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RESEARCH ARTICLE

The nonlinear impact of industrial restructuring on economic growth and carbon dioxide emissions: a panel threshold regression approach

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Abstract

Energy conservation, emission reduction, and sustainable development are the goals of achieving low-carbon economic development all over the world. Many countries are working hard to find measures, and industrial restructuring is considered to be an effective way to achieve economic development and emission reduction. However, previous studies have assumed that industrial restructuring and economic growth and emissions are simple linear relationships while neglecting nonlinear relationships. We use panel data from 32 countries from 1997 to 2017 and employ panel threshold models (Stochastic Impacts by Regression on Population, Affluence and Technology model and Solow growth model) for empirical test. The results reveal that industrial restructuring has statistically significant nonlinear effects on economic growth and carbon dioxide emissions. With the process of industrialization and urbanization, industrial restructuring has a long-term positive impact on economic growth. The relationship among industrial restructuring and carbon dioxide emissions has been found to be inverted U–shaped. Industrial restructuring is beneficial to reducing emissions. The policy implies that although industrial restructuring is considered to be an effective measure to achieve green growth, for countries with different degrees of urbanization and economic development, industrial structure transformation should adopt different policies.

Keywords Industrial restructuring · Economic growth · Emission reduction · Panel threshold regression

Introduction

Urbanization and industrialization are considered to be effective measures to promote economic growth. According to the World Bank, the world's gross domestic product (GDP) increased rapidly from 31.367 trillion (current US$) in 1998 to 85.804 trillion (current US$) in 2018. Simultaneously, with the release of a large amount of greenhouse gases, carbon emissions have attracted the attention of governments and scholars. International Energy Agency (IEA) shows that the world's carbon emissions increased from 224.1 billion tons in 1998 to 331.2 billion tons in 2018. The industrialization has not only promoted the economic development of countries around the world but also greatly increased carbon emissions (Kofi Adom et al. 2012; Xu and Lin 2017). In order to achieve energy conservation, sustainable development, and emission reduction goals, transforming the economic development model is the main measure, and industrial restructuring is considered to be an effective measure to achieve economic development and emission reduction.

Previous research literature believes that economic growth is determined by capital, labor, and industrialization. Many scholars have discussed the role of urbanization in economic development and found that urbanization is indeed beneficial to economic growth (Destek 2016; Mudakkar et al. 2013; Rekiso 2017; Samouilidis and Mitropoulos 1984; Sharif Hossain 2011; Szirmai 2012). Industrialization is a double-edged sword. The industrialization has not only promoted economic growth but also stress on the environment. Many

Highlights 1. The impact of industrial restructuring on economic growth and emissions is investigated.
2. Both linear and nonlinear panel analyses are conducted.
3. Industrial restructuring has a positive impact on economic growth and emission reduction.
4. There is an inverted U–shaped relationship between industrial restructuring and carbon emissions
5. Economic growth and urbanization promote emission reduction effect of industrial restructuring.

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studies have revealed that industrialization has increased emissions (Lin et al. 2015; Liu and Bae 2018; Xu and Lin 2015; Zhu et al. 2017). Cherniwchan (2012) reveals that the industry's share of total output increases by 1% and per capita emissions increased by 11.8%. With the development of industrialization, environmental pressures are increasing, and industrial restructuring is considered to be an effective measure to achieve economic growth and emission reduction (Feng et al. 2019; Jänicke et al. 1989; Kabiraj and Chyi Lee 2004; Peneder 2003; Wu et al. 2019; Zhang et al. 2018a). However, previous studies have assumed that industrial restructuring is a linear relationship with economic growth and emissions while neglecting nonlinear relationships. To fill the gaps in the previous research literature, this article aims to investigate the contribution of industrial restructuring in the process of economic development and emission reduction by using a panel threshold model.

There are three differences between this article and previous research literature. First, the role of industrial restructuring has not been considered in the economic growth model and the Stochastic Impacts by Regression on Population, Affluence and Technology (STIRPAT) model in the previous research literature, and this paper is the first to incorporate industrial restructuring into the growth model and STIRPAT model. Second, for the innovative application of the method in this paper, a panel threshold model is used in this article, which can analyze the nonlinear effects of industrial restructuring on economic growth and carbon dioxide emissions. Third, the problem of heteroscedasticity and missing variables is inevitable in many empirical studies. This paper overcomes the problem by adding corresponding control variables and selecting different countries and regions from seven continents. Therefore, the conclusions of our research are more reliable, complete, and comprehensive than previous research literature. Our research results can reflect heterogeneity and nonlinear differences, which can provide a more valuable reference and suggestions for decision-makers.

The purpose of this article is to investigate the nonlinear contribution of industrial restructuring in the process of economic development and emission reduction, the data from 1997 to 2017 in 32 countries. We employ the panel threshold model, the STIRPAT model, and the Solow growth model, proposed by Hansen (1999), Ehrlich and Holdren (1971), and Solow (1956), respectively, to analyze the linear and nonlinear impact of industrial restructuring on economic growth and carbon dioxide emissions. We also test the stability and long-term equilibrium of each variable by four test methods and two test methods, respectively (Breitung 2001; Choi 2001; Im et al. 2003; Kao 1999; Levin et al. 2002; Pedroni 2004). The results reveal that industrial restructuring has linear and nonlinear effects on economic growth and carbon dioxide emissions. We also find that industrial restructuring has a significantly promoted economic growth, while having a significant negative impact on emissions. A key finding is that the effect of industrial restructuring on carbon dioxide emissions turned out to be a nonlinear inverted U–shaped curve. Compared with the traditional mean regression method, the conclusions of this article are more diversified and diverse. The later finding shows that industrial restructuring has a threshold effect on economic growth, but it is not statistically significant. This paper finally verifies the long-term equilibrium relationship between industrial restructuring, economic growth, and emission reduction.

The remainder framework of this article is arranged as follows: The section "Literature review" reviews the previous research literature on industrial restructuring, economic growth, and carbon dioxide emission nexus. Method and data are presented in the section "Method and data," and the section "Results" shows the empirical results. Finally, the research conclusions and policy recommendations are provided in the section "Conclusions and policy recommendations."

Literature review

The relationship between industrial restructuring and economic growth and carbon emissions has been discussed (Botta 2009; Montobbio 2002). This paper separately reviews the economic growth and emissions from industrial restructuring.

Research about the effect of industrial structure on economic growth is relatively rich. Holland and Cooke (1992) analyzed the changes in Washington's economic structure and revealed that 48% of changes in actual output in the service production sector in Washington were related to changes in demand from foreign countries and other parts of the USA. Fagerberg (2000) found that structural changes on average are not conducive to productivity growth. Berthélemy and Söderling (2001) analyzed the long-term growth of Africa based on 27 African countries and revealed that sustainable growth needs to be based on balanced structural changes. McGillivray (2003) revealed that the economic structure adjustment plan did not stimulate Pakistan's growth, and the origin of Pakistan's post-planning growth performance was earlier than the plan. Peneder (2003) analyzed the impact of industrial structure on growth and revealed that early economic development mainly relied on industrial restructuring. Fan et al. (2003) established a new analytical framework and revealed that structural change has made a significant contribution to growth by redistributing resources from low-productivity sectors to high-productivity sectors.

Lin and Xu (2014) explored the importance of transforming China's economy into cleaner production. Gabriel et al. (2016) revealed that the increase in the growth rate of demand in the south means that its natural growth rate must also increase; that is, the level of industrial participation and economic productivity should also increase. Teixeira and

Queirós (2016) found that structural changes in high-knowledge-intensive industries have had an effect on economic growth, and structural change is positive for more developed countries (Organisation for Economic Co-operation and Development (OECD)). Li and Lin (2017) investigated the impact of investment-driven economic growth patterns and the rationalization and upgrading of industrial structures on green productivity in China and revealed that structural changes in manufacturing will negatively affect TFEE and TFCE, respectively.

Vu (2017) presented a new structural change indicator labeled effective structural change (ESC) index and revealed that structural changes promote productivity gains. Cutrini (2019) used ordered logit regression and revealed that the improvement of the efficiency of the service sector is a fundamental cause of differences in economic development. Erumban et al. (2019) used the India panel data and found that static structural changes have had a positive impact on overall productivity growth. India's structural transformation has the characteristics of absorbing the slow and stagnant employment opportunities of construction workers and services. Zhu et al. (2019) based on the measures of super-efficiency and results revealed that the reason for the improvement of China's green development efficiency is due, in large part, to the change in industrial restructuring. The rationalization and progress of the industrial structure have a positive impact on the efficiency of green development.

In the research on the relationship between industrial restructuring and carbon dioxide emission, Jänicke et al. (1989) revealed the decoupling between economic growth and industrial production processes. Minihan and Wu (2012) and Zhang and Huang (2012) revealed that a higher industrial differentiation leads to large differences in industrial carbon emissions. Mao et al. (2013) calculated the industrial impact coefficient (IIC) and revealed that the industrial restructuring based on IIC and ICEC calculations is better than the adjustment based on China's industrial structure adjustment catalog. Zhou et al. (2013) revealed that the first-order lag of industrial restructuring has effectively reduced emissions, and industrial restructuring has an important role in achieving low-carbon economic development. Zhu et al. (2014) estimated the change in industrial structure and revealed that industries such as transportation, heavy industry, oil production, light industry, chemicals, and metals are growing faster. Tian et al. (2014) revealed that the structural changes of the first, second, and third industries are highly correlated, and the structural changes of the industrial sector do not have good correspondence. Mi et al. (2015) revealed that industrial restructuring has great potential for emission reduction. If GDP grows 8.29%, adjusting the industrial structure can reduce 46.06% of CO_2 emissions. Chang (2015) revealed reducing CO_2 emissions from 5707.16 to 545,212 million tons. Chang and Li (2017) revealed that in order to develop better carbon emission reduction policies, the government should pay more attention to the industrial transformation.

Li et al. (2017) revealed that China's industrial structure has gradually improved and various links have been established between different departments. Zhang et al. (2018b) revealed that the mechanical and light industry manufacturing industry has shown rapid growth, and its carbon dioxide emissions associated with changes in carbon dioxide intensity and production structure have declined significantly. Zhang et al. (2018a) employed a dynamic decomposition model to reveal the positive effect of industrial restructuring on carbon emission reduction. Gu and Wang (2018) revealed that the investment restriction policy of China's high-energy-consuming industries has effectively promoted the adjustment of industrial structure and has significant carbon reduction effects. Zhang et al. (2019) revealed that the Yangtze River Delta has gradually developed into an industrialized structure dominated by service industries and advanced manufacturing and the slow growth of carbon dioxide intensity and production structure in the service and construction industries.

According to the previous research literature, we have summarized the relationship among industrial restructuring, economic growth, and carbon emissions as shown in Tables 1 and 2.

Method and data

Panel unit root and cointegration test

Panel unit root

The stationarity test is needed before measuring the model, and its purpose is to judge the unit root of each variable. The purpose of this method is to avoid the bias of estimation results caused by the occurrence of false regression. Four-panel data unit root test methods have been chosen for analysis: Breitung (2001), Choi (2001), Im et al. (2003), and Levin et al. (2002), respectively. The methods of Breitung and Levin et al. belong to the homogeneity test method, while those of Choi and Im et al. belong to the heterogeneity test method.

Panel cointegration test

There are two types of panel data cointegration test methods: one is based on regression residuals. Pedroni (2004), Kao (1999), McCoskey and Kao (1997), and

Table 1 Relevant literature on industrial restructuring and economic growth

	Author names	Variable	Methods	Time	Countries
1	Holland and Cooke (1992)	*Y, P, E, C, IND, S*	Panel estimations	1963–1982	Washington
2	Fagerberg (2000)	*Y, P, S, POP, I*	Panel estimations	1973–1990	39 countries
3	Berthélemy and Söderling (2001)	*Y, E, TFP, U*	Dynamic panel estimations	1960–1996	27 African countries
4	Fan et al. (2003)	*Y, E, X, T*	Solow approach	1952–1995	China
5	Peneder (2003)	*Y, POP, EMR, EDU, INVT*	Dynamic panel model	1990–1998	28 OECD countries
6	Baily et al. (2001)	*Y, X, L, EI, PS, SI*	Dynamic panel model	1972–1989	USA
7	Chen et al. (2011)	*K, L, YTFP, TC, TEC*	Panel regression model	1980–2008	China
8	Kofi Adom et al. (2012)	*C, T, TE, Y, I*	ARDL bounds cointegration test	1971–2007	Ghana, Senegal, and Morocco
9	Cherniwchan (2012)	$Y, GDP, CO_2, IND, S, URBA$	Panel regression model	1970–2000	157 countries
10	Brondino (2019)	Y, E, CO_2, S, IND, L	Subsystem approach	1995–2009	China
11	Zhu et al. (2019)	*Y, C, GDP, S, IND*	Novel integrated approach	1999–2016	China
12	Wang et al. (2019b)	*Y, IND, URB, C*	Johansen cointegration, Granger causality test	1990–2015	China
13	Feng et al. (2019)	*GTFP, EWP, ISGA*	DEA-based Malmquist productivity index approach	1994–2014	China

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Westerlund (2005) tests are based on the regression residuals of the Engle-Granger (EG) two-step method, and the other is based on maximum likelihood ratios. Larsson et al. (2001) is based on the maximum likelihood ratio. However, due to the size of sample (*N*) and time (*T*) and power, this paper chooses the Pedroni and Kao tests. According to the idea of the EG two-step method in the time series cointegration test, Kao proposed five zero hypotheses for a homogeneous panel cointegration test without a cointegration relationship, including one HAC-type and one ADF-type statistics. Pedroni introduces heterogeneity into the panel cointegration test,

Table 2 Relevant literature on industrial restructuring and carbon dioxide emission

	Author names	Variable	Methods	Time	Countries
1	Llop (2007)	Y, EC, CO_2, S	Input-output approach	1995–2000	Spanish
2	Zhou et al. (2013)	Y, CO_2, T, E, IND, U	Panel regression	1995–2009	China
3	Kofi Adom et al. (2012)	*Y, C, T, TE*	Bounds cointegration approach	1971–2007	3 African countries
4	Zhang and Huang (2012)	*Y, CRE, ACR, U, INDE*	Panel regression	1997–2007	China
5	Tian et al. (2014)	*Y, I, C, G, X, M*	Input-output analysis (IOA)	2002–2007	China
6	Mi et al. (Mi et al. 2015	Y, CO_2, IND, S, POP	Input-output model	2010–2020	China
7	Chang (2015)	Y, CO_2, S, IND, POP	Multiprogramming approach	2007	China
8	Song et al. (2015)	*A, ET, EC, Q, V, F, R*	Dynamic simulation model	2010–2025	Jilin City
9	Li and Lin (2017)	*Y, TFP, TFEE, TFCE, U*	Economic growth model	1997–2010	China
10	Li et al. (2017)	*GDP, X, A, T, E, R*	Input-output analysis SNA-IO model	2002–2012	China and Japan
11	Zhu et al. (2017)	*Y, EC, ET, C, IND, U*	Input-output analysis, structural decomposition analysis	1997–2012	China
12	Li et al. (2018b)	*Y, C, U, IND*	Panel regression	2005–2014	50 cities in China
13	Liu and Bae (2018)	*Y, C, EC, U, IND*	Autoregressive distributed lag (ARDL)	1970–2015	China
14	Chen et al. (2018)	Y, CO_2, IND, U	Panel regression	2005–2013	China
15	Rauf et al. (2018)	Y, X, CO_2, POP, IND, S	ARDL constraint test model	1968–2016	China
16	Li et al. (2019)	*Y, I, POP, GDP, TR, TH*	STIRPAT model	2003–2014	China
17	Wang et al. (2019a)	*Y, X, C, EC*	Panel tobit model	2003–2016	China
18	Chen et al. (2019)	*Y, X, E, K, L*	Semi-parametric global vector autoregressive (SGVAR) model	2001–2010	China

Collection from the author

allowing individuals to have different long-term cointegration coefficients. Although its null hypothesis also has no cointegration relationship for all individuals, the hypothesis assumes that cointegration of heterogeneous individuals is allowed. Simultaneously, Pedroni extended the unit root test from the time series to panel data and proposed seven heterogeneous panel cointegration test statistics, including four "Panel" statistics and three "Group" statistics. Some empirical studies have applied this method (Salahuddin et al. 2016; Shahbaz et al. 2017).

Basic model

This paper follows the Cobb-Douglas function and Solow growth model (Solow 1956) and expands the model by adding the industrial restructuring on this basis. The basic model is as follows:

$$Y_{it} = f(IS_{it}, K_{it}, L_{it}) \tag{1}$$

where Y denotes real per capita GDP, IS denotes industrial restructuring, K represents fixed capital, and L denotes the number of labor, where i and t denote country and time, respectively. Based on this data used in this article, i and t take values 32 and 21, respectively. The model is as follows:

$$Y_{it} = AIS_{it}^{\beta_{1i}} K_{it}^{\beta_{2i}} L_{it}^{\beta_{3i}} \tag{2}$$

where A represents productivity and β (β_1, β_2, β_3) denotes the elastic coefficient of variable. After taking the logarithm, the model is as follows:

$$LnY_{it} = \alpha_i + \beta LnIS_{it} + \beta LnK_{it} + \beta LnL_{it} + \mu_{it} \tag{3}$$

where α and μ_i represent individual heterogeneity and random error terms, respectively. In addition, after adding the control variable, the model is expanded as follows:

$$\begin{aligned} LnY_{it} = \alpha_i + \beta_1 LnIS_{it} + \beta_2 LnK_{it} + \beta_3 LnL_{it} + \beta_4 LnIND_{it} \\ + \beta_5 LnTECH_{it} + \beta_6 LnFDI_{it} + \beta_7 LnREC_{it} \\ + \beta_8 LnNREC_{it} + \beta_9 LnURBA_{it} + \mu_{it} \end{aligned} \tag{4}$$

where LnY, $LnIS$, LnK, LnL, $LnIND$, $LnTECH$, $LnFDI$, $LnURBA$, $LnREC$, and $LnNREC$ denote economic growth, industrial structure, fixed capital formation, labor, industrialization, technology, foreign direct investment, urbanization, and renewable and nonrenewable energy consumption, respectively. u is the error term. The subscripts i and t mean the country and time, respectively.

STIRPAT model

In our paper, we also employ the STIRPAT model to investigate the relationship between industrial structure and carbon emissions. The initial condition of the model is composed of four variables, for example influence, population, affluence, and technology. The method was proposed by Ehrlich and Holdren (1971). The initial model form is as follows:

$$I = P \times A \times T \tag{5}$$

In order to be able to obtain the estimation result, the model is further expanded to become an equation that can be calculated using coefficients, and thus the proportional model form is as follows:

$$I_{it} = \alpha_i P_{it}^{\beta_1} A_{it}^{\beta_2} T_{it}^{\beta_3} \tag{6}$$

In Eq. (6), the subscripts i and t represent country and time, respectively. In order to better calculate the coefficients of the model, first, the logarithm of the other side of the program was determined. Then, you can decompose the regression coefficients of each variable. The model form after the expansion is as follows:

$$LnI_{it} = \alpha_i + \beta_1 LnP_{it} + \beta_2 LnA_{it} + \beta_3 LnT_{it} + \varepsilon_t \tag{7}$$

Equation (7) can be used to calculate the coefficient. In order to meet the purpose of this study, industrial restructuring needs to be taken into account, model 8 is augmented with industrial restructuring, and the model is as follows:

$$LnI_{it} = \alpha_i + \beta_1 LnP_{it} + \beta_2 LnA_{it} + \beta_3 LnT_{it} + \beta_4 LnIS_{it} + \varepsilon_t \tag{8}$$

In this study, according to York et al. (2003) and Li et al. (2018a) and to the author's knowledge, this is one of the first studies to include industrial restructuring in the STIRPAT model. Therefore, an empirical model can be written as

$$\begin{aligned} LnCO_{2it} = \alpha_i + \beta_1 LnIS_{it} + \beta_2 LnPOP_{it} + \beta_3 LnY_{it} \\ + \beta_4 LnTECH_{it} + \beta_5 LnIND_{it} \\ + \beta_6 FDI + \beta_7 LnURBA_{it} + \varepsilon_t \end{aligned} \tag{9}$$

where $LnCO_2$, $LnIS$, $LnPOP$, LnY, $LnTECH$, $LnIND$, $LnFDI$, and $LnURBA$ denote carbon emissions, industrial restructuring, population density, affluence, technology, industrialization, foreign direct investment, and urbanization, respectively. Subscripts i and t represent the country and time, respectively.

Threshold regression approach

In order to explore the nonlinear effects of industrial restructuring in economic growth and emissions, we employed a panel threshold regression approach, following

Table 3 Variable definitions

Variables	Unit types	Types
GDPP	Current US$ for 2010	GDP per capita
IS	Percent	The share of services in GDP
CO_2	Million tons of carbon emission	From fossil fuels
POP	Number	Number of people
K	Current US$ for 2010	Gross fixed capital
L	Number	Number of labor
IND	Percent	The share of industry in GDP
NREC	Million tons of carbon emission	Nonrenewable energy consumption
TECH	Number	Total of patent
REC	Million tons of carbon emission	Renewable energy consumption
FDI	Percent	Foreign direct investment (net inflow)
URBA	Percent	The percentage of urban population to the total population

Hansen (1999). The panel threshold regression model is constructed as follows:

$$\begin{aligned} LnY_{it} = \alpha_1 &+ \beta_{11}LnIS_{it}I(g<\gamma_1) + \beta_{12}LnIS_{it}I(\gamma_1 \le g < \gamma_2) \\ &+ \beta_{13}LnIS_{it}I(g \ge \gamma_3) + \beta_{14}LnK_{it} + \beta_{15}LnL_{it} \\ &+ \beta_{16}LnIND_{it} + \beta_{17}LnTECH_{it} + \beta_{18}LnFDI_{it} \\ &+ \beta_{19}LnREC_{it} + \beta_{20}LnNREC_{it} + \beta_{21}LnURBA_{it} + \mu_{1i} \end{aligned} \tag{10}$$

$$\begin{aligned} LnY_{it} = \alpha_2 &+ \beta_{21}LnIS_{it}I(h<\lambda_1) + \beta_{22}LnIS_{it}I(\lambda_1 \le h < \lambda_2) \\ &+ \beta_{23}LnIS_{it}I(h \ge \lambda_3) + \beta_{24}LnK_{it} + \beta_{25}LnL_{it} \\ &+ \beta_{26}LnIND_{it} + \beta_{27}LnTECH_{it} + \beta_{28}LnFDI_{it} \\ &+ \beta_{29}LnREC_{it} + \beta_{30}LnNREC_{it} + \beta_{31}LnURBA_{it} + \mu_{2i} \end{aligned} \tag{11}$$

$$\begin{aligned} LnCO_{2it} = \alpha_3 &+ \beta_{31}LnIS_{it}I(d<\sigma_1) + \beta_{32}LnIS_{it}I(\sigma_1 \le d < \sigma_2) \\ &+ \beta_{33}LnIS_{it}I(d \ge \sigma_3) + \beta_{34}LnPOP_{it} + \beta_{35}LnY_{it} \\ &+ \beta_{36}LnTECH_{it} + \beta_{37}LnIND_{it} + \beta_{38}FDI_{it} \\ &+ \beta_{39}LnURBA_{it} + \mu_{3i} \end{aligned} \tag{12}$$

$$\begin{aligned} LnCO_{2it} = \alpha_4 &+ \beta_{41}LnIS_{it}I(h<\varphi_1) + \beta_{42}LnIS_{it}I(\varphi_1 \le h < \varphi_2) \\ &+ \beta_{43}LnIS_{it}I(h \ge \varphi_3) + \beta_{44}LnPOP_{it} + \beta_{45}LnY_{it} \\ &+ \beta_{46}LnTECH_{it} + \beta_{47}LnIND_{it} + \beta_{48}FDI \\ &+ \beta_{49}LnURBA_{it} + \mu_{4i} \end{aligned} \tag{13}$$

where γ, λ, σ, and φ denote the threshold values; *g*, *h*, and *d* denote the threshold variables (industrialization denoted as *g*, urbanization denoted as *h*, and economic development denoted as *d*); *I* is the indicator function if the assumption of *I*() is satisfied; and the value of *I* is 1; otherwise, it is 0. Equation 10 uses industrialization as a threshold variable to test the nonlinear impact of industrial restructuring in economic growth. Equation 11 tests the nonlinear effect of industrial restructuring in economic growth by using urbanization as a threshold variable. Tests of the nonlinear impacts of industrial restructuring on carbon dioxide emissions by using economic development level as a threshold variable are present in Eq. 12. Finally, Eq. 13 uses urbanization as a threshold variable to test the nonlinear effects of industrial restructuring in emissions.

Variables and data

Explanatory variables and response variables

In the three models (growth model, STIRPAT model, and threshold model) of this paper, industrial restructuring is

Table 4 Country list from seven continents

Continents	Country	Classification
Sub-Saharan Africa	South Africa	Lower middle income
Europe and Central Asia	Finland, Greece, Denmark, Sweden, Spain, Norway, Ireland, Germany, France, Netherlands, UK, Portugal	High income
	Turkey	Upper middle income
North America	USA	High income
East Asia and Pacific	Japan, New Zealand	High income
	China, Philippines, Thailand	Upper middle income
	Indonesia	Lower middle income
Middle East and North Africa	Israel	High income
	Iran	Upper middle income
	Egypt, Morocco	Lower middle income
South Asia	India, Bangladesh, Pakistan	Lower middle income
Latin America and the Caribbean	Mexico	Upper middle income
	Chile	High income
	Brazil, Peru	Upper middle income

Table 5 Statistical description results of all variables

Variable	Mean	SD	Minimum	Maximum	Skewness	Kurtosis	Jarque-Bera	*P* value
LPGDP	9.3940	1.3907	6.1458	11.4254	− 0.4990	2.0047	55.6300	0.0000
LCO_2	12.1489	1.4115	9.9436	16.0383	0.7402	3.0186	61.3900	0.0000
LPOP	17.608	1.5316	15.117	21.050	0.1925	2.4697	12.0300	0.0024
LK	25.2978	1.4319	22.895	31.2293	0.7493	3.1056	63.2000	0.0000
LL	16.8559	1.5661	14.264	20.4843	0.4247	2.6327	23.9800	0.0000
LREC	8.7410	2.0518	1.5098	12.9164	− 0.5671	3.9930	63.6300	0.0000
LNREC	11.1043	1.3923	8.9910	14.8116	0.6838	2.8573	52.9500	0.0000
IS	0.5797	0.0862	0.3337	0.7755	− 0.1302	2.3786	12.7100	0.0071
IND	0.2789	0.0765	0.1368	0.4964	0.7673	3.0302	65.9800	0.0000
LTECH	7.4442	2.2617	3.0910	14.0352	0.6986	3.2481	56.3900	0.0000
FDI	3.6614	6.7534	− 5.6709	87.4426	6.8066	69.449	1.3*e*+05	0.0000
URBA	0.6746	0.1887	0.2244	0.9234	− 0.7226	2.2516	74.1800	0.0000

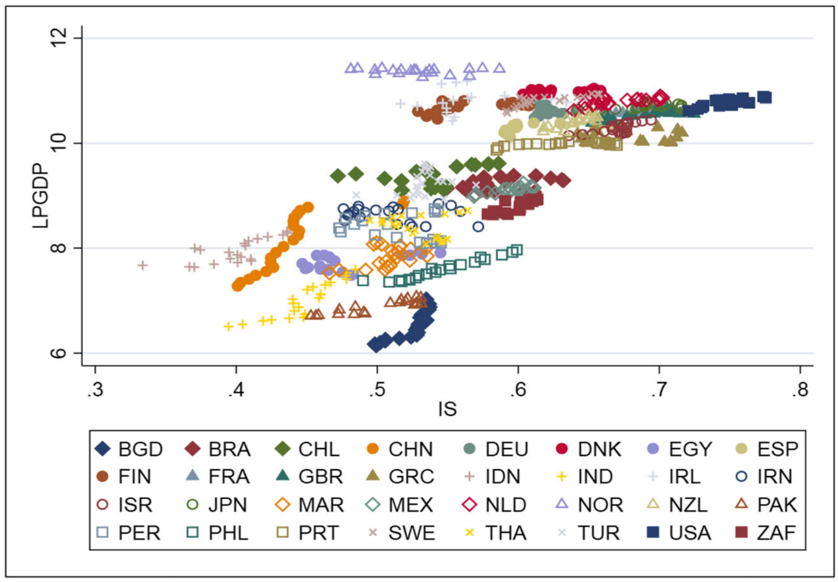

Fig. 1 Scatter plot of industrial restructuring and economic growth in 32 countries

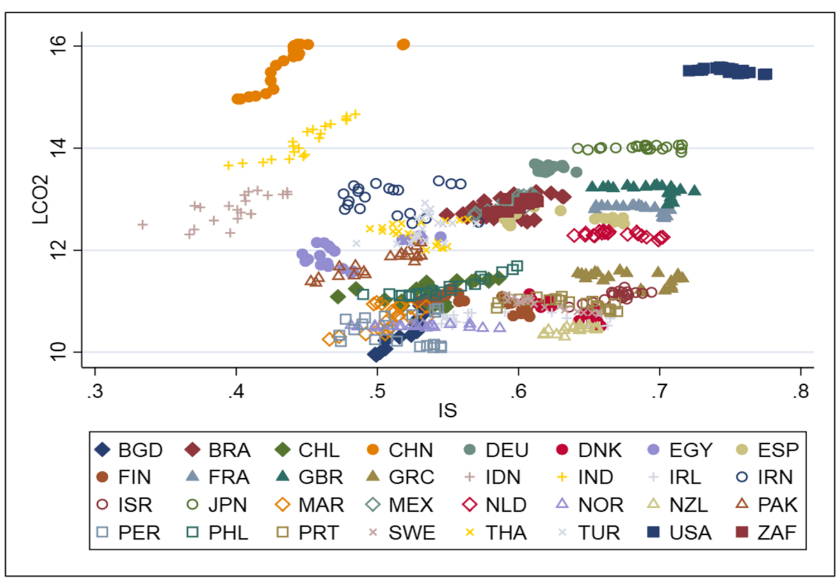

Fig. 2 Scatter plot of industrial restructuring and carbon dioxide emissions in 32 countries

Table 6 Panel unit root test result

Variables	Value	Original				First-order difference (1)			
		LLC	Breitung	Fisher ADF	IPS	(1) LLC	(1) Breitung	(1) Fisher ADF	(1) IPS
LPGDP	Value	− 0.5035	− 0.2816	41.0125	− 1.4233	− 3.4113	− 2.6859	122.4454	− 9.6249
	P	0.3073	0.3891	0.9888	0.0773	0.0000	0.0036	0.0000	0.0000
LCO_2	Value	− 1.8307	1.0904	42.9378	0.5142	− 7.4980	− 5.5343	113.3029	− 10.7198
	P	0.0336	0.8622	0.9801	0.6964	0.0000	0.0000	0.0000	0.0000
LPOP	Value	0.6515	4.4672	232.7878	− 0.3488	− 5.6936	1.8517	79.1466	− 4.7947
	P	0.7426	1.0000	0.0000	0.3636	0.0000	0.9680	0.0962	0.0000
LK	Value	− 2.1888	0.9643	36.1284	− 2.5053	− 3.9910	0.6045	74.5275	− 4.2032
	P	0.0143	0.8325	0.9981	0.0061	0.0000	0.7272	0.1731	0.0000
LL	Value	− 4.0636	4.6345	68.6352	1.8984	− 2.0889	1.4092	67.6585	− 5.2227
	P	0.0000	1.0000	0.3232	0.9712	0.0184	0.9206	0.3532	0.0000
LRE	Value	0.9282	− 0.3700	35.1446	− 5.5957	− 13.2441	− 7.1672	214.6261	− 13.0492
	P	0.8233	0.3557	0.9987	0.0000	0.0000	0.0000	0.0000	0.0000
LNRE	Value	− 2.8429	1.2966	37.1667	0.1699	− 6.8540	− 4.6884	118.0790	− 10.1385
	P	0.0022	0.9026	0.9971	0.5675	0.0000	0.0000	0.0000	0.0000
S	Value	− 3.6854	0.9100	53.5531	0.8198	− 9.5950	− 6.4830	149.7274	− 10.8363
	P	0.0001	0.8186	0.8210	0.7938	0.0000	0.0000	0.0000	0.0000
INS	Value	− 2.0964	1.6150	50.6871	0.3257	− 8.1558	− 5.7977	125.1437	− 10.4524
	P	0.0180	0.9468	0.8867	0.6277	0.0000	0.0000	0.0000	0.0000
LTECH	Value	− 2.8408	0.9798	103.7090	− 1.7172	− 10.1322	− 4.4142	188.0509	− 10.8265
	P	0.0022	0.8364	0.0012	0.0430	0.0000	0.0000	0.0000	0.0000
FDI	Value	− 5.1884	− 3.8700	111.149	− 6.1179	− 13.1393	− 9.1042	273.9845	− 12.8080
	P	0.0000	0.0001	0.0002	0.0000	0.0000	0.0000	0.0000	0.0000
URBA	Value	26.6371	1.4268	66.9487	− 3.3130	− 4.6806	− 1.6379	357.8487	− 4.3231
	P	1.0000	0.9232	0.3762	0.0005	0.0000	0.0507	0.0000	0.0000

ADF Augmented Dickey-Fuller test

introduced into these three modes as an explanatory variable (denoted by *IS*).

Table 7 The cointegration results of the Pedroni test

	Test value	Significant value	Test value	Significant value
Within				
Panel *v* test	0.1191	0.4526	− 5.2619	1.0000
Panel rho test	1.8051	0.9645	2.0491	0.9798
Panel PP test	− 11.8664	0.0000	− 16.3365	0.0000
Panel ADF test	− 10.4951	0.0000	− 12.2444	0.0000
Between				
Group rho test	4.2911	0.9999		
Group PP test	− 30.9833	0.0000		
Group ADF test	− 13.6417	0.0000		

Null hypothesis, no cointegration

According to the growth model, economic growth is introduced into this mode as a response variable. According to the STIRPAT model, carbon emissions are introduced into this mode as response variables. In the panel threshold model, both economic growth and carbon emissions are used (denoted by GDPP and CO_2, respectively).

Threshold variables and control variables

The percentage of industrial added value to GDP per country is regarded as a threshold variable (represented

Table 8 The cointegration results of the Kao test

	T value	*P* value
ADF	− 1.7825	0.0373
Residual	29.7255	
HAC	8.6261	

Null hypothesis, no cointegration

Table 9 Regression results for the growth model

Variable	Model 1	Model 2	Model 3	Model 4
IS	2.9499*** (0.2622)	0.2710* (0.1446)	1.0827*** (0.2166)	0.8931*** (0.1728)
LK		0.2898*** (0.0083)	0.2493*** (0.0087)	0.1557*** (0.0085)
LL		0.0589 (0.0370)	0.0258 (0.0353)	− 0.1077*** (0.0299)
IND			0.9901*** (0.1976)	0.7588*** (0.1644)
LTECH			0.0535*** (0.0060)	− 0.0068 (0.0058)
FDI			0.0013** (0.0006)	0.0004 (0.0005)
LREC				0.0422*** (0.0064)
LNREC				0.3045*** (0.0223)
URBA				1.1638*** (0.1195)
Constant	7.6838*** (0.1522)	0.9132* (0.5111)	1.3464*** (0.4761)	2.0553*** (0.3870)
R^2	0.1653	0.7965	0.8259	0.8902

The value in parentheses is the standard error

***Significant at 1%

**Significant at 5%

*Significant at 10%

Table 10 Regression results for the STIRPAT model

Variable	Model 1	Model 2	Model 3	Model 4
IS	1.7665*** (0.3202)	− 1.7905*** (0.2067)	− 0.5544* (0.3215)	− 0.5621* (0.3200)
LPOP		0.6789*** (0.0967)	0.6066*** (0.0961)	0.5990*** (0.0958)
LPGDP		0.6732*** (0.0402)	0.6288*** (0.0405)	0.6962*** (0.0479)
LTECH		0.0737*** (0.0091)	0.0783*** (0.0090)	0.0835*** (0.0093)
IND			1.3850*** (0.2794)	1.2558*** (0.2873)
FDI				− 0.0010 (0.0008)
URBA				− 0.5554** (0.2256)
Constant	11.1248*** (0.1858)	− 5.6406*** (1.4456)	− 5.0866*** (1.4239)	− 5.2059*** (1.4192)
R^2	0.0455	0.7234	0.7337	0.7371

The value in parentheses is the standard error

***Significant at 1%

**Significant at 5%

*Significant at 10%

by *g*) to replace the degree of industrialization in different countries. The percentage of urban population to the total population is regarded as a threshold variable (represented by *h*) to replace the degree of urbanization in different countries. The GDP per capita is regarded as a threshold variable (represented by *d*) to replace the degree of economic growth in different countries.

The following variables are based on the growth model: fixed capital formation (represented by *K*), labor (represented by *L*), industrialization (represented by *IND*), technology

Table 11 Test results for the threshold effects

Threshold	Value	RSS	MSE	*F*	*P*	10%	5%	1%
Single	0.2064	2.1171	0.0033	27.7800	0.4133	49.0460	59.8238	88.5052
Double	0.3994	2.0853	0.0032	9.9000	0.8900	46.9103	58.6975	75.4496
Triple	0.4111	2.0559	0.0032	9.3300	0.7967	29.9532	36.0450	68.1065

Table 12 Estimation results of the panel threshold model

Variables	Coefficients
LK	0.1565*** (0.0083)
LL	− 0.0546* (0.0307)
LREC	0.0444*** (0.0063)
LNREC	0.2691*** (0.0233)
IND	0.8925*** (0.1725)
LTECH	− 0.0038 (0.0057)
FDI	0.0003 (0.0005)
URBA	1.1478*** (0.1177)
IS ($g \le 0.2064$)	0.9131*** (0.1675)
IS ($0.2064 < g \le 0.3994$)	0.9582*** (0.1678)
IS ($0.3994 < g \le 0.4111$)	1.0940*** (0.1743)
IS ($g > 0.4111$)	0.7991*** (0.1741)
Constant	1.4369*** (0.3944)
Observations	672
R^2	0.8975

The value in parentheses is the standard error

***Significant at 1%

*Significant at 10%

Table 14 Estimation results of the panel threshold model

Variables	Coefficients
LK	0.1466*** (0.0080)
LL	0.0245 (0.0306)
LREC	0.0340*** (0.0059)
LNREC	0.2354*** (0.0224)
IND	0.8792*** (0.1553)
LTECH	− 0.0068 (0.0054)
FDI	0.0006 (0.0004)
URBA	1.1359*** (0.1165)
IS ($h \le 0.3059$)	0.3790** (0.1753)
IS ($0.3059 < h \le 0.5128$)	0.6272*** (0.1644)
IS ($0.5128 < h \le 0.7795$)	1.0467*** (0.1638)
IS ($h > 0.7795$)	0.9524*** (0.1635)
Constant	0.8668** (0.3864)
Observations	672
R^2	0.9066

The value in parentheses is the standard error

***Significant at 1%

**Significant at 5%

(represented by *TECH*), foreign direct investment (represented by *FDI*), renewable and nonrenewable energy use (represented by *REC* and *NREC*, respectively), and urbanization (denoted by *URBA*). After taking the logarithm, the control variables are substituted into the model.

The following variables are based on the STIRPAT model: population density (denoted by *POP*), affluence (denoted by *GDPP*), technology (denoted by *TECH*), industrialization (denoted by *IND*), foreign direct investment (denoted by *FDI*), and urbanization (denoted by *URBA*). After taking the logarithm, the control variables are substituted into the model.

Control variables used in the panel threshold model are derived from the growth model and STIRPAT model, respectively.

All variables are defined as follows (see Table 3): The data is selected from seven continents (see Table 4). This article selects data based on geospatial and economic space and missing variables, and the data comes from three income types, of which there are 17 high-income countries, 8 upper-middle-income countries, and 7 lower-middle income. The data in this article includes developed and developing countries, as well as some emerging economies and OECD countries, and considers different countries in space and geographical location. Table 4 lists the selected countries, the data from BP Statistical data (2018) and World Bank (Zhou and Li 2019).

Data description analysis

Table 5 shows the statistical description results for all variables. In general, under normal distribution conditions, the values of skewness and kurtosis should be 0 and 3, respectively. The results reveal that most of the variables are right-biased and the rest are left-biased. The Jarque-Bera statistical and *P* value results reveal that all variables do not satisfy the null hypothesis of a normal distribution.

Table 13 Test results for the threshold effects

Threshold	Value	RSS	MSE	*F*	*P*	10%	5%	1%
Single	0.3059	2.0608	0.0032	46.2900	0.3767	70.5176	80.6681	101.6170
Double	0.5128	1.9546	0.0030	35.3900	0.4467	84.3608	110.5779	132.4225
Triple	0.7795	1.8783	0.0029	26.4600	0.6600	76.6621	102.2864	145.1595

Table 15 Test results for the threshold effects

Threshold	Value	RSS	MSE	*F*	*P*	10%	5%	1%
Single	6.3946	5.6229	0.0086	146.51	0.0000	74.0338	83.5483	93.47620
Double	9.6171	4.8250	0.0074	107.66	0.1233	127.8054	186.815	250.0769
Triple	10.9689	4.2994	0.0066	79.590	0.6300	207.2833	225.282	274.1251

Figures 1 and 2 show the scatter plot of industrial restructuring and economic growth and emissions, respectively. It can be found that there is a nonlinear relationship among industrial restructuring and economic growth and carbon dioxide emissions, respectively. Therefore, it is reasonable to use the panel threshold model to investigate the role of industrial restructuring in economic development and emissions.

Results

Stationarity test of variables

Checking the stability of the data is a critical step before estimating the threshold regression model. In our paper, the four-unit root test methods are used in this paper. It can be found that all variables of the original data have unit roots, and all variables become smooth (significant at the 1% level) after the first-order difference (Table 6).

Table 16 Estimation results of the panel threshold model

Variables	Coefficients
LPOP	0.6209*** (0.0839)
LGDP	0.6977*** (0.0422)
LTECH	0.0813*** (0.0085)
LIND	0.8495*** (0.2587)
FDI	− 0.0000 (0.0007)
URBA	− 0.7119*** (0.2016)
IS ($d \leq 6.3946$)	− 1.2955*** (0.3159)
IS ($6.3946 < d \leq 9.6171$)	− 0.5391* (0.2920)
IS ($9.6171 < d \leq 10.9689$)	− 1.0693*** (0.2926)
IS ($d > 10.9689$)	− 1.5935*** (0.2953)
Constant	− 5.1952*** (1.2472)
Observations	672
R^2	0.7998

The value in parentheses is the standard error

***Significant at 1%

*Significant at 10%

Cointegration test analysis

The first-order difference data is smooth; next, we need to further test whether there is a long-term and short-term cointegration between all variables. We employ the Pedroni and Kao tests to test the cointegration relationship of variables. According to Tables 7 and 8, the results include four statistics (within the test) and three statistics (between the test), respectively. The results reveal that the two statistics (within the test) and (between the test) and Kao test are significant at a 5% level, respectively. Therefore, we confirm the presence of a long-term relationship among all variables.

Basic panel model

Growth model

According to Eqs. (1)–(4), Table 9 shows the results of four different types of models, and the purpose is to investigate the contribution of industrial restructuring in economic development. The Hausman test results are significant, so the fixed effects model is used in this paper.

The results in models 1 and 2 of Table 9 reveal that both the contribution of industrial restructuring and gross fixed capital to economic growth are positive. In models 3 and 4, the estimated coefficients of industrial restructuring and industrialization are 0.8931 and 0.7588, respectively. It reveals that the economic growth effect of industrial restructuring is larger than that of industrialization. Therefore, industrial restructuring is conducive to economic development.

STIRPAT model

According to Eqs. (5)–(9), Table 10 shows the results of four different types of models, and the purpose is to investigate the contribution of industrial restructuring in emission. Fixed effects model is supported by the Hausman test.

The results in model 1 reveal that industrial restructuring has significant effects on emissions. The reason for this positive effect is due to the omission of important variables. In STIRPAT models 2–4, the estimated coefficients of industrial restructuring and industrialization are negative and positive,

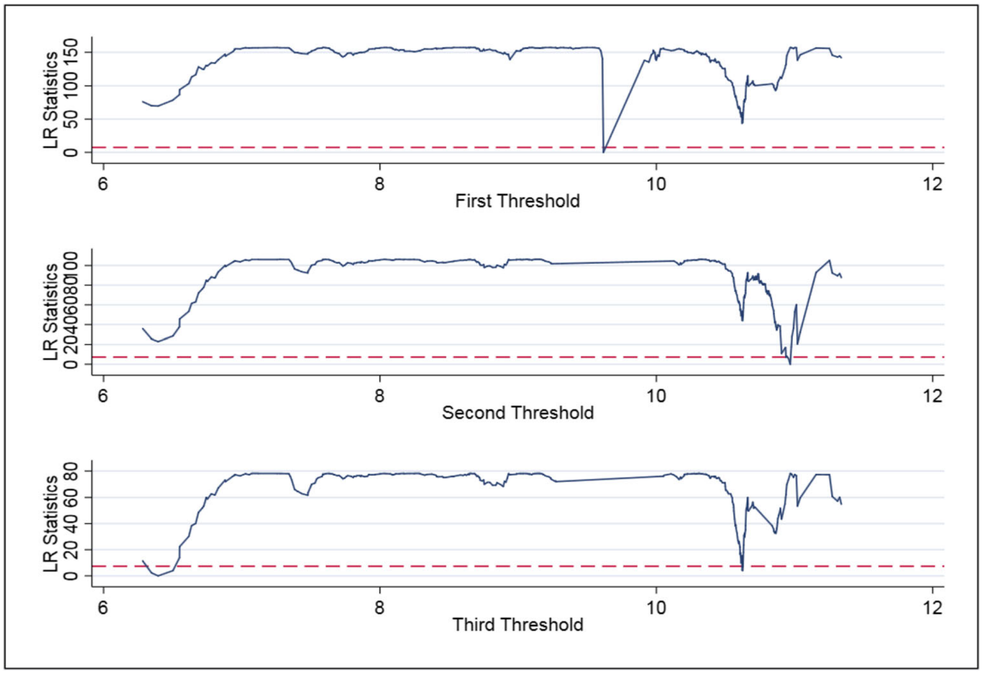

Fig. 3 Threshold parameter of economic growth. The solid blue line represents LR (gamma), and the red dotted line represents the 95% critical

respectively. It reveals that industrial restructuring plays an important role in the process of emission reduction.

Panel threshold regression approach

Panel threshold regression approach for economic growth model

According to the above analysis, it is concluded that industrial restructuring is beneficial to economic growth and emission reduction. However, the nonlinear relationship between variables is ignored. Therefore, we employ a panel threshold approach to further estimate the nonlinear effect of industrial restructuring in economic growth.

According to Eqs. (10) and (11), before building the threshold model, we must test whether the threshold effect is significant, and then the likelihood ratio (LR) value is used to calculate the threshold. At the same time, it is further checked whether the model has a double threshold, then the three thresholds are checked; finally, the threshold number is determined.

First, industrialization is used as a threshold variable. These results reveal that there are also three thresholds in Tables 11 and 12. The three threshold values are 0.2064, 0.3994, and 0.4111, respectively, but all values are not significant at the 10% level. Therefore, the threshold effect does not exist.

Secondly, urbanization is used as a threshold variable. These results reveal that there are three thresholds in Tables 13 and 14. The three threshold values are 0.3059, 0.5128, and 0.7795, respectively, but all values are not significant at the 10% level. Therefore, the threshold effect does not exist.

Panel threshold regression approach for the STIRPAT model

First, economic growth is used as a threshold variable. The results reveal that there are three thresholds in Tables 15 and 16. The three threshold values are 6.3946, 9.6171, and 10.9689, respectively, but only a single threshold value is significant at the 1% level. Therefore, there is a threshold effect. The results reveal that industrial restructuring has significant negative effects on

Table 17 Test results for the threshold effects

Threshold	Value	RSS	MSE	*F*	*P*	10%	5%	1%
Single	0.2681	6.1081	0.0094	83.1600	0.0500	64.5083	81.4893	102.2904
Double	0.6222	5.8651	0.0090	26.9700	0.7100	64.6743	94.9784	125.5097
Triple	0.7801	5.6012	0.0086	30.6700	0.6033	78.3328	99.2870	157.1263

Table 18 Estimation results of the panel threshold model

Variables	Coefficients
LPOP	0.7517*** (0.0900)
LGDP	0.5711*** (0.0462)
LTECH	0.0920*** (0.0087)
LIND	0.8123*** (0.2669)
FDI	0.0003 (0.0008)
URBA	− 0.2105 (0.2278)
IS ($h \leq 0.2681$)	− 1.3861*** (0.3211)
IS ($0.2681 < h \leq 0.6222$)	− 0.6224** (0.2955)
IS ($0.6222 < h \leq 0.7801$)	− 0.8875*** (0.2951)
IS ($h > 0.7801$)	− 1.0552*** (0.2936)
Constant	− 6.7090*** (1.3326)
Observations	672
R^2	0.7849

The value in parentheses is the standard error

***Significant at 1%

**Significant at 5%

emissions, and the estimated coefficients of industrial restructuring are − 1.2955, − 0.5391, and − 1.0693; these coefficients appear in an upward trend at the beginning, followed by a downward trend. This variation is called an inverted U–shaped trend. Figure 3 shows the threshold parameters of urbanization provided by the LR test.

Secondly, urbanization is used as a threshold variable. This result reveals that there are three thresholds in Tables 17 and 18. The three threshold values are 0.2681, 0.6222, and 0.7801, respectively, but only a single threshold value is significant at the 10% level. Therefore, there is a threshold effect. The results reveal that industrial restructuring plays an active role in reducing emissions, and the estimated coefficients of industrial restructuring are − 1.3861, − 0.6224, and − 0.8875; these coefficients appear in an upward trend at the beginning, followed by a downward trend. This variation is called an inverted U–shaped trend. Figure 4 shows the threshold parameters of urbanization provided by the LR test.

Conclusions and policy recommendations

Industrial restructuring is considered as a meaningful measure in modern energy conservation and emission reduction and sustainable economic growth. Some researchers have discussed the role of industrial restructuring in economic growth and emission reduction. However, there is a general assumption in previous studies that the relationship among the two is a linear symmetric, but the possible nonlinear relationship was neglected. Therefore, the goal of this paper is to investigate the nonlinear contribution of industrial restructuring in the process of economic growth and emission reduction, and we employ the growth model, STIRPAT model, and panel threshold regression model to test the linear and nonlinear effects of industrial restructuring on economic growth and emissions. This data

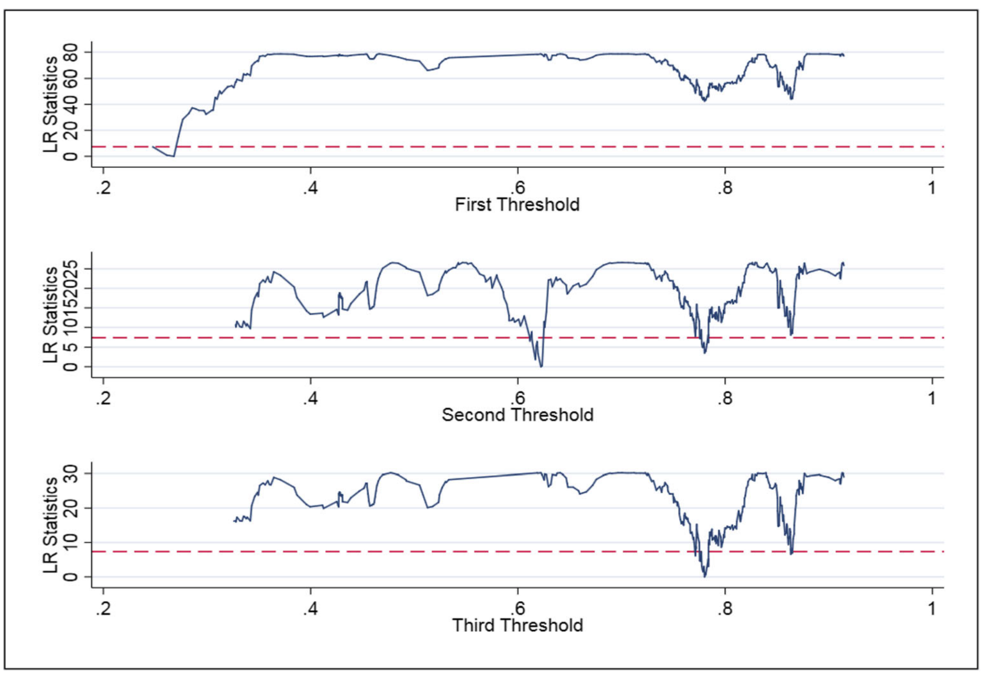

Fig. 4 Threshold parameter of urbanization. The solid blue line represents LR (gamma), and the red dotted line represents the 95% critical

covers 32 countries during the period of 1997–2017, and the empirical conclusions are provided as follows:

1) Industrial restructuring has significant linear and nonlinear effects on economic growth and emissions.
2) Industrial restructuring has a positive and significant effect on economic growth, while industrial restructuring has a significant negative effect on carbon emissions. This paper verifies that industrial restructuring is beneficial to economic growth and has major implications for emission reductions.
3) The conclusions of the panel threshold regression reveal that industrial restructuring has threshold effects in promoting economic growth and carbon emission. When we use industrialization and urbanization as threshold variables, industrial restructuring has a threshold effect in promoting economic development, but it is not significant. While industrial restructuring has a threshold effect on the process of carbon dioxide emissions, it is found that there is a nonlinear inverted U–shaped trend between the two. When using economic development or urbanization as a threshold variable, there is still a nonlinear inverted U–shaped trend among industrial restructuring and carbon dioxide emissions. These findings suggest that the industrial restructuring plays an important role in the process of economic development and emission. In general, the implementation of industrial restructuring policies is beneficial to the economic development and emission reduction targets of different countries. As far as economic growth is concerned, there is no significant threshold effect of industrial restructuring on economic growth. Therefore, in the process of industrialization and urbanization, the implementation of industrial restructuring is an effective policy. As for carbon emissions, it is found that industrial restructuring has a significant threshold effect on emission reduction, and this relationship is inverted U–shaped.

Therefore, some of the policy recommendations in this article are as follows: among the countries with low levels of economic development and urbanization, Bangladesh has a single industrial structure, mainly agriculture, and industrial restructuring is very important to the country. It can not only solve the problem of relying solely on agricultural development but also improve economic development and technological emission reduction. Simultaneously, urbanization also needs development. There are also some countries, such as India, Pakistan, Egypt, and other countries, with rich traditional agricultural resources. For these resource-rich countries, the government should pay attention to the quality of industrial structure adjustment when advancing industrial structure transformation. To optimize the industrial structure and improve the quality of industrial transformation as a breakthrough for resource-based countries to achieve sustainable development and transform and upgrade traditional resource-based industries, such as developing green industries, nurturing superior alternative industries, and accelerating the development of modern integrated high-end service industries, encourage the development of strategic emerging industries. Developed countries, such as the USA, UK, and Japan, should take advanced industrial structure as an important part of formulating industrial policies, and then accelerate the development towards the high-end of the global value chain. Therefore, the implementation of industrial restructuring needs to be prudent, and countries should balance between industrial restructuring-growth-emissions nexus. In general, industrial restructuring is ultimately conducive to energy conservation, emission reduction, and sustainable development.

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