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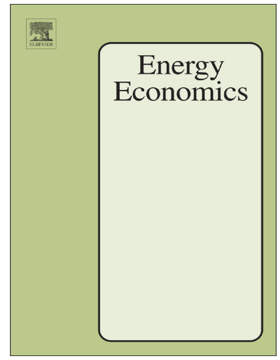

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Impact of Transportation Infrastructure on Industrial Pollution in Chinese Cities: A Spatial Econometric Analysis

Guobin Huang[a], Jie Zhang[b], Jian Yu[c,*], Xunpeng Shi[d]

Abstract: Transportation infrastructure (TI) plays a critical role in China's economic growth, but its negative impacts on the environment have not been sufficiently addressed by the government. While studies of TI's impact on air pollution exist, there are few studies examining its impact on industrial pollution. This paper fills this gap by using the Spatial Durbin model and balanced panel data from 280 of China's cities spanning 2003 to 2015. The results show that TI, represented by urban roads, aggravates the cities' industrial SO_2 emissions, industrial soot (dust) emissions, and industrial wastewater over the long run. The channel analysis further shows that TI influences industrial pollution through industrial agglomeration, but not urbanization. TI has no direct effect on the industrial pollution of neighboring cities but does influence neighboring cities' industrial pollution through the spatial spillover effects of industrial agglomeration. Provincial policymakers and city planners should together pay more attention to the role of industrial agglomeration when designing economic policies to manage the negative effects of TI on the environment, and through cross-city cooperation develop means to reduce these effects.

Keywords: Transportation infrastructure; Industrial pollution; Industrial agglomeration; Urbanization; Spatial Durbin model

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Highlights

- The impact of transportation infrastructure on industrial pollution is estimated
- Transportation infrastructure aggravates cities' industrial pollution in the long run
- Transportation infrastructure influences industrial pollution through industrial agglomeration but not urbanization
- Spatial Durbin model is used to measure the spatial spillover effects of industrial agglomeration
- The spatial spillover effects of industrial agglomeration play an important role in the impact of TI on industrial pollution

1. Introduction

The Chinese economic miracle has caused serious environmental pollution. Infrastructure investment, a key factor that has underpinned the economic miracle, has been frequently examined for its impacts on economic performance and air pollution (Lin and Chen, 2020), but few studies have examined its impact on industrial pollution[1] (Ji and Zhang, 2019). This paper aims to investigate the impact of transportation infrastructure (TI)[2] on industrial pollution at the city level through industrial agglomeration[3] and urbanization.

Over the past four decades, China's remarkable economic development has come to be known as the "China miracle" (Cheng et al., 2019; Yu et al., 2019; Zhang et al., 2020). China's gross domestic product (GDP) increased from US$293.6 billion in 1978 to US$10.8 trillion in 2018, and GDP per capita increased from US$307 to US$7,752 during the same period (all values at constant 2010 US$; World Bank, 2018). Many factors have supported China's economic success, among which the construction of transport infrastructure (TI) is regarded as critical (Coşar and Demir, 2016; Rokicki and Stępniak, 2018; Yu et al., 2019; Lin and Chen, 2020). Many studies have demonstrated that TI plays a positive role in economic growth (Duan et al., 2018).

However, the rapid development of the Chinese economy, including TI–a key driver of China's economic growth – has caused serious environmental consequences. On the one hand, the construction of roads, itself, is highly polluting. On the other hand, when TI increases, there is almost always a rapid increase in private car

[1] Environmental pollution can be broadly divided into domestic pollution (such as household garbage) and industrial pollution. Industrial pollution can be further divided into primary industry pollution (pesticide pollution, etc.), secondary industry pollution and tertiary industry pollution (such as exhaust emissions from cars). In this paper, industrial pollution refers specifically to secondary industry pollution, that is, waste gas, waste water, etc. produced by the production processes of secondary industry enterprises.

[2] There are many types of TI, e.g., airports, railways, high-speed railways, expressways and urban roads. In this paper, TI refers specifically to within-city TI of urban roads, rather than inter-city TI of airports, railways, high-speed railways, expressways, etc. See the paragraphs below for more details

[3] In this paper, industrial agglomeration refers specifically to secondary industry agglomeration.

ownership, and this leads to increases in air pollution. In China, the speed of urban road construction has lagged far behind the growth rate of private car ownership. This has inevitably led to increasingly severe urban traffic congestion. C. Sun et al. (2019) argued that rail transit has an air pollution-reducing effect in the long run, while the construction of rail transit has a negative short-term effect on air quality. Luo et al. (2018) looked at road width and road length and found that road width had a significant negative effect on PM_{10} in China, but road length had an insignificant positive effect on emissions.

According to the *China State Bulletin on Ecological Environment* (2018) (Ministry of Ecology and Environment of the People's Republic of China, 2018), the air quality in 217 (64.2%) of 338 cities at and above the prefectural level[4] exceeded the national standard in 2018.[5] Water pollution is also a problem. In 2018, the 10,168 national groundwater quality monitoring stations, the I-III class water (good quality) accounted for only 13.8% of the water quality monitoring, and the IV-V class proportion (polluted) was as high as 86.2%. Figures 1(1)-1(3) show the four quartile distributions of industrial SO_2 emissions, industrial soot (dust) emissions, and industrial wastewater, respectively, in Chinese cities. These three types of pollution are mainly concentrated in the eastern and central regions. The levels of pollution in the western region are relatively lower than those in the eastern and central regions. This is because the western region is less densely populated and has less secondary industry enterprises than eastern and central regions.

[4] There are four levels of cities according to China's administrative system, says provincial city (four municipalities, Beijing, Shanghai, Tianjin and Chongqing), vice-provincial city (capital of each province such as Guangzhou), prefecture-level city and county-level city. 338 cities at and above the prefectural level include provincial city, vice-provincial city and prefecture-level city. Besides, all the cities considered in this paper is at and above the prefectural level.

[5] The six pollutants are $PM_{2.5}$, PM_{10}, SO_2, NO_2, O_3 and CO. According to the "*Technical Regulation for Ambient Air Quality Assessment (On Trial)*" (HJ 663-2013) and the "*Ambient Air Quality Standards*" (GB 3095—2012): the annual average concentration value of $PM_{2.5}$ cannot exceed 35μg/m³, and the average annual concentration value of PM_{10} cannot exceed 70μg/m³, the annual average concentration value of SO_2 cannot exceed 60μg/m³, the annual average concentration value of NO_2 cannot exceed 40μg/m³; and the 90% quantile of the daily maximum 8-hour average concentration value of O_3 in the effective calendar year cannot exceed 160 μg/m³, and the 95% quantile of the 24-hour average concentration value of CO in the effective calendar year cannot exceed 4 mg/m³.

[Insert Figure 1 Here]

Though more and more studies have been carried out on the economic and environmental impacts of TI, gaps remain in the research in terms of its impact on industrial pollution. An increasing number of researchers have been finding that TI has a significant negative impact on the environment (Chen and Whalley, 2012; Gallego et al., 2013; Sun et al., 2018, 2014; Wei, 2019; Xu and Lin, 2016). Most of their studies have focused on the impact of TI on air pollution from vehicles and other means of transportation. The topic of industrial pollution caused by TI through industrial agglomeration and urbanization has been insufficiently investigated (Hao and Liu, 2016; Zhu et al., 2019). Ignoring the impact of TI on industrial pollution leads to incomplete analyses, insufficient cognition of TI, and biased and partial evaluation, resulting in misleading policy formulation.

This paper focuses on pollution of secondary industry because industrialization is an important driving force for China's rapid economic growth (Jiang and Lin, 2012; Mukherjee and Zhang, 2007), and industrialization is accompanied by serious secondary industry pollution (Xu and Lin, 2015). As far as the concerned topic of industrialization and industrial pollution in this article, urban road is one of the important means for local governments to attract investment ("three supplies and one leveling", supply of water, electricity and road and leveled ground, four conditions ready for further economic development), while inter-city transportations such as airports, railways, high-speed railways and expressways are planned by the central government or higher-level governments and are not fully determined by local governments. Therefore, this paper focuses on the internal transportation infrastructure of the city, emphasizing the impact of within-city industrial agglomeration (specifically secondary industry agglomeration in this paper) on secondary industry pollution caused by urban roads, rather than discussing the impact of the connectivity among cities on tertiary industry pollution (exhaust emissions by car during personal travel, etc.). Furthermore, the inter-city transportations will have impact beyond the city boundary and thus its environmental impact is hardly to be matched by the city level pollution data. In this case, we mainly focus on discussing the urban roads rather than investigating the inter-city airports, railways, high-speed railways or expressways.

From the perspective of industrial agglomeration and urbanization, we used the spatial Dubin model (SDM) to investigate the impact of TI on industrial pollution. Our data covered 280 prefecture-level cities in 31 China's provinces (excluding Hong Kong, Macao, and Taiwan) from 2003 to 2015. Our study differs from the literature in the following three aspects. First, we focused on the impact of TI on industrial pollution instead of air pollution. Industrial pollution is an important component of air pollution. Second, we examined two transmission mechanisms though which TI influences industrial pollution, namely industrial agglomeration and urbanization. We found that TI affects industrial pollution mainly through industrial agglomeration rather than urbanization. Third, we examined the spatial spillover effects of these three variables (e.g., industrial pollution, TI, and industrial agglomeration) and found that the spatial spillover effects of industrial agglomeration play an important intermediary role in the impact of TI on industrial pollution.

The rest of this paper is organized as follows. Section 2 presents a literature review and the hypotheses, section 3 sets the spatial econometric models, section 4 describes the data sources and variables selection, and section 5 presents the econometric empirical results and discussions. The final section provides the conclusions and policy implications.

2. Literature review and hypotheses

TI is often considered the engine of economic growth and development (Cheng et al., 2021; Coşar and Demir, 2016; He et al., 2020; Rokicki and Stępniak, 2018), and its effects on economic outcomes, including GDP per capita, poverty reduction, and efficient energy services, are a common subject in the literature (Barzin et al., 2018; Y. Li et al., 2017; Lin et al., 2012). Since the launching of China's reforms and opening up in 1978, the country's economic miracle over the subsequent four decades has been particularly dependent on TI (Ansar et al., 2016). Banerjee et al. (2020) investigated the impact of access to TI on the economic performance of different regions in China over a twenty-year period of rapid growth. They found that proximity to transportation networks had a moderately sized positive causal effect on per capita GDP levels across sectors, but had no effect on per capita GDP growth. Using manufacturing firm data from 1998 to 2007, Li et al. (2017) argued that infrastructure investment (e.g., road investment) contributed to an increase in manufacturing firms' productivity.

In this section, we present a literature review relevant to our three hypotheses on the overall impact and role of industrial agglomeration and urbanization as two potential channels.

Although many researchers have demonstrated that TI has a significant negative impact on the environment, especially on air pollution (D. Sun et al., 2019; Yang and He, 2016a), emissions (He and Qiu, 2016; Yang and He, 2016b), and traffic pollution (Guttikunda et al., 2014), few studies have focused on the impact of TI on industrial pollution emissions in Chinese cities. Public transportation and private cars are generally the two primary means that the general public uses to travel. Beirão and Sarsfield Cabral (2007) pointed out that the investment scale of a city's TI affects the public's travel preferences.

Using a panel of 283 prefecture-level cities in China from 2003 to 2015, Xie et al. (2019) found an inverted U-shaped relationship between traffic density and urban smog pollution in large and medium cities. They argued that direct emissions, spatial agglomeration, and technology spillover effects have been the three main channels through which traffic density influence smog pollution in China. Sun et al. (2018) found that the relationship between TI and air pollution in China differs in the short and long runs. Because the construction of urban traffic infrastructure might cause more detours and road blockages, TI has a negative effect on air pollution.

Recently, a number of studies found that environmental pollution (e.g., carbon emissions, air pollution, and SO_2 pollution) has obvious spatial spillover effects. Using the social network analysis method, Bai et al. (2020) found that the spatial association of China's provincial transportation carbon emissions exhibited an intuitive network structure and that the spatial association network presented a significant "core-edge" distribution pattern. Jiang et al. (2020) found that SO_2 pollution over the entire country exhibited a significant and positive spatial autocorrelation, with the most polluted areas concentrated over the North China Plain. Fang et al. (2020) employed panel data from 2003 to 2013 for 283 Chinese cities and found that smog pollution had obvious spatial spillover effects via the channel of manufacturing agglomerations. Liu et al. (2017) used the Air Quality Index (AQI) as the measure of haze pollution and found that there was a significant positive spatial autocorrelation of AQI values in Chinese cities. On average, the AQI of a city increased by over 0.45% for every 1% increase in the average AQI of neighboring cities.

Based on the literature review, we propose the first testable hypothesis:

H1. TI increases industrial pollution emissions in Chinese cities, and has spatial spillover effects.

TI has been observed to increase regional economic growth, reduce income inequality and energy poverty (Cheong and Wu, 2013; Zhang et al., 2019), and improve firms' production efficiency through industrial agglomeration and space overflow (Amann et al., 2016; Castells-Quintana, 2017). Many studies have demonstrated that industrial agglomeration is a critical channel for TI to influence environmental pollution (Dong et al., 2019; Han et al., 2018; Wang, 2020), but the impacts could be ambiguous due to two opposing factors. On the one hand, industrial agglomeration causes obvious effects on industrial production in a region. The concentrated production of most firms inevitably increases energy consumption and degrades the local ecological environment (Ji et al., 2019; Zhang et al., 2016). On the other hand, industrial agglomeration often engenders new production technologies and management experience which lead to improved energy efficiencies, and effectively alleviate some pressure on the local ecological environment. Wang (2020) used China's province-level data from 2000 to 2017 to estimate the mediating effects of industrial agglomeration in the relationship between TI and energy efficiency and found that TI directly affects energy efficiency but indirectly affects industrial agglomeration. Dong et al. (2019) argued that there is spatial autocorrelation between pollution agglomeration and industrial agglomeration in China, and that industrial agglomeration increased the pollution agglomeration at the national level and provincial level. Han et al. (2018) found that the specialization and diversification agglomerations of industries in China had no significant effects on a city, significantly reduced the energy efficiencies of the neighboring cities.

Given the significant but indecisive findings on the role of industrial agglomeration, we propose hypothesis 2:

H2. TI affects industrial pollution emissions in Chinese cities through industrial agglomeration.

The negative impact of urban TI construction on environment could be further amplified through the urbanization channel. On the one hand, many studies indicated that there is a close relationship between TI and urbanization. The demand for TI in particular is significantly related to increasing urbanization rates in developing countries. For India, Maparu and Mazumder (2017) found that investment in various transport infrastructure may support growth of urban population as well as its spatial spread. Maparu and Mazumder (2020) argued that there is a two-way causal relationship between TI investment and urbanization in India. TI can promote urbanization, which in turn requires more TI investment in India. For China, urban infrastructure plays an important role in determining the future of urbanization rate (Lin and Omoju, 2017). Xu and Yang (2019) pointed out that infrastructure construction in many Chinese cities is a key driving factor to accelerate the process of urbanization. The rational spatial distribution of TI, such as transportation network and public facilities, affects sustainable land use and urbanization rate. The socio-economic benefits from urban TI have been widely accepted as major tools in promoting the sustainable socio-economic development and urbanization in China (Sun and Cui, 2018). Zeng et al. (2019) found that there is a significant spatial spillover effect of infrastructure network on urbanization in Wuhan, which is the capital city of Hubei province in China.

On the other hand, more and more researchers found that urbanization is an important channel for TI to influence environment. For example, Gan et al. (2020) found that urbanization plays a mediating role in the impact of the economy (e.g., convenient transportation) on haze pollution in China. Yang et al. (2018) pointed out that the ongoing urbanization process in China, which has lasted for more than two decades, has led to a sharp increase in its urban population. They used the data of capital cities in 30 provinces of China from 2002 to 2012 to investigate the impact of TI on SO_2 emissions and demonstrated that TI increases SO_2 emissions in the short run but decreases SO_2 emissions in the long run. Zhu et al. (2019) argued that China's accelerating urbanization plays a critical role in influencing environmental pollution. Using a prefecture-level panel dataset of China's Yangtze River Economic Belt for the period of 2003-2014, they found that economic urbanization, population urbanization, and land urbanization impose no significant, significant positive, or significant negative impact on $PM_{2.5}$ concentrations, respectively. Lin and Zhu (2018) investigated the air quality in China's cities during the urbanization stage and found that the urbanization process has significant and negative effects on air pollutant concentration. Wang et al. (2020) found that the impact of urbanization on energy consumption and emissions tends to vary greatly across regions in different urbanization stages. Ji and Chen (2017) found that the impact of urbanization on energy consumption and energy efficiency of Chinese provinces is not linear but shows significant phased characteristics. However, Xie et al. (2020) used the Chinese Residential Energy Consumption Survey data and found urbanization increases residential energy consumption in total.

Based on the literature analysis, we propose hypothesis 3:

H3. TI affects industrial pollution emissions in Chinese cities through the urbanization channel.

3. Econometric methodology

Based on the hypotheses 1-3, we present the benchmark model:

$$\begin{aligned}\ln(Pollution_{it}) = \beta_0 + \beta_1 \ln(TI_{it}) + \beta_2 \ln(GDP_{it}) + \beta_3 \ln^2(GDP_{it}) + \\ \beta_4 \ln(FDI_{it}) + \gamma Z + u_i + \varepsilon_{it}\end{aligned} \quad (1)$$

Where subscript I and t represent city and time, respectively. *ln* represents the logarithm form of all nonproportional variables. $Pollution_{it}$ denotes industrial pollution, and TI_{it} denotes transportation infrastructure (TI).

The level of economic development (GDP_{it}) and its squared term, foreign direct investment (FDI_{it}) were introduced into the model as control variables according to the literature on the environmental Kuznets curve (EKC; Diao et al., 2009; Grossman and Krueger, 1995; Song et al., 2008) and pollution haven hypothesis (PHH; Cole, 2004; Eskeland and Harrison, 2003). Z represents the other set of control variables, including industrial structure, technology development, and government behavior. On the one hand, government's pursuit of fiscal revenue may cause over-investment in secondary industry and results in industrial pollution. On the other hand, government's expenditure on environmental protection would reduce industrial pollution. Thus, government behavior which is measured by the city's public fiscal expenditure divided by public fiscal revenue is added into the model. u_i is the city fixed effect, and ε_{it} is the stochastic error term.

Due to technical and institutional reasons, TI and industrial pollution may have many externalities, which lead to spatial spillover effects (Xie et al., 2019). On the one hand, in the planning and construction of local TI, consideration of the planning and construction of TI in neighboring provinces and cities is necessary. Industrial pollution spreads to surrounding areas due to natural forces such as wind and water flow. On the other hand, the positive externalities of TI and the negative externalities of industrial pollution may lead to an "Infrastructure Race" and thus "Pollution Race" between neighboring regions as a result of the Chinese government's behavior, and leading to a spatial correlation between TI and industrial pollution. Studies have also demonstrated that TI and industrial pollution have strong spatial dependence (Maddison, 2006; Zhu et al., 2019).

Due to the possibility of spatial correlation in TI, this paper adopted the relatively general SDM to investigate its impact on industrial pollution. The most-used spatial econometric models have been the spatial error model (SEM) and spatial lag model (SLM) (also called the spatial autoregression model [SAR]), respectively. As a general form of the SEM and SLM, the SDM considers the spatial hysteresis of both the independent variable and dependent variable; thus, it plays a critical role in practical applications. This feature of SDM also helps us explore the spatial effects of TI on industrial pollution more comprehensively. Therefore, based on the benchmark model, we establish the following SDM:

$$\begin{aligned}
&\ln(Pollution_{it}) = \rho\sum\nolimits_{j=1}^{N} w_{ij}\ln(Pollution_{it}) + \beta_0 + \beta_1\ln(TI_{it}) + \beta_2\ln(GDP_{it}) + \\
&\beta_3\ln^2(GDP_{it}) + \beta_4\ln(FDI_{it}) + \beta_5\sum\nolimits_{j=1}^{N} w_{ij}\ln(TI_{it}) + \beta_6\sum\nolimits_{j=1}^{N} w_{ij}\ln(GDP_{it}) + \\
&\beta_7\sum\nolimits_{j=1}^{N} w_{ij}\ln^2(GDP_{it}) + \beta_8\sum\nolimits_{j=1}^{N} w_{ij}\ln(FDI_{it}) + \gamma Z + u_i + \varepsilon_{it}
\end{aligned} \tag{2}$$

Here, w_{ij} is an element in the spatial weight matrix. Thus, we take the spatial lag terms of industrial pollution ($Pollution_{it}$), transportation infrastructure (TI_{it}), GDP_{it}

and FDI_{it} into the model simultaneously, to investigate the spatial spillover effects from the industrial pollution, TI, GDP, and FDI of a neighboring city.

Hypotheses 2 and 3 indicate that TI may affect industrial pollution through industrial agglomeration and urbanization. Thus, the following four equations are used to verify hypotheses 2 and 3.

$$Agg_{it} = \beta_0 + \beta_1 \ln(TI_{it}) + \gamma Z + u_i + \varepsilon_{it} \quad (3)$$

$$Urban_{it} = \beta_0 + \beta_1 \ln(TI_{it}) + \gamma Z + u_i + \varepsilon_{it} \quad (4)$$

$$\begin{aligned} \ln(Pollution_{it}) &= \rho\sum_{j=1}^{N} w_{ij} \ln(Pollution_{it}) + \beta_0 + \beta_1 \ln(TI_{it}) + \beta_2 Agg_{it} + \\ &\beta_3 \ln(GDP_{it}) + \beta_4 \ln^2(GDP_{it}) + \beta_5 \ln(FDI_{it}) + \beta_6 \sum_{j=1}^{N} w_{ij} \ln(TI_{it}) + \\ &\beta_7 \sum_{j=1}^{N} w_{ij} \ln(GDP_{it}) + \beta_8 \sum_{j=1}^{N} w_{ij} \ln^2(GDP_{it}) + \beta_9 \sum_{j=1}^{N} w_{ij} \ln(FDI_{it}) + \\ &\gamma Z + u_i + \varepsilon_{it} \end{aligned} \quad (5)$$

$$\begin{aligned} \ln(Pollution_{it}) &= \rho\sum_{j=1}^{N} w_{ij} \ln(Pollution_{it}) + \beta_0 + \beta_1 \ln(TI_{it}) + \beta_2 Urban_{it} + \\ &\beta_3 \ln(GDP_{it}) + \beta_4 \ln^2(GDP_{it}) + \beta_5 \ln(FDI_{it}) + \beta_6 \sum_{j=1}^{N} w_{ij} \ln(TI_{it}) + \\ &\beta_7 \sum_{j=1}^{N} w_{ij} \ln(GDP_{it}) + \beta_8 \sum_{j=1}^{N} w_{ij} \ln^2(GDP_{it}) + \beta_9 \sum_{j=1}^{N} w_{ij} \ln(FDI_{it}) + \\ &\gamma Z + u_i + \varepsilon_{it} \end{aligned} \quad (6)$$

Equations (3) and (4) inspect the impacts of TI on industrial agglomeration and urbanization, respectively. Equations (5) and (6) consider industrial agglomeration and urbanization as the explanatory variables in Equation (2). Equations (3) and (5) estimate the mediating effects of industrial agglomeration, and Equations (4) and (6) investigate the mediating effects of urbanization.

Various methods have been used to measure industrial agglomeration in the literature, for example, the industrial concentration, location quotient method (LQM), E-G index, and Herfindahl–Hirschman index. Because the dependent variable is industrial pollution, the LQM of the secondary industry was adopted as the measuring index of industrial agglomeration. The expression of Agg_{it} is $Agg_{it} = (p_{sit} / p_{it}) / (p_{snt} / p_{nt})$; here, Agg_{it} represents the LQM of the secondary industry of city *i* in year *t*, p_{sit} represents the secondary industry output value of city *i* in year *t*, p_{it} represents the total output value of city *i* in year *t*, p_{snt} represents the secondary industry output value of all cities in the country in year *t*, and p_{nt} is the total national output value in year *t*. This index measures the degree of specialization of the secondary industry in the city. The larger the index, the higher the degree of specialization in the secondary industry in the city compared with the whole country, that is, the higher the degree of agglomeration. Krugman(1991) pointed out that industrial agglomeration is the interaction result of the transportation cost, market size, and factor flow. TI can refer to transportation costs. We also measure market size by adding population size, and measure factor flow by adding FDI and government behavior, respectively, from the perspective of openness and the institutional environment.

The urbanization indicators include land urbanization and population urbanization. Land urbanization is measured by the proportion of urban land constructed, following (Zhu et al., 2019). Population urbanization is defined as the proportion of the non-agricultural population (Zhu et al., 2019). Additionally, the population size, industrial structure, and proportion of real estate investment are added as control variables.

In order to investigate the spatial spillover effects of industrial agglomeration, we introduced the spatial lag terms of industrial agglomeration and TI into Equation (3) to obtain Equation (7) and added the spatial lag terms of industrial agglomeration into Equation (5) to obtain Equation (8).

$$Agg_{it} = \rho\sum_{j=1}^{N} w_{ij} Agg_{it} + \beta_0 + \beta_1 \ln(TI_{it}) + \beta_2 \sum_{j=1}^{N} w_{ij} \ln(TI_{it}) + \gamma Z + u_i + \varepsilon_{it} \quad (7)$$

$$\begin{aligned}\ln(Pollution_{it}) = {} & \rho\sum_{j=1}^{N} w_{ij} \ln(Pollution_{it}) + \beta_0 + \beta_1 \ln(TI_{it}) + \beta_2 Agg_{it} + \beta_3 \ln(GDP_{it}) + \\ & \beta_4 \ln^2(GDP_{it}) + \beta_5 \ln(FDI_{it}) + \beta_6 \sum_{j=1}^{N} w_{ij} \ln(TI_{it}) + \beta_7 \sum_{j=1}^{N} w_{ij} Agg_{it} + \\ & \beta_8 \sum_{j=1}^{N} w_{ij} \ln(GDP_{it}) + \beta_9 \sum_{j=1}^{N} w_{ij} \ln^2(GDP_{it}) + \beta_{10} \sum_{j=1}^{N} w_{ij} \ln(FDI_{it}) + \\ & \gamma Z + u_i + \varepsilon_{it}\end{aligned} \quad (8)$$

4. Variable and data

4.1 Variable selection

Industrial pollution. Similar to most of the other relevant studies carried out to date, due to data limitations, the scope of this paper is mainly air pollution and water pollution. Air pollution is measured by industrial SO_2 emissions and industrial soot (dust) emissions, while water pollution is measured by industrial wastewater.

TI and transportation infrastructure investment (TII). Because no unified standard is available to measure TI, we used "urban road area" (unit of 10,000 m^2) to measure TI. As a stock variable, urban road area captures the long-term effects. The flow variable of the annual growth of urban road area was also adopted to capture the short-term effect, which is TII (Sun et al., 2018).

Control variables. Following the practice used in the most of the existing literature, we used GDP per capita to measure the level of economic development. Moreover, its square term was included to test the "inverted-U shape" relationship between industrial pollution and economic development, namely, the EKC. Therefore, the actual amount of foreign capital in the current year was used to measure FDI. Its impact was found to be ambiguous. On the one hand, according to the PHH (Cole, 2004; Eskeland and Harrison, 2003), transnational corporations generally move pollution-intensive enterprises to developing countries with relatively low environmental standards. On the other hand, foreign enterprises' advanced technologies typically reduce pollution emissions.

Industrial structure may affect industrial pollution. Some researchers observed that the higher the proportion of secondary industry, the more serious the pollution (Hao and Liu, 2016). Therefore, the proportion of secondary industry in GDP was adopted to measure industrial structure. Higher levels of technology often means lower pollution emissions (Zhu et al., 2019). However, the level of the technologies used in a city's industrial sectors are a function of the city's level of scientific research and development. Thus, the science and technology expenditure of the city measures the technological development level of a city. Government behavior is considered an important factor in industrial pollution. On the one hand, government's pursuit of fiscal revenue may cause over-investment in secondary industry and results in industrial pollution. On the other hand, government's expenditure on environmental protection would reduce industrial pollution. Consequently, the government behavior variable included a control variable and was measured by the city's public fiscal expenditure divided by public fiscal revenue.

Spatial weight matrix. In this paper, the commonly used spatial adjacency weight matrix was adopted. In other words, if two cities are adjacent, the weight is 1, and if two cities are not adjacent, the weight is 0. The form of the spatial weight matrix W in panel data is as follows:

$$W = \begin{bmatrix} W_{2003} & 0 & 0 \\ 0 & \ddots & 0 \\ 0 & 0 & W_{2015} \end{bmatrix} \quad (9)$$

The dimension of the spatial weight matrix W is $NT \times NT$, where N is the number of cities in the cross-section (i.e., 280), T is the time span (i.e., 13 years), and the off-diagonal elements are all zero, and the diagonal elements are the annual cross-section spatial weight matrix W_T. The dimension of W_T is $N \times N$, because the spatial geography of each city does not change with time; thus, $W_{2003} = W_{2004} = \ldots W_{2015}$.

4.2 Data sources

The data were collected from the *China City Statistical Yearbook (2004–2016), Yearbook of China's Cities (2004–2016), China Urban Construction Statistical Yearbook (2004–2016), China Statistical Yearbook on Environment (2004–2016),* and *China Environment Yearbook (2004–2016)*. The data set covered 290 prefecture-level cities in 31 provinces, municipalities directly under the central government and autonomous regions in China (excluding Hong Kong, Macao, and Taiwan). The time span was from 2003 to 2015. All nominal data were adjusted by a price index (2003 = 100) to obtain the actual value. Due to missing data for some cities, to make the empirical results more robust and the spatial econometric analysis feasible, 10 cities with serious missing data problems were excluded.[6] For a small number of other cities with slight missing data problems, linear interpolation (including interpolation and extrapolation) was used for data supplement. After processing, the original 31 provinces in the data were reduced to 30, among which Tibet is missing, and the original 290 prefecture-level cities were reduced to 280. The statistical description of the main variables is presented in Table 1.

[Insert Table 1 Here]

5. Results and discussions

5.1 Baseline results

The baseline results of Equation (1) are shown in Table 2 and Table 3. We chose the appropriate model according to the Hausman Test, which is reported in the last row. The Hausman Test shows that the fixed effect model is the appropriate one in most models.[7]

Table 2 captures the long-term effects. The regression coefficients of TI are statistically significant, suggesting that TI has a long-run impact on industrial pollution. In addition, the positive regression coefficients of TI indicate that TI will aggravate industrial pollution. For instance, in models (2), (4) and (6), if urban road construction increases 1%, industrial SO_2 emissions, industrial soot (dust) emissions, and industrial wastewater will increase by 0.116%, 0.171%, and 0.079%, respectively. Hypothesis 1 has been preliminarily verified.

[6] The 10 cities are Sansha in Hainan Province, Bijie and Tongren in Guizhou Province, Lhasa in Tibet Autonomous Region, Jiayuguan, Jinchang and Longnan in Gansu Province, Haidong in Qinghai Province, Guyuan and Zhongwei in Ningxia Hui Autonomous Region.

[7] Since the Hausman Test shows that the fixed effect model is the most appropriate, only the results of the fixed effect model are reported hereafter due to space limitations. Moreover, the estimated results of the fixed effect model resemble that of the random effect model. The random fixed regression results are also available upon request.

In terms of controlling variables, the estimation coefficients of GDP per capita and their squared terms were statistically significant only in Model (2) where industrial SO_2 emissions were treated as the dependent variable. The GDP per capita coefficient was positive while the squared term carries a negative sign. These results indicate that an "inverted-U shape" relationship, namely the EKC, exists only in industrial SO_2 pollution. As the FDI regression coefficients of FDI were not statistically significant in most models, the PHH was difficult to validate in the benchmark model. The regression coefficient of TC has a basically significant and negative effect, indicating that improvements in science and technology can reduce industrial pollution. In most of the models, the industrial structure and government behavior variables did not obtain consistent and significant results.

Table 3 captures the short-term effect. The TI regression coefficients were not statistically significant, suggesting that TI does not have a short-run impact on industrial pollution. As a robustness check, we added the control variables one by one. The estimation results are shown in Table A.1 - Table A.6 in the Appendix. All the results were consistent with Table 2 and Table 3. Because TI has a long-run impact on industrial pollution instead of a short-run impact, we focused on the long-run impact in the following section. Spatial effects are considered in the next section.

[Insert Table 2 Here]

[Insert Table 3 Here]

5.2 SDM estimation results

Before formal analysis of the spatial effects, we must assess the spatial correlation of TI and industrial pollution. In this paper, Moran's I was used to examine the spatial correlation effect. Table 4 reports the annual Moran's I of both industrial pollution variables and the TI variable. Table 4 shows that Moran's I was positive and highly significant, indicating that industrial pollution and TI have a positive spatial spillover effect at any given level of significance. Figure 2 also presents the Moran's I scatterplot in 2015. In Figure 2, industrial pollution and TI have strong positive spatial autocorrelation, which indicates the necessity of adopting the SDM.

[Insert Table 4 Here]

[Insert Figure 2 Here]

The estimation results of Equation (2) are presented in Table 5. The regression coefficients of TI were significantly positive in all models, which is consistent with the basic results. From the perspective of marginal effect, although the indirect effect was not significant, the direct and total effects were statistically significant and positive. We can conclude that TI mainly influences a city's industrial pollution, which has no obvious direct effect on the industrial pollution of adjacent cities. The insignificant regression coefficient of W×TI also confirms the aforementioned conclusion. The results demonstrate that a 1% increase in a city's urban road construction increases a city's industrial SO_2 emissions, industrial soot (dust) emissions, and industrial wastewater discharge by approximately 0.104%, 0.138%, and 0.079%, respectively.

[Insert Table 5 Here]

The spatial autoregressive coefficient ρ in all the models was positive and highly significant, indicating that industrial pollution indeed has positive spatial spillover effects. Industrial pollution between adjacent cities will affect each other, that is, a "Pollution Race" may occur. For example, when the industrial SO_2 emissions of adjacent cities increase by 1%, the city's industrial SO_2 emissions increase by 0.236% (e.g., Model (1) in Table 5). These results further verify hypothesis 1.

The conclusions of the controlling variables are basically the same as the basic results. The results with the EKC were the same as the basic results: the results with the EKC were statistically significant for only industrial SO_2 pollution. Notably, the spatial lag of GDP per capita was negative and statistically significant, indicating that the economic development of adjacent cities can reduce a city's industrial pollution. The possible reason for this finding is that in the process of attracting investment, local governments have paid too much attention to economic development while ignoring environmental costs (Xu et al., 2020). If many high-polluting enterprises move to other cities, a city's industrial pollution is effectively reduced. FDI in neighboring cities has a statistically significant effect on a city's industrial soot (dust) emissions. The development of science and technology can significantly reduce industrial pollution, and increases in the degree of industrialization can also aggravate the emissions of industrial SO_2. In addition, the regression coefficients of government behavior were not significant, meaning that government's fiscal expenditure and fiscal revenue do not influence industrial pollution.

Therefore, we can draw the following conclusions: 1) Despite the significant spatial spillover effects of industrial pollution, TI mainly aggravates a city's industrial SO_2 emissions and industrial soot (dust) emissions. The amount of industrial wastewater discharged has no effect on the industrial pollution of neighboring cities. 2) EKC was found only for industrial SO_2 emissions, and PHH was observed with respect to industrial SO_2 emissions and industrial wastewater. Improvements in science and technology can reduce industrial pollution significantly.

5.3 Robustness check

We also adopted the more commonly used SEM and SLM to perform a more robust check and found that the empirical results were all robust apart from the PHH, which no longer exists. All of the results are presented in Table 6 and are consistent with the results of the SDM.

[Insert Table 6 Here]

In Table 7, we used emission intensity and urban road density to replace the total emissions and the total area of urban roads to control the scale effect between different cities. The pollution intensity was measured by pollution emissions per square kilometer, and the road density was measured by the area of urban roads per square kilometer. After controlling the city scale effect, the estimated results were consistent with the original results. The estimated results are shown in Table 7.

[Insert Table 7 Here]

5.4 Channel analysis: industrial agglomeration or urbanization

The estimation results of Equations (3) and (5) are presented in Table 8. The TI coefficient was positive and highly significant in Model (1), indicating that TI can promote industrial agglomeration. For industrial SO_2 emissions and industrial wastewater in Models (2) and (4), the TI coefficients remained positive and statistically significant after introducing the industrial agglomeration variable. Furthermore, the regression coefficients of industry agglomeration were negative and statistically significant. All the results suggest that industrial agglomeration plays a mediating role in the association between TI and industrial SO_2 emissions (or industrial wastewater discharged), that is, TI reduces industrial SO_2 emissions and industrial wastewater through promoting industrial agglomeration.

[Insert Table 8 Here]

For industrial soot (dust) emissions in Model (3), the TI coefficients were also positive, although statistically insignificant. Additionally, the coefficients of industry agglomeration were positive and statistically significant, suggesting that industrial agglomeration also plays a reverse mediating role in the association between TI and industrial soot (dust) emissions, that is, TI promotes industrial soot (dust) emissions through aggravating industrial agglomeration.

From the perspective of marginal direct effect, industrial agglomeration has a negative and highly significant direct effect on industrial SO_2 emissions and industrial wastewater, and has a positive and highly significant direct effect on industrial soot (dust) emissions. Thus, we conclude that TI reduces a city's industrial SO_2 emissions and industrial wastewater but aggravates a city's industrial soot (dust) emissions through promoting a city's industrial agglomeration. For example, a 1% increase in a city's urban road construction will reduce a city's industrial SO_2 emissions and a city's industrial soot (dust) emissions by 0.096% (=0.083×1.151) and 0.121% (=0.083×1.452), respectively, and aggravate a city's industrial wastewater by 0.172% (=0.083×2.070).

From the perspective of marginal indirect effect, industrial agglomeration has a negative and highly significant indirect effect on industrial SO_2 emissions and industrial wastewater, and has a positive and highly significant indirect effect on industrial soot (dust) emissions. Thus, we concluded that TI reduces a neighboring city's industrial SO_2 emissions and industrial wastewater but aggravates its industrial soot (dust) emissions through promoting a city's industrial agglomeration and the spatial spillover effects of industrial pollution. For example, a 1% increase in a city's urban road construction reduces a neighboring city's industrial SO_2 emissions and neighboring city's industrial soot (dust) emissions by 0.025% (=0.083×0.295) and

0.026% (=0.083×0.309), respectively, and aggravates a neighboring cities' industrial wastewater by 0.065% (=0.083×0.785) through promoting a city's industrial agglomeration and the spatial spillover effect of industrial pollution. Hypothesis 2 has been verified.

The estimation results of Equations (4) and (6) are presented in Table 9. Because the estimation results of land urbanization and population urbanization were the same, only the estimation results of land urbanization are reported. The estimation results of population urbanization are presented in Table A.7 in the Appendix. The positive and significant TI coefficient in Model (1) in Table 9 suggests that TI can promote land urbanization. Although the TI coefficients remained positive and statistically insignificant after adding the urbanization variable in Models (2)-(4), the coefficients of the urbanization variable were neither statistically significant nor robust.[8] The direct effect, indirect effect, and total effect of urbanization were also neither significant nor robust. These findings indicate that the urbanization channel between TI and industrial pollution does not exist.

Thus, we concluded that TI exerts its influence on industrial pollution through industrial agglomeration but not urbanization. Specifically, TI reduces a city's industrial SO_2 emissions and industrial wastewater but aggravates a city's industrial soot (dust) emissions through promoting a city's industrial agglomeration. In addition, TI reduces neighboring cities' industrial SO_2 emissions and industrial wastewater but aggravates neighboring cities' industrial soot (dust) emissions through promoting a city's industrial agglomeration and the spatial spillover effects of industrial pollution.

[Insert Table 9 Here]

[8] Although the coefficients of urbanization were statistically significant in Models (3) and (4), the coefficients of urbanization were not statistically significant in the random-effect models which are not reported. Besides, the estimation results of population urbanization were also not statistically significant as shown in Table A.7 in the Appendix.

5.5 Spatial spillover effects of industrial agglomeration

We proved the spatial spillover effects of TI and industrial pollution in Subsection 5.2. In this subsection, we investigate the spatial spillover effects of industrial agglomeration. Notably, Table 4 also shows that the annual Moran's I of industrial agglomeration is positive and highly significant, indicating that industrial agglomeration had positive spatial spillover effects. Figure 3 presents the Moran's I scatterplot in 2015 and shows that industrial agglomeration has strong positive spatial autocorrelation, indicating that the settings of Equations (7) and (8) are reasonable.

The estimation results of Equation (7) are presented in Model (1) of Table 10. The spatial autoregressive coefficient ρ was positive and highly significant in Model (1), indicating that industrial agglomeration had a positive spatial spillover effect. Additionally, the direct effect and indirect effect of TI on industrial agglomeration were positive and statistically significant, suggesting that TI can promote a city's industrial agglomeration directly and improve the industrial agglomeration of neighboring cities indirectly through the spatial spillover effect of industrial agglomeration. Models (2)-(4) of Table 10 are the estimation results of Equation (8). The coefficients of W×Agg in all the models were significantly negative, indicating that the industrial agglomeration of a city reduces the industrial pollution of neighboring cities through its spatial spillover effects. From the estimation results of Equations (7) and (8), we concluded that TI reduces neighboring cities' industrial pollution through promoting a city's industrial agglomeration and the spatial spillover effects of industrial agglomeration. In this case, we concluded that TI reduces neighboring cities' industrial SO_2 emissions, industrial wastewater, and industrial soot (dust) emissions through promoting a city's industrial agglomeration and the spatial spillover effects of industrial agglomeration.

[Insert Figure 3 Here]

[Insert Table 10 Here]

6. Conclusions and implications

Because China's economic miracle has caused serious environmental pollution, the impacts of TI, a key contributing factor, have been the subject of many studies. While most of these have demonstrated that TI plays a positive role in economic growth.an increasing number of researchers have found that TI has a significant negative impact on the environment. However, previous studies have focused mainly on the impacts of TI on air pollution (D. Sun et al., 2019), smog pollution, and traffic pollution (Guttikunda et al., 2014) in Chinese cities. Few studies have investigated the impact of TI on industrial pollution emissions.

Using the SDM and a balanced panel data of Chinese 280 cities, this paper verifies that TI aggravates a city's industrial air pollution and water pollution problems in the long run. Further mechanism analysis demonstrated that TI influences industrial pollution through industrial agglomeration, but not urbanization. Specifically, there could be three paths for TI to influence industrial pollution through industrial agglomeration. First, TI aggravates a city's industrial SO_2 emissions and industrial wastewater, but reduces its industrial soot (dust) emissions through a city's industrial agglomeration. Second, TI reduces neighboring cities' industrial SO_2 emissions and industrial wastewater, but aggravates their industrial soot (dust) emissions through a city's industrial agglomeration and the spatial spillover effects of industrial pollution. Third, TI reduces neighboring cities' industrial SO_2 emissions, industrial wastewater, and industrial soot (dust) emissions through a city's industrial agglomeration and the spatial spillover effects of industrial agglomeration.

Our findings complement the existing literature on TI and the environment by adding the impacts of industrial pollution, a key factor determining total environmental pollution. Moreover, different from the existing literature that examines the environmental impacts through channels such as direct emissions, spatial agglomeration, and technology spillover effects (Xie et al., 2019;Bai et al., 2020; Fang et al., 2020), we demonstrated the additional channels of urbanization and industrial agglomeration. Our finding that TI influences industrial pollution through industrial agglomeration, but not urbanization, is new to the literature.

The policy implications are as follows. First, the negative impacts of TI on environment suggest that city planners need to integrate the broad environmental dimension into their planning process. With the additional target of minimizing industrial pollution, transportation infrastructure development decisions will likely change. Second, the insignificant channel of urbanization suggests that the negative environmental impacts of TI are avoidable if the industrial locations can be effectively managed. This might suggest that the popular industrial park model may not be favorable when evaluated from environmental perspectives. Industrial parks pool industries together, usually at a distance from residential areas. This can increase industrial agglomeration and the demand for transport services. Third, when industrial agglomerations cannot be changed, further actions can be taken to reduce the adverse environmental impacts. For example, in the promotion of industrial agglomeration, clean and green industries should be chosen to promote the positive effects of TI on industrial pollution. The finding that improved science and technology can effectively reduce industrial pollution also provides theoretical support for this suggestion. Lastly, although TI falls largely under a city's own authority, cross-city cooperation and coordination are useful as TI does influence neighboring cities' industrial pollution through the spatial spillover effects of industrial agglomeration.

Without doubt, urban transportation infrastructure can also influence air quality through changes in passenger travel. This issue has not been studied due to limitations in the data pertaining to automobile exhaust emissions and their environmental consequences. However, it should be investigated in the future when the necessary data are available.

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Figures and tables

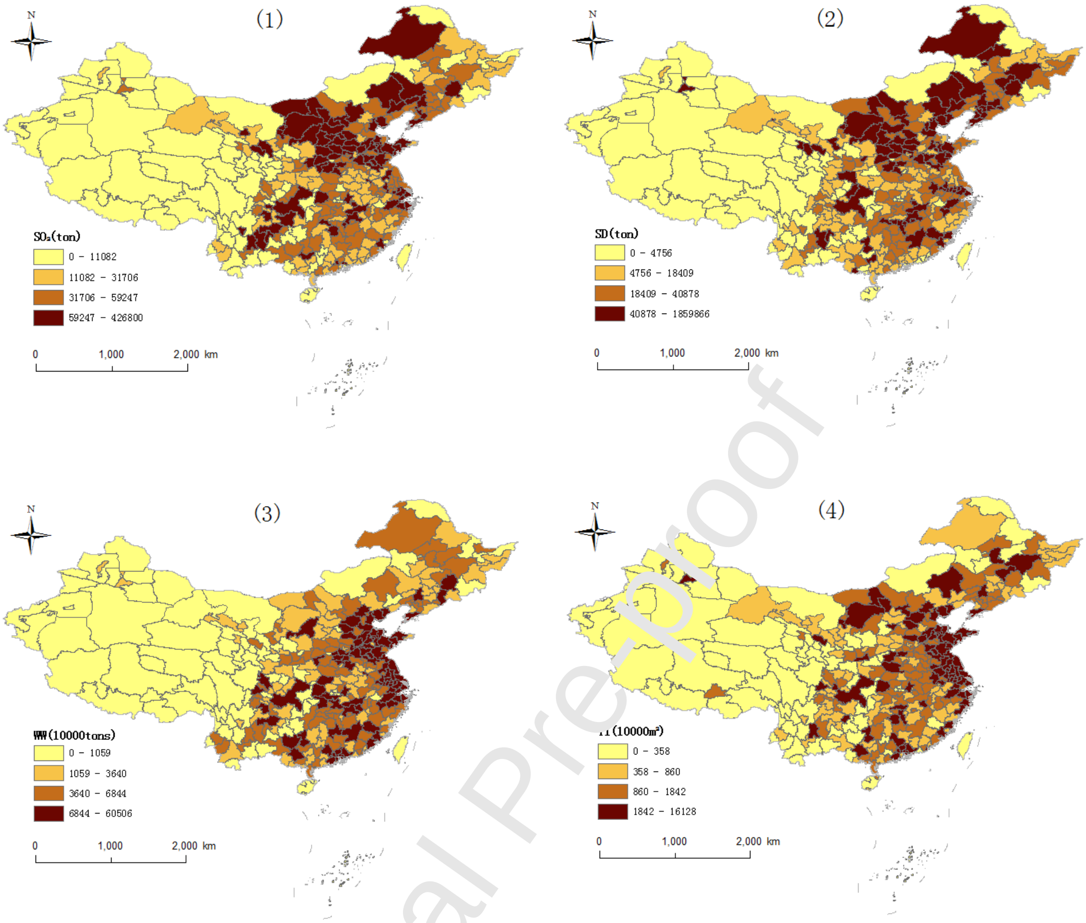

Figure 1. Spatial distribution of industrial pollution and TI in 2015

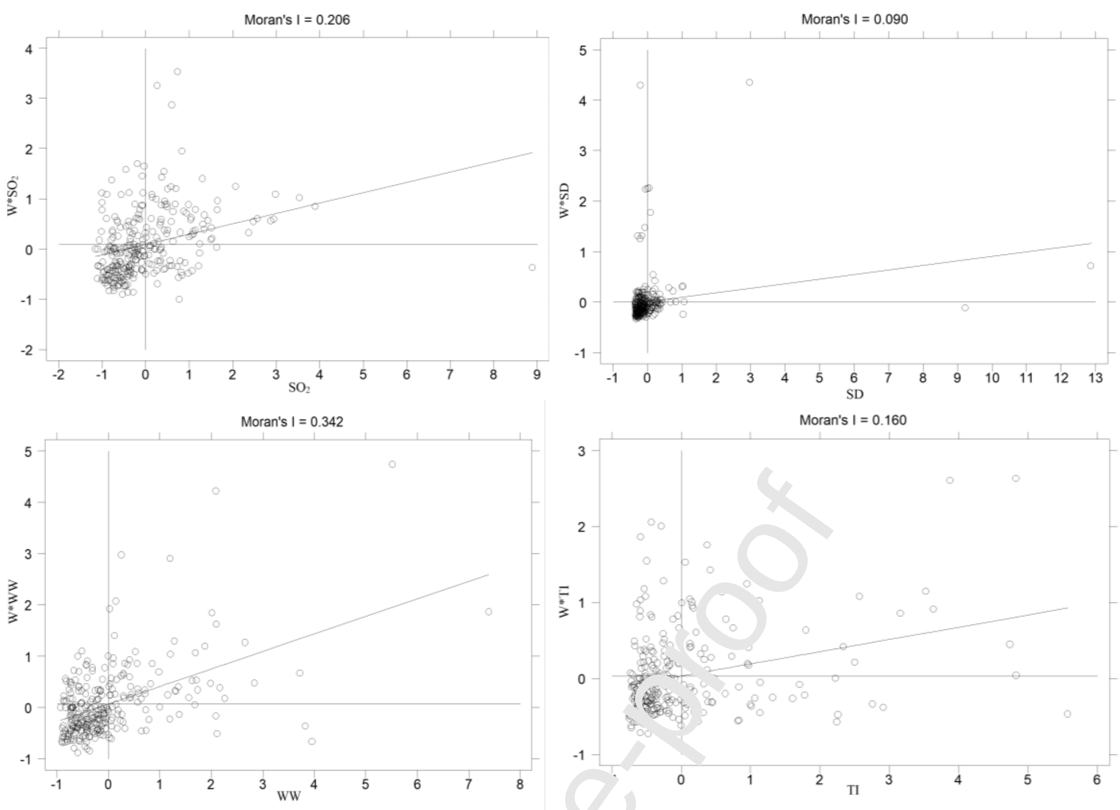

Figure 2. Moran's I scatterplots for industrial pollution and TI in 2015

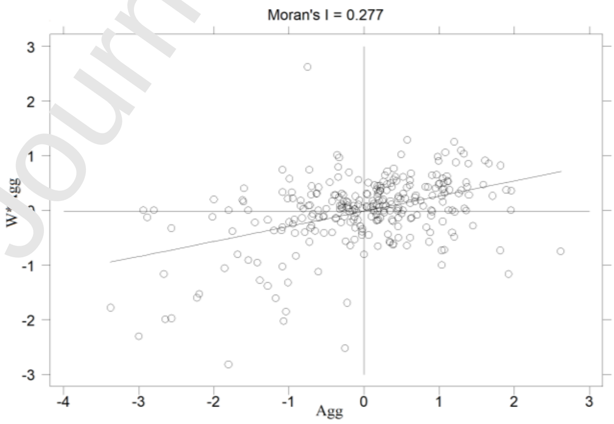

Figure 3. Moran's I scatterplots for industrial agglomeration in 2015

Table 1. Summary statistics for the key variables

Variables	Definition	Observations	Mean	S. D	Min	Max	Unit
SO_2	industrial SO_2 emissions	3,640	61,340	60,085	2	683,162	ton
SD	industrial soot (dust) emissions	3,640	33,934	125,641	34	5,168,812	ton
WW	industrial wastewater	3,640	77,040,000	98,250,000	170,000	912,600,000	ton
TI	transport infrastructure	3,640	1,415	1,986	14	21,490	10,000 m^2
TII	Transportation Infrastructure Investment	3,360	126	296	0	5,320	10,000 m^2
Agg	location quotient of the secondary industry	3,640	98.71	21.63	18.37	180.50	%
Urban	proportion of construction land	3,640	8.65	9.86	0.02	97.18	%
	proportion of non-agricultural population	3,360	28.30	20.27	1.99	100	%
GDP	GDP per capita	3,640	30,707	26,128	1892	256,877	yuan (RMB)
FDI	actual amount of foreign capital investment	3,640	6	16	0	211	100 million dollars
SI	proportion of secondary industry	3,640	49	11	3	91	%
TC	science and technology expenditure	3,640	47,731	173,592	0.13	2,877,956	10,000 yuan (RMB)
Gov	fiscal expenditure divided by fiscal revenue	3,640	2.61	1.72	0.65	39.03	
Pop	total population	3,640	436	304	30	3,375	10,000 persons
Est	proportion of investment in real estate	3,640	14.55	9.24	0.03	91.96	%
W	spatial weight matrix	280×280		0.02	0	1	

Table 2. Basic results of the estimation: Long-term Effect

Models	(1) SO_2	(2) SO_2	(3) SD	(4) SD	(5) WW	(6) WW
TI	0.094**	0.116**	0.312***	0.171**	0.096***	0.079*
	(2.158)	(2.247)	(6.119)	(2.554)	(2.594)	(1.823)
GDP		1.685**		-0.918		0.509
		(2.548)		(-0.975)		(0.881)
GDP^2		-0.086**		0.059		-0.024
		(-2.556)		(1.215)		(-0.831)
FDI		0.014**		-0.005		0.017***
		(1.982)		(-0.341)		(2.731)
SI		0.009**		-0.005		0.001
		(2.162)		(-1.174)		(0.352)
TC		-0.052***		-0.026***		-0.024***
		(-6.524)		(-3.303)		(-3.912)
Gov		0.001		-0.003		0.004
		(0.102)		(-1.555)		(0.373)
cons	9.961***	1.496	7.720***	12.610***	16.998***	14.413***
	(34.145)	(0.470)	(21.5[illegible]8)	(2.799)	(68.676)	(5.152)
Observations	3640	3640	3640	3640	3640	3640
R^2	0.154	0.178	0.094	0.070	0.296	0.270
F/Chi^2	4.656**	12.547***	37.437***	9.592***	6.731***	4.906***
λ	0.822	0.822	0.667	0.687	0.853	0.853
Effect	FE	FE	RE	FE	FE	FE
Huausman	40.060***	85.080***	0.490	45.710***	106.65***	203.93***

Notes: *t* statistics are in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. F is the F test of the fixed effect model, Chi^2 is the Wald Chi^2 test of the random effect model. λ is the fraction of variance due to individual effect. FE is the fixed effect, and RE is the random effect. Hausman is the Chi^2 value of the Hausman test. We clustered standard errors at the city level when indicated.

Table 3. Basic results of the estimation: Short-term Effect

Models	(1) SO_2	(2) SO_2	(3) SD	(4) SD	(5) WW	(6) WW
TII	-0.001	-0.002	0.005	-0.004	0.005	0.003
	(-0.092)	(-0.292)	(0.388)	(-0.337)	(0.783)	(0.506)
GDP		2.317***		-0.294		0.672
		(3.167)		(-0.282)		(1.024)
GDP^2		-0.118***		0.049		-0.031
		(-3.213)		(0.922)		(-0.948)
FDI		0.010		-0.007		0.021***
		(1.245)		(-0.494)		(3.279)
SI		0.007		-0.011**		-0.000
		(1.633)		(-2.27[illegible])		(-0.111)
TC		-0.027		-0.112**		-0.016
		(-1.294)		(-4.489)		(-0.974)
Gov		0.001		-0.002		0.001
		(0.125)		(-1.280)		(0.820)
cons	10.614***	-0.879	9.804***	9.581*	17.631***	13.934***
	(352.735)	(-0.246)	(201.[illegible]79)	(1.916)	(662.146)	(4.302)
Observations	3360	3360	3360	3360	3360	3360
R^2	0.067	0.024	0.036	0.026	0.120	0.130
F	0.009	3.425***	0.151	9.469***	0.613	2.470***
λ	0.840	0.841	0.690	0.706	0.868	0.865
Effect	FE	FE	FE	FE	FE	FE
Hausman	66.590***	1[illegible]9.89[illegible]***	36.130***	79.430***	128.040***	256.070***

Notes: *t* statistics are in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. F is the F test of the fixed effect model. λ is the fraction of variance due to individual effect u_i. FE is the fixed effect. Hausman is the Chi^2 value of the Hausman test. We clustered standard errors at the city level when indicated.

Table 4. The spatial correlation test of Moran's I

Year	SO_2	SD	WW	TI	Agg
2003	0.129***	0.19***	0.132***	0.101***	0.315***
2004	0.122***	0.214***	0.131***	0.116***	0.331***
2005	0.142***	0.313***	0.142***	0.115***	0.309***
2006	0.117***	0.33***	0.181***	0.106***	0.304***
2007	0.124***	0.298***	0.168***	0.134***	0.279***
2008	0.124***	0.248***	0.183***	0.117***	0.250***
2009	0.121***	0.201***	0.184***	0.110***	0.203***
2010	0.146***	0.183***	0.225***	0.106***	0.162***
2011	0.180***	0.021	0.262***	0.106***	0.175***
2012	0.205***	0.024***	0.292***	0.097***	0.174***
2013	0.215***	0.076***	0.298***	0.107***	0.184***
2014	0.208***	0.195***	0.264***	0.108***	0.215***
2015	0.190***	0.065**	0.265***	0.100***	0.235***

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 5. The estimation results of SDM

Models	(1) SO_2	(2) SD	(3) WW
TI	0.098**	0.120*	0.076*
	(2.148)	(1.834)	(1.886)
GDP	2.279***	1.704	1.901***
	(2.846)	(1.597)	(2.624)
GDP^2	-0.118***	-0.071	-0.091***
	(-3.126)	(-1.314)	(-2.641)
FDI	0.023***	0.013	0.025***
	(2.823)	(1.106)	(4.015)
SI	0.010**	0.001	0.002
	(2.071)	(0.183)	(0.732)
TC	-0.040***	-0.020*	-0.022***
	(-4.460)	(-2.[illegible]81)	(-3.592)
Gov	0.005	-0.004	0.012
	(0.356)	(-0.[illegible]85)	(1.082)
W*TI	0.055	0.172	0.016
	(0.597)	(1.302)	(0.201)
W*GDP	-1.282	-4.608***	-3.002***
	(-1.565)	(-3.716)	(-3.331)
$W*GDP^2$	0.066	0.224***	0.149***
	(1.557)	(3.516)	(3.290)
W*FDI	-0.069***	-0.071***	-0.024
	(-2.854)	(-3.028)	(-1.253)
ρ	0.236***	0.308***	0.213***
	(5.505)	(9.697)	(6.079)
Direct effect	0.104**	0.138**	0.079*
	(2.209)	(2.015)	(1.875)
Indirect effect	0.093	0.275	0.036
	(0.856)	(1.614)	(0.391)
Total effect	0.197	0.413**	0.114
	(1.610)	(2.112)	(1.055)
Observations	3640	3640	3640
R^2	0.014	0.019	0.040
LogL	-2.00E+03	-3.10E+03	-1.53E+03
Effect	FE	FE	FE

Notes: t statistics are in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. ρ is the spatial autoregressive coefficient. LogL is the Maximum Log-pseudolikelihood value. FE is the fixed effect. We clustered standard errors at the city level when indicated.

Table 6. The estimation results of SEM and SLM

Models	SEM			SLM		
	(1)	(2)	(3)	(4)	(5)	(6)
	SO_2	SD	WW	SO_2	SD	WW
TI	0.101^{**}	0.116^{*}	0.077^{*}	0.108^{**}	0.129^{**}	0.078^{*}
	(2.038)	(1.841)	(1.794)	(2.133)	(2.039)	(1.809)
GDP	1.800^{**}	0.109	0.877	1.528^{**}	-0.510	0.552
	(2.566)	(0.106)	(1.364)	(2.340)	(-0.575)	(0.955)
GDP^2	-0.093^{***}	0.005	-0.043	-0.080^{**}	0.033	-0.028
	(-2.602)	(0.098)	(-1.340)	(-2.396)	(0.729)	(-0.947)
FDI	0.022^{***}	0.008	0.021^{***}	0.017^{**}	0.002	0.019^{***}
	(2.859)	(0.685)	(3.407)	(2.555)	(0.124)	(2.863)
SI	0.011^{**}	0.002	0.002	0.010^{**}	-0.000	0.002
	(2.378)	(0.422)	(0.703)	(2.289)	(-0.096)	(0.578)
TC	-0.049^{***}	-0.018	-0.023^{***}	-0.041^{***}	-0.017^{**}	-0.019^{***}
	(-4.518)	(-1.499)	(-3.053)	(-5.136)	(-2.239)	(-3.286)
Gov	0.005	-0.001	0.008	0.003	-0.014	0.006
	(0.352)	(-0.081)	(0.725)	(0.220)	(-0.848)	(0.505)
ρ	0.247^{***}	0.333^{***}	$0.2[illegible]7^{***}$	0.227^{***}	0.316^{***}	0.198^{***}
	(5.822)	(9.555)	(5.586)	(5.330)	(9.963)	(5.715)
Direct effect				0.111^{**}	0.134^{**}	0.080^{*}
				(2.116)	(2.022)	(1.799)
Indirect effect				0.030^{*}	0.056^{*}	0.018^{*}
				(1.921)	(1.929)	(1.729)
Total effect				0.140^{**}	0.190^{**}	0.098^{*}
				(2.122)	(2.011)	(1.811)
Observations	3640	3640	3640	3640	3640	3640
R^2	0.172	0.092	0.256	0.120	0.049	0.250
LogL	-2.00E+03	-3.10E+03	-1.60E+03	-2.00E+03	-3.10E+03	-1.60E+03
Effect	FE	FE	FE	FE	FE	FE

Notes: *t* statistics are in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. ρ is the spatial autocorrelation parameter. LogL is the Maximum Log-pseudolikelihood value. FE is the fixed effect. We clustered standard errors at the city level when indicated.

Table 7. Robustness check of SDM

Models	(1) SO_2	(2) SD	(3) WW
TI	0.123**	0.120*	0.106**
	(2.460)	(1.796)	(2.381)
GDP	2.360***	1.785*	1.985***
	(2.952)	(1.678)	(2.727)
GDP^2	-0.121***	-0.075	-0.095***
	(-3.235)	(-1.378)	(-2.746)
FDI	0.020**	0.010	0.022***
	(2.169)	(0.892)	(3.574)
SI	0.010**	0.000	0.002
	(1.989)	(0.038)	(0.596)
TC	-0.041***	-0.021***	-0.023***
	(-4.658)	(-2.728)	(-3.860)
Gov	0.005	-0.005	0.012
	(0.361)	(-0.[illegible]28)	(1.090)
W*TI	0.048	0.122	0.002
	(0.526)	(0.953)	(0.022)
W*GDP	-1.279	-4.633***	-2.994***
	(-1.566)	(-3.757)	(-3.311)
W*GDP^2	0.065	0.227***	0.148***
	(1.538)	(3.577)	(3.256)
W*FDI	-0.068***	-0.071***	-0.024
	(-2.791)	(-3.027)	(-1.248)
ρ	0.236***	0.303***	0.212***
	(5.523)	(9.639)	(6.101)
Direct effect	0.129**	0.134*	0.108**
	(2.504)	(1.925)	(2.347)
Indirect effect	0.092	0.207	0.026
	(0.849)	(1.268)	(0.292)
Total effect	0.221*	0.342*	0.134
	(1.785)	(1.816)	(1.242)
Observations	3640	3640	3640
R^2	0.074	0.079	0.037
LogL	-1974.264	-3069.967	-1559.281
Effect	FE	FE	FE

Notes: t statistics are in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. ρ is the spatial autocorrelation parameter. LogL is the Maximum Log-pseudolikelihood value. FE is the fixed effect. We clustered standard errors at the city level when indicated.

Table 8. Regression on the mediating effect: industrial agglomeration

Models	(1) Agg	(2) SO_2	(3) SD	(4) WW
TI	0.083***	0.110**	0.1	0.091**
	(7.807)	(2.396)	(1.547)	(2.236)
Agg		-1.125***	2.047***	-1.426***
		(-3.556)	(4.596)	(-4.729)
Pop	0.068			
	(0.876)			
GDP		2.399***	1.467	2.038***
		(2.957)	(1.368)	(2.801)
GDP^2		-0.122***	-0.061	-0.097***
		(-3.242)	(-1.131)	(-2.789)
FDI	0.006	0.023***	0.014	0.024***
	(1.409)	(2.735)	(1.207)	(3.853)
SI		0.030***	-0.035***	0.028***
		(7.034)	(-4.266)	(5.790)
TC		-0.037***	-0.027***	-0.017***
		(-3.978)	(-3.336)	(-2.885)
Gov	-0.004*	0.003	-0.002	0.01
	(-1.888)	(0.244)	(-0.152)	(0.946)
cons	-0.022			
	(-0.051)			
W*TI		0.087	0.122	0.054
		(0.950)	(0.921)	(0.680)
W*GDP		-1.432*	-4.283***	-3.202***
		(-1.731)	(-3.478)	(-3.544)
$W*GDP^2$		0.073*	0.210***	0.158***
		(1.707)	(3.324)	(3.488)
W*FDI		-0.072***	-0.066***	-0.028
		(-3.058)	(-2.759)	(-1.458)
ρ		0.219***	0.297***	0.190***
		(5.068)	(9.303)	(5.172)
Direct effect				
TI		0.118**	0.114*	0.096**
		(2.470)	(1.666)	(2.248)
Agg		-1.151***	2.070***	-1.452***
		(-3.731)	(4.726)	(-4.942)
Indirect effect				
TI		0.141	0.216	0.089
		(1.294)	(1.223)	(0.985)
Agg		-0.295***	0.785***	-0.309***
		(-2.785)	(4.208)	(-3.957)

Total effect				
TI		0.259**	0.329	0.184*
		(2.065)	(1.597)	(1.676)
Agg		-1.445***	2.855***	-1.761***
		(-3.689)	(4.776)	(-5.148)
Observations	3640	3640	3640	3640
R^2	0.012	0.016	0.019	0.038
F	25.296***			
λ	0.866			
LogL		-1.90E+03	-3.10E+03	-1.51E+03
Effect	FE	FE	FE	FE

Notes: t statistics are in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. ρ is the spatial autocorrelation parameter. F is the F test of the fixed effect model. λ is the fraction of variance due to individual effect u_i. LogL is the Maximum Log-pseudolikelihood value. FE is the fixed effect. We clustered standard errors at the city level when indicated.

Table 9. Regression on the mediating effect: land urbanization

Models	(1) Unban	(2) SO_2	(3) SD	(4) WW
TI	0.687*	0.098**	0.120*	0.076*
	(1.806)	(2.148)	(1.827)	(1.895)
Urban		0.00005	-0.007*	0.003*
		(-0.02)	(-1.655)	(1.752)
Pop	4.266			
	(0.945)			
Est	0.048**			
	(2.117)			
GDP		2.279***	1.693	1.954***
		(2.843)	(1.500)	(2.700)
GDP^2		-0.118***	-0.066	-0.094***
		(-3.125)	(-1.220)	(-2.719)
FDI		0.023***	0.013	0.025***
		(2.823)	(1.094)	(4.028)
SI	0.023	0.010**	0.001	0.002
	(1.005)	(2.069)	(0.208)	(0.711)
TC		-0.040***	-0.020**	-0.022***
		(-4.460)	(-2.449)	(-3.631)
Gov		0.005	-0.004	0.01
		(0.356)	(-0.291)	(1.084)
cons	-22.846			
	(-0.897)			
W*TI		0.055	0.162	0.021
		(0.597)	(1.235)	(0.269)
W*GDP		-1.282	-4.550***	-3.032***
		(-1.561)	(-3.662)	(-3.363)
W*GDP^2		0.066	0.222***	0.150***
		(1.555)	(3.481)	(3.314)
W*FDI		-0.069***	-0.071***	-0.024
		(-2.855)	(-3.025)	(-1.260)
ρ		0.236***	0.307***	0.212***
		(5.504)	(9.743)	(6.037)
Direct effect				
TI		0.104**	0.138**	0.080*
		(2.203)	(1.992)	(1.891)
Urban		0.0001	-0.007*	0.003*
		(-0.042)	(-1.758)	(1.779)
Indirect effect				
TI		0.103	0.279	0.05
		(0.928)	(1.587)	(0.543)

Urban		0.00003	-0.003*	0.001*
		(-0.034)	(-1.682)	(1.651)
Total effect				
TI		0.208	0.417**	0.129
		(1.628)	(2.040)	(1.173)
Urban		0.0002	-0.010*	0.004*
		(-0.041)	(-1.748)	(1.772)
Observations	3640	3640	3640	3640
R^2	0.099	0.014	0.02	0.038
F	3.782**			
λ	0.763			
LogL		-2.00E+03	-3.10E+03	-1.53E+03
Effect	FE	FE	FE	FE

Notes: *t* statistics are in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. ρ is the spatial autocorrelation parameter. F is the F test of the fixed effect model. λ is the fraction of variance due to individual effect u_i. LogL is the Maximum Log-pseudolikelihood value. FE is the fixed effect. We clustered standard errors at the city level when indicated.

Table 10. Regression on the spatial spillover effects of industrial agglomeration

Models	(1) Agg	(2) SO_2	(3) SD	(4) WW
TI	0.042***	0.097**	0.086	0.081**
	(4.745)	(2.144)	(1.337)	(1.968)
Agg		-0.724*	2.437***	-1.135***
		(-1.816)	(5.040)	(-3.454)
Pop	-0.082			
	(-1.243)			
GDP		2.121**	1.198	1.820**
		(2.524)	(1.119)	(2.526)
GDP^2		-0.112***	-0.051	-0.088**
		(-2.912)	(-0.947)	(-2.576)
FDI	0.003	0.022***	0.013	0.024***
	(1.438)	(2.621)	(1.177)	(3.802)
SI		0.029***	-0.037***	0.027***
		(6.762)	(-4.430)	(5.492)
TC		-0.032***	-0.022***	-0.014**
		(-3.637)	(-2.704)	(-2.223)
Gov	-0.006**	0.002	-0.004	0.01
	(-2.476)	(0.128)	(-0.243)	(0.834)
W*TI	0.011	0.102	0.137	0.066
	(0.898)	(1.113)	(1.037)	(0.811)
W* Agg		-1.010**	-0.976**	-0.770**
		(-2.562)	(-2.300)	(-2.295)
W*GDP		-0.225	-3.121**	-2.275**
		(-0.229)	(-2.440)	(-2.265)
W*GDP^2		0.017	0.157**	0.116**
		(0.368)	(2.427)	(2.313)
W*FDI		-0.074***	-0.068***	-0.029
		(-3.245)	(-2.895)	(-1.526)
ρ	0.562***	0.217***	0.297***	0.181***
	(18.699)	(5.099)	(9.312)	(4.967)
Direct effect				
TI	0.048***	0.105**	0.101	0.085**
	(5.210)	(2.255)	(1.482)	(2.002)
Agg		-0.799**	2.399***	-1.191***
		(-2.126)	(5.132)	(-3.803)
Indirect effect				
TI	0.071***	0.156	0.23	0.099
	(3.479)	(1.459)	(1.328)	(1.093)
Agg		-1.380***	-0.315	-1.103***
		(-3.452)	(-0.642)	(-2.877)

Total effect				
TI	0.120***	0.261**	0.331	0.185*
	(4.970)	(2.147)	(1.632)	(1.673)
Agg		-2.179***	2.084***	-2.294***
		(-5.570)	(3.104)	(-5.317)
Observations	3640	3640	3640	3640
R^2	0.126	0.131	0.017	0.035
LogL	4370.288	-1.90E+03	-3.00E+03	-1.50E+03
Effect	FE	FE	FE	FE

Notes: *t* statistics are in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. ρ is the spatial autocorrelation parameter. LogL is the Maximum Log-pseudolikelihood value. FE is the fixed effect. We clustered standard errors at the city level when indicated.

Appendix

Table A.1 Robustness check of the long-term effect: SO_2

Models	(1) SO_2	(2) SO_2	(3) SO_2	(4) SO_2
TI	0.096^{*}	0.099^{*}	0.108^{**}	0.116^{**}
	(1.882)	(1.940)	(2.082)	(2.251)
GDP	2.835^{***}	2.818^{***}	2.176^{***}	1.695^{***}
	(4.816)	(4.810)	(3.503)	(2.627)
GDP^2	-0.146^{***}	-0.146^{***}	-0.115^{***}	-0.087^{***}
	(-4.784)	(-4.803)	(-3.648)	(-2.629)
FDI		0.013^{**}	0.013^{*}	0.014^{*}
		(1.969)	(1.83[illegible])	(1.961)
SI			0.009^{**}	0.009^{**}
			(2.117)	(2.128)
TC				-0.052^{***}
				(-6.501)
cons	-3.714	-3.729	-0.907	1.454
	(-1.280)	(-1.29[illegible])	(-0.304)	(0.468)
Observations	3640	3640	3640	3640
R^2	0.077	0.086	0.196	0.179
F	8.420^{***}	7.674^{***}	6.173^{***}	14.609^{***}
λ	0.829	0.828	0.820	0.823
Effect	FE	FE	FE	FE

Notes: *t* statistics are in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. F is the F test of fixed effect model. λ is the fraction of variance due to individual effect u_i. FE is the fixed effect. We clustered standard errors at the city level when indicated.

Table A.2 Robustness check of the long-term effect: SD

Models	(1) SD	(2) SD	(3) SD	(4) SD
TI	0.175***	0.174***	0.169**	0.173**
	(2.642)	(2.623)	(2.535)	(2.583)
GDP	-1.220	-1.213	-0.903	-1.137
	(-1.448)	(-1.441)	(-1.014)	(-1.229)
GDP^2	0.071	0.070	0.056	0.070
	(1.623)	(1.621)	(1.218)	(1.460)
FDI		-0.005	-0.005	-0.004
		(-0.334)	(-0.329)	(-0.287)
SI			-0.004	-0.005
			(-0.962)	(-0.979)
TC				-0.026***
				(-3.226)
cons	13.773***	13.779***	12.412***	13.564***
	(3.355)	(3.355)	(2.910)	(3.052)
Observations	3640	3640	3640	3640
R^2	0.081	0.079	0.065	0.062
F	11.085***	8.328***	7.709***	10.473***
λ	0.682	0.683	0.687	0.689
Effect	FE	FE	FE	FE

Notes: *t* statistics are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. F is the F test of the fixed effect model. λ is the fraction of variance due to individual effect u_i. FE is the fixed effect. We clustered standard errors at the city level when indicated.

Table A.3 Robustness check of the long-term effect: WW

Models	(1) WW	(2) WW	(3) WW	(4) WW
TI	0.071*	0.074*	0.075*	0.079*
	(1.651)	(1.725)	(1.743)	(1.821)
GDP	0.856	0.834	0.758	0.540
	(1.598)	(1.569)	(1.425)	(0.986)
GDP^2	-0.043	-0.042	-0.039	-0.026
	(-1.568)	(-1.569)	(-1.445)	(-0.929)
FDI		0.017**	0.017**	0.017***
		(2.525)	(2.532)	(2.686)
SI			0.001	0.001
			(0.328)	(0.308)
TC				-0.024***
				(-3.913)
cons	12.894***	12.875***	13.211***	14.279***
	(4.937)	(4.954)	(5.123)	(5.373)
Observations	3640	3640	3640	3640
R^2	0.273	0.321	0.336	0.280
F	3.019***	3.101***	2.485***	5.319***
λ	0.855	0.851	0.851	0.853
Effect	FE	FE	FE	FE

Notes: *t* statistics are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. F is the F test of fixed effect model. λ is fraction of variance due to individual effect u_i. FE is fixed effect. We cluster standard errors at the city level when indicated.

Table A.4 Robustness check of the short-term effect: SO_2

Models	(1) SO_2	(2) SO_2	(3) SO_2	(4) SO_2
TII	-0.0005	-0.001	-0.002	-0.002
	(-0.064)	(-0.098)	(-0.225)	(-0.293)
GDP	2.837^{***}	2.821^{***}	2.277^{***}	2.325^{***}
	(4.073)	(4.053)	(3.155)	(3.239)
GDP^2	-0.147^{***}	-0.147^{***}	-0.120^{***}	-0.119^{***}
	(-4.149)	(-4.144)	(-3.303)	(-3.291)
FDI		0.010	0.009	0.010
		(1.279)	(1.209)	(1.221)
SI			0.007^{*}	0.007
			(1.673)	(1.607)
TC				-0.027
				(-1.290)
cons	-2.999	-2.983	-0.539	-0.911
	(-0.876)	(-0.872)	(-0.154)	(-0.260)
Observations	3360	3360	3360	3360
R^2	0.010	0.004	0.016	0.026
F	6.117	4.917	4.090	3.492
λ	0.848	0.847	0.842	0.841
Effect	FE	FE	FE	FE

Notes: *t* statistics are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. F is the F test of the fixed effect model. λ is the fraction of variance due to individual effect u_i. FE is the fixed effect. We clustered standard errors at the city level when indicated.

Table A.5 Robustness check of the short-term effect: SD

Models	(1) SD	(2) SD	(3) SD	(4) SD
TI	-0.003	-0.003	-0.002	-0.004
	(-0.243)	(-0.223)	(-0.131)	(-0.316)
GDP	-1.246	-1.232	-0.612	-0.408
	(-1.267)	(-1.254)	(-0.596)	(-0.395)
GDP^2	0.079	0.078	0.048	0.055
	(1.566)	(1.561)	(0.922)	(1.042)
FDI		-0.008	-0.008	-0.006
		(-0.544)	(-0.52[illegible])	(-0.443)
SI			-0.00[illegible]*	-0.010**
			(-1.7[illegible]6)	(-2.152)
TC				-0.115***
				(-4.583)
cons	14.421***	14.407***	11.621**	10.047**
	(3.006)	(3.005)	(2.349)	(2.017)
Observations	3360	3360	3360	3360
R^2	0.047	0.04[illegible]	0.022	0.021
F	10.276	[illegible].[illegible]75	7.947	10.590
λ	0.688	0.689	0.697	0.707
Effect	FE	FE	FE	FE

Notes: *t* statistics are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. F is the F test of the fixed effect model. λ is the fraction of variance due to individual effect u_i. FE is the fixed effect. We clustered standard errors at the city level when indicated.

Table A.6 Robustness check of the short-term effect: WW

Models	(1) WW	(2) WW	(3) WW	(4) WW
TI	0.004	0.004	0.004	0.003
	(0.607)	(0.522)	(0.535)	(0.489)
GDP	0.701	0.666	0.695	0.722
	(1.112)	(1.067)	(1.108)	(1.143)
GDP^2	-0.034	-0.033	-0.034	-0.034
	(-1.063)	(-1.045)	(-1.091)	(-1.070)
FDI		0.021^{***}	0.021^{***}	0.021^{***}
		(3.148)	(3.158)	(3.158)
SI			-0.000	-0.001
			(-0.112)	(-0.183)
TC				-0.015
				(-0.908)
cons	14.036^{***}	14.069^{***}	13.940^{***}	13.729^{***}
	(4.511)	(4.549)	(4.521)	(4.382)
Observations	3360	3360	3360	3360
R^2	0.101	0.219	0.210	0.175
F	0.713	2.611	2.205	1.846
λ	0.867	0.863	0.863	0.863
Effect	FE	FE	FE	FE

Notes: *t* statistics are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. F is the F test of the fixed effect model. λ is the fraction of variance due to individual effect u_i. FE is the fixed effect. We clustered standard errors at the city level when indicated.

Table A.7 Regression on the mediating effect: population urbanization

Models	(1) Unban	(2) SO_2	(3) SD	(4) WW
TI	-7.484***	0.112**	0.138**	0.086**
	(-8.752)	(2.427)	(2.183)	(2.078)
Urban		-0.001	-0.002	-0.0005
		(-0.581)	(-0.649)	(-0.231)
Pop	-14.422			
	(-1.529)			
Est	-0.052			
	(-1.221)			
GDP		2.045**	1.539	1.994***
		(2.421)	(1.501)	(2.757)
GDP^2		-0.109***	-0.069	-0.096***
		(-2.896)	(-1.288)	(-2.771)
FDI		0.028***	0.018*	0.023***
		(2.690)	(1.722)	(3.653)
SI	-0.288***	0.010	0.004	0.002
	(-5.072)	(1.638)	(0.764)	(0.469)
TC		-0.041***	-0.023***	-0.022***
		(-4.228)	(-2.835)	(-3.625)
Gov		0.004	-0.006	0.01
		(0.329)	(-0.379)	(1.239)
cons	177.735***			
	(3.438)			
W*TI		0.104	0.198	0.035
		(1.157)	(1.479)	(0.436)
W*GDP		-1.172	-4.549***	-3.214***
		(-1.446)	(-3.633)	(-3.486)
W*GDP^2		0.062	0.220***	0.160***
		(1.510)	(3.418)	(3.437)
W*FDI		-0.070***	-0.076***	-0.024
		(-2.634)	(-3.062)	(-1.207)
ρ		0.230***	0.323***	0.206***
		(5.250)	(9.917)	(5.897)
Direct effect				
TI		0.121**	0.161**	0.090**
		(2.520)	(2.377)	(2.089)
Urban		-0.002	-0.002	-0.001
		(-0.647)	(-0.717)	(-0.281)
Indirect effect				
TI		0.167	0.346*	0.067
		(1.512)	(1.860)	(0.728)

Urban		-0.0005	-0.001	-0.0002
		(-0.639)	(-0.722)	(-0.307)
Total effect				
TI		0.287**	0.506**	0.158
		(2.242)	(2.347)	(1.423)
Urban		-0.002	-0.004	-0.001
		(-0.648)	(-0.721)	(-0.287)
Observations	3360	3360	3360	3360
R^2	0.005	0.011	0.020	0.039
F	67.687***			
λ	0.933			
LogL		-1.80E+03	-2.76E+03	-1.35E+03
Effect		FE	FE	FE

Notes: *t* statistics are in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The non-agricultural population data were collected from *the China Population and Employment Statistics Yearbook*, which were not published after 2015. F is the F test of the fixed effect model. λ is the fraction of variance due to individual effect u_i. LogL is the Maximum Log-pseudolikelihood value. FE is the fixed effect. We clustered standard errors at the city level when indicated.

Table A.8 Acronyms

Abbreviations	Descriptions
TI	Transportation Infrastructure
TII	Transportation Infrastructure Investment
SDM	Spatial Durbin Model
EKC	Environmental Kuznets Curve
PHH	Pollution Haven Hypothesis
SEM	Spatial Error Model
SLM	Spatial Lag Model
SAR	Spatial Autoregression Model
LQM	Location Quotient Method
HHI	Herfindahl-Hirschman Index

The authors declare no conflict of interest.

Highlights

- The impact of transportation infrastructure on industrial pollution is estimated
- Transportation infrastructure aggravates cities' industrial pollution in the long run
- Transportation infrastructure influences industrial pollution through industrial agglomeration but not urbanization
- Spatial Durbin model is used to measure the spatial spillover effects of industrial agglomeration
- The spatial spillover effects of industrial agglomeration play an important role in the impact of TI on industrial pollution