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RESEARCH ARTICLE

Direct and indirect impacts of high-tech industry development on CO_2 emissions: empirical evidence from China

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Abstract

Vigorously developing high-tech industry has been considered to be an effective way to coordinate economic growth with excessive carbon dioxide (CO_2) emissions. However, previous studies have not explored the heterogeneous impacts of high-tech industry on CO_2 emissions in regions with different levels of high-tech industry development, and not distinguished the direct and indirect impacts. Based on *STIRPAT* model, this study investigates the impacts of high-tech industry development on CO_2 emissions in China between 2005 and 2016. Adopting the K-medians cluster method, effects in regions with high, middle, and low levels of high-tech industry development are considered. Indirect effects of high-tech industry development on CO_2 emissions by affecting industry structure upgrades and economic growth are explored. Empirical results illustrate a positive U-shaped nonlinear link between the level of high-tech industry development and CO_2 emissions at the national level and regional (high, middle, and low) level. In terms of indirect impacts, high-tech industry development attenuates the reduction of CO_2 emissions due to industry structure upgrades, and promotes economic growth to increase CO_2 emissions slightly. The indirect impact intensity gradually decreases as the level of high-tech industry development decreases across three regions. Reasonable implications of our findings are proposed.

Keywords CO_2 emissions · High-tech industry · *STIRPAT* model · Heterogeneous effect · Nonlinear relationship

Introduction

Fossil fuel consumption–based economic development brings the tricky issue that the over-emitted CO_2 emissions pose a threat to people's health and lives (Gong et al. 2017). Nine billion tons of energy-related CO_2 emissions, accounting for 60% of the global output, were produced by China in 2016; however, in 1990, China's CO_2 emissions only accounted for 5% of the global output (Gu et al. 2019). According to the China Energy Outlook: World Energy Outlook 2017 (IEA 2018), China was once again the largest contributor to global CO_2 emissions. The high volume of fossil fuel consumed in promoting sustainable economic growth, rapid industrialization, and urbanization in China has attracted worldwide attention to China's contribution to greenhouse effects (Cheng et al. 2018). China values being known as a reliable and responsible country, so it continues to aim at reducing its CO_2 emissions. In 2009, China made an ambitious commitment to reduce its carbon intensity by 40–45% by 2020, relative to 2005 levels, at the United Nations Climate Change Conference in Copenhagen. In the 12th 5-year plan (2011–2015), China promised to reduce carbon intensity by 17% by 2015 relative to 2010 and achieved a 20% reduction relative to 2010 levels, a reduction that exceeded expectations. In the 13th 5-year plan (2016–2020), China committed to reduce its CO_2 emissions by 18% relative to 2015 levels by 2020. At the 21st United Nations Climate Change Conference in Paris, China signed the Paris Agreement and promised to peak CO_2 emissions around 2030 and strive to achieve it as soon as possible. This means that by 2030, CO_2 emissions per unit of gross domestic product (GDP) will be reduced by 60 to 65% compared with 2005.

Although China recognizes the necessity to reduce total CO_2 emissions and energy use, the country has prioritized

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economic growth to provide job opportunities and enhance people's life quality. Coordinating economic growth with environmental protection and climate change mitigation has become a major challenge (Liu 2016). Many measures implemented by the Chinese government have mitigated CO_2 emissions without significantly impeding economic development. These measures include adjusting the economic structure, developing alternative energy solutions, optimizing energy structure, and investing more research and development resources in developing low-carbon emissions technologies. However, the conflict between economic growth and reducing CO_2 emissions remains and requires the development of more solutions. The high-tech industry has contributed much to the growth of China's economy and has become an indispensable part of China's economic development strategy, primarily due to its knowledge-intensive and multidisciplinary technologies (Wang and Wang 2014). Therefore, much effort has been put into the growth of the high-tech industry. According to the China Statistics Yearbook on High Technology Industry, the fixed asset investment in the high-tech industry of 30 provinces and cities excluding Tibet, Hong Kong, Macao, and Taiwan, rose rapidly from 21.44 billion yuan in 2005 to 261.8 billion yuan in 2017, which is more than an 11-fold increase.

The high-tech industry refers to an industrial sector that produces high-tech products using innovative technologies, experiences rapid growth, and penetrates other industries. High-tech companies have the following characteristics: (1) they are knowledge- and technology-intensive (Wang and Wang 2014), with a large proportion of scientific and technical personnel; (2) they consume fewer resources and less energy (Liu et al. 2019); (3) they make large investments in research and development in projects with high economic return (Wang et al. 2013); (4) they experience rapid growth (Liang 2011). The high-tech industry comprises five manufacturing subsectors, according to China Statistics Yearbook on High Technology Industry; these include aerospace, electronics and communication equipment, computer and office equipment, pharmaceutical and medical equipment, and instrument and meter. Promoting the global economic layout, sustainable development, and political and military competitiveness, the development of high-tech industries embodies a country's or regional strength (Lu and Yu 2010). Since the launch of the national high-tech industry development plan (i.e., Torch Plan), China has made notable achievements in high-tech industry development. Not only can high-tech industry development optimize the economic layout and promote rapid and sustainable economic growth but it also can contribute to reducing CO_2 emissions by developing and applying high-tech technologies that conserve energy. However, according to China Statistical Yearbook, although the amount of energy consumption in high-tech industry is far less than that in manufacturing industry, the annual growth rate of energy consumption in high-tech industry is more than that in manufacturing industry between 2015 and 2017, as shown in Fig. 1. This indicates that the relationship between high-tech industry and CO_2 emissions is not simple negative correlation caused by the application of advanced energy-saving technologies, and is worthy of further exploration.

Consequently, studies that evaluate the impact of the high-tech industry on CO_2 emissions have gained in popularity (Chen et al. 2016, 2019; Cui et al. 2019; Huang et al. 2010; Li et al. 2019; Liu et al. 2019; Xu and Lin 2017, 2018). However, one area that remains less explored is the relationship between the reductions in CO_2 emissions achieved and the level of high-tech industry development (i.e., high, middle, or low level) in a given region. Studies to date have also not considered the impacts of both high-tech industry alone and its interaction with other factors on CO_2 emissions directly and indirectly. In terms of direct effects, this study investigates both linear and nonlinear effects of high-tech industry development on CO_2 emissions. The effects of industrial structure upgrades and economic growth have been correlated with CO_2 emissions. High-tech industry development has a certain effect in adjusting the upgrading of industrial structure and bringing economic prosperity, thereby influencing CO_2 emissions indirectly. Therefore, this paper explores whether these indirect effects exist in the high-tech industry and proposes possible implications.

Three questions will be considered in this paper:

(1) How does the level of high-tech industry development in China influence CO_2 emissions?
(2) Do the impacts of high-tech industry development on CO_2 emissions vary across regions with high, middle, and low level of high-tech industry development?
(3) Do indirect effects of high-tech industry development on CO_2 emissions exist, by influencing industrial structure upgrades and economic growth?

The paper is structured as follows: the second section reviews the relevant literature; the third section presents data sources and methodology; the fourth section describes empirical results and analysis; and the last section draws conclusions, discusses implications, and proposes recommendations.

Literature review

Industrial-level energy conservation and carbon emissions reduction have attracted wide attention of scholars. For example, Bhat et al. (2018), Haider and Bhat (2019), Haider et al. (2019), Haider and Mishra (2019) analyzed the energy efficiency of paper and iron and steel industry. As an emerging industry, high-tech industry is receiving increasing attention due to its role in sustainable economic growth and less

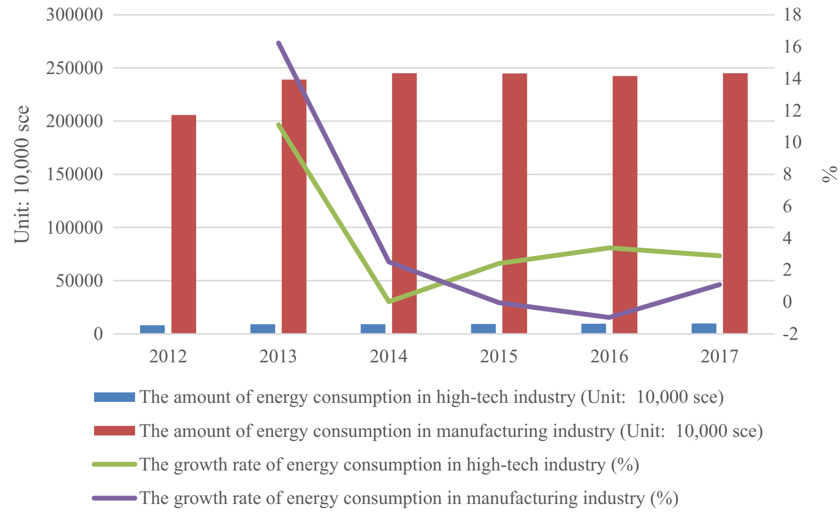

Fig. 1 Energy consumption of high-tech industry and manufacturing industry

environment burden. Many papers have investigated factors that influence CO_2 emissions. The impacts of the high-tech industry, industrial structure, and economic growth on CO_2 emissions are presented in this section. Based on a review of the literature, the contributions of this paper to the field are presented.

Impact of the high-tech industry on CO_2 emissions

The impact of the high-tech industry on CO_2 emissions in China has been studied from multiple perspectives using several methodologies. However, the conclusions drawn have not been unified. Using a nonparametric additive regression model, Xu and Lin (2017) identified nonlinear relationships between the high-tech industry and CO_2 emissions in 3 geographical regions in China from 1998 to 2014. In 2018, Xu and Lin (2018) found that the high-tech industries in eastern, central, and western China reduced CO_2 emissions to different degrees. Using a state-space model, Liu et al. (2019) investigated the effect of research and development investment on the amount of energy consumed in the five high-tech sectors (mentioned earlier in this paper) in different regions of China between 1998 and 2016. Different modes of influence on overall energy consumption, which are proportional to CO_2 emissions, were explored among the five sectors. Li et al. (2019) constructed a spatial panel STRIPAT-Durbin model for 30 provinces in China between 2004 and 2016 and examined how economic development and industrial structure influence CO_2 emissions by exploring spatial agglomeration and spillover effects based on spatial correlation. They suggested that the government needs to vigorously develop high-tech and tertiary industries to achieve the target for a low-carbon economy by promoting clean technologies. Using a temporal log-mean Divisia index (LMDI) approach, Shi et al. (2019) explored the major factors that affect CO_2 emissions from China's manufacturing industries and made comparisons between the whole manufacturing sector and its 28 subsectors from 2000 to 2015. They found that the high-tech subsectors made larger contributions to production outputs with less CO_2 emissions. Huang et al. (2010) reported that industrial restructuring is an important driver of CO_2 emissions reduction and that the role of high-tech industries in the optimization of industrial structure is becoming increasingly significant. Cui et al. (2019) proposed a hybrid method that integrated quantitative and qualitative approaches to assess the sustainability of high-tech companies. They found that the ability to control pollution emissions and financial support for the development of energy-saving and emission-reducing technologies are the most important factors. They also noted that high-tech enterprises need to satisfy the increasing awareness of consumers about environmental protection, including the reduction of CO_2 emissions. Because of the environmentally friendly characteristics of the high-tech industry, Chen et al. (2019) suggested that the government take measures to promote its development in the three urban agglomerations: Beijing-Tianjin-Hebei, the Yangtze River Delta, and the Pearl River Delta. Chen et al. (2016) identified the potential of high-tech industry development to mitigate energy consumption and CO_2 emissions in China.

Impact of industrial structure and economic growth on CO_2 emissions

To explore the indirect effects of the high-tech industry on CO_2 emissions, industrial structure, and economic growth are considered in this paper. Previous studies on the impact of industrial structure and economic growth on CO_2 emissions have revealed that industrial structure influences energy consumption and CO_2 emissions (Kofi Adom et al. 2012). The volume of energy consumption and energy efficiency differ between sectors, and energy conservation and energy efficiency improve when processes move from the industrial sector to the services sector (Li and Lin 2014). Many studies have investigated the impact of industrial structure on CO_2 emissions (Chang 2015; Li et al. 2017; Mi et al. 2015; Tian et al. 2014; Zhang et al. 2018; Zhou et al. 2013). Following the example of Grossman and Krueger (1995), multiple studies verified the environmental Kuznets curve (EKC) theory and investigated the relationship between economic growth and CO_2 emissions (Azomahou et al. 2006; Carson 2009; Dinda 2005; Dogan and Turkekul 2016; Dogan et al. 2019; Dogan and Inglesi-Lotz 2020; Galeotti et al. 2006; Kang et al. 2016; Maddison 2006; Song et al. 2008). EKC theory indicates that both the scale and development of the economy affect CO_2 emissions (Kaika and Zervas 2013; Yang et al. 2015) and an inverted U-shaped nonlinear correlation exists between economic growth and CO_2 emissions (Cheng et al. 2018). The pursuit of the economic growth causes more energy consumption, leading to higher CO_2 emissions when the economic scale is small (Li et al. 2016). When the economic scale becomes larger, demand for a better quality of life increases, and people urge the government to implement environmental policies immediately and enact regulations to reduce CO_2 emissions (Yin et al. 2015).

Contributions of this paper

Although published studies of the relationship between high-tech industry and CO_2 emissions have made significant contributions, gaps in our understanding remain. On one hand, few studies consider the heterogeneity between regions with different levels of high-tech industry development. Most studies compare regions defined by conventional classification methods, such as geographical features (eastern, central, and western regions). This type of classification is insufficient to reflect differences in the level of development of high-tech industries because the provinces in eastern, central, and western regions of China may not be at the same level of high-tech industry development. On the other hand, the indirect effects of high-tech industry development on CO_2 emissions have not been discussed in other papers; this means that the role of the high-tech industry in changing the industry structure and driving economic growth are neglected. Consequently, the impacts of industry structure and economic growth affected by high-tech industry development on CO_2 emissions are also neglected.

To address these deficiencies, this study performs an empirical analysis of the direct and indirect impacts of high-tech industry development on CO_2 emissions in 30 provinces and cities in China between 2005 and 2016 based on *STIRPAT* model. The contributions of this paper can be summarized as follows: On one hand, 30 provinces and cities are clustered into three groups by applying the K-medians method cluster to the average value of revenue from principle businesses representing the development level (high, middle, or low) of the high-tech industry. The correlations between the high-tech industry and CO_2 emissions at the national level and for each of the three levels of industrial development are explored. On the other hand, the indirect effects of the high-tech industry on CO_2 emissions through the industry's impacts on industrial structure and economic growth are explored. To the authors' best knowledge, this paper is the first time these indirect effects have been reported.

Data, models, and methodology

Data sources

All public data used in this paper are collected from the National Bureau of Statistics, including the China Statistical Yearbook, China Energy Statistical Yearbook, China Statistical Yearbook on Science and Technology, and China Statistics Yearbook on High Technology Industry, encompassing 12 years from 2005 to 2016. Due to missing data for some variables in certain years, 30 provinces and cities in China were selected for study excluding Tibet, Hong Kong, Macao, and Taiwan[1]. To eliminate the impact of inflation, GDP per capita is converted into constant prices (2005=100).

Methodology

Many researchers have explored the impacts of different factors on environmental pollution by using *PAT* identity as Eq. (1):

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

where I denotes the pollution intensity of a pollutant, P denotes the population, A represents the economic growth, and T indicates the level of technical improvements. Then, the limitation of *IPAT* model, assuming that the elasticities of all independent variables are equal to 1, has been identified by scholars. In order to address this deficiency, *STIRPAT* model was proposed by Dietz and Rosa (1997) and expressed as Eq. (2):

$$I_t = aP_t^b A_t^c T_t^d e_t \tag{2}$$

where I, P, A, and T mean the same as Eq. (1), a denotes intercept term, b, c, and d denotes the coefficients of P, A, T, and t means the year, e_t is random error term. *STIRPAT* model has been widely used for the exploration of driving factors of environmental pollution (Xu and Lin 2017; Xu and Lin 2018; Zhang and Zhao 2019; Liu and Xiao 2018). In order to reduce the possible effect of heteroscedasticity, all variables are transferred into the logarithmic terms. Then, Eq. (2) can be changed to Eq. (3) as follows:

[1] Thirty provinces and cities referred to in this paper denote provinces and cities excluding Tibet, Hong Kong, Macao, and Taiwan in China.

$$\ln I_{it} = \ln a + b\ln P_{it} + c\ln A_{it} + d\ln T_{it} + e_{it} \quad (3)$$

Based on the logarithmic pattern of *STIRPAT* model as Eq. (3), we built Eq. (4) to explore the impacts of relevant factors on CO_2 emissions, as the basis for subsequent models establishment.

$$\ln CE_{it} = \ln a + b\ln POP_{it} + c\ln GDP_{it} + d\ln EI_{it} + e_{it} \quad (4)$$

where CE denotes CO_2 emissions, POP denotes total population, and GDP denotes economic growth. EI denotes energy intensity and has been used for the exploration of the impacts of technological progress on CO_2 emissions (Belaissaouia et al. 2016; Meyers et al. 2016).

High-tech industry development and industrial structure upgrades play a significant role in affecting CO_2 emissions. Moreover, China has become a global industrial and manufacturing center, and this development continues. Foreign direct investment is increasing, along with the liberalization of the economy (Cheng et al. 2018). Although foreign direct investment consumes more energy (Tang and Tan 2015), it also brings knowledge and technology that spills over into industries, improving the technology and management skills in domestic enterprises (Lau et al. 2014). Therefore, foreign direct investment also has an effect on CO_2 emissions. Based on above analysis, we add these variables into *STIRPAT* model to build benchmark model in China as follows:

Model 1:

$$\ln CE_{it} = \alpha_0 + \alpha_1 \ln GDP_{it} + \alpha_2 \ln ISU_{it} + \alpha_3 \ln HTI_{it} + \alpha_4 \ln EI_{it} + \alpha_5 \ln POP_{it} + \alpha_6 \ln FDI_{it} + \mu_{it}, \quad (5)$$

where i denotes the individual province, t denotes the year 2005–2016, a_0 denotes a constant, a_1–a_6 denotes the coefficient of each variable, and μ_{it} is an error term. Next, the squared term of lnHTI is added to model 1 to explore whether nonlinear relationship exists between HTI and CE to build model 2:

Model 2:

$$\ln CE_{it} = \alpha_0 + \alpha_1 \ln GDP_{it} + \alpha_2 \ln ISU_{it} + \alpha_3 \ln HTI_{it} + \alpha_4 \ln EI_{it} + \alpha_5 \ln POP_{it} + \alpha_6 \ln FDI_{it} + \alpha_7 (\ln HTI_{it})^2 + \mu_{it}, \quad (6)$$

In order to explore the uncertain indirect effects of HTI on CE, the cross-term between HTI and ISU is introduced to build model 3 to explore the potential interactive effects on CO_2 emissions, based on the fact that the development of high-tech industry, primarily consisting of manufacturing industries with high-end technologies, may impact ISU. It should be noted that collinearity does not pose a problem for regressions with interaction effects. To be specific, when X_1 and X_2 are included in the model and the cross-term $X_1 \times X_2$ is added, the correlation between X_1 or X_2 and $X_1 \times X_2$ will inevitably be high, but its effect on the further discussion of regression results is negligible (Balli and Sørensen 2012).

Model 3:

$$\ln CE_{it} = \alpha_0 + \alpha_1 \ln GDP_{it} + \alpha_2 \ln ISU_{it} + \alpha_3 \ln HTI_{it} + \alpha_4 \ln EI_{it} + \alpha_5 \ln POP_{it} + \alpha_6 \ln FDI_{it} + \alpha_7 (\ln HTI_{it} \times \ln ISU_{it}) + \mu_{it}, \quad (7)$$

The high-tech industry has an effect on driving economic growth. This can be reflected in the contribution of the high-tech industry to GDP, which rose from 6.85% in 1996 to 20.42% in 2015 (Xu and Lin 2018). To evaluate the interactive effects between *HTI* and *GDP*, the cross-term is added to benchmark model to build model 4:

Model 4:

$$\ln CE_{it} = \alpha_0 + \alpha_1 \ln GDP_{it} + \alpha_2 \ln ISU_{it} + \alpha_3 \ln HTI_{it} + \alpha_4 \ln EI_{it} + \alpha_5 \ln POP_{it} + \alpha_6 \ln FDI_{it} + \alpha_7 (\ln HTI_{it} \times \ln GDP_{it}) + \mu_{it}. \quad (8)$$

Model 1–4 are built for 30 provinces and cities in China between 2005 and 2016, to explore how the level of high-tech industry development affects CO_2 emissions and whether there are interaction effects existing together with the upgrading of industrial structure and economic growth. The level of high-tech industry development may vary across regions due to different investment strength, government regulations or policies, and other possible factors. In order to identify the possible heterogeneous impacts of *HTI* on CO_2 emissions across regions, 30 provinces and cities are clustered into three groups (high, middle, and low) by a K-medians approach according to average revenue from the principal business within the high-tech industry for regional models establishment. The clustering results are shown in Fig. 2. In the high-level group, Beijing, Tianjin, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Henan, Guangdong, and Sichuan are included;

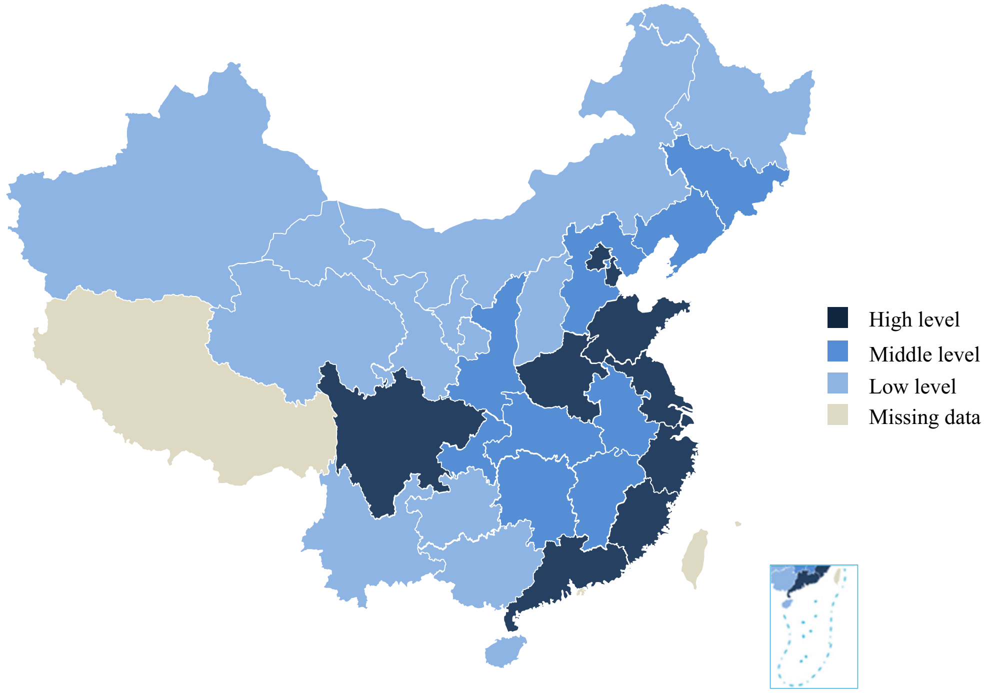

Fig. 2 30 Provinces and cities clustered by HTI

In the middle-level group, Hebei, Liaoning, Jilin, Anhui, Jiangxi, Hubei, Hunan, Chongqing, and Shaanxi are included; In the low-level group, there are 11 provinces: Shanxi, Inner Mongolia, Heilongjiang, Guangxi, Hainan, Guizhou, Yunnan, Gansu, Qinghai, Ningxia, and Xinjiang. For regions with high, medium, and low levels of *HTI*, the same models 5–8, 9–12, and 13–16 as the models 1–4 are established respectively. Compared with geographical classification (eastern, central, and western regions) of mainland China as shown in Fig. 3, the clustering results for regional models establishment could investigate more targeted regional influence mechanism between the level of high-tech industry development and CO_2 emissions.

Four types of tests are conducted before model estimation. First, multicollinearity tests are supposed to be performed because multicollinearity would decrease the reliability of the hypothesis tests and could lead to parameter estimations with low-accuracy and low-stability (Cheng et al. 2018). Second, panel unit root tests are necessary since unstable variables sequences will lead to the biased and inconsistent estimation results (Xu and Lin 2018). In this paper, Fisher-ADF, Fisher-PP, and IPS tests are used to implement stationary test. Third, if some variables sequences are non-stationary but the first-order difference sequences of all variables are stationary, panel cointegration tests are supposed to be performed to explore the existence of cointegration relationship between dependent and independent variables. Pedroni test is used for the check of cointegration relationship. Fourth, Hausman test is used to select a fixed effects (FE) model or random effects (RE) model for regression estimation.

Variables description

The dependent variable: CO_2 emissions

CO_2 emissions are calculated according to the method proposed in the Intergovernmental Panel on Climate Change (Eggleston et al. 2006). The formula is as follows.

$$CO_2 = \sum_{i=1}^{8} (CO_2)_i = \sum_{i=1}^{8} E_i \times NCV_i \times CEF_i \times COF_i \times 44/12, \tag{9}$$

where CO_2 denotes CO_2 emissions (unit: mt), *i* represents the type of fossil fuel, *E* denotes the consumption of fossil fuel, NCV denotes the low calorific value, CEF denotes carbon content provided by Intergovernmental Panel on Climate Change (Eggleston et al. 2006), and COF denotes the rate of carbon oxidation. The CO_2 emissions coefficients of the eight types of fossil fuels were obtained from the Chinese Energy Statistical Yearbook.

Core explanatory variables

(1) High-tech industry development level (HTI). Previous studies used different metrics to measure HTI, including dividing the sales revenue of the high-tech industry by the sales revenue of the industrial enterprises (Xu and Lin 2018) and the gross output of the high-tech industry (Xu and Lin 2017). This paper uses revenue from the principle business (100 million yuan) in the high-tech industry to represent the level of high-tech industry development.

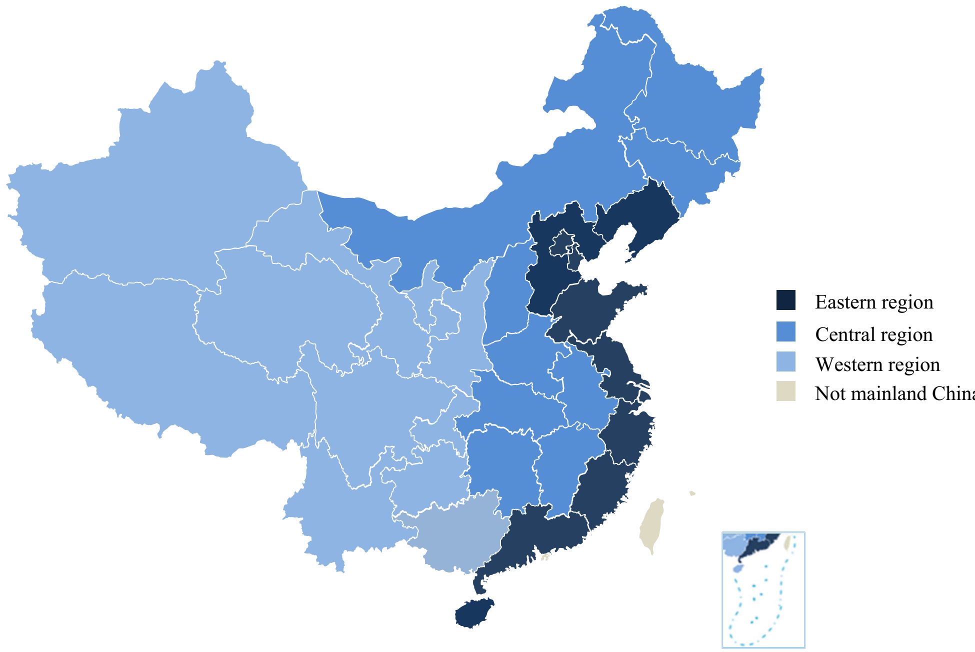

Fig. 3 Geographical classification of mainland China

(2) Industrial structure upgrades (ISU). ISU is measured as the percentage added value to the GDP of the tertiary industry according to Cheng et al. (2018).
(3) Regional per capita gross domestic product (GDP). The regional per capita gross domestic product in 30 provinces and cities are used in this paper.

Control variables

(1) Energy intensity (EI). EI is measured as energy consumption divided by GDP according to Xu and Lin (2018).
(2) Population (POP). In this study, POP is measured as the total population in the provinces.
(3) Foreign direct investment (FDI). The annual amount of regional FDI is adopted in this study.

The statistical descriptions of all variables are listed in Table 1.

Empirical results and analysis

The results of variance inflation factors (VIFs) test in Tables 9, 10, 11, and 12 of the appendix and correlation analysis in Table 2 show that all variables in the national-level, high-level, middle-level, and low-level models have no multicollinearity problem. The results of unit root test in Table 3 indicate the first-order difference sequences of all variables are stationary. Moreover, Pedroni test results in Table 4 show the existence of cointegration relationship between CO_2 emissions and its influencing factors in national and regional models.

Empirical results with the national-level models

For national-level models, the regression results of the CO_2 emission influencing factors are shown in Table 5. For model 1, HTI affects CO_2 emissions because the coefficient of lnHTI is significant at a 1% level, but the specific relationship between them is explored further in model 2.

Table 1 Statistical descriptions of variables

Variable	Unit	Mean	Std. Dev.	Min	Max
CE	10^4 tons	436.53	326.13	23.68	1835.00
GDP	10^4 yuan	2.99	1.85	0.54	10.27
ISU	%	41.68	8.78	28.6	80.2
HTI	100 million yuan	2894.19	5507.79	6.9	37765.2
EI	Tce per 10^4 yuan	4.746581	0.4913585	3.648222	6.025816
POP	10^4 persons	4438.15	2663.86	543	10999
FDI	100 billion yuan	6.63	10.08	0.05	59.41

Table 2 Results of correlation analysis

	CE	GDP	ISU	HTI	EI	POP	FDI
CE	1.0000						
GDP	0.5493***	1.0000					
ISU	0.2002***	0.5477***	1.0000				
HTI	0.6823***	0.6957***	0.3150***	1.0000			
EI	− 0.4047***	− 0.6643***	− 0.4520***	− 0.8044***	1.0000		
POP	0.6686***	0.0278***	− 0.2250***	0.6065***	− 0.3808***	1.0000	
FDI	0.6406***	0.7536***	0.3936***	0.9074***	− 0.8332***	0.4726***	1.0000

[a] ***$p < 0.01$; **$p < 0.05$; *$p < 0.1$

The significance of the squared term of lnHTI in model 2 suggests that nonlinear links exist between HTI and CO_2 emissions. In addition, the positive coefficient of the squared term denotes a positive U-shaped relationship. Specifically, when the high-tech industry begins to develop (primary stage), it primarily helps companies change, upgrade their technologies and equipment, improve production efficiency, and reduce energy consumption. These effects play essential roles in reducing CO_2 emissions. As the high-tech industry continues to develop to the next stage, the correlation between *HTI* and CO_2 emissions changes from negative to positive, which means that CO_2 emissions increase. Possible reasons are that the growth of the high-tech industry improves the country's innovation capacity. Subsequently, demands for raising product standards and quality of life increase, stimulating the manufacture of products with high performance, shorter life cycles, and frequent upgrades, which increases CO_2 emissions. On the other hand, with the increased investment and research and development efforts of high-tech industries, the technological level at a national level will improve substantially, which causes a gradual shift from primarily equipment and technologies upgrades in the primary stage of high-tech industry development to the production and manufacture of products and equipment in the next stage. More energy will be consumed in production processes than equipment upgrades, which results in higher CO_2 emissions. This also explains the positive U-shaped impact of HTI on CO_2 emissions that initially reduces and then increases emission.

In model 3, the coefficient of lnISU is negative and significant at a 1% level, while the significance of the cross-term lnHTI × lnISU is the same as lnISU, but has a positive coefficient. The results show that ISU has a role in reducing CO_2 emissions because the secondary industry consists of the mining, manufacturing, and other industries that consume large volumes of energy and emit high pollution, which are the

Table 3 Results of unit root tests

	Series	Fisher ADF		Fisher IPP		IPS	
		Constant	Trend and constant	Constant	Trend and constant	Constant	Trend and constant
Levels	CE	− 1.18616	78.1667**	26.2570	63.6475	6.20820	− 1.18616
	GDP	12.5640	95.2279***	1.81745	161.290***	10.9856	− 2.49033***
	ISU	19.0204	24.3324	11.9156	44.4819	7.85897	5.08402
	HTI	15.9176	39.3919	20.0184	54.8534	14.9285	4.61360
	EI	16.4912	83.0956**	30.2323	42.6559	6.30014	− 2.26177**
	POP	63.7389	61.8863	112.850	81.2530**	2.41548	1.02243
	FDI	12.6688	31.5805	14.6930	29.2189	14.6472	7.47765
First difference	CE	180.115***	127.099***	197.737***	190.307***	− 8.75989***	− 4.40352***
	GDP	92.5071**	101.726***	149.226***	94.6514**	− 2.61927**	− 3.71502***
	ISU	127.707***	139.968***	155.273***	243.407***	− 5.35903***	− 6.20303***
	HTI	83.6817**	98.4942**	99.1593**	141.663***	− 1.51895*	− 2.29473**
	EI	173.400***	117.714***	185.572***	171.284***	− 8.39309***	− 4.06706***
	POP	184.489***	184.192***	201.249***	269.006***	− 9.26035***	− 7.52119***
	FDI	123.322***	111.922***	131.370***	190.027***	− 2.32735***	− 2.20900**

[a] ***$p < 0.01$; **$p < 0.05$; *$p < 0.1$

Table 4 Results of co-integration test

Pedroni test	National level	High level	Middle level	Low level
Modified Phillips-Perron Statistic	7.4024***	4.0352***	4.2682***	5.1111***
Phillips-Perron Statistic	− 10.8161***	− 8.3570***	− 10.1248***	− 6.0676***
Augmented Dickey-Fuller Statistic	− 11.7392***	− 7.8482***	− 8.5087***	− 4.2074***

[a] ***$p < 0.01$; **$p < 0.05$; *$p < 0.1$

major CO_2 emission producers in China. The level of CO_2 emissions from the secondary industry is higher than that of the tertiary industry. Therefore, upgrading the industrial structure causes a shift from secondary to tertiary industry and helps reduce CO_2 emissions (Cheng et al. 2018). Interestingly, HTI weakens the effect of ISU on CO_2 emissions because the high-tech industry primarily manufactures and produces high-precision products or equipment, such as medicines, biochemical compounds, airplanes, spacecraft, and communication equipment. An increase in production will lead to an increase in CO_2 emissions.

In model 4, the coefficients of lnGDP and the cross-term lnHTI × lnGDP are positive and significant at a 1% level. With the continuous development of the economy, the positive correlation between lnGDP and lnCE can be interpreted as follows. On the one hand, still in the stage of development, China is inevitably experiencing the rising proportion of high-carbon industries, such as manufacturing industry, construction industry, and real estate industry. Those industries have a large proportion of fixed-assets investment, which consumes large amount of iron and steel, cement, oil, and coal thereby emits

Table 5 Estimation results of national-level models

Models Variables	Model 1 lnCE	Model 2 lnCE	Model 3 lnCE	Model 4 lnCE
lnGDP	0.978***	1.021***	1.026***	0.803***
	(0.0528)	(0.0440)	(0.0477)	(0.0764)
lnISU	− 0.0945	− 0.0882	− 1.120***	− 0.125
	(0.0898)	(0.0850)	(0.212)	(0.0849)
lnHTI	− 0.121***	− 0.225***	− 0.695***	− 0.141***
	(0.0115)	(0.0415)	(0.127)	(0.0166)
lnEI	0.252***	0.379***	0.420***	0.449***
	(0.0503)	(0.108)	(0.103)	(0.0955)
lnPOP	2.174***	2.222***	2.065***	2.093***
	(0.469)	(0.494)	(0.457)	(0.462)
lnFDI	0.0856**	0.0879**	0.0773**	0.0925**
	(0.0373)	(0.0412)	(0.0354)	(0.0418)
$(\mathrm{lnHTI})^2$		0.00872***		
		(0.00310)		
lnHTI × lnISU			0.162***	
			(0.0350)	
lnHTI × lnGDP				0.0403***
				(0.0129)
Constant	− 13.01***	− 13.79***	− 9.328**	− 13.15***
	(3.588)	(3.999)	(3.485)	(3.584)
F statistic	5223.55***	17720.31***	8273.80***	29590.38***
R^2	0.8599	0.8619	0.8644	0.8646
N	30	30	30	30
Observations	360	360	360	360
Hausman test	49.10***	50.25***	39.79***	50.26***
Model type	FE	FE	FE	FE

[a] Robust standard error in parentheses. ***$p < 0.01$; **$p < 0.05$; *$p < 0.1$

abundant CO_2 emissions. On the other hand, the launched environmentally friendly regulations and policies are still in the exploration stage and have not yet achieved a noticeable effect compared with the rapid speed of economic growth driven by energy consumption. Moreover, unbalanced development in China will inevitably lead to stimulation of economic competition. Regional governments in underdeveloped provinces still give priory to economic growth, which is mostly driven by low-end manufacturing industries with high CO_2 emissions. The positive coefficient of lnHTI × lnGDP implies that CO_2 emissions increase as the GDP increases by introducing indirect effects of the high-tech industry. However, the coefficient of cross-term is much lower than that of lnGDP, indicating that the increase impact of economic growth driven by high-tech industry development on CO_2 emissions is not as great as the increase effect caused by overall economic development. This result can be explained as follows: (1) Vigorously developing the high-tech industry promotes the technological progress in energy conservation and emission reduction, which has an effect on alleviating the pressure of over-emitted CO_2 emissions; (2) Based on the essential role of the high-tech industry in promoting substantial growth in GDP and national technological strength, more production and manufacturing in high-tech industry increases CO_2 emissions, which are much more than the reduced emissions caused by technical advancements in energy conservation.

In terms of control variables, lnFDI shows consistency in its significance and its positive correlation with lnCE in models 1–4, so the introduction of FDI increases CO_2 emissions. This occurs because FDI in China is primarily concentrated in low-tech processing, assembly, manufacturing, and other labor and resource-intensive industries. Although FDI may bring spillovers of knowledge and technology that reduce CO_2 emissions, it causes over-consumptions of energy that elevate CO_2 emissions (Cheng et al. 2018). The coefficient of lnEI is positive and significant in models 1–4. There is a positive correlation between EI and CO_2 emissions because the higher energy intensity will inevitably lead to more CO_2 emissions due to the low energy efficiency. Otherwise, lnPOP is positive and significant at a 1% level in four models indicating that larger population size will emit more CO_2 emissions when there are no change in terms of people's living habits, major technological innovation, and other relevant factors.

Empirical results in regions with a high level of high-tech industry development

The regression results of the CO_2 emission influencing factors for the models in region with a high level of high-tech industry development are shown in Table 6. For model 5, high-tech industry development affects CO_2 emissions because the coefficient of lnHTI is significant at a 1% level. Compared with model 2 at the national level, there is similar positive U-shaped non-linear relationship between HTI and CO_2 emissions due to the significance of the squared term $(\ln HTI)^2$ at a 1% level in model 6. As discussed above, a turning point is expected when high-tech industry development reaches a certain level under the condition that there is no regulation or control by officials. In addition, the absolute value of coefficient of $(\ln HTI)^2$ in model 6 is higher than that in model 2 in national level, indicating that the non-linear impacts of high-tech industry development on CO_2 emissions in high-level region are stronger than that in national level. This proves the superiority of the development of high-tech industry on CO_2 emissions reduction at primary stage due to the faster change of slope of positive U-shaped curve. One example is the emission

Table 6 Estimation results of high-level models

Models Variables	Model 5 lnCE	Model 6 lnCE	Model 7 lnCE	Model 8 lnCE
lnGDP	0.543***	0.363	0.335*	− 0.641
	(0.142)	(0.201)	(0.167)	(0.505)
lnISU	− 1.036***	− 1.380***	− 5.399***	− 1.458***
	(0.129)	(0.273)	(1.463)	(0.312)
lnHTI	− 0.269***	− 1.016***	− 1.959***	− 0.281***
	(0.0326)	(0.183)	(0.505)	(0.0349)
lnEI	− 1.151***	− 1.172***	− 1.135***	− 1.084***
	(0.249)	(0.293)	(0.338)	(0.276)
lnPOP	0.651**	0.708**	0.698***	0.582**
	(0.209)	(0.233)	(0.208)	(0.188)
lnFDI	0.408***	0.463***	0.353***	0.499***
	(0.0738)	(0.0781)	(0.106)	(0.0799)
$(\ln HTI)^2$		0.0526***		
		(0.0151)		
lnHTI × lnISU			0.508***	
			(0.155)	
lnHTI × lnGDP				0.125**
				(0.0418)
Constant	10.27***	13.81***	24.73***	12.21***
	(2.117)	(2.764)	(5.687)	(2.335)
F statistic	6235.35	8873.26***	13314.97***	13296.58***
R^2	0.9175	0.9266	0.9314	0.9272
N	10	10	10	10
Observations	120	120	120	120
Hausman test	64.44***	68.56***	62.97***	77.71***
Model type	FE	FE	FE	FE

[a] Robust standard error in parentheses. ***$p < 0.01$; **$p < 0.05$; *$p < 0.1$

trading scheme officially approved by the NDRC (National Development and Reform Commission) in November 2011 (Wang et al. 2015). Some of the provinces and cities in the region with a high level of high-tech industry development are concerned about low-carbon issues, in which Beijing, Guangdong, Shanghai, Shenzhen, and Tianjin, are the first regions to implement the emission trading scheme. The pilot markets may drive entities in pilot regions to move to other regions with lower emission abatement costs, fewer environmental regulation standards, and higher CO_2 emission limits. Such shifts may reduce CO_2 emissions in the pilot regions (Ju and Fujikawa 2019) and explain why the stronger CO_2 emission reduction effect exists at the primary stage. Meanwhile, as the level of high-tech industry development increases, rapid growing demands for high-tech products in high-level region stimulate more frequent products updates, which intensify the increase of CO_2 emissions at the subsequent stage after the turning point.

In terms of lnHTI × lnISU in model 7, the similarity in the negative lnISU coefficient and positive lnHTI × lnISU coefficient can be explained as model 3 for the national level, where ISU causes a decrease in CO_2 emissions, but the impact is weakened by the indirect effects of high-tech industry development. It is noted that the absolute value of coefficient of lnHTI × lnISU is much higher than that in national-level model 3, indicating that the indirect impacts of high-tech industry development on CO_2 emissions increase by adjusting ISU in high-level region are much stronger than that in national level. This mainly because the higher level of HTI enables enterprises in this region to produce more high-end products with advanced technologies than average amount of that in national country, intensifying the effect on CO_2 emissions increase. Moreover, HTI also has an effect on driving economic growth then increase CO_2 emissions indirectly. The higher absolute value of coefficient of lnHTI × lnGDP indicates that high-tech industry makes larger proportion of contribution to economic growth and thereby promotes stronger effect on the increase of CO_2 emissions.

Empirical results in regions with a middle level of high-tech industry development

The regression results of the CO_2 emission influencing factors for the models in region with a middle level of high-tech industry development are shown in Table 7. Although there are also similar negative and positive coefficients of lnHTI and $(\ln HTI)^2$, the absolute value of coefficient of $(\ln HTI)^2$ is lower than that in high-level model 6. This shows the impacts of high-tech industry development on CO_2 emissions in middle-level region are weaker than that in high-level region. The insignificance of lnHTI × lnISU can be explained by the not obvious effect of middle level of high-tech industry development on adjusting the upgrading of industrial structure. To be specific, the insufficient capabilities of high-tech products manufacturing in region with middle level of high-tech industry development lead to the insignificant effect on CO_2 emissions. The absolute value of coefficient of lnHTI × lnGDP in model 12 is lower than that in model 8, indicating weaker indirect effect of HTI on CO_2 emissions in middle-level region than that in high-level region.

Empirical results for regions with a low level of high-tech industry development

The regression results of the CO_2 emission influencing factors for the models in region with a low level of high-tech industry development are shown in Table 8. The absolute values of coefficients of $(\ln HTI)^2$ and lnHTI × lnGDP are lower than that in high-level models and that in middle-level models, indicating the slight direct and indirect impacts of high-tech industry development on CO_2 emissions in region with a low level of high-tech industry development. The insignificance of lnHTI × lnISU in model 15 suggests that provinces in low-level region have insufficient strength to develop high-tech manufacturing industry, which requires enough financial budget, qualified researchers and employees, and advanced technologies in the process of construction of fixed assets and equipment production.

Comparisons of empirical results between clustering and geographical classification

In order to reflect the impacts of different levels of high-tech industry development on CO_2 emissions, this paper divides 30 provinces and cities into three regions with high, middle, and low level of high-tech industry development by a K-medians clustering approach for regional models establishment. For comparison, we have also built similar models in eastern, central, and western region of mainland China (Tibet is excluded due to the lack of data). As shown in the Tables 13, 14, and 15 of the appendix, the core independent variables in models built for eastern, central, and western regions are not as significant as those variables in models built for regions with high, middle, and low level of HTI. This proves that geographical classification may be insignificant for our investigation and insufficient to reflect the differences of high-tech industry development due to the fact that provinces in eastern, central, and western regions of China may not be at the same level of high-tech industry development.

Table 7 Estimation results of middle-level models

Models Variables	Model 9 lnCE	Model 10 lnCE	Model 11 lnCE	Model 12 lnCE
lnGDP	1.247***	1.307***	0.876***	0.719***
	(0.0760)	(0.0788)	(0.0625)	(0.237)
lnISU	− 0.274**	− 0.410***	− 0.215	− 0.403***
	(0.112)	(0.122)	(0.549)	(0.119)
lnHTI	− 0.161***	− 0.643***	− 0.164	− 0.244***
	(0.0429)	(0.201)	(0.312)	(0.0482)
lnEI	0.624***	0.671***	0.482**	0.738***
	(0.0875)	(0.0872)	(0.163)	(0.0944)
lnPOP	1.101***	1.105***	− 0.0469	1.078***
	(0.0528)	(0.0509)	(0.392)	(0.0577)
lnFDI	0.0438	0.0393	0.123***	0.0424
	(0.0299)	(0.0289)	(0.0204)	(0.0299)
$(\ln HTI)^2$		0.0359**		
		(0.0145)		
lnHTI × lnISU			0.0346	
			(0.0877)	
lnHTI × lnGDP				0.0953***
				(0.0356)
Constant	− 5.367***	− 3.597***	4.124	− 4.843***
	(0.740)	(1.016)	(2.992)	(0.756)
F statistic/Wald statistic	1977.94***	2272.80***	1226.34***	1885.84***
R^2	Null	Null	0.9631	Null
N	12	12	12	12
Observations	108	108	108	108
Hausman test	7.85	8.72	37.80***	7.14
Model type	RE	RE	FE	RE

[a] Robust standard error in parentheses. ***$p < 0.01$; **$p < 0.05$; *$p < 0.1$

Conclusion

Based on *STIRPAT* model, this paper conducted an empirical analysis of the direct and indirect impacts of high-tech industry development on CO_2 emissions in 30 provinces and cities in China clustered into three regions by the level of high-tech industry development (high, middle, and low) during 2005–2016. The empirical results illustrate the following points: (1) There is a positive U-shaped nonlinear relationship between HTI and CO_2 emissions at the national and regional (high, middle, and low) level in China, indicating that CO_2 emissions decrease as the high-tech industry initially develops and then increase after high-tech industry development reaches a turning point. (2) The impact intensity of HTI on CO_2 emissions in regions with high, middle, and low levels of high-tech industry development gradually decreases. (3) In national-level and high-level region, the high-tech industry attenuates the reduction effect of industrial structure upgrades on CO_2 emissions because it increases the production and manufacture of products and equipment; however, in middle-level and low-level region, this indirect impact of high-tech industry development on CO_2 emissions is insignificant. (4) The indirect impact intensity of HTI on CO_2 emissions by promoting economic growth is not as great as the direct impact of GDP on CO_2 emissions, and gradually decreases across regions with high, middle, and low levels of high-tech industry development. Flourishing high-tech industry development promotes economic growth, which attracts more investment and support by the government and native entrepreneurs. A large number of plants and offices are built, leading to an increase in CO_2 emissions during construction. Blindly increasing production in the high-tech industry causes unnecessary increases in CO_2 emissions.

To achieve the targets for mitigating CO_2 emissions and sustainable economic development in China, the relationship between high-tech industry development and CO_2 emissions must be considered. Rather than focusing on the reduction that occurs when products or equipment manufactured by the high-tech industry are used, paying more attention to the construction stage and production processes of the high-tech

Table 8 Estimation results of low-level models

Models Variables	Model 13 lnCE	Model 14 lnCE	Model 15 lnCE	Model 16 lnCE
lnGDP	1.250***	1.314***	1.247***	1.044***
	(0.0707)	(0.0865)	(0.0848)	(0.0887)
lnISU	0.0405	0.0374	0.0995	− 0.0206
	(0.0716)	(0.0687)	(0.447)	(0.0756)
lnHTI	− 0.0255	− 0.207***	0.0148	− 0.0742**
	(0.0145)	(0.0530)	(0.316)	(0.0242)
lnEI	1.069***	1.212***	1.061***	1.234***
	(0.176)	(0.211)	(0.209)	(0.193)
lnPOP	1.203***	1.635***	1.197***	1.450***
	(0.360)	(0.304)	(0.347)	(0.304)
lnFDI	− 0.0292	− 0.0291	− 0.0290	− 0.0253
	(0.0360)	(0.0349)	(0.0361)	(0.0360)
$(\text{lnHTI})^2$		0.0171***		
		(0.00382)		
lnHTI × lnISU			− 0.0110	
			(0.0846)	
lnHTI × lnGDP				0.0606**
				(0.0202)
Constant	− 10.18***	− 13.81***	− 10.31**	− 12.53***
	(3.038)	(2.850)	(3.350)	(2.574)
F statistic/Wald statistic	3948.58***	7674.45***	4074.09***	5050.57***
R^2	0.9114	0.9157	0.9114	0.9148
N	11	11	11	11
Observations	132	132	132	132
Hausman test	30.11***	34.63***	24.27***	30.59***
Model type	FE	FE	FE	FE

[a] Robust standard error in parentheses. ***$p < 0.01$; **$p < 0.05$; *$p < 0.1$

industry is required. Reasonable implications and suggestions for the government are proposed as follows.

During the initial construction process of fixed assets in the high-tech industry, we propose that the government should take advantage of environmentally friendly building materials and facilities, utilize materials with high efficiency, and optimize the process of establishment. These efforts require energy-saving technologies, supply chain and production optimization, qualified architects with design capabilities, and workers practicing good implementation processes.

In terms of the production and manufacturing processes of the high-tech industry, we propose that the government should enact regulations to coordinate between increasing societal demands and rational production to avoid unnecessary but controllable CO_2 emissions caused by over-production and overly frequent product updates. The government ought to encourage research and development to improve the recycling of products or their component parts instead of blindly advocating the rapid growth of the high-tech industry, which may lead to malicious competition among enterprises. Recycling and reutilizing products after obsolescence or officially encouraging a circular economy deserves more investment and policy support for the healthy and sustainable development of the high-tech industry.

Moreover, the heterogeneous effects of the high-tech industry on regional CO_2 emissions should receive more attention from officials. Because the government allocated resources for advanced research and development and the purchase of fixed assets, some provinces achieved a high level of high-tech industry development in China, particularly Guangdong, Jiangsu, Shandon, Shanghai, Zhejiang, and Beijing. The strength of the high-tech industry in those provinces is better than that in regions with middle and low levels of high-tech industry development. It is advisable and urgent to take measures to narrow this gap. Specifically, provinces in the middle- and low-level groups should introduce mature technologies from provinces in the high-level group to avoid unnecessary CO_2 emissions due to exploration in the early stages of high-tech industry development. The provinces that can support high-tech industry development in other provinces can use patent revenues to pay tax fees and thus reduce the tax burden. Policies aimed at constraining CO_2 emission, such as emission trading schemes in some provinces in the high-level group and sharing useful experiences and strategies for implementing such policies can be extended to provinces in the middle- and low-level groups.

Industry–university collaborative research, which requires an effective management system to coordinate partnerships, resources, and tasks, plays an indispensable role in the efficient development of high-tech industry efficiency. Such collaborations not only cultivate innovation but also drive scientific results and economic performance. Specifically, enterprises in different industries can achieve a competitive advantage in terms of knowledge and human resources. For universities, increasing opportunities for field experiments train students in practical skills. For academics, alternative channels for research funding provide powerful support for the normal operation of studies.

Meanwhile, the government is also supposed to pay attention to other pollution except for CO_2 emissions caused by high-tech industry, such as liquid pollution from the pharmaceutical manufacturing industry, and heavy metal pollution from electronics equipment, instrument and meter manufacturing industries. Those pollutions may bring more severe detrimental effects than CO_2 emissions on environment, and are essential to be controlled and disposed in an appropriate way to promote the sustainable development of high-tech industry.

Finally, this paper investigated the direct and indirect effects of high-tech industry development on CO_2 emissions in different regions in China. However, in terms of indirect role, the interactive effects between high-tech industry development and the transformation of energy structure, urbanization progress, FDI, and other factors influenced by high-tech industry development need to be explored in future analysis. Considering more comprehensive factors when measuring the level of high-tech industry development in different regions will result in a more robust understanding of the effects of high-tech industry development on CO_2 emissions.

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Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

Appendix

VIF results

Table 9 VIFs in national-level models

Variable	VIF	1/VIF
lnGDP	4.27	0.234135
lnISU	1.77	0.566018
lnHTI	9.62	0.103971
lnEI	3.70	0.270204
lnPOP	3.47	0.287993
lnFDI	7.85	0.127405

Table 10 VIFs in high-level models

Variable	VIF	1/VIF
lnGDP	9.48	0.105526
lnISU	3.71	0.269717
lnHTI	6.54	0.152811
lnEI	7.09	0.140986
lnPOP	5.05	0.198091
lnFDI	6.36	0.157155

Table 11 VIFs in middle-level models

Variable	VIF	1/VIF
lnGDP	6.35	0.157534
lnISU	1.20	0.831254
lnHTI	9.57	0.104529
lnEI	3.11	0.321579
lnPOP	1.78	0.562182
lnFDI	2.97	0.337259

Table 12 VIFs in low-level models

Variable	VIF	1/VIF
lnGDP	1.76	0.568604
lnISU	1.29	0.773106
lnHTI	3.97	0.251676
lnEI	2.30	0.435721
lnPOP	2.72	0.367252
lnFDI	3.44	0.290587

Table 13 Estimation results of models in eastern region

Models Variables	Model 1 lnCE	Model 2 lnCE	Model 3 lnCE	Model 4 lnCE
lnGDP	0.819***	0.786***	0.870***	1.014***
	(0.195)	(0.188)	(0.197)	(0.226)
lnISU	− 0.334	− 0.368	− 1.949***	− 0.349
	(0.308)	(0.329)	(0.528)	(0.323)
lnHTI	− 0.118	0.115	− 0.870***	− 0.108
	(0.0877)	(0.107)	(0.206)	(0.0848)
lnEI	− 0.300	− 0.463	− 0.119	− 0.417
	(0.262)	(0.257)	(0.295)	(0.265)
lnPOP	1.575**	1.483**	1.572**	1.548**
	(0.499)	(0.484)	(0.504)	(0.490)
lnFDI	0.152	0.159*	0.142	0.151
	(0.0997)	(0.0794)	(0.108)	(0.0895)
$(\ln HTI)^2$		− 0.0176**		
		(0.00621)		
lnHTI × lnISU			0.211***	
			(0.0630)	
lnHTI × lnGDP				− 0.0285*
				(0.0155)
Constant	− 4.799	− 3.862	0.114	− 4.028
	(5.936)	(5.632)	(6.251)	(5.815)
F statistic	20320.96***	20028.81***	25171.87***	24375.44***
R^2	0.8445	0.8484	0.8490	0.8459
N	11	11	11	11
Observations	132	132	132	132
Hausman test	32.78***	33.22***	38.49***	33.18***
Model type	FE	FE	FE	FE

[a] Robust standard error in parentheses. ***$p < 0.01$; **$p < 0.05$; *$p < 0.1$

Table 14 Estimation results of models in central region

Models Variables	Model 5 lnCE	Model 6 lnCE	Model 7 lnCE	Model 8 lnCE
lnGDP	0.867***	0.774***	0.835***	0.201
	(0.0821)	(0.0710)	(0.0783)	(0.259)
lnISU	0.0285	− 0.120	0.150	− 0.0885
	(0.117)	(0.111)	(0.736)	(0.121)
lnHTI	0.0234	− 0.217	0.102	− 0.0471
	(0.0424)	(0.161)	(0.385)	(0.0473)
lnEI	0.663***	0.373***	0.619***	0.777***
	(0.101)	(0.111)	(0.107)	(0.105)
lnFDI	0.0189	0.0227	0.0207	0.0343
	(0.0391)	(0.0346)	(0.0394)	(0.0368)
$(\ln HTI)^2$		0.0173		
		(0.0126)		
lnHTI × lnISU			− 0.0203	
			(0.107)	
lnHTI × lnGDP				0.111***
				(0.0405)
Constant	1.816**	4.551***	1.571	2.024**
	(0.849)	(0.944)	(2.656)	(0.821)
Wald statistic	265.90***	312.80***	253.30***	309.41***
N	9	9	9	9
Observations	108	108	108	108
Hausman test	7.44	5.94	6.70	6.20
Model type	RE	RE	RE	RE

[a] Robust standard error in parentheses. ***$p < 0.01$; **$p < 0.05$; *$p < 0.1$

POP is excluded in models 5–8 due to collinearity problem

Table 15 Estimation results of models in western region

Models Variables	Model 9 lnCE	Model 10 lnCE	Model 11 lnCE	Model 12 lnCE
lnGDP	1.210***	1.274***	1.128***	0.852***
	(0.0668)	(0.0793)	(0.118)	(0.149)
lnISU	− 0.143	− 0.0908	− 0.548	− 0.223*
	(0.0929)	(0.110)	(0.852)	(0.115)
lnHTI	− 0.000655	− 0.168***	− 0.281	− 0.0461
	(0.0194)	(0.0564)	(0.603)	(0.0376)
lnEI	0.990***	1.151***	0.766**	1.276***
	(0.0989)	(0.109)	(0.283)	(0.127)
lnPOP	0.963***	1.452***	1.121**	1.497***
	(0.0972)	(0.0871)	(0.428)	(0.101)
lnFDI	− 0.0355	− 0.0763**	− 0.0493	− 0.0538
	(0.0286)	(0.0312)	(0.0280)	(0.0355)
$(\ln HTI)^2$		0.0177***		
		(0.00535)		
lnHTI × lnISU			0.0839	
			(0.168)	
lnHTI × lnGDP				0.0913***
				(0.0285)
Constant	− 7.404***	− 12.11***	− 6.146	− 12.75***
	(1.150)	(1.049)	(4.640)	(1.240)
F statistic/Wald statistic	521.25	704.02***	22728.94***	660.50***
R^2			0.9137	
N	12	12	12	12
Observations	120	120	120	120
Hausman test	7.27	6.49	66.64***	3.77
Model type	RE	RE	FE	RE

[a] Robust standard error in parentheses. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

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