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Abstract: Green technology innovation (GTI) is commonly seen as an essential way to decrease carbon emissions (CE). However, its advancement may result in the so-called carbon rebound effect which may offset its emission-reducing efficacy. This study examines the overall effect of GTI on CE using a fixed-effect model and a large panel dataset comprising China's 276 cities from 2007–2017. The main research findings include: 1) there exist inverted U-shaped relationships between GTI and per capita as well as total CE for the entire data sample; 2) regional heterogeneity exists regarding the relationships between GTI and CE (CE per capita). The empirical results have important policy implications on GTI to contain CE.

Keywords: green technology innovation; GTI; carbon emissions; carbon rebound effect; inverted U-shaped relationship.

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1 Introduction

The ongoing accumulation of carbon emissions (CE) has caused serious environmental problems like global warming and frequent extreme weather (Cai et al., 2021). Some nations, such as China, have realised these problems which are mainly caused by massive CE, and have been taking steps to minimise CE while boosting economic growth. China overtook the USA as the world's biggest carbon emitter and energy consumer in 2006 and 2009, respectively (BP, 2016). In the 75th United Nations General Assembly, China demonstrated its ambition by committing to achieve goals of carbon peaking and neutrality (i.e., the 'double carbon' goal) in this century. Carbon emission reduction has become an essential task for governments across the world (Töbelmann and Wendler, 2020).

Green technology innovation (GTI) is widely considered to be conducive to reducing CE (Paramati et al., 2020; Shan et al., 2021). GTI was initially defined as the technical process that produces goods with less pollution, raw materials, and energy consumption (Braun and Wield, 1994). Currently, over two-thirds of all the countries in the world are still seeking for the appropriate GTI to achieve both environmental and economic goals (Shan et al., 2021). In comparison to traditional technology innovation, the core feature of GTI is to consider the environmental impact, such as alternative energy production, energy conservation, carbon capture and storage, and reuse of waste materials (Xu et al., 2021). Among these, a few empirical studies have paid serious attention to its influence on energy savings and carbon reduction. For instance, Shan et al. (2021) distinguished that GTI mainly improves energy efficiency while the technologies related to renewable energy help to develop clean energies. As a result, in this study, we define GTI as the innovations conducive to energy conservation, paying special attention to the so-called carbon rebound effect.

A substantial body of studies has examined the GTI's impact on CE, but obtained mixed or even contradictory evidence. Some scholars claimed that GTI can significantly decrease CE by improving energy efficiency (e.g., Wang et al., 2012; Többelmann and Wendler, 2020). Others argued that GTI expands the economic scale and production level, thereby consuming more energy and increasing CE, which is called the carbon rebound effect (Lin and Liu, 2012; Wu et al., 2018). It follows that the nonlinear and comprehensive effect of GTI on CE based on the carbon rebound effect remains an important research question that needs to be answered using appropriate techniques and data (Khattak et al., 2021), which is the focus of this paper.

In response to the above problems, this study uses a fixed-effect model and a large panel dataset comprising all the Chinese prefecture-level cities with available observations for eleven years during 2007–2017 to evaluate how GTI influences CE. We focus on the Chinese cities for the data period due to the following considerations. First, China, the worldwide biggest carbon emitter and energy consumer, faces massive pressure of green transformation (Yao et al., 2022). It makes sense to study China's efforts for carbon emission reduction. Second, the GTI level and carbon emission performance vary with cities, but cities at the prefectural level have obtained less attention in the literature. Third, we set the research period between the financial crisis of 2008 and China's proposal of the 'double carbon' goal in 2020 to avoid the shock of these two events.

This article makes the following three contributions. First, this study contributes to the literature related to GTI's impact on CE by simultaneously considering the carbon rebound effect that refers to a concurrent offset of energy savings during the technological advance (especially GTI) process. We observe an inverted U-shaped impact of GTI on CE, and illustrate that using the carbon rebound effect. Second, due to inadequate statistics on energy consumption inventories, there are still few empirical studies that investigate the role of GTI on CE in Chinese cities. This study thus contributes to a fine-grained understanding of the relationship between GTI and CE at the prefectural level. Third, because the GTI's impact on CE varies with the economic level, we conduct a heterogeneity test to see whether the same relationship exists in all three main Chinese regions by dividing the entire sample into the eastern, central and western groups, and estimate the same model using different sub-samples.

We organise the remaining paper as follows. Section 2 introduces the theoretical backdrop and hypotheses. Section 3 describes the variables and methods. The empirical findings and analyses are presented in Section 4. Section 5 concludes with policy implications.

2 Theoretical background and hypotheses

2.1 Role of GTI in carbon emission reduction

Facing increasing pressure regarding climate change and resource scarcity, governments are recognising the potential benefits of GTI to carbon emission reduction. The International Patent Classification (IPC) proposed that GTI is defined as the innovation regarding environmentally friendly technologies and includes specifically alternative clean energy, energy savings, carbon capture and storage, etc. (Xu et al., 2021). From an intuitive standpoint, GTI may contribute to lowering CE due to its low-carbon and low-energy usage qualities (Braun and Wield, 1994). However, scholars have yet to reach a consensus regarding the role of GTI in decreasing CE.

Many empirical studies in the literature suggest that GTI is critical for reducing CE. At the national level, the GTI's benefits on carbon emission reduction have been observed among all the developed countries (Dong et al., 2022), the EU member states (Töbelmann and Wendler, 2020), and OECD economics (Paramati et al., 2020). Using provincial-level data in China, Wang et al. (2012) found that innovations regarding low-carbon technology are conducive to decreasing CE across all the 30 sample provinces. Using prefectural-level city data in China, Xu et al. (2021) also found that GTI considerably reduces CE by improving energy and industrial structures. Liu et al. (2021) also found that GTI can help to reduce CE in Chinese 175 cities.

Studies in the literature that is now available claim that the carbon rebound effect makes it uncertain how GTI will affect CE. Cai et al. (2021), for example, found that GTI has an insignificantly negative correlation with national CE and promotes CE in the western provinces. Additionally, many studies have explored the nonlinear effect of GTI on CE. Yin et al. (2018) claimed that technological advancement might lead to more energy consumption to have an inverted U-shaped effect in industrial enterprises. Using a panel dataset from Chinese 30 provinces, Gu et al. (2019) discovered an inverted U-shaped relationship between energy technology innovation and CE. Razzaq et al. (2021) applied the quantile regression approach to data from the BRICS member states and observed that the emissions-mitigating effect of GTI is only noticeable at the higher emission quantiles, whereas it is positively associated with CE at the lower emissions quantiles.

The carbon rebound effect is analogous to the energy rebound effect. The energy rebound effect was first described by Khazzoom (1980). It refers to a phenomenon where technical improvement may generate a fall in real costs of consuming energy in addition to promoting energy conservation, thereby increasing energy consumption and partially offsetting some potential energy savings induced by the same technology (Sorrell and Dimitropoulos, 2008). Moreover, since CE is strongly associated with energy use, the energy rebound effect may affect CE and thereby results in the carbon rebound effect (Yang and Li, 2017). Santarius and Soland (2018) further claimed that the carbon rebound effect can be generated through both economic and psychological mechanisms. According to Li et al. (2020), carbon rebound occurs when a portion of potential carbon emission reduction is not realised owning to decreased effective prices and costs of energy consumption as a result of relative technological advancement.

In summary, the carbon rebound effect complicates GTI's impact on aggregate CE (Yang and Li, 2017). Although GTI is regarded widely to be a significant driver for reducing CE, many scholars agree that the advantages of GTI on increasing carbon emission performance would be hidden to some extent because of the carbon rebound effect (Druckman et al., 2011). If the carbon rebound effect is sufficiently large, it may undermine sharply the benefits of GTI in encouraging carbon emission reduction (Sorrel and Dimitropoulos, 2008), resulting in a positive effect between them. In addition, Li et al. (2020) suggested that when advances in energy technology (similar to GTI), the carbon rebound effect shows a general reducing trend. Hence, it is reasonable to speculate that the emission-reducing efficacy of GTI will become stronger as GTI improves because of the diminished carbon rebound effect. Hence, we put forward the first hypothesis:

H1 With the improvement of the GTI level, CE will show an inverted U-shaped association with GTI.

2.2 Chinese regional GTI, carbon rebound effect and CE

Owning to the economic level and location, regional heterogeneity can be seen at the GTI level. The National Bureau of Statistics of China suggested that China can be separated into three distinct regions, namely, the eastern, central, and western regions[1] (Yao and Zhang, 2001). The eastern coastal provinces have absorbed a large amount of capital and talent necessary for GTI (Luo et al., 2021). Moreover, eastern China also closed down or moved several high-emission firms (Guo et al., 2019), improved investment in GTI (Gao et al., 2022), and introduced overseas green technologies (Luo et al., 2021) because of the early economic transition. Hence, it now becomes China's main GTI area. The central and western inland areas are more restrained by financial resources and tend to have fewer environmental regulations than their eastern counterparts. Consequently, their primary objectives of economic development and innovations are relatively more intended for productivity improvement than for environmental protection (Gao et al., 2022). Therefore, the GTI level in the central-western region is relatively lower than that in the eastern part of China (Liu and Nie, 2022).

Tables 1 and 2 report the trend of the total green patents and green invention patents, respectively, in the above regions. It can be found that the total numbers of both of them increased quickly during the data period. In comparison to central-western China, eastern China has more green patents. Moreover, the GTI level of central China is slightly greater than that of western China (see Table A1).

Due to varying GTI levels and industrial structures, the carbon rebound effect exhibits significant geographical variations (Wu et al., 2018). According to the discussion in Section 2.1, the eastern region has a lower carbon rebound effect due to its higher GTI level. Furthermore, high-energy and high-emission enterprises predominate in the industrial structure of the western section of China, where GTI may result in a stronger carbon rebound effect (Guo et al., 2019). Li et al. (2020) examined the Chinese carbon rebound effect and stated that it was generally on the decline due to improvements in energy technology, with the eastern-western section of the country experiencing a less severe carbon rebound impact than the central region. China's average carbon rebound effects in the eastern, central, and western regions were 73.34%, 61.33%, and 88.84%, respectively. These arguments indicate that the western region is more vulnerable to the carbon rebound effect than the eastern-central region (Chen et al., 2019).

Consequently, the GTI's impact on CE has obvious regional heterogeneity because of varying GTI levels in three different Chinese regions. For instance, Gao et al. (2022) argued that GTI could effectively decrease CE in the eastern-central region, while its emission-mitigating effect is inconsiderable in the west of China. Cai et al. (2021) only found the GTI's role in reducing eastern and central CE. This study discusses the nonlinear relationship between GTI and CE. Hence, we put forward our further hypothesis:

H2 The inverted U-shaped relationship between GTI and CE can be seen in the region with high-level GTI (eastern region), but not necessarily in the regions with low-level GTI (central and western regions).

3 Data and method

To assess the influence of GTI on CE, we apply a panel dataset and fixed-effect model to capture unobserved heterogeneity and unobserved time effects. To overcome the omitted variable bias problem, we control as many factors as possible based on previous studies. In addition, we lag the key explanatory variables by one year and two years, respectively, to address the reverse causality problem (Zhu et al., 2019). Moreover, carbon emission data is replaced by energy consumption to further estimate consistency and explore the connection between carbon and energy rebound. Ultimately, two low-carbon policies are considered to further reduce the endogeneity problem.

3.1 Sample and variables

The dataset for this study covers 276 cities in China during 2007–2017. China has more than 330 prefecture-level or above (metropolitan as well as sub-provincial level) cities, but some of them do not have consistent data and have to be excluded from our dataset. However, the sample cities represent over 90% of the country's population, GDP, energy consumption and CO2 emissions.

3.1.1 Dependent variables

The dependent variables are per capita CE (denoted as *PCE*) and total CE (denoted as *CE*) in the city. Given data availability, we derive directly CO_2 emission data of each county from the carbon emission accounts and datasets and then combine them to generate city-level data at the prefecture level. This dataset was calculated by Chen et al. (2020) employing night-time light data and has been widely employed in related research (Liu et al., 2021).

3.1.2 Independent variables

The GTI level serves as the primary explanatory factor in the model. R&D expenditures and patent counts are two often used measurements of technological innovation (Guo et al., 2018). Because statistics on R&D expenditure for GTI are not available, the number of green patents is used as an indication of GTI for this study. The data is gathered by searching the website of the State Intellectual Property Office (SIPO) using the IPC code of green patents (Johnstone et al., 2010).

China's patent law distinguishes three sorts of patents: invention, utility model and appearance design. Invention patents are defined as the technological advancement of new products or methods. Utility model patents represent novel technological solutions for a product's shape or structure. Appearance design patents simply safeguard a product's appearance (SIPO, 2008). Generally, inventions involve more innovations compared to the other two kinds of patents (Tian et al., 2021). In addition, compared to the patent granted, the patent application serves better as the proxy for the actual innovations. Because there is a delay in patents awarded owning to market monitoring and annual fees, patent applications can reflect the level of innovation (Lin and Ma, 2022). Finally, to further prevent the impact of population size on innovation outcomes, we use the number of green (invention) patent applications per million people, denoted as *GP* (*GIP*), as the GTI variables (Zhao et al., 2021).

3.1.3 Control variables

The following control variables are selected for the study. All monetary values are calculated using the constant 2007 prices. First, since CE is determined by human activities and outputs, we thus involve the city's population density (denoted as *PD*) in our models (Xu et al., 2021).

Second, we utilise per capita GDP (denoted as *PGDP*) as another control variable (Lin and Ma, 2022).

Third, energy consumption is also argued as one determination of CE (Lin and Ma, 2022). Owning to the inadequate data on energy consumption in Chinese cities, we use the consumption data of natural gas, electricity, and liquefied petroleum gas provided in the China City Statistical Yearbook and China Urban Construction Yearbook to estimate energy consumption (denoted as *EC*) (Sheng et al., 2019).

Fourth, the secondary (manufacturing) industry is usually more emission-intensive compared to other industries (Xu et al., 2021). The industrial structure (denoted as IS) is measured as the share of the secondary industry output in GDP. We expect its coefficient to be positive.

Fifth, there is no certain connection between urbanisation and CE (Du et al., 2019). On the one hand, urbanisation may facilitate the development of urban infrastructure, consuming more energy. On the other hand, it will also cause a strong agglomeration effect which enables cities to benefit from the scale effect of energy consumption, thus lowering CE. We utilise the proportion of non-agricultural city residents to the city's total residents to measure the urbanisation level (denoted as *URB*) (Xie et al., 2017). We collect the data from the China Population & Employment Statistics Yearbook.

Sixth, the impact of foreign direct investment (FDI) on CE might also be uncertain. The pollution haven hypothesis said that FDI may cause the movement of high-emission firms to the host nation, thereby raising CE. The pollution halo effect claimed that FDI will absorb more advanced low-carbon technologies and thus reduce CE in the host nation (Xu et al., 2021). We quantify the FDI level (denoted as *FDI*) using the proportion of FDI to all investments in fixed assets.

3.2 Descriptive statistics

Tables 1 and 2 display the descriptive statistics and correlations, respectively. The standard errors of lnPCE and lnGP are 0.685 and 1.607, respectively, indicating that the GTI and CE levels vary greatly among cities, highlighting the need to empirically test the effect of GTI on CE. Although most variables are correlated, the values of most of the correlated coefficients are less than 0.7, implying that there are no serious multicollinearity problems between these variables.

Table 1 Descriptive statistics

Var	*Observation*	*Mean*	*SD*	*Min*	*Max*
ln*PCE*	3,036	8.686	0.685	6.384	11.243
ln*CE*	3,036	7.652	0.774	5.343	10.046
ln*GP*	3,036	3.142	1.607	–1.333	8.282
ln*GIP*	3,036	2.278	1.674	–1.797	7.628
ln*PD*	3,036	5.747	0887	2.304	8.960
ln*PGDP*	3,036	10.261	0.654	4.538	12.890
ln*EC*	3,036	8.908	1.230	4.694	12.788
ln*IND*	3,036	3.868	0.239	2.705	4.511
ln*URB*	3,036	3.888	0.312	2.798	4.778
ln*FDI*	3,036	0.406	1.434	–8.210	4.012

Table 2 Correlation matrix

Var	ln*PCE*	ln*CE*	ln*GP*	ln*GIP*	ln*PD*	ln*PGDP*	ln*EC*	ln*IND*	ln*URB*	ln*FDI*
ln*PCE*	1.000									
ln*CE*	0.554	1.000								
ln*GP*	0.481	0.527	1.000							
ln*GIP*	0.460	0.510	0.967	1.000						
ln*PD*	–0.176	0.306	0.382	0.361	1.000					
ln*PGDP*	0.679	0.516	0.800	0.767	0.199	1.000				
ln*EC*	0.442	0.645	0.755	0.730	0.457	0.703	1.000			
ln*IND*	0.262	0.137	0.086	0.054	0.163	0.315	0.176	1.000		
ln*URB*	0.557	0.347	0.716	0.681	0.214	0.755	0.669	0.132	1.000	
ln*FDI*	0.204	0.336	0.308	0.281	0.381	0.334	0.360	0.0830	0.335	1.000

3.3 Model specifications

To investigate the factors driving environmental pressure, Ehrlich and Holdren developed the IPAT model in 1971: $I = PAT$. Here, I, P, A, and T represent environmental impact, population, affluence, and technology, respectively. Dietz and Rosa then modified it to be a stochastic form in 1994, namely the STIRPAT model: $I_i = aP_i^b A_i^c T_i^d e_i$, where corresponding parameters stand for the same variables as in the original form. In addition to estimating coefficients as parameters, this updated model helps to decompose various factors (Fan et al., 2006). The STIRPAT model is thereby applied to a variety of study scenarios (Xie et al., 2017).

Reformulating factor T is important in the IPAT and STIRPAT models (Dietz and Rosa, 1994). Currently, two main ways are used to measure the T in the STIRPAT model. One is using the residual term in this model, which includes all components except P and A, to interpret T. The other is interpreting it as one or several variables theorised to reflect the technological level. According to Vélez-Henao et al. (2019), few studies use the error term to represent T, while more studies used a series of variables to quantify T. In this study, we follow the second way to regard GTI as the most important technological part of affecting CE. Hence, we replace *T* with *GP* and *GIP* in the STIRPAT model, respectively. To test the inverted U-shaped relationship, we added a quadratic component of ln*GP* (or ln*GIP*) to the model after taking the logarithms of variables. Additionally, we use the population density and per capita GDP as proxies for parameters *A* and *T*, respectively. The models take the following forms:

$$\ln I_{it} = \alpha + \beta_1 \ln GP_{it} + \beta_2 \ln GP_{it}^2 + \beta_3 \ln PD_{it} + \beta_4 \ln PGDP_{it} + \varepsilon_{it} \tag{1}$$

$$\ln I_{it} = \alpha + \beta_1 \ln GIP_{it} + \beta_2 \ln GIP_{it}^2 + \beta_3 \ln PD_{it} + \beta_4 \ln PGDP_{it} + \varepsilon_{it} \tag{2}$$

In this study, we focus on both per capita and total CE as our environmental impact *I*. To adequately investigate the factors affecting CE, we extend the model as follows:

$$\begin{aligned} \ln PCE_{it} = \alpha &+ \beta_1 \ln GP_{it} + \beta_2 \ln GP_{it}^2 + \beta_3 \ln PD_{it} \\ &+ \beta_4 \ln PGDP_{it} + \beta_5 \ln EC_{it} + \beta_6 \ln IS_{it} \\ &+ \beta_7 \ln URB_{it} + \beta_8 \ln FDI_{it} + \lambda_i + \mu_t + \varepsilon_{it} \end{aligned} \tag{3}$$

$$\begin{aligned} \ln CE_{it} = \alpha + \beta_1 \ln GP_{it} + \beta_2 \ln GP_{it}^2 + \beta_3 \ln PD_{it} + \beta_4 \ln PGDP_{it} \\ + \beta_5 \ln EC_{it} + \beta_6 \ln IS_{it} + \beta_7 \ln URB_{it} + \beta_8 \ln FDI_{it} + \lambda_i + \mu_t + \varepsilon_{it} \end{aligned} \tag{4}$$

$$\begin{aligned} \ln PCE_{it} = \alpha + \beta_1 \ln GIP_{it} + \beta_2 \ln GIP_{it}^2 + \beta_3 \ln PD_{it} + \beta_4 \ln PGDP_{it} \\ + \beta_5 \ln EC_{it} + \beta_6 \ln IS_{it} + \beta_7 \ln URB_{it} + \beta_8 \ln FDI_{it} + \lambda_i + \mu_t + \varepsilon_{it} \end{aligned} \tag{5}$$

$$\begin{aligned} \ln CE_{it} = \alpha + \beta_1 \ln GIP_{it} + \beta_2 \ln GIP_{it}^2 + \beta_3 \ln PD_{it} + \beta_4 \ln PGDP_{it} \\ + \beta_5 \ln EC_{it} + \beta_6 \ln IS_{it} + \beta_7 \ln URB_{it} + \beta_8 \ln FDI_{it} + \lambda_i + \mu_t + \varepsilon_{it} \end{aligned} \tag{6}$$

where all variables like PCE_{it}, GP_{it}, PD_{it}, and $PGDP_{it}$, have been defined as above. In addition, λ_i and μ_t refer to the individual and time fixed effects, respectively. ε_{it} refers to the residual term.

4 Empirical results and analysis

4.1 Basic regressions

Table 3 lists the basic regression results for four combinations of two dependent variables and two independent ones. As shown in columns (1)–(4), the quadratic terms ($\ln GP^2$ and $\ln GIP^2$) are significantly negative at the 0.001 significant levels, implying the nonlinear effects, while the coefficients of ln*GP* and ln*GIP* are considerably positive. Hence, these results support that the GTI has an inverted U-shaped influence on CE, verifying H1.

This study interprets the notions of the GTI elasticity and the turning point to further assess the influence of GTI on CE (Gu et al., 2019). For instance, the GTI elasticity value may be determined by calculating the first partial derivative with regard to ln*GP* in column (1), namely, $\beta_1 + \beta_2 \ln GP$. And the turning point is equal to $-\beta_1/2\beta_2$ in column (3), namely, the vertices of the quadratic function. The turning point can be understood as the threshold at which GTI begins to help to reduce CE (Gu et al., 2019).

Because of the similarity of results among columns (1)-(4), it is briefer and more effective to focus on the results of columns (1) and (2). According to column (1) of

Table 3, ln*GP* belongs to [–1.333, 8.282], β_1 = 0.063 and β_2 = –0.009. Hence, we can estimate the GTI elasticity ([–0.086, 0.087]) and the turning point (3.483) in the ln*GP*-ln*PCE* linkage. In column (1), the GTI elasticity remains positive until it reaches the turning point, where it turns negative and rapidly declines. In other words, in some developed cities, the GTI's impact on urban CE has passed the turning point and started to reduce CE.

Table 3 Basic estimation results

	(1)	*(2)*	*(3)*	*(4)*
DV	ln*PCE*	ln*CE*	ln*PCE*	ln*CE*
ln*GP*	0.063***	0.049***		
	(0.009)	(0.008)		
ln*GP*^{2}	–0.009***	–0.006***		
	(0.002)	(0.001)		
ln*GIP*			0.032***	0.022***
			(0.007)	(0.005)
ln*GIP*^{2}			–0.007***	–0.004***
			(0.002)	(0.001)
ln*PD*	–0.049	0.098	–0.055	0.092
	(0.103)	(0.075)	(0.106)	(0.074)
ln*PGDP*	0.054**	0.034**	0.060**	0.039**
	(0.026)	(0.017)	(0.027)	(0.018)
ln*EC*	0.000	0.001	0.003	0.012
	(0.008)	(0.007)	(0.008)	(0.008)
ln*IND*	0.043	0.088*	0.058	0.100**
	(0.051)	(0.045)	(0.053)	(0.047)
ln*URB*	0.166***	0.141***	0.186***	0.165***
	(0.057)	(0.040)	(0.057)	(0.042)
ln*FDI*	–0.007	–0.009**	–0.008*	–0.009**
	(0.004)	(0.004)	(0.005)	(0.004)
Constant	7.343***	5.481***	7.214***	5.347***
	(0.694)	(0.420)	(0.704)	(0.416)
Year FE	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes
Sample	3,036	3,036	3,036	3,036
R^2(*within*)	0.731	0.817	0.724	0.811

Notes: DV refers to dependent variable. The robust standard errors are shown in parentheses. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

As shown in column (2) of Table 3, β_1 = 0.049 and β_2 = –0.006. Therefore, we are able to calculate the GTI elasticity ([–0.047, 0.064]) and the turning point (4.207) in the ln*GP*-ln*CE* relationship. Because 3.483 is smaller than 4.207, it is also found that the turning point of the ln*GP*-ln*PCE* relationship in general takes place before the turning point of the ln*GP*-ln*CE* nexus. This is because of the scale effect of population growth and agglomeration, which contributes to carbon emission reduction through sharing transportation infrastructure (Xie et al., 2017) and attracting human capital (Lin and Ma, 2022). It emphasises greater pressure in reducing total CE than per capita CE and the continued effort of promoting greatly GTI to reach the two turning points.

In addition, the ln*PGDP*'s coefficients are positive and significant in all columns, indicating economic development will enhance CE. As expected, the coefficients of ln*IND* also keep significantly positive in columns (2) and (4), suggesting that the increasing ratio of secondary industry output to GDP is not helpful for reducing CE. The coefficients of ln*URB* are considerably positive in different columns as well, showing the positive impact of urbanisation on CE, which is supported by Du et al. (2019). The ln*FDI*'s coefficients are negative and largely significant. It confirms the pollution halo effect and the result echoes Xu et al. (2021). Other variables' coefficients are not significant, showing their insignificant effects on CE in our sample.

4.2 Heterogeneity analysis

Because cities differ greatly in terms of GTI in different regions, there is a need for this study to divide the sample into three groups (Liu and Nie, 2022).

Table 4 First set of heterogeneity estimation results

	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
Region	*Eastern*	*Eastern*	*Central*	*Central*	*Western*	*Western*
DV	ln*PCE*	ln*PCE*	ln*PCE*	ln*PCE*	ln*PCE*	ln*PCE*
ln*GP*	0.075***		0.042**		0.013	
	(0.022)		(0.017)		(0.012)	
ln*GP*^{2}	–0.010***		–0.006*		–0.001	
	(0.003)		(0.003)		(0.003)	
ln*GIP*		0.033***		0.021**		0.007
		(0.013)		(0.009)		(0.010)
ln*GIP*^{2}		–0.007***		–0.006**		–0.001
		(0.002)		(0.002)		(0.003)
Control	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Sample	1,089	1,089	1,056	1,056	891	891
R^2 (*within*)	0.693	0.681	0.753	0.754	0.837	0.836

Notes: DV refers to dependent variable. The robust standard errors are shown in parentheses. For brevity, the estimated intercept and control variables are not reported. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

Table 4 displays the first set of findings with ln*PCE* as the dependent variable. Columns (1) to (4) show that an inverted U-shaped association between GTI and per capita CE exists in the eastern-central area but not in the western region, partly verifying H2. Similarly, the elasticity of ln*GP* ([–0.085, 0.077]) and the turning point (3.887) can be calculated from the estimated results shown in column (1). It appears that the impact of GTI on urban per capita CE has passed the turning point in the eastern-central region. This may be due to the fact that GTI has reached a relatively high level in these two regions in comparison to their western counterpart. This finding echoes (Cai et al., 2021) that GTI in the eastern-central area can significantly decrease CE.

Table 5 presents the second set of results using ln*CE* as the dependent variable, showing some different findings. The results in columns (1) and (2) indicate an inverted U-shaped effect of GTI on total CE in the eastern region but not in the other two regions, verifying H2. According to the results in column (1), we can estimate the elasticity of ln*GP* ([–0.062, 0.061]) and the turning point (4.048), indicating that the impact of GTI on total CE has also reached the turning point in the eastern region. Because 3.887 is smaller than 4.048, it suggests that more pressure is encountered in mitigating total CE than in reducing per capita carbon reduction. Interestingly, the GTI level demonstrates distinct geo-economic tiers as it moves from the east (high) to the west (low) of China. Consequently, the GTI's role in decreasing CE demonstrates a three tiers effect on the eastern (potent), to the central (less potent) and the western (least potent) region.

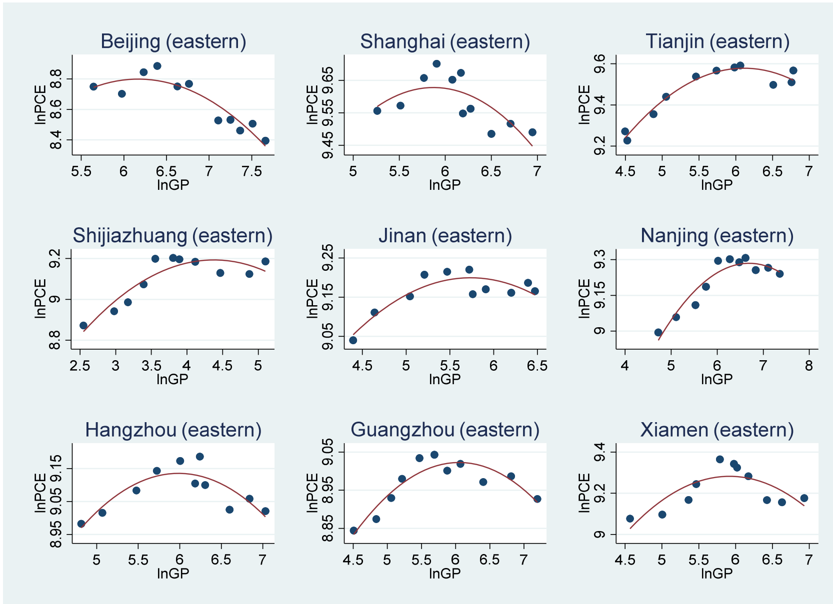
Table 5 Second set of heterogeneity estimation results

	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
Region	*Eastern*	*Eastern*	*Central*	*Central*	*Western*	*Western*
DV	*lnCE*	*lnCE*	*lnCE*	*lnCE*	*lnCE*	*lnCE*
ln*GP*	0.059*** (0.018)		0.008 (0.011)		0.013 (0.011)	
lnGP^2	–0.007*** (0.002)		0.002 (0.002)		–0.000 (0.002)	
ln*GIP*		0.021** (0.010)		0.001 (0.006)		0.005 (0.008)
lnGIP^2		–0.005*** (0.002)		0.001 (0.001)		0.001 (0.002)
Control	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Sample	*1,089*	*1,089*	*1,056*	*1,056*	*891*	*891*
R^2 *(within)*	*0.775*	*0.769*	*0.870*	*0.869*	*0.872*	*0.872*

Notes: DV refers to dependent variable. The robust standard errors are shown in parentheses. For brevity, the estimated intercept and control variables are not reported. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

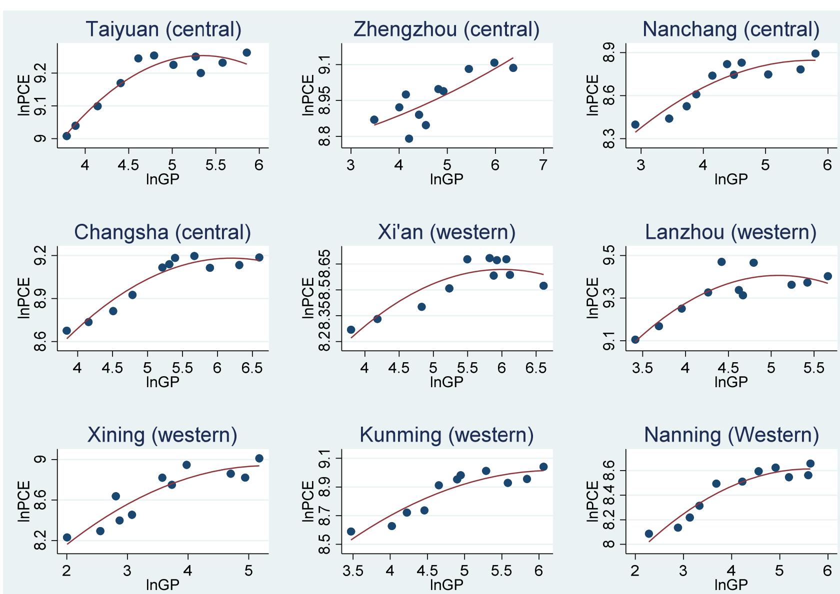
To facilitate comparison, nine provincial capital cities (excluding autonomous regions, three north-eastern provinces and several main provinces along the Yangtze River Economic Belt) were selected from the three regions to demonstrate their scatter plots and quadratic function fitting plots of ln*GP* and ln*PCE* in Figure 1 and Figure 2, respectively. It is obvious that most of the eastern and central provincial capital cities have passed their turning points in contrast to the western region.

Figure 1 The scatter plots of ln*GP* and ln*PCE* in the eastern region (see online version for colours)



Note: Red line refers to the quadratic function fitting plots of ln*GP* and ln*PCE*.

Figure 2 The scatter plots of lnGP and lnPCE in the central and western regions (see online version for colours)



Note: Red line refers to the quadratic function fitting plots of ln*GP* and lnPCE.

Different levels of lnGP are most likely responsible for the differences in ln*GP*-ln*PCE* relationships across three distinct regions. As shown in Table A2, the average value of ln*GP* in the east of China is considerably larger than in the other two regions. The former is 3.901 and the latter is 2.717 (see Table A2). According to Li et al. (2020), the eastern area saw less carbon rebound than the central region because of lower emission intensity linked with improved GTI. Hence, a low level of GTI correlates to a relatively strong carbon rebound effect, which may result in a positive correlation between GTI and CE.

4.3 Robustness check

4.3.1 Lagged measurement of independent variables

The delay between patent applications and their information disclosure will affect the timing for collecting patent data in examining its impact on CE. The time lag is typically thought to be around 18 months (Zhu et al., 2019). Moreover, there is an endogeneity concern due to the possible existence of two-way linkages between GTI and CE (Razzaq et al., 2021).

To overcome these concerns, the independent variables (GP and GIP) are replaced by green technology patent applications and green invention patent applications lagged by one year (namely, GP_{t-1} and GIP_{t-1}). The new estimated results in Table 6 are in line with those of the fundamental regressions. Because we use two different independent variables, the values of the estimated coefficients fluctuate somewhat differently, such as $\beta_1 = 0.048$ and $\beta_2 = -0.009$ in column (1), $\beta_1 = 0.023$ and $\beta_2 = -0.007$ in column (3), but the degrees of significance and signs remain unaltered, implying that the benchmark conclusions remain unchanged. Furthermore, patent application data lagged by two years are also used, and the estimated results are robust (see Table A3).

Table 6 Results for replacing independent variables

	(1)	*(2)*	*(3)*	*(4)*
DV	ln*PCE*	ln*CE*	ln*PCE*	ln*CE*
$\ln GP_{t-1}$	0.048***	0.037***		
	(0.008)	(0.007)		
$\ln GP_{t-1}^2$	–0.009***	–0.006***		
	(0.002)	(0.001)		
$\ln GIP_{t-1}$			0.023***	0.016***
			(0.006)	(0.005)
$\ln GIP_{t-1}^2$			–0.007***	–0.003***
			(0.002)	(0.001)
Control	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes
Sample	3,036	3,036	3,036	3,036
R^2 (*within*)	0.729	0.814	0.722	0.810

Note: DV refers to dependent variable. The robust standard errors are shown in parentheses. For brevity, the estimated intercept and control variables are not reported. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

4.3.2 Replacement of dependent variables

As mentioned in section 2, the energy rebound can result in a carbon rebound and thus bring in the inverted U-shaped linkage between GTI and CE. Hence, expecting the same linkage between GTI and energy use may be reasonable. Based on this logic, we further test the robustness by substituting two dependent variables (PCE and CE) with per capita and total energy consumption (donated as PEC and EC), respectively. The same control variables are selected here as in the above basic regression, excluding energy consumption (see Table 7). Table 7 presents the new regression results. An inverted U-shaped relationship is obviously identified between ln*GP*-ln*PEC* but not between ln*GP*-ln*EC*. One possible explanation is that the turning point of the ln*GP*-ln*EC* relationship occurs later than the ln*GP*-ln*PEC* linkage which has yet to take place.

Table 7 Results for replacing dependent variables

	(1)	*(2)*	*(3)*	*(4)*
DV	ln*PEC*	ln*EC*	ln*PEC*	ln*EC*
ln*GP*	0.121***	0.108***		
	(0.035)	(0.035)		
lnGP^2	–0.011**	–0.008		
	(0.005)	(0.005)		
ln*GIP*			0.063**	0.055**
			(0.025)	(0.026)
lnGIP^2			–0.010**	–0.007
			(0.005)	(0.005)
ln*PD*	0.090	0.239	0.089	0.239
	(0.133)	(0.173)	(0.133)	(0.173)
ln*PGDP*	0.134*	0.115	0.147*	0.127
	(0.080)	(0.076)	(0.082)	(0.078)
ln*IND*	0.060	0.105	0.084	0.127
	(0.156)	(0.154)	(0.156)	(0.154)
ln*URB*	0.616***	0.597***	0.653***	0.639***
	(0.171)	(0.172)	(0.179)	(0.180)
ln*FDI*	0.008	0.007	0.006	0.005
	(0.016)	(0.016)	(0.016)	(0.017)
Constant	–1.927*	3.149**	–2.161*	2.908**
	(0.127)	(1.255)	(1.143)	(1.260)
Year FE	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes
Sample	3036	3036	3036	3036
R^2 (within)	0.585	0.603	0.582	0.600

Notes: DV refers to dependent variable. The robust standard errors are shown in parentheses. For brevity, the estimated intercept and control variables are not reported. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

4.3.3 Impact of relative policies on CE

Many studies have demonstrated that the Chinese 'low-carbon pilot cities' policy (LCPC) (Zhu and Lee, 2022) and 'CE trading scheme pilots' policy (ETS) (Zhu et al., 2019), would influence both urban GTI and CE. Hence, to prevent spurious regressions, these policies must be taken into account in the empirical models for the estimation of GTI's impact on CE.

During the research period of 2007–2017, the LCPC program was executed in three batches in 2010, 2012, and 2017, covering six provinces and 81 cities. This program encouraged cities to advocate low-carbon production and lifestyle in the industrialisation and urbanisation processes. More specifically, the government required pilot areas to set regional greenhouse gas emission targets and distribute corresponding tasks for emission reduction to different sectors (Feng et al., 2021).

Table 8 Results for adding control variables

	(1)	*(2)*	*(3)*	*(4)*
DV	ln*PCE*	ln*PCE*	ln*PCE*	ln*PCE*
ln*GP*	0.063***		0.059***	
	(0.009)		(0.008)	
ln*GP*^{2}	–0.009***		–0.008***	
	(0.002)		(0.002)	
lnGIP		0.032***		0.030***
		(0.006)		(0.006)
lnGIP^2		–0.007***		–0.007***
		(0.002)		(0.001)
LCPC	–0.002	–0.001		
	(0.013)	(0.014)		
ETS			–0.092***	–0.098***
			(0.015)	(0.015)
Control	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes
Sample	3,036	3,036	3,036	3,036
R^2 (within)	0.731	0.724	0.742	0.736

Notes: DV refers to dependent variable. The robust standard errors are shown in parentheses. For brevity, the estimated intercept and control variables are not reported. *p < 0.1, **p < 0.05, ***p < 0.01.

The ETS allows for purchasing or selling additional carbon emission quotas set by the government on the market (Zhang et al., 2021). This plan allows participants to profit economically by selling any excess quota saved in the production process, thereby encouraging them to decrease CE (Gao et al., 2020). During 2007–2017, two batches of the ETS program were also implemented in 2013 (seven provinces) and 2016 (Fujian province), with the program being extended across the country after 2017.

Both the variable $LCPC_{it}$ and the variable ETS_{it} are dummy variables that equal 1 when the corresponding policy was conducted in city i and year t, otherwise, they equal

0. To avoid any possible serious multicollinearity problem, we add two policy variables into the model one by one. For brevity, we here focus on ln*PCE*.

Table 8 displays the results, showing the evidence consistent with that provided in the basic regressions. The results reaffirm the key conclusions drawn from the basic regression models, suggesting that the basis results remain robust even when the external policy shocks are properly accounted for in the sample period. The results also suggest that government carbon-reducing policies, particularly the ETS, have also contributed to the green economic development process.

5 Conclusions and policy recommendations

Reducing CE efficiently calls for a comprehensive understanding of the effect of GTI on CE. This study employs a fixed-effect model and calculates the GTI elasticity and the turning points to analyse the overall impact of GTI on total and per capita CE. Some key findings are summarised as followed. First, the empirical results suggest that the GTI has an inverted U-shaped effect on total (per capita) CE using the whole sample comprising 276 Chinese cities during 2007–2017. One probable explanation is that these years with relatively low GTI levels have a higher carbon rebound effect, resulting in a positive impact of GTI on CE. After the GTI level reaches a certain level, GTI starts to effectively decrease CE. Similarly, Gu et al. (2019), using data from Chinese 30 provinces during 2005–2016, discovered an inverted U-shaped impact of advances in energy technology on CE. Our dataset provides an updated condition and a fine-grained view. Furthermore, we observe that the turning point in the ln*GP*-lnP*CE* relationship comes up earlier than in the ln*GP*-ln*CE* relationship, which implies more pressure in containing total CE than in reducing per capita carbon reduction.

Second, the above inverted U-shaped relationship shows a significant degree of regional heterogeneity, which is in line with Wang et al. (2012). Regional heterogeneity of this inverted U-shaped relationship reflects the heterogeneous development of GTI in different Chinese regions, implying that only the economically and technologically more advanced region, (i.e., the eastern region) have clearly benefited from GTI development to contain carbon emission. It also implies that to effectively reduce CE across the entire country, GTI has to be encouraged across different regions and cities in the country and new technologies should be rapidly diffused and adopted everywhere possible.

Third, one interesting finding is that the GTI has an inverted-U impact on per capita energy use as well, suggesting the existence of the energy rebound effect and the potential association between energy and carbon rebound (Druckman et al., 2011). Ultimately, the empirical results also show that the per capita GDP level can increase CE, as well as the secondary industry share and urbanisation level. The FDI is found to have reduced CE, implying a pollution halo effect rather than a pollution paradigm effect.

Hence, to achieve a low-carbon economy and carbon emission reduction as soon as possible, this research proposes the following policy recommendations. First, China should greatly encourage national and regional investment in the development of GTI to enhance its positive role in decreasing CE. Moreover, it is also necessary for China to absorb more foreign investments regarding low-carbon technologies and promote international communications of GTI.

Second, because of the exclusivity and competitiveness of GTI, the east of China as a GTI centre may find it difficult to transfer its GTI to the other two regions. Hence, China has to strengthen regional cooperation and technology exchanges to realise the spill-over effect of green technology from the advanced regions (i.e., the eastern region) to the less developed areas (i.e., the central-western region) in terms of GTI.

Third, the government can also improve available low-carbon policies, such as the above ETS and LCPC policies, which may help to induce GTI and thus reduce CE.

Although our empirical results support the role of ETS in reducing CE, the policy is only implemented in some large firms and its effect on carbon emission reduction is rather limited. Broader program coverage is thus needed to increase the effectiveness of the ongoing policy. Moreover, the benefits of LCPC on carbon emission reduction are still insignificant, suggesting that it may have yet had a policy-induced GTI effect. One possible explanation is that regulated firms may not have enough incentive to invest in GTI to meet the requirements of low CE. The government can provide some green subsidies and technical guidance to promote low-carbon production.

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Notes

1 The eastern region includes Beijing, Tianjin, Liaoning, Shanghai, Hebei, Shandong, Zhejiang, Jiangsu, Fujian, Guangdong, Hainan, and Guangxi. The central region includes Heilongjiang, Jilin, Inner-Mongolia, Shanxi, Henan, Anhui, Jiangxi, Hubei, and Hunan. The western region includes Sichuan, Shaanxi, Guizhou, Xinjiang, Tibet, Yunnan, Gansu, Qinghai, and Ningxia.

Appendix

Figure A1 Trend of green patent in different regions of China from 2007 to 2017 (see online version for colours)

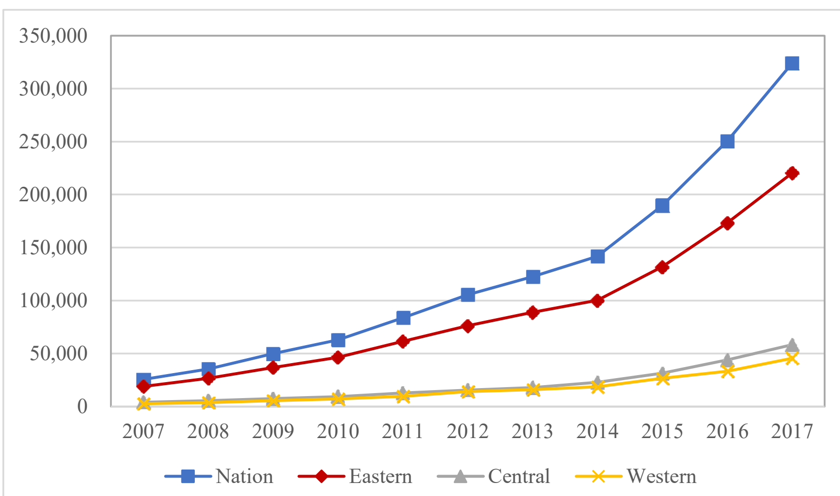

Figure A2 Trend of green invention patent in different regions of China from 2007 to 2017 (see online version for colours)

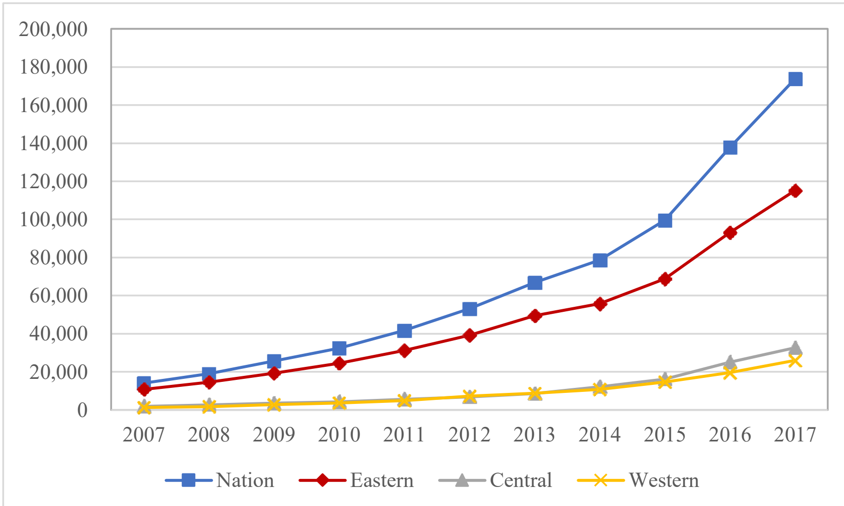

Table A1 The amount of green patent and green invention patent in different regions of China from 2007 to 2017

Year	*Nation*	*Eastern*	*Central*	*Western*
		Green patent		
2007	25,417	18,928	3,880	2,609
2008	35,398	26,492	5,370	3,536
2009	49,664	36,742	7,459	5,463
2010	62,823	46,364	9,326	7,133
2011	83,645	61,469	12,615	9,561
2012	105,534	76,184	15,382	13,968
2013	122,478	88,971	17,703	15,804
2014	141,641	100,150	22,812	18,679
2015	189,830	132,000	31,304	26,526
2016	250,523	173,271	43,957	33,295
2017	324,209	220,476	58,353	45,380
		Green invention patent		
2007	14,066	10,772	1,943	1,351
2008	18,992	14,583	2,658	1,751
2009	25,623	19,342	3,503	2,778
2010	32,413	24,565	4,210	3,638
2011	41,690	31,129	5,671	4,890
2012	53,244	39,216	6,780	7,248
2013	66,834	49,497	8,551	8,786
2014	78,613	55,681	12,109	10,823

Table A1 The amount of green patent and green invention patent in different regions of China from 2007 to 2017 (continued)

Green invention patent				
Year	*Nation*	*Eastern*	*Central*	*Western*
2015	99,683	68,821	16,182	14,680
2016	137,895	93,257	25,100	19,538
2017	173,866	115,213	32,638	26,015

Table A2 Descriptive statistics for the eastern region and the central and western regions

The eastern region					
Var	*Observation*	*Mean*	*SD*	*Min*	*Max*
ln*PCE*	1,089	8.876	0.520	7.390	10.184
ln*CE*	1,089	8.011	0.722	5.343	10.046
ln*GP*	1,089	3.901	1.578	–0.095	8.282
ln*GIP*	1,089	2.971	1.726	–1.245	7.628
ln*PD*	1,089	6.205	0.639	4.530	8.960
ln*PGDP*	1,089	10.586	0.579	9.039	12.890
ln*EC*	1,089	9.494	1.121	6.577	12.788
ln*IND*	1,089	3.871	0.203	2.915	4.338
ln*URB*	1,089	4.000	0.272	3.107	4.605
ln*FDI*	1,089	1.045	1.076	–4.996	3.167
The central and western regions					
ln*PCE*	1,947	8.579	0.742	6.384	11.243
ln*CE*	1,947	7.451	0.729	5.522	9.641
ln*GP*	1,947	2.717	1.459	–1.333	6.952
ln*GIP*	1,947	1.890	1.511	–1.797	6.609
ln*PD*	1,947	5.490	0.903	2.304	7.273
ln*PGDP*	1,947	10.079	0.621	4.538	12.255
ln*EC*	1,947	8.581	1.166	4.694	12.130
ln*IND*	1,947	3.866	0.256	2.705	4.511
ln*URB*	1,947	3.825	0.315	2.798	4.778
ln*FDI*	1,947	0.048	1.485	–8.210	4.012

Table A3 Results for replacing *GP* and *GIP* with GP_{t-2} and GIP_{t-2}, respectively

	(1)	*(2)*	*(3)*	*(4)*
DV	ln*CE*	ln*PCE*	ln*CE*	ln*PCE*
$\ln GP_{t-2}$	0.033***	0.0244***		
	(0.008)	(0.0065)		
$\ln GP_{t-2}{}^2$	–0.010***	–0.0055***		
	(0.002)	(0.0013)		
$\ln GIP_{t-2}$			0.010*	0.006
			(0.006)	(0.005)
$\ln GIP_{t-2}{}^2$			–0.007***	–0.003**
			(0.002)	(0.001)
Control	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes
Sample	3036	3036	3036	3036
R^2(within)	0.730	0.813	0.721	0.809

Notes: DV refers to dependent variable. The robust standard errors are shown in parentheses. For brevity, the estimated intercept and control variables are not reported. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.