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Research article

Can green technology reduce carbon dioxide emissions? Evidence from G7 and BRICS countries

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ABSTRACT

This study estimates the impact of green technology innovation and its interaction terms on CO_2 emission, by using the random and fixed effect estimate method, employs panel data of the G7 and BRICS countries from 1990 to 2019. The regression results show that a single type of green technological innovation has not a significant inhibitory effect on CO_2 emissions. The interaction of the two types of green technological innovations has a significant effect on the decrease of CO_2. Moreover, the study test the difference effect of green technological innovations on CO_2 emission among the G7 and BRICS countries. Furthermore, we also choose appropriate instrument variables to deal with the endogenesis of the model and examine model robustness. The findings demonstrate that the empirical conclusions can hold true in the test. Based on the findings above, we puts forward a few policy recommendations for G7 countries and BRICS countries to reduce carbon dioxide emissions.

1. Introduction

With economic growth worldwide, energy consumption has already become the main environmental degradation contributor. Global environmental pollution and ecological degradation have attracted increasing attention, and the demand of effective energy production and green development has been considered an important research topic [2,4]. Recently, due to environmental concerns have become more obvious [5,6]. Green technology innovation, a novel model of sustainable development that reduces environmental destruction, has been extensively concerned by researchers and practitioners [24,26,30].

Following the Environmental Kuznets Curve (EKC) hypothesis in Grossman and Krueger [3](the inverted U-shaped curve between per capita income and indicators of environmental pollution), considerable studies have been conducted to investigate the association of economic growth with CO_2 emission [19,22,28,37]. The main factors affecting CO_2 emissions such as economic development, energy and industrial structure, trade opening level and urbanization process have been discussed intensively [11,13,21,31,34], [38].

Existing research shows that technological factors, such as indigenous R&D activities, innovations in technology, or spillovers come from foreign direct investment (FDI) and foreign trade, all have potential impacts on environmental quality [1,5,16–18,23,25]. However, as far as we know, how and to what extent technology spillovers affect carbon emissions remains an open question.

Among the above factors, many researchers are especially concerned about technical innovation's effect on the environment [8,35]. In spite of its role in enhancing economic growth, technology also generates a variety of effects on the environment. Technology is

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like a double-edged sword. Acemoglu et al. [2] classified the technologies that cause environmental pollution as grey technologies, and those that have a positive impact on the environment or address pollution concerns as green technologies. Recently, green technology innovations have become vital tools in lowering CO_2 emissions [15,32] Theoretically, though the presence of more environmental technology-related patents is more beneficial to CO_2 reduction, few empirical findings can prove the point [15]. However, similarly, unanimous consensus has been achieved on the association of CO_2 emissions with green technology innovations.

Some existing researches have demonstrated that green technological innovation negatively affect carbon emissions, and some have drawn conclusions about how green technology innovations positively affect carbon emissions with different samples [7,14]. Weina et al. [32]. discovered that for Italia green technologies' contribution to promoting efficiency of environmental production but not play an appreciable impact in carbon emission reduction. Kerui Du et al. [15]revealed the single threshold effect of green technological innovation on level of income. Xuefeng shao et al. [27]found that heterogeneous green technologies exert a positive impact on urban carbon emissions in China. Lin et al. [20]investigated how the green technology innovation affects CO_2 emissions reduction in China. The results show that green technology innovations exist a heterogeneous impact among cities. However, there are still inconsistent conclusions above the relationship between green technological innovation and CO_2 emissions.

Thus far, few scholars have divided green technologies into different categories and studied the effect of green technologies on carbon emissions. This study refer to "environment-related technology" as green technological innovation, which including three types of patent-based indicators, that is, Green development technology (indicator of technology development), Green international collaboration technology (indicator of international collaboration) and Green diffusion technology (indicator of technology diffusion) (Data from the OECD database). The effects of these three green technology innovation on CO_2 emission were studied respectively.

This paper is similar to the study carried out by Kerui Du et al. [15]. Whereas, their difference is mainly reflected in the selection of research methods and research samples.

The main marginal contributions of the current research are:

(1) Former studies have generally discussed the green technological innovation affecting environmental change, with less attention paid to the effect of the interaction of these green technological innovation on carbon dioxide emissions. In this study, the impact of three types of technologies on CO_2 emissions is studied, including green technology development, green international cooperation technology and green technology diffusion. Meanwhile, the interaction of these three technologies is discussed for the first time. The paper has drawn some novel conclusions regarding the effect of green technological innovation on the environment.
(2) Previous studies have paid little attention to endogenesis and regional heterogeneity of green technology innovation on CO_2 emissions, leading to biased conclusions and inconsistent. To avoid the deficiency, the research further adopts the panel regression approach to estimate the endogenesis and regional heterogeneity.

The other parts in this paper are structured as below. Section 2 shows the econometric methodology. Section 3 provides variable selection and data description. Section 4 shows the results and discussion. The conclusions and policy implications are presented in Section 5.

2. The model specification and econometric method

The original model of IPAT was devised by Ehrlich &Holdren [12], and then extended by Dietz and Rosa [10]. It is a general method which can be employed to explore the factors that affecting environmental pollution. Many researchers have widely used the model to test different determinants in carbon emissions) [20,33]. The model's key factors affecting carbon emissions, including technology level, population and economic size. The model can be expressed as follows:

$$I = P \times A \times T \tag{1}$$

in Eq. (1), I, T, P, and A denote CO_2 emissions, technological level, population and economic development respectively.

To facilitate tests of the econometric estimating model, Dietz and Rosa (1997) [10]converted IPAT to the STIRPAT model, as follows:

$$I_i = \alpha P_i^b A_i^c T_i^d e_i \tag{2}$$

in Eq. (2),I, T, P, and A denote the same as in Eq. (1), and a represents the intercept term, b, c and d represents the elastic value of P, A and T, subscript i represents different observation term and ei is the random error.

Based on the analysis above, we perform logarithmic processing on Eq. (3), and construct the econometric estimating model as follows:

$$\begin{aligned} lnCO2_{i,t} = {} & \alpha_i + \beta_1 \ln Gt_{i,t} + \beta_2 \ln Gtc_{i,t} + \beta_3 \ln Gtd_{i,t} + \beta_4 \ln POP_{i,t} \\ & + \beta_5 \ln GDP_{i,t} + \beta_6 \ln URB_{i,t} + \beta_7 \ln IS_{i,t} + u_{i,t} + \varepsilon_{i,t} \end{aligned} \tag{3}$$

where $\ln Gt_{i,t}$ is the patent counts of green technology development, $\ln Gtc_{i,t}$ represents the share of patent counts of green international cooperation technology, $\ln Gtd_{i,t}$ refers to the share of patent counts of green technology diffusion, $\ln GDP_{i,t}$ denotes the scale of economic development, $\ln POP_{i,t}$ represents the population size, $\ln URB_{i,t}$ stands for the urbanization rate, $\ln IS_{i,t}$ signifies the industrialization rate, i denotes the country, t indicates the year, $u_{i,t}$ is the economy i's individual effects and $\varepsilon_{i,t}$ is the random term.

Using Eq. (3), we refer to Refs. [1,8]to introduce $\ln Gt_{i,t} \times \ln Gtd_{i,t}$ and $\ln Gtc_{i,t} \times \ln Gtd_{i,t}$ to the model. The interaction terms stand for the Interaction effects of two kind of green technologies. Considering technology spillover capacity, we propose Eq. (4) as follows:

$$\begin{aligned} lnCO2_{i,t} &= \alpha_i + \beta_1 \ln Gt_{i,t} + \beta_2 \ln Gtc_{i,t} + \beta_3 \ln Gtd_{i,t} + \beta_4 \ln GDP_{i,t} + \beta_5 \ln POP_{i,t} \\ &+ \beta_6 \ln URB_{i,t} + \beta_7 \ln IS_{i,t} + \beta_8 \ln Gt_{i,t} \times \ln Gtd_{i,t} + \beta_9 \ln Gtc_{i,t} \times \ln Gtd_{i,t} + u_{i,t} + \varepsilon_{i,t} \end{aligned} \tag{4}$$

3. Variable selection data description

3.1. Dependent variable

According to Refs. [9,29], the total CO_2 emissions and CO_2 intensity (CI) are employed as the indicators of the dependent variable. These data come from the World Bank.

3.2. Core variables

Green technology innovation is an effective method to resolve economic and environmental conflicts, which is also the key to CO_2 emission reduction [7,15]. Existing empirical papers usually measure technological innovation based on OECD statistics database. The green technology innovation data are obtained from OECD statistics database. This study applies patent counts of green technology development (Gt), patent counts of green international cooperation technology (Gtc) and patent counts of green technology diffusion as our core explanatory variables.

3.3. Control variables

In terms of the control variables, we employ the two significant variables in Du et al. [15]with per capita GDP (constant 2015 US$) as the indicator of economic development level, and the ratio of urban population as the indicator of urbanization level (URB). Following Xu and Lin [33], we take the total population in sample country as the proxy of population size (POP). This study uses industry (including construction), value added (% of GDP) as the proxy of industrial structure (IS) [36].

3.4. Data description

Table 1 lists variable description and data sources. Table 2 displays the statistical characteristics of variables by groups. It presents significant differences in carbon dioxide emissions, green technology innovation and structural types between G7 countries and BRICS countries. For example, the GDP per capita's mean of the G7 group is approximately 7.28 times that of the BRICS group, the green technology patent's mean is 7.41 times that of the BRICS group, and the CO_2 emission's mean is only 0.69 times that of the BRICS group.

4. Results and discussion

4.1. Benchmark regression

To avoid false regression, it is indispensable to test the multicollinearity of each explanatory variable by means of the variance expansion factor (VIF). From Table 3, first column, it can be seen that the value of VIF for each explanatory variable is less than 10. This implies that there is no severe multicollinearity among these explanatory variable.

In addition, to ensure the credibility of regression estimation, it is need to test the stationarity of the variable through unit root test

Table 1
Variable description and data sources.

Variable	Description	Data source
Dependent variable		
CO_2	CO_2 emissions (kt)	https://databank.worldbank.org/source
CI	CO_2 emissions (kt)/Land area (sq. km)	https://databank.worldbank.org/source
Core variables		
Gt	Patent counts of green development technology	https://stats.oecd.org/#
Gtc	Patent counts of green international collaboration technology (% of environment-related technology)	https://stats.oecd.org/#
Gtd	Patent counts of green diffusion technology	https://stats.oecd.org/#
Gt0	Patent counts of green development technology(% of environment-related technologies)	https://stats.oecd.org/#
Control variables		
GDP	GDP per capita (constant 2015 US$)	https://databank.worldbank.org/source
POP	Total population	https://databank.worldbank.org/source
URB	Urban population (% of total population)	https://databank.worldbank.org/source
IS	Industry (including construction), value added (% of GDP)	https://databank.worldbank.org/source

Table 2
Descriptive statistics for 12 countries under review.

Group	Variable	Obs	Mean	Std. Dev.	Min	Max
G7	CO_2	203	1293357	1664279	304530	5776410
	Gt	210	2538.667	2843.343	128.08	10395.72
	Gtc	210	75.05714	15.94058	38	97
	Gtd	210	10324.15	12970.61	278	42886
	GDP	203	37450.02	7360.078	27479.58	60836.77
	POP	210	1.02e+08	8.30e+07	2.77e+07	3.28e+08
	URB	210	77.835	5.526266	66.706	91.698
	IS	189	24.23443	4.339432	17.18838	34.5538
B5	CO_2	145	1887300	2457007	198260	1.03e+07
	Gt	150	342.6867	916.8483	1.75	5693.64
	Gtc	144	64.65972	28.53171	8	100
	Gtd	147	9122.741	27600.67	16	167183
	GDP	150	5142.044	2904.647	527.5145	10155.42
	POP	150	5.60e+08	5.43e+08	3.68e+07	1.41e+09
	URB	150	57.32712	20.18588	25.547	86.824
	IS	150	31.44496	8.125584	18.1885	47.5574

Note: G7 and B5 represent the G7 countries and BRICS countries, respectively.

Table 3
Test results for multicollinearity and unit root test of panel data.

Variable	VIF		LLC	IPS	Fisher-PP	Fisher-ADF
	$\ln CO_2$	lnCI				
$\ln CO_2$	–	–	−1.6012**	−1.9920**	65.0389 ***	60.0902***
lnCI	–	–	−3.0163***	−2.3488 ***	63.4323***	60.9781***
lnGt	7.33	8.76	−4.2167***	−2.5910***	59.7621***	69.3302***
LnGt0	1.71	1.92	−2.7890***	- 3.7504***	62.1524***	60.5636***
lnGtc	2.18	2.29	−5.8161***	−2.3903***	47.2901***	82.5325***
lnGtd	6.87	6.87	−6.3357***	−1.7850 **	19.3244**	55.8847 ***
lnGDP	7.07	8.24	−2.6360***	−4.8823***	9.7627**	44.8975 ***
lnPOP	7.05	7.13	−2.3121**	−0.6585**	114.7589***	59.4061 ***
lnURB	8.65	8.81	−2.4835***	−0.1970**	112.1966 ***	53.9990 ***
lnIS	2.18	2.39	−1.9233**	−2.1089**	104.2146***	82.1105***

Note: ***<0.01.** <0.05. *<0.10.

Table 4
Estimated results of benchmark regression.

	$\ln CO_2$		lnCI	
	(1)	(2)	(3)	(4)
lnGt	−0.0251	0.133***	0.728***	0.154***
	(0.0307)	(0.0254)	(0.0649)	(0.0251)
lnGtc	−0.420***	0.0336	0.373*	0.0382
	(0.0883)	(0.0402)	(0.187)	(0.0360)
lnGtd	0.214***	0.152***	−0.397***	0.113***
	(0.0336)	(0.0268)	(0.0710)	(0.0234)
lnGDP	0.458***	0.261***	0.255	0.489***
	(0.0752)	(0.0676)	(0.159)	(0.0578)
lnPOP	0.712***	0.979***	−0.176	1.538***
	(0.0527)	(0.124)	(0.111)	(0.153)
lnURB	−0.497*	1.556***	−1.753***	1.213***
	(0.202)	(0.193)	(0.427)	(0.171)
lnIS	0.997***	0.588***	1.049**	−0.171
	(0.158)	(0.0671)	(0.333)	(0.0930)
lnGtlnGtd		−0.0222***		−0.0184***
		(0.00331)		(0.00317)
Cons	−5.023**	−16.62***	1.242	−39.48***
	(1.840)	(2.426)	(3.887)	(2.831)
R^2	0.833		0.639	0.904
N	325	325	325	325

Standard errors in parentheses.
$^*p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

of panel data before regression estimation. Therefore, LLC test, IPS test, Fisher-PP test and Fisher-ADF test are used in this paper. The results of panel unit root test are shown in Table 3. It indicates that the hypothesis of null are rejected among these four approaches and for the whole variables are significantly at the level of 5%, which implies that the all variables are stationarity. Thus, it implies that the regression can be performed.

The pooled regression model, the panel random and fixed effects model are adopted for estimating Eq. (3). Table 3 shows the test results in the all sample analysis. Columns (1) and (3) adopt pooled regression. Columns (2) and (4) apply the panel random and fixed effects model regression. Besides, the explained variables are CO_2 emissions ($lnCO_2$) and carbon intensity (lnCI). Estimation results display that the partial variable of pooled regression is significant. But, the test of individual effect indicates the existence of individual effects in panel data, so pooled regression is abandoned. Therefore, it is appropriate to use random model and fixed model to test.

Hausman test is used to determine whether a random-effects test or a fixed-effects test. Hausman test indicate that $lnCO_2$ is suitable for random effect test, and lnCI is suitable for fixed effect test.

Therefore, Columns (2) in Table 4 indicate the random effect estimation results of CO_2 emissions ($lnCO_2$) and columns (4) of Table 4 show the fixed effect estimation results of CO_2 intensity (lnCI), the estimated coefficient of the independent variables lnGt and lnGtd is positively significant at the 1% level, and that of the independent variable lnGtc is not significant. According to estimation results, green technology development (lnGt) singly may not significantly reduce CO_2 emissions ($lnCO_2$) and carbon intensity (lnCI). However, according to columns (2) to (4) in Tables 4 and it can be found that the interaction term (lnGt*lnGtd) of explanatory variables is significantly negative at the level of 5% in the whole sample. This implies that a good combination of various green technology can efficiently cut down CO_2 emissions. In terms of control variables, conclusions based on Table 4 indicate that coefficient's value of lnGDP, lnPOP and lnURB are all significantly positive. This is basically keeping with the conclusion drawn by Kerui Du et al. [15].

4.2. Regional heterogeneity analysis

Fig. 1 displays a comparison of CO_2 emissions between G7 countries and BRICS countries in different periods. It can be observed thatCO_2 emissions show a steady downward trend in the G7 countries while a continuous upward trend in the B5 countries. As revealed by the comparison of green technology innovation, there exists a big gap in green technology innovation betweenG7 countries and BRICS countries, but the gap is narrowing in recent times (see Fig. 2.)

The analysis results are concluded on the basis of benchmark regression sample section. In this part, to compare the regional heterogeneity between G7 countries and BRICS countries, we use regional heterogeneity panel data models to investigate the interaction impact of green technology innovation on CO_2 emissions.

According to the results show in Columns (1) to (4) of Table 5, in the G7 countries, the impact of green technology development and green international cooperation technology on CO_2 emissions and carbon intensity are significantly positive and negative at the 1% level, separately. In the meanwhile, the impact of the interactive term (lnGt*lnGtd) of green development and green technology diffusion on CO_2 emissions and carbon intensity are significantly negative at the level of 5%. In the BRICS countries, the impact of green technology development, green international cooperation technology and green technology diffusion on CO_2 emissions and carbon intensity are significantly positive at the 1–5% level. Instead, the impact of the interactive term (lnGtc*lnGtd) of green international cooperation technology and green technology diffusion is significantly negative at the 5% level. It can be found that the above green technology innovation term efficiently reduces CO_2 emissions of G7 countries and BRICS countries, and that the conclusion of the significance of control variables is similar to that of the benchmark regression.

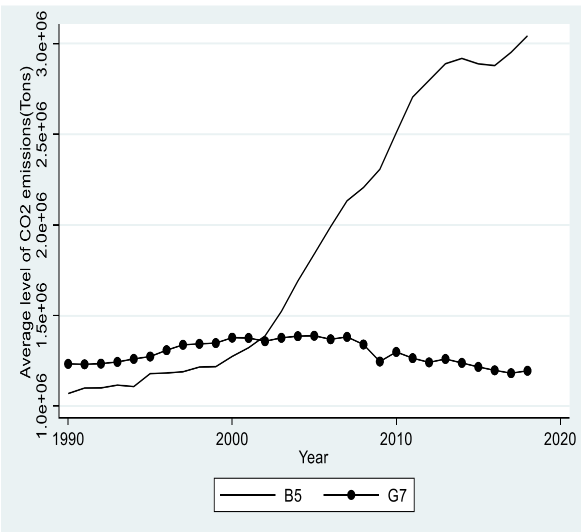

Fig. 1. CO_2 emissions in two groups over time. Note: The average in every group is shown (Unit: tons/individual country).

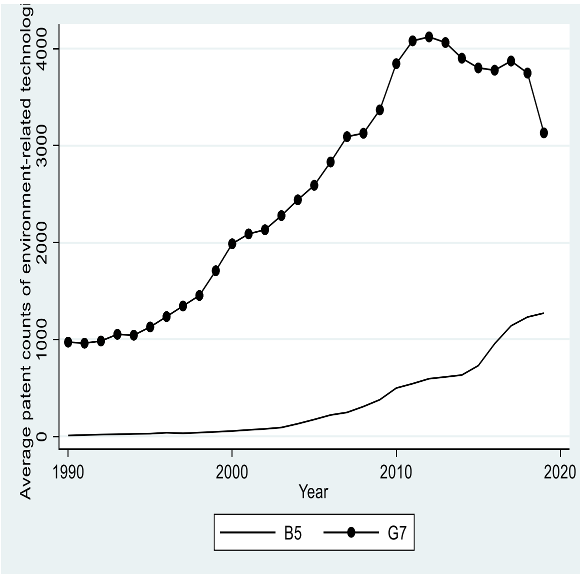

Fig. 2. Patent counts of environment-related technologies (Green technology innovation) in two groups over time. Note: The average in every group is shown (Unit: patent counts/individual country). (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

Table 5
Estimated results of regional heterogeneity regression.

	G7		B5	
	$lnCO_2$	lnCI	$lnCO_2$	lnCI
lnGt	0.245***	0.243***	0.0739***	0.0738***
	(0.0770)	(0.0771)	(0.0140)	(0.0139)
lnGtc	−0.366***	−0.362***	0.232**	0.232**
	(0.101)	(0.102)	(0.112)	(0.113)
lnGtd	0.0447	0.0411	0.162**	0.162***
	(0.0642)	(0.0642)	(0.0630)	(0.0630)
lnGtlnGtd	−0.0103**	−0.0998**		
	(0.0642)	(0.0052)		
lnGtclnGtd			−0.0399**	−0.0340**
			(0.0173)	(0.0173)
lnGDP	0.553***	0.554***	0.487***	0.488***
	(0.128)	(0.128)	(0.0797)	(0.0797)
lnPOP	0.228	0.235	1.874***	1.873***
	(0.327)	(0.328)	(0.197)	(0.197)
lnURB	1.978***	1.968***	0.362*	0.361*
	(0.343)	(0.343)	(0.174)	(0.174)
lnIS	0.657***	0.657***	−0.376***	−0.376***
	(0.139)	(0.140)	(0.0860)	(0.0860)
Cons	−6.816	−20.41***	−27.81***	−43.27***
	(5.875)	(5.880)	(3.685)	(3.684)
R^2	0.712	0.712	0.979	0.979
N	183	183	142	142

Standard errors in parentheses.
*$p < 0.05$, **$p < 0.01$, ***$p < 0.001$.

4.3. *Endogenous test*

In the previous estimates, the endogeneity of endogenous variables was not considered. Thus, in the current section, Hausman's endogeneity test is conducted, finding the endogeneity of interactions of core explanatory variables in the model.

Therefore, by introducing the lag of $lnCO_2$, lnGt, lnGtc and lnGtd as the instrument variables, we perform G2SLS random-effects IV regression and fixed-effects (within) IV regression tests (see Table 6). The estimated results indicate that the interaction term (lnGt*lnGtd) of explanatory variables is significantly negative at the level of 5% in the whole sample. Moreover, the effects of lnPOP, lnGDP and lnURB on $lnCO_2$ and lnCI are significantly positive. Thus, our empirical tests can be confirmed.

4.4. Robustness test

In order to examine the robustness of our estimated results, the patent counts **of green development technoloy (% of environment-related technologies)** (Gt0)are applied to represent patent counts **of green development technoloy** (Gt). From Table 7, we can find that the robustness results are keeping with the empirical tests of Table 4. The robustness test shows that the interaction term (lnGt0*lnGtd) of explanatory variables is significantly negative at the level 5% in the whole sample. Furthermore, the effects of lnPOP, lnGDP, lnURBon lnCO_2 and lnCI are significantly positive, indicating that the robustness test results basically consistent with the front estimates. Therefore, it can be affirmed that our empirical tests are robust.

5. Conclusions and policy implications

5.1. Conclusions

To explore the association of green technological innovation with CO_2 emission in the G7 countries and BRICS countries, we employ the random and fixed effect estimate method covering the panel data of 12 countries from 1990 to 2019. Empirical results are presented as follows:

For the full sample, the effect of green technological development and green technology diffusion on CO_2 emissions and carbon intensity are significantly positive at the level of 1%. On the contrary, the impact of its interactive term (lnGt*lnGtd) is significantly negative at the level of 1%. For G7 countries, the interactive term (lnGt*lnGtd) of green technology development and green technology diffusion are significantly negative at the level of 1%. For BRICS countries, While interactive term (lnGtc*lnGtd) of green international cooperation technology and green technology diffusion are significantly negative at the level of 1%.

The tests of endogenesis and robustness show that the effect of the interactive term (lnGt*lnGtd) is significantly negative at the level of 5%. Meanwhile, the effect of control variables like lnGDP, lnPOP and lnURB on $CO_2$is significantly positive, which is keeping with the conclusions in previous studies (Kerui Du et al., 2019) [15].

5.2. Policy implication

According to the green technological innovation and CO_2 emission average index in the G7 and BRICS countries, the green technology innovation level in the G7 countries is much higher than that in the BRICS countries, and that the CO_2 emissions of the G7 countries are controlled. In contrast, CO_2 emissions from the BRICS countries are still increasing. Therefore, this study provides some environmental benefits for policymakers. In terms of the G7 countries, they should continue to implement their green international cooperation technology, make full use combined effect of green technology development and green technology diffusion as well as maintain the sustainability of favorable ecological environment. For the BRICS countries, efforts to control CO_2 emissions should include measures of promoting in the R&D and green technology development and preventing further environmental degradation through the combined effects of green international cooperation technology and green technology diffusion, aiming to achieve the sustainability.

Author contribution statement

Wenting Tan: Wrote the paper; Conceived and designed the experiments.
Teng Cao: Contributed reagents, materials, analysis tools or data.

Additional information

Supplementary content related to this article has been published online at [URL].

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Data availability statement

Datasets related to this article can be found at https://databank.worldbank.org/source,https://stats.oecd.org/ source, an open-source online data repository hosted at World Bank database and OECD database.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

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Table 6
The regression estimation of considered instrumental variables.

	$lnCO_2$(1)	lnCI(2)
	G2SLS random-effects IV regression	Fixed-effects (within) IV regression
lnGtlnGtd	−0.00838***	−0.00762***
	(0.00231)	(0.00229)
lnGDP	0.525***	0.493***
	(0.0731)	(0.0752)
lnPOP	1.318***	1.416***
	(0.0990)	(0.132)
lnURB	1.357***	1.326***
	(0.201)	(0.207)
lnIS	0.654***	0.685***
	(0.0725)	(0.0784)
Cons	−23.46***	−39.38***
	(2.225)	(2.602)
R^2	0.798	0.799
N	317	317

Standard errors in parentheses.
*$p < 0.05$, **$p < 0.01$, ***$p < 0.001$.

Table 7
Robustness test.

	$lnCO_2$	lnCI
	(1)	(2)
lnGt0	0.222*	0.219*
	(0.0881)	(0.0881)
lnGtc	0.0509	0.0512
	(0.0382)	(0.0382)
lnGtd	−0.0818*	−0.0809*
	(0.0392)	(0.0391)
lnGt0lnGtd	−0.0348**	−0.0345**
	(0.0122)	(0.0122)
lnPOP	0.532***	0.533***
	(0.0583)	(0.0583)
lnPOP	2.073***	2.075***
	(0.129)	(0.129)
lnURB	0.829***	0.826***
	(0.163)	(0.163)
lnIS	0.0356	0.0351
	(0.0909)	(0.0909)
Cons	−33.29***	−47.72***
	(2.507)	(2.506)
Fix effects	Y	Y
Country	Y	Y
Year	Y	Y
R^2	0.893	0.893
N	325	325

Standard errors in parentheses.
*$p < 0.05$, **$p < 0.01$, ***$p < 0.001$.

Appendix

Table 1
Grouped by region.

G7 countries
Canada, France, Germany, Great Britain (United Kingdom), Japan, Italy, United States.
BRICS countries
Brazil, Russia, India, China, South Africa.

Appendix B. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.heliyon.2023.e15683.

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