RESEARCH ARTICLE



Does technology advancement reduce aggregate carbon dioxide emissions? Evidence from 66 countries with panel threshold regression model

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Abstract

The influence of technology advancement on carbon dioxide (CO_2) emissions is complex and controversial, yet existing literature ignores the level of economic development in regard to its influential effect. With the panel threshold regression model, this research investigates the marginal and non-linear impacts of technology advancement on CO_2 emissions along with the changes of economic development and presents the heterogeneity between different countries. The results are as follows: First, technology advancement and CO_2 emissions have a non-linear inverted U-shaped relationship, which is significantly affected by different levels of economic development. When economic development exceeds a certain threshold, the impact turns from positive to negative. Second, the impact varies remarkably among different countries. We provide evidence for inverted U-shaped and N-shaped correlations in the Organization for Economic Co-operation and Development (OECD) countries and high-income countries (non-OECD), respectively. Although technology advancement always promotes CO_2 emissions in middle- and low-income countries, its marginal effect is decreasing. This study not only indicates the dynamic impacts of technology advancement on CO_2 emissions in different countries, but also contributes to policymakers' understanding of the "common but differentiated responsibilities" involved in mitigating CO_2 emissions.

Keywords Technology advancement · CO2 emissions · Threshold effects · Economic development stages

Introduction

As the demand for energy grows around the world, climate change is increasingly exposing itself in many negative ways (Zhang et al. 2017; Lee and Chiu 2011; Hao et al. 2020; Lee et al. 2020). Carbon dioxide (CO_2) emission reduction is now an important international issue (Youssef et al. 2016; Moutinho et al. 2017; Chen and Lee 2020), leading to dramatic discussions on the factors influencing such a reduction. In fact, greater attention is being paid to technology

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advancement (Cheng et al. 2018; Du and Li 2019), as it not only is a process of continuous development, improvement, and replacement of environment-related technologies (Hayashi 2018), but also covers production efficiency improvement (Shapiro and Walker 2018; Chen et al. 2020; Yuan et al. 2020), which greatly contributes to economic prosperity. Technology advancement also closely relates to the levels and goals of economic development (Yuan et al. 2020). As for different economic development levels and goals, the impact of technology advancement on CO_2 emissions may exhibit a non-linear process and differ between countries (Chang and Lee 2008; Yang and Li 2017; Chen and Lee 2020).

Nearly all countries of the world emphasize that better technology can help reduce CO_2 emissions. Nonetheless, an obvious fact is that some countries, just like BRICS (Brazil, Russia, India, China, and South Africa), have experienced sharp increases in aggregate CO_2 emissions along with the industrialization as well as similarly significant progress in technology (Boden et al. 2015). Even in some developed

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countries, aggregate CO₂ emissions have recovered after a brief reduction (Li and Wang 2017), whereas France, Canada, and the USA are experiencing drops in CO_2 (Kasman and Duman 2015). This indicates that technology advancement might have different shocks on CO2 emissions due to different economic development stages (Khattak et al. 2020). Therefore, it is necessary to gain insight into the nonlinear changes of the impacts of technology advancement on CO₂ emissions during different economic development stages, because they can provide references for countries to formulate CO₂ emission reduction strategies. To this end, the present study aims to find evidence to identify different countries' marginal efforts and the non-linear process in order to shed light on the "common but differentiated responsibilities" of aggregate CO₂ emission reduction. This is the prime motivation of the research.

Literature review

Non-linear relationship between CO₂ emissions and economic growth

The environmental Kuznets curve (EKC) hypothesis postulates that economic growth and the environment share an inverted U-shaped relationship (Ang 2007), which was first proposed and tested by Grossman and Krueger (1995)—that is, when a country's economic development level is low, environmental quality sharply deteriorates along with economic growth. When economic development reaches a turning point, environmental quality achieves a notable improvement. Without considering international trade, the relationship is mainly reflected in three channels—namely, scale effect, structural effect, and technical effect (Grossman and Krueger 1995)—which closely relate to better technology (Apergis 2016). Thereafter, it is now very popular to study the effects of technology advancement and economic growth on environmental quality.

Research and development (R&D) investment theoretically can help promote environmentally friendly technologies that reduce greenhouse gas emissions (Bosetti et al. 2006; Chen and Lee 2020). In contrast, Berkhout et al. (2000) argued that technology advancement makes equipment more energy efficient and increases CO_2 emissions by boosting economic development. In other words, although countries may ameliorate economic development patterns and industrial structures, thus effectively reducing CO_2 emission intensity (Grubb 2006; Barrett 2006), they pay more attention on economic growth (Sánchez and Maldonado 2015). Considering different economies, for example, during the last few years, BRICS have experienced profound structural changes and technology advancement that continue to influence the evolution of CO_2 emissions, with potentially adverse consequences for global mitigation strategies (Tamazian et al. 2009). In contrast, Jordaan et al. (2017) stated that investments in ecoinnovation technologies have impacted CO_2 emission reduction among OECD economies. Although developing countries with rapid economic transitions and objectives of becoming developed nations, especially Malaysia and India, are on the same path that developed countries experienced, Saudi et al. (2019) argued that technological innovation could lead to a cleaner environment.

Non-linear impact of technology advancement on CO₂ emissions

Grossman and Krueger (1995) noted that technologies generally receive little attention in the early days of economic development, but as the level of economic development improves, technological progress tends to reduce pollutant emissions. Ahmad et al. (2019) captured the positive and negative innovation shocks endogenously in the EKC equation. In other words, technological progress may be a double-edged sword, as it not only provides conditions for economic development and production but also causes ecological damage and environmental pollution (Yuan et al. 2020).

In terms of the degree of economic development, Du et al. (2019) confirmed that the income level matters for the effect of technology advancement, and that the impact of green technology innovations on CO₂ emissions presents a singlethreshold effect regarding the income level. Yu and Du (2019) argued that the impact highly correlates to regional growth speed, and thus, the independent innovation of provinces with high-speed growth contributes greater toward promoting CO₂ emissions than it does for provinces with slower growth rates in China. Du and Li (2019) found that green technology innovations only influence high-income economies, and that it is difficult to find significant evidence that green technology innovations positively impact carbon productivity in less developed economies. Chen et al. (2020) presented that the nexus between technology advancement and CO₂ emissions depends on both environmental and production technological changes. Töbelmann and Wendler (2020) noted that environmental innovation contributes to the reduction of carbon dioxide emissions, while general innovative activity does not cause any decrease in emissions.

To sum up, most previous studies in the related literature have come to important and valuable conclusions, but there are still issues that need to be further addressed. The present study thus investigates the non-linear changes in the impacts of technology advancement on CO_2 emissions during economic development for the following reasons. First, this study emphasizes total factor productivity (TFP) rather than technological innovation as a form of technology advancement. As Cheng et al. (2018) and Chen et al. (2020) pointed out, technological innovation cannot essentially reflect the meaning of technology advancement. In fact, technology advancement is not only reflected in specific technological innovations, such as R&D activities (Khattak et al. 2020), but also is particularly evident in production changes as well as efficiency changes, such as management and institution innovation (Chen et al. 2020). It is worth noting that the TFP based on the DEA (data envelopment analysis) -Malmquist model illustrates both connotations (Li and Lin 2016).

Second, considering the positive and negative effects of technology advancement on CO_2 emissions, this study provides a new perspective on the combination of technology advancement and economic development for explaining the formation of the EKC. In the early stages of economic development, technology advancement focuses on the scale of economic growth while ignoring pollutant emissions (Grossman and Krueger 1995). Moreover, as the level of economic development improves, it gradually tends to balance economic growth with CO_2 emission reduction (Lee et al. 2010; Sánchez and Maldonado 2015).

Third, this study combines the STIRPAT model and panel threshold regression model (PTR) to identify the marginal and non-linear impacts of technology advancement on CO_2 emissions (Wang et al. 2017). Although structural decomposition analysis (SDA) has been widely employed (Lin and Liu 2012; Andreoni and Galmarini 2016), it ignores changes to marginal effects. Thus, the efforts that developing and developed countries have made (if there are any) might be more keenly observed from the marginal change in technology advancement on CO_2 emission reduction (Cheng et al. 2018; Wang 2012). As such, it is crucial to improve the understanding and quantification of the threshold effect of technology advancement on CO_2 emissions according to different stages of economic development.

Finally, this paper studies 66 countries with different stages of economic development and thus provides additional reference for CO_2 emission reduction, especially in developing countries. More importantly, with the deepening of globalization, technology transfer is accelerating, which means that developing countries may have more opportunities to accept technological innovations from developed countries. Hence, the turning point of EKC may appear earlier to spur efforts at reducing global carbon emissions.

The model and econometric methodology

To investigate the marginal and dynamic effects of technology advancement on CO_2 emissions, this study combines the STIRPAT model and the panel threshold regression model.

STIRPAT framework

Ehrlich and Holdren (1971) first proposed the IPAT (influence, population, affluence, and technology) model, which is widely used to describe the effects of human activities on the environment. Based on the IPAT model, the environmental impact (I) is decomposed into three main driving factors: population size (P), affluence (A), and technology (T) level. The model not only can examine the impacts of population, economic level, and technological progress on the environment but also be randomly expanded according to the specific situation of the country (Zhou et al. 2018; Chen and Lee 2020; Pham et al. 2020). The basic model runs as follows.

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

To analyze the stochastic impacts, this paper employs the STIRPAT framework (stochastic impacts by regression on population, affluence and technology) based on the IPAT model (Dietz and Rosa 1997). The STIRPAT model is the following equation:

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

$$\tag{2}$$

In Eq. (2), α is the constant term, and β_1 , β_2 , and β_3 are estimated parameters of P_{it} , A_{it} , and T_{ip} respectively. Here, ε_{it} represents the error term, i (i = 1, 2, ..., n) refers to countries, and t (t = 1, 2, ..., T) refers to the time period. Equation (2) is generally processed by taking its logarithmic form as:

$$\ln I_{it} = \alpha + \beta_1 \ln P_{it} + \beta_2 \ln A_{it} + \beta_3 \ln T_{it} + \varepsilon_{it}$$
(3)

This paper mainly focuses on the variable *T* and its coefficient β_3 . To investigate the influencing factors of CO₂ emissions, the extended model is presented as:

$$\ln \text{CO2}_{it} = \alpha + \beta_1 \ln \text{pop}_{it} + \beta_2 \ln \text{pgdp}_{it} + \beta_3 \ln \text{tech}_{it}$$
(4)
+ $\gamma_1 \ln \text{trade}_{it} + \gamma_2 \ln \text{service}_{it} + \gamma_3 \ln \text{energy}_{it}$
+ $\gamma_4 \ln \text{urban}_{it} + \gamma_5 \ln \text{fd}_{it} + \mu_i + \tau_t + \varepsilon_{it}$

Here, μ_i and τ_t capture the individual effect and time effect, respectively, CO_{2it} denotes carbon dioxide emissions, pop_{it} refers to population size, $pgdp_{it}$ refers to GDP per capita, and tech_{it} refers to technology advancement. Extended from Chen and Lee (2020), this study includes influencing factors of CO_2 emissions, such as industrial structure, urbanization, trade openness, energy intensity, and financial development.

Panel threshold model

The panel threshold regression (PTR) model proposed by Hansen (1999) can be used to both estimate the threshold value and to test the significance of the endogenous threshold effect. Based on Eq. (4), this paper employs the PTR model to investigate the impact from non-linear changes of technology advancement on CO_2 emissions via economic development. The expression is as follows:

$$\ln CO2_{it} = \alpha + \beta_1 \operatorname{lnpop}_{it} + \beta_2 \operatorname{lnpgdp}_{it} + \theta_1 \operatorname{lntech}_{it} \\ \times \varphi(q_{it} \le \delta) + \theta_2 \operatorname{lntech}_{it} \times \varphi(q_{it} > \delta) \\ + \gamma_1 \operatorname{lntrade}_{it} + \gamma_2 \operatorname{lnservice}_{it} + \gamma_3 \operatorname{lnenergy}_{it} \\ + \gamma_4 \operatorname{lnurban}_{it} + \gamma_5 \operatorname{lnfd}_{it} + \mu_i + \varepsilon_{it}$$
(5)

Equation (5) shows a single-threshold model, which needs a strong balanced data panel: {CO_{2*it*}, X_{it} : $1 \le i \le n$, $1 \le t \le T$ }, Here, $\varphi(\cdot)$ is the indicator function, q_{it} is the threshold variable, and δ is the threshold estimator.

According to whether the threshold variable q_{it} is smaller or larger than the threshold estimator δ , the samples are divided into two "regimes." If $q_{it} \leq \delta$, then $\varphi(q_{it} \leq \delta) = 1$; if not, $\varphi(q_{it} \leq \delta) = 0$. The difference between the two regimes is recognized by different regression slopes, θ_1 and θ_2 , respectively. Therefore, the hypothesis of no threshold effect can be expressed by the constraint H_0 : $\theta_1 = \theta_2$, and if the null hypothesis is rejected, then there could be threshold δ . Hence, the form of multiple thresholds can also be concluded if necessary.

Description of variables and data

Considered that a balanced data panel is needed in the panel threshold model, the data involved in this study span from 1990 to 2014, and up to 66 countries are included, split into high-income countries (OECDs), high-income countries (non-OECDs), middle-income countries (merging upper middle-income countries and middle lower-income countries), and low-income countries. Appendix Table 11 provides the list. Data of CO_2 emissions come from the European Commission's Global Climate Change Research Database (EDGAR), and the remaining indicators are from the World Bank database (see Appendix Table 11). The variables are constructed as follows.

Carbon dioxide emissions

Compared with carbon intensity, aggregate CO_2 emissions provide a more comprehensive picture of global climate change. Different from most literature employing carbon intensity as the dependent variable, this paper's empirical model adopts aggregate CO_2 emissions to describe environmental changes, which is in line with the works of Li and Wang (2017), Wang et al. (2017), and Zhang et al. (2017).

Population

Impacts due to demographics are notable for our topic of concern (Zhang et al. 2017). Most studies found that population has a significant impact on the environment. The larger the population is, the higher energy consumption is, resulting in more and more carbon emissions (Liddle 2013). Therefore, this study takes the number of total population into the STIRPAT framework.

Economic development

The threshold variable chosen in this study is GDP per capita (pgdp), which can directly affect the relationship between technology advancement and aggregate CO₂ emissions (Yu and Du 2019). As mentioned previously, the role of increased income at promoting environmental quality should be carefully interpreted in light of technological progress for environmental improvement. Therefore, it is of great significance to examine the non-linear relationship between technology advancement and CO₂ emissions under certain economic development levels. Additionally, as income greatly influences CO₂ emissions, this study also takes GDP per capita as an important explanatory variable.

Technology advancement

Based on the neoclassical economic growth model (Solow, 1957; Brock and Taylor 2010), the total factor productivity (TFP) index can be applied to represent technology advancement, which is in line with Cheng et al.'s (2018) and Chen et al.'s (2020) study. This study calculates TFP by the DEA-Malmquist index (Fare et al. 1994), which needs inputs like capital stock and labor force, as well as GDP output. Capital stock is measured by the perpetual inventory method, as in equation $K_{it} = (1 - \delta) \times K_{i(t-1)} + I_{it}$, where *i* is the country, *t* is the year, I refers to gross capital formation, K refers to capital stock, and δ refers to a capital depreciation rate of 6% (Hall and Jones 1999). For the basic capital stock of 1990, this paper uses the formula $K_{i1990} = I_{i1990}/10\%$, dividing gross capital formation in 1990 by 10% (Shan 2008; Li and Wang 2017). Furthermore, to avoid any biased estimation, this study applies the bootstrap DEA method to get the bias-corrected TFP index and use it as a robustness test.

Control variables

Trade openness The impact of international trade on the environment has attracted a wide range of discussions in the trade policy literature. On the one hand, through international trade, pollutants from one country may be transferred to other countries along with goods and services (Ali et al. 2017). However, the impact of trade openness on carbon emissions varies from country to country, because of its technical and productivity effects (Shapiro and Walker 2018). For example, trade openness benefits the environment in developed countries (Managi et al. 2009), while it mostly boosts economic activities and consumes more energy and causes pollution in

developing countries. Therefore, this study incorporates trade openness into the model and further investigates its impact in countries with different development levels.

Industrial structure Along with the upgrading of industrial structure, economic activities gradually reduce energy consumption and thus will contribute to carbon emission mitigation (Zheng and Luo 2013). The present study uses the proportion of the service industry (*service*) to investigate the impact of industrialization on aggregate CO_2 emissions (Wang et al. 2017).

Energy intensity Energy consumption is another notable issue related to CO_2 emissions (Ang 2007; Li and Wang 2017). However, energy consumption closely also relates to urbanization and industrial structure, and it may have some uncertain and complex effects in the model (Ahmad et al. 2019; Liu and Lee 2020; Shahbaz et al. 2020).

Urbanization This issue covers the process of population shifting from rural areas to cities, which has led to a significant concentration of economic activities and energy consumption (Madlener and Sunak 2011). However, due to differences in industrial structure, public transportation, etc., the impacts on CO_2 emissions differ between different countries (Rafiq et al. 2016; Du et al. 2019).

Financial development A growing body of studies confirmed that the dramatical increase in CO_2 emissions is closely associated with the corresponding economic development (Le and Ozturk 2020; Nasir et al. 2019). As a crucial part of national economic growth, financial development may also have profound effects on CO_2 emissions (Zhao and Yang 2020). The development of financial sectors in developing countries possibly encourages new projects to be environmentally unfriendly and boosts energy consumption and CO_2 emissions. In contrast, it may also contribute to green development and reduce carbon emissions in developed countries.

Data description

Table 1 lists the specific descriptions and statistics of the variables used for examining the nexus among carbon dioxide emission, economic growth, and technology advancement. It clearly shows the gap between the maximum and minimum of these values. First, carbon dioxide emissions vary from a minimum of 341.52 Kt to a maximum of 1.07e + 07 Kt, while the TFP index varies from a minimum of 0.0028 to a maximum of 23.38, and the same goes for economic development and population scales. It indicates that carbon dioxide emissions in different countries can vary greatly depending on the level of technology advancement. Economic growth, population, and technology

advancement also have potential impacts on carbon dioxide emissions. Second, for trade openness, industrial structure, energy intensity, urbanization, and financial development, these variables do not vary that much.

With regard to skewness and kurtosis, it is known that they measure symmetry and flatness of a data panel distribution, respectively. Skewness equal to 0 means that the data distribution shape is the same as that of a normal distribution; skewness > 0 (< 0) means that the data distribution shape is positively skewed (negatively skewed) compared with the normal distribution. The greater the absolute value is of skewness, the more serious the degree is of deviation in the distribution. Kurtosis equal to 0 indicates that the data distribution is as steep as a normal distribution; kurtosis > 0 indicates that the data distribution is steeper than a normal distribution. Therefore, Table 1 shows that these variables are not distributed symmetrically. Almost all variables show right skewness, meaning that they are concentrated on the right and are unevenly distributed, especially carbon dioxide emissions, technology advancement, population scales, and energy intensity, while the variables of industrial structure and urbanization level are distributed slightly to the left. In terms of kurtosis, carbon dioxide emissions, technology advancement, population scales, and energy intensity exhibit leptokurtic and thick-tailed distributions. This indicates that these variables are not only mainly concentrated on the right side but also have a very high probability density.

Based on the skewness and kurtosis results, it is found that the above variables are not normally distributed. Furthermore, the Jarque-Bera test is conducted for the goodness of fit of the sample data with the skewness and kurtosis in line with the normal distribution. Table 1 shows that the Jarque-Bera test result of the above variables is significantly greater than 1, which means that it rejects the null hypothesis of normal distribution.

Empirical results

Multicollinearity testing

In order to eliminate the influence of a variable's dimension, all variables are processed logarithmically. This study conducts an ordinary least square regression to analyze the multicollinearity of all independent variables and to evaluate the variance inflation factor (VIF). The VIF values are far from the tolerance of 10 (Table 2), which indicates that there is no multicollinearity among the independent variables (Wang et al. 2017). Table 3 exhibits the unitroot tests of LLC and ADF-Fisher. The results indicate that all variables are at stationary level.

Symbol	Variable	Definition	Min	Max	Skewness	Kurtosis	JB test
<i>C02</i>	Carbon dioxide emissions	Carbon dioxide emissions from fossil fuels and cement	341.52	1.07e + 07	5.74	41.42	$1.1e + 05^{***} (0.000)$
tech	Technology advancement	Total factor production index with the DEA-Malmquist index, taking 1990 as the base period	0.0028	23.38	3.33	14.45	1.2e + 04*** (0.000)
tech-bootstrap	Technology advancement	Total factor production index with the bootstrap DEA model, taking 1990 as the base period	0.0034	19.73	3.23	13.51	$1.0e + 04^{***} (0.000)$
dod	Population	Total population	254,826	1.36e + 09	5.00	28.12	5.0e + 04*** (0.000)
dpBdb	GDP per capita	GDP divided by mid-year population (constant 2010)	161.83	111,968.3	1.47	5.19	922.1*** (6.e - 201)
trade	Trade openness	Percentage of imports and exports in GDP, including goods and services	11.09	441.60	2.93	14.76	$1.2e + 04^{***} (0.000)$
service	Industrial structure	Percentage of service value-added in GDP	18.91	87.64	- 0.43	2.92	51.8*** (5.7e - 12)
energy	Energy intensity	Energy use (kg of oil equivalent) per US\$1000 GDP (constant 2011)	47.60	1197.44	3.98	26.43	$4.2e + 04^{***} (0.000)$
urban	Urbanization	Percentage of urban population in the total population	8.53	100.00	-0.48	2.41	86.35*** (1.8e - 19)
fd	Financial development	Domestic credit to the private sector	0.81	357.32	1.35	5.03	788.6*** (6.e - 172)
<i>p</i> values are in	parentheses. $*p < 0.1$						

 Table 1
 Description and summary statistics of variables

Variable	VIF	1/VIF
lnpgdp	3.09	0.323501
lnfd	2.43	0.412191
Inservice	2.04	0.490744
lnurban	1.94	0.514877
lnpop	1.85	0.541956
Intrade	1.57	0.638923
lnenergy	1.11	0.897581
lntech	1.02	0.982904
Mean VIF	1.88	

Basic regression result

Table 4 shows the basic regression result. Controlling a series of influencing factors, the result shows that technology advancement has no significant impact on CO₂ emissions, indicating that it does not accurately reflect the role of technology advancement on CO2 emissions, but rather only focuses on technology advancement while at the same time ignoring changes in economic development stages (Du et al. 2019). On the other hand, although the impacts are not significant, the middle-income and low-income countries show a positive effect, while the high-income countries show a negative effect. This may mean that as the level of economic development increases, the impact of technology advancement on CO2 emissions will change, which is a nonlinear process. To that end, this study incorporates economic development levels into the indicator function and further employs the PTR model to explore the impact of technology advancement on carbon emissions with changes in economic development levels.

Table 3 The panel u	unit-root tests'	results a	it the	level
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Variable	LLC	ADF- Fisher
lnCO2	- 2.1593***	5.5579***
lntech	- 6.4305***	6.6160***
lnpop	- 22.0996***	8.4566***
lnpgdp	- 2.9560***	4.8287***
Intrade	- 5.6187***	2.8415***
Inservice	- 4.7145***	3.8101***
lnenergy	- 6.0167***	4.9175***
lnurban	- 6.6553***	18.6775***
lnfd	- 2.4309***	5.7381***

***Refers to significance at the 1% level

p < 0.05p < 0.05p < 0.01

Table 4 Results of the basic regression

Variable	(1) Full sample	(2) High-income (OECD)	(3) High-income (non-OECD)	(4) Middle- income	(5) Low- income
Intech	- 0.00689	- 0.00357	- 0.0146	0.00657	0.00321
	(-0.75)	(-0.58)	(- 1.23)	(0.44)	(0.13)
lnpop	1.885***	1.281***	0.592***	1.070***	2.161***
	(34.15)	(19.37)	(5.42)	(11.62)	(15.01)
lnpgdp	1.053***	1.025***	0.778***	1.427***	0.838***
	(32.11)	(28.39)	(16.72)	(26.78)	(9.32)
Intrade	0.0230	- 0.0433*	-0.0173	-0.0857 **	-0.00415
	(1.01)	(- 1.76)	(-0.52)	(-2.28)	(-0.09)
Inservice	0.0353	- 0.134**	- 0.319***	0.0869	-0.117
	(0.74)	(-2.01)	(- 3.34)	(1.12)	(-1.19)
lnenergy	0.703***	0.814***	0.833***	1.038***	0.410***
	(20.98)	(31.19)	(13.41)	(19.86)	(5.16)
lnurban	0.227***	0.708***	0.0953	- 0.851***	0.213
	(3.12)	(7.54)	(0.46)	(- 9.49)	(1.21)
lnfd	0.0123	- 0.0923***	- 0.00210	0.0207*	0.144***
	(1.16)	(-7.97)	(- 0.08)	(1.75)	(5.54)
Individual	Yes	Yes	Yes	Yes	Yes
Time	Yes	Yes	Yes	Yes	Yes
_cons	- 34.44***	- 25.73***	- 9.339***	- 20.72***	- 36.24***
	(- 33.43)	(- 22.63)	(-3.78)	(-11.40)	(- 12.70)
Ν	1650	625	175	350	500
R^2	0.805	0.847	0.928	0.941	0.830

t statistics are in parentheses

**p* < 0.1

***p* < 0.05

***p < 0.01

Panel threshold effect test

As shown in Table 5, it is first found that there are significant triple thresholds of economic development level, and the threshold estimates and confidence interval appear in Table 6. Within the 95% confidence interval, the threshold estimates are 6.5373, 7.4191, and 9.2710 and refer to

US\$690, US\$1667, and US\$10625 per capita (in 2010 prices), respectively. Furthermore, all countries are divided into four regimes by three thresholds, as shown in Fig. 1. This indicates that the impacts vary under different regimes. At the same time, countries have transformed over different threshold regimes along with economic development changes from 1990 to 2014.

 Table 5
 Results of panel threshold testing

Model	F value	p value	F critica	al value	
			1%	5%	10%
Single threshold	80.9523***	0.0000	6.5462	4.1543	2.8690
Double thresholds	28.5316***	0.0000	6.5289	3.7547	2.6153
Triple thresholds	10.1291***	0.0000	5.2783	- 0.0735	- 2.1689

Note: p value and F critical value are the results of Bootstrap sampling for 1000 times

 Table 6
 Results of threshold estimates

Threshold	Threshold estimate	95% confid. interval of threshold
θ_1	6.5373	[6.4932, 6.5814]
θ_2	7.4191	[7.2869, 7.6837]
θ_3	9.2710	[9.0946, 9.9765]



Panel threshold regression results

The results shown in Table 7 illustrate that technology advancement has a non-linear inverted U-shaped impact on CO₂ emissions. Adding control variables step by step, the regression results presented are robust. With continuous economic growth, technology advancement increases CO₂ emissions significantly. However, when per capita GDP exceeds US\$690 (in 2010 prices), technology advancement significantly reduces CO₂ emissions. On the one hand, the result above verifies the different impacts under various economic development stages (Du et al. 2019). On the other hand, the result above also shows the gradual changing of marginal effects, which is consistent with the research findings of Ang (2007) and Apergis and Payne (2009). Therefore, technology advancement is not conducive to environmental improvement. At the early stage of economic development, technology advancement can contribute to the improvement of economic scale and productivity, but little attention gets paid to environmental protection (Grossman and Krueger 1995). When economic development reaches a certain level, technology advancement shows a remarkable contribution to CO₂ emission mitigation, in which environmental friendly technologies play great roles (Chen et al. 2020).

Table 7 also shows the impacts of population, economic abundance, trade openness, industrial structure, energy intensity, and urbanization on CO_2 emissions. First, this study concludes that population and economic scale have positive effects on CO_2 emissions, which are consistent with the findings of Ali et al. (2017), Zhang et al. (2017), and Wang et al. (2017). With an increase in population and economic scale, people will consume more resources to meet overall demand and produce more outputs as well as more CO_2 . In terms of international trade, the present study finds a significantly negative impact on CO_2 emissions, which runs in contrast to Zhang et al. (2017). The effects of trade openness on CO_2 emissions are negative following the pollution-halo hypothesis (Nguyen et al. 2020). Although international trade brings about the flow of goods and embodies carbon effects, it also accelerates technological transfer and spillover among countries (Huang et al. 2018), which can mitigate CO_2 emissions to some extent.

As for industrial structural upgrading, there is a negative effect on CO₂ emissions, but not significantly. As Jaforullah and King (2017) emphasized, energy intensity can cause systematic volatility in the model's coefficients. On the other hand, energy consumption highly correlates to the manufacturing industrial structure. Therefore, regardless of the internal structure of the manufacturing industry, the index for the proportion of service value-added only can reflect industrial structural upgrading and cannot indicate optimization of the industrial structure (Cheng et al. 2018). Urbanization also shows no significant impact on CO₂ emissions, indicating a certain gap in the quality of urbanization for different countries (Li and Lin 2015). Financial development stimulates CO₂ emissions, but not significantly, which is consistent with the full sample result of Table 4. The main reason is that the maturity of financial sectors of developing countries possibly encourages new projects and activities, but is unable to reach achievements in allocating finance for environment-friendly projects, thus boosting energy consumption and CO₂ emissions (Le and Ozturk 2020).

Thresholds in different groups

As for countries with different economic development levels, this study further investigates the marginal effects of technology advancement in different groups, shown in Table 8. The result is still robust, and there are three thresholds. The research also draws a clearer conclusion in different countries for the impacts of technology advancement on CO_2 emissions, which show a diverse non-linear process.

Table 8 presents in the initial development stage of highincome countries (OECD and non-OECD) that technology

Variable	(1)	(2)	(3)	(4)	(5)	(9)
Intech (Inpgdp $\leq \theta_I$)	0.0336^{***} (4.50)	0.0349^{***} (3.26)	0.0327*** (3.06)	0.0382*** (3.72)	0.0378^{***} (3.68)	0.0374*** (3.64)
Intech ($\theta_1 < lnpgdp \le \theta_2$)	$-0.0045^{**}(-1.97)$	$-0.0062^{**}(-2.58)$	$-0.0071^{***}(-2.93)$	$-0.0068^{***}(-2.92)$	$-0.0068^{***} (-2.91)$	$-0.0068^{***} (-2.91)$
Intech $(\theta_2 < lnpgdp \le \theta_3)$	$-0.0479^{***} (-10.41)$	$-0.0489^{***} (-14.27)$	$-0.0462^{***} (-13.87)$	$-0.0326^{***} (-11.76)$	$-0.0323^{***} (-11.85)$	$-0.0325^{***} (-11.53)$
Intech (Inpgdp> θ_3)	$-0.0239^{***} (-7.72)$	$-0.0234^{***} (-8.38)$	$-0.0229^{***}(-8.43)$	-0.0144^{***} (-7.05)	$-0.0146^{***} (-7.23)$	$-0.0148^{***} (-7.14)$
doduj	1.5893^{***} (36.19)	1.6153*** (21.82)	1.5832^{***} (21.58)	1.4978*** (21.72)	1.4672^{***} (20.12)	1.4666^{***} (20.04)
lnpgdp	0.4930^{***} (19.31)	0.5144^{***} (16.29)	0.5707^{***} (17.61)	0.9059*** (31.32)	0.8876^{***} (26.61)	0.8861^{***} (26.06)
Intrade		$-0.0668^{**}(-2.47)$	$-0.0656^{**}(-2.56)$	$-0.0550^{**}(-2.35)$	$-0.0590^{**}(-2.54)$	- 0.0597** (- 2.57)
Inservice			$-0.2849^{***}(-5.31)$	-0.0601 (-1.09)	- 0.0702 (- 1.25)	- 0.0771 (- 1.36)
lnenergy				0.7247^{***} (16.02)	0.7121^{***} (15.28)	0.7134^{***} (15.46)
lnurban					0.1214 (1.60)	0.1240 (1.61)
Infd						0.0047 (0.35)
F	20.65^{***}	20.73***	18.33^{***}	15.97^{***}	15.07^{***}	15.14^{***}
Ν	1650	1650	1650	1650	1650	1650

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t statistics are in parentheses *p < 0.1**p < 0.05***p < 0.01

Countries	Regimes (lnpgdp)	Coefficient (Intech)	t statistics	p value
High-income (OECD)	(−∞, 8.9871)	0.0659***	(4.07)	0.0001
	(8.9871, 9.9027)	0.0214***	(3.14)	0.0018
	(9.9027, 11.0295)	- 0.0160***	(-7.92)	0.0000
	(11.0295, +∞)	0.0079	(1.50)	0.1345
High-income (non-OECD)	(−∞, 9.1272)	0.0621***	(6.55)	0.0000
	(9.1272, 10.1745)	0.0097	(0.93)	0.3514
	(10.1745, 10.4317)	- 0.0223***	(-3.19)	0.0017
	(10.4317, +∞)	0.0239*	(1.70)	0.0917
Middle-income	(−∞, 7.9037)	0.1310***	(5.03)	0.0000
	(7.9038, 8.7297)	0.0485***	(7.79)	0.0000
	(8.7297, 9.1230)	0.0072	(0.68)	0.4945
	(9.1230, +∞)	0.0844***	(2.62)	0.0093
Low-income	(−∞, 6.4053)	0.0920***	(4.99)	0.0000
	(6.4053, 6.5072)	0.3084***	(3.54)	0.0004
	(6.5072, 7.4040)	0.0581***	(6.27)	0.0000
	(7.4040, +∞)	0.0173**	(2.41)	0.0161

t statistics are in parentheses

*p < 0.1

***p* < 0.05

****p* < 0.01

advancement has increased CO_2 emissions, indicating that the goal of technological progress at this time is dominated by scale effects, and insufficient attention has been paid to environmental governance. When the level of economic development exceeds the threshold, the impact of technology advancement on CO_2 emissions begins to manifest as an intensity effect and to reduce CO_2 emissions significantly.

Technology advancement and CO_2 emissions have a significantly inverted U-shaped relationship in OECD countries. Under US\$19,984 GDP per capita (in 2010 prices), technology advancement increases CO_2 emissions significantly, but the marginal effect decreases with economic development. When GDP per capita exceeds US\$19,984, technology advancement significantly reduces CO_2 emissions, implying that the EKC theory holds. However, it should be noted that, although developed countries have higher incomes and are more likely to produce low-carbon and energy-efficient technologies, they are still likely to increase CO_2 emissions (Cheng et al. 2018), especially after GDP per capita moves beyond US\$61,666.

There is also a significant turning point in high-income countries (non-OECD). When GDP per capita exceeds US26,225 (in 2010 prices), technology advancement significantly reduces CO₂ emissions. However, different from OECD countries, when it exceeds US33,917 (in 2010 prices), technology advancement significantly increases CO₂

emissions instead (Santra 2017). Overall, an N-shaped relation appears between technology advancement and CO_2 emissions in high-income countries (non-OECD).

As for middle- and low-income countries, technology advancement always promotes CO_2 emissions, meaning there is an absence of the EKC hypothesis, such as for China (Chen et al. 2020) and Malaysia (Ali et al. 2017). Interestingly, however, it can be seen that the marginal effect tends to be decreasing. This indicates that, due to the economic development level, technology advancement in middle- and lowincome countries mainly focuses on production promotion while neglecting environmental protection to a certain extent. Nevertheless, the effort on CO_2 emission mitigation can still be found as the marginal effect of technology advancement decreases with the promotion of economic development.

Figure 2 shows threshold distributions of countries with different economic development levels. Here, the OECD countries are divided into three groups. Most OECD countries, such as France, Iceland, Belgium, Germany, Finland, Japan, the UK, and the USA, are within regime 3, where there is a significantly negative effect. Turkey, Portugal, Poland, and Mexico are distributed in regime 1 and regime 2, which show a significantly positive effect. Norway and Luxembourg are distributed in regime 4. The high-income countries (non-OECD) are divided into three groups. Argentina, Russia, Uruguay, and Trinidad and Tobago are currently transforming



Fig. 2 Threshold distributions of countries with different economic development levels

from regime 1 to regime 2, in which these countries show a positive effect relying on large-scale energy production and consumption. Cyprus presents a significantly negative effect, while Brunei and Singapore are in regime 4, showing a positive effect due to population and energy consumption increasing. It is also found that most middle- and low-income countries have sustained economic growth during 1990 to 2014 and have been transforming from regime 1 to regime 4. However, the positive effect of technology advancement on CO_2 emissions remains relatively significant.

Robustness test

Considering that the TFP estimation may be biased, this study further employs the bootstrap DEA model to estimate TFP of different countries and to calculate the index, and the results are still robust. First, Table 9 shows that without considering the impact of economic development level, the impact of technology advancement on CO_2 emissions is still insignificant, and the basic regression results are consistent with Table 4. Furthermore, this study tests the threshold regression results of different countries, which also show better robustness (Table 10).

Conclusions and implications

Conclusions

This study incorporates technology advancement, economic development levels, and CO2 emissions into a unified framework and analyzes the threshold effects of technology advancement on CO₂ emissions by empirically combining the STIRPAT model and PTR model. The findings herein verify that the impact of technology advancement on CO₂ emissions closely relates to changes in the level of economic development. After considering economic development's influence on technology advancement, technology advancement and CO₂ emissions present an inverted U-shaped relationship, but this process varies for different countries. The relationship between technology advancement and CO₂ emissions has an inverted U-shaped trend in OECD countries, while highincome countries (non-OECD) show an N-shaped correlation. As for middle- and low-income countries, technology advancement always promotes CO2 emissions, meaning there is an absence of EKC. However, efforts at CO2 emission mitigation can be found as the marginal effect decreases. Moreover, when population, energy consumption, and

Variable	(1) Full sample	(2) High-income (OECD)	(3) High-income (non-OECD)	(4) Middle- income	(5) Low- income
lntech-bootstrap	- 0.00636	- 0.00359	- 0.0150	0.00561	0.00339
	(-0.67)	(-0.58)	(- 1.23)	(0.36)	(0.14)
lnpop	1.885***	1.281***	0.592***	1.070***	2.161***
	(34.15)	(19.37)	(5.43)	(11.61)	(15.01)
lnpgdp	1.053***	1.025***	0.778***	1.426***	0.838***
	(32.11)	(28.39)	(16.72)	(26.78)	(9.32)
Intrade	0.0230	- 0.0433*	-0.0173	-0.0858**	- 0.00415
	(1.01)	(- 1.76)	(-0.52)	(-2.28)	(-0.09)
Inservice	0.0350	- 0.134**	- 0.319***	0.0868	-0.117
	(0.74)	(-2.02)	(-3.34)	(1.12)	(-1.19)
lnenergy	0.703***	0.814***	0.833***	1.038***	0.410***
	(20.98)	(31.19)	(13.41)	(19.86)	(5.16)
lnurban	0.227***	0.708***	0.0970	- 0.851***	0.213
	(3.13)	(7.54)	(0.47)	(- 9.48)	(1.21)
lnfd	0.0122	- 0.0923***	- 0.00215	0.0208*	0.144***
	(1.16)	(-7.98)	(-0.08)	(1.76)	(5.54)
Individual	Yes	Yes	Yes	Yes	Yes
Time	Yes	Yes	Yes	Yes	Yes
_cons	- 34.43***	- 25.72***	- 9.343***	- 20.72***	- 36.24***
	(- 33.42)	(- 22.63)	(-3.79)	(-11.39)	(- 12.70)
Ν	1650	625	175	350	500
R^2	0.805	0.847	0.928	0.941	0.830

t statistics in parentheses

*p < 0.1

**p < 0.05

***p < 0.01

Table 10	Robustness	test of the	threshold	regression
Tuble To	1000000000000	test of the	unconora	regression

Variable	(1) Full sample	(2) High-income (OECD)	(3) High-income (non- OECD)	(4) Middle-income	(5) Low-income
$lntech-bootstrap (lnpgdp \le \theta_l)$	0.1191*** (5.6354)	0.0689*** (4.0873)	0.0750*** (6.1135)	0.1382*** (5.0356)	0.0951*** (4.8840)
$lntech-bootstrap (\theta_1 < lnpgdp \le \theta_2)$	0.0601*** (6.1890)	0.0211*** (2.9138)	0.0457*** (4.5500)	0.0491*** (7.4111)	0.3082*** (3.4119)
$lntech-bootstrap (\theta_2 < lnpgdp \le \theta_3)$	0.0325*** (7.9888)	-0.0173*** (-8.1462)	- 0.0041 (- 0.5079)	0.0043 (0.3857)	0.0575*** (5.7887)
$lntech-bootstrap (lnpgdp>\theta_3)$	-0.0112*** (-4.8183)	0.0074 (1.3621)	0.0259* (1.8354)	0.0802** (2.4225)	0.0153** (2.0083)

t statistics in parentheses

 $^*p < 0.1$

***p* < 0.05

****p* < 0.01

economic scale continue to increase, CO_2 emissions will increase accordingly, whereas trade openness reduces CO_2 emissions following the pollution-halo hypothesis. Due to differences in economic development, the service industry and financial development have a non-significant effect on carbon dioxide emission reduction.

Policy implications

Based on the above results, some policy implications for governments and residents can be drawn. First, all countries should develop their CO₂ emission reduction plans based on their corresponding stages of economic development. Technology advancement is indeed related to economic development stages. Even for OECD countries, in terms of the present study, CO₂ emissions are likely to increase if no corresponding measures are taken. Therefore, governments and enterprises not only should focus on research and development activities for economic growth but they must also improve environment-friendly activities.

Second, "common but differentiated responsibilities" should be recognized as the consensus for tackling global climate change. Therefore, developing and developed countries should cooperate closely together to reduce carbon emissions. The great efforts of developing countries around the world should be observed in regard to the marginal effect changing along with technology advancement. Consequently, high-income countries can pay more attention to environment-friendly and energy-saving technology innovation as well as deregulation of new technologies related to CO₂ emission reduction at the same time. Middle-income and low-income countries may strive to promote economic efficiency with advanced technology applications, which means countries should cooperate to establish much freer and fairer international trade networks, which may facilitate technology spillovers between different countries. As a consequence, the division of responsibilities for carbon reduction needs to be considered overall, both for developed and developing countries.

Third, except for technology advancement, governments should also pay more attention to population scale, energy consumption, and industrial transformation, which also have important impacts on CO_2 emissions. For low-income countries, such as the Philippines, policy-makers should focus on high-quality development of their economy as well as the introduction of advanced foreign direct investment and new technologies. In addition, governments should set up reasonable population policies to ensure a demographic dividend and to curb excessive population growth at the same time. For middle-income countries, like China, governments should target improving resource efficiency rather than rapid economic growth with industrial transformation and renewable energy utilization. In high-income countries (non-OECD), such as Russia and Uruguay, which excessively depend on resourcebased industries, one essential policy is industrial structure adjustment to reduce energy intensity. High-income (OECD) countries should pay attention to efficient and environmentfriendly economic growth, as well as initiate more energy conservation policies in order to reduce emissions. Moreover, governments and residents should promote lowcarbon consumption policies that help raise welfare expenditures.

Last but not the least, compared with high-income countries, the poor quality of financial development has instead promoted CO₂ emissions in middle-income countries and low-income countries, and these countries have historically emitted relatively high carbon pollutants. Therefore, these countries should improve their technological level to reduce carbon dioxide emissions, increase the availability of credit by introducing high-quality foreign direct investment and capital markets, and promote technological progress, especially in energy-saving projects and technologies. It must be emphasized that in addition to the development of the financial sector, these countries should also support and encourage energy transformation, energy structure optimization, and population growth control. In addition, it is necessary to control rapid population growth and build low-carbon development in the process of urbanization.

This paper on the whole finds a non-linear effect of technology advancement on CO₂ emissions, which is influenced by the level of economic development, but there are still limitations. First, due to the limitation of balanced panel data, the sample of non-OECD high-income countries is small, which may affect the results. Second, this study pays more attention to the comparison of different types of countries, leading to in-depth analysis of specific countries. Third, this article chooses the TFP index as the proxy variable for technology advancement, which has certain reference significance from the perspective of the neoclassical economic model. However, it ignores the endogenous structural characteristics of technology advancement and the influence of institutions on technology advancement. Future research can further expand the dataset to enrich the research sample. At the same time, technology can be further decomposed, and structural differences over the impact of technology advancement and productivity on CO_2 emissions can then be compared in greater depth.

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Authors' contributions Five authors provided critical feedback and helped shape the research, analysis, and manuscript. Ruzi Li is responsible for conceptualization, investigation, and writing of the original draft and analysis; Lin Lin is responsible for software and data curation; Lei Jiang is responsible for the paper's visualization; Yaobin Liu is responsible for its visualization and supervision; Chien-Chiang Lee is responsible for the investigation, analysis, and corresponding author.

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Data availability Data are available from the authors upon request.

Compliance with ethical standards

Appendix

Table 11 List of sample countries

Competing interests The authors declare that they have no competing interests.

Ethical approval This is an original article that did not use other information that requires ethical approval.

Consent to participate All authors participated in this article.

Consent to publish All authors have given consent to the publication of this article.

High-income (OECD) (25)		High-income (non-	Middle-income	Low-income (20)	
Australia	Mexico	OECD) (7) Argentina	(14) Algeria	Bangladesh	Philippines
Austria	Netherlands	Brunei Darussalam	Brazil	Benin	Senegal
Belgium	New Zealand	Cyprus	Bulgaria	Bolivia	Sri Lanka
Chile	Norway	Russian Federation	China	Cameroon	Sudan
Denmark	Poland	Singapore	Costa Rica	Congo	Togo
Finland	Portugal	Trinidad and Tobago	Dominican	Egypt	Ukraine
France	Spain	Uruguay	Republic	El Salvador	
Germany	Sweden		Ecuador	Honduras	
Greece	Turkey		Jordan	India	
Iceland	United		Malaysia	Indonesia	
Ireland	Kingdom		Mauritius	Kenya	
Italy	United States		Panama	Morocco	
Japan			Peru	Mozambique	
Luxembourg			South Africa Thailand	Pakistan	

Note: Based on the World Bank database

References

- Ahmad M, Khan Z, Rahman ZU, Khattak SI, Khan ZU (2019) Can innovation shocks determine CO2 emissions (CO2e) in the OECD economies? A new perspective. Econ Innov New Technol:1–21. https://doi.org/10.1080/10438599.2019.1684643
- Ali W, Abdullah A, Azam M (2017) Re-visiting the environmental Kuznets curve hypothesis for Malaysia: fresh evidence from ARDL bounds testing approach. Renew Sust Energ Rev 77:990– 1000
- Andreoni V, Galmarini S (2016) Drivers in CO2 emissions variation: a decomposition analysis for 33 world countries. Energy 103:27–37
- Ang JB (2007) CO2 emissions, energy consumption, and output in France. Energy Policy 35:4772–4778
- Apergis N (2016) Environmental Kuznets curves: new evidence on both panel and country-level CO2 emissions. Energy Econ 54:263–271
- Apergis N, Payne JE (2009) CO2 emissions, energy usage, and output in Central America. Energy Policy 37:3282–3286
- Barrett S (2006) Climate treaties and "breakthrough" technologies. Am Econ Rev 96:22–25

Berkhout PHG, Muskens JC, Velthuijsen JW (2000) Defining the rebound effect. Energy Policy 28(6):425–432

- Boden TA, Marland G, Andres RJ (2015) Global, regional, and national fossil-fuel CO2 emissions. Oak Ridge, Tenn., U.S.A.: Carbon Dioxide Information Analysis Center, Oak Ridge National Laboratory, U.S. Department of Energy. https://doi.org/10.3334/ CDIAC/00001 V2015
- Bosetti V, Carraro C, Galeotti M (2006) The dynamics of carbon and energy intensity in a model of endogenous technical change. Energy J 27:191–205
- Brock WA, Taylor MS (2010) The green Solow model. J Econ Growth 15(2):127–153
- Chang CP, Lee CC (2008) Are per capita carbon dioxide emissions converging among industrialized countries? New time series evidence with structural breaks. Environ Dev Econ 13(4):497–515
- Chen Y, Lee CC (2020) Does technological innovation reduce CO2 emissions? Cross-country evidence. J Clean Prod 263:121550
- Chen J, Gao M, Mangla SK, Song M, Wen J (2020) Effects of technological changes on China's carbon emissions. Technol Forecast Soc Chang 153:119938
- Cheng ZH, Li LS, Liu J (2018) Industrial structure, technical progress and carbon intensity in China's provinces. Renew Sust Energ Rev 81: 2935–2946
- Dietz T, Rosa EA (1997) Effects of population and affluence on CO2 emissions. Proc Natl Acad Sci 94(1):175–179
- Du K, Li J (2019) Towards a green world: how do green technology innovations affect total-factor carbon productivity. Energy Policy 131:240–250
- Du K, Li P, Yan Z (2019) Do green technology innovations contribute to carbon dioxide emission reduction? Empirical evidence from patent data. Technol Forecast Soc Chang 146:297–303
- Ehrlich PR, Holdren JP (1971) The impact of population growth. Science 171:1212–1217
- Fare R, Grosskopf S, Norris M, Zhang Z (1994) Productivity growth technical progress and efficiency change in industrialised Countries. Am Econ Rev 84:66–83
- Grossman GM, Krueger AB (1995) Economic growth and the environment. Q J Econ 110:353–377
- Grubb M (2006) Technology innovation and climate change policy: an overview of issues and options. Keio Econ Stud 41:103–132
- Hall RE, Jones CI (1999) Why do some countries produce so much more output than others? Q J Econ 114:83–116
- Hansen BE (1999) Threshold effects in non-dynamic panels: estimation, testing, and inference. J Econ 93:345–368
- Hao Y, Wang L, Lee CC (2020) Financial development, energy consumption and China's economic growth: new evidence from provincial panel data. Int Rev Econ Financ 69:1132–1151
- Hayashi D (2018) Knowledge flow in low-carbon technology transfer: a case of India's wind power industry. Energy Policy 123:104–116
- Huang J, Liu Q, Cai X, Hao Y, Lei H (2018) The effect of technological factors on China's carbon intensity: new evidence from a panel threshold model. Energy Policy 115:32–42
- Jaforullah M, King A (2017) The econometric consequences of an energy consumption variable in a model of CO 2 emissions[J]. Energy Econ 63:84–91
- Jordaan SM, Romo-Rabago E, Mcleary R et al (2017) The role of energy technology innovation in reducing greenhouse gas emissions: a case study of Canada. Renew Sustain Energy Rev 78:1397–1409
- Kasman A, Duman YS (2015) CO2 emissions, economic growth, energy consumption, trade and urbanization in new EU member and candidate countries: a panel data analysis. Econ Model 44:97–103
- Khattak SI, Ahmad M, Khan ZU, Khan A (2020) Exploring the impact of innovation, renewable energy consumption, and income on CO2 emissions: new evidence from the BRICS economies. Environ Sci Pollut Res 27:13866–13881

- Le HP, Ozturk I (2020) The impacts of globalization, financial development, government expenditures, and institutional quality on CO 2 emissions in the presence of environmental Kuznets curve. Environ Sci Pollut Res 27:22680–22697
- Lee CC, Chiu YB (2011) Electricity demand elasticities and temperature: evidence from panel smooth transition regression with instrumental variable approach. Energy Econ 33(5):896–902
- Lee CC, Chiu YB, Sun CH (2010) The environmental Kuznets curve hypothesis for water pollution: do regions matter? Energy Policy 38(1):12–23
- Lee CC, Wang CW, Ho SJ (2020) The impact of natural disaster on energy consumption: international evidence. Energy Econ:105021. https://doi.org/10.1016/j.eneco.2020.105021
- Li K, Lin B (2015) Impacts of urbanization and industrialization on energy consumption/CO2 emissions: does the level of development matter? Renew Sust Energ Rev 52:1107–1122
- Li K, Lin B (2016) Heterogeneity analysis of the effects of technology progress on carbon intensity in China. Int J Clim Change Strat Manag 8(1):129–152
- Li M, Wang Q (2017) Will technology advances alleviate climate change? Dual effects of technology change on aggregate carbon dioxide emissions. Energy Sustain Dev 41:61–68
- Liddle B (2013) Population, affluence, and environmental impact across development: evidence from panel cointegration modeling. Environ Model Softw 40:255–266
- Lin B, Liu X (2012) Dilemma between economic development and energy conservation: energy rebound effect in China. Energy 45:867– 873
- Liu TY, Lee CC (2020) Convergence of the world's energy use. Resour Energy Econ 62:101199
- Madlener R, Sunak Y (2011) Impacts of urbanization on urban structures and energy demand: what can we learn for urban energy planning and urbanization management? Sustain Cities Soc 1(1):45–53
- Managi S, Hibiki A, Tsurumi T (2009) Does trade openness improve environmental quality? J Environ Econ Manag 58(3):346–363
- Moutinho V, Varum C, Madaleno M (2017) How economic growth affects emissions? An investigation of the environmental Kuznets curve in Portuguese and Spanish economic activity sectors. Energy Policy 106:326–344
- Nasir MA, Huynh TLD, Tram HTX (2019) Role of financial development, economic growth & foreign direct investment in driving climate change: a case of emerging ASEAN. J Environ Manag 242: 131–141
- Nguyen TT, Pham TAT, Tram HTX (2020) Role of information and communication technologies and innovation in driving carbon emissions and economic growth in selected G-20 countries. J Environ Manag 261:110162
- Pham NM, Huynh TLD, Nasir MA (2020) Environmental consequences of population, affluence and technological progress for European countries: a Malthusian view. J Environ Manag 260:110143
- Rafiq S, Salim R, Nielsen I (2016) Urbanization, openness, emissions, and energy intensity: a study of increasingly urbanized emerging economies. Energy Econ 56:20–28
- Sánchez PPI, Maldonado MCJ (2015) R&D activity of university spinoffs: comparative analysis through the measurement of their economic impact. Int J Innov Learn 18(1):45–64
- Santra S (2017) The effect of technological innovation on productionbased energy and CO2 emission productivity: evidence from BRICS countries. Afr J Sci Technol Innov Dev 9(5):503–512
- Saudi MHM, Sinaga O, Jabarullah NH (2019) The role of renewable, non-renewable energy consumption and technology innovation in testing environmental Kuznets curve in Malaysia. Int J Energy Econ Policy 9(1):299–307
- Shahbaz M, Kablan S, Hammoudeh S, Nasir MA, Kontoleon A (2020) Environmental implications of increased US oil production and

liberal growth agenda in post -Paris Agreement era. J Environ Manag 271:110785

- Shan H (2008) Reestimating the Capital Stock of China:1952~2006. J Quant Tech Econ 25:17–31
- Shapiro JS, Walker R (2018) Why is pollution from US manufacturing declining? The roles of environmental regulation, productivity, and trade. Am Econ Rev 108(12):3814–3854
- Tamazian A, Chousa JP, Vadlamannati KC (2009) Does higher economic and financial development lead to environmental degradation: evidence from BRIC countries. Energy Policy 37:246–253
- Töbelmann D, Wendler T (2020) The impact of environmental innovation on carbon dioxide emissions. J Clean Prod 244:118787
- Wang KM (2012) Modelling the nonlinear relationship between CO2 emissions from oil and economic growth. Econ Model 29:1537– 1547
- Wang C, Wang F, Zhang X, Yang Y, Su Y, Ye Y, Zhang H (2017) Examining the driving factors of energy related carbon emissions using the extended STIRPAT model based on IPAT identity in Xinjiang. Renew Sust Energ Rev 67:51–61
- Yang L, Li Z (2017) Technology advance and the carbon dioxide emissions in China–Empirical research based on the rebound effect. Energy Policy 101:150–161

- Youssef AB, Hammoudeh S, Omri A (2016) Simultaneity modeling analysis of the environmental Kuznets curve hypothesis. Energy Econ 60:266–274
- Yu Y, Du Y (2019) Impact of technological innovation on CO2 emissions and emissions trend prediction on 'New Normal' economy in China. Atmos Pollut Res 10(1):152–161
- Yuan H, Feng Y, Lee CC, Chen Y (2020) How does manufacturing agglomeration affect green economic efficiency? Energy Econ 92: 104944
- Zhang N, Yu K, Chen Z (2017) How does urbanization affect carbon dioxide emissions? A cross-country panel data analysis. Energy Policy 107:678–687
- Zhao B, Yang W (2020) Does financial development influence CO2 emissions? A Chinese province-level study. Energy 200:117523
- Zheng Y, Luo D (2013) Industrial structure and oil consumption growth path of China: Empirical evidence. Energy 57:336–343
- Zhou C, Wang S, Feng K (2018) Examining the socioeconomic determinants of CO2 emissions in China: a historical and prospective analysis. Resour Conserv Recycl 130:1–11

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