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RESEARCH ARTICLE

Does technological innovation improve energy-environmental efficiency? New evidence from China's transportation sector

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Abstract
The rapid modernization of the transportation sector has greatly escalated many problems, especially the high energy consumption and vehicle exhaust pollution. How to reduce pollution in the transportation sector has attracted widespread attention in recent years. Based on a balanced panel dataset of 30 Chinese provinces spanning the period of 2005–2017, this study attempts to investigate the influence of technological innovation on the energy-environmental efficiency of the transportation sector (EETS) using the spatial econometric approach. The empirical results suggest that first, transportation-related technological innovation and EETS exhibited obvious hot spots and cold spots at the provincial level in China. Second, technological innovation could facilitate the energy-environmental efficiency of transportation sector in China. Third, one province developing transportation-related technological innovations might promote EETS in its neighboring provinces. Fourth, the transportation-related technological innovation in eastern China could boost EETS, while the transportation-related technological innovation in central and western China had a rebound effect on EETS. One possible innovation is that this study extends the relationship between technological innovation and energy-environmental efficiency to the transportation sector.

Keywords Technological innovation · Energy-environmental efficiency · Transportation sector · Spatial econometric model · DEA model · China

Introduction

Accelerated development in the global economy has brought many serious problems, among which environmental pollution, ecological destruction, and resource shortage have become global crises (Landrigan et al. 2018; Zhu et al. 2020). Energy-environmental efficiency is a cost-effective means to ameliorate the energy-shortage situation, cut pollution emissions, and protect the ecological environment, thus enabling to attain sustainable development goals (Malinauskaite et al. 2020). China's transportation sector has made astounding advances over the last two decades, but it has a high dependence on energy sources, therefore, facing increasing environmental pressure (Dong and Liu 2020; Hua et al. 2021). Figure 1 exhibits that the count of private car in China soared from 18.48 million in 2005 to 185.15 million in 2017. Transportation-related CO_2 emissions in China increased rapidly from 337.8 million tons in 2005 to 696.3 million tons in 2017. The ratio of transportation-related CO_2 emissions (TCEs) to total CO_2 emissions showed an upward trend from 2005 to 2017. Notably, the annual growth rate of TCEs was obviously higher than that of total CO_2 emissions, except in 2010, 2011, and 2013 (Fig. 1). Hence, how to raise EETS is one of the core issues to be solved for China's sustainable development (Martínez et al. 2019).

In response to environmental pollution, the Chinese government has issued a basket of transportation targets and policies for the transition to low-carbon travel. For instance, in 2015, the Ministry of Transport of China proposed that new energy vehicles will be given priority in public transportation. In 2019, the Chinese government issued the Outline for Building a Powerful Transportation Country. This outline pointed out that China's transportation sector should optimize the transportation energy structure and promote the

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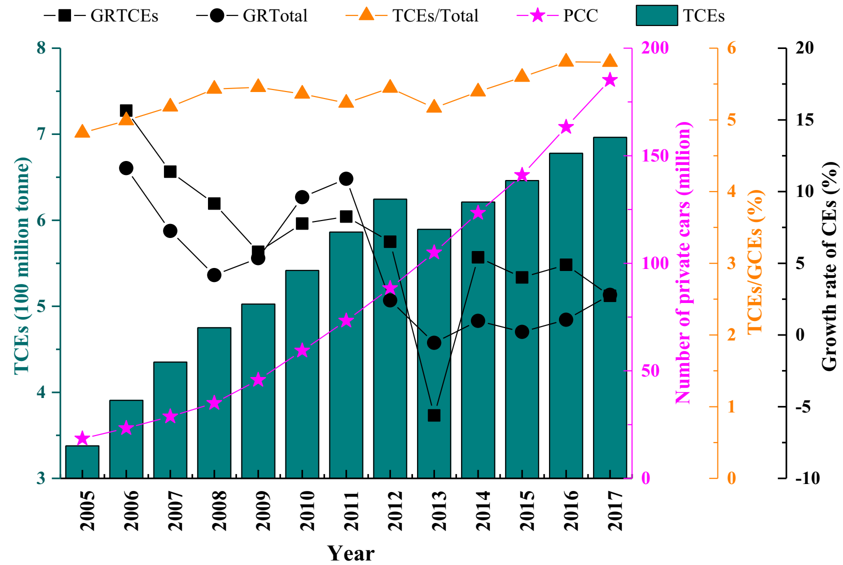


Fig. 1 Transportation CO_2 emissions and private car count in China, 2005–2017. Note: GRTCEs represents the growth rate of TCEs; GRTotal means the growth rate of total CO_2 emissions; GRTCEs and GRTotal are based on the previous year. Total represents total CO_2 emissions; PCC is the private car count. TCEs/Total denotes the ratio of transportation-related CO_2 emissions to total CO_2 emissions. Source: CSY (n.d.); CESY (n.d.)

application of new and clean energy. Besides, some researchers have thrown light on the measures of energy efficiency in the transportation sector (Cui and Li 2014; Zhang et al. 2020a; Zhu et al. 2020). Although evidence on the impact of technological innovation on energy efficiency has been documented in some studies (Irandoust 2019; Ohene-Asare et al. 2020; Sohag et al. 2015; Wang and Wang 2020), there are very few detailed investigations of the relationship between technological innovation and energy-environmental efficiency in the transportation sector. Thus, based on a balanced panel dataset of 30 Chinese provinces, this study seeks to elaborate the relationship between transportation-related technological innovation and EETS using the spatial econometric approach.

Compared to extant literature, this study has two new contributions. First, this work brings insights on the effect of technological innovation on energy efficiency in the transportation sector, which, despite its significance for sustainable development, has rarely been paid attention to in existing studies. Second, this work is related to the small but growing literature on economic geography (Song et al. 2018; Zhang et al. 2018). The development of the transportation sector is closely related to economy, population, and natural environment, which makes the transportation sector spatially dependent in real life, but the spatial agglomeration of the transportation sector has received little attention in previous studies. In this study, the geographical space adjacency is taken into account when examining the influence of transportation-related technological innovation on EETS.

The remainder of the study proceeds: "Related literature" reviews related literature from two aspects: methods applied to measure energy efficiency and the influence of technological innovation on energy efficiency; "Variable construction and empirical models" describes the variable construction and empirical models; "Results" and "Discussion" show and discuss the estimated results of the spatial econometric approach; "Conclusions and implications" is the conclusions and recommendations.

Related literature

Methods applied to measure energy efficiency

In general, the indicators used for measuring energy efficiency can be divided into single-factor indicators (SFIs) and total-factor indicators (TFIs). SFIs include monetary energy efficiency indicators and physical indicators (Bhadbhade et al. 2020). The monetary energy efficiency indicators are mainly constructed by the energy consumption/economic output. For instance, Irandoust (2019) used the energy consumption/GDP to proxy energy performance. The physical indicators relate the total energy consumed to some physical activities (Zuberi et al. 2020; Ren et al. 2020). For instance, Malinauskaite et al. (2020) used the energy consumption indicators to study the industrial energy performance in the European Union, Slovenia, and Spain respectively, and they found that Slovenia and Spain, which are highly dependent on imported energy, have shown great potential for improving energy efficiency. It is worth noting that single factor indicators are mostly result-oriented, therefore, failing to consider the entire input-output process of production.

The DEA models that perform well in complex systems are widely utilized to define TFIs (Chen and Xu 2019; Li et al. 2021; Ohene-Asare et al. 2020; Song et al. 2018). Using the spatial two-stage DEA approach, Simona et al. (2019) surveyed the environmental and energy efficiency for EU electricity industry in the period of 2006–2014, and they found that there is a two-way influence between environmental regulations and total-factor productivity. Besides, in real life, there are not only desirable outputs (GDP) but also undesirable outputs (environmental pollution) after energy consumption. To this end, some researchers have developed the DEA model with undesirable output, but the traditional undesirable DEA model cannot sort the effective decision-making units. Accordingly, Andersen and Petersen (1993) developed an undesirable super-SBM model that performs well in the ranking of decision-making units. Using the DEA model, Iram et al. (2020) investigated energy and environmental efficiency in OECD countries.

As for the transportation sector, existing literature mostly utilizes DEA models to evaluate energy efficiency. For example, Cui and Li (2014) used the three-stage virtual frontier DEA mode to assess the EETS in China during 2003–2012, and they found that transport structure and management measures obviously affect EETS. Taking the 30 Chinese provinces as an example, Zhang et al. (2020a) studied the growth-adjusted energy efficiency in the transportation sector through the Metaglobal frontier DEA model. They found that the EETS in central China is relatively high. Based on the improved DEA mode, Zhu et al. (2020) found that some economically developed regions in China have poor sustainable transportation efficiency.

Technological innovation and energy efficiency

According to the neoclassical growth theory, the key factors affecting aggregate production output are labor, capital, and technological change (Solow 1999). In practical terms, technological change consists of developing new technologies and updating old technologies (Kopytov et al. 2018). Updating old technologies aims to improve existing technologies, and developing new technologies aims to create technologies that do not currently exist. Technological innovation can reduce the energy intensity of production enterprises, therefore, enabling to drive energy efficiency (Irandoust 2019). Numerous researchers have investigated the influence of technological innovation on energy efficiency, and they detected a positive influence. For example, Sohag et al. (2015) utilized the autoregressive distributed lag to examine how technological innovation affects energy use in Malaysia, and they revealed a negative impact. Using the structure vector auto-regression, Pan et al. (2019) demonstrated that technological innovation contributes significantly to energy efficiency. Taking 46 African countries as an example, Ohene-Asare et al. (2020) analyzed the relationship between energy efficiency and economic development, and they empirically found a positive influence. Taking a woolen textile facility as an example, Ozturk et al. (2020) explored whether appropriate techniques can reduce energy consumption and air emissions. They confirmed that the energy consumption and pollutant emissions in the woolen textile facility can be reduced by 12–28% and 23–45% respectively due to the application of energy efficiency technologies. Based on the China–Japan comparison, Liao and Ren et al. (2020) investigated the effects of energy-biased technology on energy efficiency, and they argued that technological innovation in China's manufacturing industry positively affects the energy efficiency at this stage. Using the Meta-frontier DEA model, Feng and Wang (2018) investigated the TEE in China during 2006–2014, and they proposed that technological progress has driven significant improvements in transport energy efficiency.

Besides, technological innovation can develop energy-biased technology, improve the efficiency of energy resource utilization, and thus cut energy prices. In a market economy, the reduction of energy prices is bound to bring about an increase in energy demand. This energy demand increase is referred to as the rebound effect or Jevons paradox, as it offsets the drop in energy demand caused by increased efficiency (Aydin et al. 2017; Sheng et al. 2019). Evidence of the rebound effect has been documented in a number of studies. Taking China's transportation sector as an example, Liu et al. (2018) calculated the energy rebound effect in the period of 1981–2015 using the translog production function, and they reported that there is an energy rebound effect in China's transportation sector, with an average rebound effect of 68.3%. Yu (2020) found that technological innovation has no significant effect on total-factor energy efficiency in China. Based on the Chinese 284 cities, Wang and Wang (2020) studied how technological innovation affects energy efficiency through the system GMM model, and they suggested that technological innovation negatively affects the energy efficiency in the central region. Using the Geographically Temporally Weighted Regression, Zhang et al. (2020b) surveyed the driving factors of China's energy efficiency during 2000–2015, and they detected a negative influence of technical level on the energy efficiency in the western region.

Summary of the literature review

Surveying prior studied on technological innovation and energy efficiency, we found that to date, studies investigating the influence of technological innovation on energy efficiency have produced equivocal results. Moreover, very few researchers pay attention to how technological innovation affects energy-environmental efficiency in the transportation sector, while the transportation sector is commonly regarded as the industry with high energy consumption and high environmental pollution. Notably, existing studies on technological innovation and EETS focus on the technological progress of the whole society, and none of them focus on transportation-related technological innovation in their investigation. In addition, in real life, the development of the transportation sector is significantly influenced by spatial location, but the spatial agglomeration of the transportation sector has rarely been considered in previous studies. Therefore, this study attempts to find out the impact of transportation-related technology innovation on EETS using the spatial econometric approach.

Variable construction and empirical models

Variable construction

Dependent variable

The dependent variable is set as EETS. The basic idea of this study to assess energy-environmental efficiency is to minimize the undesirable output (transportation-related CO_2 emissions) in the case of maximizing desirable output (transportation-related GDP). Figure 2 shows the diagram of EETS.

Suppose there are n decision-making units$DMU_j (j = 1, 2, 3, \ldots, n)$, m inputs$U = [u_1, \ u_2, \ldots, u_n] \in R^{m \times n}$, s_1 desirable outputs$O^g = \left[o_1^g, \ o_2^g, \ldots, o_n^g\right] \in R^{s_1 \times n}$, and s_2 undesirable outputs $O^b = \left[o_1^b, \ o_2^b, \ldots, o_n^b\right] \in R^{s_2 \times n}$. The production possibility set is expressed by Eq. (1):

$$P = \left\{ \left(u, \ o^g, \ o^b\right) \middle| u \geq U\xi, \ o^g \leq O\xi, \ o^b \geq O\xi, \ \xi \geq 0 \right\} \tag{1}$$

where ξ represents the non-negative intensity vector. Following Tone (2004), we constructed the SBM model with undesirable output as follows:

$$\theta^* = \min \frac{1 - \frac{1}{m} \sum_{i=1}^{m} \frac{s_i}{u_{i0}}}{1 + \frac{1}{s_1 + s_2} \left(\sum_{r=1}^{s_1} \frac{s_r^g}{o_{r0}^g} + \sum_{r=1}^{s_2} \frac{s_r^b}{o_{r0}^b} \right)}$$
$$s.t. \begin{cases} u_0 = U\xi + s \\ o_0^b = O^b \xi + s^b \\ o_0^g = O^g \xi - s^g \\ s^b \geq 0 \ , s \geq 0 \ , \ s^g \geq 0, \ \xi \geq 0 \end{cases} \tag{2}$$

where θ^* is the calculated efficiency score of DMU, and it has a range of [0,1]. s is the input slack vector. s^g and s^b are output slack vectors. Using Charnes-Cooper transformation, we transformed the nonlinear Eq. (2) into the linear Eq. (3):

$$\varphi^* = \min \left(k - \frac{1}{m} \sum_{i=1}^{m} \frac{s_i}{u_{i0}} \right)$$
$$s.t \begin{cases} k + \frac{1}{s_1 + s_2} \left(\sum_{r=1}^{s_1} \frac{s_r^g}{o_{r0}^g} + \sum_{r=1}^{s_2} \frac{s_r^b}{o_{r0}^b} \right) = 1 \\ k u_0 = \vartheta U + s \\ k o_0^b = \vartheta O^b + s^b \\ k o_0^g = \vartheta O^g - s^g \\ s^b \geq 0 \ , \ s \geq 0 \ , \ s^g \geq 0 \\ \vartheta \geq 0 \ , \ k \geq 0 \end{cases} \tag{3}$$

It is worth noting that there will be multiple DMUs whose efficiency score is 1 when Eq. (3) is performed. In other words, Eq. (3) fails in discriminating those effective DMUs. To this end, we improved Eq. (3) and constructed the undesirable super-SBM model (Andersen and Petersen 1993; Tone 2002):

$$\eta^* = \min \left[\frac{\frac{1}{m} \sum_{i=1}^{m} \frac{\overline{u_i}}{u_{i0}}}{\frac{1}{s_1 + s_2} \left(\sum_{r=1}^{s_1} \frac{\overline{o}_r^g}{o_{r0}^g} + \sum_{r=1}^{s_2} \frac{\overline{o}_r^b}{o_{r0}^b} \right)} \right]$$
$$s.t \begin{cases} \overline{u} \geq \sum_{j=1, \ \neq 0}^{n} \xi_j u_j \\ \overline{o}^g \leq \sum_{j=1, \ \neq 0}^{n} \xi_j o_j^g \\ \overline{o}^b \geq \sum_{j=1, \ \neq 0}^{n} \xi_j o_j^b \\ \overline{u} \geq u_0, \ \overline{o}^g \leq o_0^g, \overline{o}^b \geq o_0^b, \ \overline{o}^g \geq 0, \ \xi \geq 0 \end{cases} \tag{4}$$

where η^* is the calculated efficiency score of DMU, and $\eta^* \geq 0$. In our case, the transportation-related inputs and outputs were assumed to be constant returns to scale. Following Zhang et al. (2020a) and Zhu et al. (2020), inputs $U = [u_1, \ u_2, \ldots, u_n] \in R^{m \times n}$ in our case are set to transportation-related capital (tcapit), transportation-related labor (tlabor), and transportation-related energy consumption

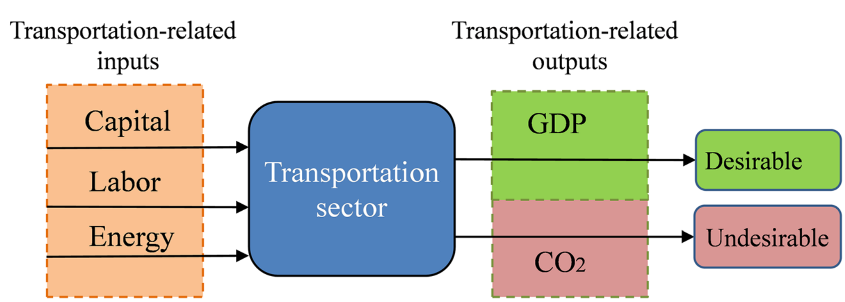


Fig. 2 Diagram of EETS

(tconsu); desirable output $O^g = \left[o_1^g,\ o_2^g, \ldots, o_n^g\right] \in R^{s_1 \times n}$ is transportation-related GDP (tgdp); undesirable output $O^b = \left[o_1^b,\ o_2^b, \ldots, o_n^b\right] \in R^{s_2 \times n}$ is transportation-related carbon emissions (tcarbo). The data on tgdp, tcapit, and tlabor are obtained by CSY. The data on tcarbo was calculated by the fuel-based carbon footprint model (Appendix 1) Appendix Table 8.

Explanatory variable

Inconsistent with existing related research, the technological innovation in this study refers to transportation-related technological innovation rather than the technological innovation of the whole society. Transportation-related technological innovation (TTI) is considered as the main explanatory variable. Various proxy measures of technological innovation are available in previous studies, such as the number of patent applications, research and development investment, and technological progress (Omri and Bel Hadj 2020; Zameer et al. 2020). Following previous research (Ahmad et al. 2020; Yasmeen et al. 2020), the number of the transportation-related patent is used as the proxy for transportation-related technological innovation. The transportation-related technology in this study involves five aspects, namely general vehicle, railway, trackless land vehicle, ship-related equipment, and aircraft (Table 1). Using the International Patent Classification (IPC) code, we obtained the counts of transportation-related patents from the official search website (http://pss-system.cnipa.gov.cn/).

Control variables

Based on the previous studies and data availability, this study selects three socio-economic indicators as control variables, namely GDP per capita, industrial agglomeration, and urbanization level.

(1) GDP per capita (PGDP). Regions with high GDP per capita generally have advanced energy utilization technologies and pay more attention to environmental regulations. Extensive studies have confirmed the positive relationship between GDP per capita and energy efficiency (Lv et al. 2020; Ohene-Asare et al. 2020).

(2) Industrial agglomeration (IA). Industrial agglomeration is beneficial to shorten the distance of transportation and improve transportation efficiency. Besides, industrial agglomeration leads to pollution agglomeration aggravating regional environmental pollution (Dong et al. 2020). Following Morrissey (2014), this study uses the location quotient index to calculate industrial agglomeration:

$$IA_i = \frac{indu_i / \sum\limits_{i=1}^{n} indu_i}{GDP_i / \sum\limits_{i=1}^{n} GDP_i} \tag{5}$$

where $indu_i$ denotes the added value of the secondary industry in province i. n stands for the count of provinces. GDP_i represents the GDP of province i.

(3) Urbanization level (UL). Regions with high levels of urbanization generally have good transportation infrastructure. In addition, rapid urbanization leads to lower woody plant coverage and more energy consumption, which is not conducive to emission reduction (Dong et al. 2019). The level of urbanization is represented by the share of the urban population in the total population of the province.

Data sources

The study area (Appendix Figure 8) includes a representative sample of 30 Chinese provinces (Tibet, Hong Kong, Macau, and Taiwan are not included due to lack of data). 2005 was an important time point for China's CO_2 emissions since China's per capita CO_2 emissions after 2005 were significantly higher than the world level. Thus, the time span of the sample in this study is from 2005 to 2017. Besides, the data on tcapit, tgdp, and PGDP is converted into the 2005 constant price. Table 2 details the statistical description and data sources for the above variables. The data on PGDP, IA, and UL are collected by CSY. Figure 3 illustrates the analytical framework of this study.

Table 1 Patent IPC code related to transportation

	Energy type	IPC codes
Transportation-related technological innovation	General vehicle	B60
	Railway	B61
	Trackless land vehicle	B62
	Ship-related equipment	B63
	Aircraft; aviation; space navigation	B64

Table 2 Statistical description and data sources of the variables

Indicators	Variables	Unit	Mean	Max.	Min.	S.D.
Explained variable	EETS	-	0.51	1.38	0.10	0.29
Main explanatory variable	TTI	Item	3,562.02	46,711.00	5.00	6,138.48
Control variables	PGDP	10^3 yuan	38.74	128.99	5.05	24.18
	IA	-	0.97	1.21	0.44	0.16
	UL	%	52.96	89.60	26.87	13.94

Empirical models

In this section, the empirical models used to explore how transportation-related technological innovation influences EETS are presented. First, we examined whether EETS and transportation-related technological innovation are spatially dependent. Through the spatial autocorrelation model, we conducted a spatial autocorrelation test on transportation-related technological innovation and EETS ("Spatial autocorrelation test"). Then, we sought to find out the relationship between transportation-related technological innovation and EETS using the spatial panel econometric approach ("Model for assessing the influence of transportation-related technological innovation on EETS").

Spatial autocorrelation test

Spatial autocorrelation test consists of the global Moran's I (MI^{global}) and local Moran's I (MI^{local}) (Moran 1953). The MI^{global} assesses the spatial dependence of the overall study region (Dong et al. 2019), and the MI^{local} focuses on the local regions:

$$\begin{cases} MI^{global} = \dfrac{n\sum_{i=1}^{n}\sum_{j=1,\ i\neq j}^{n} W_{ij}\left(X_i-\overline{X}\right)\left(X_j-\overline{X}\right)}{\left(\sum_{i=1}^{n}\sum_{j=1,\ i\neq j}^{n} W_{ij}\right)\sum_i^n\left(X_i-\overline{X}\right)^2} \\ MI^{local} = \dfrac{n\left(X_i-\overline{X}\right)\sum_{j=1,\ i\neq j}^{n} W_{ij}\left(X_j-\overline{X}\right)}{\sum_i^n\left(X_i-\overline{X}\right)^2} \end{cases} \tag{6}$$

where X means variables (i.e., EETS and TTI). X_i and X_j respectively represent the X in area i and area j. n stands for the count of regions. $\overline{X}$ is the mean value of X among the n regions. W_{ij} means the spatial weight, which defines the spatial relationship among regions. Considering the characteristics of the transportation sector, the spatial adjacent weight matrix was used to define the spatial relationship of regions in our case:

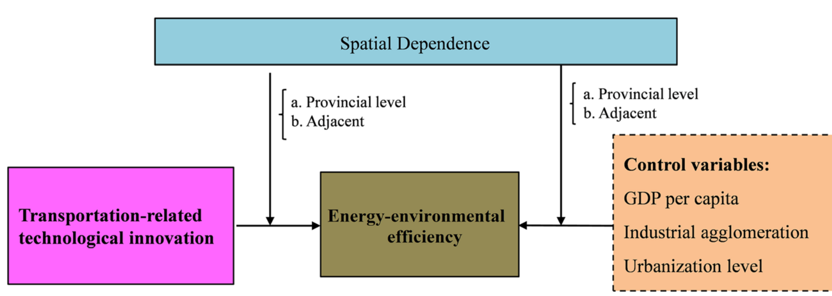
$$W_{ij} = \begin{cases} 1 & \text{if area } i \text{ and area } j \text{ are adjacent} \\ 0 & \text{if area } i \text{ and area } j \text{ are not adjacent} \end{cases} \tag{7}$$

The estimated results of MI^{local} exhibit four types of cluster: High-High (hot spot), High-Low, Low-Low (cold spot), and Low-High. The High-High cluster means that provinces with high EETS are surrounded by neighbors with high EETS. The High-Low cluster suggests that provinces with high EETS are surrounded by neighbors with low EETS.

Model for assessing the influence of transportation-related technological innovation on EETS

Spatial panel econometric model is an improved panel ordinary least square model (POLS), which considers spatial dependence in explanatory variables, explained variable, and error term (Wang and Zhu 2020). The spatial panel lag model (SPLM) captures the spatial dependence in the explained variable; the spatial panel error model (SPEM) captures the spatial dependence in the error term; the spatial panel Dubin model (SPDM) captures the spatial dependence in explanatory and explained variables (Zhu et al. 2019). The spatial panel econometric model was constructed by Eq. (8):

Fig. 3 Analytical framework



$$\begin{cases} y_{it} = \alpha_i + \beta \overrightarrow{X}_{it} + \pi \sum\limits_{j=1}^{n} W_{ij} y_{jt} + \chi \sum\limits_{j=1}^{n} W_{ij} \overrightarrow{X}_{jti} + e_{it} \\ e_{it} = \gamma W e_{it} + \varepsilon_{it} \end{cases} \tag{8}$$

where y_{it} denotes explained variable. $\overrightarrow{X}_{it}$ means the vector consisting of explanatory variables. W_{ij} is the spatial weight matrix obtained by Eq. (7). β denotes the coefficient. α_i is the constant. Parameters π, χ, and γ represent the spatial regression coefficients. e_{it} denotes the error term. When $\pi = \chi = \gamma = 0$, Eq. (8) is the POLS model; when $\pi \neq 0$, $\chi = \gamma = 0$, Eq. (8) represents the SPLM model; when $\pi = \chi = 0$, $\gamma \neq 0$, Eq. (8) is the SPEM model; when $\pi \neq 0$, $\chi \neq 0$, $\gamma = 0$, Eq. (8) is transformed into the SPDM model (Zhu et al. 2019; Zhu et al. 2020a). According to Eq. (8), the spatial panel econometric model of transportation-related technological innovation on EETS was constructed:

$$\begin{cases} EETS_{it} = \alpha_i + \beta_1 TTI_{it} + \beta_2 PGDP_{it} + \beta_3 IA_{it} + \beta_4 UL_{it} + \psi \sum\limits_{j=1}^{n} W_{ij} EETS_{jt} + \\ \varpi_1 \sum\limits_{j=1}^{n} W_{ij} TTI_{it} + \varpi_2 \sum\limits_{j=1}^{n} W_{ij} PGDP_{it} + \varpi_3 \sum\limits_{j=1}^{n} W_{ij} IA_{it} + \varpi_4 \sum\limits_{j=1}^{n} W_{ij} UL_{it} + e_{it} \\ e_{it} = \tau W e_{it} + \varepsilon_{it} \end{cases} \tag{9}$$

Results

Spatial characteristics of EETS

According to Eq. (4), the energy-environmental efficiency in China's transportation sector was evaluated (see Fig. 4). We selected three time points in 2005, 2011, and 2017 (i.e., starting, intermediate, and ending points) to draw the spatial patterns of EETS in China. In general, the annual average value of EETS exhibited a downward trend, dropping from 0.563 in 2005 to 0.473 in 2017. Figure 5a–c illustrates that there were obvious spatial distribution differences in China's provincial-level EETS in 2005, 2011, and 2017. To be specific, eastern China, such as Hebei, Tianjin, Shandong, Fujian, and Jiangsu, had relative advantages in the EETS. The average values of EETS for these provinces were all above 0.7, suggesting that these provinces were more effective in terms of transportation-related energy inputs and outputs. The provinces with low EETS, such as Xinjiang, Yunnan, Sichuan, Qinghai, Guangxi, and Chongqing, were mainly located in the western region.

Spatial autocorrelation analysis

According to Eq. (6), the spatial autocorrelation model was established to investigate whether EETS in one province benefits from its neighboring provinces. The MI^{global} values of EETS tended to increase in the study period of 2005–2017 (Fig. 6), indicating that the provincial-level EETS was correlated among neighboring provinces in China. In addition, we conducted a spatial correlation analysis for the transportation-related technological innovation. The MI^{global} values of TTI all passed the 5% significance test, suggesting that during the sample period, the transportation-related technological

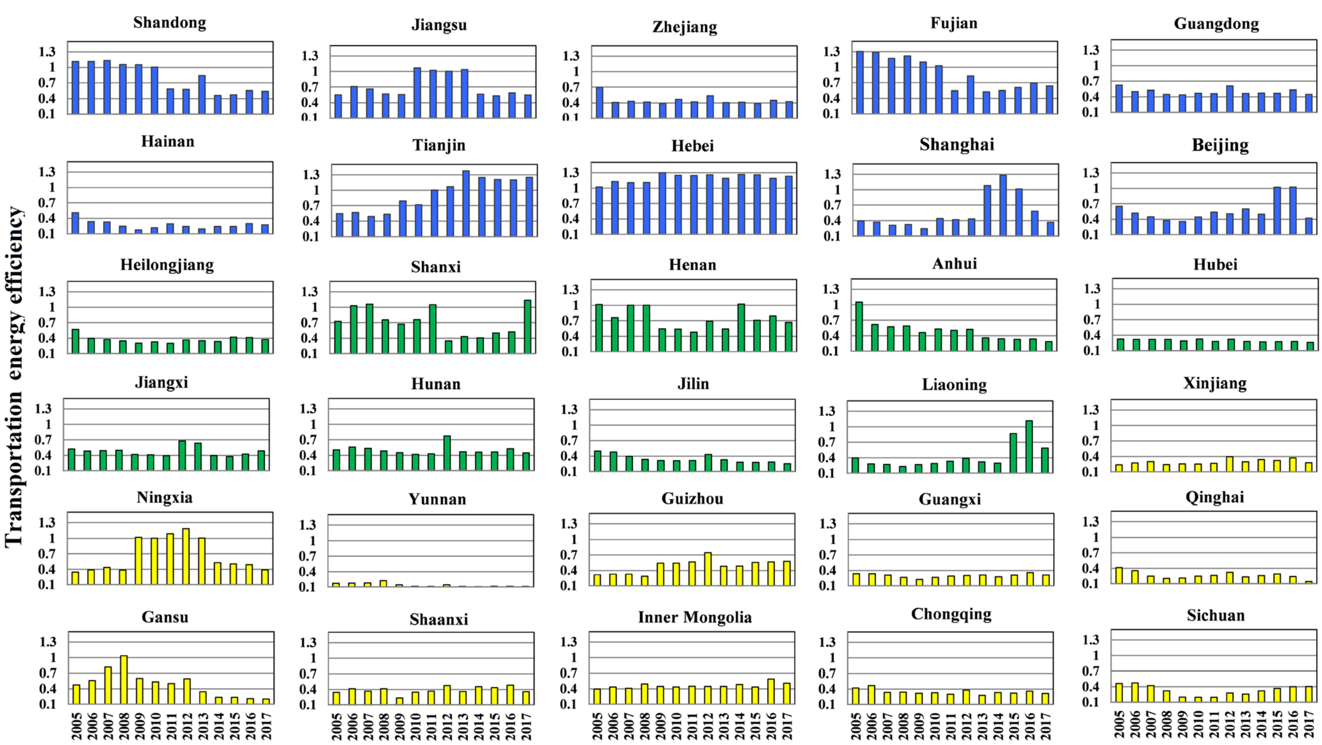


Fig. 4 Calculated results of EETS in China, 2005–2017. Notes: Eq. (3) is used to calculate for EETS. Blue indicates eastern China; green represents central China; yellow denotes western China

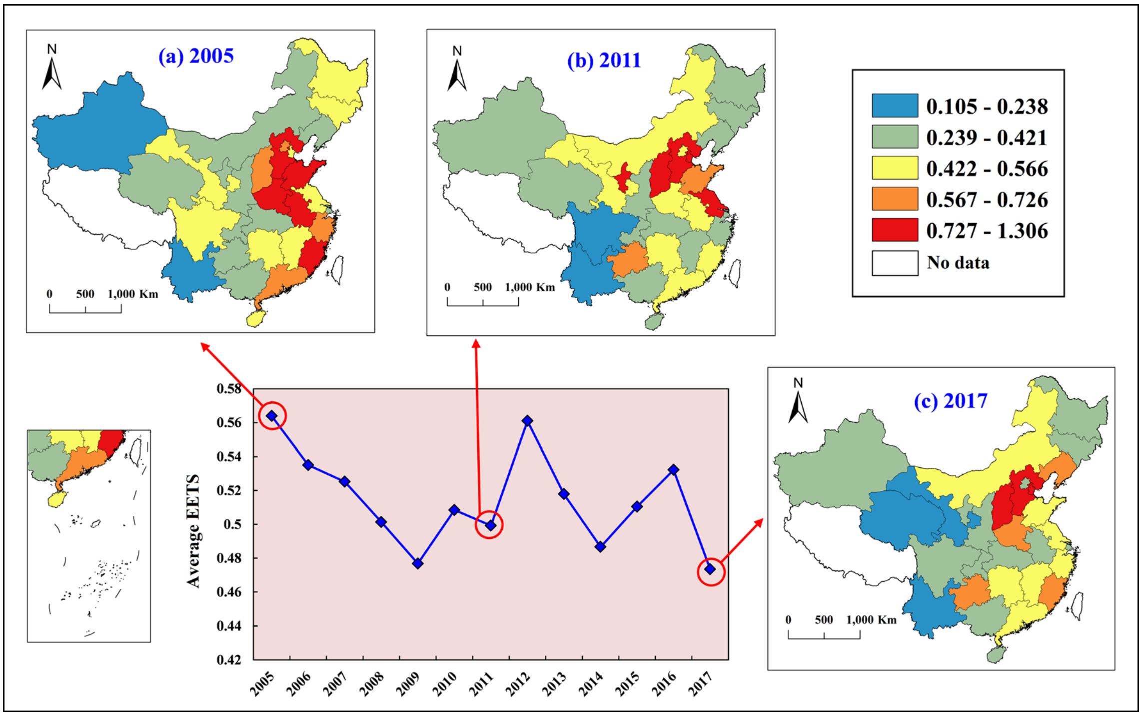


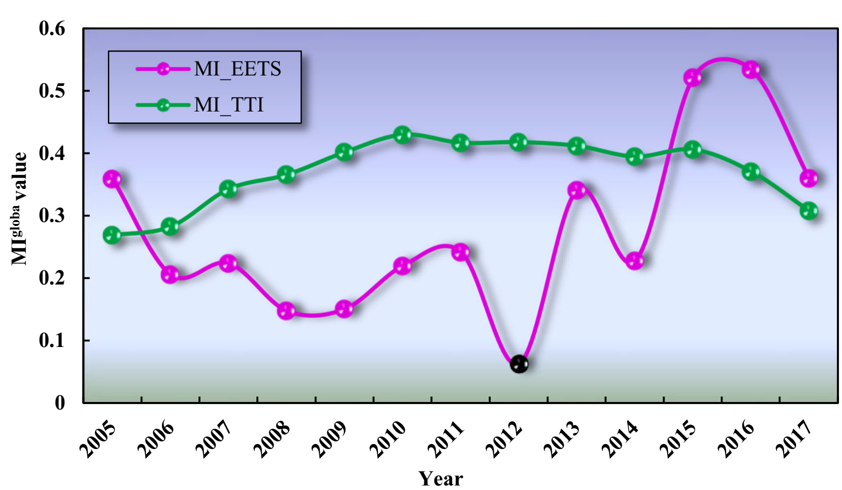
Fig. 5 Spatial pattern of EETS in China

innovation in China had a significant spatial adjacent dependence at the provincial level.

The MI^{global} values of EETS and TTI were positive, indicating that there may be hot or cold spots in the EETS and transportation-related technological innovation. To verify this conjecture, we conducted the local spatial autocorrelation test for the EETS and transportation-related technological innovation, as shown in Fig. 7. There were obviously hot and cold spots in China's province-level EETS. Specifically, in 2005, there were High-High cluster (Henan-Shandong), Low-High cluster (Jiangxi-Jiangsu), and Low-Low cluster (Yunnan-Guizhou-Sichuan-Chongqing-Gansu) in the EETS (Fig. 7a). In 2017, the hot-spot area of EETS included Shanxi and Hebei; the cold-spot area was composed of Xinjiang, Sichuan, and Qinghai (Fig. 7b).

Besides, in 2005, the transportation-related technological innovation had three province-level spatial clusters in China (Fig. 7c), namely High-High cluster (Jiangsu-Shanghai), Low-High cluster (Anhui-Fujian), and Low-Low cluster (Xinjiang-Gansu-Ningxia-Sichuan-Inner Mongolia). In 2017, Ningxia and Sichuan exited the Low-Low cluster; Anhui and Zhejiang joined the High-High cluster; Jiangxi joined the Low-High cluster; Sichuan joined the High-Low cluster. These findings suggest that Anhui and Sichuan have performed well in developing transportation-related technological innovations. In conclusion, during the study period,

Fig. 6 MI^{global} results of EETS and transportation-related technological innovation, 2005–2017. Note: TTI represents transportation-related technological innovation. Black dot denotes the MI^{global} value failed the significance test ($p > 0.1$)



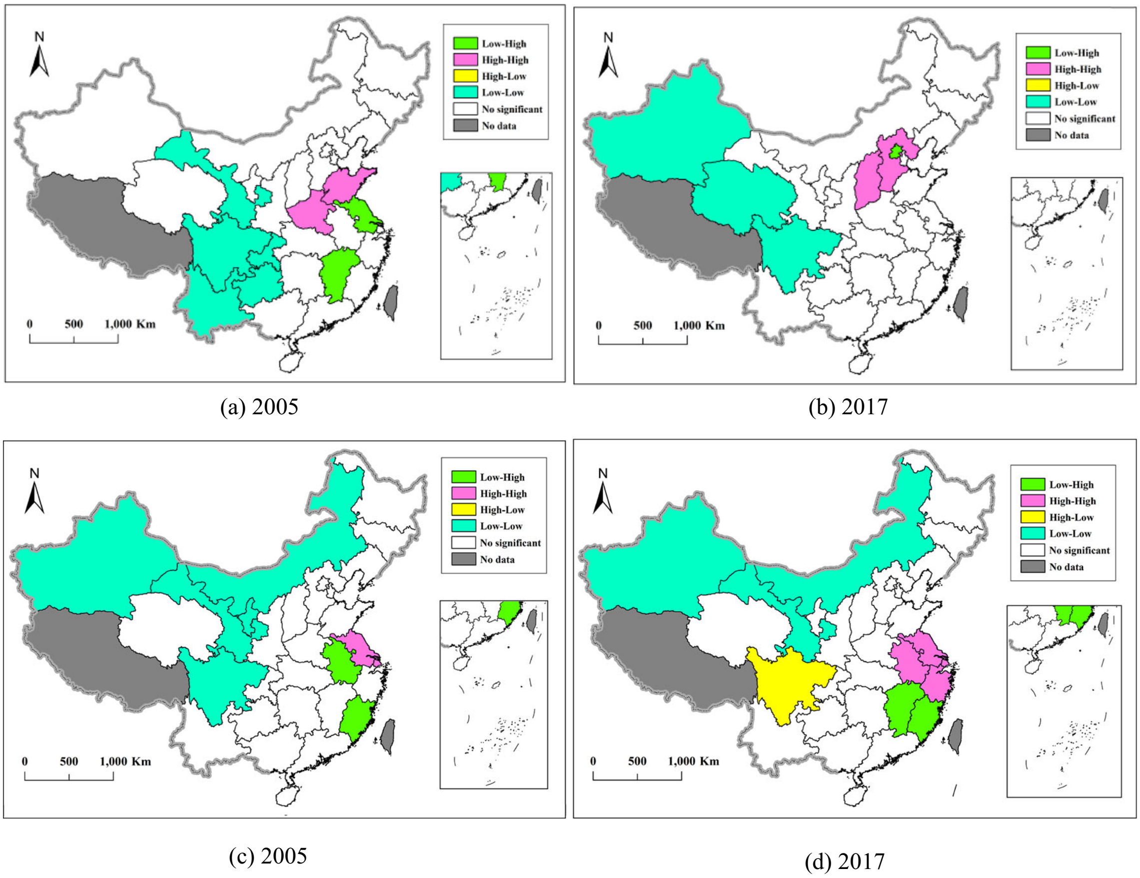


Fig. 7 Results of local spatial correlation test for EETS and transportation-related technological innovation in 2005 and 2017. Note: (**a**) and (**b**) are EETS; (**c**) and (**d**) are transportation-related technological innovation

China's province-level EETS and transportation-related technological innovation deviated from the spatial uniform distribution. Considering the spatial difference and correlation, we used the spatial econometric model to investigate how transportation-related technological innovation affects EETS (Fig. 8).

Spatial econometric analysis

Before carrying out spatial econometric analysis, we need to test the model specification (LeSage and Pace 2009). We first constructed the non-space model (i.e., POLS model) and then conducted the LM tests on the non-space model. The estimated results of the LM tests indicate that the non-spatial model was not suitable for our case due to its overlook of geographic spatial differences.

Second, we constructed the spatial econometric model based on Eq. (9) to investigate how transportation-related technological innovation affects EETS. The Hausman test of the spatial econometric model failed the significance level test, and thus, we considered the spatial econometric model under the random effect (Table 3). The Wald tests rejected the null hypotheses at the 5% level, which means that the SPDM model was suitable for our case. Thus, the SPDM model was utilized to explain the relationship between transportation-related technological innovation and EETS.

As shown in Table 3, the coefficient lnTTI was − 0.111 (t = − 2.185, $p < 0.05$), suggesting that the transportation-related technological innovation was negatively associated with the EETS. A 1% increase in the transportation-related technological innovation would result in a 0.111% decrease in the EETS. The coefficient lnPGDP was 0.775 (t = 3.870, $p < 0.01$), implying that the regional economic development contributed to improving the EETS. Every unit increase in the economic development would contribute to 0.234 units increase in the EETS. The coefficient lnIA means that industrial agglomeration would cut the EETS in China. The coefficient lnUL was − 1.498 (t = − 3.812, $p < 0.01$), suggesting that the level of urbanization would weaken the EETS in China, and every unit increase in the urbanization level would reduce the EETS by 0.190 units. This result is consistent with Lv et al. (2020), who believed that urbanization level exerts a negative effect on energy efficiency. In addition, the coefficient W×lnTTI was positive with a 5% significance level, indicating that the transportation-related technological innovation of a province could facilitate the EETS of its adjacent provinces.

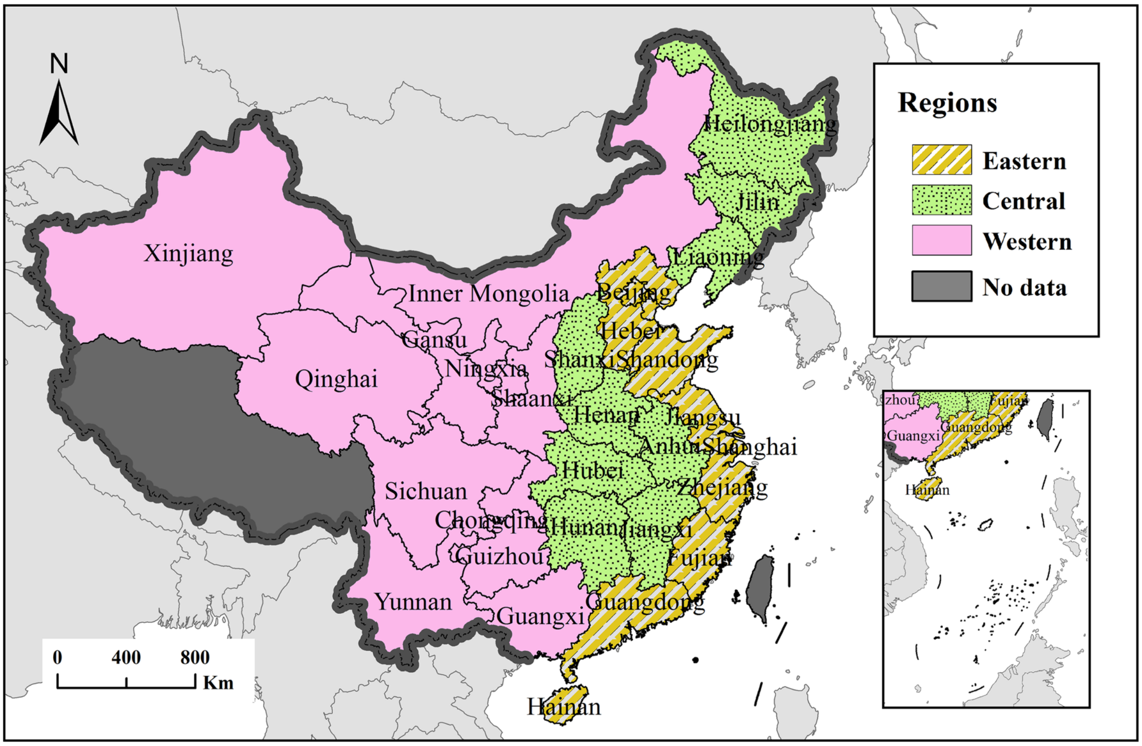


Fig. 8 Map of eastern, central, and western China

Table 3 Results of the influence of transportation-related technological innovation on EETS

Variables	Non-space	SPDM	SPLM	SPEM
lnTTI	0.056** (2.582)	− 0.111** (− 2.185)	− 0.042 (− 1.055)	− 0.047 (− 1.100)
lnPGDP	− 0.157 (− 1.635)	0.775*** (3.870)	0.146 (1.392)	0.127 (1.149)
lnIA	0.513*** (3.817)	− 0.931*** (− 4.559)	− 0.693*** (− 3.609)	− 0.727*** (− 3.748)
lnUL	0.612*** (2.852)	− 1.498*** (− 3.812)	− 0.455 (− 1.406)	− 0.361 (− 1.094)
intercept	0.280 (0.339)		6.923*** (6.157)	7.534*** (6.542)
W × lnTTI		0.182** (2.402)		
W × lnPGDP		− 0.125 (− 0.474)		
W × lnIA		− 0.495 (− 1.405)		
W × lnUL		0.869 (1.361)		
R^2	0.095	0.718	0.700	0.699
σ^2	0.251	0.076	0.082	0.082
Nobs	390	390	390	390
Fixed effect	N	N	N	N
Random effect	N	Y	Y	Y
LM_{lag}	23.644***	-	-	-
LM_{error}	34.718***	-	-	-
Robust LM_{lag}	4.100**	-	-	-
Robust LM_{error}	15.392***	-	-	-
$Wald_{spatial\ lag}$	-	20.536***	-	-
$Wald_{spatial\ error}$	-	19.169***	-	-
Hausman			9.993 (p = 0.351)	

Note: lnTTI means the logarithm of the variable TTI, also similar cases for lnPGDP, lnIA, and lnUL. * is $p < 0.1$; ** means $p < 0.05$; *** represents $p < 0.01$. t-statistics in (). "N" denotes no. "Y" means yes

Sensitivity analysis

Testing of time lag

In practical terms, there may be a time lag when transportation-related technological innovation influences EETS. Moreover, time lag on explanatory variables can effectively overcome endogenous problems. To this end, we performed a first-order lag and a second-order lag on the explanatory variables and re-estimated the foregoing models. Table 4 reveals that the first-order lag and second-order lag of lnTTI were positive and significant. This finding suggests that the previous technological innovation has continuous influences on current EETS.

Testing of different spatial weights

Spatial weight plays an important role in the spatial econometric model (LeSage and Pace 2009; Wang and Zhu 2020; Zhu et al. 2020a). The foregoing results were based on the spatial adjacent matrix that can only describe the adjacency relationship among the sub-regions. Do the above results hold for different spatial weights? To answer this question, we constructed a geospatial-distance weight and (W^G) an economic-distance weight (W^E). The geospatial-distance weight (W^G) measures the geographical distance among sub-regions using the latitude and longitude of the provincial capitals. The economic distance matrix (W^E) measures the economic gap among regions:

$$W_{ij}^G = \begin{cases} \dfrac{1}{dist_{ij}^2} & (i \neq j) \\ 0 & (i = j) \end{cases}, \qquad W_{ij}^E = \begin{cases} \dfrac{1}{\left|\overline{gdp_i} - \overline{gdp_j}\right|} & (i \neq j) \\ 0 & (i = j) \end{cases} \tag{10}$$

where $dist_{ij}$ denotes the geographical distance among provinces. gdp_i denotes the mean value of per capita GDP in the sub-region i during the sample period. Table 5 lists the robust

Table 4 Empirical results of the spatial econometric model with year lag

Variables	First-year lag			Second-year lag		
	SPDM	SPLM	SPEM	SPDM	SPLM	SPEM
lnTTI	− 0.240***	− 0.178***	0.176***	− 0.178**	− 0.155**	− 0.155**
	(− 3.609)	(− 2.647)	(− 2.637)	(− 2.502)	(− 2.138)	(− 2.144)
lnPGDP	0.665***	0.400*	0.392	0.472*	0.342	0.332
	(2.646)	(1.659)	(1.639)	(1.693)	(1.283)	(1.258)
lnIA	− 0.869***	− 0.780***	− 1.407***	− 0.754**	− 0.706**	− 0.699**
	(− 3.088)	(− 2.712)	(− 3.070)	(− 2.406)	(− 2.224)	(− 2.190)
lnUL	− 1.477***	− 1.413***		− 1.908***	− 1.649***	− 1.639***
	(− 2.852)	(− 3.040)		(− 3.195)	(− 3.135)	(− 3.169)
Intercept						
W × lnTTI	0.277***			0.107		
	(2.603)			(0.950)		
W × lnPGDP	− 0.282			− 0.291		
	(− 0.897)			(− 0.759)		
W × lnIA	− 0.170			0.070		
	(− 0.333)			(0.121)		
W × lnUL	− 0.216		0.760	0.663		
	(− 0.217)		0.075	(0.564)		
R^2	0.766	0.760	360	0.767	0.765	0.765
σ^2	0.065	0.075	Y	0.066	0.076	0.076
N	360	360	N	330	330	330
Fixed effect	Y	Y		Y	Y	Y
Random effect	N	N		N	N	N
Wald $_{lag}$	7.620			1.441		
Wald $_{error}$	8.140*			1.797		
LR $_{lag}$	7.600			1.473		
LR $_{error}$	7.867*			1.640		
Hausman	15.477* (p = 0.078)			17.118** (p = 0.046)		

Note: * is $p < 0.1$; ** means $p < 0.05$; *** represents $p < 0.01$. t-statistics in (). "N" denotes no. "Y" means yes

Table 5 Empirical results of econometric models with different spatial weights

Variables	W^G			W^E		
	SPDM	SPLM	SPEM	SPDM	SPLM	SPEM
lnTTI	− 0.117*	− 0.141**	− 0.148**	− 0.091*	− 0.054	− 0.079*
	(− 1.906)	(− 2.227)	(− 2.362)	(− 1.841)	(− 1.334)	(− 1.848)
lnPGDP	0.469**	0.514**	0.537**	0.612***	0.168	0.156
	(2.140)	(2.257)	(2.369)	(3.000)	(1.594)	(1.360)
lnIA	− 0.897***	− 0.899***	− 0.908***	− 0.711***	− 0.597***	− 0.572***
	(− 3.330)	(− 3.320)	(− 3.290)	(− 3.190)	(− 3.120)	(− 2.977)
lnUL	− 0.925*	− 1.190***	− 1.155***	− 0.772*	− 0.479	− 0.186
	(− 1.904)	(− 2.795)	(− 2.838)	(− 1.853)	(− 1.458)	(− 0.556)
Intercept					6.061***	6.092***
					(5.268)	(5.345)
W × lnTTI	− 0.261*			0.251*		
	(− 1.760)			(1.792)		
W × lnPGDP	0.425			− 0.146		
	(0.799)			(− 0.310)		
W × lnIA	0.032			− 1.373***		
	(0.045)			(− 3.213)		
W × lnUL	− 0.824			− 0.767		
	(− 0.778)			(− 0.821)		
R^2	0.749	0.744	0.742	0.732	0.711	0.708
σ^2	0.069	0.078	0.078	0.072	0.079	0.080
N	390	390	390	390	390	390
Fixed effect	Y	Y	Y	N	N	N
Random effect	N	N	N	Y	Y	Y
Wald_{lag}	4.577	-	-	21.178***	-	-
$\text{Wald}_{\text{error}}$	3.408	-	-	22.974***	-	-
LR_{lag}	4.508	-	-	-	-	-
LR_{error}	3.404	-	-	-	-	-
Hausman	18.789*** (p = 0.027)			12.460 (p = 0.188)		

Note: * is $p < 0.1$; ** means $p < 0.05$; *** represents $p < 0.01$. *t*-statistics in (). "N" denotes no. "Y" means yes

test results of spatial econometric models with different spatial weights. Comparing Table 5 with Tables 3 and 4, the signs and significance of lnTTI were consistent. This result means that the above results have good robustness.

Discussion

Based on the representative sample of 30 Chinese provinces during 2005–2017, this study attempts to elaborate transportation-related technological innovation and EETS in terms of (a) whether there is spatial dependence among Chinese provinces in EETS; (b) Does transportation-related technological innovation improve EETS?

The spatial pattern of EETS indicated the existence of spatial disparity in the provincial EETS. This finding coincides with previous studies that emphasize the importance of geographic space for energy efficiency (Buylova 2020; Irandoust 2019; Malinauskaite et al. 2020). This finding may enrich the theories related to the energy environment and help local governments formulate energy development strategies following local conditions. According to the results of the spatial autocorrelation test, there was a stable spatial dependence in China's province-level EETS during 2005–2017. This result coincides with the broader studies on geographical autocorrelation of energy efficiencies, such as Li et al. (2018), Wang et al. (2019), and Zhong et al. (2020). China's provincial transportation-related technological innovation exhibited obvious hot spots and cold spots, which supports the previous work of Jang et al. (2017) for Korea.

Technological innovation exerted a negative impact on EETS in China during 2005–2017, which is inconsistent with the previous studies, such as Liao and Ren et al. (2020) for China and Japan, Ozturk et al. (2020) for 46 African countries, and Ohene-Asare et al. (2020) for Turkey. This is possible because although advanced transportation technology can improve the performance of individual transportation products, it can also promote the popularization of transportation vehicles (Aydin et al. 2017; Irandoust 2019; Liu et al. 2018). Besides, developing countries are immature in the treatment technology of traffic exhaust, and the rapid development in the transportation sector is bound to bring huge environmental pressure (Huang et al. 2020; Romero et al. 2020). This finding may support the notion that developing countries should pay more attention to controlling transportation pollution as they modernize their transportation sector.

In addition, Table 6 reported that the spatial coefficient W×lnTTI was positive and significant. This finding suggests that transportation-related technological innovation would exert an adjacent space spillover effect on EETS. To verify this conjecture, we conducted a decomposition test on the SPDM model of Table 3 utilizing the partial differential method. The decomposition test confirms the existence of the adjacent space spillover effect (Table 6). Namely, one province developing transportation-related technological innovations might improve EETS in its neighboring provinces, which is in line with the work of Carlino and Kerr (2015) and Zhu et al. (2020a). This finding may be of great significance to cross-regional cooperation in province clusters. In our case, if Shandong, Henan, Hubei, Jiangxi, and Fujian want to improve EETS through technological innovation, they may benefit from the spatial spillover of the H-H cluster of transportation-related technological innovation (Jiangsu-Anhui-Shanghai-Zhejiang).

Besides, we investigated the influences of transportation-related technological innovation on EETS in the eastern, central, and western regions to find out how this influence differs across the regions of China (Table 7). Interestingly, the transportation-related technological innovation in eastern China was positively associated with the EETS, while the transportation-related technological innovation in central and western China adversely influenced the EETS. This result is possibly attributed to two reasons: (1) the development of renewable energy technology innovation in eastern China was significantly faster than that in central and western China (Wang and Zhu 2020), and thus, eastern China has relatively advanced pollution treatment technology; (2) eastern China with the high level of social development is receptive to new energy technologies. For example, according to the special survey on China's auto market 2018–2024, the top five provinces (Guangdong, Zhejiang, Shandong, Shanghai, and Beijing) in terms of new energy vehicle sales in 2018 were all located in the eastern region.

Table 6 Decomposition test of SPDM model in Table 3 (random effect)

Variables	Direct effects	Indirect effects	Total effects
lnTTI	− 0.110** (0.040)	0.185** (0.026)	0.074 (0.329)
lnPGDP	0.784*** (0.000)	− 0.093 (0.736)	0.691** (0.034)
lnIA	− 0.939*** (0.000)	− 0.553 (0.139)	− 1.492*** (0.002)
lnUL	− 1.514*** (0.001)	0.824 (0.229)	− 0.689 (0.328)3

Notes: values in () are p-statistics. ** means $p < 0.05$. *** denotes $p < 0.01$

Conclusions and implications

Conclusions

Taking 30 Chinese provinces as an example, this study attempts to explore how transportation-related technological innovation affects EETS through the undesirable super-SBM model and the spatial empirical method. The spatial empirical results suggest that during the sample period of 2005–2017, China's province-level EETS and transportation-related technological innovation deviated from the spatial uniform distribution. Transportation-related technological innovation would exert a negative effect on China's EETS. Besides, place-based conditions may play an important role in the influence of transportation-related technological innovation on the EETS.

Implications

The current study has three theoretical implications for the existing literature: First, our findings, gained from a provincial cluster, hold the view that spatial proximity has an indispensable role in energy efficiency research. These results may extend the literature on agglomeration externalities by using the meso-geography of EETS within China's provincial cluster. Second, this study is related to the existing literature on the influence of technological innovation on energy efficiency. The general result of previous studies is that advanced technology facilitates energy efficiency (Liao and Ren 2020; Ohene-Asare et al. 2020; Ozturk et al. 2020), while this study supports the notion that technological innovation has a rebound effect on the energy efficiency in transportation sector. Third, this study extends the literature on human–environment interactions to geography through the application of geospatial methods, which may build a bridge between social science research and natural science research.

Besides, this study proposes the two practical implications for improving EETS: First, the government needs to incorporate considerations of regional differences into the policy formulation towards transportation development. Specifically, provinces in the hot-spot area of EETS (Shanxi and Hebei) could strengthen inter-provincial cooperation to obtain energy-environmental efficiency spillovers from neighboring

Table 7 Effects of transportation-related technological innovation in different regions on EETS

	Eastern region		Central region		Western region	
Variables	Non-space	SPDM	Non-space	SPDM	Non-space	SPDM
lnTTI	0.314**	0.284*	− 0.368***	− 0.449***	− 0.227***	− 0.186**
	(2.275)	(1.874)	(− 3.086)	(− 3.806)	(− 2.679)	(− 2.518)
lnPGDP	− 1.012**	− 1.371***	− 0.293	− 0.787*	2.078***	2.166***
	(− 2.396)	(− 2.817)	(− 0.594)	(− 1.679)	(6.228)	(7.611)
lnIA	− 1.682**	− 2.052***	0.055	1.423***	− 1.184***	− 1.477***
	(− 2.581)	(− 3.147)	(0.134)	(3.337)	(− 2.764)	(− 3.300)
lnUL	− 0.773	− 0.965	0.434	0.338	− 3.483***	− 2.850***
	(− 0.890)	(− 1.171)	(0.672)	(0.357)	(− 4.021)	(− 3.712)
W × lnTTI		0.623**		− 0.488**		− 0.034
		(2.313)		(− 1.993)		(− 0.189)
W × lnPGDP		− 1.409**		− 1.128		2.445***
		(− 2.299)		(− 1.279)		(3.296)
W × lnIA		− 1.381*		3.090***		− 0.943
		(− 1.683)		(3.684)		(− 1.050)
W × lnUL		− 3.585**		0.941		0.181
		(− 2.367)		(0.987)		(0.102)
R^2	0.289	0.814	0.145	0.741	0.245	0.833
N	130	130	117	117	143	143
Fixed effect	Y	Y	Y	Y	Y	Y
LM_{lag}	0.129		3.818*		11.500***	
LM_{error}	2.930*		3.732*		13.176***	
Robust LM_{lag}	17.234***		0.087		0.157	
Robust LM_{error}	20.035***		0.0012		1.833	
$Wald_{lag}$		34.590***		26.286***		28.637***
$Wald_{error}$		23.891***		-		11.968**
LR_{lag}		29.333***		21.189***		18.433***
LR_{error}		25.171***		-		10.242**

Note: * is $p < 0.1$; ** means $p < 0.05$; *** represents $p < 0.01$. *t*-statistics in (). "N" denotes no. "Y" means yes

provinces. In contrast, provinces in the cold-spot area of EETS (Xinjiang, Sichuan, and Qinghai) should give priority to improving their infrastructure to attract more capital investment and talents. Second, the impact of technological innovation on EETS is positive in the eastern region and negative in the central and western regions. Thus, formulating transportation-related innovation policies should vary from region to region. For example, eastern China can use preferential policies (e.g., tax incentives and talent rewards) to encourage enterprises to carry out transportation-related technological innovations. Central China should take advantage of its location adjacent to eastern China and actively establishes cooperation in green transportation technologies with the eastern provinces. Western China may give priority to strengthen environmental regulations and control traffic pollution.

Limitations and future research

Taking the transportation sector with high energy consumption and high environmental pollution as an example, this study investigates the impact of technological innovation on energy-environmental efficiency. Future research can select other sectors (i.e., industry) to verify the empirical results obtained in this study. Besides, in real life, spatial location plays an important role in the transportation sector, and thus, this study explores the relationship between technological innovation and energy-environmental efficiency from the perspective of geographic space. Future research can investigate the relationship between technological innovation and energy-environmental efficiency for different transportation sectors, such as general vehicle, railway, trackless land vehicle, ship-related equipment, and aircraft.

Appendix 1. The fuel-based carbon footprint model.

$$TCE_{it} = \sum_{g=1}^{8} TEC_g * NCV_g * CEF_g * F_g \qquad (11)$$

where TCE_{it} means transportation-related CO_2 emissions, g (g = 1, 2..., 8) represents energy type. TEC_k denotes the transportation-related energy consumption of g energy type. NCV_g, CEF_g, and F_g are detailed in Appendix Table 8.

Table 8 CO_2 emission factors for the fuel-based carbon footprint model

Energy Type (g)	NCV_g (kJ/kg)	CEF_g (kg/TJ)^2	F
Coal	20908	95333	1
Diesel oil	42652	74100	1
Gasoline	43070	70000	1
Natural gas	38931	56100	1
Coke	28435	10700	1
Crude Oil	41816	73300	1
Kerosene	43070	71500	1
Fuel oil	41816	77400	1

Sources: IPCC 2006

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Author contribution Conceptualization: Yongfeng Zhu, Zilong Wang; Methodology: Yongfeng Zhu, Lingling Zhu; Formal analysis and investigation: Yongfeng Zhu; Writing — original draft preparation: Yongfeng Zhu; Writing — review and editing: Zilong Wang, Lingling Zhu; Funding acquisition: Zilong Wang; Supervision: Zilong Wang.

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Data availability The datasets analyzed during the current study are available from the corresponding author on reasonable request.

Declarations

Ethics approval and consent to participate Not applicable

Consent for publication Not applicable

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