economic development.

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