ORIGINAL PAPER

Green innovation efficiency: a threshold effect of research and development

Xiao Luo[1] · Weiye Zhang[1]

Abstract

Green innovation is an important topic of research worldwide currently due to the attention to climate change and environmental issues. To have an understanding of the green innovation evaluation, this study measured the green innovation efficiency by using a meta-frontier Malmquist–Luenberger productivity index. The study results indicated that the growth rate of green innovation efficiency found differs greatly based on the environmental issues. Taking the research capacity of research and development institutions as the threshold variable, a double threshold effect is found as an inverted N-shaped. The study explored that the educational level and maturity of the technology market have a significant positive correlation with regional green innovation efficiency. Unlike environmental regulation and degree of openness, an improvement in green innovation efficiency is found fully dependent on the technological progress and regional green innovation efficiency. This study will be useful for policymakers and researchers to enhance green innovation efficiency in China and the rest of the world with similar economic settings.

Graphic abstract
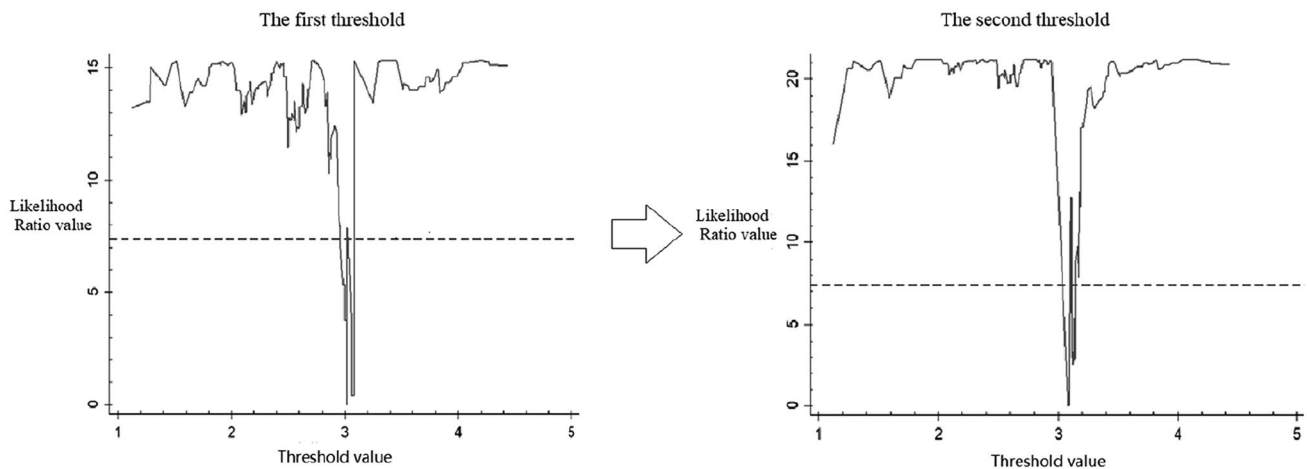
Keywords Green innovation efficiency · MML productive index · Threshold effect · Research and development

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Abbreviation

MML	Meta-frontier Malmquist–Luenberger productivity index
R&D	Research and development
DEA	Data envelopment analysis
RAM	Range adjusted measure
SFA	Stochastic frontier approach

TOPSIS	Technique for order preference by similarity to an ideal solution
SBM	Slack-based model
DMU	Decision-making units
TC	Technical change
EC	Efficiency change
ML	Malmquist–Luenberger index
TE	Technical efficiency
BPR	Best practice gap ratio
TGR	Technical gap ratio
BPC	Best practice gap change
TGC	Technical gap ratio change
Pgdp	Per capita GDP
GDP	Gross domestic product
Egdp	Proportion of total environmental investment to GDP
Stu	Number of students in colleges and universities per 0.1 M population
FDI	Foreign direct investment
Market	Technical market turnover
RD	R&D projects of R&D institutions
SO_2	Sulfur dioxide
GEC	Group frontier efficiency change
GTC	Group frontier technical change
GML	Group frontier Malmquist–Luenberger productivity index
MEC	Meta-frontier efficiency change
MTC	Meta-frontier technical change
LR	Likelihood ratio
EKC	Environmental Kuznets curve

Introduction

Owing to climate change and ongoing development activities resulted in significant degrees of pollution in many countries over time (Huq et al. 2006). Several research works referred with enhanced attention to environmental concerns (D'Amato et al. 2017), along with the concept of innovative circular economy, performance evaluation of green environment, digitalization of production systems, models for sustainable innovation in industry and smart manufacturing processes (ludbrook et al. 2019). It is factual by recent scientific evidence that the environmental crisis is becoming increasingly serious concern all over the world (Howard 2019). Some research works are more focusing on technology-driven sharing economy, consumer attitudes and behaviors on digitalization of production systems, sustainable innovation and motivations for participating in collaborative consumption (Graessley et al. 2019).

Researchers along with policymakers have realized that human activities aimed for high-speed development are detrimental to innovation and growth (Milward et al. 2019).

Consequently, it has gained attention on how to transform the existing developmental mode of society with growth and expansion (Udell et al. 2019). Especially, recently more attention is given to sustainable development and how conventional developmental growth can be transformed from the brown to clean (Ge and Zhi 2016). An increasing number of countries have aimed to study how society should focus and favor the mode of green development and innovation too (Gao et al. 2018). The relevant research works have established the positive effect of green development, knowledge-sharing mechanisms, technological innovation and efficiency on green innovation (Shin et al. 2018).

The existing literature is mainly classified as the definition of green innovation into two categories. The first definition is the adaptation of new products and methods to reduce the adverse impact on the environment (Huber 2008). The second definition is more conducive to a positive impact on the environment (Triguero et al. 2013).[1] The relevant literature indicated that methods of green innovation efficiency are relatively abundant, such as data envelopment analysis (DEA) (Li and Zeng 2020), DEA-RAM (Wang et al. 2017), Malmquist-based DEA combined efficiency model (Luo et al. 2019), stochastic frontier approach (SFA) (Miao et al. 2017), TOPSIS method (Sun et al. 2017), slack-based model (SBM) (Hu and Liu 2019) and Super-SBM (Feng et al. 2018) among others.

Recently, an increasing number of works have discussed the spatial effect of green innovation performance combined with spatial econometric analysis (Song et al. 2018). Convergence analysis has also been conducted to evaluate the efficiency of green technology innovation (Lin et al. 2018). Evaluating and measuring the green innovation efficiency in various regions help us to have a comprehensive understanding of the development and trend of green innovation. In order to develop green innovation, the key is to improve the utilization efficiency of resources and reduce the damage to the environment (Li et al. 2013). Also, environmentally beneficial technologies are equally important and addressed in many contemporary works on how to manage environmental innovation, sensing, smart and sustainable technologies, knowledge production and economic growth toward a smart automated society as specially addressed recently by Milward et al. (2019) and Udell et al. (2019), and earlier by Maroušek (2013), Mardoyan and Braun (2015) and Maroušek et al. (2015) with corresponding strong research references. Optimizing environmental quality and promoting sustainable development of people and society are important contents of green innovation. R&D investment's impact on the environmental effect presents an inverted U-shaped

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[1] This study refers green innovation as a kind of innovative activity which is based on the concept of sustainable development.

relationship, an increase of R&D deteriorates environment quality, however, there would be a turning point in the long run (Wang and Wang 2016). However, some researches indicated that scientific and technological progress plays a certain positive role in promoting environmental governance and environmental quality (Antonioli et al. 2016). For instance, according to the results of chemical and physical analyses, the new production methods of solid biofuels production are hygienically and environmentally beneficial (Haskova 2017). If using simple filters with biochar filling, the body of the filter will become a complex organo-mineral fertilizer that is sorbed on the soil-improving agent, which will help to clean up the wastewater and improve water resource's recycling (Maroušek et al. 2019).

Gao and Wang (2018) explored that scientific and technological innovation has a significant positive impact on green innovation. However, some studies referred that R&D capital hinders the improvement in green technology innovation efficiency (Luo and Liang 2016). Costantini et al. (2017) indicated that both the direct and indirect effects of eco-innovations helped to reduce environmental stress, however, those vary across the value chain depending on the technology adoption and the type of green innovation. There is some evidence found that besides environmental regulation and policy instruments, eco-labels, technology spillover, green development and innovation efficiency also play a role as determinants of innovative behavior (Dechezleprêtre et al. 2019).

Though some researchers directed uncertainties on the environmental regulation and policy instruments alone on green innovation efficiency, the synergistic mechanism between technological innovation and ecological environment is found more important than regulation and policy instruments (Lambin et al. 2014). Thus, even if sustainable frameworks were established, the impact of scientific and technological innovation on the environment can be uncertain based on country-specific resource distribution and structural transformation. The synergistic mechanism between the regional scientific and technological innovation and ecological environment has not yet been established (Li and Zhang 2016). In general, the existing literature does not clearly clarify the impact mechanism of scientific and technological innovation on green innovation.

Therefore, it is of boundless importance both using theoretical and practical knowledge to explore the impact of the brown to a green economy, technology spillover effects, concept and performance evaluation of green invention on the innovation efficiency which are literally uncertain in many institutional environments. China is a country with many regions and also experienced uneven regional economic development, and the level of development in each region does not represent an equal overall national development. In order to understand the broad spectrum of the uneven development and transformation issue, some studies used

before the traditional Malmquist index method to observe optimizing resource allocation, structural transformation and regional technological progress (Färe et al. 1994). However, the traditional Malmquist index method does not consider the non-expected output in the production process and structural transformation. With this background, it thus remains unclear whether green development alone can effectively improve the green innovation efficiency in investing regions, provinces or countries, especially in China, where optimizing resource allocation, achieving regional technological progress and structural transformation are boundless based on the uneven economy. Thus, it must be further investigated with additional dimensions and based on the regional developmental dynamics. This study aims to establish a meta-frontier-based Malmquist–Luenberger index model as a novel application to measure the green innovation efficiency of different provinces in China.

In this study, it used as a case study for China to explore the improvement in green innovation efficiency by using technological progress and R&D injection. R&D institutions are important parts of the construction of scientific and technological basic capacity, which can gather a large number of scientific and technological talents, leading force to promote the progress of science and technology (Mulyanto 2016). Due to the differences in the green innovation capabilities and R&D institution's research capabilities among provinces in China, the impact of research capabilities on the efficiency of green innovation inevitably is affected by certain characteristics of the provinces. The effect of the research capability of R&D institutions on green innovation will help better comprehend the impact mechanism of scientific and technological innovation on green innovation. Thus, it is important to understand the degree to which the R&D institution's research capability of each province which may have a nonlinear impact on its green innovation efficiency and those may be more in line with China's economic reality.

Study hypotheses

Based on the background outlined in the introduction, this study discussed the measurement of green innovation efficiency in provincial regions of China and tried to understand whether there is a nonlinear relationship between the research capacity of R&D institutions and regional green innovation efficiency. Taking the research capacity of R&D institutions as the threshold variable, provincial regional green innovation efficiency was explored by a double threshold effect. Firstly, following on the connotation of green innovation, and considering the factors of environment and resource input, we have measured the green innovation efficiency in different regions in China based on panel data. Secondly, we have used the threshold regression model to

analyze the impact of the research capacity of R&D institutions on green innovation efficiency based on the following hypotheses:

H1 Research capacity of R&D institutions has an inverted N-shaped effect on green innovation efficiency.

H2 Technological progress has a positive effect on the performance of green innovation.

H3 Educational level and technology market maturity have a positive role in promoting green innovation efficiency.

The hypotheses oversee how the studied regression technique is suited to reflect the nonlinear relationship between the variables as compared to the restricted regression model. Finally, the outcomes are expected to be used as a focal point of guidelines or suggestions to improve the efficiency of the regional green innovation.

Research methods, variables and data

This study used a nonparametric linear programming method with data envelopment analysis to aim our desired objective. The detailed research methods, variables and data (sampling process) are addressed below.

MML index

The Malmquist index method is widely used to measure changes in productivity. Färe et al. (1994) further developed the Malmquist productivity index method to calculate the input–output productivity by constructing a distance function model. Assume that there are "n" decision-making units (DMUs), "x" inputs and "y" outputs from period "t" to "$t+1$." Thus, the Malmquist productivity index[2] of the DMU n can be expressed as:

$$M_n\left(x^{t+1}, y^{t+1}, x^t, y^t\right) = \sqrt{\left(\frac{D_n^t\left(x^{t+1}, y^{t+1}\right)}{D_n^t(x^t, y^t)} * \frac{D_n^{t+1}\left(x^{t+1}, y^{t+1}\right)}{D_n^{t+1}(x^t, y^t)}\right)}$$

(1)

In Eq. (1), x^t and x^{t+1}, respectively, represent the input vector of the DMU n in period t and $t+1$, y^t and y^{t+1}, respectively, represent the output vector of the DMU n in period t and $t+1$, where $D_n^t(x^t, y^t)$ and $D_n^{t+1}\left(x^{t+1}, y^{t+1}\right)$, respectively, represent the distance functions of the DMU n in period t and $t+1$. $D_n^t\left(x^{t+1}, y^{t+1}\right)$ is represented the productivity efficiency of the DMU n in period $t+1$ based on the production frontier in period t. $D_n^{t+1}(x^t, y^t)$ refers to the distance function that is used to measure the maximum change in output required to make (x^t, y^t) at period $t+1$ relative to technical feasibility.

The distance function of ML index[3] can be used to describe the technical relationship between multiple inputs and outputs. The ML index can be divided into components of productivity growth, described as efficiency change (EC) and technical change (TC). Rather using ML index, Oh (2010) suggested using the MML index which can be defined as follows:

$$MML\left(x^t, y^t, b^t, x^{t+1}, y^{t+1}, b^{t+1}\right) = \frac{1 + \underset{D}{\rightarrow} G(x^t, y^t, b^t)}{1 + \underset{D}{\rightarrow} G\left(x^{t+1}, y^{t+1}, b^{t+1}\right)}.$$

(2)

In Eq. (2), x^t, y^t and b^t, respectively, represent the inputs, desirable outputs and undesirable outputs of the DMU in period t. x^{t+1}, y^{t+1}, b^{t+1}, respectively, represent the inputs, desirable outputs and undesirable outputs of the DMU in period $t+1$. $\underset{D}{\rightarrow} G(x^t, y^t, b^t)$ and $\underset{D}{\rightarrow} G\left(x^{t+1}, y^{t+1}, b^{t+1}\right)$, respectively, represent the global directional distance function of the DMU in period t and $t+1$.

The global directional distance function is defined as:

$$\underset{D^G}{\rightarrow} (x, y, b) = \inf \left\{\beta | (x, y + \beta y, b - \beta b) \in P^G\right\}$$

(3)

In Eq. (3), the global distance function $\underset{D^G}{\rightarrow} (x, y, b) = \inf \left\{\beta | (x, y + \beta y, b - \beta b) \in P^G\right\}$ is defined on the global benchmark technology set P^G of all groups. $P^G = P_{R_1}^I \cup P_{R_2}^I \cup \cdots \cup P_{R_H}^I$, and then $P_{R_H}^I = P_{R_H}^1 \cup P_{R_H}^2 \cup \cdots \cup P_{R_H}^T$, which means the union set of intertemporal benchmark technology of the group R_H from period 1 to period T. Referring the view of Oh (2010), the direction vector and the directional distance function were depicted with a DMU F, and then, the direction of the directional distance function of the DMU F was represented by an arrow which was represented as β.

Subsequently, the MML index can be described as follows:

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[2] Malmquist productivity index represents an index of change, specifically depicting the degree of change in productivity of the DMU from period t to $t+1$, rather than a specific year.

[3] Chung et al. (1997) proposed ML index to introduce the directional distance function of bad output into Malmquist index.

$$\text{MML}\left(x^t, y^t, b^t, x^{t+1}, y^{t+1}, b^{t+1}\right) = \frac{1 + \overrightarrow{D} G(x^t, y^t, b^t)}{1 + \overrightarrow{D} G\left(x^{t+1}, y^{t+1}, b^{t+1}\right)}$$

$$= \frac{1 + \overrightarrow{D} t(x^t, y^t, b^t)}{1 + \overrightarrow{D} t + 1\left(x^{t+1}, y^{t+1}, b^{t+1}\right)} * \frac{\left(1 + \overrightarrow{D} I(x^t, y^t, b^t)\right) / \left(1 + \overrightarrow{D} t(x^t, y^t, b^t)\right)}{\left(1 + \overrightarrow{D} I\left(x^{t+1}, y^{t+1}, b^{t+1}\right)\right) / \left(1 + \overrightarrow{D} t + 1\left(x^{t+1}, y^{t+1}, b^{t+1}\right)\right)}$$

$$* \frac{\left(1 + \overrightarrow{D} G(x^t, y^t, b^t)\right) / \left(1 + \overrightarrow{D} I(x^t, y^t, b^t)\right)}{\left(1 + \overrightarrow{D} G\left(x^{t+1}, y^{t+1}, b^{t+1}\right)\right) / \left(1 + \overrightarrow{D} I\left(x^{t+1}, y^{t+1}, b^{t+1}\right)\right)} = \frac{\text{TE}^{t+1}}{\text{TE}^t} * \frac{\text{BPR}^{t+1}}{\text{BPR}^t} * \frac{\text{TGR}^{t+1}}{\text{TGR}^t} \tag{4}$$

$$= \text{EC} * \text{BPC} * \text{TGC}$$

In Eq. (4), $\overrightarrow{D} t(x^t, y^t, b^t)$ indicates the contemporaneous distance function at period t, $\overrightarrow{D} I(x^t, y^t, b^t)$ represents the intertemporal distance function at period t. TE^t and TE^{t+1}, respectively, indicate the technical efficiency at period t and $t+1$. BPR and BPR^{t+1}, respectively, represent the best practice gap ratio between the contemporaneous benchmark and intertemporal benchmark technologies at period t and $t+1$, and they stand for the change in the best practice gap ratio during the two periods. TGR^t and TGR^{t+1} are, respectively, defined as the ratio of the technical efficiency under the meta-frontier and the efficiency under the group frontier at period t and $t+1$. The smaller the TGR is, the farther the group front is from the global front, and more technological improvements are needed. The larger the TGR, the closer the front of the group is to the global front, which indicates that the technical level of the group is closer to the global level. When TGR is 1, it represents that the DMU is on the meta-frontier, which shows it has a leading position in creating new technologies. EC[4] is a change in technical efficiency during two periods from the time t to $t+1$. BPC[5] indicates the best practice gap change, which represented the relative rate of change of best practice gaps during two periods. TGC[6] represents the change of the technical gap ratio in two periods.

Threshold regression model

This study adopts the threshold panel regression model[7] and takes the number of research and development institutions as the threshold variable to investigate whether it has an impact on the efficiency of regional green innovation, along with its significance. The mathematical expressions of single and double threshold models are represented by Eq. (5) and (6), and final mathematical expression of multiple threshold regression is analogous which can be expressed as below:

$$\begin{aligned} \text{LnMML}_{it} = {} & \mu_i + \theta_1 \ln \text{Pgdp}_{it} + \theta_2 \ln \text{Egdp}_{it} + \theta_3 \text{Stu}_{it} \\ & + \theta_4 \ln \text{FDI}_{it} + \theta_5 \ln \text{Market}_{it} \\ & + \beta_1 \ln \text{RD}_{it} I\left(\ln \text{RD}_{it} \le \gamma_1\right) \\ & + \beta_2 \ln \text{RD}_{it} I\left(\ln \text{RD}_{it} > \gamma_2\right) + \varepsilon_{it} \end{aligned} \tag{5}$$

$$\begin{aligned} \text{LnMML}_{it} = {} & \mu_i + \theta_1 \ln \text{Pgdp}_{it} + \theta_2 \ln \text{Egdp}_{it} + \theta_3 \ln \text{Stu}_{it} \\ & + \theta_4 \ln \text{FDI}_{it} + \theta_5 \ln \text{Market}_{it} + \beta_1 \ln \text{RD}_{it} I\left(\ln \text{RD}_{it} \le \gamma_1\right) \\ & + \beta_2 \ln \text{RD}_{it} I\left(\gamma_1 < \ln \text{RD}_{it} \le \gamma_2\right) + \beta_3 \ln \text{RD}_{it} I\left(\ln RD_{it} > \gamma_3\right) + \varepsilon_{it} \end{aligned} \tag{6}$$

In Eq. (5) and (6), μ is the intercept term; $\theta_1, \theta_2, \theta_3, \theta_4$ and θ_5 are the regression coefficients of each control variable; β is the regression coefficient of the threshold variable; ε is the residual term; i represents the provincial administrative regions; and t represents the statistical time. MML_{it}: Meta-frontier Malmquist–Luenberger productivity index of the region "i" at period "t," Pgdp_{it}: Per capita GDP of the region "i" at period "t," Egdp_{it}: Proportion of total environmental investment to GDP of the region "i" at period "t," Stu_{it}: Number of students in colleges and universities per 0.1 M population of the region "i" at period "t," FDI_{it}: Foreign direct investment of the region "i" at period "t," Market_{it}: Technical market turnover of the region "i" at period "t," RD_{it}: R&D projects of R&D institutions of the region "i" at period "t," γ_1: the first threshold, γ_2: the second threshold, and γ_3: the third threshold.

The representative indicators of each variable are as follows:

Explained variable Regional green innovation efficiency is the explained variable, which is represented by MML productive index calculated.

Threshold variable R&D institutions are units that specialize in scientific and technological research and trans-

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[4] If EC > 1, it implies that the technical efficiency has improved.

[5] If BPC > 1, it means that the contemporaneous benchmark technology frontier has shifted towards the intertemporal benchmark technology frontier (Oh 2010).

[6] If TGC > 1, it refers that technical gap ratio is decreased in a technical gap and the global frontier technology.

[7] Referring the scope is proposed by Hansen (1999).

Table 1 Description of the main variables

Variable	Definition	Obs	Mean	SD	Min	Max
lnRD	R&D projects of R&D institutions (unit)	310	2.787	0.909	0.425	5.654
lnPgdp	Per capita GDP (0.15USD)[a]	310	1.255	0.552	−0.369	2.470
lnFDI	Foreign direct investment (0.1G USD)	310	6.110	1.386	3.083	9.082
lnMarket	Technical market turnover (1.47 k USD)	310	3.879	1.752	−0.588	8.279
lnEgdp	Proportion of total environmental investment in GDP (%)	310	4.836	0.467	3.401	6.050
lnStu	Number of students in colleges and universities per 0.1 M population (person)	310	7.725	0.351	6.807	8.828

(1) "ln" in the table refers to the logarithmic form of the variables. (2) The data are from China Statistical Yearbook (2007–2017), China Statistical Yearbook on Science and Technology (2007–2017) and China Statistical Yearbook on Environment (2007–2017) and authors' calculations
CNY 1 = US$ 0.15

Table 2 Index setting for green innovation efficiency

Category	Context	Data resource
Input variables	R&D internal expenses (1.47 k USD)	China statistical yearbook (2007–2017)
	R&D personnel full-time equivalents (man/y)	China statistical yearbook (2007–2017)
	Total energy consumption (10ktce)	China energy statistical yearbook (2007–2017)
Expected output variables	Sales revenue of the new product (1.47 k USD)	China statistical yearbook on science and technology (2007–2017)
	Patent licensing (piece)	China statistical yearbook on science and technology (2007–2017)
Non-expected output variables	Waste water emission (10kt)	China statistical yearbook on environment (2007–2017)
	SO_2 emission (10kt)	China statistical yearbook on environment (2007–2017)
	Hazardous waste emission (10kt)	China statistical yearbook on environment (2007–2017)

lating research results into practical applications. In this study, the research capacity of R&D institutions is taken as the threshold variable, represented by R&D projects of R&D institutions for investigating the degree of their influence on the efficiency of regional green innovation. *Control variable* According to the relevant literature, the efficiency of green innovation is influenced by some factors, such as economic development level and foreign direct investment (Guo et al. 2020), technology competence (Liao and Tsai 2019) and education (Tayouga and Gagne 2016), etc. Therefore, in this study, economic level, educational level, environmental regulation, technology market maturity and degree of openness are regarded as control variables. The regional economic level is measured by per capita GDP, educational level is represented by the number of students in colleges and universities per 0.1 M population, environmental regulation is expressed by the proportion of total environmental investment in GDP, technology market maturity is expressed by technical market turnover, and degree of openness is expressed by FDI.

In order to reduce the instability in the data, the threshold and control variables in this study are all treated

logarithmically. The descriptive statistics of the main variables are shown in Table 1.

As can be observed from Table 1, the sample size of the variables is 310, and the mean value and standard deviation of lnRD are 2.787 and 0.909, respectively. The mean value of lnPgdp is 1.255, and the standard deviation is 0.552. In addition, the values for lnFDI are 6.11 and 1.386, respectively, whereas the mean value and standard deviation of lnMarket are 3.879 and 1.752, respectively.

Index design of green innovation efficiency

This study used the creative work of R&D personnel is inseparable from energy input, and green innovation was used as an indicator to aim at reducing pollution and improving energy efficiency. According to the production process (whether it is Cobb–Douglas or classical or neo-classical production function[8]), human and financial inputs are the two basic production factors that are considered the main factor inputs. On the other hand, R&D is used as a driver of

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[8] This study used the similar study scope as addressed by Miao et al. (2017).

Table 3 Statistical description of regional green innovation efficiency in China

Region (province)	Mean value						
	GEC	GTC	GML	MEC	MTC	MML	TGR
BJ	1.000	1.179	1.179	1.000	1.179	1.179	1.000
TJ	1.075	1.098	1.180	1.075	1.098	1.180	0.999
HE	1.012	1.129	1.143	1.012	1.109	1.123	1.108
LN	0.986	1.106	1.090	0.986	1.113	1.098	0.993
SH	1.000	1.156	1.156	1.000	1.157	1.157	0.999
JS	1.037	1.224	1.269	1.037	1.224	1.269	1.000
ZJ	1.000	1.100	1.100	1.000	1.101	1.101	0.999
FJ	0.938	1.067	1.001	0.938	1.092	1.024	0.977
SD	0.999	1.173	1.172	0.999	1.194	1.193	0.982
GD	1.000	1.171	1.171	1.000	1.186	1.186	0.988
HI	0.854	1.083	0.925	0.854	1.083	0.925	1.000
Eastern region	0.991	1.135	1.126	0.991	1.140	1.130	0.996
SX	0.878	1.104	0.970	0.856	1.081	1.011	0.935
JL	1.038	1.072	1.113	1.039	1.095	1.137	0.979
HL	0.888	1.071	0.951	0.963	1.103	1.061	0.971
AH	1.000	1.095	1.095	1.043	1.297	1.353	0.844
JX	1.000	1.232	1.232	1.111	1.117	1.241	1.103
HA	1.000	1.134	1.134	1.016	1.137	1.155	0.998
HB	1.000	1.196	1.196	1.042	1.134	1.182	1.055
HN	1.000	1.171	1.171	1.089	1.163	1.266	1.007
Central region	0.976	1.134	1.108	1.020	1.153	1.176	0.987
NM	0.876	1.143	1.001	0.934	1.036	0.968	1.104
GX	1.000	1.129	1.129	1.008	1.084	1.063	1.042
CQ	1.000	1.070	1.070	1.065	1.082	1.152	0.988
SC	0.929	1.341	1.246	1.000	1.118	1.119	1.199
GZ	1.054	1.191	1.255	0.987	1.001	0.988	1.190
YN	0.873	1.161	1.013	0.937	1.059	0.992	1.096
SN	1.000	1.377	1.377	1.018	1.142	1.162	1.206
GS	0.955	1.167	1.114	1.006	1.071	1.078	1.090
QH	0.943	1.117	1.053	0.998	1.046	1.044	1.068
NX	0.871	0.989	0.861	0.858	1.056	0.906	0.936
XJ	0.896	1.148	1.028	0.884	1.047	0.925	1.096
Western region	0.945	1.167	1.104	0.972	1.068	1.039	1.092

GEC = group frontier efficiency change, GTC = group frontier technical change, GML = group frontier Malmquist–Luenberger productivity index, MEC = meta-frontier efficiency change, MTC = meta-frontier technical change, MML = meta-frontier Malmquist–Luenberger productivity index, TGR = technical gap ratio

economic growth, which promotes a competitive advantage in the market by improving their innovation ability. Finally, total energy consumption was selected as a resource input.[9]

In this study, new product sales revenue and patent licensing[10] are considered as expected output, which is intended to be achieved by green innovation activities. Additionally, some output indicators are also not expected in green innovation activities, such as environmental pollution indicators. Thus, the emission of wastewater, SO_2 and hazardous waste are thus considered as the non-expected output variables in the estimation process. The input variables, expected output variables and non-expected output variables are described in Table 2.

Sample selection and data sources

To evaluate the regional green innovation ability scientifically, comprehensively and objectively, this study selected

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[9] The resource used as indicated by Chen et al. (2018).

[10] Patents contain an important indicator to measure the green technology (Fujii and Managi 2019).
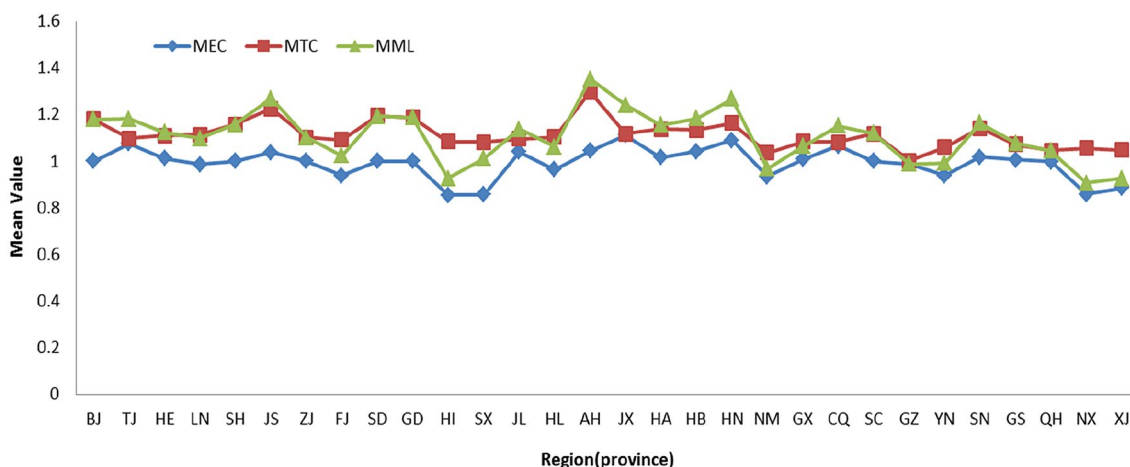
Fig. 1 Mean values of MEC, MTC and MML of regional green innovation

Table 4 Correlation matrix

Variable	MML	lnRD	lnStu	lnEgdp	lnPgdp	lnFDI	lnMarket
MML	1						
lnRD	0.055	1					
lnStu	0.096	0.597	1				
lnEgdp	−0.005	−0.200	0.007	1			
lnPgdp	−0.014	0.483	0.705	0.040	1		
lnFDI	0.007	0.654	0.601	−0.321	0.685	1	
lnMarket	0.107	0.728	0.708	−0.155	0.648	0.682	1

"ln" in the table refers to the logarithmic form of the variables

30 provincial administrative regions in China except for Hong Kong, Taiwan, Macao and Tibet from 2006 to 2016 used as a source of data. The selected data were taken from China Statistical Yearbook on Science and Technology (2007–2017), China Energy Statistical Yearbook (2007–2017), China Statistical Yearbook on Environment (2007–2017) and China Statistical Yearbook (2007-2017).

Results and findings

Regional green innovation efficiency

This study used 30 provincial regions in China, and all regions are divided into eastern, central and western regions.[11] Due to different regional locations and levels of economic development, the central and western regions exhibit unbalanced development. The green innovation efficiency values of each province have calculated under group and meta frontiers,

and all estimations are expressed by GML (Group frontier Malmquist–Luenberger Productivity Index) and MML (Meta-frontier Malmquist–Luenberger Productivity Index), respectively. The mean values of Malmquist productivity, technological efficiency and technological change rate are shown in Table 3.

Table 3 shows the geometric mean value and composition of the green innovation productivity index of all selected provinces from 2006 to 2016. This study adopts the meta-frontier Malmquist index to compare the green innovation productivity across provinces and cities.[12] Figure 1 shows the Malmquist index, technology change rate and efficiency change rate of meta-frontier green innovation of all selected provinces. According to the findings (Table 3, Fig. 1), the regions AH, JS and HN are ranked as the top three places for the average growth rate of green innovation productivity with values of 35.3%, 26.9% and 26.6%, respectively.

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[11] Each region has its own provincial-level administrative structure, and abbreviations are used to represent different provinces in this study.

[12] The Malmquist index in the group frontier is mainly a comparison between each indicator region, representing the situation of the region, while the Malmquist index and each indicator in the meta-frontier represent the status of the country.

Table 5 Threshold value estimation and threshold effect test results

Model	F value	p value	Critical value			BS time	Threshold estimate value	95% Confidence interval
			1%	5%	10%			
Single threshold	7.145**	0.023	9.130	4.721	2.563	300	3.143	[1.118, 4.473]
Double threshold	18.312***	0.010	17.847	7.090	3.811	300	3.088	[3.086, 3.142]
							3.018	[2.966, 3.081]
Triple threshold	4.763**	0.043	7.744	4.671	2.736	300	2.600	[1.132, 3.142]

(1) The test result is obtained after 300 times of bootstrap approach simulation. (2) ** and *** indicate the significance at 5% and 1% levels, respectively
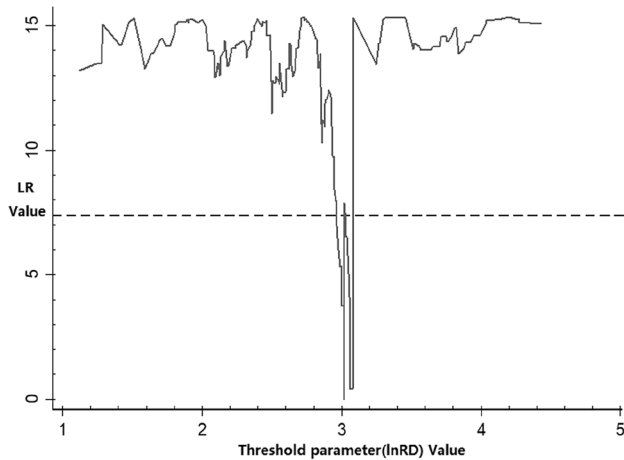
Fig. 2 Confidence interval construction in single threshold model
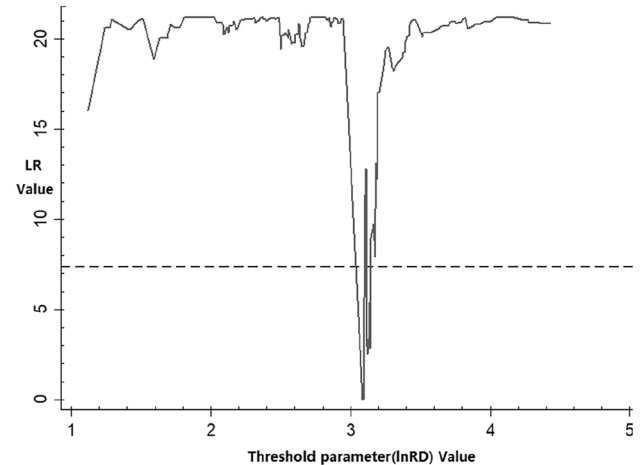
Fig. 3 Confidence interval construction in double threshold model

However, the average growth rate in the bottom three provinces of HI, XJ and NX bottom exhibited negative growth, with average growth rates of −7.5%, −7.5% and −9.4%, respectively. The growth rate of green innovation found the highest in the central region, followed by the eastern and the western regions, with average growth rates of 17.6%, 13% and 3.9%, respectively. The rate of technological change in the provinces was greater than one, which indicates that the improvement in green innovation efficiency is mainly depended on technological progress.

Threshold regression results

In this study, Pearson test was used to investigate the correlation between the various variables, and a correlation matrix among the main variables is shown in Table 4. It is illustrated that the regional green innovation efficiency is observed to be negatively correlated with environmental regulation and economic level, whereas it was positively correlated with other variables. In addition, the correlation coefficient higher than 0.8 was taken as the basis of strong correlation, and the correlation coefficients between the respective variables were less than 0.8, which indicated

Table 6 Results of threshold regression

Variable	Estimated coefficient	t value	SD
lnStu	0.3195**	2.002	0.1596
lnEgdp	0.0134	0.160	0.0835
lnPgdp	−0.2900***	−2.664	0.1087
lnFDI	−0.0172	−0.396	0.0434
lnMarket	0.0856**	2.465	0.0347
$lnRD_1$	−0.3057***	−5.054	0.0605
$lnRD_2$	0.1852**	2.232	0.0830
$lnRD_3$	−0.2702***	−4.555	0.0593
_cons	−0.9474	−0.819	1.1573
N	310		
R^2	0.1141		
F-statistics (p value)	4.69***(0.000)		

(1) LnRD1, lnRD2 and lnRD3 represent lnRD less than or equal to 3.088, lnRD greater than 3.088 but less than or equal to 3.018 and lnRD greater than 3.018. (2) ** and ***indicate the significance at 5% and 1% levels, respectively

that there was no obvious multicollinearity in the model estimation.

Table 5 reports the threshold value estimation and threshold effect test results after 300 times of bootstrap approach simulation using the research capacity of R&D institutions as a threshold variable. It exhibits the impact (threshold value and 95% confidence interval) of the research capacity of R&D institutions on regional green innovation efficiency, where the estimated values of the double threshold are found 3.088 and 3.018, respectively. The F values and p values of the single threshold, double threshold and triple threshold models are 7.145, 18.312, 4.763 and 0.023, 0.010, 0.043, respectively. It is obvious that single, double and triple threshold effects are significant at the levels of 5%, 1% and 5%, respectively. This study adopted a double threshold model in order to distinguish effectively the impact of the research capacity of R&D institutions on regional green innovation efficiency under different thresholds.

Meanwhile, the likelihood ratio (LR) was used to identify the threshold value, which can better understand the authenticity of the threshold estimation value and confidence interval. Subsequently, the likelihood ratio function graph of the two threshold estimates (Figs. 2, 3) was drawn, respectively. Research capacity of R&D institutions is the threshold estimation value when the LR value is 0. As presented in Figs. 2 and 3, the corresponding threshold parameter values are 3.018 and 3.088, respectively, when the LR value is 0. Moreover, the 95% confidence interval of the threshold estimation values 3.018 and 3.088 are [2.966, 3.081] and [3.086, 3.142], respectively.

According to the findings, Table 6 shows the R&D projects of R&D institutions which have a significant effect on the regional green innovation MML productivity index ($F = 4.69$, $p < 0.01$). The regression results of lnRD on MML for lnRD are less than or equal to 3.088, lnRD greater than 3.088 but less than or equal to 3.018 and lnRD greater than 3.018, respectively. Considering lnRD, the value is found less than or equal to 3.088, and statistical results showed that the coefficient of lnRD is significant at 1% significance level with a negative sign. According to the first threshold level, i.e., lnRD is greater than 3.088 but less than or equal to 3.018, and the coefficient of lnRD is significant at the 5% significance level with a positive sign.

Thus, the value indicated that the number of subjects of R&D institutions has a positive effect on the regional green innovational MML productivity index. On the other hand, the value of lnRD crossed the second threshold, i.e., lnRD is greater than 3.018, the coefficient of lnRD is significantly negative at the 1% level. Thus, the value indicated that the number of subjects in R&D institutions on regional green innovational MML productivity index turned to positive inhibition. Therefore, it is observed that the influence of R&D projects of R&D institutions on regional green innovational MML productivity index exhibited an inverted N-type trend.

This phenomenon may result due to several reasons. Firstly, a large number of resources such as manpower and capital investment needed to be spent in the initial stage to apply for R&D projects, and many of the initial initiatives may result in the wastage of some resources. Some research illustrated that new product development was dependent on the creation of new knowledge, whose creation required many time and resources (Richtner et al. 2014). Additionally, the increasing number of R&D scientific projects may bring a positive effect to technological innovation and promote the performance of local green innovation at the second stage. Thus, though the number of R&D projects in R&D institutions may increase, however, the transformation from the scientific research achievements to actual productivity may not be optimally realized. Secondly, most developed countries kept the conversion rate of scientific and technological achievements at 75%, whereas it is 30% for China which limited the improvement in China's scientific and technological capabilities (Hu et al. 2014).

By observing the coefficients of various control variables, it is observed that the regression coefficient of educational level to regional green innovation performance reached 0.3195, which ranked first among the influencing factors at 5% significance level. This regression coefficient showed the improvement in the educational level which played a positive role in promoting the efficiency of regional green innovation. The higher the level of education, the more favorable it was to accept new technologies and improve the utilization of resources. Therefore, the improvement in the education level of residents is conducive to the improvement in the efficiency of the green total factor of industrial water resources (Jin et al. 2019). With the improved education level, high-quality labor force absorbs, digest and innovate technology at a higher stage and those promote innovation resource to be more efficient in the innovation practice.

The regression coefficient of technology market maturity is found 0.0856 at 5% significance level. Thus, this regression coefficient showed that the addition of the technology market played a positive role in promoting the performance of regional green innovation. With the exchange of knowledge products, the technology markets can effectively transform the innovative ideas into innovative achievements by linking science and technology which is supported by the recent scientific study by Cao and Yu (2015). The mature technology market provides an optimal market environment for the realization of the market value of the innovation results (Cao and Yu 2015). The higher the turnover of the technology market is, the more active the technology market is, which promotes the transformation of scientific and technological achievements into productivity as well as improves the performance of green innovation.

The regression coefficient of economic level is found −0.2900 at 1% significance level. Thus, this regression coefficient indicated that economic development occasionally played a somewhat negative role in regional green innovation efficiency. Research has shown that economic growth is associated with the accelerated degradation of the environment, and in turn, this will result in an exponential increase in harmful emissions (Badulescu et al. 2019). Therefore, economic development may bring more harmful pollutant emissions, which have a negative impact on the environment and thus affect the efficiency of green innovation. Finally, the regression coefficient of both environmental regulation and the degree of openness has found no significant level irrespective of their values. Thus, neither the environmental regulation nor the degree of openness has an insignificant influence on the efficiency of regional green innovation in this study.

Discussion

The findings explored by this study will be helpful to better understand the effect of research capacity of R&D institutions on green innovation efficiency, especially in China; however, the rest of the world with similar ecology and economic settings will be equality benefited by the study nature and model applied. This study considers linear programming-based meta-frontier Malmquist–Luenberger (MML) productivity index to understand the green innovation and innovation efficiency. This model represents an index of change, specifically depicting the degree of change in the productivity of the DMU from period t to $t + 1$ which shows the maximum change in output required to make $x\hat{}t$, $y\hat{}t$ at period $t + 1$ relative to technical feasibility. Therefore, the model uses in this study indicates the best practice gap change, which represents the relative rate of change of best practice gaps during two periods and applicable to any country with an uneven research capacity of R&D regardless difference in environmental regulation, innovation efficiency, technological progress, educational level, technology market maturity, degree of openness (expressed by FDI) or regions. The only mechanism that needs to be adjusted is explained variables, threshold parameters, control variables to reduce the instability in the data, and threshold and control variables need to treat logarithmically based on country-specific environmental regulation, innovation efficiency, degree of transformation, technological progress, technology market maturity and degree of openness.

Commonly, in this study, the growth rate of green innovation is found the highest in the central region, followed by the eastern region and the lowest in the western region. Thus, it is obvious that the performance of green innovation in different regions of China is unbalanced. Besides, the improvement in green innovation efficiency in 30 provinces mainly depended on technological progress. Thus, the findings support our study hypothesis, H-2.

This study also analyzed the impact on the efficiency of regional green innovation by taking the research capacity of R&D institutions as the threshold variable. The study results indicate that the research capacity of R&D institutions has a double threshold effect on the efficiency of regional green innovation (Yeh et al. 2010). Specifically, the research capacity has a limited effect on the efficiency of regional green innovation at the beginning. However, once the research capacity crosses the first threshold, it poses a positive promoting effect on the efficiency of regional green innovation (Guo et al. 2017). Moreover, once the research capacity of R&D institutions crosses the second threshold, it presents a negative limited effect on efficiency. Overall, the research capacity of R&D institutions has an inverted N-shaped effect on the efficiency of regional green innovation. Thus, the findings support our study hypothesis, H-1.

This study identified that during the process of transformation of scientific and technological achievements, sometimes the characteristics of achievements such as maturity and economic feasibility were often neglected by scientific research institutions. These characteristics to a large extent determined the degree of difficulty toward the transformation of scientific and technological achievements which may affect the final success or failure. Scientific and technological achievements needed certain maturity and market value (Spurgeon 1995). Otherwise, scientific and technological achievements that were difficult to be successfully transformed would consume the resources of scientific research institutions and hindered the transformation of other scientific and technological achievements too as supported by Ou et al. (2013).

Therefore, the R&D projects of R&D institutions may have a restraining effect on the performance of green innovation in the third stage (Chen 2008). In contrast, the regression coefficient of economic level studied in this study indicated that economic development infrequently plays a fairly negative role in the regional green innovation efficiency. It is common that if a country's level of economic development is low, the degree of environmental pollution is relatively low. However, with an increase in per capita income, environmental pollution rises, and the degree of environmental deterioration increases. Therefore, the study findings can be verified with the concept of the environmental Kuznets curve (EKC), which indicates that income inequality rises firstly and subsequently falls with economic growth; thus, EKC presents an inverted u-shaped curve.

On the other hand, Grossman and Krueger (1991, 1995) reported that economic growth has a negative impact on environmental quality from two aspects: on the one hand, economic growth increases input necessities and enhances the use of resources and, on the other hand, increases outputs lead to enhance pollution. It was observed in this study that the economic development in some regions has hindered the local green innovation efficiency. Although the per capita GDP of some regions is relatively high, significant pollutant emissions and energy consumption at the time of economic development negatively impact the local environmental conditions. FDI has also reported not only promote rapid economic growth but also affected the country's environmental quality through technology spillover (Song et al. 2015). However, economic growth does not lead to a continuous deterioration of the environment as observed by EKC. As the economy develops to a certain degree, the environmental deterioration generally slows down. This study is expected to be the same for the case of China.

Moreover, like FDI and R&D projects, human resources represent a dynamic force for technological innovation which cannot be ignored (Certa et al. 2009). Increasing numbers of people equipped with higher education are more likely to provide talent reserve for the improvement in scientific and technological innovation ability. Talent provides intellectual support for green innovation activities. Thus, human resources represent a vital force for regional development (Acemoglu et al. 2014). Overall, science and technology is the primary productive force, and human resources are the driving force for scientific and technological innovation.

This study identified that educational level and technology market maturity play a positive role in promoting regional green innovation efficiency, while the degree of openness and environmental regulation have no obvious effect on efficiency. Developed educational capacity with a mature technology market provides a balanced market environment for realizing the market value of innovation achievements (Bitat 2018). Therefore, a developed educational level has a positive effect on regional green innovation. Thus, the findings support our study hypothesis, H-3.

Study limitations

This study used a nonparametric linear programming method with data envelopment analysis. There are certain advantages of using our method for sure and acknowledged by many scientific findings. However, we also acknowledged some of the disadvantages which are, firstly, the study results can be very sensitive to the selection of variables and the test may unable to find the best specification based on the targeted goal. And sometimes this study method is unable to identify random variation in the estimation process and unable to identify how to improve the efficiency of the study variables and statistical errors. Secondly, the data in this study are all from the provincial statistical yearbook of relevant years, which are secondary data source and may have errors with the actual situation. In future, other researchers should overcome the nonparametric linear programming method with data envelopment analysis and identify random variation in detail in the estimation process to improve the efficiency with taking care of all (related) statistical errors. Additionally, future study should carry out a more practical investigation in the research and strive to obtain primary data source to make the calculation results more accurate.

Conclusions

This study used a meta-frontier Malmquist–Luenberger (MML) productivity index to understand the green innovation evaluation and green innovation efficiency. The study results indicated that the growth rate of green innovation efficiency is uneven in the different provinces and taking the research capacity of R&D institutions as the threshold variable, a double threshold effect is found as an inverted N-shaped. Unlike environmental regulation and degree of openness, an improvement in green innovation efficiency is found fully dependent on regional green innovation efficiency and technological progress. The different economic development in each province is found to play a somewhat asymmetrical role in regional green innovation efficiency. The study explored that higher educational level and greater technology market maturity have a significant positive correlation with regional green innovation efficiency.

The model used in this study indicates the best practice gap in innovation change and explores the relative gaps between the two periods (e.g., period t and $t+1$, relative to technical feasibility). Importantly, the study model is also able to apply to any country with an uneven research capacity (e.g., x^t, y^t from period t to $t+1$) regardless of the dissimilarity of the degree of innovation openness, degree of evaluation, innovation inefficiency, technological advancement, market immaturity on technology, degree of trade openness and especially regardless of regions. This study thus has significance in the contemporary study score from a global point of view to understand and measure the threshold effect of research and development (R&D) for green innovation efficiency regardless any boundary. Therefore, findings from this study will be helpful to better understand the effect of the research capacity of R&D institutions on green innovation efficiency in China and the rest of the world with similar ecology and economic settings.

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