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RESEARCH ARTICLE

On transportation, economic agglomeration, and CO2 emissions in China, 2003–2017

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Abstract
This study analyzes the effects of transportation infrastructure on carbon emissions (CE) based on the level of urban economic agglomeration. For this purpose, 281 Chinese cities are considered during the period 2003–2017. A Moran's *I* index is used to assess the spatial distribution characteristics of transportation infrastructure and CE. In addition, a spatial Durbin model is employed to explore the spatial spillover effect of transportation infrastructure on CE. Furthermore, economic agglomeration is considered as a crucial transmission mechanism. The empirical results show that (1) a significant spatial autocorrelation exists between transportation infrastructure and CE. (2) Transportation infrastructure significantly aggravates CE, with the "neighboring effect" being surprisingly more potent than the "local effect." (3) Economic agglomeration is a valid transmission channel through which transportation infrastructure affects CE, the intensity of which varies with the level of economic agglomeration. Our recommendation is that policy-makers should pay attention to the development of local transportation, as well as their neighboring cities, and should accelerate the advancement of green transportation.

Keywords Transportation infrastructure · Economic agglomeration · Carbon emission · Spatial Durbin model

JEL C21 · H54 · Q54 · R12

Introduction

Over the past 40 years of reform and opening up, China's rapid economic growth has attracted global attention. Currently, China's economy continues to grow at astonishing rates, and its GDP is the second largest in the world. However, high economic growth has resulted in resource depletion and environmental pollution, thereby limiting China's regional coordination and sustainable development. In particular, greenhouse gas emissions have resulted in global warming (Tang et al. 2019; Tang and Hailu 2020; Tang et al. 2022). Figure 1 illustrates that besides economic growth, carbon emission (hereafter, the "CE") has been increasing year by year. Currently, the world is faced with a challenging situation of reducing carbon (CO_2), the main greenhouse gas. As the largest CO_2 emitter, China has been facing increasing pressure and challenges (Chen and Santos 2013; Tang et al. 2022). As a responsible developing country, China has been making constant efforts to reduce CE intensity (Wang et al. 2020). At the United Nations General Assembly held on September 2020, China proposed to "strive to reach the peak of CE before 2030 and to achieve carbon neutrality by 2060" (hereafter, the "dual carbon goals"). However, achieving "dual carbon goals" is difficult for China, as the country is undergoing a rapid urbanization and industrialization process characterized by high energy consumption (Miao et al. 2019). This implies that China needs to do everything in its power to reduce CE while maintaining a steady rate of economic growth (Shi et al. 2018).

With the rapid development of China's economy, urban transportation infrastructure has expanded rapidly (Li et al. 2019). China's highway mileage increased from 1.15 million kilometers to 5.01 million kilometers from 1995 to 2019. The positive effect of transportation infrastructure on economic growth is irrefutable. Modern transportation

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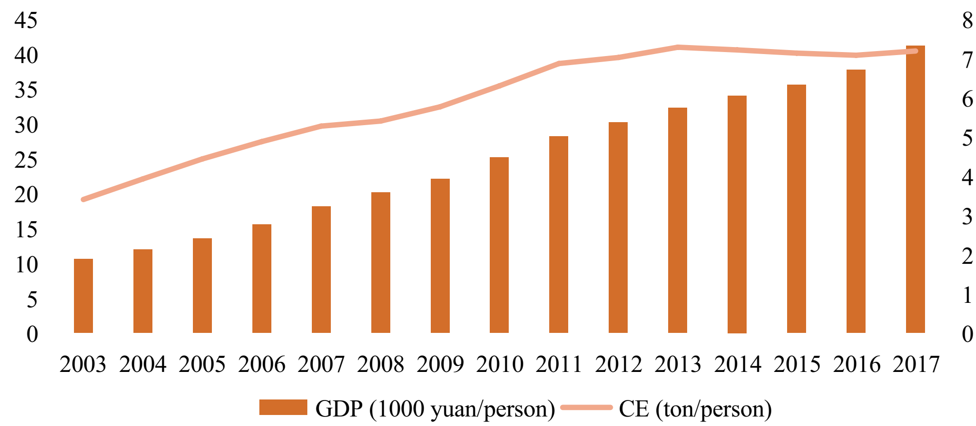

Fig. 1 Per capita real GDP and CE in China, 2003–2017. Source: World Bank Database and China Statistical Yearbook

infrastructure can shorten travel distances and times, save transportation costs, and promote business exchanges between regions, thereby achieving economic growth (Lin and Chen 2020). Notably, transportation infrastructure is closely related to the environment. However, no consistent response exists concerning the effects of transportation infrastructure on CE. Some scholars have opined that transportation infrastructure increases CE (Akerman 2011; Jiang et al. 2017; Fan et al. 2018). Others have claimed that advanced transportation infrastructure can effectively mitigate CE (Jia et al. 2021). Thus, the exact role of transportation infrastructure in increasing CE and how transportation infrastructure affects CE remain unclear. Accordingly, conducting an empirical study on the effects of transportation infrastructure on CE would help understand the relation between the two, thereby helping formulate effective policies aimed at energy saving and emission reduction goals.

The environmental effects of transportation infrastructure have gradually received considerable emphasis with the increasing prominence of the economic benefits of transportation infrastructure. Transportation infrastructure affects CE in two main ways: On the one hand, the construction and operation of transportation infrastructure directly result in CO_2 emission. Raw materials such as steel and cement used in the construction of transportation infrastructure may increase energy consumption and CE (Lin and Chen 2020). On the other hand, transportation infrastructure affects economic activities, thus indirectly affecting CE. Related studies are usually based on an empirical analysis to determine the factors affecting CE, thus exploring the overall effect of transportation (Dietz and Rosa 1997; Wang et al. 2019). Specifically, transportation infrastructure can promote technological progress, facilitate economic agglomeration, reduce costs, and improve energy efficiency (Achtymichuk and Checkel 2010). Furthermore, transportation infrastructure may affect CE by restructuring industries (Jia et al. 2021).

A few scholars have begun to focus on the association between transportation infrastructure and CE. However, there still exists room for improvement in existing research. Numerous existing studies have used the ordinary panel model for discussion, largely overlooking the externalization of local transportation infrastructure in the neighboring regions. Moreover, some studies have indicated a significant spatial correlation in CE between countries or regions (Rios and Gianmoena 2018; You and Lv 2018; Lv and Li 2021). In other words, neighboring countries can affect a country's CE. Likewise, CE between provinces and cities within a country should also be inter-connected (Kang et al. 2016). Furthermore, researchers have demonstrated a positive spatial correlation of CE across Chinese cities (Tang et al. 2021b). Getis (2007) documented that a conventional OLS regression could not overcome the problem of correlation between individuals through the fixed effect model approach on account of a spatial dependence between regions. Accordingly, spatial econometric models should be used to avoid biased estimated results. With regard to the transmission mechanism issue, some studies have mentioned that transportation infrastructure may affect CE through economic agglomeration (Wu et al. 2021a, b). More importantly, few scholars have considered whether the effect of transportation infrastructure on CE differs based on different levels of economic development.

Accordingly, in this study, 281 prefecture-level cities in China during the period 2003–17 were considered to analyze the effects of urban transportation infrastructure on CE. A spatial Durbin model (SDM) was used to examine the local and neighboring effects of transportation infrastructure on CE. Furthermore, economic agglomeration was used as an intermediate transmission mechanism to effectively understand the effects of transportation infrastructure on CE. The potential contributions of this paper include the following aspects: (1) An analytical framework has been constructed concerning the effects of transportation infrastructure on CE. The "local effect" and "spillover effect" of transportation infrastructure on CE have been comprehensively explored using the SDM. (2) Considering economic agglomeration as a breakthrough, the mechanism of the role of transportation infrastructure in CE has been examined from a new perspective. (3) The heterogeneous effect of transportation infrastructure on CE has been further explained by differentiating the samples based on the levels of economic agglomeration.

The rest of this paper is organized as follows. The "Literature review and research hypotheses" section reviews the literature and elaborates the hypotheses. The "Model, variables, and data" section presents the model and data. The "Empirical results" section presents and discusses the empirical results. The last section concludes with some policy recommendations.

Literature review and research hypotheses

Transportation infrastructure and CE

In the past few decades, although transportation infrastructure has been the main determinant of economic growth, it has considerably affected the natural environment with the rising CE (Li and Tang 2017). A large amount of asphalt is consumed during the construction of transportation infrastructure. Road maintenance during operation also consumes energy (Lee et al. 2013). More importantly, the improvement of transportation infrastructure may result in vehicle operation, thereby increasing air pollution. In addition to the direct effects of transportation activities on CE, the interaction between transportation infrastructure and other economic factors may affect CE in the local and neighboring areas (Xie et al. 2019). For instance, urban transportation infrastructure can reduce population movement and cargo transportation costs. With low transportation costs, people and firms may be concentrated to meet the needs of urban development. Finally, citizens may be concentrated in urban centers (Fujita and Thisse 2003), leading to the so-called scale effect of population on CE (Zhu and Peng 2012; Wang et al. 2014). In addition, transportation infrastructure improves accessibility between regions, strengthens trade exchanges and cooperation between regions, and contributes to market expansion (Xie et al. 2017). Notably, the emission of pollutants will also be affected by the increases in the scale of production (Liu et al. 2017). However, the expansion of economic scale will inevitably increase CE. Based on this discussion, the first hypothesis is proposed as follows:

H1: A positive correlation exists between transportation infrastructure and CE.

Transportation infrastructure, economic agglomeration, and CE

Transportation infrastructure may directly and indirectly aggravate CE through intermediate effects. According to the theory of agglomeration and economic development, although the importance of nearby natural resources may decline over time, firms and households can make optimal decisions to locate in their preferred cities owing to the development of transportation infrastructure (Fujita and Thisse 2003). In particular, advanced transportation infrastructure can shorten the travel time between regions, reduce the cost of cross-regional communication, and help attract business investment and population clustering (Ahlfeldt and Feddersen 2015). First, advanced transportation infrastructure enables search for suppliers and customers at a lower cost and helps enterprises and employees in making two-way choices in a larger spatial area, thereby helping them search for a more suitable workforce and enjoy higher knowledge spillover effects. This benefit increases productivity, and cities with good transportation infrastructure become the optimal choice for some enterprises to locate (Holl 2004). Second, the externality of transportation infrastructure is mainly reflected in the construction system of transportation infrastructure. In addition to affecting the local economy, the externality can affect the economic development of the surrounding areas, reflecting a spatial spillover effect. The spatial spillover effect of transportation infrastructure will attract more resources to the areas with better transportation infrastructure and enhance economic agglomeration. Empirical findings suggest that expressways affect the spatial distribution of economic activities, and the construction of local intercontinental highways promotes the flow of economic activities from adjacent areas to the areas of concern (Thompson 2000). Firms are more willing to build manufacturing sites in areas adjacent to the newly built highways, thereby positively affecting economic gatherings in other neighboring areas (Holl 2004). The lack of transportation barriers help workers more freely choose their employment areas as well as living locations (Meijers et al. 2012). Moreover, Shao et al. (2017) confirmed that the higher the service intensity of transportation infrastructure, the greater is its effect on urban agglomeration. Overall, a well-developed transportation infrastructure can increase the degree of local economic agglomeration.

Several studies have indicated a significant association between economic agglomeration and CE. On the one hand, economic agglomeration has positive externalities on CE. Economic agglomeration reduces the distance between elements and enhances resource sharing, resulting in technology spillover effects (Duranton and Puga 2004) and thereby reducing CE. On the other hand, economic agglomeration may have negative externalities on CE. Furthermore, the "congestion effect" caused by excessive agglomeration may lead to population and production expansion, resulting in increased energy consumption and CE (Cheng 2016; Wang et al. 2018). In addition, claims regarding the effects of economic agglomeration on CE are mixed. Agglomeration can affect carbon emissions through scale effect, technology effect, and structural effect, but the strength of these three effects varies in different regions (Wu et al. 2021a, b). In general, the effect of economic agglomeration on CE depends on the strength of its technical effect, as well as its scale effect.

However, some scholars have observed that the technology spillover effect of economic agglomeration is more likely to appear in the more developed cities. Cities with high levels of economic development are more likely to contribute to low carbon development (Jia et al. 2018). Most companies focus more on economic efficiency than on environmental protection in cities with poorer economic development. Furthermore, the level of technology and the level of human capital are also not high at that point. Accordingly, the effect of economic agglomeration on knowledge spillover may be minimal. In highly developed cities, the specialized division of labor and the "learning effect" are more conducive to the proliferation of environmental protection and energy-saving technologies, thereby resulting in energy saving and reduction of CE (Glaeser et al. 1992). In addition to this, factors such as environmental conditions, regional development policies, city size, and city-level environmental policies can contribute to city-level heterogeneity (Wu et al. 2019; Wu et al. 2021a, b). In other words, cities may experience varying effects of economic agglomeration on CE. Thus, the second hypothesis is proposed as follows:

H2: Economic agglomeration mediates the effect of transportation infrastructure on CE, and different levels of economic agglomeration may differently affect CE.

Combined with the above discussion, a theoretical framework based on the two hypotheses is presented in Fig. 2.

Model, variables, and data

Model

According to the Stochastic Impacts by Regression on Population, Affluence, and Technology (STIRPAT) model developed by Dietz and Rosa (1997), the present study considers the traditional demographic variables, level of economic development, and technological progress as the basic explanatory variables for CE. Furthermore, urban transportation infrastructure is considered as the main explanatory variable. The basic empirical model is defined in Eq. (1) as follows:

$$\ln I_{it} = \alpha_0 + \alpha_1 \ln TI_{it} + \alpha_2 \ln P_{it} + \alpha_3 \ln A_{it} + \alpha_4 \ln T_{it} + u_i + v_t + \epsilon_{it} \tag{1}$$

where i and t denote the city and year, respectively; α_0 denotes the constant term; u_i and v_t denote the city and time fixed effects, respectively; ε_{it} is an error term; I_{it} denotes the amount of CE; P denotes population; A denotes the level of economic development; T denotes the technological level; and TI denotes transportation infrastructure. Although the model considers the effects of population, the level of economic development, and the technological change on the environment, it may overlook other relevant variables. Moreover, the environmental Kuznets curve (EKC) hypothesis mentions a functional relation of environmental quality with GDP and its squared term. Considering the aforementioned issues, the improved STIRPAT model is redefined in Eq. (2).

$$\begin{aligned}\ln CE_{it} = {} & \alpha_0 + \alpha_1 \ln TI_{it} + \alpha_2 \ln Y_{it} + \alpha_3 (\ln Y)^2 \\ & + \alpha_4 \ln PD_{it} + \alpha_5 \ln T_{it} + \alpha_6 \ln IS_{it} \\ & + \alpha_7 \ln ER_{it} + \alpha_8 \ln U_{it} + u_i + v_t + \epsilon_{it}\end{aligned} \tag{2}$$

where Y denotes per capita GDP measuring the level of economic development, PD denotes population density, T denotes technological progress, IS denotes industrial structure, ER denotes environmental regulations, and U denotes the level of urbanization.

Urban transportation infrastructure and CE may have economic externalities, which are referred to as the spatial spillover effect (Xie et al. 2019). The positive externalities of transportation infrastructure and the negative externalities of CE may lead to an "infrastructure race" or even a "CE race" between neighboring cities. More importantly, existing studies have revealed a spatial correlation between urban transportation infrastructure and

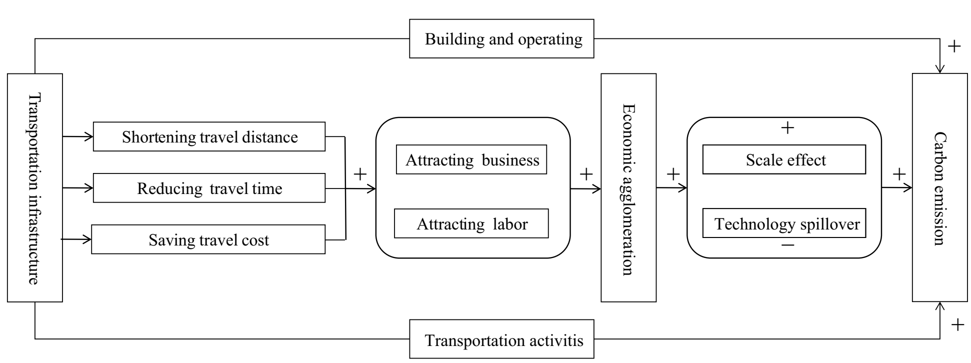

Fig. 2 A logical framework of the relation among transportation infrastructure, economic agglomeration, and carbon emissions

CE. Getis (2007) revealed that the conventional OLS regression could not overcome the correlation problem between individuals through the fixed effect model when regions were spatially dependent on others. Consequently, spatial econometric models would be more appropriate to avoid spurious regression results.

Examining whether the variables have spatial dependence and correlation is crucial before determining the spatial measurement method to be used. Several methods have been used for testing spatial autocorrelation, including the Moran's I, the Geary, and the Getis-Ord indexes. The Geary index is not influenced by sample size and spatial weights. The Getis-Ord index requires that the statistical sample I should not equal to sample j. Moran's I index is more robust than the Geary index. Furthermore, compared with the Getis-Ord index, Moran's I index is highly applicable (Moran 1950; Getis and Ord 1992; Anselin 1995). Accordingly, the present study uses Moran's I index to assess the spatial correlation of variables. Before calculating the Moran's I value, a spatial weight matrix needs to be constructed. The geographical adjacency weight matrix is used to determine the matrix elements: geographical adjacency spatial weight matrix W_{ij}; if cities i and j are geographically adjacent, $W_{ij}=1$, and $W_{ij}=0$ otherwise. The Moran's I index is defined as follows:

$$I = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(\ln Y_i - \ln\overline{Y})(\ln Y_j - \ln\overline{Y})}{S^2\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}} \tag{3}$$

$$S^2 = \frac{1}{n}\sum_{i=1}^{n}\left(\ln Y_i - \ln\overline{Y}\right)^2 \tag{4}$$

where $\ln Y_i$ denotes CE or transportation infrastructure of the ith city, n denotes the number of cities, and w_{ij} denotes the spatial weight matrix. The value of Moran's I is between -1 and 1. If $I>0$, a positive spatial correlation exists; if $I<0$, a negative spatial correlation exists; and if $I=0$, no spatial correlation exists.

The spatial autocorrelation model (SLM), spatial error model (SEM), and SDM are the commonly used spatial measurement models. The SLM assumes that all the explanatory variables in the model have a spatial transmission mechanism. The SEM assumes that only the error term has the spatial interaction effect, and the spatial spillover effect between regions is caused by random shocks (Anselin 1988). The SDM simultaneously includes both the assumptions, more comprehensively reflecting the effects of transportation infrastructure on CE. Thus, the SDM is used in this study. Combined with Eq. (2) with reference to some existent studies (Zhao et al. 2014), Eq. (5) is defined to include the spatial spillover effect, as follows:

$$\begin{aligned} ln\ CE_{it} = {} & \rho \textstyle\sum_{j=1}^{N} w_{ij} \ln\ CE_{it} + \alpha_0 + \alpha_1 ln\ TI_{it} + \alpha_2 ln\ Y_{it} + \alpha_3(\ln\ Y)^2 + \alpha_4 ln\ PD_{it} + \alpha_5 ln\ T_{it} + \alpha_6 ln\ IS_{it} \\ & + \alpha_7 ln\ ER_{it} + \alpha_8 ln\ U_{it} + \beta_1 \textstyle\sum_{j=1}^{N} w_{ij} ln\ TI_{it} + \beta_2 \sum_{j=1}^{N} w_{ij} ln\ Y_{it} + \beta_3 \sum_{j=1}^{N} w_{ij}(\ln\ Y)^2 \\ & + \beta_4 \textstyle\sum_{j=1}^{N} w_{ij} ln\ PD_{it} + \beta_5 \sum_{j=1}^{N} w_{ij} \ln\ T_{it} + \beta_6 \sum_{j=1}^{N} w_{ij} \ln\ IS_{it} + \beta_7 \sum_{j=1}^{N} w_{ij} \ln\ ER_{it} \\ & + \beta_8 \textstyle\sum_{j=1}^{N} w_{ij} \ln\ U_{it} + u_i + v_t + \epsilon_{it} \end{aligned} \tag{5}$$

where ρ denotes the spatial autocorrelation coefficient of the explained variable, w_{ij} denotes the spatial weight matrix, and β denotes the spatial lag coefficient. The other variables have been defined previously.

Based on H2, transportation infrastructure may affect CE through economic agglomeration. A standardized mediating effect model is adopted, and further empirical investigations are conducted based on the spatial measurement methods to assess whether economic agglomeration acts as a mediating variable. The stepwise method proposed by Baron and Kenny (1986) is widely used to assess the mediation effect (Zhou et al. 2020; Tang et al. 2021a). The test process is mainly based on whether the following two conditions are met: (1) if the explanatory variable significantly affects the explained variable and for any variable in the causal chain, after controlling the previous variables (including the explained variables), it will significantly affect its subsequent variables; (2) if the aforementioned conditions are true, it means that the mediation effect is significant. The mediation effect corresponds to the partial mediation effect and the complete mediation effect according to the significant/insignificant coefficients of the explanatory variables after the mediation variable is added. To test H2, CE is treated as the explained variable Y, economic agglomeration as the mediating variable M, and transportation infrastructure as the explanatory variable X, controlling for all the other variables.

The specific mediating effect test model is set out as follows. First, it evaluates whether transportation infrastructure significantly affects CE by estimating Eq. (5). Equation (6) is used to assess whether transportation infrastructure affects economic agglomeration.

$$
\begin{aligned}
ln\ EA_{it} = \rho \textstyle\sum_{j=1}^{N} w_{ij} \ln\ EA_{it} + \alpha_0 + \alpha_1 ln\ TI_{it} + \alpha_2 ln\ Y_{it} + \alpha_3 ln\ PD_{it} + \alpha_4 ln\ T_{it} + \alpha_5 ln\ IS_{it} + \alpha_6 ln\ ER_{it} + \alpha_7 ln\ U_{it} \\
+\beta_1 \textstyle\sum_{j=1}^{N} w_{ij} ln\ TI_{it} + \beta_2 \sum_{j=1}^{N} w_{ij} ln\ Y_{it} + \beta_3 \sum_{j=1}^{N} w_{ij} ln\ PD_{it} + \beta_4 \sum_{j=1}^{N} w_{ij} \ln\ T_{it} + \beta_5 \sum_{j=1}^{N} w_{ij} \ln\ IS_{it} \\
+\beta_6 \textstyle\sum_{j=1}^{N} w_{ij} \ln\ ER_{it} + \beta_7 \sum_{j=1}^{N} w_{ij} \ln\ U_{it} + u_i + v_t + \epsilon_{it}
\end{aligned} \tag{6}
$$

Second, transportation infrastructure and economic agglomeration are included in the spatial measurement model as in Eq. (7) to assess whether the mediating effect of economic agglomeration is upheld.

$$
\begin{aligned}
ln\ CE_{it} = \rho \textstyle\sum_{j=1}^{N} w_{ij} \ln\ CE_{it} + \alpha_0 + \alpha_1 ln\ TI_{it} + \alpha_2 ln\ EA_{it} + \alpha_3 ln\ Y_{it} + \alpha_4 (\ln\ Y)^2 + \alpha_5 ln\ PD_{it} + \alpha_6 ln\ T_{it} + \alpha_7 ln\ IS_{it} \\
+\alpha_8 ln\ ER_{it} + \alpha_9 ln\ U_{it} + \beta_1 \textstyle\sum_{j=1}^{N} w_{ij} ln\ TI_{it} + \beta_2 \sum_{j=1}^{N} w_{ij} ln\ EA_{it} + \beta_3 \sum_{j=1}^{N} w_{ij} ln\ Y_{it} + \beta_4 \sum_{j=1}^{N} w_{ij} (\ln\ Y)^2 \\
+\beta_5 \textstyle\sum_{j=1}^{N} w_{ij} ln\ PD_{it} + \beta_6 \sum_{j=1}^{N} w_{ij} \ln\ T_{it} + \beta_7 \sum_{j=1}^{N} w_{ij} \ln\ IS_{it} + \beta_8 \sum_{j=1}^{N} w_{ij} \ln\ ER_{it} \\
+\beta_9 \textstyle\sum_{j=1}^{N} w_{ij} \ln\ U_{it} + u_i + v_t + \epsilon_{it}
\end{aligned} \tag{7}
$$

Specifically, Eq. (6) does not include the squared term of economic growth as in Eq. (5), although all the other control variables remain constant. The control variables in Eqs. (5) and (7) are exactly the same. If α_1 in Eq. (5) is significantly positive, it implies that transportation infrastructure will significantly increase CE. If α_1 in Eq. (6) is significantly positive, it implies that the transportation infrastructure will promote economic agglomeration. If both α_1 and α_2 are significant in Eq. (7), it implies a partial mediating role of economic agglomeration in the relation between transportation infrastructure and CE. If α_1 in Eq. (7) is significant but α_2 is not, it implies a fully mediating role of economic agglomeration in the relation between transportation infrastructure and CE.

Definitions of variables

(1) Per capita CE. The data are obtained from the CEADs database, which uses the particle swarm optimization-backpropagation algorithm to unify the scale of DMSP/OLS and NPP/VIIRS satellite images to estimate CE from 2735 counties in China from 1997 to 2017. Notably, due to limited data updates for some sample cities, we could only calculate as far back as 2017. If the update time is extended, more samples would be missed.

(2) Urban Transportation Infrastructure (TI). China's transportation infrastructure mainly includes railways, roads, waterways, and airports. Among these, railways, waterways, and airports are mainly planned by the central government. It is difficult for local governments to participate in the decision-making of the central government. This study examines the effect of infrastructure on urban CE. Airports, railways, and waterways are intercity transportation facilities, the CE of which is difficult to define within any city boundary (Huang et al. 2020). Figure 3 presents the freight volumes by rail, road, water, and air of the sample cities in China during 2003–2017. As far as the absolute freight volumes are concerned without considering travel distances, road transportation is the most important form of transport at the city level, constituting approximately 80% of the total freight volumes. Accordingly, this study mainly discusses the effects of urban roads on CE, excluding the CE caused by air, rail, and water transport. Currently, no unified standard is available to measure urban transportation infrastructure. The present study uses the method proposed by Xie et al.

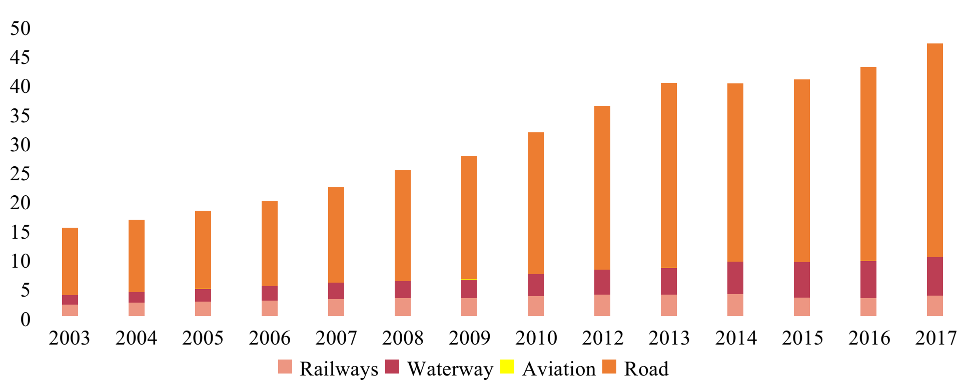

Fig. 3 Freight volumes of the sample cities in China (100 million tons). Source: China Statistical Yearbook

(2017) to represent TI based on the road surface area per capita. Following Huang et al. (2020), this study uses road density (TII), defined as road surface area per square kilometer of land area, as an alternative measurement for transportation infrastructure to assess the robustness of regression results.

(3) Economic agglomeration (EA). The measurement methods of economic agglomeration mainly consider employment density and economic density as indicators. Ciccone and Hall (1995) suggested that economic density could effectively reflect the degree of economic agglomeration. Following their suggestion, the GDP/area ratio is used to denote economic agglomeration in this study. Urban output mainly depends on secondary and tertiary industries rather than the primary industry. Therefore, the ratio of the total value added of the secondary and tertiary industries to the urban construction area is used as an alternative measurement to reflect economic agglomeration for the robustness test.

(4) Control variables. The level of economic development (Y) is defined as real per capita GDP. Population density (PD) is defined as the number of permanent residents per square kilometer. Population density may affect CE through the scale and agglomeration effects (Jia et al. 2021). The increase in population density may increase the size of the economy and thereby CE. The agglomeration of the population may also lead to cost savings and technology spillovers, consequently reducing CE. Technological progress (T) is defined as the number of patents per 10,000 people. Industrial structure (IS) is defined as the manufacturing industry's value added as a proportion of GDP. Several industries with high energy consumption and high pollution exist in the manufacturing sector. Numerous studies have suggested that the manufacturing industry causes more pollution than the other industries in the national economy (Hao and Liu 2016). Environmental regulation (ER) is defined as the utilization rate of industrial solid waste to measure the intensity of environmental regulations as suggested by Jia et al. (2021). Strict environmental regulations may reduce energy consumption and CE. Urbanization (U) is defined as a proportion of the total population in a particular city to indicate the level of urbanization. Some studies have indicated that urbanization may increase energy demand and thereby CE (York et al. 2003). Other studies have suggested that urbanization increases resource utilization and reduces CE (Cairnes and Lorraine 1996; Burton 2000). The positive or negative effects of the level of urbanization on CE will depend on the relative strengths of the two counteractive forces.

Data

After excluding cities with missing data, a total of 281 prefecture-level cities in China during 2003–2017 are selected. Relevant data are collected from *China Statistical Yearbook*, *China City Yearbook*, *China Energy Statistical Yearbook*, and *China Environmental Statistical Yearbook*. For consistency, the values of all the economic variables are calculated using the constant prices in 2003 and expressed in natural logarithms. Table 1 presents the basic statistics of the variables.

Empirical results

Spatial autocorrelation test

Table 2 presents the test results of the Moran's *I* index. The index measures CE and transportation infrastructure during 2003–2017. All the values are significantly greater than 0 and appear to have risen over time. This suggests that CE and transportation infrastructure of the sample cities have a positive and rising spatial relevance with clear characteristics of spatial agglomeration.

Two representative years, 2003 and 2017, are selected to produce the Moran's *I* index scatter plots (Fig. 4) in the forms

Table 1 Descriptive statistics of variables

Variables	Definitions	*N*	Mean	Std. dev	Min	Max
lnCE	ln (CE per capita)	4215	1.642	0.712	0.162	3.357
lnTI	ln (road area per capita)	4215	3.166	0.548	1.940	4.319
lnTII	ln (road density)	4215	0.899	0.919	− 1.049	2.906
lnEA	ln (economic agglomeration)	4215	6.441	1.349	0.338	12.305
lnY	ln (GDP per capita)	4215	9.935	0.741	8.345	11.396
lnPD	ln (population density)	4215	5.729	0.854	3.439	6.992
lnT	ln (patents/10,000 people)	4215	− 2.156	1.767	− 5.437	1.920
lnIS	ln (manufacturing value added/GDP)	4215	3.853	0.236	3.156	4.273
lnER	ln (solid waste utilization rate)	4215	4.296	0.415	2.827	4.605
lnU	ln (urbanized population)	4215	3.340	0.669	1.958	4.605

Table 2 Tests of spatial autocorrelation between transportation infrastructure and CE by Moran's *I*

Year	lnTI			lnCE		
	Moran's *I*	*z*	*P*-value	Moran's *I*	*z*	*P*-value
2003	0.360***	9.517	0.000	0.541***	13.230	0.000
2004	0.395***	9.682	0.000	0.557***	13.630	0.000
2005	0.420***	10.290	0.000	0.568***	13.884	0.000
2006	0.385***	9.413	0.000	0.576***	14.086	0.000
2007	0.403***	9.853	0.000	0.582***	14.237	0.000
2008	0.396***	9.682	0.000	0.586***	14.338	0.000
2009	0.399***	9.746	0.000	0.585***	14.305	0.000
2010	0.385***	9.430	0.000	0.586***	14.325	0.000
2011	0.400***	9.786	0.000	0.385***	9.456	0.000
2012	0.411***	10.053	0.000	0.590***	14.432	0.000
2013	0.433***	10.587	0.000	0.590***	14.440	0.000
2014	0.422 ***	10.326	0.000	0.591***	14.467	0.000
2015	0.423***	10.357	0.000	0.591***	14.461	0.000
2016	0.426***	10.427	0.000	0.596***	14.577	0.000
2017	0.429***	10.517	0.000	0.593***	14.505	0.000

***, **, and * imply 1%, 5%, and 10% levels of significance, respectively

of lnTI and lnCE, to effectively reflect the spatial characteristics of transportation infrastructure and CE. The abscissa of the Moran's *I* index scatter plot is *z*, indicating the observation value of the space unit after standardization. The ordinate is W_z, denoting the average value of the average observation value of the adjacent unit after standardization. The results suggest that most cities are located in the first quadrant (high–high) and third quadrant (low–low), and only a few cities have points in the second quadrant (low–high) and fourth quadrant (high–low). Additionally, cities with high CE (or transportation infrastructure) are surrounded by the cities with high CE (or transportation infrastructure). Furthermore, cities with low CE (or transportation infrastructure) are surrounded by the cities with low CE (or transportation infrastructure).

Spatial spillover effect of transportation infrastructure on CE

Prior to a spatial econometric analysis, this study examines the association between transportation infrastructure and CE using the traditional panel data model. The LM (robust) test results (Table 3) reject the hypothesis that no spatial lag and spatial autocorrelation exist at 1% significance level. This finding implies that a SAR or SEM can be used to evaluate the spatial spillover effect of transportation infrastructure on CE. Based on the uniqueness principle of the model, the Wald and LR tests show that the SDM cannot be reduced to a spatial autocorrelation (SAR) model or a SEM. This implies that the use of the spatial autocorrelation or spatial lag model may lead to biased results. The Hausman test result rejects the null hypothesis at 1% significance level. In short, for the most robust consideration, this study uses the SDM with time and city fixed effects to analyze the spatial spillover effects of transportation infrastructure on CE. Table 3 presents the test results.

The estimated results of the OLS, SAR, SEM, and SDM models with time and city fixed effects are presented in Table 4. These results are used to compare and assess the robustness of the parameter estimation of each variable. The spatial autocorrelation coefficient (ρ) of the SDM model is positive at 1% significance level, verifying the spatial correlation of CE. In addition, CE in the neighboring cities positively affects the level of CE in the city under concern. In the SDM model, the coefficient of urban transportation infrastructure and its spatial lag coefficient are significantly positive.

Lesage and Pace (2009) documented that analyzing the spillover effects in regions through simple point estimation may lead to inaccurate conclusions. They recommended using the partial differential method to calculate the direct, indirect, and total effects of the explanatory variables on the explained variables. This implies that the direct effect accounts for the effects of a regional independent variable on the dependent variable of the region, and the indirect effect accounts for the effects of a regional independent variable on the dependent variable of other regions. The total effect is the sum of the direct and indirect effects. Accordingly, the Lesage and Pace (2009) methods are used to further decompose the direct and indirect effects of the SDM model under the geographic matrix to objectively and accurately explore the effects of transportation infrastructure on CE (Table 5).

With regard to the total effect, the effect of transportation infrastructure on CE is significantly positive. This result

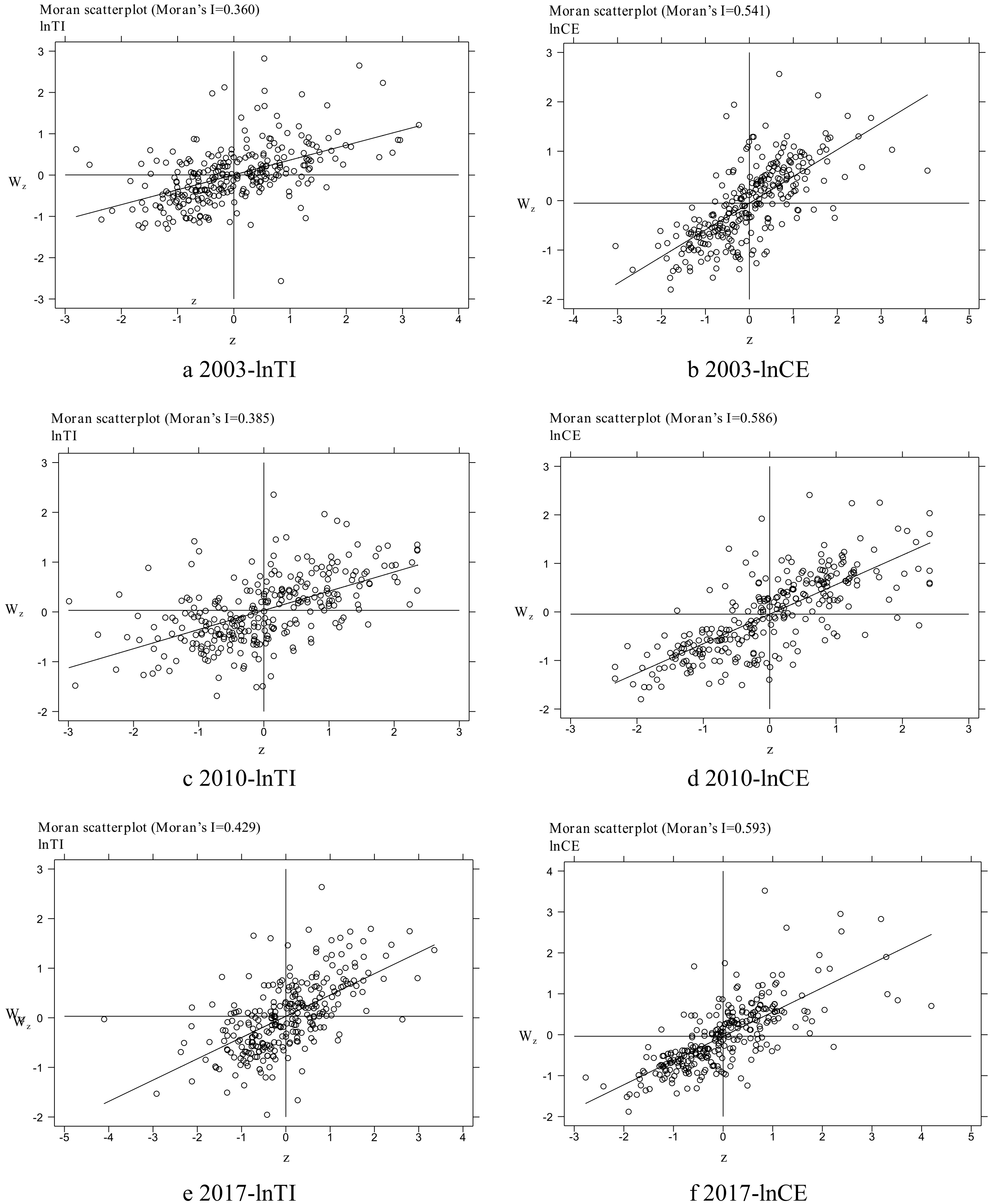

Fig. 4 Moran's *I* index scatter plots of lnTI and lnCE

Table 3 Test results of the ordinary panel model

Test	Statistics	Test	Statistics
LM (lag) test	2145.448***	Wald spatial lag test	12.63***
Robust LM (lag) test	137.865***	LR spatial lag test	60.70***
LM (error) test	2729.619***	Wald spatial error test	36.27***
Robust LM (error) test	722.036***	LR spatial error test	57.11***
Hausman test	39.64***		

***, **, and * imply 1%, 5%, and 10% levels of significance, respectively

implies that transportation infrastructure increases CE, thus verifying H1. The construction of transportation infrastructure requires more energy and thereby produces more CE. The improvement of transportation infrastructure can increase car ownership, resulting in more energy consumption. The significant direct effect indicates that for every 1% increase in transportation infrastructure, CE increases by 0.059%. Furthermore, the significant spillover effect indicates that the increase in transportation infrastructure in the neighboring areas increases CE in the region under concern. This may be because an improvement of transportation infrastructure in surrounding areas may promote business exchanges between regions, expand the market scale, increase population mobility, and thereby increase CE across regions. More importantly, the spillover effect of transportation infrastructure on CE exceeded the direct effect. This implies that the positive effect of transportation infrastructure on CE in the surrounding neighboring areas ("neighboring effect") is greater than that of the local transportation infrastructure ("local effect"). This finding suggests that the effects of neighboring areas should be considered in addition to the effects of transportation infrastructure in the region when examining the effects of urban transportation infrastructure on CE. It also highlights the importance of spatial measurement methods in assessing the effects of transportation infrastructure on CE.

The results for other control variables are also noteworthy. The coefficients of lnY and $(\ln Y)^2$ are significantly positive and negative, respectively. This finding verifies the EKC hypothesis between economic development and CE based on the Chinese city-level panel data. Scholars have excessively discussed the EKC. Most countries such as the USA, Italy, and Turkey have been shown to have an inverted U-shaped relation between economic growth and environmental pollution (Al-Rawashdeh et al. 2015; Mazzanti et al. 2007). Further, some developing countries have not yet witnessed the inflection point of the inverted U-shaped curve (Marzio

Table 4 Estimation results of transportation infrastructure and CE (carbon emissions, lnCE)

Variables	OLS	SAR	SEM	SDM
lnTI	0.186 (0.012)***	0.098 (0.011)***	0.133 (0.014)***	0.046 (0.016)***
lnY	0.993 (0.118)***	0.717 (0.104)***	1.013 (0.117)***	0.709 (0.121)***
$(\ln Y)^2$	−0.034 (0.006)***	−0.026 (0.005)***	−0.035 (0.006)***	−0.025 (0.006)***
lnPD	0.226 (0.068)***	−0.044 (0.061)	−0.004 (0.066)	−0.191 (0.067)***
lnT	0.022 (0.004)***	0.013 (0.004)***	0.032 (0.004)***	0.022 (0.005)***
lnIS	0.053 (0.026)**	0.054 (0.023)**	0.009 (0.026)	0.043 (0.028)
lnER	0.010 (0.011)	0.006 (0.010)	0.008 (0.010)	0.001 (0.010)
lnU	−0.022 (0.018)	0.007 (0.016)	0.024(0.017)	0.022 (0.016)
_cons	−6.875 (0.635)***			
W*lnTI				0.088 (0.019)***
W*lnY				−0.231 (0.176)
$W^*(\ln Y)^2$				0.011 (0.009)
W*lnPD				0.660 (0.103)***
W*lnT				−0.022 (0.007)***
W*lnIS				−0.018 (0.038)
W*lnER				−0.014 (0.019)
W*lnU				−0.134 (0.029)***
ρ		0.423 (0.016)***		0.412 (0.017)***
City fe	Yes	Yes	Yes	Yes
Year fe	Yes	Yes	Yes	Yes
n	4215	4215	4215	4215
R^2	0.678	0.685	0.674	0.694

Numbers in parentheses represent standard errors, and ***, **, * imply 1%, 5%, and 10% significance levels, respectively

Table 5 Estimated results of direct, indirect, and total effects (DV = lnCE)

Variables	Direct effects	Indirect effects	Total effects
lnTI	0.059 (0.015)***	0.172 (0.023)***	0.231 (0.023)***
lnY	0.711 (0.115)***	0.103 (0.250)	0.815 (0.272)***
$(\ln Y)^2$	−0.025 (0.006)***	0.001 (0.013)	−0.024 (0.014)*
lnPD	−0.123 (0.064)*	0.935 (0.161)***	0.812 (0.174)***
lnT	0.021 (0.005)***	−0.020 (0.019)	0.001 (0.009)
lnIS	0.044 (0.026)*	0.000 (0.054)	0.044 (0.055)
lnER	−0.001 (0.011)	−0.025 (0.029)	−0.026 (0.034)
lnU	0.007 (0.016)	−0.197 (0.046)***	−0.189 (0.051)***

Numbers in parentheses represent standard errors, and ***, **, * imply 1%, 5%, and 10% significance levels, respectively

Table 6 Effects of transportation infrastructure on economic agglomeration (DV = ln*EA*)

Variables	(1) DV = lnEA-high	(2) DV = lnEA-low
lnTI	0.038 (0.012)***	0.049 (0.017)***
lnY	0.820 (0.016)***	0.961 (0.019)***
lnPD	1.679 (0.092)***	0.704 (0.138)***
lnT	0.060 (0.005)***	0.006 (0.007)
lnIS	−0.201 (0.036)***	−0.016 (0.035)
lnER	0.024 (0.021)	−0.011 (0.022)
lnU	−0.116 (0.028)***	−0.058 (0.046)

Numbers in parentheses represent standard errors, and ***, **, * imply 1%, 5%, and 10% significance levels, respectively

et al. 2006). In this study, the direct effect is significantly negative for population density. Its indirect and total effects are significantly positive. This finding implies that a high population density reduces CE; however, the rising population density in the neighboring areas increases CE in the region under concern. When the total effect of population density is positive, population agglomeration may lead to cost-saving knowledge spillovers and may increase energy consumption in the surrounding areas. The direct effect of technological progress is significantly positive; however, the spillover effect and the total effect are insignificant. This finding indicates that technological progress increases CE but does not significantly affect the neighboring regions. The effect of technological progress on CE is two-fold. On the one hand, technological progress may lead to economic expansion, which may increase CE. On the other hand, technological progress may reduce energy consumption intensity, thereby improving energy efficiency and reducing CE (Yao and Zhang 2021). The net impact of technological progress on CE depends on the combination of the two counteractive effects. The significant and positive direct effect of the industrial structure indicates the inclusion of more energy-intensive industries in the secondary industry. However, the nonsignificant indirect and total effects imply that industrial structure only affects CE of the local area. The nonsignificant direct, indirect, and total effects of environmental regulations imply that environmental regulations do not affect CE in the sample. Only the spillover effect of urbanization is significantly negative, suggesting that urbanization in the neighboring areas affects the level of CE in the region under concern. The overall effect of urbanization is nonsignificant possibly because the levels of urbanization in Chinese cities do not significantly differ as all the cities had experienced rapid expansion in the sample period.

Transportation infrastructure and CE: importance of economic agglomeration

Theoretical and empirical analyses have indicated that transportation infrastructure significantly aggravates CE. However, the impact transmission path remains unknown. Thus, this study assesses the mediating effect of economic agglomeration on the relation between infrastructure development and CE to identify the transmission mechanism. At different levels of economic agglomeration, the effect of infrastructure development on CE may differ. Therefore, the ranking of cities in terms of levels of economic agglomeration in 2017 is used as the benchmark to categorize the sample data into high-level and low-level groups based on economic agglomeration. The number of cities in the high-level and low-level groups is 140 and 141, respectively. Determining whether transportation infrastructure can affect economic agglomeration is essential for determining whether economic agglomeration is a mediating variable. The test results are presented in Table 6.

Due to space limitation, this article reports only the results of the total effects. The results in columns (1) and (2) indicate a significant association between transportation infrastructure and economic agglomeration; however, the differences in coefficients imply that the transportation infrastructure differently affects economic agglomeration based on the levels of economic agglomeration. The promotion effect of transportation infrastructure on high levels of economic agglomeration is lower than that on low levels of economic agglomeration. This is because economic agglomeration depends on transportation infrastructure and the contribution of high-tech industries and talents. Under low levels of economic agglomeration, infrastructure can shorten the physical distance between elements, reduce transportation costs, and attract enterprises and talents, thus becoming the main determinant of economic agglomeration.

Further, transportation infrastructure, economic agglomeration, and CE are included in the same model to verify

Table 7 Regression on the meditation effect: economic agglomeration (DV = lnCE)

Variables	Direct effects		Indirect effects		Total effects	
	(3)	(4)	(5)	(6)	(7)	(8)
lnTI	0.100 (0.025)***	0.058 (0.017)***	0.094 (0.031)***	0.185 (0.029)***	0.195 (0.027)***	0.243 (0.031)***
lnEA-high	0.046 (0.051)		0.232 (0.077)***		0.278 (0.085)***	
lnEA-low		0.088 (0.022)***		0.362 (0.058)***		0.450 (0.069)***
lnY	0.552 (0.245)**	0.661 (0.138)***	0.132 (0.370)	− 1.414 (0.319)***	0.684 (0.402)*	− 0.753 (0.385)*
$(\ln Y)^2$	− 0.018 (0.012)	− 0.027 (0.007)***	− 0.014 (0.018)	0.061 (0.016)***	− 0.032 (0.020)	0.034 (0.019)*
lnPD	− 0.030 (0.113)	− 0.265 (0.080)***	0.537 (0.200)***	0.801 (0.202)***	0.507 (0.231)**	0.535 (0.240)**
lnT	0.034 (0.008)***	0.005 (0.005)	− 0.034 (0.011)***	0.011 (0.010)	0.000 (0.011)	0.015 (0.011)
lnIS	0.126 (0.060)**	0.030 (0.027)	0.046 (0.082)	0.068 (0.053)	0.172 (0.086)**	0.098 (0.059)*
lnER	0.003 (0.021)	− 0.002 (0.010)	− 0.005 (0.034)	− 0.023 (0.027)	− 0.001 (0.042)	− 0.025 (0.033)
lnU	0.023 (0.025)	− 0.025 (0.021)	− 0.063 (0.048)	− 0.305(0.059)***	− 0.040 (0.058)	− 0.330 (0.071)***

Numbers in parentheses represent standard errors, and ***, **, * imply 1%, 5%, and 10% significance levels, respectively

the mediating role of economic agglomeration. The results are presented in Table 7, showing that the total effects of transportation infrastructure and economic agglomeration on CE are significant at 1% level. This result indicates a significant mediating role of economic agglomeration in the relation between transportation infrastructure and CE. Furthermore, it verifies that economic agglomeration is a valid transmission path between transportation infrastructure and CE, thereby verifying H2 put forward in this paper.

The mediating effect of economic agglomeration differs depending on the level of economic agglomeration. Cities with a relatively high level of economic agglomeration do not significantly directly affect CE; however, the indirect and total effects are significant and positive. The direct, indirect, and total effects of cities with lower levels of economic agglomeration on CE are also significant and positive. A comparison of the two indicates that although their coefficients are positive, the impact coefficients of cities with low levels of economic agglomeration on CE exceed those of cities with high levels of economic agglomeration. Regardless of whether it is a high-level group or a low-level group, the economic agglomeration positively affects CE. This may be explained by the fact that the effect of economic agglomeration on the scale of output exceeds its cost-saving effect. The impact coefficient of the low-level group being higher than that of the high-level group may be explained by the fact that most cities with high levels of economic agglomeration are developed areas with a higher level of urbanization, whereas most cities with lower levels of economic agglomeration are still at a relatively low level of industrialization. The latter cities are more likely to depend on labor-intensive and energy-intensive industries for economic development and/or be located at the lower end of the industrial value chains. The agglomeration of such enterprises will consume high energy and produce a large amount of CO_2. In the urbanization process, cities with high levels of economic

Table 8 Robustness test results replacing core explanatory variables (DV = lnCE)

Variables	Direct effects		Indirect effects		Total effects	
	(9)	(10)	(11)	(12)	(13)	(14)
lnTII	0.027 (0.022)	0.037 (0.016)**	0.123 (0.028)***	0.206 (0.028)***	0.150 (0.025)***	0.243 (0.030)***
	(0.022)	(0.016)	(0.028)	(0.028)	(0.025)	(0.030)
lnEA-high	0.051 (0.051)		0.260 (0.077)***		0.311 (0.086)***	
lnEA-low		0.086 (0.022)***		0.353 (0.058)***		0.439 (0.069)***
lnY	0.726 (0.244)***	0.694 (0.137)***	0.067 (0.372)	− 1.285 (0.311)***	0.793 (0.410)*	− 0.591 (0.374)
$(\ln Y)^2$	− 0.026 (0.012)**	− 0.029 (0.007)***	− 0.012 (0.018)	0.054 (0.016)***	− 0.038 (0.021)*	0.026 (0.019)
lnPD	− 0.106 (0.111)	− 0.320 (0.079)***	0.508 (0.201)**	0.615 (0.197)***	0.402 (0.234)*	0.294 (0.233)
lnT	0.036 (0.008)***	0.005 (0.005)	− 0.040 (0.011)***	0.010 (0.010)	− 0.004 (0.011)	0.015 (0.011)
lnIS	0.131 (0.060)**	0.029 (0.027)	0.044 (0.083)	0.067 (0.052)	0.174 (0.088)**	0.096 (0.058)*
lnER	0.003 (0.021)	− 0.002 (0.010)	− 0.002 (0.034)	− 0.023 (0.027)	0.000 (0.042)	− 0.026 (0.033)
lnU	0.024 (0.025)	− 0.022 (0.021)	− 0.058 (0.049)	− 0.291 (0.059)***	− 0.034 (0.059)	− 0.314 (0.071)***

Numbers in parentheses represent standard errors, and ***, **, * imply 1%, 5%, and 10% significance levels, respectively

Table 9 Robustness test results after controlling for other variables (DV = lnCE)

Variables	Direct effects		Indirect effects		Total effects	
	(15)	(16)	(17)	(18)	(19)	(20)
lnTI	0.099 (0.025)***	0.058 (0.017)***	0.091 (0.028)***	0.184 (0.026)***	0.189 (0.027)***	0.242 (0.030)***
lnEA-high	0.044 (0.051)		0.222 (0.083)***		0.266 (0.090)***	
lnEA-low		0.087 (0.022)***		0.362 (0.061)***		0.448 (0.071)***
lnY	0.539 (0.242)**	0.656 (0.132)***	0.169 (0.373)	− 1.474 (0.294)***	0.708 (0.363)*	− 0.818 (0.337)**
$(\ln Y)^2$	− 0.017 (0.012)	− 0.027 (0.007)***	− 0.015 (0.019)	0.064 (0.016)***	− 0.032 (0.019)*	0.038 (0.018)**
lnPD	− 0.040 (0.114)	− 0.274 (0.080)***	0.489 (0.199)**	0.745 (0.192)***	0.448 (0.234)*	0.471 (0.230)**
lnT	0.035 (0.008)***	0.004 (0.005)	− 0.032 (0.012)***	0.009 (0.010)	0.003 (0.013)	0.013 (0.012)
lnIS	0.128 (0.060)**	0.033 (0.027)	0.050 (0.072)	0.078 (0.046)*	0.178 (0.078)**	0.111 (0.054)**
lnER	0.002 (0.021)	− 0.003 (0.010)	− 0.016 (0.036)	− 0.026 (0.028)	− 0.014 (0.043)	− 0.029 (0.034)
lnU	0.021 (0.025)	− 0.024 (0.021)	− 0.060 (0.048)	− 0.302 (0.059)***	− 0.039 (0.058)	− 0.326 (0.071)***
HSR	0.003 (0.012)	0.017 (0.009)*	0.035(0.019)*	0.017 (0.023)	0.038 (0.023)*	0.034 (0.027)

Numbers in parentheses represent standard errors, and ***, **, * imply 1%, 5%, and 10% significance levels, respectively

agglomeration may also bring about production-scale economies with more high-tech enterprises. Thus, the economic agglomeration of such enterprises may result in knowledge spillover, thereby alleviating the effect of economic agglomeration on CE.

Robustness test

Following Huang et al. (2020), road area per capita (lnTI) is replaced by the urban road density (lnTII), which is measured by the road surface area per square kilometer of the territorial area. The estimation results are presented in Table 8.

High-speed rail is a new mode of modern transportation. Several studies have suggested that high-speed rail has a substitution effect on road transportation, with important implications on CE. Thus, a new dummy variable for high-speed rail is added to the regression model. Its value is 1 if the city is connected by a high-speed rail in a particular year and 0 otherwise. Table 9 presents the estimation results.

After replacing the core explanatory variables or controlling for other variables, the significance and direction of the main explanatory variables were similar to those from the basic regression model. This result suggests that conclusions drawn from the previous regressions remain unchanged and that the basic models are robust. The robustness test results reinforce that the transportation infrastructure aggravates CE and that the "neighboring effect" is greater than the "local effect" in the same direction. Furthermore, the results indicate a partial mediating effect of economic agglomeration on the relation between transportation infrastructure and CE. This implies that economic agglomeration is a significant transmission channel through which transportation infrastructure affects CE. However, its mediating effect differs at different levels of economic agglomeration between cities. Most interestingly, a low level of economic agglomeration has a greater mediating effect than a high level of economic agglomeration.

Conclusions and policy recommendations

This study considers 281 prefecture-level cities in China during 2003–2017 as the research sample and uses the Moran's *I* index to measure the spatial distribution of China's transportation infrastructure and CE. It further uses the SDM to explore the mechanism underlying the effect of transportation infrastructure on CE. The findings indicate a partial mediating role of economic agglomeration. The study also uses some robustness tests to reaffirm the basic regression results.

Based on the theoretical and empirical analyses, the following conclusions are derived. First, a positive spatial correlation exists between urban transportation infrastructure and CE. Second, transportation infrastructure aggravates CE, and the "neighboring effect" is greater than the "local effect." Third, The partial mediating effect of economic agglomeration is greater in cities with low economic agglomeration than in cities with high economic agglomeration.

The research findings and conclusions have important policy implications. First, policymakers should focus on the development of local transportation, as well as on their neighboring cities. The central/provincial governments should facilitate and strengthen the joint efforts of city governments to plan for the development of local transportation infrastructure with respect to the overall CE reduction. Second, the implementation of green transportation and smart transportation should be accelerated. Furthermore, greener energy should be used in transportation. Third, cities should introduce more low-carbon and environmentally friendly enterprises, attract talents, and maximize the benefits of knowledge spillovers to effectively alleviate CE when cities attract companies to invest and move in.

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Declarations

Ethical approval Not applicable.

Consent to participate Not applicable.

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References

Achtymichuk DS, Checkel MD (2010) Investigating the effects of transportation infrastructure development on energy consumption and emissions. University of Alberta (canada) 49(02):173–179

Ahlfeldt GM, Feddersen A (2015) From periphery to core: measuring agglomeration effects using high-speed rail. Journal of Economics Geography 18(2):355–390

Akerman J (2011) The role of high-speed rail in mitigating climate change – the Swedish case Europabanan from a life cycle perspective. Transp Res Part D 16:208–217

Al-Rawashdeh R, Jaradat AQ, Al-Shboul M (2015) Air pollution and economic growth in MENA countries: testing EKC hypothesis. Environ Res Eng Manag 4(70):54–65

Anselin L (1988) Spatial econometrics: methods and models. Kluwer Academic, Dordrecht

Anselin L (1995) Local indicators of spatial association-LISA. Geogr Anal 27(2):93–115

Baron DA, Kenny (1986) The moderator-mediator variable distinction in social psychological research: conceptual, strategic, and statistical considerations. J Pers Soc Psychol 51(6):1173–1182

Burton E (2000) The compact city: just or just compact? A Preliminary Analysis Urban Studies 37(11):1969–2006

Cairnes and Lorraine (1996) The compact city: a sustainable urban form. Urban Design International 1:293–294

Chen S, Santos Paulino AU (2013) Energy consumption restricted productivity re-estimates and industrial sustainability analysis in post–reform China. Energy Policy 57:52–60

Cheng Z (2016) The spatial correlation and interaction between manufacturing agglomeration and environmental pollution. Ecol Ind 61:1024–1032

Dietz T, Rosa EA (1997) Effects of population and affluence on CO2 emissions. Proc Natl Acad Sci 94(1):175–179

Fan YV, Perry S, Kleme JJ, Lee CT (2018) A review on air emissions assessment: transportation. J Clean Prod 194:673–684

Fujita M, Thisse JF (2003) Does geographical agglomeration foster economic growth? And who gains and losses from it? Japanese Economic Review 54(2):121–145

Getis A (2007) Reflections on spatial autocorrelation. Reg Sci Urban Econ 37(4):491–496

Getis A, Ord JK (1992) The analysis of spatial association by use of distance statistics. Geogr Anal 24:189–206

Glaeser EL, Kallal HD, Scheinkman JA et al (1992) Growth in cities. J Polit Econ 100(6):1126–1152

Hao Y, Liu YM (2016) The influential factors of urban PM2.5 concentrations in China: a spatial econometric analysis. J Clean Prod 112:1443–1453

Holl A (2004) Manufacturing location and impacts of road transport infrastructure: empirical evidence from Spain. Reg Sci Urban Econ 34:341–363

Huang GB, Zhang J, Yu J, Shi XP (2020) Impact of transportation infrastructure on industrial pollution in Chinese cities: a spatial econometric analysis. Energy Economics 92:104973

Jia P, Li K, Shao S (2018) Choice of technological change for China's low-carbon development: evidence from three urban agglomerations. J Environ Manage 206:1308–1319

Jia RN, Shao S, Yang LL (2021) High-speed rail and CO_2 emissions in urban china: a spatial difference-in-differences approach. Energy Economics 99:105271

Jiang J, Ye B, Xie D, Li J, Miao L, Yang P (2017) Sector decomposition of China's national economic carbon emissions and its policy implication for national ETS development. Renewable Sustainable Energy Reviews 75:855–867

Kang YQ, Zhao T, Yang YY (2016) Environmental Kuznets curve for CO2 emissions in china: a spatial panel data approach. Ecol Ind 63:231–239

Lee J, Edil TB, Benson CH, Tinjum JM (2013) Building environmentally and economically sustainable transportation infrastructure: green highway rating system. J Constr Eng Manag 139(12):A4013006

Lesage J, Pace RK (2009) Introduction to spatial econometrics. CRC Press, Boca Raton, pp 56–58

Li XY, Tang BJ (2017) Incorporating the transport sector into carbon emission trading scheme: an overview and outlook. Nat Hazards 88:683–698

Li Y, Du Q, Lu X, Wu J, Han X (2019) Relationship between the development and CO_2 emissions of transport sector in China. Transportation Research Part D-Transport and Environment 74:1–14

Lin BQ, Chen Y (2020) Will land transport infrastructure affect the energy and carbon dioxide emissions performance of China's manufacturing industry? Appl Energy 260:114266

Liu Y, Ji Y, Shao S, Zhong F, Zhang N, Chen Y (2017) Scale of production, agglomeration and agricultural pollutant treatment: Evidence from a survey in China. Ecol Econ 140:30–45

Lv ZK, Li SS (2021) How financial development affects CO_2 emissions: a spatial econometric analysis. J Environ Manage 277:111397

Marzio G, Lanza A, Pauli F (2006) Reassessing the environmental Kuznets curve for CO2 emissions: a robustness exercise. Ecol Econ 57(1):152–163

Meijers E, Hoekstra J, Leijten M, Louw E, Spaans M (2012) Connecting the periphery: distributive effects of new infrastructure. J Transp Geogr 22:187–198

Miao Z, Baležentis T, Tian Z, Shao S, Geng Y, Wu R (2019) Environmental performance and regulation effect of China's atmospheric pollutant emissions: evidence from "three regions and ten urban agglomerations." Environ Resource Econ 74(1):211–242

Moran P (1950) Notes on continuous stochastic phenomena. Biometrika 37:17–23

Rios V, Gianmoena L (2018) Convergence in co2 emissions: a spatial economic analysis with cross-country interactions. Energy Economics 75:222–238

Shao S, Tian Z, Yang L (2017) High speed rail and urban service industry agglomeration: evidence from China's Yangtze River Delta region. J Transp Geogr 64:174–183

Shi K, Chen Y, Li L, Huang C (2018) Spatiotemporal variations of urban CO_2 emissions in China: a multiscale perspective. Appl Energy 211:218–229

Tang K, Hailu A (2020) Smallholder farms' adaptation to the impacts of climate change: evidence from china's loess plateau. Land Use Policy 91:104353

Tang K, He C, Ma C et al (2019) Does carbon farming provide a cost-effective option to mitigate GHG emissions? Evidence from China. Australian Journal of Agricultural and Resource Economics 63(3):575–592

Tang K, Liu Y, Zhou D et al (2021a) Urban carbon emission intensity under emission trading system in a developing economy: evidence from 273 Chinese cities. Environ Sci Pollut Res 28(5):5168–5179

Tang K, Xiong C, Wang Y et al (2021b) Carbon emissions performance trend across Chinese cities: evidence from efficiency and convergence evaluation. Environ Sci Pollut Res 28(2):1533–1544

Tang K, Chen Q, Tan W et al (2022) The impact of financial deepening on carbon reductions in China: evidence from city-and enterprise-level data. Int J Environ Res Public Health 18(19):11355

Thompson AC (2000) Does public infrastructure affect economic activity? Evidence from the rural interstate highway system. Reg Sci Urban Econ 30(4):457–490

Wang SJ, Fang CL, Guan XL, Pang B, Ma HT (2014) Urbanization, energy consumption, and carbon dioxide emissions in China: a panel data analysis of China's provinces. Appl Energy 136:738–749

Wang Y, Yan W, Ma D, Zhang C (2018) Carbon emissions and optimal scale of China's manufacturing agglomeration under heterogeneous environmental regulation. J Clean Prod 176:140–150

Wang L, Zhao Z, Xue X et al (2019) Spillover effects of railway and road on CO2 emission in China: a spatiotemporal analysis. J Clean Prod 234:797–809

Wang C, Guo Y, Shao S, Fan M, Chen S (2020) Regional carbon imbalance within China: an application of the Kaya-Zenga index. J Environ Manage 262:110378

Wu J, Ma C, Kai T (2019) The static and dynamic heterogeneity and determinants of marginal abatement cost of CO2 emissions in chinese cities. Energy 178:685–694

Wu J, Feng Z, Tang K (2021a) The dynamics and drivers of environmental performance in Chinese cities: a decomposition analysis. Environ Sci Pollut Res 28(24):30626–30641

Wu JX, Xu H, Tang K (2021b) Industrial agglomeration, CO2 emissions and regional development programs: a decomposition analysis based on 286 chinese cities. Energy 225:120239

Xie R, Fang J, Liu C (2017) The effects of transportation infrastructure on urban carbon emissions. Appl Energy 196:199–207

Xie R, Wei D, Han F, Lu Y, Fang J, J., Liu, Y., (2019) The effect of traffic density on smog pollution: evidence from Chinese cities. Technol Forecast Soc Chang 144:421–427

Yao S, Zhang S (2021) Energy mix, financial development and carbon emissions in China: a directed technical change perspective. Environ Sci Pollut Res 28(44):62959–62974

York R, Rosa EA, Dietz T (2003) STIRPAT, IPAT and ImPACT: analytic tools for unpacking the driving forces of environmental impacts. Ecol Econ 46(3):351–365

You W, Lv Z (2018) Spillover effects of economic globalization on CO2 emissions: a spatial panel approach. Energy Economics 73:248–257

Zhao X, Burnett JW, Fletcher JJ (2014) Spatial analysis of China province-level CO_2 emission intensity. Renew Sustain Energy Rev 33:1–10

Zhou D, Liang X, Zhou Y et al (2020) Does emission trading boost carbon productivity? Evidence from China's pilot emission trading scheme. International Journal of Environmental Research and Public Health 17(15):5522

Zhu Q, Peng X (2012) The impacts of population change on carbon emissions in China during 1978–2008. Environ Impact Assess Rev 36:1–8

Ciccone A, Hall RE (1995) Productivity and the density of economic activity. Economics Working Papers

Duranton G, Puga D (2004) Chapter 48 micro-foundations of urban agglomeration economies. Handbook of Regional and Urban Economics. 2063–2117

Mazzanti M, Montini A, Zoboli R (2007) Economic dynamics, emission trends and the EKC hypothesis new evidence using NAMEA and provincial panel data for Italy. Climate Change Modelling and Policy Working Papers