How Do Different Types of Environmental Regulations Affect Green Innovation Efficiency?

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Environmental regulation policies are being continuously enriched today. To effectively improve green innovation efficiency through environmental regulations, it is urgent to better understand the impact of different environmental regulations on green innovation efficiency (GIE). However, due to the defects of previous methods for measuring GIE, existing studies may have deviations when analysing the effect of environmental regulations on GIE. To fill this gap, using Shaanxi, China, as a case study, the present study proposes a network data envelopment analysis (DEA) model based on neutral cross-efficiency evaluation to accurately measure the GIE of Shaanxi during the period of 2001–2017. On this basis, this study further analysed the impact of different types of environmental regulations on GIE from three aspects: causality, evolutionary relationships, and effect paths. The results indicate that (1) the GIE of Shaanxi Province showed a “fluctuation-slow growth-steady growth” trend during 2001–2017, and after 2014, the problem of an uncoordinated relationship between technology research and design (R&D) and technology transformation began to appear; (2) there was a linear evolutionary relationship between command-and-control environmental regulation and GIE and a “U”-shaped evolutionary relationship between market-based/voluntary environmental regulation and GIE; and (3) command-and-control environmental regulation and voluntary environmental regulation affected GIE mainly at the technology R&D stage, while market-based environmental regulation ran through the entire process of green innovation activities. This study improves the evaluation methods and theoretical systems of GIE and provides the scientific basis for government decision-makers to formulate environmental regulation policies.

1. Introduction

As an important means to eliminate the constraints of both resources and the environment to achieve sustainable development, green innovation is being continuously accepted by more countries [1]. Unlike traditional technological innovation, green innovation mainly solves the contradiction between economic development and the ecological environment. It introduces the concept of environmental protection into technological innovation activities, effectively improving environmental quality while maintaining the original economic development level and then making full use of resources to achieve sustainable development [1]. Green innovation efficiency (GIE) is the ratio of input to output in green innovation activities considering environmental pollution, an important indicator reflecting green innovation capacity [2]. In the face of increasingly serious environmental problems, it is urgent to improve GIE to achieve sustainable development.

Due to the negative externality of environmental pollution, it is unrealistic to improve GIE by relying only on the market mechanism. Hence, the requirement for environmental regulation. In general, environmental regulation can be divided into three types: command-and-control environmental regulation (CER), market-based environmental regulation (MER), and voluntary environmental regulation
(VER). CER forces enterprises to carry out green innovation to reduce their pollutant discharge [3]. Compared with CER, MER and VER are more flexible. MER relies on economic incentives to affect GIE, while VER stimulates enterprises to green innovation through public supervision and other means [4, 5]. Identifying the effect of three types of environmental regulation on GIE could provide a scientific basis for the formulation and implementation of environmental regulation policies, which has a critical sense to improve GIE by environmental regulation effectively.

However, existing studies may have deviations when analysing the effect of environmental regulations on GIE. The lack of effectiveness of the measurement method for GIE is one of the main reasons. Currently, network DEA is the most widely used method for measuring GIE. The network DEA method is mainly based on self-efficiency evaluation or cross-efficiency evaluation. It is worth noting that network DEA based on self-efficiency evaluation maximises each decision-making unit’s (DMU) own efficiency, which may cause a decline in the objectivity of measurement results [6]. Although network DEA based on cross-efficiency evaluation improves objectivity, its measurement results are greatly influenced by researchers’ subjectivity due to the non-uniqueness of the optimal combination coefficient of DMUs [7, 8]. Hence, the above defect of network DEA may hinder the correct efficiency ordering of the DMUs, leading deviations in analysing the effect of environmental regulations on GIE.

As a response to the above problem, this study aims to develop an improved network DEA method to effectively measure GIE and further reveal the effect of different environmental regulations on GIE. By combining the neutral cross-efficiency evaluation, the improved network DEA method avoids researchers’ subjective choice on the optimal combination coefficient of DMUs, improving the effectiveness of measuring GIE. Based on effectively measuring GIE, this study further applied the Granger test, curve fitting equation, and Tobit regression model to analyse the effect of different types of environmental regulations on GIE from three aspects: causality, evolution relationship, and effect difference. Shaanxi, China, was chosen as the object of this study, and the reasons are as follows: (1) in the past forty years, China has achieved not only rapid economic growth but has also paid a substantial environmental price, and currently, China’s development model urgently needs to change to a sustainable direction led by green innovation; and (2) Shaanxi Province is one of the most representative provinces in China, especially in recent years. Under the promotion of the “catch-up” policy, its pace of green innovation is accelerating. Therefore, the example of Shaanxi, China, can provide a valuable reference for other countries to move towards sustainable development. This study improves the evaluation methods and theoretical systems of GIE and provides the scientific basis for government decision-makers to formulate environmental regulation policies.

The rest of the study is structured as follows. The “Literature Review” section describes the development status of environmental regulations and green innovation efficiency and proposes research gaps. The “Methodology” section provides research models and data descriptions. The “Empirical Results” section reports the results of green innovation efficiency analysis and the effect of environmental regulations on green innovation efficiency and the path of the environmental regulation effect on green innovation efficiency. The “Discussion and Recommendation” section puts forward suggestions through the analysis of empirical results. The “Conclusions” section provides the important conclusions of this study.

2. Literature Review

2.1. Environmental Regulation. Environmental regulation is an integral part of regulation theory, and the academic understanding of environmental regulation is constantly changing. In the initial stage, environmental regulation is defined as the government intervention using command-and-control regulations, including nonmarket transferable licensing systems and prohibitions. Due to the high information cost and low economic efficiency of CER, MER is gradually introduced, enriching the meaning of environmental regulations. In addition to CER and MER, VER is also an essential part of environmental regulation.

CER refers to the government’s laws, regulations, and policies on its authority to govern environmental issues [9]. CER requires regulated companies to strictly follow what is regulated or face severe penalties; thus, CER is mandatory. This feature makes CER encourage enterprises to improve their environmental performance in a relatively short time. However, compulsory government supervision may have the problem of excessive rigidity of CER, which may have a negative impact on the autonomy of enterprises in technological innovation.

MER refers to levying taxes on companies that excessively generate pollution while giving subsidies to companies that effectively control pollution [10]. The main feature of MER is that the government implements regulation through the market mechanism, which is an indirect approach [11]. MER not only gives enterprises more autonomy but also has the drawback of a slow regulatory effect, causing a certain lag period for its effect in the implementation process. The main reason is that after the implementation of MERs, companies may be in a wait-and-see state and take action only after they have obtained sufficient market feedback.

VER refers to the regulation of enterprise activities relying on enterprise consciousness and public participation [12]. The consciousness of enterprises is mainly reflected in their voluntary disclosure of environmental information and participation in recognising environmental signs. Such behaviour may increase the enterprise’s public influence, thereby making up for the cost of the company’s prework. Public participation means that the public consciously monitors enterprises’ production activities and complaints to enterprises that cause severe environmental pollution. Continuous public supervision can effectively put pressure on companies to improve their environmental performance. However, compared with CER and MER, the application of VER is not very extensive [13].
2.2. Green Innovation Efficiency. Green innovation refers to using as little innovation input as possible to obtain more innovation output in green development. Different from traditional innovation, the improvement of GIE is first manifested as a specific environmental benefit. According to the innovation value chain theory [14], green innovation activities are divided into two stages: technology R&D and achievement transformation [1]. The technology R&D stage is mainly a process in which an innovation entity invests resources to realise patent and other R&D achievements. The achievement transformation stage is how the innovator puts the outputs of the previous stage of R&D into the market and translates them into economic and environmental benefits.

At present, scholars have conducted detailed research on GIE at three levels: region, industry, and enterprise. At the regional level, Li [15] combined the DEA model with the fuzzy evaluation method to assess the GIE, finding that GIE was mainly affected by R&D intensity. Based on panel data from 2005 to 2010, Liu [16] used the DEA-Malmquist productivity index method to evaluate GIE in China to explore the cause of spatial heterogeneity. The empirical results showed that technological backwardness is the main reason for the low GIE in various regions. At the industry level, Du et al. [1] evaluated the GIE of China's industry and found that there is spatial heterogeneity in GIE, but the technology gap among regions narrowed. Luochen et al. [2] found that the average value of GIE in China’s high-end manufacturing industry was between 0.7 and 0.8 during 2011–2017, and GIE among regions was polarised. Compared with the regional and industrial levels, there is relatively less research on GIE at the enterprise level. Based on China’s pollution-intensive enterprises’ panel data during 2007–2012, Zhao and Sun [17] conducted an analysis on the relationship between environmental regulations and the GIE of enterprises, finding that technology innovation was more important than dealing with pollution for pollution-intensive companies.

2.3. Environmental Regulation and Green Innovation Efficiency. Essentially, GIE belongs to the category of technical efficiency. Therefore, to explore the relationship between environmental regulation and GIE, we can start with the relevant literature on environmental regulation and technical efficiency. Neoclassical economic theorists believed that environmental regulation would bring an economic burden to enterprises, resulting in increased production costs of enterprises, which was not conducive to improving technical efficiency. However, Porter [18] held the opinion that environmental regulation could promote the technology innovation of enterprises and then improve technical efficiency, which was called the “Porter Hypothesis.” Since then, discussions on the validity of the “Porter Hypothesis” have never ceased, and three main views have been formed: “Environmental regulation is conducive to technical efficiency,” “Environmental regulation is not conducive to technical efficiency,” and “The impact of environmental regulation on technical efficiency is uncertain.”

The first view is a verification of the “Porter Hypothesis.” Lanjouw and Mody [19] studied environmental innovation and its diffusion effect in the United States, Japan, and Germany and found that the effect of environmental regulations on technical efficiency is positive. Jaffe and Palmer [20] found that environmental regulation improved the American manufacturing industry’s technical efficiency. Brunnermeier and Cohen [21] also verified the “Porter Hypothesis” with an empirical study of the American manufacturing industry. The second view is the denial of the “Porter Hypothesis.” This view has a profound neoclassical economic theory foundation and suggests that environmental regulation leads to an increased production cost, which is not conducive to the improvement of technical efficiency. For example, based on 56 American power companies’ panel data during 1973–1979, Gollop and Roberts [22] studied the relationship between environmental regulation and total factor productivity. They found that due to the use of high-cost and low-sulfur fuels, environmental regulation hindered the growth of total factor productivity. With the deepening of empirical studies, the third viewpoint began to appear. Lanoie et al. [23] found that the effect of environmental regulations on Canadian manufacturing productivity is inconsistent in the short and long term. Alpay et al. [24] conducted an analysis of the food processing industry in the United States and Mexico and found clear regional differences in the effect of environmental regulations on industry productivity. In addition, Yang et al. [25] found a “U” relationship between environmental regulation and total factor productivity, and the effect of environmental regulation on total factor productivity was different before and after the inflexion point.

Returning to the study on the effect of environmental regulation on GIE, Feng and Chen [26] found that environmental regulation produced positive effects on China industry’s green development by encouraging green technology innovation. He [27] also found that environmental regulation improved the GIE of manufacturing enterprises in the Pearl River Delta in China. Based on panel data of 30 provinces in China during 2009–2015, Guo et al. [28] concluded that environmental regulations had a significant positive effect on GIE. However, in the empirical study of Xi’an City, China, Li et al. [29] found that the effect of environmental regulations on GIE was not pronounced.

2.4. Knowledge Gap. As elucidated in the comprehensive literature review, the knowledge gap can be summarised as follows. (1) As the most widely used method for measuring GIE, the traditional DEA model needs to be improved, (2) there is still a limited focus on the effect of different types of environmental regulations on GIE, and (3) Shaanxi Province is located in the northwestern part of China, and its ecological environment is relatively fragile. Research on its green innovation efficiency could provide a useful reference for developing other provinces or regions. To narrow the gap, this research study has performed the following work: (1) developing a network DEA model based on a neutral cross-efficiency evaluation to measure GIE accurately and
(2) analysing the effect of different types of environmental regulations on GIE by taking Shaanxi, China, as an empirical study object.

3. Methodology

3.1. Network DEA Model Based on Neutral Cross-Efficiency Evaluation. According to the innovation value chain theory [14], green innovation activities can be defined as a system of two stages: technology R&D and technology transformation. In the stage of technology R&D, innovative resources such as human resources and funds are used to carry out research and development to produce scientific and technological achievements such as patents [1]. In the stage of technology transformation, scientific and technology achievements are further transformed into economic benefits. In general, the stage of technology transformation involves production activities [29]. Therefore, this stage would also inevitably produce a series of undesirable outputs, such as wastewater and waste gas, in addition to economic benefits. Referring to the classic two-stage model proposed by Chiang [30], which transforms a network system into a series system, each stage in the series is a parallel structure composed of a set of processes by introducing dummy processes. To effectively evaluate the GIE, a model describing the relationship between the system and the two stages needs to be established. This study constructed the green innovation activity model, as shown in Figure 1. \( X^1, Z^1, \text{and } Y^1 \) represent the input, intermediate output, and final output of the system, respectively, and \( Y^1 \) is composed of two parts: desirable outputs and undesirable outputs. \( X^2 \) represents the capital investment used to mitigate the negative effect of undesirable output on green innovation activities during the technology transformation stage.

According to the green innovation activity model in Figure 1, this study proposed a network DEA model based on a neutral cross-efficiency evaluation to measure GIE effectively. Compared with the traditional DEA model, this network DEA used a neutral cross-efficiency evaluation method, improving the objectivity and differentiation of GIE measurement results.

Suppose there are \( n \) decision-making units (DMUs), and each DMU has \( m \) inputs and \( s \) outputs. \( X_{ij}, (i=1,\ldots,m) \) and \( Y_{rij}, (r=1,\ldots,s) \) represent the \( i^{th} \) input and \( r^{th} \) output of DMU \( j; (j=1,\ldots,n) \), respectively. \( v_i \) and \( u_i \) are the weights of the \( i^{th} \) input and \( r^{th} \) output, respectively. \( E_{kk} \) represents the self-evaluation efficiency of the \( k^{th} \) DMU. By solving model (1) \( n \) times, a matrix containing the optimal combination coefficients of all DMUs can be obtained. Then, the input and output data of each DMU are multiplied by this matrix to obtain the cross-efficiency. For example, \( E_{kj} = \sum_{r=1}^{s} u_{rk} Y_{rj} / \sum_{i=1}^{m} v_{ik} X_{ij} \) is the mutual evaluation efficiency of DMU \( j \) relative to DMU \( k \), and \( E_j = (1/n) \sum_{k=1}^{n} E_{kj} \) is the cross-efficiency of DMU \( j \).

\[
E_{kk} = \max \sum_{r=1}^{s} u_{rk} Y_{rk}, \\
\text{s.t.} \quad \sum_{i=1}^{m} v_{ik} X_{ik} = 1, \\
\sum_{r=1}^{s} u_{rk} Y_{rj} - \sum_{i=1}^{m} v_{ik} X_{ij} \leq 0, \quad j = 1, 2, \ldots, n, \\
u_{r}x_{ik}, v_{ik} \geq 0, \quad r = 1, 2, \ldots, s, i = 1, 2, \ldots, m.
\]

In model (1), for the same DMU, there may be multiple sets of optimal combination coefficients, which would cause the nonuniqueness of cross-efficiency evaluation results [31]. Dolye and Green introduced a secondary goal to the model and proposed the benevolent formulation and the aggressive formulation of cross-efficiency evaluation [32]. The benevolent formulation of cross-efficiency evaluation maximises the cross-efficiencies of other DMUs, while the aggressive formulation of cross-efficiency evaluation minimises the cross-efficiencies of other DMUs. However, different formulations of cross-efficiency evaluation may lead to different efficiency evaluation results. Subsequently, Wang and Chin proposed a neutral cross-efficiency evaluation model without perspective selection [33] and optimised the model in subsequent studies [34], as shown in model (2). This model improves the objectivity of the evaluation results, effectively reduces the number of zero weights, and fully uses input-output data. In model (2), \( \alpha \geq 0 \) and \( \beta \geq 0 \) represent the weight coefficients of targets \( \delta \) and \( \gamma \), respectively, and satisfy the condition of \( \alpha + \beta = 1 \). \( E_{kk}^{\ast} \) is the self-evaluation efficiency of the DMU, which is obtained from model (1). The process of applying model (2) to calculate the neutral cross-efficiency of the DMU is the same as that of model (1).

\[
\max \alpha \cdot \delta + \beta \cdot \gamma \\
\sum_{i=1}^{m} v_{ik} X_{ik} = 1, \\
\sum_{r=1}^{s} u_{rk} Y_{rk} = E_{kk}^{\ast}, \\
\text{s.t.} \quad \sum_{r=1}^{s} u_{rk} Y_{rj} - \sum_{i=1}^{m} v_{ik} X_{ij} \leq 0, \quad j = 1, 2, \ldots, n, j \neq k, \\
u_{r}x_{ik}, v_{ik} \geq 0, \quad r = 1, \ldots, s, i = 1, \ldots, m, \\
\delta, \gamma \geq 0.
\]
For DMU $j (j = 1, \ldots, n)$, the neutral cross-efficiency of the two subsystems measured by model (2) is represented as $E_j^{(1)}$ and $E_j^{(2)}$, respectively. On the premise that each subsystem meets the CRS assumption, the green innovation activity model shown in Figure 1 can be regarded as a chain combination of the two subsystems. This study applied the entropy method proposed by Wu et al. [35] to obtain the subsystem weight coefficient $w_j (p = 1, 2)$, and then, the overall system efficiency $E_{overall}$ of DMU $j$ is determined, as shown in the following model.

$$E_{overall} = w_1 E_j^{(1)} + w_2 E_j^{(2)},$$

$$w_p = \frac{1 - H_p}{n - \sum_{p=1}^{n} H_p},$$

$$H_p = -k \sum_{i=1}^{n} f_i^{(p)} \ln f_i^{(p)},$$

$$f_i^{(p)} = \frac{E_i^{(p)}}{\sum_{i=1}^{n} E_i^{(p)}},$$

$$k = \frac{1}{\ln n},$$

$$p = 1, 2.$$

### 3.2. Regression Model

In this study, the effect of different environmental regulations on GIE was analysed incrementally using the Granger causality test, curve fitting equation, and Tobit regression model. First, the Granger causality test was applied to explore the causality relationship between different types of environmental regulations and GIE. Second, with the curve fitting equation, the evolutionary relationship between different types of environmental regulation and GIE was further analysed. Finally, this study employed the Tobit regression model to analyse the heterogeneity of different environmental regulations on GIE.

#### 3.2.1. Granger Causality Test

The Granger causality test was proposed by Granger and used to test whether Granger causality exists between variables. The Granger causality test assumes that the predicted information of the variable is included in its time series. This method tests whether the explained variable $y_t$ has a lag value by increasing the lag value of the explanatory variable $x_t$ to test whether it can significantly enhance the regression interpretation ability [36]. In general, the lag period is chosen as 2 or 3 years. This study chose 2 years as the lag period to test whether environmental regulation was the Granger cause of the GIE in Shaanxi Province. The general form of the Granger causality test is as follows:

$$y_t = \sum_{i=1}^{q} \alpha_i x_{t-i} + \sum_{j=1}^{q} \beta_j y_{t-j} + u_t,$$

$$x_t = \sum_{i=1}^{q} \lambda_i x_{t-i} + \sum_{j=1}^{q} \delta_j y_{t-j} + u_{2t}.$$

In model (4), $y_t$ and $x_t$ are the test variables, $\alpha_i, \beta_j, \lambda_i,$ and $\delta_j$ are the correlation coefficients, and $x_{t-i}$ and $y_{t-j}$ are the corresponding lag values. $u_t$ and $u_{2t}$ are the white noises and assumed that they are not related. Stationary time series is the premise of the Granger causality test. This study applied the ADF unit root test to judge whether the time series was stable.

#### 3.2.2. Curve Fitting Equation

The curve fitting equation is an effective method to analyse the relationship between two variables. In this study, a curve fitting equation was applied to analyse the evolutionary relationship between the GIE and different types of environmental regulations. Its general form is shown in model (5). GIT represents the GIE, and $x$ represents the corresponding type of environmental regulations. Other letters in the model are coefficients. In the actual process, this study conducted linear, quadratic, and cubic function fitting analysis on each environmental regulation in turn and identified the best fitting relationship based on the significance and curve fitting condition.

$$GIT = a + bx,$$

$$GIT = a + b_1 x + b_2 x^2,$$

$$GIT = a + b_1 x + b_2 x^2 + b_3 x^3.$$

#### 3.2.3. Tobit Regression Model

In this study, the explained variable is the GIE of Shaanxi Province during 2001–2017, whose value is between 0 and 1. Therefore, the GIE is truncated on both sides, belonging to the restricted dependent variable. For this kind of GIE, it is appropriate to adopt a restricted dependent variable regression model for analysis [37]. The Tobit regression model was first proposed by Tobin, which has outstanding advantages in dealing with the restricted dependent variable problem and has been widely used to analyse the influencing factors on technical efficiency [38, 39]. Hence, this study applied a Tobit regression model to analyse the effect of different environmental regulation types on the GIE in Shaanxi Province. The general form of the Tobit regression model is as follows:

$$y_{it} = \beta_0 + \beta_1 x_{it} + \theta X + \epsilon_{it},$$

$$Y_i = \begin{cases} Y_i, & Y_i > 0, \\ 0, & Y_i \leq 0. \end{cases}$$

In model (6), $y_{it}$ is the explained variable, and $x_{it}$ is the explanatory variable. $X$ represents a set of control variables, $\epsilon_{it}$ is the random error, and $\beta_1$ and $\theta$ are the corresponding coefficients. Among them, $\epsilon$ is independent and conforms to the normal distribution.
3.3. Dataset and Indicators

3.3.1. Dependent Variable. In this study, the GIE of Shaanxi Province during 2001–2017 was selected as the explained variable. GI-T, GI-1, and GI-2 represent system efficiency, technology R&D efficiency, and technology transformation efficiency, respectively. By referring to the GIE evaluation index system in previous studies, this study determined the following GIE evaluation index system of two stages, as given in Table 1. In the technology R&D stage, the number of R&D staff and investment in R&D are selected as input indicators. Researchers and funds are the most direct guarantees of innovation output, and the output is patent applications. In the technology transformation stage, the intermediate output generated during the technology R&D stage, such as patents, does not immediately withdraw from the innovation system but is redeveloped as an input. The output of the first stage (number of patent applications) is used as the input, while investment in environmental pollution treatment is used as the financial input for this stage. To realise the green innovation’s purpose to increase economic and environmental benefits, this study selects the transaction value in the technical market as a desirable output and the environmental pollution index as an undesirable output.

3.3.2. Independent Variables. Environmental regulation is the explanatory variable in this study. As mentioned earlier, environmental regulation can be divided into three types: CER, MER, and VER. In some studies, the intensity CER is characterised by the number of environmental laws [13]. The number of environmental laws mostly reflects the legislation in an area and does not represent the real implementation conditions of environmental regulations. CER focuses on controlling environmental pollution with strict regulations. Considering this, referring to Li and Ramanathan [40], this study selected the natural logarithm form of environmental administrative punishment cases to represent the intensity of CER. Since the storage amount of sewage charge has been widely used to characterise the intensity of MER [41, 42], this study also selected its natural logarithm form to represent MER. The number of environmental letters and visits reflects local residents’ participation in environmental pollution control activities [12, 13]; thus, this study selected its natural logarithm form to represent VER.

3.3.3. Control Variables. To ensure the regression results’ accuracy, this study summarised the control variables into three categories: opening degree, industrial structure, and economic development level by referring to relevant literature. Some empirical studies have shown that the effect of the opening degree on GIE is complex and uncertain [13]. On the one hand, a higher opening degree would facilitate the introduction of advanced technologies into the area, which may improve the GIE. On the other hand, in some cases, a higher opening degree may also result in the transfer of polluting enterprises. Based on the study of Li et al. [43], this study used the natural logarithm form of foreign direct investment to characterise the opening degree, represented as OPEN. The industrial structure would also affect GIE. In general, it is believed that the secondary industry is the main source of pollution [26]. Referring to the study of Shang et al. [44], the ratio of the secondary industry’s output value to the GDP was used to characterise the industrial structure, represented as IP. In addition, the economic development level is the base of green innovation and is generally considered to promote the development of GIE [13, 41]. According to Shi’s study [45], this study used the natural logarithm form of GDP per capita to characterise the economic development level, represented as ECO. Referring to the research of Xie et al. [12], this study selected the number of students enrolled in higher education per 100,000 people to represent the level of education, represented as EDU. Each variable’s description is given in Table 2, and the descriptive statistics of the data are given in Table 3.

4. Empirical Results

4.1. Analysis of Green Innovation Efficiency

4.1.1. Green Innovation Efficiency Evaluation. Figure 2 shows that the GIE of Shaanxi Province shows a “fluctuation-slow growth-steady growth” trend during 2001–2017. Based on the trend, this study divided the observation period into three stages: (1) 2001–2005, (2) 2006–2009, and (3) 2010–2017.

During 2001–2005, GIE of Shaanxi province is fluctuating. GI-1 remains unchanged overall, while GI-2 has a large fluctuation. Therefore, the change in GI-2 can be considered the main reason for the fluctuation of GIE in this period. The change in GIE and its components indicates that during 2001–2005, Shaanxi Province faced the problem of slow growth in technology R&D efficiency and large fluctuations in technology conversion efficiency.

During 2006–2009, the GIE of Shaanxi Province increased from 0.247 to 0.354, with an average annual increase of 0.036. GI-1 increased from 0.256 to 0.377, which is the main reason for the improvement of GIE. Meanwhile, GI-2 grew at a relatively low speed from 0.261 to 0.327. In this period, Shaanxi Province eliminated the slow growth of GI-1, but its GI-2 still needed further improvement.

During 2010–2017, the GIE of Shaanxi Province grew sharply from 0.410 to 0.934, with an average annual increase of 0.075, which was more than double the 2006–2009
period’s growth rate. During 2010–2013, GI-1 and GI-2 increased at similar rates, jointly improving GIE in this period. However, between 2014 and 2017, GI-1 and GI-2 showed an opposite trend, which indicates that the problem of the uncoordinated relationship between GI-1 and GI-2 has begun to appear since 2014.

4.1.2. Method Comparison Analysis. To better illustrate the advancement of the GIE measurement method proposed in this study, in addition to the network DEA model based on neutral cross-efficiency evaluation, we also applied the classic DEA model based on self-efficiency evaluation to measure the GIE of Shaanxi Province during 2001–2017 and
4.2.1. Granger Causality Analysis. The prerequisite for the Granger causality test is that the time series data are stable. To guarantee this, before the Granger causality test, the ADF test is used to test whether the time series data have unit roots. The test result is given in Table 4. From the table, it can be seen that the ADF test result rejects the null hypothesis that unit roots exist, which indicates that the time series data are stable, satisfying the prerequisite for the Granger causality test.

As given in Table 5, the first line’s $P$ value is 0.1953, indicating that the null hypothesis is accepted. Therefore, CER is not the Granger cause of GI-T. In addition, the $P$ value of the second line was 0.1024, which was near 0.10. It can be considered that the null hypothesis is rejected at the 10% significance level, which indicates that MER is the Granger cause of GI-T. Meanwhile, the null hypothesis that VER is not the Granger cause of GI-T is strongly rejected at the 1% significance level. According to the Granger causality test results, MER and VER are Granger causes of GIE in Shaanxi Province, while CER is not. The Granger causality test reveals that MER and VER may affect GI-T. However, since Granger causality is not real causality, it is necessary to confirm their relationship with further analysis.

4.2.2. Evolution Relationship Analysis. In this study, the curve fitting equation was applied to analyse the evolutionary relationship between GIE and different types of environmental regulations. In the analysis process, linear, quadratic, and cubic functions were simulated to identify the evolutionary relationship sequentially. As given in Table 6, there is a linear function evolution relationship between CER and GI-T at the significance level of 10%. The estimated coefficient is 0.575, indicating that as CER increases, GI-T increases linearly. However, as shown in Figure 4, the linear fitting evolution relationship between CER and GI-T is not ideal, which indicates that there is still some uncertainty in the relationship.

As given in Table 7, there is a quadratic function evolution relationship between MER and GI-T at the significance level of 1%. From the curve fitting relationship between MER and GI-T in Figure 5, the quadratic function’s turning point is between 10 and 10.25. On the left side of the turning point, the estimated coefficient is $-15.959$, while the right side is 0.839. The change in estimated coefficients indicates that with the turning point as the boundary, there is a clear difference in the development trend of GIE. When the MER intensity is greater than the value of the turning point, with the increase in MER, GIE also increases, which indicates that MER should be kept at a relatively high level.

As given in Table 8, there is also a quadratic function evolution relationship between VER and GI-T, and the significance level is 1%. According to the curve fitting relationship between VER and GI-T in Figure 6, the turning point is approximately 9.5. On the left side, the estimated coefficient is $-4.916$, indicating that as the intensity of VER increases, GIE in Shaanxi Province decreases. However, on the right side of the turning point, with the increase in VER, GIE also increases.

4.2.3. Effect Path Analysis. This study further applied a Tobit regression model to analyse the effect path of three types of environmental regulation on GIE. As given in Table 9, CER, MER, and VER all have a significant effect on GIE. The estimated coefficient of CER is 0.1127, indicating that the effect of CER on GIE is positive, which also validates the...
Table 4: Unit root test results.

| ADF test       | GI-T       | CER       | MER       | VER       |
|----------------|------------|-----------|-----------|-----------|
| Z statistics   | −2.706271∗(0.0959) | −4.195934∗∗(0.0243) | −2.859138∗(0.0724) | −4.480887∗∗(0.0151) |

∗∗Significance level is 5% and ∗significance level is 10%.

Table 5: Granger causality test results (the lag period is 2 years).

| Null hypothesis                  | Obs | F-statistic | Probability |
|----------------------------------|-----|-------------|-------------|
| CER is not the Granger cause of GI-T | 15  | 1.93173     | 0.1953      |
| MER is not the Granger cause of GI-T | 15  | 2.88632     | 0.1024      |
| VER is not the Granger cause of GI-T | 15  | 9.33923     | 0.0052      |

Table 6: Results of evolution relationship analysis on CER and GI-T.

| Equation | R² | F      | df | Significance | Constant | B1       |
|----------|----|--------|----|--------------|----------|----------|
| Linear   | 0.204 | 3.844  | 1  | 0.069        | −3.777   | 0.575∗   |

*The level of significance is 10%.
Table 7: Results of evolution relationship analysis on MER and GI-T.

| Equation   | R²   | F     | df | Significance | Constant | B1        | B2        |
|------------|------|-------|----|--------------|----------|-----------|-----------|
| Quadratic  | 0.880| 51.196| 2  | 0.000        | 85.875***| 15.959*** | 0.839***  |

**Significant at the 1% level.

![Figure 5: Curve fitting relationship between MER and GI-T.](image)

Table 8: Results of evolution relationship analysis on VER and GI-T.

| Equation   | R²   | F     | df | Significance | Constant | B1        | B2        |
|------------|------|-------|----|--------------|----------|-----------|-----------|
| Quadratic  | 0.621| 11.972| 2  | 0.001        | 23.737***| −4.916*** | 0.257***  |

**Significant at the 1% level.

![Figure 6: Curve fitting relationship between VER and GI-T.](image)

Table 9: Results of the Tobit regression model.

| Variable | GI-T          | GI-1        | GI-2        |
|----------|---------------|-------------|-------------|
| CER      | 0.1126626**   | 0.0196060   | 0.2085059*  |
| MER      | −0.4178697*** | −0.5162887*** | −0.3402434* |
| VER      | −0.0671508*** | −0.0221430  | −0.1157624*** |
| OPEN     | 0.0349200     | 0.2149886   | −0.1369412  |
| IP       | −0.0453262    | 0.0526397   | −0.1550041  |
| ECO      | 0.4653167**   | 0.3515238   | 0.5792363   |
| Cons     | −0.3322387    | −0.0909676  | −0.4320889  |

**Significance at the level of 1%; **significance at the level of 5%; *significance at the level of 10%.
finding in 4.2.2 that there is a linear evolutionary relationship between CER and GIE. In addition, according to the regression results of GI-1 and GI-2, the positive effect of CER on GI-2 is significant, while GI-1 is not, which indicates that CER improves GIE mainly by promoting technology transformation.

For MER, its estimated coefficient is $-0.4179$, at the significance level of 1%. The negative effect of MER on GIE indicates that Shaanxi Province should further improve its MER. Also, from the regression results of GI-1 and GI-2, it can be seen that MER has a significant negative effect on both GI-1 and GI-2, indicating that the effect of MER on GIE runs through the whole process of green innovation activities. The estimated coefficient of GI-1 is $-0.5163$, while that of GI-2 is 0.3402, which shows that MER has a stronger negative effect on technology R&D.

As shown in Table 9, the estimated coefficient of VER is approximately $-0.0672$, which is lower than MER’s estimated coefficient of $-0.4179$. This means that the negative effect of VER on GIE is weaker than that of MER. Moreover, from the regression results of GI-1 and GI-2, it can be seen that the negative effect of VER on GI-1 is not significant, but its effect on GI-2 is significant at the 1% level, which indicates that the negative effect of VER on the GIE of Shaanxi Province occurs mainly at the technology transformation stage.

Considering that the omission of variables may influence the regression results, this study introduced the education level as an independent variable into the Tobit model to conduct a robustness test. Referring to the study of Xie et al. [12], the education level is characterised by the number of students enrolled in higher education per 100,000 people and represented as EDU. As given in Table 10, there are no evident changes in the estimated coefficients of relevant variables. Therefore, it can be considered that the regression result is robust and has high credibility.

5. Discussion and Recommendation

The study results suggest that the efficiency of green innovation is on the rise in Shaanxi Province. According to the results of the Granger causality test, curve fitting equation, and Tobit regression, the effect of different types of environmental regulations on GIE is different. As for CER, it has a positive effect on GIE. Compared with the technology transformation stage, CER’s effect on the technology R&D stage is less. CER mainly focuses on the control of environmental pollution with coercive measures. In the technology R&D stage, since the technology has not yet been implemented, the environmental pollution generated in this stage is relatively limited [1]. However, in the technology transformation stage, the technology has been applied to actual production, and with the spread of technology, the scale and scope of technology applications would continue to expand; thus, environmental pollution would also increase. CER restricts the environmental pollution caused by production activities through government mandatory laws, regulations, technical standards, and emission standards [44]. Therefore, CER mainly affects the technology transformation stage. Therefore, the government can enhance the strength of CER to promote the growth of GIE. However, the linear evolution relationship between CER and GIE is not ideal. Therefore, when enhancing the strength of CER, the government should pay attention to the principle of moderation, especially to overcome the problems of rigidity, incoordination, and inefficiency of the system. Besides, the government should guide all innovation entities to allocate resources such as personnel, information, and funds and pay attention to green patents’ output and the development of green technologies. At the same time, each innovation subject should introduce high-tech talent and increase green technology development investment. Each innovation subject also needs to promptly put technological R&D into the market and convert them into economic and environmental benefits.

MER and GIE showed a U-shaped evolution relationship consistent with Yang et al.’s [25] finding. On the left side of the U-shaped curve, MER has a negative effect on GIE. The main reason is that there may be a window period for companies before taking actions after implementing MER. Only after obtaining excellent market feedback would companies take actions to invest in technology R&D [45]. When feedback appears gradually, companies begin to invest. After that, MER shows a positive effect on GIE. The study of Managi and Kaneko [47] also showed that the relationship between environmental regulation and GIE is not linear in the long term. Considering the “U”-shaped evolution relationship between MER and GIE, this study believes that the indirectness of MER mainly causes the negative effect. Therefore, MER should be further improved to exceed the turning point to stimulate MER’s induction effect on GIE. Specifically, the effective combination of environmental regulation and market mechanisms should be promoted, including marketisation of emissions trading, tax reduction, and R&D funding subsidies.

VER and GIE also show a U-shaped evolution relationship. VER mainly relies on enterprise consciousness and public participation to regulate enterprise activities [48]. On the left side of the turning point, VER has a negative effect on GIE and mainly affects the technology transformation stage. Inadequate disclosure of environmental information during the technology R&D stage may be the cause of this phenomenon. The lack of environmental information disclosure at the technology R&D stage has prevented stakeholders such as communities and citizens from playing a good supervisory role in this process. At the beginning of the VER implementation, the public awareness of environmental protection may not be strong enough, and there would be a lack of motivation for environmental supervision. This has led to the relatively weak restriction of VER on pollution [49]. Specifically, the negative effect of VER on GIE in Shaanxi Province mainly occurs in the technology transformation stage. This is because the public can only make environmental complaints after environmental pollution occurs. In contrast, in the technology R&D stage, pollution has either not yet occurred, or the degree is not apparent; thus, the public cannot participate in environmental protection supervision. Therefore, this study believes that
Shaanxi Province can encourage voluntary disclosure of environmental information and participation in the recognition of environmental labels and accelerate the improvement of corporate environmental information disclosure to make full use of public environmental supervision. By this, the public would be able to participate in environmental supervision early, improving the effectiveness of VER.

6. Conclusions

This study has developed an improved method to measure GIE and analysed the effect of different environmental regulations on GIE. Shaanxi, China, was selected as the case. The main conclusions are as follows:

(1) During 2001–2017, the trend of GIE in Shaanxi Province can be divided into three stages: 2001–2005, 2006–2009, and 2010–2017. In the first stage, GIE shows a relatively flat trend of increasing first and then decreasing, with slow growth in technology R&D efficiency and large fluctuations in technology transformation efficiency. In the second stage, GIE increases from 0.247 to 0.354, and the increase in technology R&D efficiency is the main driving force for the improvement of GIE. In the third stage, GIE increases sharply from 0.410 to 0.934, and the growth rate is also obviously accelerated. However, after 2014, the relationship between technology R&D and technology transformation began to be uncoordinated.

(2) In the observation period, CER and GIE show a linear evolutionary relationship, while MER and GIE and VER and GIE show a U-shaped evolutionary relationship in Shaanxi Province. However, the linear evolution relationship between CER and GIE is not ideal.

(3) The effects of the three types of environmental regulations on GIE are clearly different. CER has a positive effect on GIE and mainly affects the technology transformation stage. MER has a negative effect on GIE, and its effect runs through the whole process of green innovation activity. In addition, VER also has a negative effect on GIE by mainly affecting the technology transformation stage, but its negative effect on GIE is weaker than that on MER.

This study improves the evaluation methods and theoretical systems of GIE and provides the scientific basis for government decision-makers to formulate environmental regulation policies. This study’s limitation is that the interaction of environmental regulations and other control variables is not considered. Therefore, we believe that future research can be extended to explore how to build the interaction of environmental regulations and other control variables.

### Appendix

#### Classic DEA Model Based on Self-Efficiency Evaluation

To illustrate the advanced nature of the method proposed in this study, the classic DEA model based on self-efficiency evaluation was also applied to measure GIE in Shaanxi province during 2001–2017. The classic DEA model is only for initial input and final output and adopts the method of self-efficiency evaluation. The general form of the classic DEA model based on self-efficiency evaluation is shown as follows. In the model, $\rho^*$ is the GIE value. $s^-$, $s^g$, and $s^b$ represent the slack variable of input $x_0$, desirable output $y_0^g$, and undesirable output $y_0^b$, respectively, as shown in the following model.

$$\rho^* = \min \left\{ \frac{1 - (1/m)\sum_{i=1}^{m} x_i^0 / x_0}{1 + (1/s_1 + s_2) \left( \sum_{r=1}^{r^1} g^r_0 + \sum_{r=1}^{r^2} b^r_0 \right)} \right\}$$

$$x_0 = X\lambda + s^-,$n

$$y_0^g = Y^g\lambda - s^g,$n

$$y_0^b = Y^b\lambda + s^b,$n

$$s^- \geq 0, s^g \geq 0, s^b \geq 0, \lambda \geq 0.$$

(A.1)

### Data Availability

The data used to support the findings of this study are included within the article.
Conflicts of Interest
The authors declare that they have no conflicts of interest.

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