

Research Article

The Impact of Green R&D Activities on SO₂ Emissions: Evidence from China

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Prior research on the effectiveness of improving environmental performance has acknowledged the importance of domestic research and development (R&D) activities. However, these studies remain general and ambiguous because they assume that all R&D operations are associated with environmental performance. The corresponding empirical evidence is inexact and ambiguous. In this study, we focus on the effect of green R&D activities on SO₂ emission. Considering that heterogeneity exists in green R&D activities, we divide them into two groups for two purposes. The empirical results, explored based on China's interprovincial data between 2000 and 2016, suggest that green R&D activities critically influence the reduction of SO₂ emissions. However, the R&D activities of different purposes show statistically differentiated effects on SO₂ emissions. Primarily, utility-type R&D activities show the most significant positive impact on SO₂ emissions reduction. Subsequent research based on the panel threshold also indicates that the impact of green R&D activities on SO₂ emissions shows nonlinear characteristics, depending on the technology's absorptive ability.

1. Introduction

China's rapid economic growth during the past four decades, after its opening up and economic reforms, has led to rapid industrialization and urbanization. At the same time, China's air pollution problems have also become severe, attracting worldwide attention. As a major source of air pollutants, SO₂ emissions are of great concern owing to the serious threats they pose to human health. In the past decade, China has adopted a series of creative environmental protection measures to control air pollution, such as the Air Pollution Prevention and Control Action Plan (Action Plan) released in 2013 and the Three-Year Plan for Defending the Blue Sky announced in 2018. The country's top priority is balancing the new model of urbanization with ecological civilization to achieve sustainable economic development. Though China's overall air pollution has been controlled to some degree through effective energy policy measures and active transformation of the industrial system, the country's

SO₂ emissions are still the second highest in the world at 8.4 million tons at the end of 2016. Against this background, analyzing the factors contributing to SO₂ emissions has important implications in resolving the conflict between environmental preservation and economic growth.

Most scholars who investigated the drivers of SO₂ emission changes found that technological innovation and change in industrial structure are necessary for reducing SO₂ emission [1–3]. Technological innovation and deindustrialization were frequently identified as powerful impetus to reduction in SO₂ emission. Many recent studies have also examined how the drivers of technological innovation, such as domestic research and development (R&D) activities or technology spillovers through openness, influence SO₂ emission. Most of these studies have found that R&D activities can significantly decrease pollutant emissions. Xu et al. [4] extended the STRIPAT model and used China's provincial panel data to investigate the regional differences in SO₂ emission. Overall, it was found that R&D decreased

air pollutants. Chen et al. [5] used statistical data from 1997 to 2014 of 30 Chinese provinces to explore CO₂ emission trends and drivers in China. They believe that R&D intensity is useful in cutting down CO₂ emission. In a study on the industry, Shen and Lin [6] reported that R&D input has a positive correlation to energy intensity reduction in China's 27 manufacturing industrial sectors and subsectors over the period 2001–2014. The abovementioned literature demonstrates how increased R&D investments help reduce SO₂ emissions; however, it only considers the effect of overall R&D investments on SO₂ emission and does not distinguish between R&D activities that relate to green innovation and those that do not. Indeed, not all R&D activities affect environmental variables and only some can contribute to energy-saving technological innovation. Most previous studies did not address this issue and captured only the role, general R&D activities, played in SO₂ emission. As a result, the research conclusions and policy recommendations obtained from the abovementioned studies are not adequate or specific. Therefore, to explore the impact of R&D activities on SO₂ emissions at a deeper level, it is necessary to focus on green R&D innovation activities.

Further, significant heterogeneities exist within green R&D innovation activities. Various types of green R&D innovation activities result in differentiated ecological outcomes. For example, they can be divided into utility-type and innovation-type operations, each having a different impact on environmental variables. For instance, utility-type activities focus on practical values and thus have strong motivation for solving practical energy consumption problems, which may have a greater impact on reducing SO₂ emissions. Innovation-type activities pay more attention to advanced technologies; however, they are primarily occupied with theoretical value and less with application value for SO₂ emissions reduction in practice. Therefore, innovation-type activities may compromise the efficiency in reducing SO₂ emissions. As a result, the ecological outcomes of different types of energy-saving R&D activities will differ greatly. As earlier related studies overlooked the heterogeneity and discussed R&D activities as a whole, it is meaningful to study the various reasons underlying the implementation of green R&D activities.

Furthermore, the effect of green R&D activities on SO₂ emissions closely relates to technology absorptive ability. For instance, while R&D operations are more likely to benefit enterprises with high levels of technology absorption, those with low levels of technology absorption capacity may experience negative spillover effects. Therefore, there is a possible association between SO₂ emissions and green R&D activities as the technology absorptive ability changes. However, most previous studies have not paid adequate attention to this aspect and only a few studies were relevant. For instance, in terms of the panel threshold model as well as China's provincial dataset during the period 2000–2016, Huang and Chen [7] report that with negligible human capital stock, provinces will likely face difficulties in achieving a positive energy intensity reduction effect from domestic R&D activities. Roy and Schoenherr [8] suggest that nonlinear discontinuities are associated with the impact

of logistical policy interventions. Therefore, the capacity of green R&D activities to reduce SO₂ emissions is influenced by the technology absorptive ability which may be influenced by policy interventions [9].

The present study differs from the previous research in three major ways. First, to provide valid policy implications for governments, total R&D activities are narrowed to green R&D operations. Second, green R&D operations are classified according to their purpose, based on detailed information regarding the impact of their activities on SO₂ emissions. Third, technology absorptive ability is also incorporated as a significant element influencing the effect of green R&D operations on SO₂ emissions. The application of a panel threshold model revealed nonlinear impacts of green R&D activities on SO₂ emissions. Figure 1 presents the analytical framework used in the current study.

The remainder of the paper is structured as follows. The next section presents the literature review based on factors that influence SO₂ emissions. Section 3 describes the methodology and data management. Empirical results from linear regression and a thresholds model are introduced in Section 4. The conclusions and discussion are presented in Section 5, together with the policy implications.

2. Literature Review

To study the driving force behind the change in SO₂ emissions, decomposition analysis, which includes structural decomposition analysis (SDA) and index decomposition analysis (IDA), and econometrics analysis were widely used. The decomposition analysis can accurately identify whether structural change or technological innovation has been a more effective factor in driving down SO₂ emissions. However, owing to factors behind technological innovation (e.g., R&D activities) that cannot be included in the decomposition analysis, more scholars apply the econometrics analysis.

2.1. Decomposition Method. Both SDA and IDA are popular methods to assess the influence of sectoral shifts and technology changes on a variety of environmental indicators. These methods typically break down SO₂ emissions and then estimate the contribution of each factor to changes in SO₂ emissions. The SDA method is based on an input-output framework, so it can more accurately decompose the economic and technical effects. IDA has a low demand for data and allows more detailed studies at the temporal and regional levels. Studies have widely used either SDA or IDA to analyze the effect of structural change and technological innovation on SO₂ emissions. For instance, Chen et al. [2] based their research on SDA to analyze the change pattern and driving factors of SO₂ emissions embodied in inter-provincial trade in China during 2007–2012. Liu et al. [10] examined the environmental and economic factors for SO₂ emission reductions during 2002–2010 in China and evaluated the contribution of each factor using the SDA approach based on nested multiregion input-output MRIO tables (MRIO-SDA). Studies have carried out research in

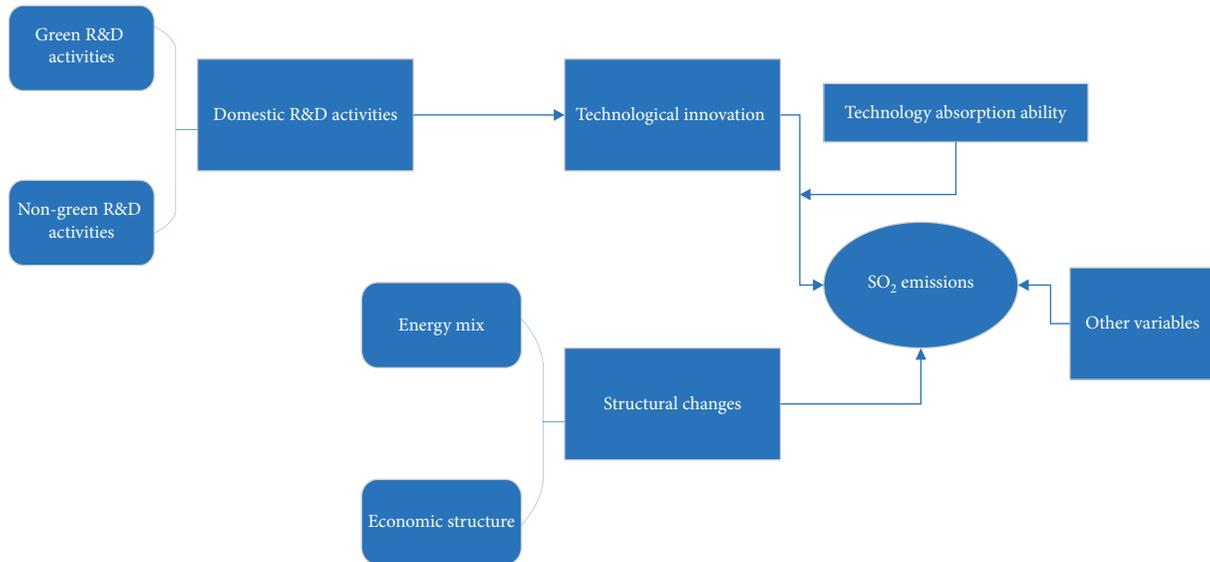


FIGURE 1: Theoretical analytical framework of this paper.

either a single region or several regions using IDA. For example, Zhang et al. [11] used the IDA model to investigate the socioeconomic factors of PM_{2.5} concentrations in 152 Chinese cities. Wang et al. [12] studied seven socioeconomic drivers of the changes in CO₂ emissions in eight Chinese regions though IDA analysis. However, such decomposition methods have limitations, as their influence factors are relatively fixed and it is easy to miss some important variables. In China, the increase in SO₂ concentration is inseparable from rapid industrialization and urbanization, and the decomposition method cannot consider both of these important factors at the same time.

2.2. Econometrics Method. The econometrics method, which directly adds each influencing factor to the econometrics model for regression analysis, is a relatively popular method at present. Since it can consider the important impact factors that cannot be added to the decomposition method, econometrics analysis has become the mainstream method for the study of SO₂ emissions.

2.2.1. Technological Innovation and SO₂ Emissions. Most literatures using econometrics analysis indicate that technological innovation is negatively related to SO₂ emissions. Some recent studies have investigated the factors behind technological innovation (e.g., R&D and technology spillovers) in detail.

R&D inputs are a typical driver of economic performance and crucial for technological innovation. Increasing R&D inputs can improve technological innovation effectively [13]. Most studies conclude that R&D activities are crucial in improving environmental performance by directly analyzing the total effect of R&D inputs on the environmental index, such as SO₂ intensity and energy intensity [7, 14, 15]. There is significant heterogeneity within the R&D activities. Only green R&D activities will contribute to

energy-saving technological innovation or reduce SO₂ emissions. Therefore, these studies only capture an average effect of total R&D activities on SO₂ emissions, and the argument that R&D activities in any technological field can influence SO₂ emissions may not be convincing.

Unlike total R&D activities, green R&D activities aid the overall green development of both society and economy [16]. They save energy more effectively and have greater significance for a sustainable society. The higher the level of inputs in green R&D activities, the more advanced the energy-saving technology would be, making a direct and stronger contribution to reducing SO₂ emissions. Therefore, the utilization of R&D activities to reduce SO₂ emissions should emphasize on green R&D activities.

2.2.2. Structural Change and SO₂ Emissions. Structural changes, closely related to SO₂ emissions, encompass energy structure and industry structure. With recent research, the environmental effects of structural changes have become more obvious, and unreasonable structures exacerbate SO₂ emissions. The first factor is the current energy mix. The huge demand for fossil fuel energy from the industrial sector directly drives the SO₂ emissions in China [17]. Here, the definition of energy mix is the ratio of coal use to total energy use. China is rich in coal resources, which occupy an absolute position in China's disposable energy structure. However, burning coal in large quantities produces harmful gases, including SO₂. Therefore, it can be expected that China's energy consumption structure, which is mainly based on coal, would be difficult to change in the short term, and the current energy structure would increase SO₂ emissions [18, 19]. In economic structure, the changes in the industrial structure have caused a shift from pollution-intensive industrial sectors to less-polluting sectors, making them a powerful tool for reducing emissions [19, 20]. However, rapid industrialization and urbanization have resulted in substantial energy requirements, impeding the

progress of SO₂ emission reduction. Therefore, most scholars agree that the higher the industry's share and contribution in the economy, the higher will be the SO₂ emissions in China [21, 22].

2.2.3. GDP and SO₂ Emissions. Several studies have indicated an inverted U relationship, also known as the environmental Kuznets curve (EKC), between pollutant emissions and income [23, 24]. This indicates that as the income level of low-income countries increases, their pollutant emissions increase. This study finds that the relationship between the emission of SO₂ and economic growth fits the EKC. There are additional studies that provide evidence on the EKC [25–28]. However, some researchers suggest that because of regional differences, relationships between pollution and economic growth were diverse. For example, this diversity is reflected in the N-shaped curve, the inverted N-shaped curve, and the dumbbell-shaped curve [29]. Wang et al. [30] used provincial panel data together with semiparametric panel fixed-effect regression and found an EKC for SO₂ emission. Zhou et al. [31] studied the nexus of SO₂ emissions and economic development by employing the spatial panel model and suggested an inversely N-shaped EKC. Another study investigated different forms of relationships by using different pollution indicators [32]. Research shows that there is no uniform relationship between economic growth and pollutant emissions [33–35].

2.2.4. Urbanization and SO₂ Emissions. China is at a critical phase of urbanization. The process of urbanization shows no signs of abating; instead, it is growing exponentially. Many researchers agree that urbanization is an important factor influencing SO₂ emissions. On the one hand, urbanization is accompanied by population aggregation and resource integration, which is beneficial in mitigating SO₂ emissions due to the scale economy effect. On the other hand, urbanization contributes to improving residents' incomes and promoting national economic development, which in turn raises energy consumption [36–38] and SO₂ emissions [39]. As China's urbanization is accelerating, it plays an important role in increasing pollutant emissions [40, 41].

3. Methodology and Data Management

3.1. Theoretical Framework. The Impact = Population-Affluence-Technology (IPAT) model has been widely applied to explore the impact of economic activities such as population growth, economic growth, and technological innovation on environmental performance, which is shown as

$$I = P \cdot A \cdot T, \quad (1)$$

where I denotes environmental performance, P stands for population scale, A represents affluence of the economy, and T represents technological innovation. However, this model suffers from the shortcoming that the effects of individual and limited factors on environmental performance are disproportionate. Dietz and Rosa [42] reformulate the IPAT model, forming the STRIPAT model as

$$I = a \cdot P^b \cdot A^c \cdot T^d \cdot e. \quad (2)$$

With the logarithm, we can show the empirical model for our estimation as

$$\ln SO_{i,t} = \beta_0 + \beta_1 \ln P_{i,t} + \beta_2 A_{i,t} + \beta_3 T_{i,t} + \varepsilon_{i,t}. \quad (3)$$

In the above equation, i represents the province, t stands for time, β_0 represents a constant term, and $\varepsilon_{i,t}$ is the random interference term. β_m ($m = 1, 2, 3$) are the parameters to be estimated, including the impact of population size and level of economic and technological development on SO₂ emissions. Based on the STRIPAT model, we explore how different factors, including economic growth and technological innovation, influence SO₂ emissions. Considering that SO₂ emissions per capita can better depict the evolution of SO₂ emissions, it is selected as our dependent variable.

3.2. Conventional Empirical Model. Considering the limitations of related literature and the actual situation in China, this study chooses four variables that may affect SO₂ emissions, namely, economic structure, energy mix, economic growth, and urbanization.

Based on the STRIPAT model, we incorporate technological innovation as the key independent variable into our empirical model. To test whether an EKC between SO₂ emissions and economic development level exists, the study further checks whether the existence of the EKC relationship between SO₂ emissions per capita and ln GDP (gross domestic product (GDP) per capita in logarithm), together with its quadratic term (to capture the nonlinear environmental effects of GDP), reflects economic growth, which is incorporated into our empirical model, presented as

$$\begin{aligned} \ln PSO_{i,t} = & \beta + \beta_1 \ln T_{i,t} + \beta_2 \ln GDP_{i,t}^2 + \beta_3 [\ln GDP_{i,t}]^2 \\ & + \beta \ln \mathbf{X} + \varepsilon_{i,t}. \end{aligned} \quad (4)$$

In the above formula, PSO represents SO₂ emissions per capita, \mathbf{X} stands for the vector matrix of control variables, β reflects the corresponding coefficient matrix, and $\varepsilon_{i,t}$ represents the disturbance terms. The symbol "ln" stands for the natural logarithm. Other subscripts and variables are the same as in model 2. The existence of the EKC can be judged by analyzing the sign and significance of the coefficient on the ln GDP together with its quadratic term, ln GDP².

Based on the literature review and the ground situation in China, urbanization was selected as the main variable affecting SO₂ emissions. In accordance with most researches, urbanization is defined as a ratio, i.e., urban population divided by total population [40, 41, 43]. In addition, the energy structure may help energy-intensive sectors such as coal to expand, resulting in increased SO₂ emissions. The proportion of coal consumption in the total energy consumption is expressed by energy structure [19, 44]. China is modernizing its economy, accelerating urbanization as well as industrialization, making the economic structure an important variable affecting its SO₂ emissions. We choose

the rate of the added value in the secondary industries in GDP to express the economic structure [45–47]. Therefore, these variables are utilized to examine the effects on SO₂ emission reduction in China.

Previous studies on the effectiveness of improving environmental performance have acknowledged the importance of R&D activities. However, these studies remain general and ambiguous because they assume that all R&D activities are related to environmental performance. To explore the impact of R&D activities on SO₂ more specifically, it is necessary to focus on green R&D innovation activities.

We present the empirical model with general R&D activities (GRD) as the main variable for SO₂ emissions in the following equation:

$$\ln \text{PSO}_{i,t} = \beta + \beta_1 \ln \text{GDP}_{i,t} + \beta_2 [\ln \text{GDP}_{i,t}]^2 + \beta_3 \ln \text{GRD}_{i,t} + \beta \ln \mathbf{X} + \varepsilon_{i,t}. \quad (5)$$

We include the control variables into equation (5), subsequently assessing utility-type R&D operations (UGRD) and creation R&D operations (CGRD) as panel data framework, demonstrated as follows:

$$\begin{aligned} \ln \text{PSO}_{i,t} = & \eta + \lambda_1 \ln \text{CGRD}_{i,t} + \lambda_2 \ln \text{UGRD}_{i,t} \\ & + \lambda_3 \ln \text{GDP}_{i,t} + \lambda_4 [\ln \text{GDP}_{i,t}]^2 + \lambda_5 \ln \text{IND}_{i,t} \\ & + \lambda_6 \ln \text{ENSTR}_{i,t} + \lambda_7 \ln \text{UR}_{i,t} + \varepsilon_{i,t}. \end{aligned} \quad (6)$$

As green R&D activities can be categorized based on their purpose, and the two kinds of R&D operations will probably show disparate effects on SO₂ emissions, considering the heterogeneity of the R&D operations, the empirical model is given as

$$\begin{aligned} \ln \text{PSO}_{i,t} = & \eta + \lambda_1 \ln \text{CGRD}_{i,t} + \lambda_2 \ln \text{UGRD}_{i,t} \\ & + \lambda_3 \ln \text{GDP}_{i,t} + \lambda_4 [\ln \text{GDP}_{i,t}]^2 + \lambda_5 \ln \text{IND}_{i,t} \\ & + \lambda_6 \ln \text{ENSTR}_{i,t} + \lambda_7 \ln \text{UR}_{i,t} + \varepsilon_{i,t}. \end{aligned} \quad (7)$$

In the above formula, λ_1 and λ_2 represent the coefficients of CGRD and UGRD, respectively. λ_m ($m = 5, 6, 7$) indicate the coefficients of control variables: IND, ENSTR, and UR, denoting the composition of secondary industry added value to GDP, energy structure, and urbanization, respectively.

Since green R&D operations may enhance the positive impact of utility-type green R&D activities on cutting SO₂ emissions, we incorporate the cross-term (i.e., $\ln \text{CGRD} * \ln \text{UGRD}$) into our empirical model to test whether this effect exists, shown as

$$\begin{aligned} \ln \text{PSO}_{i,t} = & \eta + \lambda_1 \ln \text{CGRD}_{i,t} + \lambda_2 \ln \text{UGRD}_{i,t} \\ & + \lambda_3 \ln \text{CGRD}_{i,t} * \ln \text{UGRD}_{i,t} + \lambda_4 \ln \text{GDP}_{i,t} \\ & + \lambda_5 [\ln \text{GDP}_{i,t}]^2 + \lambda_m \mathbf{X} + \varepsilon_{i,t}. \end{aligned} \quad (8)$$

In the model above, we focus on the coefficient of λ_3 . If the coefficient is significant and negative, the creation of green R&D operations is beneficial in helping utility-type green R&D activities to reduce SO₂ emissions.

3.3. Panel Threshold Model. Linear analysis in the traditional method can merely show the impact of green R&D activities on SO₂ emissions on average and cannot reflect the nonlinear effects under different technology absorption capacities. Based on this, the study considers the full-time equivalent of R&D personnel (FEP), which is the product of the number of R&D operating staff and their working hours per year as the threshold variables, constructs a nonlinear impact model of various green R&D activities on SO₂ emissions, and examines the threshold effect of those activities and the degree of FEP.

By applying Hansen's endogenous threshold approach (before continuing the nonlinear analysis, it is essential to assess the threshold influence via the null hypothesis: H_0 ($\beta_1 = \beta_2$). When the null hypothesis is true, there is no threshold influence; therefore, the model is a linear model), we can explore the variations in the influence of the FEP on SO₂ emissions at various degrees. Subsequent to Hansen [48], the panel threshold model that has one threshold value is presented as follows:

$$\ln \text{PSO}_{i,t} = \begin{cases} \alpha_i + X_{i,t} \beta_1 + u_{i,t} & q_{i,t} < \gamma, \\ \alpha_i + X_{i,t} \beta_2 + u_{i,t} & q_{i,t} \geq \gamma. \end{cases} \quad (9)$$

In the above equation, q_i represents a cohort of threshold variables that we select to reflect FEP, γ denotes the threshold value, and X stands for a vector to explain variables, including relevant patents and systematical transformation. If q_i is higher than the threshold value γ , the threshold coefficient of q_i would be β_2 . Otherwise, the threshold coefficient of q_i is β_1 .

After verifying the single threshold, checking if two thresholds exist in the model is important. The equation is presented as follows:

$$\ln \text{PSO}_{i,t} = \begin{cases} \alpha_i + X_{i,t}' \beta_1 + u_i & q_i < \gamma_1, \\ \alpha_i + X_{i,t}' \beta_2 + u_i & \gamma_2 \leq q_i, \\ \alpha_i + X_{i,t}' \beta_3 + u_i & \gamma_3 \leq q_i, \end{cases} \quad (10)$$

In the above equation, β_1 , β_2 , and β_3 are the coefficients of the threshold variables for the three dimensions of the threshold. The rest of the variables resemble equation (9). Huang and Yu [49]; Lai et al. [50]; and Cohen and Levinthal

[51] indicate that FEP can serve as a main driver for both speeding up technological development and improving technology absorption ability. Consequently, FEP is typically considered to be a tool to measure technology absorption ability. We use the figure of R&D personnel as well as their work time to indicate FEP.

3.4. Data Source and Management. A panel dataset that includes China's 30 provinces from 2000 to 2016 is used in the sample analysis because the data for Tibet, Hong Kong, Macao, and Taiwan are unavailable.

The explained variable (i.e., SO₂ emissions) is presented as the ratio of SO₂ consumption divided by the overall population (unit: ton/person). The data on population and SO₂ emissions are collected from China Statistical Yearbooks (CSY) between 2001 and 2017. Before calculating GDP per capita (ratio of GDP to population), the statistics on GDP were adjusted to the 2000 constant price via the GDP deflator, both sourced from CSY.

Green R&D activity is presented as the number of energy-saving patents, which were sourced from the Chinese patent database. The green patent system is a public policy that combines green technology innovation, which is considered a positive means to develop the economy and the key to SO₂ reduction. There are seven major categories of green innovation: waste management, energy-saving technologies, administrative supervision, transportation management, nuclear power generation, alternative energy, and agriculture and forestry management. Our empirical data comprise the sum of these categories and we obtained the number of green patents using the standard application date. The number of utility-type R&D activities and creation R&D operations denote the various purposes of green R&D operations. Although utility-type R&D patents are less technological than creation R&D patents, which primarily represent green R&D proposals on new products and materials, they emphasize practical application value.

The rate of the added value in secondary industries over GDP denotes the economic structure. The impact of urbanization upon SO₂ emissions is obtained from the ratio of urban population to total population. The ratio of coal use to total energy use denotes the composition of energy, with relative data obtained from CSY. Table 1 provides detailed information on every variable and Table 2 shows the descriptive analysis correlation coefficient matrix.

4. Results and Discussion

4.1. Results from Linear Regression Analysis. First, we choose fixed effects (FE) for the econometrics analyses, which are the conventional panel regression approaches. With regard to the potential bias problem, the Driscoll and Kraay (DK) estimator is introduced into our empirical analysis to identify autocorrelations or heteroskedasticity. According to Hoechle [52], the DK estimator can provide a more robust standard error in general forms of cross-sectional and temporal dependence. After carefully considering the applicability of the estimation method, models (1) to (3) are

estimated through FE and DK estimators. Based on equations (6)–(8), models (1) to (3) adopt the fixed-effects model and the DK approach, respectively, to determine the linear relationship between various sources of technological innovation and China's SO₂ emissions shown in Table 3. We employ FE in our models. Additionally, both heteroskedasticity and serial correlation are found [53, 54]. Consequently, the DK estimator is applied. The results of model 1 provided by the FE and DK estimators are shown in columns 2 and 3, respectively. Columns 3 and 4 show the estimates of model 2, and the final two columns provide the estimates of model 3.

While evaluating the impact of green R&D activities, we used general R&D patents in equation (6) and added utility-type patents and creation patents in equation (7). Next, we used a cross-term of utility-type patents and creation patents in equation (8) as variables. With regard to general green R&D activities, the coefficient (i.e., $\ln GRD$) is negative and significant, as expected. This suggests that general green R&D operations will positively affect SO₂ emissions reduction. A 1% increase in total patents will lead to an approximately 5.6% decrease in SO₂ emissions.

When considering the green R&D activities for various purposes (i.e., $\ln UGRD$ and $\ln CGRD$), we employ DK estimators to reevaluate the model. Table 3 shows the empirical results. Although utility-type R&D activities are equipped with lower-level technology compared to creation activities, they solve practical problems and emphasize practicability. Utility patents are significantly negative for SO₂ emissions (−0.076), while creation patents are insignificant, which implies that creation patents are not beneficial to environmental improvement as they are not intended for practical application. It is surprising to note the major differences in terms of the coefficients in $\ln UGRD$ and $\ln CGRD$. Between the two different purposes of green R&D activities, only utility-type activities show a positive and significant role in reducing SO₂ emissions, indicating that utility-type activities, rather than creation activities, have a strong positive impact on SO₂ emission reduction.

To acquire detailed information on how green R&D activities affect SO₂ emissions, we applied DK to estimate the cross-term model. As shown, the coefficient on the cross-term (i.e., $\ln UGRD * \ln CGRD$) is significant and negative, implying that utility-type activities will help creation activities to reduce SO₂ emissions.

The other variables and test results are similar to the results shown in the earlier models. For example, the EKC hypothesis of SO₂ emissions still holds. According to the results presented in Table 3, the first-order coefficient of GDP per capita is positive and the second-order coefficient is negative, indicating that China's EKC has an inflection point and the characteristics of an inverted u-shaped curve. The empirical study indicates that, first, environmental quality deteriorates with increased economic growth and subsequently shows an improving trend. The regression results show that the proportion of secondary industries has a significant positive effect on SO₂ emissions, indicating that unreasonable industrial structures will increase environmental pollution. Although the industrial structures of most

TABLE 1: Definition and data description of the variables.

Code	Definition	Proxy variables
PSO	SO ₂ emissions per capita	The ratio of the SO ₂ emissions divided by population
PGDP	GDP per capita	The rate of GDP divided by the population gross
IND	Economic structure	The rate of the added value in the secondary industries in GDP
ENSTR	Energy structure	The rate of coal consumption in total energy
UR	Urbanization	The ratio of urban population to the population gross
GRD	Green R&D operations	The figure of green patents
UGRD	Utility green R&D operations	The figure of utility green patents
CGRD	Creation green R&D activities	The figure of creation green patents
FEP	Full-time equivalent of R&D personnel	The figure of R&D staff recruited regarding their working hours

TABLE 2: Descriptive analysis correlation coefficient matrix.

	ln PSO	ln GRD	ln CGRD	ln UGRD	ln PGDP	ln PGDP ²	ln IND	ln ENSTR	ln UR
ln PSO	1								
ln GRD	-0.261	1							
ln CGRD	-0.271	0.987	1						
ln UGRD	-0.249	0.979	0.943	1					
ln PGDP	-0.197	0.822	0.824	0.8	1				
ln PGDP ²	-0.222	0.636	0.635	0.622	0.764	1			
ln IND	0.472	0.201	0.164	0.252	0.17	-0.0024	1		
ln ENSTR	0.511	-0.101	-0.14	-0.0599	-0.24	-0.255	0.524	1	
ln UR	-0.139	0.648	0.667	0.602	0.876	0.646	0.0731	-0.342	1

TABLE 3: The results of different green R&D activities on SO₂ emissions.

	d1		d2		d3	
	FE	DK	FE	DK	FE	DK
ln PGDP	0.247*** (0.093)	0.247*** (0.068)	0.287*** (0.094)	0.287*** (0.073)	0.148 (0.091)	0.148 (0.014)
ln PGDP ²	-0.171*** (0.029)	-0.171*** (0.039)	-0.162*** (0.029)	-0.162*** (0.038)	-0.014 (0.033)	-0.014 (0.031)
ln IND	0.666*** (0.102)	0.666*** (0.127)	0.635*** (0.103)	0.635*** (0.129)	0.599*** (0.097)	0.599*** (0.129)
ln ENSTR	0.830*** (0.085)	0.830*** (0.068)	0.800*** (0.086)	0.800*** (0.067)	0.660*** (0.083)	0.660*** (0.061)
ln UR	-0.276 (0.2)	-0.276 (0.171)	-0.216 (0.201)	-0.216 (0.166)	0.13 (0.195)	0.13 (0.154)
ln GRD	-0.056* (0.032)	-0.056* (0.024)				
ln UGRD			-0.076** (0.03)	-0.076** (0.014)	0.069** (0.034)	0.069** (0.016)
ln CGRD			-0.012 (0.029)	-0.012 (0.024)	0.097*** (0.03)	0.097*** (0.021)
ln ICGRD * ln IUGRD				-0.036***	-0.036*** (0.005)	(0.002)
_cons	-1.785** (0.895)	-1.785** (0.933)	-1.719* (0.89)	-1.719* (0.893)	-2.735*** (0.85)	-2.735*** (0.618)
Vif	4.11		6.30		5.29	
Heteroscedasticity test	2077.44***		2076.36***		2195.37***	
Autocorrelation test	78.148***		75.523***		70.041***	
CD	28.623***		28.309***		28.196***	
N	510	510	510	510	510	510

Notes: (a) ***, **, and * represent a respective significance level at 1%, 5%, and 10%. (b) Values in () stand for the standard error for the coefficient. (c) The null hypothesis for the heteroscedasticity test is that no heteroscedasticity exists. (d) The null hypothesis for the autocorrelation test is that no first-order autocorrelation exists. (e) The CD test examines cross-sectional dependence of residuals. In the CD test, the null hypothesis is cross-section independent.

provinces in China are developing rationally, some provinces continue to overly depend on secondary industries, and the problems of high resource and energy consumption and serious environmental pollution undoubtedly still exist. Adjusting and optimizing the industrial structure are still a crucial issue in China's current stage of economic growth.

Second, the results show that energy mix has a positive effect on SO₂ emissions and is significant at the 1% level, indicating that the current energy mix prompts the community to emit more pollutants but, at the same time, improves SO₂ emissions. This is because China is still in high-speed industrialization, with a strong dependence on coal, especially for the heavy industry. Compared with other developed countries, China still relies on the development of the coal industry; consequently, the problems of high energy consumption and serious environmental pollution continue. Moreover, the price advantages of coal determine the coal-dominated energy mix, leading to massive use of coal in economic development, affecting the energy mix and SO₂ emissions. However, the negative value of the coefficient of urbanization implies that industrial agglomeration and population concentration have saved construction efforts and intensified the use of resources, thus improving the urban environment.

The above analysis has an endogeneity problem, common to environmental analyses. Therefore, a robustness test is further employed. First, the effect of policy is considered as another control variable in the model [15]. The Chinese government has been strictly controlling emissions of pollutants since 2013; therefore, a policy dummy variable is introduced, which is equal to one since 2013 and zero before that. It is expected that this energy-saving policy would strongly decrease SO₂ emissions. The empirical outcomes are listed in columns 1 to 3 of Table 4. The other estimator is almost identical to the results presented in Table 3, implying the robustness of the empirical results in the study.

A second factor is openness. Throughout the last 40 years, China has continually expanded its foreign capital inflows and exports. This openness in terms of export has positively impacted economic growth [55], while also affecting environmental performance. In accordance with Xu et al. [4], export is defined as exports divided by GDP. The empirical outcomes are listed in columns 4 to 6 of Table 4. All estimators are almost identical to the results presented in Table 3, proving the robustness of the empirical results in the present study.

4.2. Results from the Nonlinear Analysis. The panel threshold model was adopted for comprehensively revealing how technology absorption capacity affects the innovations that influence China's SO₂ emissions. Before conducting the nonlinear analysis, it is necessary to examine if there is a threshold effect between technological innovations and China's SO₂ emissions using the bootstrap method introduced by Hansen. Tables 5 and 6 show the results of the threshold effects. After applying the bootstrap method to test if a threshold impact exists, the number of thresholds is estimated as follows.

As evident in Table 5, the impact of various innovations on China's SO₂ emissions is not linear but shows a structural break. When the level of FEP is the threshold variable, the triple threshold of F-statistics is significant at the 1% level, suggesting that the impact of FEP on China's SO₂ emissions is not linear. The above empirical evidence reveals that various innovations manifest high sensitivity toward changes in FEP.

Table 6 presents the nonlinear evaluation results by applying the panel threshold model when FEP is at varied levels. When selecting general patents (ln GRD), utility-type patents (ln UGRD), and invention patents (ln CGRD) as the variables of concern, the rejection of three nonexistent thresholds for these patents reached significance at the 1% level. Summarizing these results, Table 5 shows that the impact of green R&D activities generated by various channels on SO₂ emissions in China has a significant threshold effect, which changes with the FEP input and is very sensitive. Table 5 shows the specific estimation findings using the threshold panel model.

As demonstrated in row 2 of Table 6, FEP serves as the threshold variable. The impact of green R&D activities generated by general patents on SO₂ emissions varies as the level of FEP input changes. When the FEP entry level is lower than the first threshold (i.e., 1.866), the green R&D impact of general patents can reduce SO₂ emissions, although the impact is less significant. However, once the FEP surpasses the first threshold but is less than the second threshold value (i.e., 3.087), the technological spillover generated by general patents can significantly reduce SO₂ emissions to the 10% level. When FEP further increases (i.e., $3.087 < \gamma < 9.435$), green R&D activities generated by general patents will reduce SO₂ emissions to a 1% significant level with a coefficient of -0.093 . The higher the FEP input, the greater is the effect of general patents on SO₂ emissions reduction. When FEP exceeds the third threshold value (9.435), the coefficient of general patents is -0.128 and is significant. This indicates that increase in FEP can enhance the positive spillover effect of general patents on reducing SO₂ emissions.

Rows 3 and 4 of Table 6 show that when the selected threshold variable is FEP, the impact of green R&D activities generated by utility patents on SO₂ emissions changes as FEP varies. When FEP investment is lower than the first threshold (1.866), green R&D activities from utility patents can reduce SO₂ emissions, although the effect is less significant. Once FEP is greater than the first threshold, regardless of the range, the green R&D activities generated by utility patents can play a role in reducing SO₂ emissions, which is comparable to the results for general patents. As mentioned above, the empirical results of selecting FEP as a threshold variable show that the rise in FEP level can enhance the positive spillover effect of utility-type patents on reducing SO₂ emissions.

Rows 5 to 6 of Table 6 show the impact of green R&D activities generated by creation patents on SO₂ emissions when the selected threshold variable is FEP. When FEP investment is lower than the first threshold (1.866), the creation patents increase SO₂ emissions, although it is not

TABLE 4: The results of different green R&D activities on SO₂ emissions (robustness test).

	d1	d2	d3	d4	d5	d6
ln PGDP	0.293*** (0.094)	0.336*** (0.096)	0.197** (0.092)	0.219** (0.097)	0.259*** (0.099)	0.181* (0.094)
(ln PGDP) ²	-0.165*** (0.029)	-0.156*** (0.029)	-0.009 (0.033)	-0.166*** (0.029)	-0.158*** (0.029)	-0.012 (0.033)
ln IND	0.562*** (0.11)	0.532*** (0.11)	0.500*** (0.104)	0.688*** (0.104)	0.655*** (0.105)	0.568*** (0.1)
ln ENSTR	0.816*** (0.084)	0.787*** (0.085)	0.648*** (0.082)	0.840*** (0.085)	0.809*** (0.086)	0.640*** (0.084)
ln UR	-0.298 (0.199)	-0.237 (0.2)	0.108 (0.194)	-0.209 (0.21)	-0.159 (0.21)	0.065 (0.2)
ln GRD	-0.049 (0.032)			-0.056* (0.032)		
ln UGRD		-0.072*** (0.03)	0.072** (0.034)		-0.075** (0.03)	0.075** (0.035)
ln CGRD		-0.01 (0.028)	0.098*** (0.03)		-0.011 (0.029)	0.102*** (0.031)
ln ICGRD * ln IUGRD		-0.036***			-0.038***	
_cons	-1.3 (0.911)	-1.232 (0.907)	-2.262*** (0.865)	-2.237** (0.997)	-2.116** (0.994)	-2.203*** (0.937)
Heteroscedasticity test	1969.17***	1951.03***	2071.71***	2077.44***	2062.93***	2164.13***
Autocorrelation test	55.793***	67.573***	62.006***	62.119***	60.71***	57.975***
CD	30.151***	29.758***	29.617***	29.493***	29.062***	27.196***
N	510	510	510	510	510	510

Notes: (a) ***, **, and * represent a respective significance level at 1%, 5%, and 10%. (b) Values in () stand for the standard error for the coefficient. (c) The null hypothesis for the heteroscedasticity test is that no heteroscedasticity exists. (d) The null hypothesis for the autocorrelation test is that no first-order autocorrelation exists. (e) The CD test examines cross-sectional dependence of residuals. In the CD test, the null hypothesis is cross-section independent. (f) Since DK and FE are similar in results, we only provide FE results.

TABLE 5: Test of threshold effects by selecting the FEP as the threshold variable.

Threshold variable	Independent variable		Threshold value	F	p value	5% critical value
FEP	ln GRD	Single threshold effect	9.435	21.727	0	3.716
		Double threshold effect	1.866, 9.435	18.414	0	4.122
		Triple threshold effect	1.866, 3.087, 9.435	10.227	0	3.822
	ln UGRD	Single threshold effect	1.866	20.653	0	3.513
		Double threshold effect	1.866, 9.435	19.933	0	3.478
		Triple threshold effect	1.866, 3.087, 9.435	10.113	0	3.926
	ln CGRD	Single threshold effect	9.435	19.948	0	3.626
		Double threshold effect	3.087, 9.435	18.072	0	3.291
		Triple threshold effect	1.866, 3.331, 9.435	8.585	0	3.612

significant. When FEP continues to increase and surpasses the first threshold but is less than the second threshold ($1.866 < \gamma < 3.331$), the creation patents have no significant impact on SO₂ emissions, although they can reduce it. When FEP increases further, creation patents can reduce SO₂ emissions and are significant at 5% and 1% levels, respectively. The result clearly shows that the increase in FEP level has changed the negative influence of creation patents on SO₂ emissions.

The increase in FEP level can result in a more significant impact of utility patents on SO₂ emission reduction because enterprises engaged in the production of goods will actively absorb the SO₂ emissions reduction knowledge and technology, which will help various channels to create a positive spillover effect on reducing SO₂ emissions. The empirical

findings show that the purpose of FEP investment using utility patents is clear as it can directly reduce SO₂ emissions. The conclusion is in line with the findings of Wang et al. [19], who studied the nonlinear effect of indigenous innovations on the export channel of China's industrial energy intensity, and Huang et al. [38], who studied the technological spillover effect of independent innovations on export channels on China's interprovincial energy intensity. This does not negate the classic theory that increasing human capital investment will promote the absorption of new incoming knowledge and technology. Such empirical conclusions may be because creation patents are less involved in the field of practice and do not have well-defined purpose, thereby rendering their role considerable.

TABLE 6: The nonlinear effect of green R&D activities on SO₂ emissions.

Threshold variable	Independent variable	Threshold value	Variable	Coefficient	Threshold value	Variable	Coefficient	Threshold value	Variable	Coefficient	Threshold value	Variable	Coefficient
FEP	ln GRD	$\gamma < 1.866$	ln GRD	-0.021	$1.866 < \gamma < 3.087$	ln GRD	-0.063***	$3.087 < \gamma < 9.435$	ln GRD	-0.093***	$9.435 < \gamma$	ln GRD	-0.128***
			ln UGRD	-0.008	$1.866 < \gamma < 3.087$	ln UGRD	-0.063***	$3.087 < \gamma < 9.435$	ln UGRD	-0.100***	$9.435 < \gamma$	ln UGRD	-0.136***
	ln UGRD	$\gamma < 1.866$	ln CGRD	-0.021	$1.866 < \gamma < 3.087$	ln CGRD	-0.021	$3.087 < \gamma < 9.435$	ln CGRD	-0.021	$9.435 < \gamma$	ln CGRD	-0.021
			ln UGRD	-0.055*	$1.866 < \gamma < 3.331$	ln UGRD	-0.055**	$3.331 < \gamma < 9.435$	ln UGRD	-0.055**	$9.435 < \gamma$	ln UGRD	-0.055*
	ln CGRD	$\gamma < 1.866$	ln CGRD	0.014	$1.866 < \gamma < 3.331$	ln CGRD	-0.031	$3.331 < \gamma < 9.435$	ln CGRD	-0.063**	$9.435 < \gamma$	ln CGRD	-0.100***
			ln CGRD	0.014	$1.866 < \gamma < 3.331$	ln CGRD	-0.031	$3.331 < \gamma < 9.435$	ln CGRD	-0.063**	$9.435 < \gamma$	ln CGRD	-0.100***

Based on the experimental results discussed above, the influence of green innovation R&D activities on SO₂ emissions is always seen to be nonlinear; it is also sensitive to the change of FEP. Therefore, it can be suggested that the technology spillover through green innovation R&D activities is weaker than for utility patents.

5. Conclusions and Policy Implications

This study describes the creation of a unified analysis framework that includes technological innovation formed by green R&D operations to analyze their impact on SO₂ emissions in China, using interprovincial panel data from 2000 to 2016. First, the study applies a fixed-effect model to explore and compare the influence of various green R&D activities on SO₂ emissions. Second, given that the obvious differences in technology absorption capacity may lead to differentiated effects of green R&D on the SO₂ emissions, the study also applies the threshold panel model to analyze the characteristics of the impact of FEP on SO₂ emissions through various green R&D activities. The main research conclusions and policy recommendations are summarized as follows.

5.1. Conclusions. The regression results on the basis of the linear model show that among various sources of technological innovation, green R&D operations are essential for reducing SO₂ emissions in China. However, significant heterogeneities exist within green R&D activities. Categorizing the green R&D operations by different purposes makes it possible to obtain findings that are more insightful. Second, utility-type green R&D activities are a major contributor to reducing SO₂ emissions. Utility-type patents can also reduce SO₂ emissions, while the green R&D activities formed by creation patents have no significant effect on them. However, the impact of such creation activities facilitates utility-type patents in reducing SO₂ emissions.

Structural changes also affect SO₂ emissions. The share of secondary industries in GDP as a proxy variable for economic composition promotes SO₂ emissions. Notably, secondary industries account for the majority share of energy consumption and emissions that contribute to pollution. A country's energy mix is another structural factor that affects SO₂ emissions because coal consumption is closely linked with SO₂ emissions. The higher an economy's dependence on coal, the greater the contribution to SO₂ emissions will be.

It is possible for Chinese provinces to increase efficient production and lower operating costs by absorbing, digesting, and applying external experience. The technology absorption ability is among the most important determinants of SO₂ emission. Huang et al. [38] and Adom [56] found that the impact of green R&D on energy intensity depends on the strength of the technology absorption ability, while traditional linear analysis methods can merely show the average influence of various explaining variables upon the explained variables. This research developed a nonlinear

model to investigate the nonlinear relationship between various green R&D operations and SO₂ emissions in China.

Empirical studies using the threshold panel model show that the influence of green R&D formed by various channels on SO₂ emissions has a nonlinear effect, which is closely related to factors such as FEP. When the level of FEP is low, green R&D activities generated by general patents and utility-type patents can reduce SO₂ emissions, but the effect is not significant. When the FEP level increases, the impact of general patent and utility-type patents on SO₂ emissions will be significantly heavy. Unlike the impact of the former two patents on SO₂ emissions, the effect of green R&D activities generated by creation patents will vary from positive to negative as the level of FEP increases. This shows that creation patents need more upfront investment to have a positive effect, which will lead to greater SO₂ emission reductions in China to curb pollution.

5.2. Policy Implications. First, the public policy and associated governmental regulatory implications play a critical role in determining the supply chain of the energy industry. In response to the current evolution of SO₂ emissions, the government should promptly reform energy pricing and implement differential energy taxation and subsidy policies for high and low energy consumption industries, while simultaneously promoting technology upgrades in high energy-consumption industries and encouraging enterprises to introduce energy-saving production equipment. Second, reasonable environmental regulatory policies need to be formulated and appropriate environmental regulations enacted to stimulate corporate green technological innovation, improve energy use efficiency, and reduce SO₂ emissions. Finally, the manufacturing industry may consider increasing the R&D capital and high-level human capital investment to improve energy use efficiency. Based on the combination of technology introduction and absorption, technological transformation and reinnovation can be carried out to effectively utilize technology introduction. It can also be used to solve the problem of redundancy in the internal managements of enterprises and the diseconomies of scale in energy consumption caused by excessive industrial concentration. This could aid in eventually reducing SO₂ emissions.

The findings show that to reduce SO₂ emissions, China must continue to adhere to "sustainable" development paths such as green R&D activities and regard these green technologies as the most important tool for this purpose. Green R&D activities in various channels are important factors affecting SO₂ emissions, particularly utility-type patents. To promote the positive spillover effect of creation patents on reducing SO₂ emission, in addition to the new policies on patent protection, China must combine green R&D policies with sustainable economic development strategies. Policy-makers must consider the characteristics of the influence of various green R&D initiatives on SO₂ when formulating relevant policies. To maximize the positive spillover effect of various green R&D activities, the FEP level must be appropriately increased, with emphasis on strengthening

utility-type R&D activities. In addition, the government must improve both energy and industrial structures and adopt measures specifically focused on reducing the share of secondary and energy-intensive industries.

Although the empirical evidence in this study reveals the impact mechanism of various green R&D activities on China's SO₂ emissions, due to data limitations (e.g., no data available on some patents), the constructed indicators cannot fully and accurately reflect the characteristics of technological absorption capacity of green R&D activities, affecting per capita SO₂ emissions in China.

Data Availability

The data underlying the findings of the paper are publicly available and also available on request to the authors.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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