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Summary

Existing studies have investigated the environmental dividends of substituting high-speed rail for other energy-intensive vehicles from an engineering standpoint, but they have yet to explore the economic effects of high-speed rail and the associated carbon emission reduction benefits. To fill the research gap, we use panel data from 285 Chinese cities between 2004 and 2014, and employ a difference-in-difference model to empirically examine the impact of high-speed rail opening on CO_2 emissions. Our results show that the opening of high-speed rail reduces local carbon emissions significantly. This finding is robust and is unaffected by outliers, control group selection, time trends, geography and expectation factors, or endogeneity. The mechanism test reveals that the structure, innovation, and FDI effects are three intermediate influence channels. Further research finds that the emission reduction benefit rises as the intensity of high-speed rail opening climbs the ladder, and high-speed rail service has a spillover effect within an 80-kilometer radius. Moreover, the carbon benefit of the Beijing-Shanghai high-speed rail line far surpasses its carbon footprint, indicating that the line is green. Based on these findings, we recommend that China should support the expansion of high-speed rail in order to reduce carbon emissions in a scientific and responsible manner.

Keywords: High-speed rail, CO_2 emissions, Impact mechanism, Difference-in-difference, China

JEL Classification: Q54, Q56, O13, R11, P28

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Is high-speed rail green?
Evidence from a quasi-natural experiment in China

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Abstract: Existing studies have investigated the environmental dividends of substituting high-speed rail for other energy-intensive vehicles from an engineering standpoint, but they have yet to explore the economic effects of high-speed rail and the associated carbon emission reduction benefits. To fill the research gap, we use panel data from 285 Chinese cities between 2004 and 2014, and employ a difference-in-difference model to empirically examine the impact of high-speed rail opening on CO_2 emissions. Our results show that the opening of high-speed rail reduces local carbon emissions significantly. This finding is robust and is unaffected by outliers, control group selection, time trends, geography and expectation factors, or endogeneity. The mechanism test reveals that the structure, innovation, and FDI effects are three intermediate influence channels. Further research finds that the emission reduction benefit rises as the intensity of high-speed rail opening climbs the ladder, and high-speed rail service has a spillover effect within an 80-kilometer radius. Moreover, the carbon benefit of the Beijing-Shanghai high-speed rail line far surpasses its carbon footprint, indicating that the line is green. Based on these findings, we recommend that China should support the expansion of high-speed rail in order to reduce carbon emissions in a scientific and responsible manner.

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1. Introduction

Climate change has put ecosystems and human survival in jeopardy, and the international community is making efforts towards tackling global climate change. China, as the world's largest carbon emitter, emits more than that of the United States, European Union and Japan combined (BP, 2021), and thus has a lot of room to reduce its carbon emissions. As a concerted effort to respond to the global climate crisis, China has taken its due responsibility and in September 2020 committed to carbon emissions peak by 2030 and carbon neutrality by 2060. For some time to come, energy conservation and emission reduction will remain a major concern in China's economic and social development and a key component towards carbon neutrality (Zhang, 2015, 2017 and 2021).

The transportation sector, one of the most important industries for the national economy and people's lives, is a major user of fossil fuels and a key emitter of carbon dioxide. The International Energy Agency (IEA) estimates that China's transportation sector accounted for 9.6% of total CO_2 emissions in 2018, following just the energy and industrial sectors, and this figure is obviously rising.[1] Li *et al*. (2017) predicted that transportation-related CO_2 emissions will contribute to 30-40% of total CO_2 emissions in China for the foreseeable future, similar to current levels in North America and Europe. Given this, managing the relationship between transportation industry expansion and CO_2 emissions while maintaining rapid economic growth is a critical challenge for China to overcome as it moves toward carbon neutrality.

China's high-speed railway network has expanded substantially over the last decade or so. By the end of 2020, over 37,900 kilometers (km) of high-speed railway were operating in China, accounting for two-thirds of the worldwide total.[2] It is predicted that China's high-speed rail (HSR) network will reach 700,000 km by 2035, and that all cities with a population of more than 500,000 will have their own HSR stations.[3] Generally speaking, HSR is viewed as cleaner and greener than road vehicles and airplanes due to its scalable transport capacity and lack of tail pipe emissions (Chang *et al.*, 2019). In comparison with a scenario without HSR, Krishnan *et al*. (2015) estimated that if HSR accounts for 30% of the transportation network, gasoline and jet fuel consumption for interstate passenger journeys would decrease by 34%, and CO_2 emissions would drop by 0.8 billion short tons. The popularity of HSR has changed people's travel habits and provided China with a new way to achieve low-carbon transportation. However, in the current academic domain, scholars have debated whether HSR can genuinely reduce CO_2 emissions.

Some academics have performed preliminary research on the carbon footprint of HSR at various stages using an economic input-output life cycle assessment (EIO-LCA) method. Lee *et al*. (2020) assessed greenhouse gas emissions throughout the construction phase of a HSR line infrastructure from Osong to Gwangju in Korea. Similarly, Chang and Kendall (2011) estimated that building a HSR line from San Francisco to Anaheim would result in 2.4 million metric tons of CO_2 emissions, with material fabrication accounting for 80% and construction material transportation accounting for 16%. A hybrid input-output life cycle method was applied by Cheng *et al*. (2020) to evaluate the carbon footprint of Beijing-Tianjin intercity HSR during the construction stage, and their findings revealed that bridges contribute the most CO_2 emissions

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[1] See https://www.iea.org/data-and-statistics/data-browser.

[2] The data comes from the International Railway Union.

[3] The data comes from the "Outline of the National Comprehensive Three-Dimensional Transportation Network Planning" and the "Mid- to Long-term Railway Network Plan" released by the State Council of China in 2021 and 2016, respectively.

(63.1%), followed by rails (15.1%) and electric multiple units (10.0%). In addition to construction, Jones *et al*. (2017) and Lin *et al*. (2019) also estimated carbon emissions during various stages of the HSR life cycle. Specifically, Jones *et al*. (2017) found that train operation contributes the most to overall environmental emissions, followed by train manufacture. Lin *et al*. (2019) employed an EIO-LCA method to estimate the carbon footprint of the Beijing-Shanghai HSR line at various stages, and they found that operation contributes the largest (71%), followed by construction (20%) and maintenance (9%).

Based on these preparations, scholars investigated whether substituting HSR for other energy-intensive vehicles would reduce emissions and the extent to which this replacement could compensate for the carbon footprint generated during the HSR construction and operation stages. For example, Tsai (2017) proved that Taiwan's HSR, with a carbon footprint one-third that of a passenger car, has made a significant contribution to reducing atmospheric pollution. Åkerman (2011) estimated that the Europabanan, a proposed HSR line in Sweden, will save 550,000 tons of CO_2-equivalents per year by 2025/2030 based on a life cycle study. Unlike Tsai (2017) and Åkerman (2011), who studied the substitution of HSR for other modes of transportation in general, Westin and Kågeson (2012) believed that in order to compensate for the embedded emissions from a HSR line, the majority of traffic diverted from other modes must come from aviation. Based on Westin and Kågeson (2012), Robertson (2016) estimated the amount of emissions saved by replacing aircraft with HSR. The avoided annual life cycle CO_2 emissions in the target year 2056 were estimated to be 0.37 metric tons, representing an 18% reduction when compared to the air cycle alone on the city pair. In contrast to the studies described above, Chen *et al.* (2016) examined China's HSR investment using a dynamic recursive computable general equilibrium (CGE) framework, concluding that emissions reductions from rail substitution for other modes were small and offset by output expansion due to the lowered rail transport costs and induced demand.

Following a review of the preceding research, we discover that the majority of the literature employs engineering methods to estimate the carbon emissions of a single HSR line during its construction, operation, and maintenance phases, and then investigates the emission reduction benefits of substituting HSR for other energy-intensive vehicles. In fact, encouraging residents to switch modes of transportation is only a surface-level explanation for HSR's contribution to CO_2 reductions. In depth, HSR promotes the tertiary sector, which includes tourism, catering, and hotels, while crowding out the secondary sector in station cities, resulting in an upgrade of local industrial structure and a reduction in CO_2 emissions. In addition, HSR supports the movement of highly skilled labor among station cities that stimulates the development of local low-carbon technology. Third, HSR raises the reputation of station cities, making it easier for them to attract green FDI. Unfortunately, few studies have investigated the impact of HSR on local CO_2 emissions from the economic perspectives described above. It should be emphasized that if we assess the emission reduction effect of HSR that results from substituting it for other modes of transportation while ignoring its potential economic benefits, the contribution of HSR to low-carbon development would be significantly underestimated. Given this, we employ a quasi-natural experimental analysis method—the Difference-in-Difference (DID) Model—on panel data from 285 Chinese cities between 2004 and 2014 to estimate the impact of HSR on CO_2 emissions.

In comparison to earlier research, the contributions of this study are apparent in the following aspects. First, we examine the impact of HSR on carbon emissions from an economic standpoint and employ a mediating effect model to explore the internal impact processes through three channels: structure effect, innovation effect, and FDI effect. Second, after investigating the impact of cities opening or not opening HSR lines on carbon emissions with a dummy variable, we apply the concept of degree centrality from social network theory to establish a continuous DID model to explore the emission reduction effect of HSR opening intensity. Third, we examine the geographic spillover of HSRs’ s emission reduction effect and its maximum range by varying the distance threshold. Fourth, the Beijing-Shanghai HSR line is used to conduct a basic carbon cost-benefit analysis to illustrate its significance in green development.

The rest of the paper is structured as follows. Section 2 provides a brief history of HSR in China. Section 3 offers the theoretical hypothesis for this study. Section 4 discusses variable selection, model specification, and data sources. In Section 5, we empirically examine the impact of HSR service on CO_2 emissions and conduct a series of robustness and heterogeneity tests. The potential impact mechanism between them is also explored. Section 6 studies the impact of HSR opening intensity on CO_2 emissions and the geographic spillover of HSR. In addition, we undertake a simple carbon cost-benefit analysis for the Beijing-Shanghai HSR line. Section 7 outlines the conclusions and their policy implications.

2. The History of China’s HSR

The Qinhuangdao-Shenyang line, China’s first high-speed passenger railway, went into service on October 12, 2003, and its design, construction, and operation provided a wealth of reference information for subsequent HSR. In 2004, the State Council approved the “Mid- to Long-term Railway Network Plan” (MLTRP) , a guideline for China to build railways during the follow-up period, which proposed to construct a high-speed passenger railway network of more than 12,000 kilometers, including four lines running north-south and four lines running east-west (also known as the “Four Vertical and Four Horizontal” network; FVFHN).[4] On August 1, 2008, the Beijing-Tianjin Intercity Railway, China‘s first HSR with autonomous property rights and a peak speed of 350 km/h, entered into operation, setting off a period of fast expansion for China’s HSR. By the end of 2017, China had 19,000 kilometers of HSR lines in service, far exceeding the number for the rest of the world, and the FVFHL was completed and opened to traffic three years ahead of schedule. To better serve national economic growth, the Chinese government updated the MLTRP in July 2016 (hereinafter referred to as the 2016 Revision), announcing plans to extend the FVFHN to a new “Eight Vertical and Eight Horizontal” HSR network (EVEHN).[5] According to the 2016 Revision, China‘s HSR network will reach approximately 70,000 kilometers by 2035, connecting provincial capitals and other large and medium-sized cities with populations of more than 500,000 people, while creating a 1-4-hour traffic circle between adjacent large and medium-sized cities and a 0.5-2-hour traffic circle within the city cluster.

[4] The four north-south HSR routes are the Beijing-Harbin line, the Beijing-Shanghai line, the Beijing-Hong Kong line, and the Hangzhou-Shenzhen line. The four east-west HSR routes are the Qingdao-Taiyuan line, the Xuzhou-Lanzhou line, the Shanghai-Chengdu line, and the Shanghai-Kunming line.

[5] The new network, which is nearly twice as long as the FVFHN, consists of eight north-south (“vertical”) and eight east-west (“horizontal”) corridors. The eight north-south HSR corridors are the Coastal corridor, Beijing-Shanghai corridor, Beijing-Hong Kong (Taipei) corridor, Beijing-Harbin, Beijing-Hong Kong (Macau) corridor, Hohhot-Nanning corridor, Beijing-Kunming corridor, Baotou (Yinchuan)-Hainan corridor, and Lanzhou (Xining)-Guangzhou corridor. The eight east-west HSR corridors are the Suifenhe-Manzhouli corridor, Beijing-Lanzhou corridor, Qingdao-Yinchuan corridor, Eurasia Continental Bridge corridor, Yangtze River corridor, Shanghai-Kunming corridor, Xiamen-Chongqing corridor, and Guangzhou-Kunming corridor.

We collect and visualize data on additional HSR lines and station cities in China between 2008 and 2020 (Fig. 1A – Fig. 1D). As shown in Fig. 1, China's HSR lines expanded from 4 in 2008 to 143 in 2020. HSR cities grew gradually from 16 in 2008 to 237 in 2020, accounting for more than 80% of all cities in the nation. A HSR network that connects key regions of the country is nearly complete.

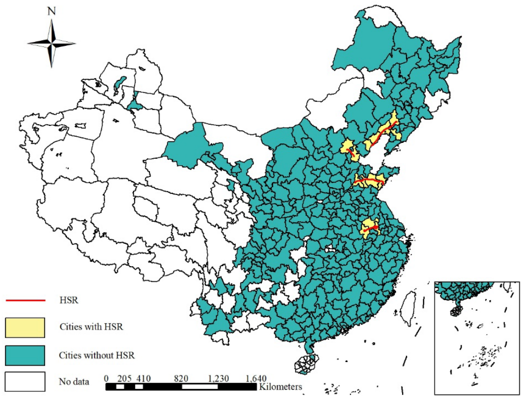

Fig. 1A. China's HSR in 2008.

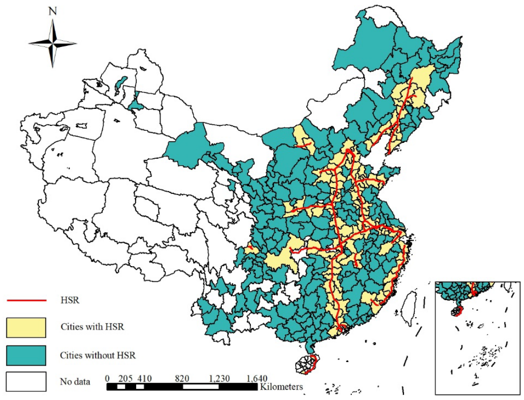

Fig. 1B. China's HSR in 2012.

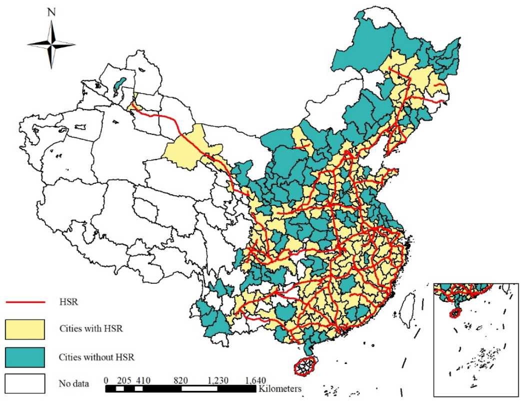

Fig. 1C. China's HSR in 2016.

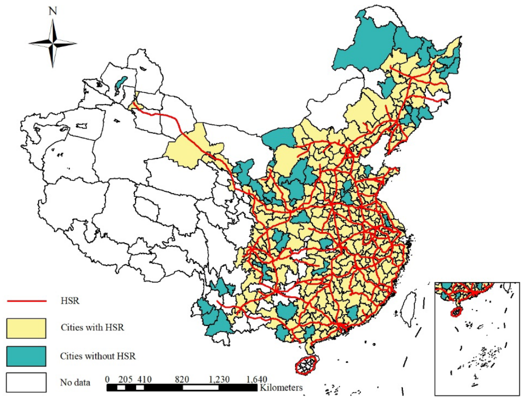

Fig. 1D. China's HSR in 2020.

As HSR has grown significantly in recent years, China has paid increased attention to its environmental impact. In the 2016 Revisions, China set a goal of establishing a green and comprehensive transportation system and used it as a guideline for the development of HSR over the next five years (2016–2025). To graphically depict the effect of HSR on CO_2 emissions, we create a histogram displaying the emissions levels of HSR and non-HSR cities, as well as a broken-line graph highlighting the gaps between the two groups in Fig. 2.[6] It is obvious that HSR cities emit more carbon emissions than non-HSR cities, and the gap between the two groups grows initially and then narrows. Prior to 2008, the CO_2 emissions gap grew with each passing year. Since China began large-scale HSR construction in 2008, the gap has shrunk year by year. This evidence suggests that the opening of HSR may have a significant impact on reducing carbon emissions. It is important to highlight that the conclusion derived from Fig. 2 is tentative. To accurately identify the causal relationship between the opening of HSR and carbon emissions, we

6 See Section 4.2 for data sources.

employ an econometric model to conduct empirical research.

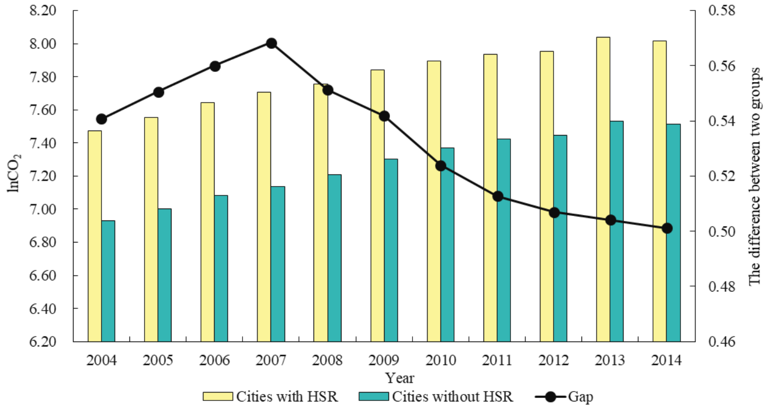

Fig. 2. The carbon emissions levels of HSR and non-HSR cities and the gap between them.

3. **Theoretical hypothesis**

3.1 Impact of HSR on CO_2 emissions

According to the IEA, the transportation sector accounts for more than half of worldwide oil consumption and around one-quarter of global CO_2 emissions from fuel combustion.[7] Given this, transportation changes are essential for achieving global carbon reductions. HSR, as we all know, is typically a green mode of transportation. Railways have a higher capacity, use less energy, and emit less greenhouse gases than other modes of transportation. The high-speed railway, in which China has made significant investments in recent years, attracts people away from other high-emissions modes of transportation, such as planes and cars. Chang *et al*. (2019) estimated that when three vehicles are fully loaded, the greenhouse gas emissions per unit passenger kilometers traveled by HSR are 36% of those emitted by airlines and 40% of those emitted by oil-fired cars. Given the fact that traction motors are three to four times more efficient than internal combustion engines, replacing the latter, which power aircraft, cars, and motor vehicles, with the former, which can be powered by multiple energy sources delivered via the electric grid, will result in significant emission reduction benefits. Electricity as an energy carrier can be generated from a mix of sources. As part of its carbon-neutral agenda, China aims to add more renewable energy to the grid, such as solar and wind energy. In the coming years, China's grid is expected to grow increasingly green. Given this, we propose the following hypothesis:

Hypothesis 1. The opening of HSR has a direct impact on reducing carbon emissions.

3.2 The mechanism

HSR service has a negative impact on carbon emissions through structure effect. HSR is a major mode of passenger transportation. The tertiary industry, often known as the service sector, is more vulnerable to HSR than the primary and secondary industries as a result of the need for fast transit to stay in contact with the market (Qin, 2017). The operation of HSR stations generates a large number of passengers, supporting the agglomeration of urban service sectors such as tourism, catering, and hotels, as well as increasing job density in these industries (Sun and Lin, 2018). Increased passenger volume and a rising service industry drive up land prices around stations and even throughout the city, while putting pressure on local environmental regulations. High land

[7] See https://www.iea.org/data-and-statistics/data-browser.

prices and stringent environmental restrictions raise the production costs of industrial enterprises, especially those that emit a lot of pollution, pushing them to go green or migrate away from HSR cities. As a result, the opening of HSR serves to expand the tertiary sector while crowding out the secondary sector in station cities, thus lowering local carbon emissions.

HSR service has a negative impact on carbon emissions through innovation effect. As a key mode of transportation for people, HSR service removes barriers to labor mobility caused by insufficient traffic links and encourages knowledge spillover among regions (Chen and Haynes, 2017), which has a significant influence on the innovation activities of cities along the line. The advantages of HSR, such as large capacity, rapid speed, strict punctuality, and adequate security, can meet the need for highly skilled laborers who are time-sensitive but price-insensitive. These employees convey a large amount of technical information, and their movement across regions can accelerate knowledge diffusion and spillover, which has an important impact on regional innovation activity. Furthermore, because of its rapid speed, HSR saves passengers time and shortens the distance between cities. This space-time compression effect prevents unnecessary knowledge leakage and content distortion during information diffusion. In a nutshell, the opening of HSR contributes to knowledge spillover and technological innovation, thus decreasing carbon emissions.

HSR service has a negative impact on carbon emissions through foreign direct investment (FDI) effect. The opening of HSR increases the reputation of station cities and, in particular, their attraction to FDI. Existing literature shows that FDI prefers to settle in locations with convenient public transportation and great business environments in order to earn high returns on capital (Majocchi and Presutti, 2009; Contractor et al., 2020). The opening of HSR allows for face-to-face communication between investors and investees from diverse areas, as well as a reduction in the negative impact of information asymmetry and transaction costs on decision making, which favors HSR cities attracting more FDI. According to the "pollution halo" hypothesis (Duan and Jiang, 2021), FDI involves advanced technology that improves production processes, operating procedures, management skills, and collaboration levels of enterprises in the host country through demonstration, spillover, and competition effects, resulting in carbon emissions reductions.

Based on the above analysis, we propose the second research hypothesis:

Hypothesis 2. The opening of HSR indirectly reduces CO_2 emissions through structure, innovation, and FDI effects.

4. **Methodology and data**

4.1 Econometric model

We employ a DID method to investigate the impact of HSR service on CO_2 emissions. The benchmark regression specification is

$$\ln CO_{2\,it} = \alpha + \beta\, HSR_{it} + \boldsymbol{\gamma}\mathbf{X_{it}} + \mu_i + \upsilon_t + \varepsilon_{it}\,, \tag{1}$$

where $\ln CO_{2\,it}$ is the logarithmic value of CO_2 emissions in city *i* during year *t*; *HSR* is the core independent variable that indicates whether or not city *i* has a HSR station in year *t*, and it is 1 after the HSR station opens, otherwise it is 0; $\mathbf{X_{it}}$ is a set of control variables; μ_i represents city fixed effects; υ_t represents year fixed effects; ε_{it} is an error term. In Eq. (1), β is the key estimated parameter, representing the net effect of HSR opening on carbon emissions.

To investigate the indirect impact mechanism between HSR opening and CO_2 emissions, we employ the approach described in Zhang *et al*. (2020) to establish a mediating effect model:

$$Mediator_{it} = \alpha + \beta_1 HSR_{it} + \boldsymbol{\gamma}\mathbf{X_{it}} + \mu_i + \upsilon_t + \varepsilon_{it}, \tag{2}$$

$$\ln CO_{2\,it} = \alpha + \beta_2 HSR_{it} + \beta_3 Mediator_{it} + \boldsymbol{\gamma}\mathbf{X_{it}} + \mu_i + \upsilon_t + \varepsilon_{it}, \tag{3}$$

where $Mediator_{it}$ is a mediator variable; the remaining symbols have the same meaning as Eq. (1). According to Sobel (1982) and Baron and Kenny (1986), the following evidence must be obtained in order to demonstrate that $Mediator_{it}$ is a mediator variable between HSR and CO_2 emissions. First, the estimated coefficient β is significantly negative in Eq. (1), suggesting that HSR service has a significant inhibitory effect on carbon emissions. Second, the coefficient β_1 is statistically significant in Eq. (2), indicating that HSR service has a significant effect on the mediator variable. Third, the coefficient β_3 in Eq. (3) is statistically significant, meaning that the mediator variable has a significant influence on CO_2 emissions. Fourth, the estimated coefficient β_2 in Eq. (3) varies from the coefficient β in Eq. (1). Specifically, if β_2 is still significant but its absolute value decreases, the mediator variable has a partial mediating role. If β_2 is insignificant, the mediator variable has a full mediating role.

In fact, employing a dummy variable to measure the core independent variable fails to distinguish gaps in HSR opening intensity among station cities. To address this issue, we follow Moser and Voena (2012) and replace the core independent variable with $After_{it} \times DC_{it}$ to establish a continuous DID model. As shown in Eq. (4), $After_{it}$ is a time dummy variable that equals 0 in all years before city *i* opens HSR and 1 otherwise.[8] DC_{it} is degree centrality, which indicates the HSR opening intensity or, more specifically, the importance of station city *i* in the HSR network. A larger DC_{it} implies that more cities are directly connected to node *i* through the HSR network.

$$\ln CO_{2\,it} = \alpha + \beta After_{it} \times DC_{it} + \boldsymbol{\gamma}\mathbf{X_{it}} + \mu_i + \upsilon_t + \varepsilon_{it}. \tag{4}$$

The above models investigate the impact of HSR services on local carbon emissions in station cities. So, does HSR service have a spillover effect? In other words, how would the launch of a city's HSR affect carbon emissions in neighboring cities? To answer this question, we construct the following econometric model on the basis of Eq. (1):

$$\ln CO_{2\,it} = \alpha + \beta Near_{it}^{x} + \boldsymbol{\gamma}\mathbf{X_{it}} + \mu_i + \upsilon_t + \varepsilon_{it}. \tag{5}$$

We use Gaode map to acquire the latitude and longitude of HSR stations in treatment-group cities during the research period, and then we draw a set of circles with HSR stations as centers and *x* kilometers as radiuses.[9] If city *i* is located inside this set of circles in year *t*, it is considered to be affected by the HSR spillover effect, and $Near_{it}^{x}$=1.[10] If city *i* is outside of this set of circles in year *t*, it is considered to be unaffected by the HSR spillover effect, and $Near_{it}^{x}$=0. The estimated coefficient β defines the HSR spillover effect.

4.2 Variable selection and data description

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[8] In actuality, the variable HSR_{it} in Eqs. (1), (2), and (3) can be written as $After_{it} \times Treat_i$, where $Treat_i$ represents whether city *i* is in the treatment group and does not vary over time.

[9] If a city has more than one HSR station, we will focus our study on the first one to open. It should be noted that the longitude and latitude in WGS-84 coordinates used in this paper are converted from those in GCJ-02 coordinates acquired from Gaode Map by QGIS software.

[10] The coordinates of a city are defined as its government office.

(1) CO_2 emissions. At the moment, it is difficult to accurately estimate the carbon emissions of China's various cities since energy consumption and emission factors (EFs; the ratio of pollutant emitted per unit of fuel burned) are uncertain (Liu *et al*., 2015). Official national emissions estimates, for example, are inconsistent with the sum of provincial-level data, and CO_2 emission factors can differ by orders of magnitude. In this paper, we employ the Peking University CO_2 Mappings to capture the carbon emissions of various Chinese cities, according to Shao *et al.* (2019).[11] To reduce bias, the Peking University CO_2 Mappings is constructed around 64 fuel sub-types in 5 categories, with two new and comprehensive sets of measured EFs for Chinese fuel (Liu *et al*., 2015). The emission inventory has a spatial resolution of 0.1 degree $\times$ 0.1 degree and a monthly temporal resolution covering the period from 1960 to 2014. We use ArcGIS software to extract 12 sets of monthly data from the annual Peking University CO_2 Mappings. The annual carbon emissions of each city from 2004 to 2014 are computed by merging the extracted monthly data. Carbon emissions are logarithmized in the following empirical research to remove heteroscedasticity.

(2) HSR. Academics are still split on which routes should be labeled as HSR. HSR was described by the International Union of Railways as new lines designed for speeds of 250 km/h or above, as well as existing lines upgraded for speeds of up to 200 or even 220 km/h.[12] The Ministry of Railways, China's official railway regulator and operator until 2013[13], defined HSR as "newly-built passenger-dedicated rail lines designed for electrical multiple unit train sets traveling at no less than 250 km/h (including lines with reserved capacity upgraded to 250 km/h), with initial service operating at no less than 200 km/h". In this study, we adopt the Chinese government's official definition. Although the first HSR in China can be traced back to the Qinhuangdao–Shenyang passenger railway, which opened in 2003, existing research generally views the Beijing–Tianjin intercity railway with autonomous property rights, which began operations in 2008, as evidence that the country has truly entered its HSR age (Shaw *et al*., 2014; Yao *et al*., 2019). Based on the available literature, we employ a similar disposal strategy. The start of HSR service in a city that has opened multiple HSR lines in a few years is defined as the year when its first line becomes operational. Despite the lack of HSR stations in urban regions, a city is considered a HSR city if a county under its authority has one. The data on the opening of HSR lines and stations between 2004 and 2014 comes from the Chinese Research Data Services (CNRDS). We use a dummy variable to indicate if a city has HSR service. Given that many Chinese HSR lines open in late December to increase transit capacity for the upcoming Spring Festival, we create this dummy variable in the manner of Deng *et al*. (2019). Specifically, if a HSR line opens in the first half of the year (before June 30th), service is considered available before the end of the year. If a HSR line opens in the second half of the year (after June 30th), service is not considered available until next year. According to the background described in Section 2, the availability of HSR service in different cities varies over time, thus a heterogeneous timing DID model is employed here in reference to Beck *et al*. (2010).

(3) Control variables. Since carbon emissions are affected by many complex factors, we add a set of control variables in the regression equation to reduce the omitted-variable bias. The control variables include GDP per capita, population density, environmental regulations, R&D

[11] See http://inventory.pku.edu.cn/home.html.

[12] See https://uic.org/passenger/highspeed.

[13] In 2013, the Ministry of Railways was divided into the China Railway Corporation, which operates the railway network, and the National Railway Administration, which regulates and oversees the corporation.

investment, overcrowding levels, and human capital investment. GDP per capita (*GDP*) is measured using satellite-derived nighttime light (NTL) that comes from the Defense Meteorological Satellite Program's Operational Linescan System (DMSP-OLS) and the Suomi National Polar-Orbiting Partnership Visible Infrared Imaging Radiometer Suite (NPP-VIIRS).[14] Population density (*PD*) is defined as the ratio of a city's total population to the areas under its control. Environmental regulations (*ER*) are measured in accordance with Levinson (2003). R&D investment (*RD*) is measured by the percentage of government spending on science and technology as opposed to total fiscal expenditure. Overcrowding levels (*OL*) are measured by the inverse of the paved road area per capita. Human capital investment (*HC*) is measured by the ratio of middle school students to the total population. All of the data presented above, with the exception of GDP per capita, come from the *China City Statistical Yearbook* between 2004 and 2014.

(4) Instrumental variable. Self-selection bias may be captured in this study if carbon emission trends in HSR cities and non-HSR cities vary over time. Furthermore, we are unable to account for all of the variables that impact CO_2 emissions. An endogeneity problem occurs as a result of self-selection bias and omitted-variable bias. According to Faber (2014), we employ the "least cost path spanning tree network" (*LCP*) as an instrument for variable *HSR*.

LCP is constructed in a two-step procedure. The first step is to use digital elevation data to compute least cost HSR construction paths between all possible targeted cities. To that end, we establish Eq. (6), which assigns various construction costs to a large number of land parcels classified by river, slope, and relief information. A construction cost surface covering China, as a result, is generated via a raster grid made up of cost cells. The optimal route algorithm, as defined by Dijkstra (1959), is then used to create the lowest-cost pathways between all possible targeted destination pairs composed of municipalities, provincial capitals, and sub-provincial cities. In the second step, we extract these estimated bilateral cost parameters and input them into the minimum spanning tree algorithm described in Kruskal (1956). This algorithm identifies the subset of routes that connect all targeted cities on a single continuous network while minimizing global construction costs. As of now, we have a dummy variable that indicates which cities "should" open HSR based on a mix of least cost path and minimum spanning tree algorithms. ArcGIS is used to complete all of the steps. Data for the shuttle radar topography mission 90m digital elevation model is provided by the Geospatial Data Cloud.[15]

$$Cost_i = 0.3 \times Water_i + 0.4 \times Slope_i + 0.3 \times Grads_i \tag{6}$$

(5) Mediator variables. According to Section 3.2, HSR service reduces CO_2 emissions through structure, innovation, and FDI effects. Specifically, structure effect (*SE*) is measured by the ratio of the added value of the tertiary sector to that of the secondary sector. Innovation effect (*IE*) is measured by the number of green invention patents in each city. FDI effect (*FE*) is measured by the amount of foreign capital actually utilized by each city. The *China City Statistical*

[14] It should be emphasized that these two data sets have quite different spatial and radiometric properties. If they are merged and used without any adjustments, we may end up with a biased research. In this paper, the two data sets are calibrated using the approach described in Zhao *et al.* (2019) to create a temporally consistent NTL data set for the period 2004–2014.

[15] Please visit the open data platform established by the Computer Network Information Center of Chinese Academy Sciences (http://www.gscloud.cn/). A Digital Elevation Model (DEM) is a representation of the bare ground (bare earth) topographic surface of the Earth that includes various landform elements, such as slope, aspect, height, and so on.

Yearbook provides data on industrial structure and FDI, while the CNRDS provides data on green patents.

(6) Degree centrality. This variable defines the importance of a city's geographic location in the HSR network in terms of connectivity to other cities. The HSR network can be defined using line-based P-space, station-based L-space, and train-based R-space (Zhang *et al.*, 2019). The EVEHN proposed in the MLTRP depicts the high-speed railway network from the standpoint of lines connecting cities. Given this, we follow China's official practice of defining the HSR network in P-space. Specifically, all HSR station cities are defined as network nodes (V). If at least one railway (R) operates between two cities, they are considered to be connected on an edge (E). All nodes, railways, and edges combine to form a HSR network, which is denoted as G=(V, E, R). The degree centrality (*DC*) of node *i* in the network is expressed as:

$$DC_{it} = \frac{k_{it}}{N-1}, \tag{7}$$

where k_{it} represents the number of nodes that are directly connected to city *i* in year *t*, *N* is the total number of nodes, and $N-1$ denotes the maximum potential degree of a node. Degree centrality measures the degree of direct correlation between city *i* and other nodes. A higher degree centrality indicates that city *i* is connected to more network nodes or that city *i* has a larger network breadth.

Table 1 shows the descriptive statistics for the variables mentioned in Section 4.2.

Table 1

Descriptive statistics of variables.

Variable	Unit	Number	Mean	Sd	Min	Max
CO_2	10^4 tons	3135	2336.996	1884.269	81.106	20520.760
HSR	–	3135	0.125	0.330	0.000	1.000
GDP	digital number values	3135	7.627	8.169	0.149	58.353
PD	people/km^2	3135	422.196	324.545	4.700	2661.540
ER	%	3135	2.027	3.208	0.029	91.635
RD	%	3135	0.188	0.047	0.010	0.494
OL	10^7 people/km^2	3135	0.016	0.090	0.001	5.000
HC	%	3135	0.059	0.016	0.006	0.387
LCP	–	3135	0.404	0.491	0.000	1.000
SE	%	3135	0.800	0.395	0.094	3.758
IE	10^4 pieces	3131	0.280	0.838	0.000	12.536
FE	10^9 yuan	2995	0.008	0.014	0.000	0.137
DC	%	3135	2.135	7.591	0.000	73.000
$Near^{40}$	–	3135	0.027	0.162	0.000	1.000
$Near^{60}$	–	3135	0.072	0.259	0.000	1.000
$Near^{80}$	–	3135	0.128	0.334	0.000	1.000
$Near^{100}$	–	3135	0.168	0.374	0.000	1.000

5. Results and discussion

5.1 Test of common trends assumption

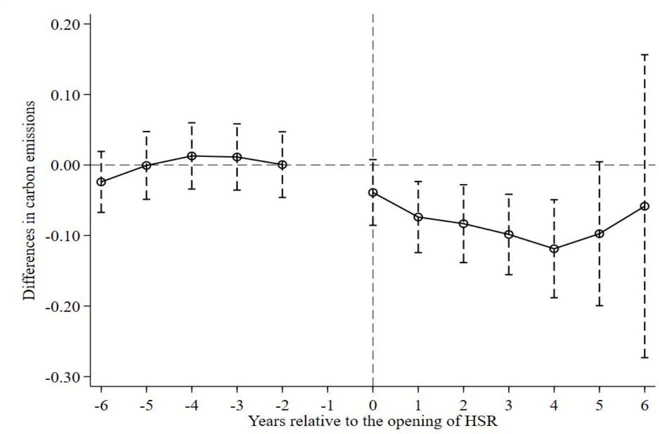
A prerequisite (also known as the common trends assumption) for the validity of DID design is that there is no systematic gap in CO_2 emission trends between treatment and control groups before HSR service becomes available, or that if there is a gap, it is time-invariant. Referring to Beck *et al*. (2010) and Qin (2017), we employ an "event study regression" to test this assumption. The regression is shown below:

$$\ln CO_{2\,it} = \alpha + \sum_{\substack{k \ge -6, \\ k \ne -1}}^{6} \beta_k D_{it}^{k} + \boldsymbol{\gamma}\mathbf{X_{it}} + \mu_i + \upsilon_t + \varepsilon_{it}\,, \tag{8}$$

where D_{it}^{k} is a dummy variable that represents the "event" of HSR opening. The year in which city i opens its first HSR station is denoted by s_i. The rule for assigning values to D_{it}^{k} is as follows: if $t - s_i \le -6$, then $D_{it}^{-6} = 1$, otherwise $D_{it}^{-6} = 0$; if $t - s_i = k$ ($k \in [-6, 6]$ and $k \ne -1$), then $D_{it}^{k} = 1$, otherwise $D_{it}^{k} = 0$; if $t - s_i \ge 6$, then $D_{it}^{6+} = 1$, otherwise $D_{it}^{6+} = 0$.[16] To avoid multicollinearity, we define the year preceding the opening of HSR as a reference; that is, the scenario that meets $k = -1$ is omitted. The symbols that remain in Eq. (8) have the same meaning as those in Eq. (1). Our primary focus is β_k, a set of estimated coefficients that indicate the annual impact of HSR opening on CO_2 emissions. Unlike Eq. (1), which merely evaluates an average effect, Eq. (4) investigates the dynamic effect of HSR opening on carbon emissions over time, in addition to testing the common trends assumption.

In order to convey the test results of the common trends assumption in an accessible manner, Fig. 3 depicts the estimated coefficients β_k and their 95% confidence intervals. The horizontal axis is bounded by 0, with the left half representing years before HSR opens and the right half representing years after HSR opens. For example, -6 denotes the 6th and preceding years before HSR opens, and 5 denotes the 5th year after HSR opens. As shown in Fig. 3, there is insufficient evidence to reject the null hypothesis that the difference in carbon emissions between cities in treatment and control groups equals 0 before HSR service becomes available. Therefore, the outcome variable meets the common trends assumption, and the DID design is acceptable for this study.

Following that, we examine the economic significance of the results shown in Figure 3. The estimated coefficient β_0 is insignificant in the year when HSR service is just available, indicating that there is a time lag for the emission reduction potential of HSR. In the first year after HSR opens, CO_2 emissions in treatment-group cities decrease by 5.47% significantly. In the second year, CO_2 emissions decrease by 6.33% significantly. In the next two years, carbon emissions decline further, and the effect does not diminish until the 5th year after HSR opens.



[16] According to the criteria established in the preceding paper, the time gap between the year city i opened its first HSR and 2014 is no more than six years. As a result, there is no occurrence where $t - s_i > 6$ is satisfied.

Fig. 3. The difference in carbon emissions before and after the opening of HSR.

5.2 Benchmark results

Table 2 shows the benchmark results for the impact of HSR opening on CO_2 emissions. Column (1) reports the estimated coefficients of a model that accounts for the city and year fixed effects but does not include control variables. For robustness, Columns (2)-(7) report the estimated results of models with control variables introduced one by one. In Columns (1)-(7), the coefficients of *HSR* are all less than zero at the 1% level of significance, and their values are close, indicating that our results are very robust. We use the results reported in Column (7) as a baseline to explore the economic meaning of the estimated coefficient of *HSR*. Specifically, assuming all other factors remain constant, HSR opening allows cities in the treatment group to reduce carbon emissions by an average of 6.4% when compared to those in the control group. Given that the average CO_2 emissions of all samples throughout the research period are 23.370 million tons/city; hence, HSR opening reduces carbon emissions in the treatment group by 1.500 ($23.370 \times 6.4\%$) million tons/city from 2008 to 2014. The above findings demonstrate that HSR opening helps to decrease local CO_2 emissions; that is, HSR opening has an emissions reduction effect. Hypothesis 1 is now confirmed.

Table 2

Estimated results of HSR opening on CO_2 emissions.

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)
HSR	-0.064***	-0.067***	-0.067***	-0.066***	-0.063***	-0.063***	-0.064***
	(-4.74)	(-4.94)	(-4.93)	(-4.90)	(-4.68)	(-4.68)	(-4.72)
GDP		0.005*	0.005*	0.005*	0.006*	0.006*	0.006*
		(1.75)	(1.76)	(1.72)	(1.90)	(1.90)	(1.90)
lnPD			-0.005	-0.005	-0.005	-0.005	-0.006
			(-0.20)	(-0.20)	(-0.18)	(-0.18)	(-0.22)
ER				0.001	0.002	0.002	0.002
				(0.83)	(0.94)	(0.94)	(0.92)
RD					-0.433***	-0.433***	-0.419***
					(-3.19)	(-3.18)	(-3.07)
OL						-0.004	-0.003
						(-0.10)	(-0.09)
HC							-0.363
							(-1.04)
City FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	3135	3135	3135	3135	3135	3135	3135
R^2	0.566	0.567	0.567	0.567	0.568	0.568	0.568

Notes: The values in parentheses are t statistics; ***, **, and * represent significant levels of 1%, 5%, and 10%. respectively.

5.3 Robustness test

To assess the credibility of our benchmark findings, we conduct a series of robustness tests.

(1) Extreme samples and observations are removed. (i) Given that municipalities, provincial capitals, and sub-provincial cities have more developed economies and are more likely to be the beneficiaries of certain policies, using samples from these cities may result in a biased research. We remove samples from all three regions and re-run the regression, with the estimated results reported in Column (1) of Table 3. (ii) To exclude extreme observations, the dependent variable is winsorized at 5th and 95th percentiles; that is, values smaller than the 5th percentile is replaced by the 5th percentile, and the similar thing is done with the 95th percentile. The refitting results are shown in Column (2) of Table 3. In the two robustness tests, the estimated coefficients of *HSR* are significantly negative and very close to those in the benchmark model, indicating that the preceding results are reliable.

(2) The control group is confined to neighboring cities. The preceding study uses all non-HSR cities in the entire country as the control group. In this robustness test, cities bordering on HSR cities are chosen as the control group from all non-HSR cities to make them more comparable to those in the treatment group. Column (3) of Table 3 shows the refitting results. The estimated coefficient of *HSR* remains significantly negative, demonstrating that altering the control group has no influence on our findings.

(3) City-specific time trends are controlled. Given that each city's carbon emissions may exhibit different trends over time, we perform two robustness tests: (i) A term denoting city-specific linear time trends is added to Eq. (1); (ii) In order to address the different time trends for the treatment and control groups, $treat \times t$ is added to the benchmark model. The two test results reported in Columns (4) and (5) of Table 3 indicate that the estimated coefficients of *HSR* are significantly negative at the 1% level, and that our benchmark findings are robust.

(4) The expectation factor is eliminated. It should take a long time to discuss and plan the construction of a HSR station in a city. Residents in different cities have varied expectations and preparations for the external shock of HSR opening. A biased result might arise if these expectation factors are not controlled. To eliminate the expectation factor, we add a dummy variable (HSR_before_i) in the regression that represents the year before HSR opens. Column (6) of Table 3 shows the test results. As can be seen, the estimated coefficient of *HSR* remains significantly negative, suggesting that the benchmark results in Table 2 are robust.

(5) Gaps in geographically related features are controlled. In China, cities on opposing sides of the Hu Huanyong Line have distinct demographics and economies. The majority of HSR cities are located on the east side of the Line. If geographic location-related factors are not accounted for, a biased result may occur. In order to remove the influence of the Hu Huanyong Line-related factors, an interaction ($HHY_i \times t$) between a dummy variable representing both sides of the Line and a time trend is added to Eq. (1). Column (7) of Table 3 displays the test results. As can be seen, the coefficient of *HSR* is very close to the one reported in Table 2, indicating that the Hu Huanyong Line-related factors have little influence on our findings.

(6) Endogeneity is eliminated. Despite our best efforts to remove omitted-variable and self-selection biases, certain non-random factors remain to impact where and when a HSR station is built. If these factors have an impact on CO_2 emissions, *HSR* will become an endogenous variable, causing its estimated coefficient to be biased. Given this, we re-estimate Eq. (1) using the two-stage least squares (2SLS) method, with *LCP* regarded as an instrument for *HSR*. The regression coefficients are reported in Column (8) of Table 3. We find that the 2SLS results are generally consistent with our benchmarks.

Table 3

Test results of robustness.

Variable	(1) Special cities	(2) Winsorizing	(3) Neighboring cities	(4) t	(5) $treat \times t$	(6) HSR_before_i	(7) $HHY_i \times t$	(8) IV
HSR	-0.046***	-0.061***	-0.070***	-0.064***	-0.066***	-0.083***	-0.069***	-0.209***
	(-2.89)	(-4.67)	(-5.21)	(-4.72)	(-3.62)	(-5.31)	(-5.00)	(-4.06)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	2750	3135	2486	3135	3135	3135	3135	3135
R^2	0.578	0.536	0.604	0.568	0.568	0.569	0.569	0.551

Notes: The values in parentheses are t or z statistics; ***, **, and * represent significant levels of 1%, 5%, and 10%, respectively.

(7) Sample selection bias is excluded. To eliminate systematic differences between cities in the treatment and control groups, we perform a robustness test using a propensity-score matching adjusted difference-in-difference (PSM-DID) method. Specifically, we run a logistic regression with a dummy variable (*treat*) indicating whether cities open HSR as the dependent variable and control variables from the benchmark model as independent variables to generate the propensity score. Then, the non-HSR cities with the closest propensity scores to each HSR city are selected to establish a new control group.[17] With the original treatment group and the new control group as samples, we re-estimate Eq. (1) using the DID method. Columns (1)-(4) of Table 4 report the estimated results based on data from 2004, 2005, 2006, and 2007 as matched samples, respectively. Column (5) reports the regression results, which are estimated using an average data set from 2004 to 2007 as a matched sample. Column (6) shows the estimated results based on a matched sample of data from all years prior to the opening of HSR during the research period.

Table 4

PSM-DID regression results for the influence of HSR opening on CO_2 emissions.

Variable	(1) 2004	(2) 2005	(3) 2006	(4) 2007	(5) Average for 2004–2007	(6) Average before HSR opens
HSR	-0.040***	-0.030**	-0.027*	-0.044***	-0.036**	-0.048***
	(-2.66)	(-2.00)	(-1.81)	(-2.97)	(-2.43)	(-3.29)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	2882	2849	2882	2904	2871	2904
R^2	0.584	0.586	0.590	0.584	0.585	0.584

Notes: The values in parentheses are t statistics; ***, **, and * represent significant levels of 1%, 5%, and 10%. respectively.

[17] Cities are matched 1:1 by nearest-neighbor matching with replacement (caliper size, 0.05).

5.4 Placebo test

To check the extent to which our benchmark results are influenced by any omitted variables, we conduct a placebo test by randomly picking a time and city to open HSR (Chetty *et al*., 2009). During the sample period there are 7 years in which additional cities open HSR.[18] To preserve this fact and allow for at least one year before the policy shock (as required by the DID design), seven years between 2005 and 2014 are chosen at random, and cities within each year are randomly assigned to the treatment group. For example, t_1, ..., t_7 are randomly selected from the time period 2005–2014. Then, at time t_1, 3 cities are selected from all samples at random to enter the treatment group. At time t_2, 12 cities are randomly selected from the remainder to become HSR cities. This random selection process is repeated until the last 25 cities are chosen from the remaining non-HSR cities to enter the treatment group at time t_7. We re-estimate Eq. (1) by replacing the original *HSR* with the false one. To increase the identification power of the placebo test, the preceding steps are repeated 1000 and 2000 times, respectively. Given the random data generation process, most HSR^{false} should have insignificant estimated coefficients with magnitudes close to zero; otherwise, it would indicate a mis-specification of the DID design.

Fig. 4 depicts the distribution of HSR^{false} estimates in two simulations. As can been seen, the estimated coefficients are mostly centered on zero. More computations are performed, and we find that the average treatment effects in both simulations are 1.099×10^{-3} and 1.104×10^{-3}, which are far greater than the benchmark coefficient of -0.064 (described by the dotted line in Fig. 4) reported in Table 2. In 1000 simulations, there are 19 estimates with values less than -0.064 and P values less than or equal to 0.1, suggesting that the benchmark result is far from the 98.10% $(1-19/1000)$ HSR^{false} estimates. In 2000 simulations, there are 31 estimates with values less than -0.064 and P values less than or equal to 0.1, indicating that the benchmark result is far from the 98.45% $(1-31/2000)$ HSR^{false} estimates. These findings demonstrate that the negative and significant effect of HSR opening on CO_2 emissions is not due to unobservable factors.

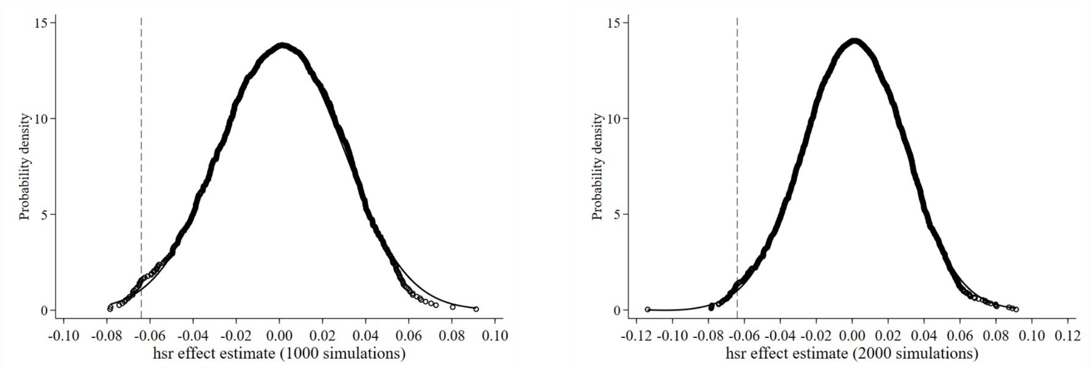


Fig. 4 The simulation results for cases in which HSR cities are assigned at random.

5.5 Test of impact mechanism

The preceding four subsections demonstrate that HSR opening can reduce carbon emissions, but the internal impact mechanism is not thoroughly discussed. In this subsection, we use a mediating effect model to test the impact mechanism of HSR opening on CO_2 emissions through three channels: structure effect, innovation effect, and FDI effect, in accordance with the theoretical hypothesis. Table 5 displays the test results, with Columns (1), (3), and (5) representing

[18] 3, 12, 23, 26, 3, 22, and 25 cities opened HSR between 2008 and 2014, respectively.

the estimated results of Eq. (2), and Columns (2), (4), and (6) representing the estimated results of Eq (3).

Table 5

Test results of impact mechanism.

Variable	(1) *SE*	(2) lnCO_2	(3) *IE*	(4) lnCO_2	(5) *FE*	(6) lnCO_2
HSR	0.107***	-0.049***	0.026***	-0.047***	0.002***	-0.053***
	(9.25)	(-3.61)	(12.37)	(-3.36)	(4.54)	(-3.88)
SE		-0.137***				
		(-6.25)				
IE				-0.533***		
				(-4.28)		
FE						-1.236*
						(-1.86)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	3135	3135	3066	3066	2995	2995
R^2	0.152	0.574	0.167	0.563	0.158	0.568

Notes: The values in parentheses are t or z statistics; ***, **, and * represent significant levels of 1%, 5%, and 10%. respectively.

As shown in Column (1) of Table 4, the estimated coefficient of *HSR* is 0.107 with a significance level of 1%, indicating that HSR opening helps to optimize and upgrade the industrial structure. In Column (2), the estimated coefficient of *SE* is -0.137, implying that improving industrial structure has a negative impact on CO_2 emissions. Overall, Columns (1) and (2) show that HSR opening reduces carbon emissions by promoting structural transformation; moreover, *SE* has a -0.015 (0.107 × -0.137) mediating effect, accounting for approximately 23.4% (-0.015/-0.064) of the total. According to Column (3), the estimated coefficient of *HSR* is 0.026 with a significance level of 1%, which shows that HSR opening improves green innovation in station cities. The estimated coefficient of *IE* in Column (4) is -0.533 and statistically significant at the 1% level, indicating that encouraging green innovation helps reduce carbon emissions. Columns (3) and (4) combine to show that HSR opening reduces carbon emissions by boosting technological innovation; and the mediating effect of *IE* is -0.014 (0.026 × -0.533), accounting for approximately 21.9% (-0.014/-0.064) of the total. In Column (5), the estimated coefficient of *HSR* is 0.002, indicating that HSR opening helps station cities attract foreign investment. In Column (6), the estimated coefficient of *FE* is -1.236, meaning that FDI has a negative impact on carbon emissions. Columns (5) and (6) together show that HSR opening reduces carbon emissions by attracting more foreign capital to station cities; furthermore, *FE* has a -0.002 (0.002 × -1.236) mediating effect, accounting for approximately 3.1% (-0.002/-0.064) of the total.

When the three effects are compared, we find that the structure effect is the greatest, followed by the innovation effect, and the foreign investment effect is the smallest. In summary, Table 5 proves that the structure, innovation, and FDI effects are three mediating channels through which HSR opening reduces carbon emissions. Research hypothesis 2 is verified.

5.6 Heterogeneity analysis

The preceding sections examine the general effect of HSR opening on carbon emissions, but the analysis based on a complete sample may mask potential regional heterogeneity. China, in particular, has a vast territory with significant geographic, economic, and cultural differences, resulting in diverse carbon emissions and HSR lines across regions. In this section, we examine regional heterogeneity of the effect of HSR opening on carbon emissions. As suggested by Lin and Du (2015), we split the total dataset into an eastern and central subsample and a western subsample. Columns (1) and (2) of Table 6 present the regression results. It is clear that the impact of HSR opening on CO_2 emissions is more significant in eastern and central cities than in western cities. This could be due to a time lag in the emission-cutting effect of HSR opening. HSR is not available in western cities until later, so its potential to reduce emissions is not fully exhibited during the study period.

Recently, the Chinese government has sanctioned and established a number of national-level city clusters in order to rely on core cities to support a coordinated regional development strategy. In this part, we study regional heterogeneity using four major city clusters as research samples. Columns (3)-(6) of Table 4 report the regression results for the Beijing-Tianjin-Hebei (BTH) region, the Yangtze River Delta (YRD) region, the Pearl River Delta (PRD) region, and the Chengdu-Chongqing (CC) region, respectively. As shown in Table 3, the opening of HSR in the YRD and the PRD reduces emissions significantly. Indeed, these two regions are the most economically developed city clusters in China. A well-established HSR network promotes clean industries, innovative individuals, and green foreign investment within the cluster to migrate to core cities, resulting in significant emissions reductions. In the CC Region, HSR opening has no significant effect on carbon emissions. This cluster is located in western China, and the bulk of its member cities have yet to build HSR lines. The HSR network can only serve a small number of cities, so its emission-cutting potential has not been fully exploited. It is unexpected that HSR opening has no significant influence on carbon emissions in the BTH region. This might due to the fact that economic links between cities in the BTH region are less than in the YRD and the PRD. In this region, the construction of a HSR network is insufficient to remove the huge administrative obstacles that exist among cities. Since factor resources cannot be properly allocated within the cluster, the structure, innovation, and FDI effects of HSR are hindered.

Table 6

Test results for regional heterogeneity.

Variable	(1)	(2)	(3)	(4)	(5)	(6)
	Eastern and central cities	Western cities	BTH region	YRD region	PRD region	CC region
HSR	-0.041***	-0.019	0.025	-0.185***	-0.156**	-0.021
	(-2.90)	(-0.39)	(0.53)	(-6.06)	(-2.12)	(-0.25)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	2211	924	154	286	165	176
R^2	0.573	0.582	0.550	0.693	0.531	0.873

Notes: The values in parentheses are t statistics; ***, **, and * represent significant levels of 1%, 5%, and 10%. respectively.

Aside from the geography described above, additional factors such as population, innovation, and economy may have an impact on the potential of HSR to reduce emissions. Next, we test these factors one by one.

Based on a criterion established by the State Council of China, we define cities with a population of more than one million as "big" and those with a population of less than one million as "small and midsize". Columns (1) and (2) of Table 7 report the estimated results. As can be shown, building HSR in big cities reduces emissions more than in small and midsize ones. This can be attributed to two causes: (i) The effect of HSR on emissions reductions is dependent on well-established infrastructure and other "soft environments" of a city. Considering these disparities, it is difficult for medium-sized cities to catch up to big ones in a short period of time; (ii) Big cities have an inherent advantage when it comes to attracting technical talent and financial investment. Construction of HSR decreases transportation costs and speeds up resource transfer across regions. Big cities may reduce carbon emissions more easily by absorbing high-quality industries, FDI, and labor from small and medium-sized cities.

Cities in China vary greatly in their ability to innovate. We divide the sample in half based on the number of green invention patents applied by each city to investigate the heterogeneity of emission reduction benefits. Columns (3) and (4) of Table 7 report the results. As can be shown, HSR opening has a more significant impact on carbon reductions in places with higher levels of innovation. The reason for this is that constructing a HSR network breaks down city borders, allowing skilled labor with extensive technical knowledge to travel across areas. Cities with a higher level of innovation are more likely to embrace and absorb cutting-edge technology from other locations that can help them reduce emissions.

Economic development in the area might have an impact on the potential of HSR to reduce emissions. To investigate economic heterogeneity, we divide all samples into two groups based on their GDP size. Specifically, cities with GDPs above the median are labeled as developed, while those with GDPs below the median are labeled as developing. The estimated results are reported in Columns (5) and (6) of Table 7. It is clear that HSR has a more significant impact on emissions reductions in developed cities than in developing ones. A well-established economy helps a city attract more high-skilled workers and high-quality international investment, thus boosting local green transitions. Additionally, building a HSR network could break down regional barriers and provide adequate resources for structural transformation. However, a low level of economic growth may limit the above-mentioned effects.

Table 7

Test results for heterogeneous impacts based on population, innovation, and economy.

Variable	(1)	(2)	(3)	(4)	(5)	(6)
	Big	Small and midsize	High-innovation	Low-innovation	Developed	Developing
HSR	-0.057***	-0.045*	-0.047***	-0.022	-0.040***	-0.029
	(-3.61)	(-1.78)	(-2.99)	(-0.77)	(-2.76)	(-0.96)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes

Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	1540	1595	1573	1562	1573	1562
R^2	0.587	0.564	0.564	0.591	0.602	0.563

Notes: The values in parentheses are t statistics; ***, **, and * represent significant levels of 1%, 5%, and 10%. respectively.

6. Further research

6.1 Consider the impact of HSR opening intensity

The classic DID model only studies the impact of cities opening or not opening HSR lines on carbon emissions, but it cannot quantify the size of the treatment effect if a city launches several lines. Given this, we employ the degree centrality (described in Section 4.2) to define the connecting breadth of a station city in the HSR network. A continuous DID model based on Moser and Voena (2012) is established to examine the impact of HSR opening intensity on carbon emissions. The estimated results are reported in Column (2) of Table 8. Moreover, for robustness, Column (1) reports the results without adding control variables, Column (3) reports the results after excluding samples from municipalities, provincial capitals, and sub-provincial cities, and Column (4) reports the PSM-DID estimated results.

Table 8

Estimated results of HSR opening intensity on CO_2 emissions.

Variable	(1)	(2)	(3)	(4)
$After \times DC$	-0.002***	-0.002***	-0.002***	-0.002***
	(-4.55)	(-4.45)	(-2.93)	(-2.60)
Controls	No	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Obs.	3135	3135	2750	2871
R^2	0.566	0.570	0.578	0.585

Notes: The values in parentheses are t statistics; ***, **, and * represent significant levels of 1%, 5%, and 10%. respectively.

In the four models, the estimated coefficient of $After \times DC$ is significantly negative at the 1% level, suggesting that the emission reduction benefit of HSR grows as a station city's degree centrality climbs the ladder. A larger degree centrality means that the station city has more HSR lines connecting to other cities or a higher transportation status in the railway network. Its geographical advantages attract a lot of clean industries, creative talent, and green foreign investment, all of which contribute to the emission-cutting effect of HSR.

6.2 Spatial spillover effect of HSR

The preceding sections reveal that HSR opening can help to reduce local carbon emissions. In this section, we explore the spillover effect of this emission-cutting benefit, or, more specifically, how cities launching HSR affect carbon emissions in neighboring cities. Columns (1), (2), (3), and (4) of Table 9 show the estimated coefficients of $Near_{it}^{x}$ for distance thresholds of 40, 60, 80, and 100 kilometers, respectively.[19] Panel A represents the complete sample. Panels B and C represent subsamples of HSR and non-HSR cities, respectively.

Table 9

Test results for the spatial spillover effect of HSR opening.

Variable	(1)	(2)	(3)	(4)
Panel A. Complete sample				
$Near^{40}$	-0.083***			
	(-3.25)			
$Near^{60}$		-0.060***		
		(-3.57)		
$Near^{80}$			-0.036***	
			(-2.63)	
$Near^{100}$				-0.012
				(-0.92)
Controls	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Obs.	3135	3135	3135	3135
R^2	0.567	0.567	0.566	0.565
Panel B. HSR cities				
$Near^{40}$	0.034			
	(1.24)			
$Near^{60}$		0.003		
		(0.18)		
$Near^{80}$			-0.005	
			(-0.30)	
$Near^{100}$				-0.008
				(-0.50)
Controls	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Obs.	1254	1254	1254	1254
R^2	0.622	0.622	0.622	0.622
Panel C. Non-HSR cities				
$Near^{40}$	-0.242***			
	(-5.23)			
$Near^{60}$		-0.184***		
		(-5.04)		
$Near^{80}$			-0.047**	
			(-1.96)	

[19] In general, the maximum radius of a Chinese city is 40 kilometers. Beijing, for example, has a radius of around 40 kilometers, and Shanghai has a radius of about 43.6 kilometers. Given this, we set the bottom limit of the spillover effect at 40 kilometers.

Near[100]				0.012
				(0.57)
Controls	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Obs.	1881	1881	1881	1881
R^2	0.558	0.557	0.556	0.551

Notes: The values in parentheses are t statistics; ***, **, and * represent significant levels of 1%, 5%, and 10%. respectively.

In the complete sample, HSR cities have significant emission reduction spillovers to neighboring cities within an 80-kilometer radius, but insignificant spillovers to cities beyond that radius. After comparing the estimates for HSR and non-HSR subsamples, we find that the spillover effect occurs exclusively in the latter; in other words, if a city opens HSR, it helps to reduce emissions in nearby non-HSR cities but not in nearby HSR cities. Additionally, as shown in Panels A and C, the spillover effect reduces as the distance threshold climbs the ladder. These findings are crucial for China's western region, where numerous cities have yet to open HSR. The western region has less economic growth and population density, so its stations and lines cannot be as crowded as those in the eastern region. Given this, the central government should carefully consider the spillover effects of HSR in future railway construction plans, and use limited resources to maximize emission reduction benefits.

6.3 A carbon cost-benefit analysis for the Beijing-Shanghai HSR line.

In the last section, we briefly examine the carbon cost-benefit of China's HSR. It should be noted that a detailed and complete material inventory of the HSR infrastructure is generally missing, and the power sources in China's HSR grid are very complex. It is hard to tell how much of the electricity required for HSR operations is generated by thermal, hydro, or wind power. Given this, estimating the carbon cost of all Chinese high-speed trains throughout their whole life cycle is impossible. In this section, we only compute the carbon cost-benefit of China's Beijing-Shanghai HSR line, based on Lin *et al.* (2019). Specifically, Lin *et al.* (2019) applied an EIO-LCA method to estimate the carbon footprint of the Beijing-Shanghai HSR line, and found that the carbon footprint of the line was 3,002 kilotonnes (kt) per year between 2011 and 2014.[20] Next, we just need to assess the line's emission reduction benefit and compare it to the carbon footprint predicted by Lin *et al.* (2019) to determine if the Beijing-Shanghai HSR line is viable in terms of a carbon economy. Table 10 reports the DID estimates using station cities along the Beijing-Shanghai HSR line as a treatment group. Column (1) is the estimated result of a model with non-HSR cities bordering on station cities as a control group. Column (2) is the estimated result of a model employing non-HSR cities in provinces where station cities are situated as a control group. Column (3) is the estimated result of a model that uses all non-HSR rail cities in eastern China as a control group. Additionally, in the three models, we employ *LCP* as an instrumental variable for *HSR* to ensure that the estimated coefficients are consistent.

[20] The carbon footprint of HSR includes all emissions produced during the operation, construction, and maintenance stages.

Table 10

Estimated emission-cutting effects of Beijing-Shanghai HSR line.

Variable	(1) Neighboring cities	(2) Cities in the same provinces	(3) Eastern cities
HSR	-0.100**	-0.183***	-0.288***
	(-2.03)	(-3.50)	(-4.77)
Controls	Yes	Yes	Yes
City FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Obs.	429	528	660
R^2	0.605	0.628	0.532

Notes: The values in parentheses are z statistics; ***, **, and * represent significant levels of 1%, 5%, and 10%. respectively.

As can be seen, the absolute value of the estimated coefficient in Column (1) is the smallest, so we use it as a baseline to compute the minimum emission-cutting benefit of the Beijing-Shanghai HSR line. When all other factors remain constant, HSR opening allows cities in the treatment group to reduce carbon emissions by an average of 10% when compared to those in the control group. During the research period, the average carbon emissions from the 39 sample cities are 32,365.620 kt/city; thus, HSR opening could reduce carbon emissions by an average of 3,236.562 kt/city. Given the fact that the Beijing-Shanghai line opened in 2011, the DID design captures a 4-year average treatment effect across the entire research period. As a result, HSR opening reduces carbon emissions by 15,373.670 ($3{,}236.562 \times 19/4$) kt per year in all 19 station cities along the line. The annual carbon benefit assessed here is considerably larger than the carbon cost of 3,002 kt predicted by Lin *et al.* (2019), indicating that the Beijing-Shanghai HSR line is green. In fact, our estimated carbon benefit is smaller than the actual value created by the Beijing-Shanghai line, because we do not account for the HSR spillover effect.

7. Conclusions and implications

Over the last decade or so, China's fast expansion of high-speed railways has not only contributed significantly to the country's economic growth, but has also paved the path for the country to achieve low-carbon development. A large majority of previous research assesses the carbon footprint of HSR from an engineering standpoint and compares it to the carbon benefit created by replacing other high-emission vehicles. To the best of our knowledge, few studies have examined the economic consequences of HSR expansion and the subsequent decrease in carbon emissions. Given this, a large number of cities launching HSR at different times is viewed as a quasi-natural experiment. We use a DID model with variation in treatment timing based on panel data from 285 Chinese cities between 2004 and 2014 to assess the impact of HSR opening on CO_2 emissions.

Our research reveals that HSR cities reduce CO_2 emissions by an average of 6.4% when compared to non-HSR cities, so HSR opening has an emission reduction benefit. This remains robust even if extreme samples and observations are removed, the control group is confined to neighboring cities, city-specific time trends are controlled, the expectation factor and geographic features are eliminated, and endogeneity is excluded. Heterogeneous tests indicate that HSR has a greater effect on carbon reductions in the eastern and central regions, the Yangtze River Delta, the Pearl River Delta, and cities with larger populations, higher levels of innovation, and more developed economies. Impact mechanism tests show that HSR opening reduces carbon emissions through structure, innovation, and FDI effects, with the first being the largest, followed by the second, and the third being the smallest. Further research finds that as the connecting breadth of a station city in the HSR network expands—that is, as the intensity of HSR opening expands—so does the emissions reduction effect. There is a significant spillover effect with a radius of around 80 kilometers, which means that, in addition to decreasing carbon emissions in station cities, HSR opening helps to reduce emissions in neighboring non-HSR cities. Moreover, we find that the carbon benefit of the Beijing-Shanghai HSR line far outweighs its carbon footprint, suggesting that the line is green.

Our findings have several policy implications for HSR expansion and low-carbon development in China. First, the Chinese government should provide scientific and rational support for HSR construction to fulfill its emission-reduction role and achieve green transportation development. Western cities, in particular, must do so due to poor train network density. Additionally, for low-carbon travel, residents might be encouraged to use HSR instead of high-emission vehicles such as cars and aircraft. Second, the government should work to expand the transmission channel through which HSR contributes to carbon emissions reductions. Specifically, local governments should view the launching of HSR as an opportunity to create unique travel destinations, science and technology parks, and other special projects that will aid in the transformation of the industrial structure. To ensure enterprise technology innovation, station cities must provide the necessary employment security and skill training to the workforce attracted by the opening of HSR lines, converting them into local human resources. HSR cities could establish a screening mechanism for FDI projects that would increase green and low-carbon foreign investment inflows. Third, non-HSR cities need to expand their road and water networks, as well as build extensive links with HSR cities, to maximize the emission reduction spillover effect of HSR.

Finally, it should be emphasized that, due to data constraints, the work can only establish the study viewpoint on macro prefecture-level cities. When microdata becomes available, it may be possible to derive more detailed findings. Moreover, the Beijing-Shanghai route runs through areas of China experiencing rapid economic expansion, so it may not reflect the overall features of national high-speed train lines. As a result, our carbon cost-benefit analysis for HSR is poorly represented. In the future, more microscopic and detailed data on HSR and CO_2 emissions could be used to go deeper into this topic.

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