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Do green technology innovations contribute to carbon dioxide emission reduction? Empirical evidence from patent data

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ABSTRACT

This paper investigates the impact of green technology innovations on carbon dioxide (CO_2) emissions based on a data panel covering 71 economies from 1996 to 2012. Specifically, we examine whether the level of income matters for the effect of green technology innovations. It is found that the impact of green technology innovations exists a single threshold effect regarding the income level. Specifically, green technology innovations do not significantly contribute to reducing CO_2 emissions for the economies whose income levels are below the threshold while the mitigation effect becomes significant for those whose income levels surpass the threshold. But the transition of regime occurs at an extremely high-income level. In addition, we find that the relationship between per capita CO_2 emissions and per capita GDP is inverted U-shaped, and urbanization level, industrial structure, trade openness, and energy consumption structure also significantly affect CO_2 emissions. Finally, this paper suggests that mechanism innovations should be implemented to reduce the diffusion cost of green technology in undeveloped economies.

1. Introduction

It is widely acknowledged that human activity such as burning coal and oil is one of the leading causes of global warming. Ever since the Industrial Revolution, the global economy has been evolving at a fast pace, and people's living conditions have been significantly improved, but improved productivity also brought severe air pollution worldwide. The World Energy Outlook 2017 cautions: “Despite their recent flattening, global energy-related CO_2 emissions increase slightly to 2040 in the New Policies Scenario. This outcome is far from enough to avoid severe impacts of climate change.” Therefore, human activity is the genesis of global warming, and now humans are in urgent need of taking effective measures to protect the earth from climate disasters. Among various paths of climate change mitigation, the green technology (including renewable energy technology, energy efficiency technology, etc.) is expected to be a dominant factor that theoretically contributes to over 60% of targeted CO_2 reduction in the International Energy Agency's (IEA's) 450 Scenario (IEA, 2013). But in different countries or regions, the research development and diffusion of green technology are typically not at the same pace. Hence the actual impact of green technology innovations might depend on specific social or economic circumstances (IEA, 2015). Thus, understanding the detailed relationship between human activity, green technology innovations, and CO_2 emissions helps to protect the environment that we depend on.

Since Grossman and Krueger (1991) first postulate the Environmental Kuznets Curve (EKC) hypothesis (which suggests an inverted U-shaped relationship between indicators of environmetal pollutions and per capita income), a growing number of studies have devoted to investigating the factors affecting CO_2 emissions (Gill et al., 2018; Lean and Smyth, 2010; Liu et al., 2017; Perman and Stern, 2003; Stokey, 1998; Yang et al., 2015). Influencing factors such as prosperity, industrial structure, international trade, urbanization and energy structure have been discussed intensively. For instance, Yao et al. (2018) find that urbanization contributes to declines in China's CO_2 emissions. Munir and Ameer (2018) show that trade openness increases SO_2 emissions while urbanization reduces SO_2 emissions in Asian emerging economies. Sun et al. (2019) find that urbanization aggravates environmental pollution in China. Li et al. (2019b) reveal that the impact of manufacturing structural rationalization on CO_2 emission mitigation is subjected to the level of resource dependence and industrialization.

Recently, green technology innovations have grown up to be an important means of reducing CO_2 emissions all around the globe

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(Weina et al., 2016; Nikzad and Sedigh, 2017). Although it is theoretically predicted that the higher the number of climate-related technologies the better for combating climate change, there are very few empirical evidences to support this (Su and Moaniba, 2017). Some previous studies suggest that the effect of green technology innovations on CO_2 emissions can be positive or negative under different conditions (Acemoglu et al., 2012; Jaffe et al., 2002), and can also be influenced by various factors, such as income and time. Braungardt et al. (2016) demonstrate that even though green innovations are generally considered as an essential element towards a green growth strategy, the impact on climate goals has been subjected to a long-running debate due to the existence of the rebound effect. Wang et al. (2012) find that energy technology patents do not play a significant role in reducing China's CO_2 emissions and energy patents with free-carbon technologies contribute to CO_2 emission reduction only in the eastern area of China. Weina et al. (2016) reveal that for Italia green innovations improve environmental productivity but not play a significant role in CO_2 emission reduction. Song et al. (2018) use the afforestation expanse from the environmental technology input as the proxy of green technology and explore its role in R&D efficiency and profit in manufacturing.

Understanding the real effect of green innovations in minimizing CO_2 emission deserves further study. Based on the existing studies, we pose two fundamental questions which need to be addressed. First, can green technology innovations effectively reduce CO_2 emissions? Second, are there some regime transitions for the effect of green technology innovations on CO_2 emissions under different income levels? As noted by Popp (2012), the using of green technology often entails an initial cost, which makes the poor economies unable to use advanced abatement technology and to achieve environmental goals.

This paper aims to empirically explore the above questions in depth using a new data set. Contributions of this paper are mainly twofold. First, the existing studies mainly focus on the impact of general technological advancement on CO_2 emissions. But few studies investigate the role of green technology innovations. This paper provides new evidence on the effect of green technology innovations on CO_2 emissions. Second, previous studies generally treat green technology innovations and income as general explanatory variables of CO_2 emissions, thus neglecting the interaction effect of income and green technology innovations on CO_2 emissions. Intuitively, the impact of green technology innovations might depend on the income level since using green technologies usually entail high costs. This paper is among the first to make income as a threshold to study the effects of green technology innovations on CO_2 emissions at different income levels.

The rest of the paper is organized as follows. In Section 2, we explain the econometric methodology. Section 3 details the data and results. Section 4 concludes the paper.

2. The model and econometric methodology

To investigate the effect of green technology innovations and income on CO_2 emissions, we consider the following reduced-form econometric model:

$$\mathrm{Ln}(Per\_CO_2)_{it} = \mathrm{Ln}(Patent)_{it}\beta_1 + X_{it}'\gamma + u_i + \varepsilon_{it} \quad (1)$$

where Ln(Per_CO_2)$_{it}$ is the dependent variable defined as the logarithm per capita CO_2 emissions of economy i in year t. Ln($Patent$)$_{it}$ is the core explanatory variable that denotes the logarithm of the number of green technology patents applied by economy i in year t.[1] X_{it}' represents a vector of control variables including per capita GDP, industrial structure, urbanization level, energy consumption structure, and trade openness, etc. u_i is the individual effects of economy i, and ε_{it} is the random error.

To further investigate whether the effects of green technology innovations depend on the level of income, we include a dummy variable D which equals to 1 if the economy belongs to the high-income group.[2]

$$\mathrm{Ln}(Per\_CO2)_{it} = \mathrm{Ln}(Patent)_{it}\beta_1 + [\mathrm{Ln}(Patent)_{it} \times D]\beta_2 + X_{it}'\gamma + u_i + \varepsilon_{it} \quad (2)$$

By the introduction of D, we can easily compare the effects of green technology innovations between different income groups. However, Eq. (2) still has some disadvantages. Firstly, the sample separation criteria are exogenous. Secondly, economies are assigned to a specific group that is not changed throughout the given years; but with the development of economy, some less developed economies will enter the high-income group. To solve these problems, we use Hansen (1999) panel threshold model. The single threshold model is written as:

$$\mathrm{Ln}(Per\_CO2)_{it} = [\mathrm{Ln}(Patent)_{it} I(q_{it} \le \gamma)]\beta_1 + [\mathrm{Ln}(Patent)_{it} I(q_{it} > \gamma)]\beta_2 + X_{it}'\gamma + u_i + \varepsilon_{it} \quad (3)$$

where q_{it} is the threshold variable, γ is the threshold parameter that divides Eq. (2) into two regimes with coefficients of β_1 and β_2. But generally, there may be K thresholds; and the model is written as:

$$\mathrm{Ln}(Per\_CO_2)_{it} = [\mathrm{Ln}(Patent)_{it} I(\mathrm{q}_{it})]\beta + X_{it}'\gamma + u_i + \varepsilon_{it} \quad (4)$$

where β is a K-dimensional vector, K is the number of thresholds,[3] $I(\cdot)$ is a vector of indicator functions of which the kth component can be expressed as:

$$I_k(\mathrm{q}_{it}) = \begin{cases} 1, & \text{if } c_{k-1} < \mathrm{q}_{it} \le c_k \\ 0, & \text{otherwise} \end{cases} \quad (5)$$

where $k \in \{1, \dots, K+1\}$; $c_0 = -\infty$, $c_{K+1} = +\infty$ and $c_1, \dots, c_K$ are K threshold parameters for estimation. The panel threshold model has been popularly applied to explore the nonlinear relationship between independent and dependent variables (Li et al., 2019a).

3. Data description and results

In this paper, we compile a balanced data panel covering 71 economies from 1996 to 2012. The economy list is provided in Table A1. The variables are constructed as follows.

3.1. Per capita CO_2 emission (denoted as Per_CO_2)

Following Ahmed et al. (2017) and Su and Moaniba (2017), we use per capita CO_2 emission as the proxy of CO_2 emission performance. The data of CO_2 emissions are collected from the World Bank.

3.2. Green patent counts (denoted as Patent)

Green technology innovation is an effective tool to address the conflict between economy and environment; it can effectively improve the energy efficiency which is vital to reduce CO_2 emissions (Braungardt et al., 2016). In this paper, we follow Su and Moaniba (2017) and Hasan and Tucci (2010) to utilize patent counts in environment-related technologies as the indicator of green technology innovations.[4] The data on green technology patent counts are collected

[1] Note we actually use the logarithm transformation of (1+ patents) to avoid generating missing values when patents = 0.

[2] We group the economies based on the World Bank's classification of economies (http://data.worldbank.org/about/country-classifications/country-and-lending-groups).

[3] The number of thresholds can be determined through the procedure developed in Hansen (1999).

[4] Another widely used indicators is expenditure on research and development (R&D). Expenditure on R&D is the input of innovation activities. It might not be in line with technology advancements which is generally taken as the out-come

from OECD statistics database (Yan et al., 2017). Referring to the methodology of OECD statistics, the patents labeled as "environment-related technologies" are counted and assigned to different countries according to bibliographic information on the inventor's residential country.

3.3. Per capita GDP (denoted as Per_GDP)

The studies of Environmental Kuznets Curve (Esteve and Tamarit, 2012; Tucker, 1995) highlight the non-linear relationship between per capita CO_2 emissions and per capita GDP. To test the EKC (Environmental Kuznets Curve) hypothesis, we include per capita GDP in our models as Du et al. (2012) have done. The data on real GDP and population are collected from PWT version 9.0 and the World Bank respectively.

3.4. Trade openness (denoted as Ratio_trade)

Grossman and Krueger (1991) argue that the effect of trade openness on CO_2 emissions can be decomposed into scale effect, structure effect and technology effect respectively. Firstly, trade liberalization decreases friction, which will further enhance the scale of production, thus affecting the CO_2 emissions. Secondly, trade openness can affect industrial structure through specialization, which will further affect CO_2 emissions. Thirdly, technology can be transferred from technologically advanced economies to backward economies. It makes technology importer increases the efficiency of energy utilization, which may reduce CO_2 emissions. In this paper, we use the ratio of trade to GDP as the proxy of trade openness. The data are collected from the World Bank.

3.5. Urbanization level (denoted as Ratio_urban)

Du et al. (2012) point out that the relationship between urbanization level and CO_2 emissions might be uncertain. Firstly, urbanization will inevitably facilitate the development of urban infrastructure, which may facilitate energy consumption and CO_2 emissions. Secondly, as the center of regional development, the urban area has a strong agglomeration effect, and the urban area can benefit from the scale effect in energy use, which may reduce CO_2 emissions. We use the share of urban population as the proxy of urbanization level. The data are directly collected from the World Bank.

3.6. Industrial structure (denoted as Ratio_ind)

Industrial structure influences CO2 emission mainly through two channels. Firstly, the change of industrial structure may affect the income growth of an economy, thus directly affecting the emission of CO_2. Secondly, since the second industry is more energy-intensive and pollution-intensive, the industrial structural change may directly influence CO_2 emissions. Considering this effect, we use the output share of the industrial sector in the whole economy as the proxy of industrial structure. The data are directly obtained from CSMAR database.

3.7. Energy consumption structure (denoted as Ratio_renew)

Different energy has different CO_2 emission coefficient.[5] Compared to renewable energy, fossil fuels emit more CO_2 given equivalent fuels and cause more damage to the environment (Capellan-Perez et al., 2014; Liu et al., 2017; Seow et al., 2016). Many economies are starting to adjust their energy consumption structures to reduce per unit GDP CO_2 emission (Kahia et al., 2016). Considering this effect, we use the share of renewable energy consumption in the total energy consumption as the proxy of energy consumption structure. The data are collected from World Bank.

3.8. Per capita output gap ratio (denoted as Ratio_gap)

In this paper we use per capita output gap ratio which is defined as $\mathbf{Ratio\_gap}_{it} = \mathbf{Per\_GDP}_{it}/\max\{\mathbf{Per\_GDP}_{it}\}$ as the threshold variable. It reflects the income level of an economy relative to the observation with the highest income during the sample period. In addition, it also satisfies the stationarity condition of the transition variable.

Table 1 reports the descriptive statistics of variables by groups. It shows remarkable variations of economic development, CO_2 emissions, and green technology innovations and structural features between high-income economies and middle-income economies. For instance, the mean of GDP per capita in the high-income group is about four times as that in the middle-income group; the mean of green technology patents is five times more than that in the middle-income group; the mean of CO_2 emissions per capita is about two times as that in the middle-income group.

4. Estimation results and explanations

4.1. Estimation results of exogenous sample segment

We use the panel fixed effect model to estimate the Eqs. (1) and (2). The results are summarized in Table 2. According to Table 2, we can see that in all the models the Hausman test significantly rejects the null hypothesis, suggesting that there is correlation between regressors and the unobserved individual effects. Thus, using the fixed effects estimator to estimate the Eqs. (1) and (2) turns out to be reasonable. The result in Model I shows that the coefficient of Ln(*Patent*) is estimated as -0.0134, insignificant at the 10% level. It indicates that overall, we do not find evidence supporting that green technology innovations can effectively curb CO_2 emissions. In Model II we consider the intersection term of green technology innovations and the group classification (Ln(*Patent*) × D). The result shows that the coefficient of Ln(*Patent*) is estimated as 0.0127, not significant even at the 10% level; but the coefficient of Ln(*Patent*) × D is estimated as -0.0660 and significant at the 1% level. Considering that there may be bidirectional causality between green technology innovations and CO_2 emissions, we replace Ln(*Patent*) by the first-order lag term $\mathrm{Ln}(Patent)_{-1}$ in Model III and Model IV. The results show a similar picture. In Model III, the coefficient of $\mathrm{Ln}(Patent)_{-1}$ is estimated as -0.0129, insignificant at the 10% level. In Model IV, this coefficient becomes 0.0156, not significant even at the 10% level while the coefficient of $\mathrm{Ln}(Patent)_{-1} \times D$ is estimated as -0.0710, significant at the 1% level. It indicates that green technology innovations have negative effect on CO_2 emission only in the high-income group in which a 1% increase in green technology innovations would lead to a 0.0710% decrease in CO_2 emissions.

The results above are consistent with our intuition. We explain the results from two aspects. (1) From the perspective of the market, the application of green technology is on a cost-benefit basis that depends on an economy's prosperity status to a certain degree. Due to the relatively poor productivity and low marketization level in the undeveloped economies, applying green technology in practice would lead to high manufacturing cost. Consequently, there might be some green technology innovations in the underdeveloped economies, but the cost of diffusion is typically unaffordable for local firms or residents. (2) From the perspective of government, available governmental resources vary significantly across economies with different income levels, which makes the motivation of developing green technology

(*footnote continued*)
of innovation activities.

[5] Generally speaking, coal products have the highest coefficient of CO_2 emissions in fossil energy followed by oil products and natural gas (Wang and Feng, 2017). In contrast to fossil energy, renewable energy such as wind and solar energy do not emit CO_2 directly.

Table 1
Summary statistics of variables by groups.

Group	Variable	Unit	Mean	SD	Min	Median	Max
M	Patent	–	101.764	472.292	0	5.29	5581.92
	Per_CO$_2$	Tons/person	3.861	2.873	0.294	3.63	12.811
	Per_GDP	2011US$/person	8154.931	4702.145	1427.32	7394.929	24,065.33
	Ratio_trade	%	77.125	39.66	0.027	68.025	220.407
	Ratio_urban	%	57.115	18.854	18.297	56.778	91.295
	Ratio_ind	%	19.168	8.375	0.65	17.795	58.98
	Ratio_renew	%	9.975	13.316	0	4.424	64.817
H	Patent	–	626.07	1692.144	0	60.87	11,292.07
	Per_CO$_2$	Tons/person	9.227	4.12	2.678	8.508	25.221
	Per_GDP	2011US$/person	31,078.91	12,271.3	8617.783	31,299.77	84,270.29
	Ratio_trade	%	103.255	76.912	18.756	80.845	449.993
	Ratio_urban	%	76.582	12.303	49.856	77.889	100
	Ratio_ind	%	16.729	5.691	1.52	16.91	31.37
	Ratio_renew	%	14.974	16.933	0	10.478	89.725

Note: M and H represent middle-income and high-income groups, respectively.

Table 2
Estimation results of panel data model with exogenous sample segment.

	Model I	Model II	Model III	Model IVs
Ln(*Patent*)	−0.0134	0.0127		
	(0.0143)	(0.0153)		
Ln(*Patent*) × *D*		−0.0660**		
		(0.0275)		
Ln(*Patent*)$_{-1}$			−0.0129	0.0156
			(0.0130)	(0.0136)
Ln(*Patent*)$_{-1}$ × *D*				−0.0710***
				(0.0262)
Ln(*Per_GDP*)	1.6228***	1.1502**	1.5959***	1.1261**
	(0.5781)	(0.5500)	(0.5636)	(0.5360)
[Ln(*Per_GDP*)]^2	−0.0807**	−0.0549*	−0.0791**	−0.0536*
	(0.0310)	(0.0292)	(0.0303)	(0.0285)
Ratio_trade	−0.0006	−0.0005	−0.0007	−0.0005
	(0.0006)	(0.0006)	(0.0006)	(0.0006)
Ratio_urban	0.0251***	0.0235***	0.0249***	0.0233***
	(0.0077)	(0.0073)	(0.0080)	(0.0075)
Ratio_ind	0.0065*	0.0049	0.0064*	0.0046
	(0.0037)	(0.0039)	(0.0035)	(0.0037)
Ratio_renew	−0.0114***	−0.0112***	−0.0112***	−0.0109***
	(0.0042)	(0.0041)	(0.0041)	(0.0039)
Constant	−8.0190***	−5.6953**	−7.9022***	−5.5749**
	(2.7561)	(2.6807)	(2.7164)	(2.6261)
Hausman test	54.47***	71.84***	55.32***	74.92***
	{0.000}	{0.000}	{0.000}	{0.000}
No. of observations	1207	1207	1136	1136
No. of id	71	71	71	71

Note: Robust standard errors in parentheses; *P*-value in brace.
*** $p < 0.01$.
** $p < 0.05$.
* $p < 0.1$.

Table 3
Estimation results of panel data model with endogenous thresholds.

	Model V	Model VI
Threshold estimates		
c	0.4117	0.4117
95% confidence interval	[0.4049,0.4139]	[0.4045,0.4122]
Ln(*Patent*) × *I*(*Ratio_gap* ≤ *c*)	−0.0098	
	(0.0071)	
Ln(*Patent*) × *I*(*Ratio_gap* > *c*)	−0.0283***	
	(0.0074)	
Ln(*Patent*)$_{-1}$ × *I*(*Ratio_gap* ≤ *c*)		−0.0099
		(0.0072)
Ln(*Patent*)$_{-1}$ × *I*(*Ratio_gap* > *c*)		−0.0277***
		(0.0076)
Ln(*Per_GDP*)	1.2629***	1.2800***
	(0.1777)	(0.1794)
[Ln(*Per_GDP*)]^2	−0.0610***	−0.0618***
	(0.0099)	(0.0100)
Ratio_trade	−0.0005**	−0.0005**
	(0.0002)	(0.0002)
Ratio_urban	0.0267***	0.0270***
	(0.0021)	(0.0022)
Ratio_ind	0.0048***	0.0048***
	(0.0015)	(0.0016)
Ratio_renew	−0.0119***	−0.0118***
	(0.0013)	(0.0013)
Constant	−6.4770***	−6.559***
	(0.8108)	(0.8167)
Likelihood ratio test		
H$_0$: Linearity	47.75*	43.87*
	{0.0760}	{0.0680}
H$_0$: One threshold	22.55	25.61
	{0.4320}	{0.2680}
No. of observations	1207	1136
No. of id	71	71

Note:
(1) Standard errors in parentheses; P-value in brace.
(2) The bootstrapping times for the likelihood ratio test is 500.
*** $p < 0.01$.
** $p < 0.05$.
* $p < 0.1$.

inconsistent among groups. For the group of undeveloped economies, governments concentrate more on developing the economy to improve people's living standards. Due to lack of enough material foundation, it is costly for them to promote green technology innovations into real applications. Thus, the impacts of green technology innovations on CO_2 emission are not significant in undeveloped economies. On the contrary, for developed economies, people's desire for a better living environment will be stronger, and governments are more capable of promoting green technology innovations into real application in society. Therefore, green technology innovations play a significant role in mitigating CO_2 emission in the high-income group.

4.2. Estimation results with endogenous thresholds

The above analysis is based on the exogenous sample segment. In this subsection, we use panel threshold models to further investigates the interaction effects of green technology innovations and income on CO_2 emissions. The results are presented in Table 3. In Model V and Model VI, the results of the likelihood test show that the linearity hypothesis is rejected at the 10% significant level, but the single threshold hypothesis cannot be rejected. It means that there are regime transitions for the effect of green technology innovations on CO_2 emissions which depends on the income level. In other words, when per capita income reaches a certain level, the effects of green technology innovations on CO_2 emissions would change. The threshold parameter is estimated at 0.4117 (it is equivalent to 34,694.0782011 US dollars per

Table 4
The group classification based on the estimated threshold parameter.

Classification	Economy			
Upper regime	Switzerland	Luxembourg	United States of America (USA)	
	Norway			
Transition from lower regime to upper regime	Australia	Austria	Belgium	Canada
	Germany	Denmark	Finland	France
	Great Britain (United Kingdom)		Hong Kong	Ireland
	Iceland	Italy	Japan	Netherlands
	Saudi Arabia	Singapore	Sweden	
Lower regime	Argentina	Armenia	Azerbaijan	Bulgaria
	Belarus	Brazil	Chile	China
	Colombia	Cyprus	Czech Republic	Spain
	Estonia	Georgia	Greece	Croatia
	Hungary	Indonesia	India	Iran
	Iraq	Israel	Kyrgyzstan	South Korea
	Lebanon	Sri Lanka	Lithuania	Latvia
	Morocco	Moldova	Mexico	Malaysia
	New Zealand	Pakistan	The Philippines	Poland
	Portugal	Romania	Russian Federation	Slovakia
	Slovenia	Thailand	Tajikistan	Turkmenistan
	Turkey	Ukraine	Uzbekistan	Venezuela
	South Africa			

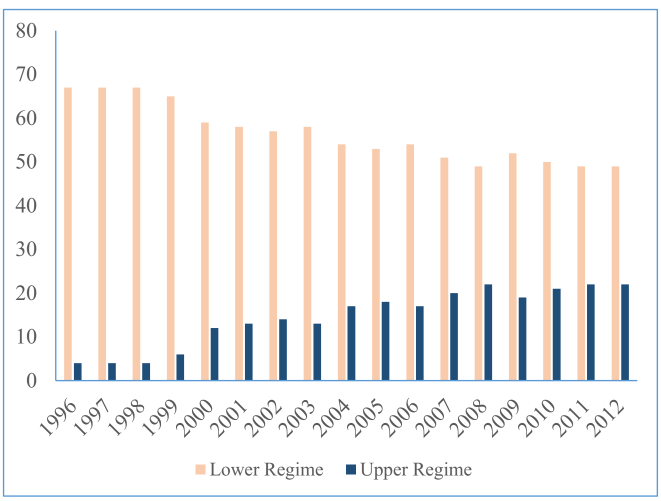

Fig. 1. Number of economies by groups over times.

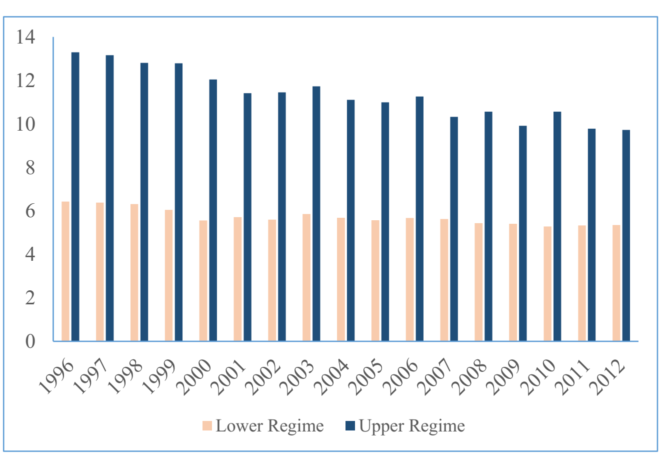

Fig. 2. Carbon dioxide emissions by groups over times.
Note: Average values by group are presented (Unit: Tons/person).

Fig. 3. Green technology patents by groups over times. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)
Note: Average values by group are presented.

capita). Table 4 shows the sample grouping results based on the estimated threshold parameter. We find that only four most developed economies (Norway, Switzerland, Luxembourg and the United States) lie in the upper regime; 49 developing economies such as China, India, and Brazil lie in the lower regime; the other 18 economies such as Britain and Japan successfully realized the transformation from the lower regime to the upper regime during the research period. Fig. 1 shows the number of observations in upper and lower regimes over times. It can be seen that before 1999 the number of economies in the upper regime is staying at 4, and after that, the number increases continuously and eventually becomes stable around 20. Fig. 2 presents a comparison of CO_2 emissions between different regimes. It shows that CO_2 emissions declined substantially in the upper-regime group while the lower-regime group did not evidence a declining trend obviously. Fig. 3 compares green technology innovations between the two groups. We can find that there are large gaps of green technology innovations between the lower and upper regimes; furthermore, the gaps are enlarging over times.

For Model VI, when *Ratio_gap* is < 0.4117, the estimated coefficient of Ln(*Patent*) is -0.0099, insignificant at the 1% level; When *Ratio_gap* is > 0.4117, the coefficient of Ln(Patent) is estimated as -0.0277, significant at the 1% level. The results reported in Model VI show a similar picture. Thus it is a robust result that green technology innovations contribute to reducing CO_2 emissions only when the income level of the economy surpasses a certain level. In other words, green technology innovations do not play a significant role in CO_2 emission reduction for underdeveloped economies.

With regard to the control variables, we obtain some conclusions from Table 3. The coefficients of Ln(*Per_GDP*) are all significantly positive, and the coefficients of $[\mathrm{Ln}(Per\_GDP)]^2$ are all significantly negative, indicating that the Environmental Kuznets Curve hypothesis is documented. That is to say, the inverted U-shaped relationship between per capita CO_2 emissions and per capita GDP is supported. The coefficient of *Ratio_renew* is negative and significant at the 1% level, indicating that the increasing share of renewable energy consumption would lead decline in CO_2 emissions. Similarly, the coefficients of *Ratio_trade* are negative and significant even at the 5% level, suggesting that there is a negative relationship between foreign trade and CO_2 emissions. In other words, we find a contradictory evidence of "pollution haven hypothesis". The coefficients of *Ratio_urban* and *Ratio_ind* are all positive, indicating that the increases in the urbanization level and the output share of the industrial sector have positive effects on CO_2

emissions. The results are similar to the findings of Li and Lin (2015).

5. Conclusion and policy implications

This paper explores the heterogeneous impact of green technology innovations on CO_2 emissions by using the panel threshold model proposed by Hansen (1999). Our empirical study provides ample evidence that income levels drive the non-linear nexus between green technology innovations and CO_2 emissions. We find that the effect of green technology innovations exists a single threshold effect with regard to the income level. To be specific, the effect of green technology innovations on reducing CO_2 emissions is more significant for the economies whose income level surpass 34,694.078 US dollars in the 2011 price level. It means that the transition of regime occurs at an extremely high-income level.

The above results have some policy implications for climate change mitigation. Firstly, the world is in urgent need of fostering developing economies' green innovation capacities, given that combating climate change is the mutual task for all economies, and that green technology innovation can reduce CO_2 emissions while stimulating economic growth. Secondly, green technology innovations are still playing a vital role in climate change mitigation (Zhang et al., 2016), although they only take effect when the economy reaches a high-income level. Zhang et al. (2018) document that scientific research funds play an important role in stimulating technological progress. Thus, the government of the developed economies should allocate more resources in R&D and encourage enterprises to make green technology innovations. Thirdly, it is necessary to construct a new framework regarding worldwide diffusion and application of green technology. Since the green technology is typically expensive for individuals in low-income economies, some mechanism innovations in intellectual property, green finance, and governmental support should be initiated for accelerating diffusion and application of green technology. Additionally, the low-income economies should promote the application of green management which can improve resource utilization efficiency given the production technology (Raharjo, 2019). Fourthly, while only three economies were on the right side of the inverted U-shaped curve from 1995 to 2012, another 19 economies successfully reached the turning point for CO_2 emissions; thus, governments of the lower regime should vigorously seek paths of green growth and raise the national income level to transform at an earlier date.

Finally, it is worth pointing out that this paper attempts to provide new evidence on the heterogeneous impact of green technology innovations on CO_2 emissions whereas measuring green technology innovations is a challenging issue. Due to data availability, we employ the patent counts in environment-related technology as the proxy of the green technology innovations which has some potential limitations. Although the patent-based indicator has been widely employed in the existing literature, the potential limitations should be also duly noted. First, it can reflect technological development, but cannot represent the situation of technology adoption.[6] Second, patent counts simply add up the patents which might not neglect various values of different innovations.

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[6] In view of this, some recent studies attempt to account for environmental technology progress based on the production-theory framework. Examples of such studies include Shao et al. (2016), Yu et al. (2017), Song and Wang (2018), and Jin et al. (2019). However, in this context some particular assumptions are required for estimation. Consequently, different methods generally lead to greatly various estimates of environmental technology progress.

Table A1
List of economies and the group classification based on World Bank.

Classification	Economy			
High income	Australia	Austria	Belgium	Canada
D = 1	Switzerland	Chile	Cyprus	Czech Republic
	Germany	Denmark	Spain	Estonia
	Finland	France	Great Britain (United Kingdom)	
	Greece	Hong Kong	Croatia	Hungary
	Ireland	Iceland	Israel	Italy
	Japan	South Korea	Lithuania	Luxembourg
	Latvia	Netherlands	Norway	New Zealand
	Poland	Portugal	Saudi Arabia	Singapore
	Slovakia	Slovenia	Sweden	
	United States of America (USA)			
Middle income	Argentina	Armenia	Azerbaijan	Bulgaria
	Belarus	Brazil	China	Colombia
D = 0	Georgia	Indonesia	India	Iran
	Iraq	Kyrgyzstan	Lebanon	Sri Lanka
	Morocco	Moldova	Mexico	Malaysia
	Pakistan	The Philippines	Romania	Russian Federation
	Thailand	Tajikistan	Turkmenistan	Turkey
	Ukraine	Uzbekistan	Venezuela	South Africa

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