Front. Energy 2020, 14(1): 57–70
https://doi.org/10.1007/s11708-019-0654-7

RESEARCH ARTICLE

Xiaoqian SONG, Yong GENG, Ke LI, Xi ZHANG, Fei WU, Hengyu PAN, Yiqing ZHANG

Does environmental infrastructure investment contribute to emissions reduction? A case of China

Abstract Environmental infrastructure investment (EII) is an important environmental policy instrument on responding to greenhouse gas (GHG) emission and air pollution. This paper employs an improved stochastic impact by regression on population, affluence and technology (STRIPAT) model by using panel data from 30 Chinese provinces and municipalities for the period of 2003–2015 to investigate the effect of EII on CO_2 emissions, SO_2 emissions, and $PM_{2.5}$ pollution. The results indicate that EII has a positive and significant effect on mitigating CO_2 emission. However, the effect of EII on SO_2 emission fluctuated although it still contributes to the reduction of $PM_{2.5}$ pollution through technology innovations. Energy intensity has the largest impact on GHG emissions and air pollution, followed by GDP per capita and industrial structure. In addition, the effect of EII on environmental issues varies in different regions. Such findings suggest that policies on EII should be region-specific so that more appropriate mitigation policies can be raised by considering the local realities.

Keywords environmental infrastructure investment (EII), CO_2 emission, SO_2 emission, $PM_{2.5}$ pollution, stochastic impact by regression on population, affluence and technology (STIRPAT) model, governance

Received Jul. 6, 2019; accepted Sept. 16, 2019; online Dec. 25, 2019

Xiaoqian SONG
China Institute of Urban Governance, Shanghai Jiao Tong University, Shanghai 200030

Yong GENG (✉)
School of International and Public Affairs, Shanghai Jiao Tong University, Shanghai 200030, China; China Institute of Urban Governance, Shanghai Jiao Tong University, Shanghai 200030, China; School of Management, China University of Mining and Technology, Xuzhou 221116, China; Shanghai Institute of Pollution Control and Ecological Security, Shanghai 200092, China
E-mail: ygeng@sjtu.edu.cn

Ke LI
College of Mathematics & Computer Science, Hunan Normal University, Changsha 410081, China

Xi ZHANG, Fei WU, Hengyu PAN
School of Environmental Science and Engineering, Shanghai Jiao Tong University, Shanghai 200240, China

Yiqing ZHANG
Collaborative Innovation Centre for Energy Economy of Shandong, Shandong Technology and Business University, Yantai 264005, China

1 Introduction

China's rapid development is based upon consumption of a large amount of fossil fuels [1], leading to corresponding air pollution and climate change issues [2]. China has become the world's largest carbon dioxide (CO_2) emission country since 2006 [3,4]. To respond to climate change, China signed the United Nations Framework Convention on Climate Change (UNFCCC) and promised to achieve the CO_2 emission peak around 2030. Besides,, China has planned to reduce its CO_2 emission per unit of GDP by 60%–65% by 2030 compared with its emission level in 2005 [5]. With regard to air pollution, China focuses on both sulfur dioxide (SO_2) emission and $PM_{2.5}$ emissions. China became the largest SO_2 emission country in 2006 [6]. Although significant efforts made have helped China reduce its 75% SO_2 emission, it still accounted for 25% of the global SO_2 emissions during 2007–2017 [6]. $PM_{2.5}$ is a synthesis of many small particles, such as sulphates, nitrates, ammonium salts, and organic carbon. It includes various metallic elements, such as aluminum, magnesium, calcium, cadmium, arsenic, zinc, sodium, and copper [7,8]. $PM_{2.5}$ particles pose several health risks because they are extremely small and therefore can be easily inhaled and quickly penetrate the blood [8]. In 2010, $PM_{2.5}$ pollution caused approximately 1.25 million deaths in China, which accounted for nearly 40% of deaths caused by $PM_{2.5}$ worldwide [9]. Therefore, $PM_{2.5}$ pollution is another key issue to which China has to find an urgent solution [10].

EII is the investment of infrastructure related to environmental construction and pollution improvement, such as the investments on sewage treatment facilities, waste treatment facilities, industrial waste disposal system, energy infrastructure, pollution control system and public transport infrastructure, etc. EII has been considered as an important measure of environmental governance, especially in the field of CO_2 emission reduction and air pollution control. China has invested a large amount of money on updating its environmental infrastructure. The total investment on environmental infrastructure increased from 1.23 billion US dollars in 2000 to 139.89 billion US dollars in 2016 [11]. It is expected that China's EII will be no less than 3.5% of the GDP in 2020 [11]. The total investment is 2.56 trillion US dollars in China's 13th Five-Year Plan (2016–2020), in which a significant part will be spent on environmental infrastructure, with an estimated total investment of 1.2 trillion US dollars [12]. Figure 1 depicts the air pollution and EII levels in 2003, 2009, and 2015 respectively. It shows that CO_2 and SO_2 emissions are severe in provinces with more EII, such as Shandong, Jiangsu, and Liaoning. In terms of $PM_{2.5}$ pollution, those provinces with more EII have less $PM_{2.5}$ pollution. However, whether EII has a positive effect on pollution abatement remains unknown.

The existing studies have yet to reach a unified conclusion. At the national scale, several studies have found that EII is positively related to emissions reduction. For instance, Gruver [13] used one neoclassical growth model to investigate the impact of investment on pollution control and found that appropriate investment policies could contribute to pollution reduction. Wietschel et al. [14] uncovered that hydrogen infrastructure resulted in a notable level of CO_2 reduction in European countries. Jayaraman et al. [15] demonstrated that investment was beneficial for environment and decreased CO_2 emission in the United Arab Emirates. However, some evidences confirmed that investment had a negative impact on emission reduction and energy consumption increased CO_2 emission in Indonesia, Malaysia, the Philippines, Singapore, and Thailand [16]. In addition, Denafas et al. [17] found that CO_2 and SO_2 emissions from Baltic countries would continue to increase with the increasing investment on energy infrastructure, leading to a high electricity demand. Similarly, investment on green infrastructure has not significantly improved air quality in Australia, although additional environmental benefits can be obtained, such as improved building energy efficiency [18]. At the regional scale, Barandica et al. [19] found that road infrastructure investment had a significant positive correlation with CO_2 emission. However, circumstances are different at the micro-level and pre-investment in air pollution control can increase long-term financial risk, which is not conducive to business operation [20].

For the case in China, Peters et al. [21] found that infrastructure construction had exceeded efficiency improvements in the growth of CO_2 emission, and urbanization and lifestyle changes increased the infrastructure investment. Besides, CO_2 emissions from various types of transportation infrastructure construction were estimated in different regions of China and the results indicated that over 80% of the total CO_2 emission was generated by raw material production, and only 10% and 3% of the total CO_2 emission were generated by on-site construction and material transportation [19,20]. Another life cycle assessment study found that the highway infrastructure construction cost was positively correlated with GHG emission, but it was not significant during the investment period based on a multi-objective optimization model [22]. As such, investment on urban traffic infrastructure increases SO_2 emission in the short-term because of the low-speed traffic caused by road congestion, but it will have a positive impact on the reduction of SO_2 emission in the long-term. In addition, environmental control can effectively mitigate SO_2 emission. However, disputes exist on the relationship between infrastructure investment and air pollution control. In this regard, Jayasooriya et al. [18] and Bottalico et al. [23] found that urban green infrastructure played an important role in $PM_{2.5}$ reduction. By adopting a quantile regression approach, Xu and Lin [24] found that driving forces of $PM_{2.5}$ pollution were different in different regions in China. Moreover, the construction of environmental infrastructure may cause environmental pollution and therefore deserves more attentions. In particular, it is crucial to investigate if such investments will lead to the reduction of environmental pollution, and if so, to what extent? Similarly, it is necessary to investigate if there is any special heterogeneity in the effect of EII on environmental pollution.

The human impact, population, affluence, technology (IPAT) model can examine the factors which drive environmental pressure [25]. This model has been widely used to investigate the effect of activities on environment. For instance, Feng et al. [26] examined the impacts of lifestyle and technology on CO_2 emission. Unfortunately, the IPAT model assumes proportionality between the key determinant factors and cannot be used for driving factors with non-monotonic and non-proportional changes [26,27]. To solve such a problem, York et al. [28] reformulated the IPAT model in a stochastic form, which was known as stochastic impacts by regression on population, affluence, and technology (STIRPAT) model. Such a STIRPAT model can identify key factors that influence CO_2 emission and help prepare more comprehensive and realistic mitigation solutions. This model has now been widely applied to investigate the effects of impact factors on GHG emission and air pollution [25,29,30]. For instance, Li and Sun [31] examined air pollution driving factors in China's economically developed areas by using the STIRPAT model. As such, Wang et al. [32] Xu and Lin [33] investigated the different impacts of the driving forces on $PM_{2.5}$ pollution in Chinese

Fig. 1 CO_2 emission, SO_2 emission, $PM_{2.5}$ pollution, and EII in China in 2003, 2009, and 2015.
(a) 2003; (b) 2009; (c) 2015.

provinces. One STIRPAT model allows for the estimation of coefficients as parameters and can decompose various factors in different research contexts [28,33]. Consequently, several scholars endeavored to add explanatory variables to investigate the effects of different factors, such as urbanization [34–36], energy intensity [35] and industrial structure [37] on GHG emission and air pollution. Moreover, one STIRPAT model can be transformed into a random form of the ordinary least squares regression (OLS) model, which allows the subjective determination of variables before choosing the independent variable to deal with the uncertainty of reality [38]. However, these studies do not account for the effects of EII and therefore cannot explain the relationship between EII and emissions reduction. Such a reality makes it difficult to predict the effectiveness of environmental policies.

In general, previous studies focus on infrastructure investment across many sectors, such as energy [14], transportation [22], building [39], and urban infrastructure [40]. However, few of them investigated the effects of EII on emissions reduction. Particularly, few of them accounted for both climate change and air pollution. Under such a circumstance, this paper employs an improved STIRPAT model to investigate the relationships between EII and air pollution (including CO_2 and SO_2 emissions, and $PM_{2.5}$ pollution) by using panel data from 30 Chinese provinces for the period of 2003–2015. It also analyzed both temporal and special effects of EII on emissions reduction so that more appropriate EII policies can be raised.

It is expected that three academic contributions can be made in this paper. First, climate change and air pollution are addressed together. Three variables are chosen, including CO_2 emission, SO_2 emission, and $PM_{2.5}$ pollution, and the effects of EII on each of them is compared. Second, regional heterogeneity is taken into account. Because of imbalanced economic development across different areas in China, more region-specific mitigation policies should be prepared by considering the local realities. Finally, temporal analysis is conducted so that the historical trend can be better presented. Such results will help formulate more appropriate policies to efficiently mitigate China's overall emissions.

2 Methods and data

2.1 STIRPAT model

Ehrlich and Holdren [25] proposed the IPAT model to explore the effects of human activities on the environment in 1971. One IPAT model specifies the environmental impact (I) by three key driving forces, including population (P), affluence (A), and technology (T). Based on the IPAT model, York et al. [28] formulated the model in a stochastic form, which is known as the STIRPAT model. Such a model is presented in Eq. (1).

$$I_{it} = aP_{it}^{b}A_{it}^{c}T_{it}^{d}\varepsilon_{it}, \tag{1}$$

where I denotes environmental impact, which is decomposed into P (pollution), A (affluence), and T (technology); ε represents the random error term, while subscripts i ($i=1,2,\ldots,n$) and t ($t=1,2,\ldots,n$) represent places and time, respectively. After taking logarithms, this model is transformed to Eq. (2).

$$\ln I_{it} = \alpha + b\ln P_{it} + c\ln A_{it} + d\ln T_{it} + \ln\varepsilon_{it}. \tag{2}$$

By referring to previous studies, both economic and social factors are introduced, including population size, GDP per capita, technology progress [29], industrial structure [34–36], energy intensity [41,42], and urbanization rate [34–36]. Since few studies have investigated the effects of EII on environmental pollution, EII is introduced as one factor in this paper. Thus, the STIRPAT model can be expressed in Eq. (3).

$$\begin{aligned}\ln I_{it} = {} & \alpha_0 + \alpha_1\ln \mathrm{EII}_{it} + \alpha_2\ln A_{it} + \\ & \alpha_3\ln \mathrm{IS}_{it} + \alpha_4\ln \mathrm{EI}_{it} + \alpha_5\ln P_{it} + \\ & \alpha_6\ln T_{it} + \alpha_7\ln U_{it} + \varepsilon_{it},\end{aligned} \tag{3}$$

where i represents one province or municipality; t denotes a year; α_0 is a constant term; ε_{it} is an error term, and I represents environmental impacts, namely, CO_2 emission, SO_2 emission, and $PM_{2.5}$ pollution; EII is environmental infrastructure investment; P is population size; A represents affluence calculated by GDP per capita; T represents technology progress; IS represents industrial structure; EI stands for energy consumption per unit GDP; and U refers to urbanization.

In general, the EII scale varies at different economic development levels, population sizes, and technology levels. To reveal different effects, the interaction terms of EII and the above mentioned factors are added. Therefore, this model can be re-expressed in Eqs. (4–6).

$$\begin{aligned}\ln I_{it} = {} & \alpha_0 + \alpha_1\ln \mathrm{EII}_{it} + \alpha_2\ln A_{it} + \alpha_3\ln \mathrm{IS}_{it} + \\ & \alpha_4\ln \mathrm{EI}_{it} + \alpha_5\ln P_{it} + \alpha_6\ln T_{it} + \\ & \alpha_7\ln U_{it} + \alpha_8\ln \mathrm{EII}\times\ln A_{it} + \varepsilon_{it},\end{aligned} \tag{4}$$

$$\begin{aligned}\ln I_{it} = {} & \alpha_0 + \alpha_1\ln \mathrm{EII}_{it} + \alpha_2\ln A_{it} + \alpha_3\ln \mathrm{IS}_{it} + \\ & \alpha_4\ln \mathrm{EI}_{it} + \alpha_5\ln P_{it} + \alpha_6\ln T_{it} + \\ & \alpha_7\ln U_{it} + \alpha_8\ln \mathrm{EII}\times\ln P_{it} + \varepsilon_{it},\end{aligned} \tag{5}$$

$$\begin{aligned}\ln I_{it} = {} & \alpha_0 + \alpha_1\ln \mathrm{EII}_{it} + \alpha_2\ln A_{it} + \alpha_3\ln \mathrm{IS}_{it} + \\ & \alpha_4\ln \mathrm{EI}_{it} + \alpha_5\ln P_{it} + \alpha_6\ln T_{it} + \\ & \alpha_7\ln U_{it} + \alpha_8\ln \mathrm{EII}\times\ln T_{it} + \varepsilon_{it}.\end{aligned} \tag{6}$$

2.2 Data sources and treatment

The data for such a comprehensive study have to be collected from different sources. In this paper, the data are obtained from China Statistical Yearbooks on Environment, China Statistical Yearbooks for Regional Economy, China City Statistical Yearbooks, Chinese Energy Statistical Yearbooks, China Population and Employment Statistical Yearbooks, official documents of United Nations Environment Program (UNEP), and various governmental environmental notices. The data of Tibet Autonomous Region are incomplete because historically such data have been excluded from China's statistics. Therefore, Tibet is excluded from this paper. The panel data for other 30 Chinese provinces and municipalities are used. In addition, due to data availability, the data from 2003 to 2015 were chosen. Thus, the year 2003 is the beginning year for this study. All monetary data are revised based on the 2003 prices.

The variables in this paper are illustrated as follows. The explained variables in the STRIPAT model include CO_2 emissions (CO_2), SO_2 emissions (SO_2), and $PM_{2.5}$ pollution ($PM_{2.5}$). CO_2 emissions are calculated based on the energy consumption data and up-to-date emission factors [43], in which the data for the period of 2003–2015 are derived from the China Emission Accounts and Data sets (CEADs) [44].

In the model, the main explanatory variable is EII, which refers to material engineering facilities that provide environmental public services for social production and residents. It is a public service system that is used to protect and improve the atmospheric, water, and soil pollution control, such as general material conditions on which society depends. Such data are available from the China Environment Statistical Yearbooks. There are also some other explanatory variables. For population size (P), the year-end total population of various Chinese provinces and municipalities is used. The GDP per capita is used to measure affluence (A), while the capital-labor ratio is adopted to measure technology level (T) [45]. Due to a lack of relevant data, extant literatures are used to estimate urban fixed capital stocks and refer to urban employments of the year to evaluate the labor quantity. As energy efficiency is an important factor for reducing air pollution, such as CO_2 and SO_2 emissions [46], energy intensity (EI) is added to the model. Finally, the ratio of urban residents to the total population and the proportions of secondary industry to the total industrial production are adopted to measure utilization (U) and industrial structure (IS), respectively [47]. Table 1 lists the statistical data associated with these variables.

3 Results

3.1 Results for basic models

The results of Hausman tests and F-tests show that the null hypothesis of random effect is rejected. Therefore, a fixed-effects model is adopted to estimate the effects of EII, population size, GDP per capita, technology progress, industrial structure, energy intensity and urbanization on CO_2 emission, SO_2 emission, and $PM_{2.5}$ pollution, respectively. Table 2 outlines the estimation results. In the first column, CO_2 emission is one dependent variable, while in the second and third columns, the dependent variable is SO_2 emission and $PM_{2.5}$ pollution, respectively.

Column (1) indicates that the construction of environmental infrastructure has a positive effect on CO_2 emission. Specifically, each 1% EII increase leads to an increase in CO_2 emission by 0.0470% at the 5% significance level. This result is in consistent with previous studies [37,44]. There are also significant positive correlations between CO_2 emission and GDP per capita, energy intensity, population size, at the $p = 0.05$ level. More specifically, the statistical tests demonstrate that each 1% increase in GDP per capita and population size lead to a 0.827% and a 0.969% increase in CO_2 emissions, respectively. Such findings are similar to those in previous studies [48–50]. Energy intensity has the most dominant effect on CO_2 emission as each 1% increase in energy intensity leads to a 1.221% increase in CO_2 emission.

Column (2) lists the results associated with SO_2 emissions, which indicate that there is no significant correlation between EII and SO_2 emission. In addition, the GDP per capita, energy intensity, and industry structure are significantly and positively related to SO_2 emissions, while population size has a significantly negative relation with SO_2 emission. More specifically, each 1% increase in energy intensity leads to a 0.930% increase in SO_2 emission and each 1% increase population will lead to a 0.0617% reduction in SO_2 emission, which are similar to those in earlier studies [45–47]. This can also be explained by the fact that heavily polluted industries normally locate far away from residential areas, according to China's Environmental Impact Assessment Law.

Column (3) lists the results associated with $PM_{2.5}$ pollution, which indicate that EII and technology progress have a significantly negative impact on $PM_{2.5}$ pollution,

Table 1 Descriptive statistical data associated with these variables

Variables	Mean	Std. Dev.	Min	Max
CO_2 emissions/(10^6t)	277.73	230.32	0.0005	155.38
SO_2 emissions/(10^6t)	6.410	3.860	0.210	17.200
$PM_{2.5}$ pollution/(10^5t)	54.70	33.00	3.09	167.00
EII/(10^9 yuan)	78.025	89.492	1.167	1047.230
A/(10^4yuan)	2.491	1.634	0.369	8.731
U/%	0.504	0.145	0.248	0.896
IS/%	0.469	0.078	0.197	0.590
EI/(10^4 yuan)	1.449	0.743	0.362	4.535
$P \times 10^4$	4402.10	2647.71	534.00	10849
T	3.385	3.065	0.362	16.192

Table 2 Regression analysis of effects of EII on CO_2 emission, SO_2 emission, and $PM_{2.5}$ pollution

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	CO_2 emission	SO_2 emission	$PM_{2.5}$ pollution	CO_2 emission	SO_2 emission	$PM_{2.5}$ pollution
EII	0.0470**	0.0104	– 0.0405***	-	-	-
	(0.0220)	(0.0227)	(0.0143)	-	-	-
A	0.827***	0.526***	0.240***	1.107***	0.424***	0.345**
	(0.127)	(0.131)	(0.0822)	(0.132)	(0.150)	(0.141)
A^2	-	-	-	-0.447***	-0.431***	-0.593***
	-	-	-	(0.0807)	(0.0916)	(0.0864)
IS	– 0.00156	0.413***	– 0.0657	-	-	-
	(0.131)	(0.135)	(0.0849)	-	-	-
EI	1.221***	0.930***	0.0620	-	-	-
	(0.113)	(0.116)	(0.0730)	-	-	-
P	0.696***	– 0.617***	– 0.124	-	-	-
	(0.221)	(0.228)	(0.143)	-	-	-
T	0.273***	– 0.102	– 0.111**	-	-	-
	(0.0835)	(0.0862)	(0.0542)	-	-	-
U	0.276	– 0.253	– 0.0190	-	-	-
	(0.186)	(0.192)	(0.121)	-	-	-
Constant	– 1.494	17.70***	16.23***	4.926***	13.18***	15.51***
	(1.721)	(1.775)	(1.117)	(0.0596)	(0.0677)	(0.0639)
F-test	249.42***	24.57***	2.47**	-	-	-
Hausman	309.7***	35197.04***	– 11.3	-	-	-
Observations	390	390	390	390	390	390
Number of no	30	30	30	30	30	30
R-squared	0.832	0.328	0.047	0.184	0.072	0.217

Notes: Robust standard errors are presented in parentheses. *$p < 0.1$; **$p < 0.05$; and ***$p < 0.01$.

with a correlation coefficient of –0.0405 and –0.111, respectively. However, GDP per capita is significantly and positively related with $PM_{2.5}$ pollution, which is also confirmed by a previous study [51].

3.2 Path effects of EII on environmental pollution

Generally, the relation between EII and environmental pollution depends on population size, economic development, and technology progress. EII can lead to economic growth and increase the total demand on raw materials, which will bring to an increase in GHG emission and air pollution [48,49]. As such, the appropriate EII will improve the living standards of urban residents and create a better environment, attracting more migrants to move in and leading to people agglomeration [21,51–54]. To further explore the pathway through which EII affects environmental pollution, Eqs. (4) – (6) are adopted to examine the effects of economic development, population size, and technology progress, respectively. When the interaction terms are introduced to the model, the interpretation will differ and should be used with caution [54]. According to Hamilton [55], central processing is used in this paper to treat independent variables. Figure 2 exhibits the marginal effects of EII on environmental pollution with different interaction items. Table 3 tabulates the estimation results of these equations. In the Columns (1 – 3), CO_2 emission is a dependent variable, in Columns (4 – 6), SO_2 emission is a dependent variable, and in Columns (7 – 9), $PM_{2.5}$ pollution is a dependent variable.

With regard to the effect of economic growth, the iteration items for EII and GDP per capita significantly and positively affect CO_2 emission and SO_2 emission. But the interaction item cannot significantly affect $PM_{2.5}$ pollution. The studies conducted by Wooldridge [56] and Zhang et al. [37] are referred to as the basis for the investigation of the effect of economic growth. When using an interaction term, the division is taken by lnEII to both sides of Eq. (4) so that the partial regression coefficient can be rewritten as $\alpha_1 + \alpha_8 \ln A$. By using the mean of ln$A$, the fact is obtained that the partial effect of EII on CO_2 emission and SO_2 emission is 0.624 and 0.0378, respectively. This means that a higher EII will lead to a higher CO_2 emission and SO_2 emission from an economic growth perspective.

Table 3 Path analysis of effects of EII on CO_2, SO_2 emissions, and $PM_{2.5}$ pollution

Variables	CO_2 emission			SO_2 emission			$PM_{2.5}$ pollution		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
EII	0.0829***	0.774***	0.0732***	0.0747***	0.706***	0.0462*	−0.0504***	−0.0965	−0.0515***
	(0.0245)	(0.160)	(0.0248)	(0.0245)	(0.165)	(0.0255)	(0.0161)	(0.107)	(0.0162)
A	0.980***	0.779***	0.797***	0.800***	0.480***	0.484***	0.198**	0.244***	0.253***
	(0.134)	(0.124)	(0.127)	(0.134)	(0.128)	(0.130)	(0.0878)	(0.0825)	(0.0825)
IS	− 0.0534	−0.0108	− 0.0513	0.320**	0.405***	0.346**	−0.0513	−0.0650	− 0.0448
	(0.130)	(0.127)	(0.132)	(0.130)	(0.132)	(0.135)	(0.0854)	(0.0850)	(0.0860)
EI	1.158***	1.069***	1.199***	0.816***	0.785***	0.900***	0.0796	0.0737	0.0713
	(0.113)	(0.114)	(0.112)	(0.113)	(0.118)	(0.115)	(0.0741)	(0.0764)	(0.0732)
P	0.883***	0.739***	0.822***	−0.282	−0.576**	−0.445*	−0.176	−0.127	−0.177
	(0.226)	(0.215)	(0.227)	(0.226)	(0.223)	(0.233)	(0.148)	(0.144)	(0.148)
T	0.278***	0.237***	0.409***	− 0.0946	−0.137	0.0828	−0.113**	−0.109**	−0.169**
	(0.0825)	(0.0817)	(0.103)	(0.0825)	(0.0846)	(0.105)	(0.0542)	(0.0545)	(0.0669)
U	0.243	0.447**	0.235	−0.312*	−0.0892	−0.310	−0.00983	−0.0322	−0.00141
	(0.184)	(0.185)	(0.186)	(0.184)	(0.191)	(0.191)	(0.121)	(0.123)	(0.121)
EII × *A*	−0.0518***			−0.0929***			0.0144		
	(0.0161)			(0.0161)			(0.0106)		
EII × *P*		−0.0892*-**			−0.0854***			0.00687	
		(0.0194)			(0.0201)			(0.0130)	
EII × *T*			−0.0312**			−0.0426***			0.0131
			(0.0139)			(0.0142)			(0.00903)
Constant	−3.149*	−1.579	−2.664	14.73***	17.61***	16.10***	16.69***	16.23***	16.72***
	(1.775)	(1.674)	(1.788)	(1.776)	(1.734)	(1.835)	(1.166)	(1.118)	(1.166)
Observation	390	390	390	390	390	390	390	390	390
N	30	30	30	30	0.360	0.344	0.052	0.047	0.052
R-squared	0.837	0.841	0.834	0.385	30	30	30	30	30

Notes: Robust standard errors are presented in parentheses. ***$p < 0.01$, **$p < 0.05$, and *$p < 0.1$.

With respect to the effect of popular size, the interaction between EII and popular size significantly and positively affects CO_2 emission and SO_2 emission. When using an interaction term, the division is taken by lnEII to both sides of Eq. (5) so that the partial regression coefficient can be rewritten as $\alpha_1 + \alpha_8 \ln P$. By using the mean of $\ln P$, it is obtained that the partial effect of EII on CO_2 emission and SO_2 emission is 0.449 and 0.0395, respectively. The results indicate that an additional increase of population size amplifies the positive effect of EII on CO_2 emission and SO_2 emission. Different from the conclusion that population agglomeration benefits for the reduction of CO_2 emission by decreasing energy consumption [57], it is also different to the path effect of transport infrastructure on CO_2 emission [37]. But the interaction effect between EII and population size on $PM_{2.5}$ pollution is not significant.

As far as the effect of technology progress is concerned, the interaction between EII and technology progress significantly and negatively affects CO_2 emission and SO_2 emission, but not $PM_{2.5}$ pollution. The partial regression coefficients of EII on CO_2 and SO_2 emissions are -0.715 and -0.024, respectively. This means that technology progress may lead to a higher decrease in CO_2 emission and SO_2 emission for larger EII. In other words, more EII will lead to more reduction in CO_2 emission and SO_2 emission with the application of more advanced technologies. Such results confirm that EII will improve technology progress although achieving CO_2 emission reduction and maintaining economic growth simultaneously is difficult in China [37].

3.3 Regional heterogeneity analysis

Generally, China can be divided into three regions: the east, the central, and the west, according to China's 7th Five-Year Plan (1986–1990) [58]. Historically, imbalanced economic development occurred across different regions [59], resulting in the fact that EII may have different effects

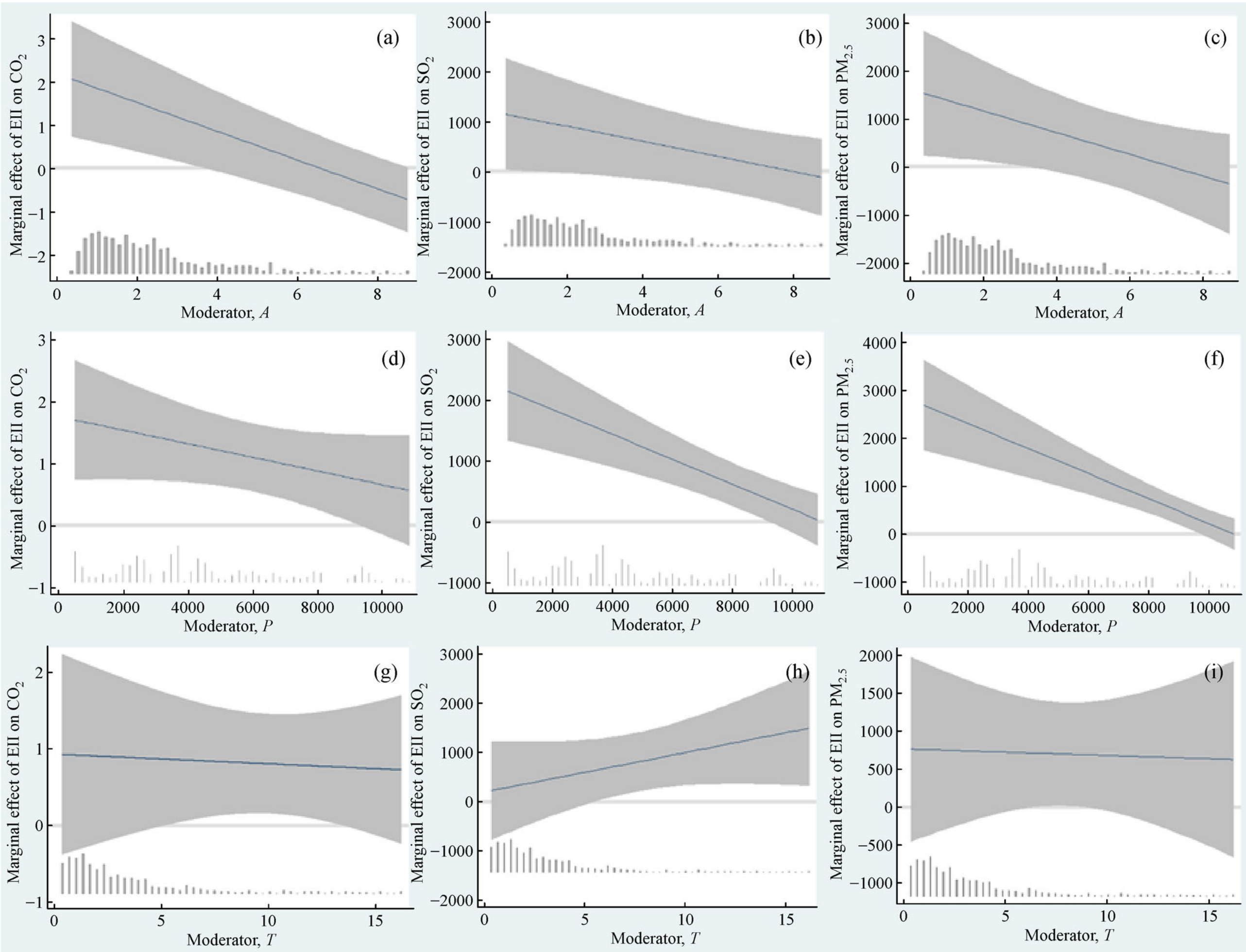

Fig. 2 Marginal effects of EII on CO_2 emission.

(a) SO_2 emission; (b) $PM_{2.5}$ pollution; (c) marginal effects of EII on CO_2 emission through economic growth path; (d) SO_2 emission; (e) $PM_{2.5}$ pollution; (f) marginal effects of EII on CO_2 emission through population size path and economic growth path; (g) SO_2 emission; (h) $PM_{2.5}$ pollution; (i) through the technical innovation path.

on pollution reduction in different regions. To uncover regional disparity, the Chinese provinces and municipalities are divided into three categories: provinces in the eastern region ($N = 12$), provinces in the central region ($N = 9$), and provinces in the western region ($N = 9$) [59]. Relevant results are shown in Table 4. In Columns (1), (4), and (7), CO_2 emission is the explained variable, in Column (2), (5), and (8), SO_2 emission is the explained variable, and in Column (3), (6), and (9), $PM_{2.5}$ pollution is the explained variable.

In the eastern region, EII significantly and positively affects CO_2 emission at the $p = 0.1$ level, while EII has a significant and negative effect on $PM_{2.5}$ pollution at the 10% significant level. GDP per capita significantly and positively affects CO_2 emission and SO_2 emission, with coefficients of 1.275 at the 1% significance level and 0.476 at the 5% significance level, respectively. Moreover, energy intensity has the most significant effect on CO_2 emission and SO_2 emission with coefficients of 1.426 and 1.034 at the 1% significance level, respectively. Population size also significantly and positively affects CO_2 emission in the eastern region. As for technology progress, each 1% increase results in a 0.200% decrease in $PM_{2.5}$ pollution.

In the central region, EII has both significant and positive effects on CO_2 emissions, but has significant and negative effects on SO_2 emission and $PM_{2.5}$ pollution. More specifically, each 1% increase in EII results in a 0.127% increase in CO_2 emission, a 0.0624% decrease in SO_2 emission, and a 0.0851% decrease in $PM_{2.5}$ pollution. Furthermore, energy intensity has a positive effect on CO_2 emission and SO_2 emission with coefficients of 1.274 and 0.416 at the 1% significance level, respectively. However, industrial structure has a negative effect on SO_2 emission and $PM_{2.5}$ pollution. Each 1% increase in industrial structure will lead to a 0.514% increase in CO_2 emission and a 0.343% decrease in $PM_{2.5}$ pollution. Finally, urbanization will decrease SO_2 emission significantly with a coefficient of -0.927.

Table 4 Effects of EII on CO_2 emission, SO_2 emissions, and $PM_{2.5}$ pollution by region

Variables	Eastern			Central			Western		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	CO_2 emission	SO_2 emission	$PM_{2.5}$ pollution	CO_2 emission	SO_2 emission	$PM_{2.5}$ pollution	CO_2 emission	SO_2 emission	$PM_{2.5}$ pollution
EII	0.0704*	−0.0119	−0.0405*	0.127**	− 0.0624*	−0.0851**	−0.0401	0.0217	−0.0176
	(0.0367)	(0.0389)	(0.0215)	(0.0523)	(0.0364)	(0.0390)	(0.0311)	(0.0374)	(0.0208)
A	1.275***	0.476**	0.179	0.192	0.332*	0.335*	1.336***	1.141***	0.231*
	(0.202)	(0.214)	(0.118)	(0.267)	(0.186)	(0.199)	(0.203)	(0.244)	(0.136)
IS	0.495*	0.630**	0.227	−0.0532	0.514***	−0.343**	−0.201	−0.255	0.115
	(0.296)	(0.313)	(0.173)	(0.198)	(0.138)	(0.147)	(0.230)	(0.277)	(0.154)
EI	1.426***	1.034***	−0.138	1.274***	0.416***	−0.201	1.010***	0.750***	0.315***
	(0.245)	(0.259)	(0.143)	(0.213)	(0.148)	(0.159)	(0.173)	(0.208)	(0.116)
P	1.013***	−0.160	0.0770	3.288***	0.845	−2.070***	0.903	2.199***	−0.537
	(0.324)	(0.343)	(0.189)	(1.038)	(0.722)	(0.773)	(0.580)	(0.698)	(0.389)
T	−0.115	−0.249	−0.200**	0.717***	0.0309	−0.124	0.0951	−0.681***	−0.124
	(0.147)	(0.156)	(0.0860)	(0.169)	(0.118)	(0.126)	(0.151)	(0.182)	(0.101)
U	0.268	0.157	0.277*	0.118	−0.729***	−0.0728	−0.641	−0.258	0.0879
	(0.259)	(0.274)	(0.151)	(0.330)	(0.230)	(0.246)	(0.527)	(0.634)	(0.354)
Constant	−3.937	14.74***	14.64***	−23.58***	5.943	33.23***	−3.824	−5.055	19.51***
	(2.530)	(2.679)	(1.478)	(8.700)	(6.058)	(6.484)	(4.331)	(5.211)	(2.905)
Observation	156	156	156	117	117	117	117	117	117
R-squared	0.804	0.518	0.117	0.865	0.349	0.240	0.906	0.407	0.184
N	12	12	12	9	9	9	9	9	9

Notes: Robust standard errors are presented in parentheses. ***$p < 0.01$, **$p < 0.05$, and *$p < 0.1$.

In the western region, EII has no significant effect on CO_2 emission, SO_2 emission, and $PM_{2.5}$ pollution. But energy intensity has a significant and positive effect on CO_2 emission, SO_2 emission, and $PM_{2.5}$ pollution, with a coefficient of 1.336, 1.414, and 0.231 at the 1% significance level, respectively. However, population size has the most significant effect on CO_2 emission and $PM_{2.5}$. Each 1% increase in population size will lead to a 3.288% increase in CO_2 emission and a 2.070% decrease in $PM_{2.5}$ pollution at the 1% significance level. Regarding technology progress, each 1% increase will lead to a 0.681% decrease in SO_2 emissions at the 1% significance level.

In general, the effect of EII on CO_2 emission in the central region is more significant than those in the eastern and western region. Such results can be explained by the fact that the Central Government has tried to optimize the industrial structure in these heavy industry concentrated central provinces by encouraging more advanced industrial operations [60]. The implementation of this policy has promoted local economic development, but with a result of more CO_2 emission. However, the effect of EII on $PM_{2.5}$ pollution is not significant. In addition, energy intensity has the dominant effect on the increase of CO_2 emission and SO_2 emission in the whole country, and it also increased $PM_{2.5}$ pollution in the western region due to their rich coal reserves. Finally, technology innovation has a significant effect on $PM_{2.5}$ pollution reduction in the eastern region and SO_2 emissions reduction in the western region.

3.4 Evolutional analysis

Evolutional analysis is important as it can help examine whether the effect of EII on emissions reduction varies in different years. In this regard, a time-varying coefficient model is applied to analyze the dynamic and evolutional effect of EII. The year 2003 was chosen as the base year, and the effect of EII for the period of 2004–2014 was measured.

Table 5 lists the results. First, the coefficient estimate of the effect of EII on CO_2 emission is significant and ranged from 0.0721 in 2004 to –0.017 in 2015, of which the values during 2004–2014 are positive. The impact of EII on CO_2 emission changes from positive to negative, indicating that the effect of EII on the increase of CO_2 emission has gradually decreased. In the long run, EII would decrease CO_2 emission eventually.

Second, the effect of EII on SO_2 emission is not significant until 2007. During 2007–2015, except 2009, the coefficient ranges from 0.0758 in 2007 to –0.164 in 2015,

Table 5 Time-varying effects

EII	CO_2 emission	SO_2 emission	$PM_{2.5}$ pollution
EII × 2004	0.0721*	−0.09612	−0.0562***
	(0.0132)	(0.0126)	(0.00743)
EII × 2005	0.067*	0.11247	−0.0113**
	(0.0143)	(0.0137)	(0.00810)
EII × 2006	0.0525***	0.103943	0.0065***
	(0.0157)	(0.0150)	(0.00886)
EII × 2007	0.0302***	0.0758*	0.0143***
	(0.0172)	(0.0164)	(0.00970)
EII × 2008	0.0328***	0.0431***	0.0063***
	(0.0182)	(0.0173)	(0.0102)
EII × 2009	0.0323***	0.0127	0.003***
	(0.0191)	(0.0183)	(0.0108)
EII × 2010	0.022***	0.005***	0.0025***
	(0.0204)	(0.0195)	(0.0115)
EII × 2011	0.0196***	0.0074***	−0.0076*
	(0.0223)	(0.0213)	(0.0126)
EII × 2012	0.0028***	−0.009***	−0.0076
	(0.0231)	(0.0220)	(0.0130)
EII × 2013	0.0129***	−0.013***	0.0114***
	(0.0246)	(0.0234)	(0.0139)
EII × 2014	0.0041***	−0.029***	0.0012**
	(0.0258)	(0.0246)	(0.0146)
EII × 2015	−0.017***	−0.164***	0.0366**
	(0.0278)	(0.0265)	(0.0157)
Constant	−4.324**	13.23***	17.39***
	(1.902)	(1.816)	(1.074)
Control variables	Yes	Yes	Yes
Observations	390	390	390
R-squared	0.843	0.462	0.326

Notes: Robust standard errors are enclosed in parentheses. ***$p < 0.01$; **$p < 0.05$; and *$p < 0.1$.

of which the values during 2004–2011 are positive, while such values during 2012–2015 are negative. Such results show that the effect of EII on SO_2 emission gradually has decreased. This is in consistent with the fact that SO_2 emission peaks around 2006 and then begins to decrease.

Finally, the effect of EII on $PM_{2.5}$ pollution is significant but fluctuates. In particular, the coefficient ranges from –0.0562 in 2004 to –0.0366 in 2015, of which the values are negative in 2004 and 2005, positive from 2006 to 2010, negative in 2011 and 2012, and positive from 2013 to 2015. This indicates the difficulty of controlling haze. In the reality, the Chinese government has paid more attention on $PM_{2.5}$ pollution reduction, especially after the unprecedented heavy haze in 2013, although more efforts should be further made.

3.5 Environmental Kuznets analysis

The results of environmental Kuznet analysis are listed in Columns (4–6) in Table 2. It is clearly observed that there is an inverted U-shape relationship between GDP per capita and CO_2 emission in China. Relationships between GDP per capita, CO_2 emission, SO_2 emission, and $PM_{2.5}$ pollution are also significantly positive, with a value of 1.107, 0.424 and 0.345, respectively. Such findings support the environmental Kuznets curve (EKC) theory.

The turning points of GDP per capita are 1.238, 0.491, and 0.291 for CO_2 emission, SO_2 emission, and $PM_{2.5}$ pollution, respectively. It is clearly noticed that China's economy has already achieved the turning points. However, environmental emissions may continue to increase mainly due to factors such as EII, population size, technology progress, and energy consumption, etc.

4 Discussion

China will continue to increase its investment on environmental infrastructure to mitigate its overall environmental emissions. But the relationship between environmental investment and emissions reduction is still unclear [61,62]. This paper indicates that EII increases CO_2 and SO_2 emission. Energy intensity has the most positive effect on the increase of pollutant emissions. Besides, the effect of EII has both regional and temporal differences. In general, EII is still in its early stage, indicating that it is crucial to prepare more appropriate policies so that environmental infrastructure can reduce the overall emissions. By considering the Chinese realities, several policy recommendations are proposed so that valuable insights can be shared by policy makers.

First, the results indicate that EII increases CO_2 emission significantly. Consequently, the Chinese government need to plan the construction of environmental infrastructure carefully. Energy saving and emission reduction policies should be incorporated into such a process. For instance, economic incentive policies, such as lower tax rates, prices, and subsides, should be prepared to encourage the use of green material for the construction of environmental infrastructure. Green building standards, such as the LEED standard in US and the CASBEE standard in Japan, should be released by referring to international practices. Moreover, an effective way to mitigate corresponding CO_2 emission is to encourage the use of recycled materials in environmental infrastructure construction. For example, local governments should develop regional resource recycled material trade platforms to facilitate waste exchanges.

Second, the regression analysis shows that energy intensity has the most contribution to increasing CO_2 emission and SO_2 emission because China's energy consumption is mainly fossil fuels (especially coal) based [63,64]. Under such a circumstance, it is crucial to optimize energy structure by encouraging more applications of clean and renewable energy, such as solar power, wind power, geothermal power. Actually, China has become the world's largest solar and wind power generator. However, due to unstable supply, decreased demand, less flexibility, and imbalanced economic development, solar and wind facilities are increasingly abandoned in some regions [65]. These issues cannot be solved by any single policy. Therefore, a policy portfolio should be initiated, including national target on developing renewable energy, market-based instruments, investment on long distance energy delivery facilities, governmental subsidies, more research and development, and capacity-building efforts. Besides, energy infrastructure on natural gas, shale gas, and methane should be developed because these energy sources can significantly reduce air pollution, compared with coal. In addition, more financial channels should be provided so that private funds, such as Build-Operate-Transfer (BOT) and Public-Private Partnership (PPP) [60] can enter this field.

Next, region disparity exists in terms of the effect of EII on CO_2 emission, SO_2 emission, and $PM_{2.5}$ pollution. In the eastern region, EII and technology progress has decreased SO_2 emission and $PM_{2.5}$ pollution, while in the central and western regions, industrial structure and population size have had significant positive effects on CO_2 emission, SO_2 emission, and $PM_{2.5}$ pollution. Therefore, region-specific investment policies should be made to avoid the one-size-fits-all problem. More specifically, the eastern provinces should actively transfer their advanced technologies and management experiences to their central and western counterparts, while the central and west provinces should establish necessary platforms to accept and apply the leading technologies. Apart from this, the central and western provinces should make their own efforts to encourage more innovations. A good example is that an outdoor air-purifying system has been established and operated in Xi'an, a typical large city in north-west China. Initiated by the Chinese Academy of Sciences, the University of Minnesota, and Xi'an Jiao Tong University, this system is powered by solar energy and has been very effective for the reduction of $PM_{2.5}$ pollution. Compared with the eastern region, urbanization in the central and western regions are slow and their industrial structure is more energy intensive. Consequently, it is necessary to optimize their industrial structure by encouraging more service industry and cleaner production. This is not an easy mission and needs a systematic effort. More dirty and energy intensive industries have been transferred from the east region to the central and western regions due to their less strict environmental standards and eagerness for attracting more investment projects. This requires that the central and western regions should raise their environmental standards and strengthen their environment consciousness so that the newly established companies can significantly reduce their energy and emissions intensity, instead of regarding the central and west regions as a place for them to release pollutants. At the same time, these governments should make more appropriate policies to encourage service industry since service industry is significantly less energy intensive and can create more job opportunities. However, service industry is based upon relevant talents and local resource endowments. Thus, these governments should seek to attract more talents and train local citizens so that they can engage in service industry. Again, regional cooperation is the key. The companies in the more developed eastern region should be encouraged to help their counterparts in the central and western region to develop their service industry.

Finally, clean and low carbon energy transition should be accelerated. Energy intensity has the most effect on air pollution. Therefore, it is critical to reduce energy intensity by encouraging the application of renewable and clean energy. Another effective measure is to improve energy efficiency. Different actions should be taken at different levels. The provincial governments should establish their energy efficiency targets and strictly pursue such targets, especially in those key energy intensive companies while the local governments should actively promote circular economy by developing eco-industrial parks. China has initiated over 126 eco-industrial parks. However, most of these parks are located in the eastern region [61]. The main reason for this is that industrial parks in the central and western region are reluctant to apply for such a title due to its complicated procedures, lack of financial support, and management capacities [61]. Thus, necessary awareness raising activities should be organized so that more urban/industrial symbiosis opportunities can be identified and implemented in the central and west regions. In companies, measures such as eco-design, cleaner production, energy audit, and efficient end-of-life treatments can be promoted. A close Government-University-Industry partnership should be established so that different stakeholders can work together toward the same target, namely, improving the overall energy efficiency of one company.

5 Conclusions

China has to balance economic development and environmental challenges by increasing its EII. It is therefore important to examine the effect of EII on emissions reduction. This paper has investigated whether EII affects CO_2 emission, SO_2 emission, and $PM_{2.5}$ pollution by considering various factors, including economic growth, population size, technology progress, industrial structure, urbanization, and energy intensity. An improved STIRPAT model has been employed to analyze the effect of EII on emission reduction across 30 Chinese provinces for the period of 2003–2015. Regional effect and time-varying effect of EII on emissions reduction have been specifically detailed. The following conclusions are made:

First, the construction of environmental infrastructure increases CO_2 emission. Economic growth, energy intensity, and population size are key factors for such increases. GDP per capita, energy intensity, and industry structure are key factors increasing SO_2 emission. Technology progress is a key factor to decrease $PM_{2.5}$ pollution.

Second, EII has an interaction effect with population size, technology progress and economic growth. Economic growth and population size associated with EII increase CO_2 emission and SO_2 emission. Technology progress associated with EII is conducive to decreasing CO_2 emission and SO_2 emission, but has no effect on $PM_{2.5}$ pollution.

Next, regional disparity exists in terms of the effect of EII on emissions reduction. The construction of environmental infrastructure has a positive effect on CO_2 emission and a negative effect on $PM_{2.5}$ pollution in the eastern region. EII increases CO_2 emission in the central region, but decreases SO_2 emission and $PM_{2.5}$ pollution. In the western region, the construction of environmental infrastructure has no significant effect on CO_2 emission, SO_2 emission, and $PM_{2.5}$ pollution, but energy intensity has a significant and positive effect on them.

Finally, EII also has a time-varying effect on emissions reduction. EII increased CO_2 emissions from 2004 to 2014 and decreased CO_2 emission in 2015. EII significantly increased SO_2 emission in 2007–2011, except 2009, then decreased SO_2 emission from 2012 to 2015. The effect of EII on $PM_{2.5}$ pollution is significant but fluctuated, because it decreased $PM_{2.5}$ pollution in 2004, 2005, 2011, and 2012, increased $PM_{2.5}$ pollution in 2006–2010, and in 2013–2015.

Based upon these results, several policy recommendations, such as energy and industrial structure optimization, energy efficiency improvement are raised. However, the effective implementation of these policies relies on local practitioners since different regions are facing different challenges with different endowments.

Acknowledgements This work was supported by the National Natural Science Foundation of China (Grant Nos. 71810107001, 71690241), the Natural Science Foundation of Shandong Province (ZR2017MG019), the Postdoctoral fund (No. 18Z102060077), China Youth Foundation Project of Humanities and Social Sciences of the Ministry of Education (No. 18YJC630148), Shandong Social Science Planning Project (No. 15CGLG19), and a Special Fund for Big Data of Shanghai Jiao Tong University (SJTU-2019UGBD-03).

References

1. Krey V, O'Neill B C, Van Ruijven B, Chaturvedi V, Daioglou V, Eom J, Jiang L, Nagai Y, Pachauri S, Ren X. Urban and rural energy use and carbon dioxide emissions in Asia. Energy Economics, 2012, 34(S3): 272–283
2. Song X Q, Geng Y, Dong H J, Chen W. Social network analysis on industrial symbiosis: a case of Gujiao eco-industrial park. Journal of Cleaner Production, 2018, 193: 414–423
3. Gao Z, Geng Y, Wu R, Chen W, Wu F, Tian X. Analysis of energy-related CO_2 emissions in China's pharmaceutical industry and its driving forces. Journal of Cleaner Production, 2019, 223: 94–108
4. Strand J, Miller S, Siddiqui S. Long-run carbon emission implications of energy-intensive infrastructure investments with a retrofit option. Energy Economics, 2014, 46: 308–317
5. Wu R, Dai H C, Geng Y, Xie Y, Tian X. Impacts of export restructuring on national economy and CO_2 emissions : a general equilibrium analysis for China. Applied Energy, 2019, 248: 64–78
6. Li C, McLinden C, Fioletov V, Krotkov N, Carn S, Joiner J, Streets D, He H, Ren X, Li Z, Dickerson R R. India is overtaking China as the world's largest emitter of anthropogenic sulfur dioxide. Scientific Reports, 2017, 7(1): 1–7
7. Wang Q, Zhao J, Du W, Ana G, Wang Z, Sun L, Wang Y, Zhang F, Li Z, Ye X, Sun Y. Characterization of submicron aerosols at a suburban site in central China. Atmospheric Environment, 2016, 131: 115–123
8. Tian X, Dai H, Geng Y, Wilson J, Wu R, Xie Y, Hao H. Economic impacts from $PM_{2.5}$ pollution-related health effects in China's road transport sector: a provincial-level analysis. Environmental Science & Technology, 2018, 115: 220–229
9. Wang S, Zhou C, Wang Z, Feng K, Hubacek K. The characteristics and drivers of fine particulate matter ($PM_{2.5}$) distribution in China. Journal of Cleaner Production, 2017, 142: 1800–1809
10. Nagpure A S, Ramaswami A, Russell A. Characterizing the spatial and temporal patterns of open burning of municipal solid waste (MSW) in Indian cities. Environmental Science & Technology, 2015, 49(21): 12904–12912
11. National Bureau of Statistics of the People's Republic of China. China Statistical Yearbook on Environment 2016. Beijing: Statistics Press, 2017
12. China Daily. Environmental infrastructure investment will reach 17 trillion yuan, PPP projects are under strict control. 2017–12–04, available at website of baidu
13. Gruver G W. Optimal investment in pollution control capital in a neoclassical growth context. Journal of Environmental Economics and Management, 1976, 3(3): 165–177
14. Wietschel M, Hasenauer U, de Groot A. Development of European hydrogen infrastructure scenarios-CO_2 reduction potential and infrastructure investment. Energy Policy, 2006, 34(11): 1284–1298
15. Jayaraman R, Torre D L, Malik T, Pearson Y E. A polynomial goal programming model with application to energy consumption and emissions in United Arab Emirates. In: Proceedings of the International Conference on Industrial Engineering and Operations Management, Dubai, United Arab Emirates, 2015: 249–253
16. Zhu H, Xia H, Guo Y, Peng C. The heterogeneous effects of urbanization and income inequality on CO_2 emissions in BRICS economies: evidence from panel quantile regression. Environmental Science and Pollution Research International, 2018, 25(17): 17176–17193
17. Denafas G, Sitnikovas D, Galinis A, Kudrenickis I, Klavs G, Kuusik

R. Predicting CO_2 and SO_2 emissions in the Baltic States through reorganization of energy infrastructure. Environment International, 2004, 30(8): 1045–1053

18. Jayasooriya V M, Ng A W M, Muthukumaran S, Perera B J C. Green infrastructure practices for improvement of urban air quality. Urban Forestry & Urban Greening, 2017, 21: 34–47
19. Barandica J M, Fernández-Sánchez G, Berzosa Á, Delgado J A, Acosta F J. Applying life cycle thinking to reduce greenhouse gas emissions from road projects. Journal of Cleaner Production, 2013, 57: 79–91
20. Fuller S, Gillis M, Parnell C, Ramaiye r A. Effect of investment in air pollution controls on financial performance of Texas cotton gins: a simulation analysis. Departmental Reports, 1997, 171: 71–76
21. Peters G P, Weber C L, Dabo G, Hubacek K. China's growing CO_2 emissions–a race between increasing consumption and efficiency gains. Environmental Science & Technology, 2007, 41(17): 5939–5944
22. Ozcan-Deniz G, Zhu Y. Multi-objective optimization of greenhouse gas emissions in highway construction projects. Sustainable Cities and Society, 2017, 28: 162–171
23. Bottalico F, Chirici G, Giannetti F, De Marco A, Nocentini S, Paoletti E, Salbitano F, Sanesi G, Serenelli C, Travaglini D. Air pollution removal by green infrastructures and urban forests in the city of Florence. Agriculture and Agricultural Science Procedia, 2016, 8: 243–251
24. Xu B, Lin B. Regional differences of pollution emissions in China: contributing factors and mitigation strategies. Journal of Cleaner Production, 2016, 112: 1454–1463
25. Ehrlich P R, Holdren J P. Impact of population growth. Science, 1971, 171(3977): 1212–1217
26. Feng K, Hubacek K, Guan D. Lifestyles, technology and CO_2 emissions in China: a regional comparative analysis. Ecological Economics, 2009, 69(1): 145–154
27. Shafiei S, Salim R A. Non-renewable and renewable energy consumption and CO_2 emissions in OECD countries: a comparative analysis. Energy Policy, 2014, 66: 547–556
28. York R, Rosa E A, Dietz T. STIRPAT, IPAT and IMPACT: analytic tools for unpacking the driving forces of environmental impacts. Ecological Economics, 2003, 46(3): 351–365
29. Dietz T, Rosa E A. Rethinking the environmental impacts of population, affluence and technology. Human Ecology Review, 1994, 1: 277–300
30. Liddle B. What are the carbon emissions elasticities for income and population? Bridging STIRPAT and EKC via robust heterogeneous panel estimates. Global Environmental Change, 2015, 31: 62–73
31. Li W, Sun S. Air pollution driving factors analysis: evidence from economically developed area in China. Environmental Progress & Sustainable Energy, 2016, 35(4): 1231–1239
32. Wang Y W, Han R, Kubota J. Is there an environmental Kuznets curve for SO_2 emissions? A semi-parametric panel data analysis for China. Renewable & Sustainable Energy Reviews, 2016, 54: 1182–1188
33. Xu B, Lin B. What cause large regional differences in $PM_{2.5}$ pollutions in China? Evidence from quantile regression model. Journal of Cleaner Production, 2018, 174: 447–461
34. Fan Y, Liu L C, Wu G, Wei Y M. Analyzing impact factors of CO_2 emissions using the STIRPAT model. Environmental Impact Assessment Review, 2006, 26(4): 377–395
35. Rafiq S, Salim R, Nielsen I. Urbanization, openness, emissions, and energy intensity: a study of increasingly urbanized emerging economies. Energy Economics, 2016, 56: 20–28
36. Poumanyvong P, Kaneko S. Does urbanization lead to less energy use and lower CO_2 emissions? A cross-country analysis. Ecological Economics, 2010, 70(2): 434–444
37. Xie R, Fang J, Liu C. The effects of transportation infrastructure on urban carbon emissions. Applied Energy, 2017, 196:199–207
38. Jia J, Deng H, Duan J, Zhao J. Analysis of the major drivers of the ecological footprint using the STIRPAT model and the PLS method—a case study in Henan province, China. Ecological Economics, 2009, 68(11): 2818–2824
39. Sahely H R, Kennedy C A, Adams B J. Developing sustainability criteria for urban infrastructure systems. Canadian Journal of Civil Engineering, 2005, 32(1): 72–85
40. Li K, Zhang N, Liu Y. The energy rebound effects across China's industrial sectors: an output distance function approach. Applied Energy, 2016, 187: 1165–1175
41. Liu M, Huang Y, Jin Z, Ma Z, Liu X, Zhang B, Liu Y, Yu Y, Wang J, Bi J, Kinney P L. The nexus between urbanization and $PM_{2.5}$ related mortality in China. Environmental Pollution, 2017, 227: 15–23
42. Prashant Kumar B I. Footprints of air pollution and changing environment on the sustainability of built infrastructure. Science of the Total Environment, 2013, 444: 85–101
43. Liu Z, Guan D, Wei W, Davis S J, Ciais P, Bai J, Peng S, Zhang Q, Hubacek K, Marland G, Andres R J, Crawford-Brown D, Lin J, Zhao H, Hong C, Boden T A, Feng K, Peters G P, Xi F, Liu J, Li Y, Zhao Y, Zeng N, He K. Reduced carbon emission estimates from fossil fuel combustion and cement production in China. Nature, 2015, 524(7565): 335–338
44. Guan D, Meng J, Reiner D M, Zhang N, Shan Y, Mi Z, Shao S, Liu Z, Zhang Q, Davis S J. Structural decline in China's CO_2 emissions through transitions in industry and energy systems. Nature Geoscience, 2018, 11(8): 551–555
45. Li K, Lin B. How to promote energy efficiency through technological progress in China? Energy, 2018, 143: 812–821
46. Li K, Lin B. Impacts of urbanization and industrialization on energy consumption/CO_2 emissions: does the level of development matter? Renewable & Sustainable Energy Reviews, 2015, 52: 1107–1122
47. Li K, Lin B. The nonlinear impacts of industrial structure on China's energy intensity. Energy, 2014, 69: 258–265
48. Wang Y, Sun Y, Wei L I. Research on the impact of population-related factors on carbon emission: an empirical analysis based on the varying-intercept model. Ecological Economics, 2017, 33: 19–23
49. Fan F, Lei Y. Factor analysis of energy-related carbon emissions: a case study of Beijing. Journal of Cleaner Production, 2017, 163: 277–283
50. Yang Y, Zhao T, Wang Y, Shi Z. Research on impacts of population-related factors on carbon emissions in Beijing from 1984 to 2012. Environmental Impact Assessment Review, 2015, 55: 45–53
51. Zhang N, Yu K, Chen Z. How does urbanization affect carbon

dioxide emissions? A cross-country panel data analysis. Energy Policy, 2017, 107: 678–687
52. Fujita M, Krugman P R, Venables A J. The Spatial Economy: Cities, Regions, and International Trade. Boston: MIT Press, 2011, 86: 283–285
53. Fujita M, Thisse J F. Does geographical agglomeration foster economic growth? And who gains and losses from it? Japanese Economic Review, 2003, 54(2): 121–145
54. Wooldridge M, Jennings N R, Kinny D. A methodology for agent-oriented analysis and design. The third annual conference,1999. 2019–10–08, available at website of citeseerx.ist.psu.edu
55. Hamilton L C. Statistics with STATA –Version 12. Boston: Cengage Learning, 2012
56. Wooldridge J M. Introductory Econometrics: a Modern Approach. Nelson Education, 2015
57. Liddle B. Impact of population, age structure, and urbanization on carbon emissions/energy consumption: evidence from macro-level, cross-country analyses. Population and Environment, 2014, 35(3): 286–304
58. Finance and Economics Committee of the National People's Congress. The 7th Five-Year Plan of People's Republic of China (1986–1990). Beijing: People's Publishing Press, 1987
59. Lin W X. The causes of the unbalanced economic development between the east and the west in the history of China. Ideological Front, 2001, 27: 1–9
60. Liu Y. Proposal on rise of the central region. Journal of Zhengzhou Institute of Aeronautical Industry Management, 2005, 23: 1–8 (in Chinese)
61. Ono K A, Boness D J, Oftedal O T. The effect of a natural environmental disturbance on maternal investment and pup behavior in the California sea lion. Behavioral Ecology and Sociobiology, 1987, 21(2): 109–118
62. Nehrt C. Time and intensity effects of environmental investments. Strategic Management Journal, 2015, 17(7): 535–547
63. He J. Pollution haven hypothesis and environmental impacts of foreign direct investment: the case of industrial emission of sulfur dioxide (SO) in Chinese provinces. Ecological Economics, 2007, 60 (1): 228–245
64. Zhang Y, Liu C, Ke L, Zhou YStrategy on China's regional coal consumption control: a case study of Shandong province. Energy Policy, 2018, 112: 316–327
65. Li Y, Zhang F, Yuan J. Research on China's renewable portfolio standards from the perspectives of policy networks. Journal of Cleaner Production, 2019, 222: 986–997