



# Will China's R&D investment improve green innovation performance? An empirical study

Jundi Fan<sup>1</sup> · Thompson Teo<sup>2</sup>

Received: 17 September 2021 / Accepted: 29 December 2021 / Published online: 31 January 2022  
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## Abstract

In 2020, China's R&D investment reached 2442.6 billion RMB, and it ranks second in the world, but the performance of green innovation has not proportionately improved. The question of how to promote the improvement of green innovation performance is particularly important in order to mitigate future environmental problems and issues due to rapid development of China's economy. While past research has examined the relationship between R&D investment and green innovation, they have not explicitly considered the effect of regional technological innovation level on this relationship. Hence, we fill this gap by exploring the relationship between R&D investment and green innovation performance using data from various regions in China from 2015 to 2019, under the effect of a threshold variable, namely, technological innovation. We explore the impact of economic development level, environmental regulation level, foreign direct investment, and science and technology in fiscal expenditures on green innovation performance. The empirical results show that when the regional technological innovation level is used as the threshold variable, the R&D investment has a significant double-threshold effect with the lagging three-phase green innovation performance. When the technological innovation level is low ( $< 0.1082$ ), R&D investment has a negative impact on green innovation performance. Moreover, when the technological innovation level is high ( $> 0.5837$ ), the impact of regional R&D investment on green innovation performance is sub-optimal. Consequently, the range of  $[0.1082$  to  $0.5837]$  is the best range for the positive impact of R&D investment on green innovation performance. Furthermore, among China's 30 provinces and cities, 24% (mostly areas located in the southwest and northeast of China) have the technological innovation level in the optimal range. Our results help explain the current status of China's R&D investment and green innovation development, and provide a theoretical basis for the formulation of government innovation investment policies.

**Keywords** R&D investment · Green innovation performance · Technological innovation level · Panel threshold model · SBM-DDF model

## Introduction

Due to the continual deterioration of the environment, there is increased emphasis on environmental protection (Du et al. 2019). Global warming and climate change will

promote an increase in international pressure, and energy and environmental issues are significant challenges facing mankind (and China) today. Coal consumption in the BRIC countries (Brazil, Russia, India, China, and South Africa) will increase carbon dioxide emissions, which can lead to severe global warming (Adedoyin et al. 2020). China is currently facing significant energy and environmental dilemma, the shortage of oil and gas resources, and carbon dioxide emissions are significant hindrances to China's green and high-quality economic development (Zhan et al. 2021). In addition, the massive consumption of energy and the lack of environmental protection measures have led to serious air and water pollution in many areas of China. About two-thirds of China's cities do not meet basic air quality standards (Liu et al. 2021). Therefore, promoting green innovation performance, i.e.,

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Responsible Editor: Nicholas Apergis

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✉ Jundi Fan  
1115660416@qq.com  
Thompson Teo  
bizteosh@nus.edu.sg

<sup>1</sup> School of Economics and Management, Harbin Engineering University, Harbin, China

<sup>2</sup> Department of Analytics & Operations, National University of Singapore, Singapore, Singapore

the effectiveness of green innovation, is a key priority in China. Note that green innovation refers to innovation that are related to sustainable development.

R&D investment is an important driving force for regional green innovation and an important factor affecting the performance of regional green innovation (He et al. 2021). Research has found that the R&D expenditures of 28 EU countries are closely related to the ecological footprint (Adedoyin et al. 2020). In recent years, China has also actively implemented the innovation-driven development strategy and has continuously increased its R&D investment (Guo et al. 2021). At present, China Science and Technology Statistical Yearbook shows that China's R&D investment has been increasing in the past ten years, specifically 706.258 billion RMB in 2010 to 22143.58 billion RMB in 2019. It increased by 31.35 times in ten years, and its ratio to China's GDP in 2019 is 2.40%. While investment in R&D has continued to increase, China's environmental pollution has become increasingly serious, and regional green innovation performance has not increased proportionately (Hao et al. 2021). Therefore, in the process of implementing the innovation-driven strategy, the issue of how to coordinate and rationally allocate R&D resources so as to improve the regional green innovation performance effectively has become increasingly critical.

The level of technological innovation is also an important factor affecting the performance of green innovation (Wang et al. 2021). At the same time, the level of regional heterogeneity of technological innovation can nonlinearly affect regional green innovation performance, and ignoring this nonlinear threshold effect of technological innovation will lead to biased estimation results (Zhai and An 2021). With the rapid development of China's economy, differences in technological innovation resources and technological innovation levels between regions have gradually emerged (Zhou et al. 2021a). The distribution of regional technological innovation resources in various regions in China is uneven, and there is a large gap in the level of technological innovation development among different regions (Wang et al. 2021).

The China Regional Science and Technology Innovation Evaluation Report 2020 divides the technological innovation capabilities of 31 regions across China into three echelons: The first echelon comprises six regions—Shanghai, Beijing, Guangdong, Tianjin, Jiangsu and Zhejiang. The second echelon comprises 17 regions including Chongqing, Hubei, Shaanxi and Anhui. The third echelon comprises 8 regions—Inner Mongolia, Guangxi, Yunnan, Guizhou, Hainan, Qinghai, Xinjiang, and Tibet. These echelons indicate that the eastern coastal areas of China (first echelon) are rich in technological innovation resources, while the western regions (third echelon) are relatively backward in technological innovation development (Hao and Deng 2019).

With the increasing attention to green innovation, we need to address the issue of mitigating adverse environmental impact in the context where technological innovation has become an important issue for China (Du et al. 2021). However, while China's R&D investment has been increasing, the performance of green innovation has not been improved proportionally (Hao et al. 2021). In recent years, scholars have focused on the impact of R&D investment on green innovation performance and the impact of technological innovation on green innovation performance (Wang et al. 2021). But they did not combine these three variables to explore the nonlinear impact of R&D investment on green innovation performance when the level of technological innovation is used as the threshold variable. Therefore, we combine R&D investment, technological innovation level and green innovation performance variables, and explore the impact of R&D investment in 30 provinces and cities in China on green innovation performance under the effect of technological innovation level variable.

The novelties of this research are as follows. First, scholars have conducted research on the direction of R&D investment on regional innovation efficiency, CO<sub>2</sub> emissions, technological upgrading and economic growth, but there are few studies on the direction of green innovation performance (Tang et al. 2021; Boeing et al. 2022; Kihombo et al. 2021). Further, past research has often focused on the measurement of green innovation performance (Luo et al. 2021). However, scholars have seldom focused on the impact of China's R&D investment on green innovation performance. Therefore, we examine the impact of China's regional R&D investment on green innovation performance, and explore the different effects of R&D investment in different stages on green innovation performance. This paper fills the research gap in this direction. Second, scholars have not used the threshold regression model to explore the relationship between R&D investment, technological innovation level, and green innovation performance. Past research showed that a large number of nonlinear relationships embodied in economic variables had been ignored in past studies (Anderson et al. 2015). Ignoring this non-linear threshold of technological innovation leads to biased estimation results (Zhai and An 2021). We introduce the level of technological innovation as a threshold variable, and use the threshold regression model to introduce a new threshold variable to study the combined effect of the three variables. Then, explore the impact of R&D investment on green innovation performance under the effect of the level of technological innovation in different regions of China. This paper fills the research gap in this direction and provides a new research perspective.

Third, scholars have conducted research on the impact of China's economic development level, environmental regulation level, foreign direct investment, and government expenditure on scientific and technological on the

performance of green innovation in fiscal expenditures, but they seldom use them as control variables in the threshold model to discuss the impact on green innovation performance (Zhou and Zhao 2021; Peng et al. 2021). This paper incorporates it as a model control variable into the model to study its impact on green innovation performance, providing a new research perspective. Fourth, past research have not divided the scope of policy investment based on the level of technological innovation. This paper explores the impact of R&D investment on green innovation performance under the effect of different regional technological innovation levels and provides empirical evidence for decision-makers to formulate R&D investment policies. It provides a new perspective for the formulation of regional R&D investment policies (Zhao et al. 2019; Yi and Xiao-li 2018). The rest of the paper is organized as follows. The “Literature review” section describes the literature review on green innovation, the relationship between R&D investment and green innovation performance, and the relationship between technological innovation and green innovation performance. The “Research design” section elaborates on variable selection and model construction, including the slack-based model-directional distance function (SBM-DDF) model and panel threshold model. The “Empirical research” section reveals the empirical results, including threshold regression results, threshold regression coefficients and tests, likelihood ratio function graphs and the distribution of threshold values in each province and city. The “Discussion” section discusses the empirical results and the “Conclusion” section concludes the paper.

## Literature review

### Green innovation

Green innovation is the general term referring to technologies, processes or products that are used to reduce environmental pollution, save raw materials and energy, and achieve cleaner production (Yang et al. 2021). Past research on green innovation has mostly focused on the antecedent factors of green innovation and the measurement of green innovation performance. Specifically, research has discussed the impact of financing constraints on corporate green innovation (Yu et al. 2021), explored the relationship between financial development and corporate green innovation (Lv et al. 2021), analyzed the impact of different environmental regulations on regional green innovation (Luo et al. 2021), and discussed the impact of the government's behavior in setting economic growth targets on regional green innovation (Shen et al. 2021). Other research has used various models such as the SBM-DDF model to measure: the green innovation performance of Xi'an in China from 2003 to 2016

(Zhang et al. 2018), the green innovation efficiency of 235 cities in China from 2004 to 2016 (Fan et al. 2021), and the efficiency of green innovation in 30 provinces and cities in China (Fan and Xiao 2021). Other models include the DEA model to measure China's provincial green innovation efficiency from 1997 to 2018 (Huang et al. 2021), and the super-SBM model to measure the green innovation performance of 30 provinces in China from 2003 to 2017 (Zeng et al. 2021).

### R&D investment and technological innovation versus green innovation

Past research has compared the impact of R&D investment in different regions of China and foreign technology spillovers on green innovation performance, and concluded that the positive impact of R&D investment on green innovation performance is greater than that of foreign technology (Luo et al. 2021). Other research has found that government R&D expenditures can increase the green innovation performance of energy-intensive companies by 54.1% (Bai et al. 2019), green growth depends on technological innovation, GDP, human capital, economic globalization and R&D expenditures (Wang et al. 2021), and R&D investment has played a leading role in increasing regional green patent applications (Zhou et al. 2021b).

In addition, research has found that the higher the administrative level of a city, the more obvious the effect of technological innovation on the green development of the city (Zhang et al. 2018). Technological innovation has a positive impact on regional green innovation performance (Guo et al. 2017) and can improve energy efficiency, reduce energy consumption, and improve regional green innovation performance (Huang et al. 2017). Although technological innovation has a positive effect on green growth (Wang et al. 2021), it has a heterogeneous impact on the efficiency of the green economy among different cities in China (Liu et al. 2021). In a similar vein, research found that there are variations in the impact of technological innovation on the green growth of the 28 Organization for Economic Cooperation and Development (OECD) economies, grouped into Oceania, America, Asia and Europe (Mensah et al. 2019).

## Research design

### Variable selection

Various indicators have been used to measure green innovation performance. For example, scholars have used full-time equivalents of R&D personnel, R&D capital investment as input indicators, the number of patent applications and sales of new products as expected output indicators, and industrial SO<sub>2</sub> emissions as undesired output indicators (Zhang

et al. 2021). Another research have used R&D personnel, R&D expenditures and total urban gas supply as input indicators, the number of authorized invention patents and per capita GDP and greening rate as expected output indicators, and SO<sub>2</sub> as undesired output indicators (Zhang et al. 2020). Moreover scholars have used the total number of employees in prefecture-level cities, the total fixed assets and energy consumption of the whole society as input indicators, the gross domestic product as expected output indicators, the amount of industrial wastewater and sulfur dioxide emissions, and the amount of industrial smoke as undesired output indicators (Sun et al. 2020). This paper combines the mentioned literature and selects the following indicators to measure China's green innovation performance based on the availability of data and the actual situation in China. The indicators are divided into input indicators, output indicators, and undesired output indicators (Zhang et al. 2021) (Table 1). The input indicators are the full-time equivalent of R&D personnel (Jiang et al. 2021), R&D expenditure input (Bai et al. 2019) and total energy consumption (Sun et al. 2019). The desired output indicators are the amount of patents applications (Li et al. 2018) and the sales revenue of new products (Li and Du 2021). The undesired output indicators are industrial wastewater emissions, sulfur dioxide, nitrogen oxides, soot and dust, and industrial solid waste emissions indicators (Zhang et al. 2020). Principal component analysis is used to fit the five indicators to the industrial environmental pollution comprehensive index for measurement (Liu et al. 2018).

The level of regional technological innovation is used as the threshold variable. Threshold variables refer to variables that will affect the degree of the explanatory variable's influence on the explained variable. Under different levels of the threshold variable, the explanatory variable will have different effects on the explained variable. Scholars have used a single index to measure the level of regional innovation, e.g., patent grant volume index (Chen et al. 2020), and new

product sales revenue index (Jianmin and Li 2020). Other scholars have used comprehensive indicators to measure the regional innovation level, e.g., the number of papers included, the number of patent authorizations, the turnover of the technology market (Mensah et al. 2019), the number of foreign scientific and technological papers, the number of patent applications accepted, the proportion of new product revenue to the main business revenue, and the number of technical market transaction contracts to measure regional innovation level (Liu and Dong 2021). Since a single index measuring the regional innovation level is not representative, this paper measures regional innovation level by selecting four indicators commonly used in past research: patent authorization amount, new product sales revenue, number of scientific and technological papers included in foreign search tools, and number of technical market transaction contracts.

Scholars have used R&D expenditure to measure R&D investment (Wang et al. 2021; Luo et al. 2021), explored the relationship between R&D investment and energy intensity in China's manufacturing industry (Shen and Lin 2020), and the impact of innovation network scale and R&D investment on regional innovation performance (Min et al. 2020). Existing studies have shown that the impact of R&D investment on technology performance often has a lag effect (Liu and Dong 2021). In this paper, in line with Su and Yu (2020), we select the internal expenditure of R&D funds three periods ahead as the core explanatory variable.

Environmental regulation level, government expenditure on science and technology, economic development level and foreign direct investment were chosen as control variables for the following reasons: Environmental regulations have an important impact on the performance of green innovation (Guo et al. 2017). from the perspective of formulating laws and regulations and environmental protection measures (Du et al. 2021). Moreover, the level of economic development is an important factor affecting the performance of regional green innovation (Su and Yu 2020) as it influences the level

**Table 1** Selection and description of input and output indicators

Indicators	Measure	Units	Sources
Input	Personnel investment	full-time equivalent of R&D personnel personnel	China Science and Technology Statistical Yearbook
	Fund investment	R&D expenditure	China Science and Technology Statistical Yearbook
	Energy investment	total energy consumption	China Statistical Yearbook
Desired Output	Patent output	amount of patents applications	China Science and Technology Statistical Yearbook
	Product output	sales revenue of new products	China Science and Technology Statistical Yearbook
Undesired output	Waste water	industrial wastewater emissions	China Statistical Yearbook
	Exhaust gas	sulfur dioxide	China Statistical Yearbook
		nitrogen oxides	China Statistical Yearbook
		soot and dust	China Statistical Yearbook
Solid waste	industrial solid waste emissions	China Statistical Yearbook	

of technological innovation (Miao et al. 2021). Furthermore, developing countries tend to lower environmental standards to attract foreign direct investment to promote economic growth (Shen et al. 2021). Foreign direct investment will have an important impact on green innovation performance through the interaction of capital and technology (Amen-dolagine et al. 2021). Finally, the Chinese government plays a leading role in green innovation, often in the form of funding. Therefore, science and technology in fiscal expenditures will also have an important impact on green innovation performance (Wu and Hu 2020).

### Model construction

This paper divides the green innovation performance indicators into three parts: input, desired output, and undesired output, uses the SBM-DDF model to measure green innovation performance, and then uses the regional technological innovation level as a threshold variable to explore the impact of R&D investment on green innovation performance.

### SBM-DDF model

In this paper, the province is the decision-making unit to construct the production frontier of provincial green innovation performance for each period. Assuming that  $n$  types of inputs  $x = (x_1, \dots, x_n) \in R_N$  are used to obtain  $m$  types of expected output  $y = (y_1, \dots, y_m) \in R_M$  and  $l$  undesired output  $b = (b_1, \dots, b_l) \in R_L$ ; then, the input-output value in the  $k$  region during period  $t$  is  $(x^{t,k}, y^{t,k}, b^{t,k})$ . The SBM directional distance function is as follows:

$$S_v^-(x^{t,k}, y^{t,k}, b^{t,k}; g^x, g^y, g^b) = \max_{s^x, s^y, s^b} \frac{\frac{1}{N} \sum_{n=1}^N \frac{g_n^x}{g_n^x + s_n^x} + \frac{1}{M+L} \left( \sum_{m=1}^M \frac{g_m^y}{g_m^y + s_m^y} + \sum_{l=1}^L \frac{g_l^b}{g_l^b + s_l^b} \right)}{2} \quad (1)$$

$$\begin{aligned} \text{s.t. } & \sum_{k=1}^K \lambda_k^t x_{kn}^t + s_n^x = x_{kn}^t, \quad \sum_{k=1}^K \lambda_k^t x_{kl}^t + s_l^x = x_{kl}^t \\ & +s_m^x = x_{km}^t, \quad \text{s.t. } \sum_{k=1}^K \lambda_k^t x_{kl}^t + s_l^x = x_{kl}^t \end{aligned} \quad (2)$$

$$\sum_{k=1}^K \lambda_k^t = 1; \lambda_k^t \geq 0; s_n^x \geq 0; s_m^y \geq 0; s_l^b \geq 0 \quad (3)$$

where,  $S_v^! bb$  represents the directional distance function under variable returns to scale, when the constraint condition  $\sum_{k=1}^K \lambda_k^t = 1$  is removed, which is expressed as the directional distance function of constant returns to scale.  $(x^{t,k}, y^{t,k}, b^{t,k})$ ,  $(g^x, g^y, g^b)$ , and  $(s_n^x, s_m^y, s_l^b)$  represents the input and output vectors, the direction vectors, and the relaxation vectors, respectively.

In the linear programming of the SBM-DDF model, the constraints are expressed in the form of inequalities. This could be regarded as a kind of “loose” constraint, which is

the foundation for the existence of slack variables. In Figure 1,  $P'$  is the projection of  $P$  on the boundary, but compared with point  $A$ , the generation of  $P'$  is insufficient ( $P'A$  segment). If  $X_t - X_\alpha = 0$  or  $y_t - Y_\alpha = 0$ , there is no input slack variable or output slack variable in the model. The significance of the slack variable in the model is that the observation point is best when each of its elements is at 0, otherwise there is room to be improved. Then, this paper considers environmental factors in the model. The definition is as follows:

$$\rightarrow_D \left( x, y, b; \rightarrow_g \right) = \sup \left\{ \beta : \left( y, b + \beta \rightarrow_g \in P(x) \right) \right\} \quad (4)$$

In the equation,  $x$  is the input vector,  $y$  and  $g$  are the desirable output vectors, and undesired output vectors are  $b$  and  $g$ .  $\rightarrow_g = \left( \rightarrow_{g_x}, \rightarrow_{g_y}, \rightarrow_{g_b} \right)$  is the direction vector,  $\beta$  is the maximum possible value for the desirable output of  $y$  growth and the undesired output of  $b$  reduction. Suppose each decision making unit (DMU) uses  $N$  inputs  $x = (x_1, \dots, x_N) \in R_N^+$  to obtain  $M$  kinds of desirable outputs  $y = (y_1, \dots, y_M) \in R_M^+$  and  $I$  kinds of undesired outputs  $b = (b_1, \dots, b_L) \in R_L^+$ .  $P^t(x)$  denotes the set of production possibilities for the  $t=1, \dots, T$  period:  $P^t(x) = \{ (y^t, b^t) : x^t \rightarrow (y^t, b^t), x \in R_+^N \}$ . We place the input, desirable output, and undesired output variables into the model, then use the Maxdea software to get the empirical results.

### Threshold regression model

This paper examines the impact of China's R&D investment on green innovation performance at different technological levels.

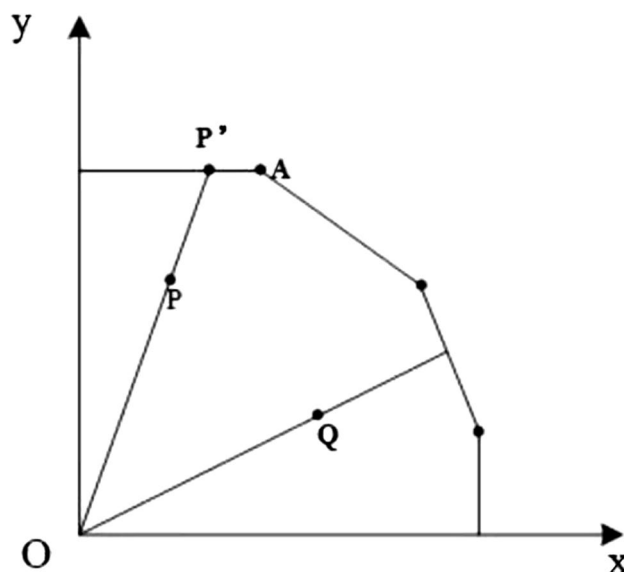


Fig. 1 Slack variables diagram

Threshold regression analysis explores the nonlinear relationship between the core explanatory variable and the explained variable under the action of the threshold variable (Zhou and Zhao 2021). It uses threshold variables to determine structural change points, and then forms observations to estimate the true threshold, so as to deal with nonlinear problems more accurately (Hansen 1999). It can be used in the combination of three variables and the situation of nonlinear effects (Yi and Xiao-li 2018); (Wang and Liu 2019). Hence, it is deemed suitable for our study. In order to avoid the bias caused by artificially dividing the technological innovation level interval and ensure the authenticity of the threshold regression results, this paper uses the Hensen threshold regression model to analyze and test the threshold effect between variables. The single threshold model for R&D investment is as follows:

$$GIP_{it} = \theta + \alpha_1 RIE_{it} + \alpha_2 ERC_{it} + \alpha_3 FDI_{it} + \alpha_4 FEL_{it} + \beta_1 RDE_{it-3} I(T_{it} \leq \gamma) + \beta_2 RDE_{it-3} I(T_{it} > \gamma) + \mu_i + v_t + \varepsilon_{it} \tag{5}$$

Among them  $I(\bullet)$  is the indicative function,  $T_{it}$  is the threshold variable regional technological innovation level, GIP is the explained variable green innovation performance, RIE is the level of economic development, ERC is the level of environmental regulation, FDI is the amount of foreign direct investment, and FEL is the science and technology in fiscal expenditures. RDE is the core explanatory variable R&D expenditure input,  $\gamma$  is the variable threshold,  $\mu_i$  is the individual specific effect,  $v_t$  is the time effect, and  $\varepsilon_{it}$  is the random disturbance item. The two-threshold model that can be promoted is as follows:

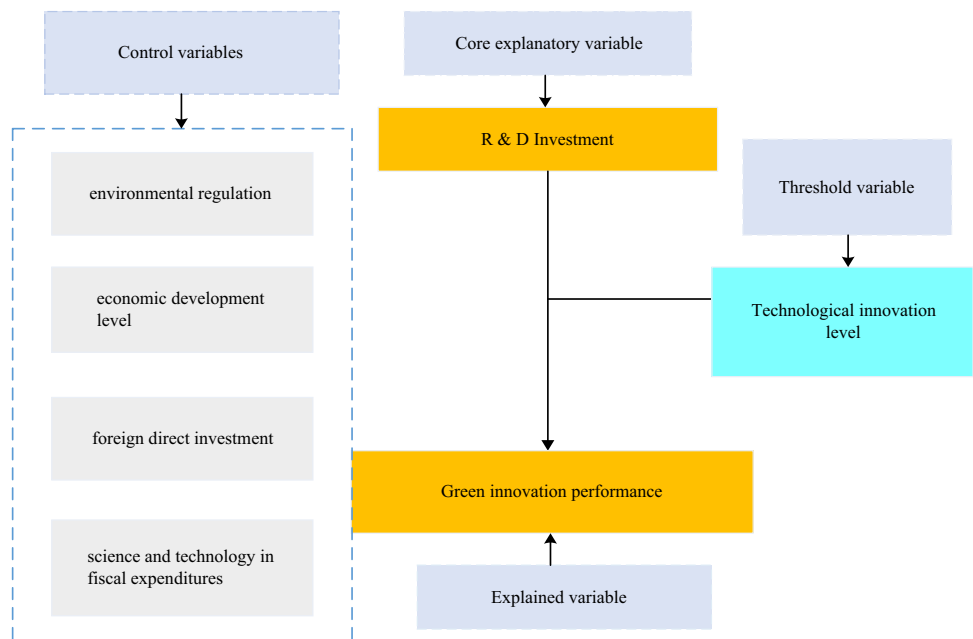
$$GIP_{it} = \theta + \alpha_1 RIE_{it} + \alpha_2 ERC_{it} + \alpha_3 FDI_{it} + \alpha_4 FEL_{it} + \beta_1 RDE_{it-3} I(T_{it} \leq \gamma_1) + \beta_2 RDE_{it-3} I(\gamma_1 < T_{it} \leq \gamma_2) + \beta_3 RDE_{it-3} I(T_{it} > \gamma_2) + \mu_i + v_t + \varepsilon_{it} \tag{6}$$

Among them,  $\gamma_1 \cdot \gamma_2$  represents the double threshold value, and the other symbols are the same as formula (5). Figure 2 is the threshold model diagram.

### Empirical research

This paper conducted threshold regression based on the panel data of 30 provinces and cities in China from 2015 to 2019, and excluded the Tibet Autonomous Region, Hong Kong and Macao administrative regions due to the lack of data. The data were obtained from the «China Statistical Yearbook» and «China Science and Technology Statistical Yearbook». The amount of R&D input (RDE) three periods ahead is the core explanatory variable, green innovation performance is the explained variable, and technological innovation level is the threshold variable. The level of economic development (RIE), government expenditure on science and technology (FEL), foreign direct investment (FDI), and environmental regulation (ERC), are the control variables. A single/double/triple threshold(s) means that the influence function has one/two/three inflection point(s), and the influence function is divided into two/three/four different degrees of influence intervals. The single threshold, double threshold and triple threshold models were tested and the results are shown in Table 2.

Fig. 2 Threshold model diagram



**Table 2** Threshold regression results

	Threshold estimate	<i>p</i>	BS frequency	95% confidence interval
Single threshold model	0.1082	0.0133	300	[0.1018,0.1688]
Double threshold model	0.1082,0.5837	0.0367	300	[0.1018,0.1688] [0.5764,0.5903]
Triple threshold model	0.5289	0.5667	300	[0.5253,0.5307]

The estimated threshold of the single threshold model is significant (0.1082,  $p < 0.05$ ). The estimated thresholds of the double threshold model are also significant (0.1082 and 0.5837,  $p < 0.05$ ). The estimated threshold of the triple threshold model is not significant (0.5289,  $p > 0.05$ ). Hence, this paper is based on the analysis of the double threshold model. The threshold model coefficients and related tests are shown in Table 3.

When the level of technological innovation is used as the threshold variable, there is an obvious non-linear relationship between the R&D investment and the performance of green innovation. When the technological innovation level is less than 0.1082, there is a negative relationship between R&D investment 3 periods ahead and green innovation performance (coef = -5.7983,  $p < 0.01$ ). This indicates that for every increase of one unit of R&D investment 3 periods ahead, the performance of green innovation decreases by 5.7983 units. This shows that the level of regional innovation is low, and the region's attention to green innovation is also low. In other words, R&D investment has a negative effect on regional green innovation performance.

Similarly, when the technological innovation level is between 0.1082 and 0.5837, there is a positive relationship between R&D investment and green innovation performance (coef = 9.5377,  $p < 0.001$ ). This indicates that for every increase of one unit of R&D investment 3 periods ahead, the green innovation performance increases strongly

by 9.5377 units. Although there is a certain accumulation of regional technological innovation, the level of technological innovation is not at a high level. At this level of technological innovation, relatively few pollutants are produced, and the pollutants produced are within the range that the region can afford. Although the level of green innovation at this interval is also low, China's regional R&D investment has a greater positive effect on regional green innovation performance (relative to the third interval). Previous research also showed that R&D investment and emission taxes can reduce CO<sub>2</sub> (Ma et al. 2021). Investment in energy and technological innovation helps to reduce emissions (Guo et al. 2021).

When the technological innovation level is higher than 0.5837, there is a positive relationship between R&D investment and green innovation performance (coef = 5.0918,  $p < 0.001$ ). This indicates that for every increase of one unit of R&D investment 3 periods ahead, the green innovation performance increases by 5.0918 units. At this time, R&D investment have a positive impact on green innovation performance, but the impact is lower than the [0.1082, 0.5837] interval. In this interval, the regional technological innovation level is at a relatively high level, but the green innovation technology has not yet been developed and perfected (relative to the second interval). After the R&D investment is used in technological innovation, the pollutants generated by technological innovation exceed the transformable level of green innovation, and the pollutants generated are beyond the range that the region can afford. Therefore, although

**Table 3** Threshold regression coefficient and test

Single threshold model			Double threshold model		
GIP	Coef	<i>p</i>	GIP	Coef	<i>p</i>
RIE	-1.2421	0.088	RIE	-1.2913	0.077
FEL	0.0678	0.000	FEL	0.0895	0.003
FDI	0.0001	0.848	FDI	0.0113	0.142
ERC	0.3363	0.247	ERC	0.3007	0.106
RDE (CD ≤ 0.1082)	-3.3481	0.000	RDE (CD ≤ 0.1082)	-5.7983	0.001
RDE (CD > 0.1082)	4.0928	0.003	RDE(0.1082 < CD ≤ 0.5837)	9.5377	0.000
			RDE(CD > 0.5837)	5.0918	0.000
Constant	-0.4129	0.000	Constant	-0.4217	0.089

GIP-green innovation performance, RIE-level of economic development, FEL-science and technology in fiscal expenditures, FDI-amount of foreign direct investment, ERC-level of environmental regulation, RDE -R&D expenditure input, CD-technological innovation level (threshold)

China's regional R&D investment has a positive impact on green innovation performance when the technological innovation level is higher than 0.5837, the degree of positive impact is relatively small. Regarding the control variables, science and technology in fiscal expenditures have positive impacts on the performance of green innovation (coef=0.0678,  $p < 0.001$ ). This result is consistent with previous research, which found that science and technology in fiscal expenditures had positive impacts on the performance of green innovation (Liu 2011). Figures 3 and 4 are the likelihood ratio function diagrams drawn according to the double threshold model. With the help of the likelihood ratio function diagram, the threshold estimates and confidence intervals can be observed more intuitively, and the consistency between them and the true threshold can be tested.

Specifically, we use the likelihood ratio  $LR$  to construct the “technological innovation level non-rejection region.” The “technological innovation level non-rejection region” at the confidence level of  $1 - \alpha$  is a series of values that belong to  $LR \leq c(\alpha)$ . When  $LR \leq c(\alpha) = -2\ln(1 - \sqrt{1 - \alpha})$  ( $\alpha$  is the level of significance, and  $c(\alpha) = 7.35$  at the 95% confidence level), we cannot reject the null hypothesis that the technological innovation level threshold estimate is equal to the true value ( $H_0 : \gamma = \gamma_0$ ) (Hansen 1999). When  $LR = 0$ , the corresponding values are the technological innovation level threshold estimates, namely 0.108 (Figure 1) and 0.584 (Figure 2). The 95% confidence interval means that the LR value is lower than the critical value  $-2\ln(1 - \alpha)$ , that is, the technological innovation level estimated value interval when it is lower than 7.7532, which corresponds to the interval below the dotted line in the figure. Therefore, the technological innovation level threshold estimates are all within the corresponding confidence interval, so the

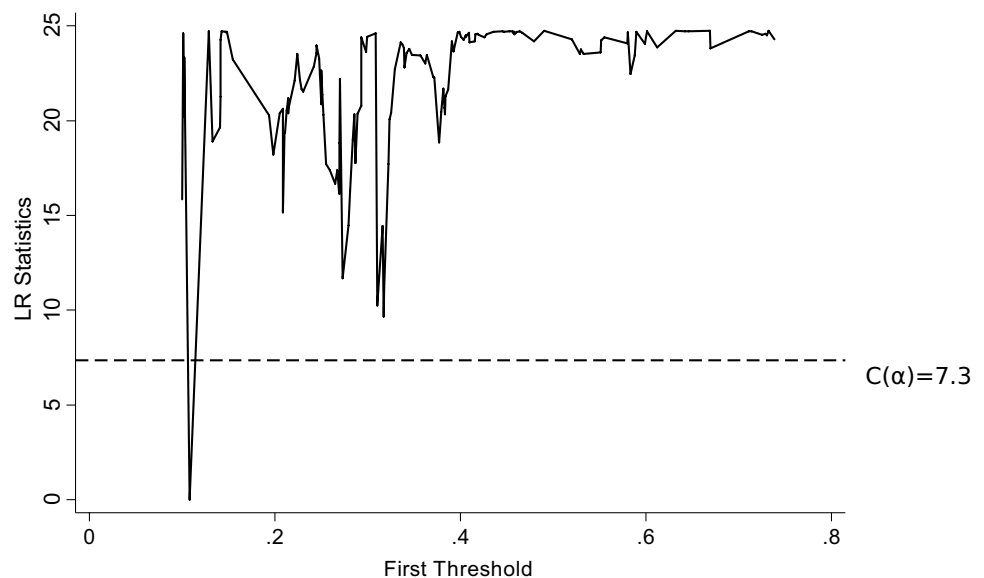
technological innovation level threshold estimates are consistent with the true values. We analyzed the technological innovation levels of 30 provinces and cities from 2015 to 2019 based on the estimated threshold values. The distribution is shown in Table 4.

From 2015 to 2019, about 12% of China's 30 provinces and cities have a technological innovation level of less than 0.1082. Such regions are located in remote areas of western China, and their technological innovation and economic development levels are relatively backward. Among the 30 provinces and cities in China, those with technological innovation levels between 0.1082 and 0.5837 accounted for about 24%. Such regions are mostly located in the southwest and northeast of China. The level of technological innovation has improved compared with the remote areas in the west, but is still low. About 64% of China's 30 provinces and cities have a technological innovation level of 0.5837. Such regions are mostly located in the central and east of China. The infrastructure construction in such areas is relatively complete, and the level of economic development and technological innovation is relatively high.

Among them, the R&D investment of provinces and cities with technological innovation level lower than 0.1082 has a negative impact on green innovation performance. It shows that such regions are located in remote areas of western China. Although natural resources are abundant, the economic development speed and technological innovation level are low, and the awareness of green innovation is weak. This region should pay attention to the promotion of regional technological innovation level and green innovation awareness. A substantial increase in R&D investment should be made after the level of technological innovation is improved.

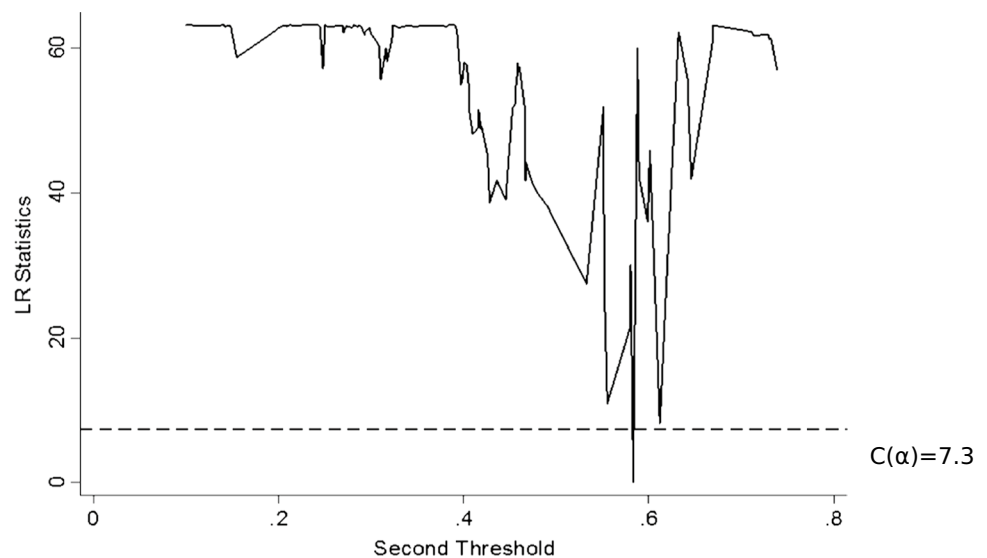
For provinces and cities with technological innovation levels between 0.1082 and 0.5837, their R&D investment has

**Fig. 3** The first threshold estimate likelihood ratio function graph





**Fig. 4** The second threshold estimate likelihood ratio function graph



a relatively significant role in promoting green innovation performance. Such regions are mostly located in the central, southwest and northeast of China. The level of technological innovation and green innovation in such regions is relatively low, indicating that such regions should improve their level of technological innovation and awareness of green innovation. However, due to the low level of technological innovation and fewer pollutants, regional R&D investment has a greater effect on the performance of green innovation. Therefore, in such regions, the amount of regional R&D investment should be increased, and the degree of attention to such regions should be increased, so as to promote more reasonable and effective green innovation in the region.

Provinces and cities with a technological innovation level higher than 0.5837 have a relatively high technological innovation level. However, the green innovation infrastructure is not perfect, the awareness of green innovation is still weak, and the ability of green innovation is poor. Therefore, although the impact of R&D investment on green innovation performance is positive, the impact is lower than the previous range. In such areas, we should pay attention to the promotion of green innovation awareness, improve the construction of green innovation infrastructure, and actively develop and introduce green innovation technologies. We should also pay attention to the improvement of cleaner production and green innovation capabilities. The government should appropriately increase R&D investment. The threshold variable technology innovation level is calculated based on the amount of patent authorization, the sales revenue of new product, the number of scientific and technological papers included in foreign search tools and the number of technical market transaction contracts in each region. The government can measure the level of regional technological innovation based on the indicators above and

adopt different R&D investment policies according to different regional technological innovation levels.

## Discussion

This paper measured the technological innovation level and green innovation performance of 30 provinces and cities in China, and explored the heterogeneous impact of R&D investment on green innovation performance under the effect of different technological innovation level thresholds in China. Our empirical results suggest the following:

First, there is a double threshold effect based on the level of technological innovation between China's regional R&D investment and green innovation performance. The threshold estimate obtained through the likelihood ratio function graph is consistent with the true threshold. Our result belongs to the new conclusion. Previous studies did not combine the three researches, but conducted related research on the relationship between R&D investment and green innovation performance. Studies found that increasing R&D investment can reduce carbon dioxide emissions and promote green innovation (Afrifa et al. 2020). In addition, although R&D investment might not be conducive to green economic growth in the short term, it had a positive impact on green economic growth in the long term (Song et al. 2019). Furthermore, technological innovations in climate change can help promote green economic growth in the European Union (Nosheen et al. 2021).

Second, the worst range of the impact of China's regional R&D investment on green innovation perfor-

**Table 4** Distribution of thresholds in various provinces and cities

Year	$CD \leq 0.1082$	$0.1082 < CD \leq 0.5837$	$CD > 0.5837$
2015	Inner Mongolia, Hainan, Guizhou, Qinghai, Ningxia, Xinjiang	Hebei, Tianjin, Shanxi, Liaoning, Jilin, Heilongjiang, Henan, Anhui, Jiangxi, Guangxi, Fujian, Yunnan, Sichuan, Gansu, Chongqing, Shaanxi, Hubei, Hunan	Beijing, Jiangsu, Guangdong, Shanghai, Zhejiang, Shandong,
2016	Inner Mongolia, Hainan, Qinghai, Ningxia, Xinjiang	Hebei, Shanxi, Liaoning, Jilin, Heilongjiang, Hunan, Jiangxi, Chongqing, Guangxi, Fujian, Shaanxi, Guizhou, Gansu, Yunnan	Beijing, Tianjin, Jiangsu, Guangdong, Shanghai, Zhejiang, Anhui, Shandong, Henan, Hubei, Sichuan
2017	Inner Mongolia, Hainan, Qinghai, Ningxia	Shanxi, Liaoning, Jilin, Heilongjiang, Jiangxi, Chongqing, Guangxi, Fujian, Shaanxi, Guizhou, Yunnan, Gansu	Beijing, Jiangsu, Tianjin, Hebei, Shanghai, Zhejiang, Anhui, Shandong, Henan, Hubei, Hunan, Sichuan, Xinjiang, Guangdong
2018	Hainan, Qinghai, Ningxia	Hebei, Shanxi, Liaoning, Jilin, Heilongjiang, Guangxi, Shaanxi, Guizhou, Yunnan, Gansu	Beijing, Jiangsu, Tianjin, Inner Mongolia, Shanghai, Zhejiang, Anhui, Fujian, Jiangxi, Shandong, Henan, Hubei, Hunan, Chongqing, Sichuan, Xinjiang, Guangdong
2019	Hainan, Qinghai, Ningxia	Hebei, Shanxi, Liaoning, Jilin, Heilongjiang, Jiangxi, Guangxi, Guizhou, Yunnan, Gansu	Beijing, Jiangsu, Guangdong, Tianjin, Inner Mongolia, Shanghai, Zhejiang, Anhui, Fujian, Shandong, Henan, Hubei, Hunan, Chongqing, Sichuan, Shaanxi, Xinjiang

CD - technological innovation level (threshold)

mance is that the level of technological innovation is lower than the 0.1082 range. For every increase of 1 unit of R&D investment in this interval 3 periods ahead, green innovation performance will decrease by 5.7983 units. This result belongs to the new conclusion. Previous studies found that R&D investment can have a negative effect on regional green innovation performance (Song et al. 2019). When the level of regional technological innovation was extremely low, the region pays less attention to green innovation and clean energy (Chen and Lee 2020; Yi et al. 2021). Therefore, when R&D funding is invested, R&D investment cannot have a positive impact on regional green innovation performance.

Third, the best range for the impact of China's regional R&D investment on green innovation performance is in the [0.1082, 0.3904] technological innovation level range. For every 1 unit increase in R&D investment 3 periods ahead, the green innovation performance increases by 9.5377 units. This result belongs to the new conclusion. Previous studies proposed that R&D investment can promote the improvement of green innovation performance (Wang et al. 2021). Electricity R&D investment can reduce CO<sub>2</sub> emissions (Koçak and Ulucak 2019). When the level of regional technological innovation is low, relatively few pollutants are generated, which is within the scope of the regional affordability (Yi and Xiao-li 2018). Therefore, R&D investment at this stage has a greater impact on green innovation performance.

Fourth, the second best range of the impact of China's regional R&D investment on green innovation performance is that the level of technological innovation is higher than the 0.3904 range. For every 1 unit increase in R&D expenditures 3 periods ahead, the green innovation performance will increase by 5.0918 units. This result belongs to the new conclusion. Scholars found that R&D investment may have a positive impact on green innovation performance (Luo et al. 2021). R&D investment can reduce carbon emissions in economies in West Asia and the Middle East (Kihombo et al. 2021). When the level of regional technological innovation is high, the pollutants produced are relatively high. At this time, the clean production technology and green innovation technology are not matched, and the pollutants generated are in the range that the region cannot afford (Su and Yu 2020). Therefore, R&D investment at this stage will have a positive impact on green innovation performance, but the impact is in the sub-optimal range.

Fifth, China's economic development level has a negative impact on green innovation performance. Our result is consistent with previous studies, which found that the increase in EU per capita GDP can increase carbon emis-

sions (Fatai Adedoyin et al. 2021, b). In the process of increasing British GDP per capita, British carbon dioxide emissions have increased at an annual rate of 0.0950% (Adedoyin and Zakari 2020). For every unit increase in Japan's per capita GDP, long-term carbon emissions can increase by 0.84–0.96% (Adedoyin et al. 2021b). The level of environmental regulation, science and technology in fiscal expenditures, and foreign direct investment will have a positive impact on green innovation performance. Sixth, R&D investment in remote areas in western China has a negative impact on green innovation performance. It is necessary to focus on the improvement of the level of technological innovation and promote the use of alternative energy and green energy. This result belongs to the new conclusion. As the western region of China is rich in natural resources but the urban ecological efficiency is low, attention should be paid to the promotion of green innovation consciousness (Xue et al. 2021). The use of alternative energy, green energy and ensuring energy security will promote the reduction of pollutants (Fatai Adedoyin et al. 2021, b) and effectively promote the increase of ecological footprint (Shittu et al. 2021). The central, southwest, and northeastern regions of China are in the optimal range for the impact of R&D expenditures on green innovation performance, and the eastern region is in the sub-optimal range. This result belongs to the new conclusion. At present, China's overall green innovation awareness is relatively weak, and the level of green innovation is low (Fan and Xiao 2021). Hence, the promotion of China's overall green innovation awareness, the development of green innovation technologies and the policies of environmental protection should be strengthened (Jiang et al. 2020; Adedoyin et al. 2021a).

## Conclusion

This paper used a threshold regression model to test the threshold effect of regional R&D investment on green innovation performance based on the provincial panel data of 30 provinces in China from 2015 to 2019. Taking the regional technological innovation level as the threshold variable, and the environmental regulation level, government expenditure on science and technology, economic development level and foreign direct investment as control variables, we studied the relationship between regional R&D investment and green innovation performance.

Our results suggest that there is a double threshold effect between China's regional R&D investment and green innovation performance. When China's regional technological innovation level is lower than 0.1082, the regional R&D investment will have a negative impact on the performance

of green innovation. When China's regional technological innovation level is higher than 0.5837, the regional R&D investment has a positive impact on the performance of green innovation. Furthermore, when China's technological innovation level is in the range of [0.1082, 0.5837], it is the best range, and the range higher than 0.5837 is the sub-optimal range of the impact of regional R&D investment on green innovation performance. In addition, China's economic development level has a negative impact on green innovation performance, and the level of environmental regulation, foreign direct investment and science and technology in fiscal expenditures have a positive impact on green innovation performance. Finally, among the 30 provinces and cities in China, the provinces and cities with the best technological innovation level account for about 24%. Such regions are mostly located in the southwest and northeast of China. The level of technological innovation in the eastern region of China is in the sub-optimal range.

**Author contribution** **Jundi Fan\***: Data Curation, Writing-Original Draft. Conceptualization, Methodology. Visualization, Investigation. Software, Validation. **Thompson Teo**: Writing-Reviewing and Editing.

**Funding** The China Scholarship council.(Item Number:202006680076)

**Data availability** Not applicable

## Declarations

**Ethics approval** Not applicable

**Consent to participate** Not applicable

**Consent for publication** Not applicable

**Competing interests** The authors declare no competing interests.

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