

Spatio-Temporal Distribution of Chinese Cities' Air Quality and the Impact of High-Speed Rail to Promote Carbon Neutrality



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Abstract With China's continuous urbanization and industrialization, the emissions in Chinese cities have become increasingly serious. Chinese government has set a goal to reach carbon peak and achieve carbon neutrality, endeavoring to gradually realize net-zero carbon dioxide (CO₂) emission. Moreover, the new transport technology has also been fast developed, represented by the quick expansion of the high-speed rail (HSR) system. Based on the Air Quality Index (AQI) of 286 Chinese cities over the 2016–2019 period, this paper first adopts the spatial auto-correlation analysis to quantify the spatio-temporal characteristics of Chinese cities' AQI. Then, a spatial difference-in-differences (SDID) model is estimated to shed light on how Chinese cities' air quality can be affected by HSR. Our paper identifies apparent spatio-temporal distribution patterns in Chinese cities' air quality. Our empirical results that the HSR opening can help reduce emissions to improve the city's air quality. Moreover, HSR opening in the adjacent city can also improve one city's air quality (i.e., the neighboring effect). We also highlight and verify the mechanism of such a positive HSR impact on the city's air quality. First, as a cleaner transport mode, HSR helps divert traffic from other more polluting modes (i.e., positive direct "transport substitution effect"). HSR also helps promote the city's tertiary industry, leading to fewer emissions (i.e., positive indirect "industrial structure effect"). Our heterogeneous analyses further demonstrate that HSR is more effective to improve

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the air quality in eastern and western regions. But the neighboring effect is only obvious in eastern China as the cities are closer to each other in terms of economic relations and geographic locations.

Keywords Air quality · Emissions · High-speed rail · Spatio-temporal analysis · Spatial difference-in-differences (SDID)

1 Introduction

Since its economic reform and opening up in 1980s, China has experienced rapid economic development, accompanied by the fast industrialization and urbanization. Although the rapid economic development improved people's living standards, China's energy consumption has also been increased rapidly, especially from fossil energy sources (e.g., coal, natural gas, oil). The carbon dioxide (CO₂) emission and other related air pollutants have risen accordingly, seriously damaging the climate and people's health threatening the sustainable development of the whole country. Chinese government thus formulated the carbon neutral and carbon peak target to control the emissions and air pollution.

The Technical Specification for Ambient Air Quality Index (Trial) formulated by China puts forward the standard of Air Quality Index (AQI) to carry out quantitative monitoring of air pollution in various regions [1]. Since 2016, the Chinese government has adopted GB 3095–2012 air quality standards, replacing the original air pollution index (API) with the air quality index (AQI). The pollutant indicators add fine particulate matter (PM_{2.5}), carbon monoxide (CO) and ozone (O₃) to the original inhalable particulate matter (PM₁₀), nitrogen dioxide(NO₂), and sulfur dioxide (SO₂) to reflect the overall situation of air quality. With the frequent occurrences of air pollution problems, the characteristics of regional distribution of air pollution attracted more attention from public and academic research. The analysis of spatio-temporal distributions and patterns of the air quality in among regions and its influencing factors have also become a research hotspot.

Among different sources of emissions and air pollution, transport is an dominant one in China. Fuel powered vehicles emit a large number of organic compounds, nitrogen oxides and other chemical substances, leading to the greenhouse effect and increasing ground-level ozone concentration [2]. According to the China Mobile Source Environmental Management Annual Report (2020) published by the Ministry of Ecology and Environment of China, private cars are the main source of pollutants, and the policy of limiting the purchase and driving of private cars in cities cannot effectively solve the urban air pollution problem [3]. In addition, China's transport composition is not reasonable enough. For the inter-city travel, road transport, dominated by diesel vehicles, contributes about 73.0% of goods transport and 74% of passenger transport. The advantages of low energy consumption and low emission of railway and water transport have not been fully exerted [4].

Transport infrastructure is one of the key factors in promoting national economic growth. Zheng, Kahn and Zhang found that the opening of the high-speed rail (HSR) is conducive to integrating regional resources, promoting coordinated economic development, and promoting economic growth in cities along the way [5, 6]. Air Pollution Prevention and Control Briefing published by China's Ministry of Ecology and Environment suggests that the country should focus on optimizing the structure of transport, shifting from road transport to rail transport. Compared with normal-speed railway, HSR has obvious advantages in terms of economic and environmental benefits [7, 8]. Therefore, based on the development of green transport, promoting regional development and other factors, the environmental benefit of developing HSR is obvious.

Based on such background, this paper first quantifies the spatio-temporal evolution of Chinese cities' air quality over the 2016–2019 period. Then, the spatial difference-in-differences (SDID) model is employed to study the HSR impact on Chinese city's air quality. The contributions of this paper are multi-fold. First, this is one of the first studies to adopt spatial auto-correlation approach to quantify the spatio-temporal distribution and characteristics of Chinese cities' air quality. Second and more importantly, this paper provides one of the first rigorous empirical examinations on the impact of HSR opening on city's air quality. The spatial spillover effect of HSR impact is also identified. In addition to the overall effect, we investigate the mechanism of such HSR impact. Specifically, we consider the direct effect brought by the change of transport traffic volume and the modal splits, and the indirect effect caused by HSR on the city's industrial structure and production scale. The heterogeneous analysis is also done to shed light on the HSR impacts on different kinds of cities that can be categorized by the geographic location and the degree of economic development.

The spatio-temporal analysis of AQI shows clear inter-annual and seasonal patterns of air quality among Chinese cities. Moreover, the spatial pattern suggests the southern and coastal regions have overall better air quality than northern China and inland regions. This is mainly related to the climate type, terrain, economic development levels. The northern cities are low-lying, where pollutants are difficult to diffuse, and where economic development and industrialization progress are rapid, causing more serious environmental damage. Most coastal cities in southern China have a tropical or subtropical monsoon climate, and the terrain is relatively flat. Air quality in China has obvious positive spatial auto-correlation, and also demonstrates obvious aggregation trend over time. The cities with severe air pollution could have a negative impact on the air quality of neighboring cities, suggesting strong negative spatial spillover effect.

In addition, our SDID estimations suggest that the HSR opening in one city can reduce the emission and improve its air quality (i.e., defined as the local effect), while the HSR opening in the adjacent city can also improve the city's air quality (i.e., defined as the neighboring effect). We also highlight and verify the mechanism of such positive HSR environmental impact. First, as a cleaner transport mode, HSR helps divert traffic from other more polluting modes (i.e., positive direct transport

substitution effect). Moreover, HSR helps promote the city's tertiary industry development (i.e., the service sectors, such as tourism, high-tech industries), leading to fewer emissions (i.e., positive indirect "industrial structure effect"). Our heterogeneous analyses further demonstrate that HSR is more effective to improve the air quality in the eastern and western regions of China, given the more prevailing transport substitution effect and industrial structure effect, respectively. But the neighboring effect of HSR is only obvious in the eastern China as the cities are closer with each other in terms of economic relations and geographic locations within this region. Moreover, the HSR proves to improve air quality in more economically developed cities, as the HSR traffic is larger in this region and thus plays a more significant role.

The rest of the paper is organized as below. Section 2 reviews the relevant literature. The detailed research design and methodology are discussed in Sect. 3. Section 4 quantifies the spatio-temporal distribution characteristics of China's AQI. The estimation results of the HSR impact on city's air quality are presented and discussed in Sect. 5. Section 6 summarizes this study.

2 Literature Review

This study is related to three streams of literature, namely the spatio-temporal distribution of city's emissions and air quality, the influencing factors of city's air quality, and the impact of HSR opening on city's air quality. In the subsequent subsections, we review the relevant literature for each stream, respectively.

2.1 *The Spatio-Temporal Distribution of City's Air Quality*

The temporal studies on air quality can be done at annual, quarterly or intra-day dimension. In the annual analysis, Xu, Liu, and Wang explored the changes of China's urban AQI from 2014 to 2016, and found that the AQI showed a downward trend and the number of cities with air pollution decreased [9]. Guo, Lin, and Bian discussed the spatial and temporal distribution characteristics of air quality in China from 2015 to 2017, and found that air quality was improving year by year [10]. In the quarterly analysis, most studies concluded that the temporal variation characteristics of city's air quality in China are seasonal. Niu et al. found that the seasonal distribution of air pollution in China is U-shaped, and the main pollutants change with the seasons. This is because China has a northwest monsoon in winter and a southeast monsoon in summer. Meanwhile, man-made emissions lead to a sharp rise in the level of particulate matter in winter, so the proportion of particulate matter in the air in winter is the highest, and the pollution of fine particulate matter is the most serious [11]. Yan et al. and Chen et al. believed that the poor air quality in winter is mainly due to seasonal straw burning and coal burning for heating in winter, which produces a large amount of PM_{2.5} [12, 13].

Many scholars believe that there is also spatial correlation between air quality among Chinese cities. Fang et al., Zhang and Luo found that the Moran Index showed that the AQI measure values of Chinese cities had positive spatial auto-correlation, and the spatial distribution of high AQI values tended to aggregate rather than disperse [14, 15]. Dai and Zhou adopted PMFG network method and found that the AQI in the sample period presented obvious spatial positive correlation [16]. Fang based on the STIRPAT model and the environment Kuznets curve (EKC) hypothesis, using a spatial difference-in-differences approach, concluded that city's smog pollution exhibits strong spatial correlations [17, 18]. Lin and Wang used LISA aggregation map to assert that the spatial aggregation trend of city's air quality in China has been increasing year by year, showing the characteristics of pollution diffusion from key cities to overall regional pollution. Therefore, air pollution control should also be initiated by key cities, and regional pollution should be jointly controlled [19].

Li et al., Zhang and Luo concluded that China's topography is high in the south and low in the north, high in the west and low in the east, which has a significant impact on the distribution of air pollutants. Therefore, the spatial distribution of air pollutants has a significant difference between the east and the west. High-AQI urban agglomerations are mainly distributed in the north and northwest, while low-AQI urban agglomerations are mainly distributed in the south and southwest [15, 20]. Particularly, Jia found that the CO₂ emission reduction effect of HSR is more significant in eastern China, large cities, and resource-based cities. Higher levels of HSR service intensity in large cities and resource-based cities are not conducive to reducing CO₂ emissions in neighboring cities [21].

2.2 Air Quality Influencing Factors

Many scholars have summarized the socioeconomic factors that influence air quality in Chinese cities. Some scholars believed that population gathering and traffic congestion caused by industrialization and urbanization are the main causes of air pollution. Zhang and Griffin argued that city's air quality is affected by both environmental and socioeconomic factors, especially the urbanization development and industrial enterprise agglomeration [22, 23]. Wang believed that population density, highway passenger volume and vehicle ownership are all important factors that aggravate city's air pollution [24]. Fang et al. believed that the increase in the proportion of secondary industry and population density is the main reason for frequent air pollution incidents [14]. Therefore, the vigorous development of public transport can alleviate air pollution problems which caused by excessive urban population density and traffic congestion [25]. Fang found that the relationship between per capita GDP, urban population and urban smog pollution all follow n-shaped curve, and smog is proved to reduce to a certain extent as per capita GDP increases [18].

Other scholars believe that the energy consumption accompanied by economic growth is closely related to the atmospheric environment. Chi et al. found that although the level of urban economic development is positively correlated with air

quality, the level of economic development does not play a decisive role in the change of air quality. This is because the environmental Kuznets curve is inverted U-shaped, and economic growth will lead to environmental quality deterioration and then improvement [26]. Bi et al. and Grey et al. proposed that total energy consumption and economic growth have a serious impact on air quality, and the improvement of scientific and technological level will improve the air quality [27, 28]. According to the research of Ying, the average labor input, average fixed asset input, average energy consumption, average GDP and average CO₂ emission efficiency of high-income cities are significantly higher than those of upper-middle income cities [29]. Lin and Wang believed that energy consumption and industrialization are important factors of causing air pollution in cities, but by the regional natural environment and the limitation of social and economic development stage, all kinds of social and economic factors on the air quality in different cities have different degrees of influence, so there is a need for subregional research [19].

However, scholars have different views on the effect of urban greening degree on air quality. The study of Jiang et al. showed that the increase of the proportion of tertiary industry and urban greening coverage rate is conducive to improve air quality in the Yangtze River Economic Belt, supporting the theory of “pollution sanctuary” [25, 30]. Another view is that urban greening does little to improve air quality. Wang and Wang constructed the panel model of 31 provincial capital cities in China to explore the main factors of air quality, and found that the level of urban greening could not significantly improve city’s air quality [31].

2.3 The Impact of HSR on City’s Air Quality

With fast HSR development, especially in China, more scholars have paid attention on HSR’s impact on the air pollution. To quantify the HSR development, many studies developed indexes to measure the HSR connectivity or accessibility. For example, Zhang et al. and Jiao et al. defined the HSR connectivity as the number of HSR lines or the train frequency passing through the city and the weighted centrality in the passenger train network [32, 33]. Liu et al. used HSR accessibility measured by the shortest HSR travel time between two cities [34]. Zhang et al. and Zhu et al. used the “with or without comparison method” to reflect the actual effects of policies by comparing the data in the two states of “with HSR line” and “without HSR line”. This method is adapted to the difference-in-differences (DID) method, which is applicable to measure the impact of HSR on environment [35, 36].

Existing research did not reach a consensus on the impact of railway or HSR on city’s air quality. Some studies found that the development of rail transport can effectively improve the city’s air quality. For example, Qin and Chen studied the impact of Beijing-Shanghai the high-speed railway on the air quality of cities along the route by using the breakpoint regression method, and found that the operation of Beijing-Shanghai the high-speed railway significantly improved the air quality of cities along the route by replacing private cars and reducing the number of ordinary

railway trains with high energy consumption [37]. Yu et al. found through augmented gravity model research that railway services are improved under the drive of speed, and air passengers turn to railway transport, leading to a reduction in carbon dioxide emissions, and optimizing the traffic structure to reduce carbon dioxide [38]. The traffic substitution effect is due to the fact that the development of rail transit encourages travelers to reduce the original ground transport mode, to reduce the exhaust emissions of private cars, and to improve city's air quality [39]. Zhang and Feng used the DID model to study the significant improvement of haze pollution from the perspectives of scale effect, structure effect and technology effect [40]. Fang used causal mediation analysis method to test the two mechanisms related to the HSR, and found that industrial structure upgrading can reduce haze pollution, while real estate market development can increase haze pollution [18]. Jia adopt a continuous spatial difference-in-differences (SDID) model to investigate the effect and its mechanism of HSR service intensity on CO₂ emissions, and the results show that due to the influence of transport substitution, market integration, industrial structure and technological innovation, the intensity of the high-speed railway service greatly reduces city's carbon dioxide emission [21]. Another view is that the development of rail transit does not have a significant positive impact on city's air quality: Beaudoin and Lin found that rail transit did not significantly reduce the emission concentration of air pollutants, because of the traffic creation effect that the development of rail transit will promote urban population aggregation and economic development, aggravating the air pollution problem [41].

3 Research Design

The research framework and methodology are specified in this section. First, we highlight the theoretical mechanisms of HSR impact on city's air quality (see Sect. 3.1). Then, the detailed empirical research methods are introduced in Sect. 3.2. Last, Sect. 3.3 introduces our data sources.

3.1 Theoretical Mechanism

Figure 1 illustrates the mechanism of the HSR's impact on the city's air quality, which can be divided into the direct and indirect impacts. First, the direct impact includes the transport substitution effect and inducing effect. HSR is a cleaner and more emission efficient transport mode compared to the highway and aviation [36]. HSR is attractive to passengers with short and medium distance mobility demand. When HSR attracts more than 10 million passengers from other transport modes, net emission reduction can be achieved, improving the overall air quality [33, 42]. However, HSR could also stimulate new traffic demand, thus aggravating the greenhouse effect (i.e., the inducing effect) [43].

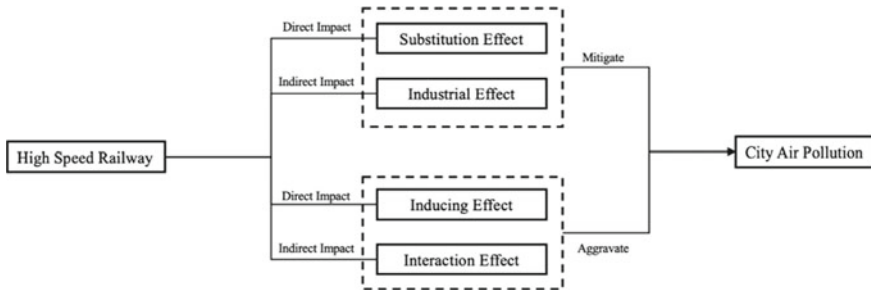


Fig. 1 The mechanism of HSR’s impact on city’s air quality

The indirect impact of HSR on air quality is achieved by the impact on other urban economic variables, such as GDP, population, urban area and industrial compositions, and then to affect city’s air quality indirectly. For example, HSR is conducive to improving the accessibility of cities along the railway line, promoting the accumulation of technology and capital in these cities. HSR could help reduce costs of transporting passengers and goods, thus stimulating the service industries and facilitating the industrial upgrading to high tech but low pollution industries [35]. This can reduce the emissions from fossil energy consumption, thus improves the city’s air quality. However, the transport cost reduction brought by HSR can also enhance the industrial agglomeration, enlarging the production and population size of the city. Especially, some large cities will further utilize the resources from the nearby cities with HSR to quickly expand the city size (i.e., the so-called Siphon effect). This would increase the energy consumption and possibly deteriorate the air quality.

Given the existence of both direct and indirect impacts and the complex mechanisms, the current empirical studies have not yet clearly identified the impact of HSR on city’s air quality. Thus, in this paper, we not only identify the overall impact of HSR on China’s city’s air quality, but also try to distinguish the different causes.

3.2 Research Methods

In this paper, we first adopt the spatial auto-correlation analysis to quantify the spatio-temporal patterns of Chinese cities’ air quality over recent years (see Sect. 3.2.1). Then, the spatial difference-in-differences (SDID) model is proposed in Sect. 3.2.2 to examine the HSR impact on city’s air quality, while accounting for the possible spatial spillover effects as well.

3.2.1 Spatial Auto-correlation Analysis

First, our quantitative study is conducted to quantify and describe the spatio-temporal characteristics of Chinese cities' AQI. In particular, the spatial autocorrelation method is used to account for the spatial spillover effect of neighboring region's AQI on one city's AQI. This method detects whether the observed value of a certain point in space is correlated with the observed value of an adjacent (or neighboring) point. Global Moran index and local Moran index are the most commonly used spatial auto-correlation functions, to represent the correlation degree and clustering mode of geographical variables. The positive and negative values of statistics represent the positive and negative values of spatial auto-correlation. The larger the statistic is, the stronger the spatial auto-correlation is. The global Moran index measures global spatial correlation, as shown below:

$$I = \frac{n}{\sum_{i=1}^n \sum_{j=1}^n w_{ij}} \frac{\sum_{i=1}^n \sum_{j=1}^n w_{ij} (x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^n (x_i - \bar{x})^2} \tag{1}$$

where n is the total number of cities; x_i and x_j are the observed values of urban environment monitoring points in cities i and j , respectively; \bar{x} is the mean of x ; w_{ij} is the entry of the spatial weight matrix, if the city i is adjacent to the city j , $w_{ij} = 1$ ($w_{ij} = 0$, otherwise). The range of the global Moran index is $[-1, 1]$. $I > 0$ indicates that city's air quality has an aggregation trend, and $I < 0$ implies that the city's air quality has a discretization trend. When I is equal to 0, the city's air quality is spatially independent and distributed irregularly and randomly.

Local spatial auto-correlation captures the spatial relationships among cities, so it can effectively measure the degree of spatial correlation between observed cities and other cities. In the local spatial auto-correlation, we can compute the local Moran index as [44, 45]:

$$I_i = \frac{n(x_i - \bar{x}) \sum_{j=1, j \neq i}^n w_{ij} (x_j - \bar{x})}{\sum_{i=1}^n (x_i - \bar{x})^2} \tag{2}$$

where n is the total number of cities; x_i and x_j are the observed values of urban environment monitoring points in city i and j , respectively; \bar{x} is the mean of x ; w_{ij} is the element of the spatial weight matrix, when the city i is adjacent to the city j , $w_{ij} = 1$, otherwise $w_{ij} = 0$. I_i is used to compared the degree of spatial agglomeration between region i and the surrounding areas, and we can classify the association modes into four types: high-high (HH), high-low (HL), low-high (LH), and low-low (LL). HH and LL groups indicate that the air quality of the city i is consistent with that of the neighboring cities. On the other hand, HL and LH groups indicate that the city i 's air quality is a high (or low) value in a low (or high) air quality neighborhood.

3.2.2 Spatial Econometric Model

In addition to the spatial auto-correlation analysis of AQI, we examine the impact of HSR on AQI. Specifically, a spatial difference-in-differences (SDID) method is used. SDID analysis takes into account that air pollution often spreads to surrounding areas through atmospheric circulation and spatial spillover effects measured by spatial weight matrix $W_{\{ij\}}$. Given that not all the cities have access to the HSR service, the sample cities with HSR operation are classified into the experimental group, while the rest cities without HSR operation are the control group [46, 47]. Considering different years of HSR operation in different cities, this paper adopts the multi-phase DID model on the experimental group and the control group [48]:

$$\begin{aligned}
 AQI_{it} = & \alpha + \beta_1 Open_{it} \times Year_{it} + \beta_2 \sum_j w_{ij} Open_{it} \times Year_{it} \\
 & + \gamma X_{it} + \theta \sum_j w_{ij} X_{it} + \rho \sum_j w_{ij} AQI_{it} \\
 & + \lambda \sum_j w_{ij} \varepsilon_{it} + A_i + B_t + \varepsilon_{it}
 \end{aligned} \tag{3}$$

where i represents the index for cities, t represents the index for periods; AQI_{it} represents the air quality index of city i in period t , $Open_{it}$ is a dummy variable, which equals to 1 if the HSR is available in the period t in city i , otherwise, this variable equals 0. $Year_{it}$ is the dummy variable of the year in which HSR is opened. w_{ij} is the spatial adjacency weight matrix. $Open_{it} \times Year_{it}$ is the core explanatory variable, which represents the effect after the opening of HSR between the experiment group and the control group. X are several control variables selected in this paper (as shown in Table 1). A_i , B_t is a dummy variable to control for the fixed effect of city and time, respectively. ε_{it} is the residual term. α is a constant term. β_1 , β_2 , γ , θ , ρ , and λ are the coefficients.

3.3 Data Sources

This paper selects the data of cities in China from 2016 to 2019 as the research object. As a dimensionless index, AQI data can quantitatively describe the air quality within certain region in a certain period, and the value ranges from 0 to 500. The higher the AQI, the worse the air quality. All AQI data are obtained from <https://www.AQIstudy.cn>. We use the 24-h average AQI value of the day as the daily data, the monthly average AQI as the monthly data, and the quarterly AQI and annual AQI definitions are similar. The data of cities are mainly from “Statistical Yearbook of Chinese Cities”. After removing the cities with serious missing data, a total of 286 sample cities are obtained [49–51]. There are a few data missing problems in the sample cities, and this paper uses SPSS to make interpolation calculation for supplement.

Table 1 Definitions of the control variables

Variable types	Variable name	Explanations	Measurements
City variables	Area	Urban size	The administrative area of land
	Urban	Urbanization level	Proportion of urban construction land in the area of the district
	Pop	The urban population	Average annual population
Urban environmental protection variables	Green	Development of urban green spaces	The area of urban green space
	Bus	Degree of public transport development	The actual number of bus operation at the end of the year
Economic variables	GDP	GDP	Gross regional product
	Growth	Economic growth rate	GDP growth rate

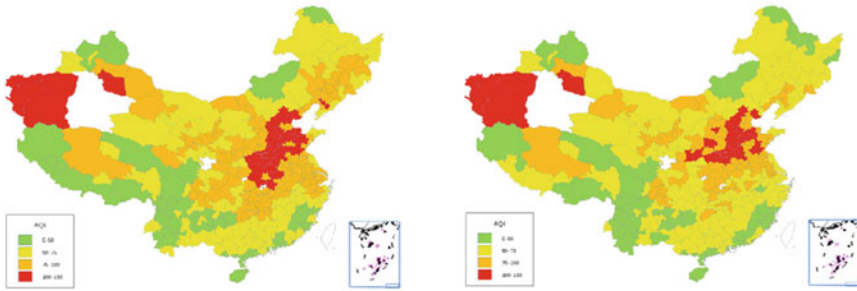
The data of opening time of the high-speed railway stations are from China High-speed Railway Route Database (CRAD) in China Research Data Service Platform (CNRDS).

4 Spatio-Temporal Distribution Characteristics of AQI

This section reports the calculated spatio-temporal distribution of Chinese cities' air quality for the study period. The Sect. 4.1 focuses on the temporal distribution characteristics of AQI, while the Sect. 4.2 discusses the spatial distribution. Then, in the Sect. 4.3, we present the Moran index to quantitatively analyze the spatio-temporal characteristics of Chinese cities' air quality.

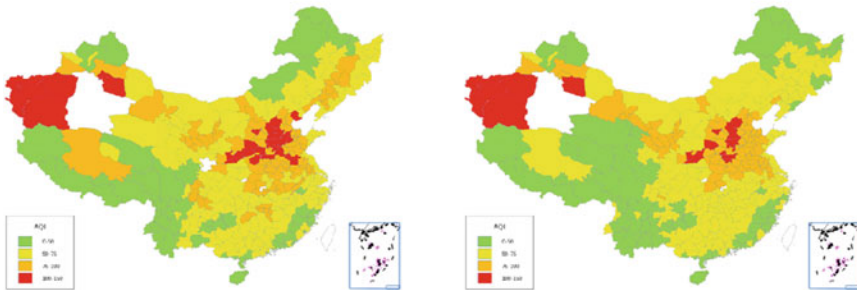
4.1 Temporal Distribution Characteristics of AQI

In 2016–2019 period, the evolution of Chinese cities' AQI is depicted in Fig. 2. It is observed that the AQI values in China evolves over time but demonstrates a decreasing trend. This reflects the significant improvement of the air quality in Chinese cities in recent years. In terms of the degree of air quality improvement, the number of cities that experienced air quality improvement accounted for 82.1% of the sample cities, among which the cities with more than 20% improvement accounted for 31.9%. In terms of air pollution degree, the proportion of cities with air quality reaching light pollution level (AQI annual mean > 100) decreased year by year, from 15% in 2016 to only 4.9% in 2019.



(a) Distribution of annual average AQI values in China in 2016

(b) Distribution of annual average AQI values in China in 2017



(c) Distribution of annual average AQI values in China in 2018

(d) Distribution of annual average AQI values in China in 2019

Fig. 2 Annual average AQI distribution in China from 2016 to 2019

As can be seen from Fig. 3, the seasonal average value of AQI is characterized by winter, spring, autumn, and summer, with the highest AQI index and the most serious pollution degree in winter, the lowest AQI index and the best air quality in summer. The main reason for the quarterly variation characteristics of AQI is that the winter temperature in the north is low, and the demand for heating has led to a substantial increase in the amount of coal burned. At the same time, it also increases the pollutants released by fuel combustion. In addition, the winter climate in the north is dry, and the reduction of precipitation is not conducive to diluting the pollutants in the atmosphere, making the AQI value reaches the highest level of the year. Precipitation increases in summer, and frequent rainfall and strong winds are conducive to disperse pollutants in the air, so the AQI value is the lowest in summer. Spring is windy and sandy, and dust storms bring a lot of dust, so the air quality in many areas is still not optimistic in spring. Autumn is drier than summer, and the burning of plant stalks after autumn harvest releases a large number of pollutants,

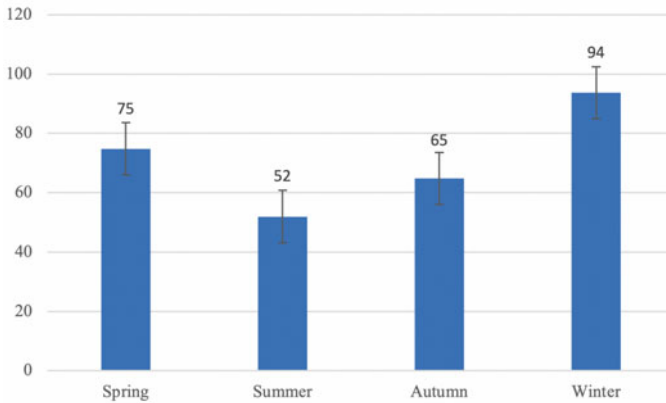


Fig. 3 Average AQI of four seasons in China from 2016 to 2019

leading to a decline in air quality in autumn, but it is slightly better than winter and spring.

4.2 Spatial Distribution Characteristics of AQI

To focus on the discussion of the spatial distribution of AQI, this subsection selects one particular year, 2019, for the analysis. As shown in Fig. 4, the air quality of coastal cities in Hainan and Fujian is relatively better. This is because the southeast part of China has a tropical or subtropical monsoon climate, and the terrain is relatively flat. The humid monsoon from the ocean is conducive to the diffusion of urban pollutants in summer. The cities' air quality in the high-altitude areas represented by Yunnan and Xizang also at a relatively good level. This is because there are few human activities in the high-altitude west southern region, which causes little damage to the ecological environment.

The cities with poor air quality are concentrated in north and northwest parts of China. The air quality and topography of the north China are potentially related to the east Asian monsoon, leading to the accumulation of regional air pollutants. Northern China, represented by Shijiazhuang, has the problem of low vegetation coverage, which is unable to resist the dust from the northwest. In addition, because of the low terrain in north China, the conditions for the diffusion of air pollutants are poor. In north China, the problem of high population density, rapid economic development and industrialization and urbanization still exist, so that the damage to the environment is quite serious. In cities in northwest China, such as Urumqi, water vapor is difficult to reach far away from the sea, so there is less precipitation, scarce vegetation and bad natural environment. All these reasons lead to poor air quality in northwest China.

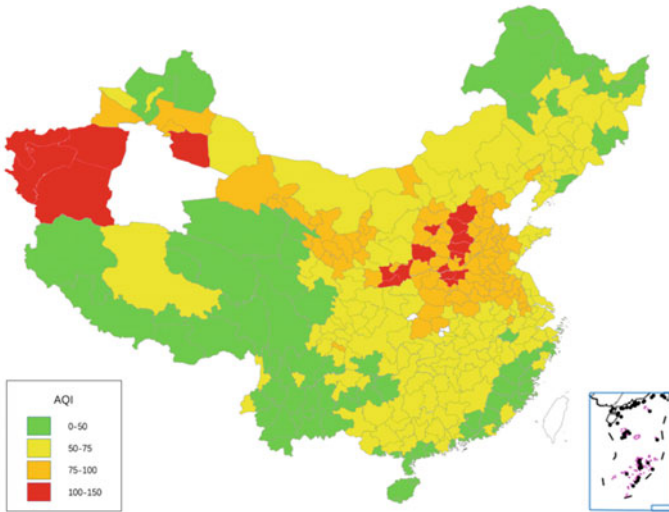


Fig. 4 Air quality distribution in China in 2019

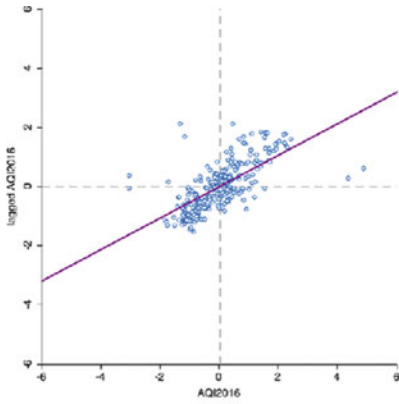
4.3 Spatial Auto-Correlation Analysis Based on Moran Index

In this paper, daily AQI data of the sample cities from 2016 to 2019 are used to calculate the annual average. The global Moran index and local Moran index of each city are also calculated with the equations Eqs. (1–2). The results are reported in Table 2. Moran index calculation results passed the statistics test at a significance level of 5%. Moran index statistics are all positive, ranging between 0.5 and 0.6, The highest value in 2017 is 0.572 and the lowest in 2018 is 0.530, which shows that Chinese cities’ air quality demonstrates an obvious positive space correlation. It can be concluded that the air quality of Chinese cities is also significantly affected by their surrounding cities and even provinces.

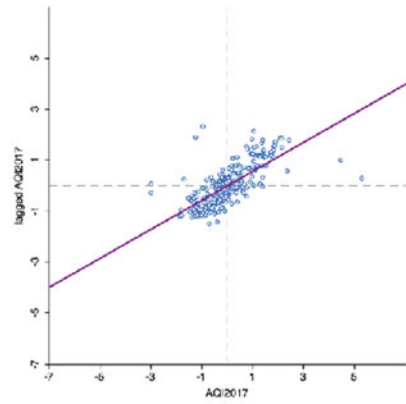
In this paper, the local spatial auto-correlation analysis is carried out through the Moran scatter plot in Fig. 5. The AQI samples in China are mostly concentrated in the first quadrant (H–H) and the third quadrant (L–L), which indicates that most provinces in China have the characteristics of spatial dependence, while other provinces have characteristics of spatial heterogeneity.

Table 2 Global Moran Index from 2016 to 2019

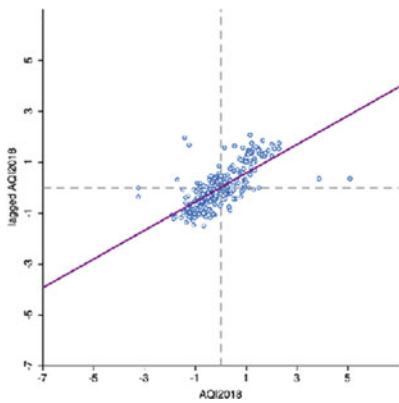
Year	Moran index
2016	0.533
2017	0.572
2018	0.562
2019	0.530



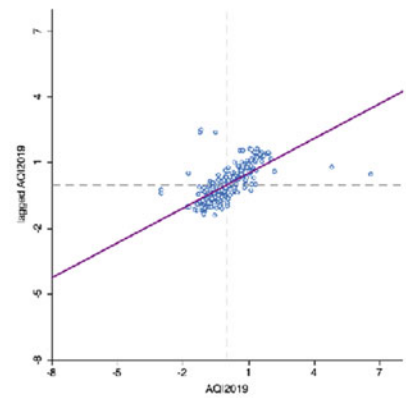
(a) The Moran Scatter Chart of the National AQI Annual Mean in 2016



(b) The Moran Scatter Chart of the National AQI Annual Mean in 2017



(c) The Moran Scatter Chart of the National AQI Annual Mean in 2018



(d) The Moran Scatter Chart of the National AQI Annual Mean in 2019

Fig. 5 Scatter chart of Moran index from 2016 to 2019

It can be seen from Fig. 6 that H-H aggregation areas in China are mainly distributed in north and central China, and the AQI index of cities in these regions is high, and the surrounding cities have similarly high AQI indexes. L-L aggregation areas in China are mainly distributed in the southwest and the southern regions, and their distribution characteristics are related to the fact that these cities are located in the coastal areas, which is conducive to the diffusion of pollutants, or to the fact that they are located in the plateau areas and there are few human activities. There are fewer cities in H-L and L-H regions, which are mainly distributed in the northwest and northern China.

Through the above analysis, it can be seen that the city's air quality in China exhibits an obvious trend of aggregation. Therefore, it is necessary to focus on the

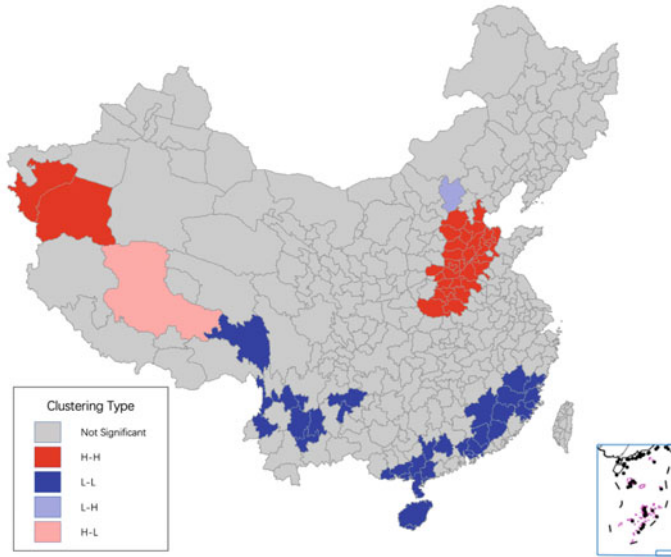


Fig. 6 LISA aggregation of city's air quality in China in 2019

control of air pollution in H–H aggregation areas to prevent its diffusion effect from continuing to reduce the air quality of surrounding cities and maintain good air quality in L–L aggregation areas.

5 Estimations of HSR Impact on City's Air Quality

This section presents the SDID estimation results to investigate the HSR impacts on city's air quality. Specifically, the Sect. 5.1 summarizes and discusses the benchmark estimation results. Then, Sect. 5.2 empirically verifies the mechanisms of such HSR impact by referring to our proposed theoretical mechanism in Sect. 3.1. In the Sect. 5.3, heterogeneous analysis are conducted on sub-sampled cities, categorized by the geographic locations and the degree of economic development.

5.1 Benchmark Estimation Results

This paper selects the panel data of 286 cities in China from 2016 to 2019 to build a multi-phase DID model to study the impact of HSR on city's air quality. The natural logarithm has been taken for all the variables (except dummy variables), including urbanization level, proportion of secondary industry and economic growth rate as the control variables.

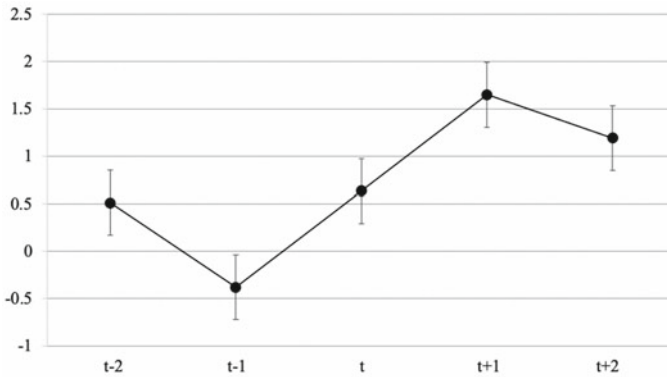


Fig. 7 Parallel trend test result

$$\begin{aligned}
 \ln(AQI_{it}) = & \alpha + \beta_1 Open_{it} \times Year_{it} + \beta_2 \sum_j w_{ij} Open_{it} \times Year_{it} \\
 & + \gamma_1 \ln(Area_{it}) + \gamma_2 Urban_{it} + \gamma_3 \ln(Pop_{it}) + \gamma_4 \ln(Green_{it}) \\
 & + \gamma_5 \ln(Bus_{it}) + \gamma_6 \ln(GDP_{it}) + \gamma_7 Growth_{it} + \theta \sum_j w_{ij} X_{it} \\
 & + \rho \sum_j w_{ij} AQI_{it} + \delta \sum_j w_{ij} \varepsilon_{it} + A_i + B_t + \varepsilon_{it} \tag{4}
 \end{aligned}$$

Since HSR opening time are different for different cities. Thus, we adapt the conventional DID model by using the SDID model. As a premise for valid DID analysis, it is still necessary to test whether the air quality index of the control cities and the experimental cities can meet the parallel trend. As can be seen from Fig. 7, there is no statistically significant time trend differences between the control and experimental cities in the two periods before HSR opening. Therefore, this model can satisfy the assumption of parallel trend to justify the use of DID method.

The spatial correlation of spatial econometric model can be caused by dependent variable, independent variable or error term. Spatial Dubin Model (SDM) is general because it can not only represent the spatial correlation of the above three aspects, but also can be transformed into the Spatial Lag Model (SLM) or the Spatial Error Model (SEM) under different coefficient settings. The following Table 3 shows the benchmark regression results of this paper. Models 1–4 are SLM, SEM, Spatial Lagged X(SLX) and SDM, respectively.

According to the estimation results in Table 3, the basic correlation of the benchmark model comes from dependent variables, independent variables and error terms, such that SDM cannot be decomposed into SLM and SEM. Therefore, we shall restrict our attention to the Model 4 (SDM). The core variable $Open \times Year$ is significantly negative in all models. According to Model 4, the opening of HSR in Chinese cities significantly reduces AQI by about 4%. This shows that HSR opening in one city can help improve this city's air quality. In the Model 4, the spatial autocorrelation coefficient ρ is 0.0897 and significant, suggesting that the air quality of a

Table 3 Benchmark regression results

Explanatory variables	Model 1 SLM	Model 2 SEM	Model 3 SLX	Model 4 SDM
Open*Year	-0.0392*** (0.0027)	-0.0491*** (0.0007)	-0.0402** (0.0408)	-0.0417** (0.0335)
lnArea	-0.0923 (0.561)	-0.0823 (0.426)	-0.0904 (0.2369)	-0.0891 (0.628)
Urban	0.0028 (0.2711)	0.0109 (0.3386)	0.0012 (0.1248)	0.0047 (0.5628)
lnPop	0.0158 (0.3192)	0.0026 (0.7832)	0.003 (0.8233)	0.0384 (0.6738)
lnGreen	-0.0201*** (0.0032)	-0.0159*** (0.0007)	-0.0144*** (0.0016)	-0.0311*** (0.0047)
lnBus	-0.034 (0.4716)	-0.0294 (0.7948)	-0.016 (0.335)	-0.067 (0.578)
lnGDP	-0.0308** (0.0227)	-0.0197*** (0.0051)	-0.0242*** (0.0064)	-0.0494*** (0.0085)
Growth	0.0031* (0.0668)	0.0022** (0.0289)	0.0042** (0.0466)	0.0056** (0.0359)
w*Open*Year			-0.0127* (0.0623)	-0.0136* (0.0742)
w*lnArea			0.2547 (0.3661)	0.436 (0.7531)
w*Urban			0.9276 (0.2855)	0.8355 (0.5321)
w*lnPop			0.1214* (0.0747)	0.2545* (0.0512)
w*lnGreen			-0.3731** (0.0265)	-0.5433* (0.0429)
w*lnBus			0.0807 (0.1921)	0.0754 (0.5643)
w*lnGDP			0.1214 (0.7471)	0.4537 (0.845)
w*Growth			0.3996 (0.1209)	0.4002 (0.5783)
w*lnAQI(ρ)	0.0975*** (0.0000)			0.0897*** (0.0000)
w* $\epsilon(\lambda)$		0.5378** (0.0246)		
N	1144	1144	1144	1144
R-squared	0.6417	0.6437	0.6532	0.6586

Note 1. The values in parenthesis are P values of the estimated coefficients
 2. ***, ** and * indicate significant levels of 1%, 5% and 10%, respectively
 3. Without specification, the above two notes apply to all the following tables of estimation results

city will be significantly affected by surrounding cities. In addition, the HSR also has a spatial spillover effect due to the high level of ρ . The opening of HSR in one city's neighboring cities can further reduce this city's AQI by 1.3%. Such findings calls for cautions when evaluating the HSR's environmental impact because the neglect of such spatial spillover (i.e., the neighboring effect) will lead to an underestimated benefit of HSR opening to improve city's air quality.

Moreover, it is interesting to notice that several socioeconomic factors are found to affect city's air quality insignificantly, such as city's area size, urbanization degree, and population size. On the other hand, the city's economic development is found to downgrade the city's air quality. Such result shows the existence of considerable heterogeneous patterns of air quality among Chinese cities, and the economic development is more vital to determine the city's air quality, compared to other socioeconomic factors. Thus, we would examine such heterogeneous patterns in more details (see Sect. 5.3).

5.2 Mechanism Analysis

According to the previous analysis, HSR can affect the emissions and city's air quality through transport substitution and industrial structure (see our research frameworkhighlighted in Fig. 1). The following two-stage mediating effect model is thus constructed on the basis of SDM to verify and disentangle such mechanism. In the first stage, we test the impact of HSR opening on potential mechanism variables M_{it} (i.e., the mediator) based on the following equations.

$$\begin{aligned}
 M_{it} = & \tau_0 + \tau_1 Open_{it} \times Year_{it} + \tau_2 \sum_j w_{ij} Open_{it} \times Year_{it} + \phi X'_{it} \\
 & + \psi \sum_j w_{ij} X'_{it} + \tau_3 \sum_j w_{ij} M_{it} + H_t + V_t + \kappa_{it}
 \end{aligned} \tag{5}$$

Second, this paper tests the influence of mechanism variables on AQI based on the following equation:

$$\begin{aligned}
 \ln(AQI_{it}) = & \sigma_0 + \sigma_1 M_{it} + \omega X_{it} + \lambda \sum_j w_{ij} X_{it} + \sigma_2 \sum_j w_{ij} M_{it} \\
 & + \sigma_3 \sum_j w_{ij} \ln(AQI_{it}) + P_t + Q_t + \mu_{it}
 \end{aligned} \tag{6}$$

Here, our mediator variables M_{it} refer to transport substitution (TS) and industrial structure (IS). TS variable is the ratio of HSR passenger traffic to airline passenger traffic for one city. IS variable is the ratio of the city's tertiary industry to the secondary industry. The control variables remain the same as before. According to the theoretical framework shown in Fig. 1, the transport substitution effect (TS) is the direct effect to

Table 4 Estimation of the positive mediating effect of HSR on city's air quality

	Model 1 (TS)	Model 2 (AQI)	Model 3 (IS)	Model 4 (AQI)
Open*Year	0.0252* (0.0717)		0.0131*** (0.0035)	
TS		-0.0623*** (0.0043)		
IS				-0.0422*** (0.0027)
Control variables	Yes	Yes	Yes	Yes
N	1144	1144	1144	1144
R-squared	0.0178	0.652	0.096	0.6497

help improve city's air quality, while the industrial structure effect (IS) is the indirect effect to help improve city's air quality.

As shown in Table 4, in model 1 (TS), the coefficient of $Open_{it} \times Year_{it}$ is significantly positive, indicating that the opening of HSR can significantly increase the market share of railway compared to airline traffic. This suggests an obvious transport substitution effect. Then model 2 (AQI) confirms the significant positive impact of the transport substitution to improve city's air quality. Then, as shown by model 3 (IS), the opening of HSR also brought apparent industrial structure effect, promoting the shares of tertiary industry relative to other sectors. Then, the estimation results of model 4(AQI) show that such industrial upgrading also helps improve the city's air quality. Although, as also shown in Fig. 1, HSR could also aggravate emissions and damage air quality through other direct effect (i.e., traffic inducing effect) or indirect effect (i.e., industry interaction effect), our estimation results in the benchmark and this mediation regressions suggest that the positive emission mitigation brought by the HSR is more dominant and lead to an overall lower emissions and better air quality.

5.3 Heterogeneity Analysis

This subsection explores the possible regional heterogeneity in HSR impact on the city's air quality. Specifically, we categorize our 286 sample cities based on geographic locations and the economic development. Our SDID regressions are then conducted again for different sub-sampled cities to distinguish the heterogeneous HSR impacts. First, according to the geographic locations and economic characteristics, sample cities are divided into the "eastern region", "northeast region", "western region" and "central region". Table 5 summarizes the regions and the corresponding cities in each region.

Table 6 collects our SDID estimation results for each region. We focus on the local and spatial effects of HSR impacts on city's air quality. In terms of the local

Table 5 Regional division of China

Region	Included provinces and cities
The eastern region	Beijing, Tianjin, Hebei, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong and Hainan
The northeast region	Liaoning, Jilin and Heilongjiang
The western region	Inner Mongolia, Chongqing, Guangxi, Sichuan, Guizhou, Yunnan, Tibet, Shaanxi, Qinghai, Gansu, Ningxia and Xinjiang
The central region	Shanxi, Henan, Hubei, Hunan, Anhui and Jiangxi

effects, it is found that the opening of HSR significantly improved air quality of western and eastern China, while the impacts on the northeast and central region are not statistically significant. Such results are sensible in that HSR can help upgrade the industrial structure, especially promoting the tertiary industries that are environmentally friendly. Western China cities benefit more in such industrial upgrading, reflected by better air quality. On the other hand, the transport substitution effect could be more dominant in eastern China, where highway and normal-speed railway systems are the most developed. Thus, HSR, as a cleaner mode, can attract more traffic than other modes, which improves the air quality. For the neighboring effect, it only significantly exists in eastern region. That is, HSR opening in one neighboring city can also improve this city's air quality. The city density in eastern China is high such that their economy and transport correlations are closer. However, in other regions, especially western China, the cities are distributed sparsely and the economic linkage is looser, so that the neighboring effect is not significant.

In addition to above categorization based on geographic locations, the sample cities can also be grouped by their economic development degrees. Although the overall economy and people's income have grown dramatically over the past decades, China has a large population base and exists huge income disparity among different cities. The impact of HSR opening could also depend on the city's economic development, which can be divided by its per capita GDP as shown in Table 7.

According to Table 8, in terms of both local and neighboring effects, HSR opening is shown to significantly improve the air quality of those developed cities, especially those relatively developed cities. Many of these cities traditionally rely on the manufacturing and other pollutant industries to develop the economy. HSR can help them to

Table 6 Estimation results of each region

	Eastern Region	Northeast	Western Region	Central Region
Local effects	-0.0588* (0.0837)	-0.0519 (0.6943)	-0.0752** (0.027)	-0.0631 (0.1312)
Neighboring effects	-0.0137** (0.0321)	-0.0015 (0.5511)	-0.055 (0.1047)	-0.0478 (0.5829)
N	300	136	348	360
R-squared	0.752	0.793	0.766	0.719

Table 7 Classification of GDP per capita

Economy development level	Number of cities	Range
Developed	16	US\$20,000 \leq per capita GDP
Relatively developed	29	The world average (US\$14,660) \leq per capita GDP < US\$20,000
Medium level	93	US\$8,000 \leq per capita GDP < the world average (US\$14,660)
Low poverty	129	US\$4,000 \leq per capita GDP < US\$8,000
Medium to high poverty	19	per capita GDP < US\$4,000

Table 8 Estimated results of HSR opening effect on cities classified by economy development

	Developed	Relatively developed	Medium level	Low poverty	Medium to high poverty
Local effect	-0.0323* (0.0911)	-0.0983* (0.0606)	-0.0488 (0.1171)	-0.056* (0.0648)	0.084 (0.8849)
Neighboring effect	-0.0227* (0.0244)	-0.0362* (0.0921)	-0.0835 (0.4267)	-0.0352 (0.3922)	0.0572 (0.4632)
N	64	116	372	516	76
R-squared	0.8368	0.6534	0.6368	0.5935	0.7581

upgrade industrial structure to cleaner production and service industries. Moreover, the traffic volume is higher in these cities, such that the HSR transport substitution effect could be stronger as more residents have relatively high income and can afford HSR service. However, for those less developed cities, HSR demand is lower and its impact on industrial structure upgrading and transport substitution effect is limited.

6 Conclusions

This paper first quantified the spatio-temporal evolution of city's air quality in China. Then, a SDID model was employed to study the HSR impact on city's air quality. The contributions of this paper are multi-fold. First, this is one of the first studies to adopt spatial auto-correlation approach to quantify the spatio-temporal distribution and characteristics of Chinese cities' air quality. Second and more importantly, this paper provides one of the first rigorous empirical examinations on the local and spatial impact of HSR opening on city's air quality. In addition to the overall effect, we investigate the mechanism of the HSR impact. Specifically, we consider the direct effect brought by the change of traffic volume and the modal splits, and the indirect effect caused by HSR on the city's industrial structure and production scale. The heterogeneous analysis is also done to shed light on the HSR impacts on different

kinds of cities categorized by the geographic location and the degree of economy development.

The spatio-temporal analysis of air quality first shows clear inter-annual and seasonal patterns of air quality among Chinese cities. Moreover, the spatial pattern demonstrates the southern China and coastal region have overall better air quality than northern China and inland areas. This is mainly related to climate type, terrain, economic development level and other factors. The northern cities are low-lying, where pollutants are difficult to diffuse, and economic development and industrialization progress are rapid, causing serious environmental damage. Most coastal cities in southern China have a tropical or subtropical monsoon climate, and the terrain is relatively flat. Air quality in China has obvious positive spatial auto-correlation, and also demonstrate obvious aggregation trend over time. Cities with severe air pollution will have a negative impact on the air quality of neighboring cities.

Our SDID estimations suggested that the HSR opening can reduce the emissions and improve the air quality (i.e., the local effect), while the HSR opening in the adjacent city can also improve the city's air quality (i.e., the neighboring effect). We also highlight and verify the mechanism of such positive HSR impact on city's air quality. First, as a cleaner transport mode, HSR helps reduce traffic in other more pollutant modes (i.e., positive direct transport substitution effect). In addition, HSR helps promote the city's tertiary industry, leading to fewer emissions (i.e., positive indirect industrial structure effect). Our heterogeneous analysis further exhibits that HSR is more effective to improve the air quality in eastern and western regions of China, given the more prevailing transport substitution effect and industrial structure effect. But the neighboring effect of HSR is only significant in the eastern China as the cities are closer with each other in terms of economic relation and geographic locations in this region. Moreover, the HSR proves to improve air quality in more economically developed cities, as the HSR traffic is larger in this region.

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