

Article

Haze Pollution Levels, Spatial Spillover Influence, and Impacts of the Digital Economy: Empirical Evidence from China

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Abstract: With the development of digital technologies such as the Internet and digital industries such as e-commerce, the digital economy has become a new form of economic and social development, which has brought forth a new perspective for environmental governance, energy conservation, and emission reduction. Based on data from 30 Chinese provinces from 2011 to 2018, this study applies the space and threshold models to empirically examine the digital economy's influence on haze pollution and its spatial spillover. Furthermore, it investigates the spatial diffusion effect of regional digital economic development and haze pollution by constructing a spatial weight matrix. Subsequently, an instrumental variable robustness test is performed. Results indicate the following: (1) Haze pollution has spatial spillover effects and high emission aggregation characteristics, with haze pollution in neighbouring provinces significantly aggravating pollution levels in the focal province. (2) China's digital economy has positively impacted haze pollution, with digital economic development having a significant effect (i.e., most prominent in eastern China) on reducing haze pollution. (3) Changing the energy structure and supporting innovation can restrain haze pollution, and the digital economy can reduce the path mechanism of haze pollution through the mediating effect of an advanced industrial structure. It shows a non-linear characteristic that the influence of haze reduction continues to weaken. Thus, policymakers should include the digital economy as a mechanism for ecologically sustainable development in haze pollution control.

Keywords: haze pollution; digital economy; industrial structure; spatial spillover



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1. Introduction

Since China's reform and opening up, factor cost advantages have enabled the nation to achieve rapid economic development. However, this long-term and extensive economic development model has caused severe environmental pollution. As haze effects are wide-ranging, long-lasting, and difficult to treat, this form of air pollution has attracted extensive attention from many researchers. Many studies show that severe haze pollution greatly harms people's physical and mental health and reduces life expectancy, and the resulting welfare cost hinders sustainable economic development [1–4]. Thus, haze pollution detracts from improvements to health, living standards, and quality of economic development, making its effective control a priority.

Scholars have studied the influence of haze on different aspects, such as the economy [5,6], population [7–11], and energy [12–15]. The existing research has comprehensively explored the mechanism of haze pollution. However, technological and industrial revolutions, global warming, water pollution, air pollution [16,17], and other environmental problems have occurred frequently. Thus, cloud computing, 5G, artificial intelligence, big data, and other digital technologies attempt to break the information asymmetry, and they are expected to play an important role in global environmental governance [18–20]. Moreover, the low-cost, high-efficiency digital economy industry has witnessed constant

development; as a consequence, many new industries have appeared. The transformation and upgrading of traditional industries have been accelerated, particularly as the Chinese government has been making efforts to coordinate environmental protection and economic development. At the national level, the digital economy is becoming increasingly important for societal development. According to China's Digital Economy Development White Paper [21], the digital economy grew by 15.6% annually to 35.8 trillion yuan in 2019 or 36.2% of the gross domestic product (GDP). Societies worldwide are moving toward rapid optimal allocation and regeneration of resources through the digital industry. This is reflected, for example, in the 'Made in China 2025' strategy and the 'Industrial Internet' in the United States. The influence of emerging industries on environmental governance can be analysed through the identification, selection, filtering, storage, and use of big data.

Whether digital technology can improve environmental pollution is related to whether digitalisation can help reduce both energy consumption and the cost of environmental governance. The previous literature has studied the overall association between economy-wide energy consumption and information and communication technologies (ICTs). Some scholars argue that ICT has reduced the demand for energy through energy efficiency and sectoral changes. Schulte et al. [22] found that in the Organisation for Economic Cooperation and Development (OECD) countries, 'a 1% increase in ICT capital results in a 0.235% reduction in energy demand'. This is not due to a decrease in electricity consumption but a decline in other non-electric energy sources, possibly arising from the direct impact of ICTs and services on electricity and the indirect impact on non-electric energy carriers in other parts of the economy. ICTs can enrich environmental quality through dematerialisation of production, thereby supporting a less resource-intensive and lightweight economy [23,24]. Ren et al. [25] used the provincial data, systematic GMM method, and intermediate effect model of China from 2006 to 2017 to demonstrate that the relationship between Internet development and energy consumption structure has a negative impact. However, some scholars believe that ICT application will increase energy consumption due to the 'rebound effect' [26]; Zhou et al. [27] analysed the carbon emissions at the industry level in China by using the input-output method; the ICT sector can induce a large amount of emissions by requiring carbon-intensive intermediate inputs from non-ICT sectors. In other words, the application of ICT does not significantly improve the environment and may even worsen environmental problems. Some scholars believe that this influence is not good or bad. Noussan and Tagliapietra [28] forecasted the future European scenario and analysed the potential impact of digital technologies such as the Internet of Things on energy consumption and carbon dioxide emissions in the transportation field. The impact on green sustainability depends on user behaviour, economic conditions, transport, and environmental policies.

Information asymmetry is another challenge in environmental governance. It not only increases environmental governance costs and weakens the effectiveness of environmental policies, but it also leads to a lack of regulatory bodies in environmental governance and reduces the public's enthusiasm for environmental governance. In 2016, China launched an ecological and environmental protection big data service platform as part of the Belt and Road Initiative. 'Internet +', big data, remote sensing satellites, and other information technologies provide environmental information support to China and other countries along the initiative. The Internet's openness, interactivity, and real-time nature make public participation in environmental governance both possible and convenient [29]. Moreover, the Internet promotes environmental supervision, management, intelligence, accurate services, and rectifies previous environmental governance deficiencies [30,31]. Zuo et al. [32] made recommendations to adopt IOT technology to dynamically collect real-time product data related to energy consumption to improve energy efficiency and large-scale utilisation of clean energy. Li et al. [33] empirically concluded that digital technology promotes environmental sustainability in Chinese manufacturing.

Simultaneously, the digital economy is reshaping the global value chain. According to the 'smiling curve' theory, high added value is located at both tails of the curve,

representing the upstream (pre-production research and development) and downstream (post-production services) of the value chain. Processing and assembly activities are located at the midpoint of the curve, indicating little added value [34]. In the past, China's manufacturing sector embraced economies of scale for profitability with high volume, low-value production that also created severe air pollution. As the energy factor shifts from the industrial to the service sector, growth in the more energy-efficient sectors will reduce emissions; consequently, the overall economy will be more energy efficient [35–37]. Original elements and resources are transferred from industries with low distribution efficiency to technology-intensive industries with high distribution efficiency [38]. Thus, upgrades to the industrial structure would have a substantial impact on pollution.

Additionally, a characteristic of the digital economy is the physical sharing of information. Spatial changes have completely overhauled logistics links, resulting in the emergence of new industries, such as e-commerce, which is witnessing rapid growth due to the high penetration of the Internet and the large numbers of mobile users [39]. E-commerce can improve environmental pollution, as it significantly reduces information search costs and product prices and does a better job of matching. Thus, these supply–demand resources significantly reduce transportation and distribution costs, require less energy consumption, and reduce carbon dioxide emissions compared to in-person shopping [40]. E-commerce can also significantly optimise the corporate structure and management, thereby improving production efficiency [41]. The digital economy changes the smile curve, reconstructs the industrial value chain, and realises green development under the value chain sharing economy.

By reviewing the previous literature, we find that, first, the existing literature discusses the impact of digitisation on carbon emissions, SO₂ emissions and energy consumption through the use of the Internet, output value proportion of the tertiary industry, and investment in the ICT industry as proxy indicators. It is worth noting that the digital economy has received more and more attention, while little empirical research has been conducted to explore whether the development of the digital economy can improve air pollution in China. Second, previous studies have always carried out regression analysis on ordinary panels or dynamic panels, ignoring the spatial correlation and spatial spillover effect of haze pollution. In reality, the diffusion of haze between different regions will lead to spatial correlation and spatial dependence. In spatial econometrics, neglecting spatial effects may lead to errors in estimation and analysis. In a digital environment, search costs are lower, which increases the potential scope and quality of the search. Digital products are often not competitors; that is, they can be replicated at zero cost. As the cost of transporting digital goods and information approaches zero, the role of geographical distance is also expected to change. Digital technology makes it easier to track behaviour [32], and the digital economy containing the above characteristics undoubtedly brings a new perspective for environmental governance. Therefore, we must ask, what impact does the digital economy have on haze pollution? Moreover, what are the channels through which this influence is generated? To answer the above questions, we empirically test the effects of the digital economy on haze pollution and its spatial spillover using data from 30 provinces in China. This study aims to provide insights into the potential impact of the digital economy on future environmental governance. It argues that to take full advantage of the digital economy in environmental sustainability, it is necessary to adopt appropriate policies, support efficient deployment, and shape the digital process politically and socially [42].

This study's main contributions are as follows: First, we construct the second-level indicators of digital infrastructure (representing digital technology) and digital industry (representing emerging industries) and evaluate the development of the digital economy using the entropy weight method. Second, from the perspective of spatiotemporal evolution characteristics of the digital economy and haze pollution, the relationship between them is discussed using the spatial model, filling the gap between the digital economy and ecological geography. Third, accurately solving the two-way causality between haze pollution and the digital economy leads to endogeneity problems. Two methods were

used to test the robustness: the replacement of spatial matrix, and the construction of instrumental variables. The number of telephones per 10,000 people per city in 1984 further confirms the robust results of our quantitative research. Finally, this study discusses the mechanism of digital economy influencing haze pollution through industrial structure change using the threshold model.

2. Methodology and Data

2.1. Construction of the Spatial Weight Matrix

The spatial weight matrix reflects the spatial interaction between different regional research samples. Spatial statistical analysis begins with the establishment of a spatial weight matrix. In this study, we set up a spatial weight matrix with sample size n . All elements of W_{ij} are $i, j = 1, \dots, n$, and the 0–1 adjacency weight matrix ($W1$) is expressed as

$$W_{ij} = \begin{pmatrix} W_{11} & W_{12} & \dots & W_{1n} \\ W_{21} & W_{22} & \dots & W_{2n} \\ \dots & \dots & \dots & \dots \\ W_{n1} & W_{n2} & \dots & W_{nn} \end{pmatrix} \quad (1)$$

where $W_{ij} = W_{ji}$; at $W_{ij} = 0$, location j is not a neighbour of location i ; and at $W_{ij} = 1$, location j is the neighbour of location i , where $i = 1, 2, \dots, n$; $j = 1, 2, \dots, n$. At $W_{ij} = 1$, province i has a common boundary with province j ; otherwise, $W_{ij} = 0$.

Then, we constructed the weight matrix of geographical distance ($W2$), which is expressed as follows:

$$W_{ij} = \begin{cases} W_{ij} = \frac{1}{d_{ij}} \\ W_{ij} = 0 \end{cases} \quad (2)$$

Let the distance between the geographic centres of province i and province j be d_{ij} ; the latitude and longitude of geographic centre point A of province i be β_1 and α_1 , respectively; and the latitude and longitude of geographic centre point B of province j be β_2 and α_2 , respectively. The Earth's radius is:

$$d_{ij} = R \cdot \arccos[\cos\beta_1 \cos\beta_2 \cos(\alpha_1 - \alpha_2) + \sin\beta_1 \sin\beta_2] \quad (3)$$

2.2. Spatial Autocorrelation Analysis

For a comprehensive investigation of the spatial spillover effect of haze pollution and the digital economy, we use the global and local spatial correlation indexes. First, we test whether the research object has a spatial effect by conducting a spatial autocorrelation test for the development index of the digital economy and haze pollution. Spatial correlation analysis can measure the spatial effect of each year in the geographical distance matrix. We calculate the global Moran's index (Moran's I) as

$$I = \frac{n \sum_{i=1}^n \sum_{j=1}^n W_{ij} |x_i - \bar{x}| |x_j - \bar{x}|}{\sum_{i=1}^n \sum_{j=1}^n W_{ij} \sum_{i=1}^n (x_i - \bar{x})^2} \quad (4)$$

The value range of Moran's I is $[-1, 1]$. When $I > 0$, a positive autocorrelation exists between the two regions. Haze pollution or the development of the digital economy is characterised by spatial agglomeration. When $I < 0$, a negative correlation exists between the two regions or spatial discreteness. When $I = 0$, the distribution of haze pollution is random, and no spatial autocorrelation exists.

Global spatial correlation analysis examines the aggregation of the entire space. Local spatial correlation analysis is used to understand the development of the digital economy

within each region or the degree of correlation between the haze pollution level in the focal region and nearby regions. The local Moran's I is calculated as

$$I = \frac{n|x_i - \bar{x}| \sum_{j=1}^n W_{ij}|x_j - \bar{x}|}{\sum_{i=1}^n (x_i - \bar{x})^2} \quad (5)$$

Here, a positive I represents some areas with high (low) values surrounded by other regions with high (low) values—either high–high (H–H) or low–low (L–L). Moreover, a negative I represents an area with high (or low) values surrounded by other areas with a low (or high) value—either high–low (H–L) or low–high (L–H).

2.3. Econometric Methodology

The following model was established:

$$\ln PM2.5_{i,t} = \alpha_0 + \alpha_1 \ln DIGE_{i,t} + \alpha_2 X_{control i,t} + \mu_i + \delta_t + \varepsilon_{i,t} \quad (6)$$

Here, $DIGE_{i,t}$ is an indicator of the development level of the digital economy in province i in period t ; $X_{control i,t}$ is a series of control variables: population structure (PS), fixed assets (FA), energy situation (ES), and degree of innovation (IN) in Equation (6); μ_i refers to the individual fixed effect of province i that is time-invariant; δ_t controls the time fixed effect; and $\varepsilon_{i,t}$ is a random perturbation term.

2.3.1. Spatial Autoregressive Model

Spatial correlation existed between our variables, and OLS may lead to inconsistencies in the parameter estimates. Therefore, this study introduced a spatial econometric model and analysed the influence of the digital economy on haze pollution in depth from both the space and time perspective. We selected the spatial autoregressive model (SAR) and spatial error model (SEM). The SAR is

$$Y = \alpha + \rho WY + X\beta + \varepsilon, \varepsilon \sim N[0, \sigma^2 I] \quad (7)$$

A variable is affected not only by its explanatory variable but also by variables in other spaces. Here, Y is the explained variable, X is the independent variable, α is the constant term, W is the spatial weight matrix, WY is a vector of the spatial lag dependent variable, ρ denotes a spatial regression coefficient reflecting the spatial dependence of the sample observations, and ε is a random perturbation term. Substituting Equation (6) into the test of Equation (7), we obtain the following spatial econometric model:

$$\ln PM2.5_{i,t} = \alpha + \rho W \ln PM2.5_{i,t-1} + \beta_1 \ln DIGE_{i,t} + \beta_2 X_{control i,t} + \varepsilon \quad (8)$$

2.3.2. Spatial Error Model

Equation (9) represents the SEM. The space disturbance term is related to the space population, and the disturbance term of a particular space affects and other spaces via the space effect.

$$Y = \alpha + X\beta + \varepsilon, \varepsilon = \lambda W\varepsilon + \mu, \mu \sim N[0, \sigma^2 I] \quad (9)$$

where Y is the explained variable; X is the independent variable of exogenous influencing factors; α is the constant term; ε is a random error term; β represents the influence of the independent variable on the dependent variable; λ is the unevaluated coefficient of the spatial autocorrelation error term (also known as the spatial autocorrelation coefficient); and μ is an error term. Substituting Equation (6) into the test of Equation (9), we obtain the following spatial econometric model:

$$\ln PM2.5_{i,t} = \alpha + \beta_1 \ln DIGE_{i,t} + \beta_2 X_{control i,t} + \lambda W\varepsilon + \mu \quad (10)$$

2.3.3. Threshold Model

This study tested whether the industrial structure mediates the relationship between the digital economy and haze pollution measured as particulate matter (PM2.5). The specific steps are as follows: in the digital economy development index (DIGE), the coefficient of α_1 is significant throughout the analysis in the linear regression model (6) for haze pollution of PM2.5, based on the construction of DIGE for the mediating variable IS in the linear regression equation of the industrial structure and DIGE for IS in the regression equation of PM2.5 by $\beta_1, \gamma_1, \gamma_2$. The significance of the regression coefficient determines whether a mediation effect exists. The specific form of the regression model is

$$\ln IS_{i,t} = \beta_0 + \beta_1 \ln DIGE_{i,t} + \beta_2 X_{control\ i,t} + \mu_i + \delta_t + \varepsilon_{i,t} \quad (11)$$

and

$$\ln PM2.5_{i,t} = \gamma_0 + \gamma_1 \ln DIGE_{i,t} + \gamma_2 \ln IS_{i,t} + \gamma_3 X_{control\ i,t} + \mu_i + \delta_t + \varepsilon_{i,t} \quad (12)$$

In addition to the mediating effect model, the empirical test for the indirect transmission mechanism should consider Metcalfe's law—the value of the Internet is proportional to the square of the number of users. The development level and industrial structure upgrading of the digital economy may also indirectly reduce the non-linear dynamic spillover of haze pollution in the digital economy. Therefore, in order to study whether the digital economy has a non-linear impact on haze pollution through the intermediary mechanism of industrial structure change, the following panel threshold model is set:

$$\begin{aligned} \ln PM2.5_{i,t} = & \phi_0 + \phi_1 \ln DIGE_{i,t} \times I(Adj_{i,t} \leq \theta) + \\ & \phi_2 \ln DIGE_{i,t} \times I(Adj_{i,t} > \theta) + \phi_3 X_{control\ i,t} + \mu_i + \delta_t \end{aligned} \quad (13)$$

In Equation (13), $Adj_{i,t}$ is a threshold variable such as the digital economy and industrial structure, and $I(\cdot)$ represents indicator functions valued at 1 or 0, which meet the conditions in the parentheses—namely 1; otherwise 0. Equation (13) considers a single threshold case.

2.4. Data Source

2.4.1. Explained Variable

PM2.5 ($\mu\text{g}/\text{m}^3$). To address the lack of historical data on PM2.5 concentration levels, we used raster data from the atmospheric composition analysis group based on the annual average of global PM2.5 concentrations monitored by satellites [43]. Using ArcGIS software, we analysed the specific value of the annual mean PM2.5 concentration in Chinese provinces from 2011 to 2018. Using these data, the difficulty in using surface monitoring data based on point source data to measure the PM2.5 concentration of an area accurately was addressed.

2.4.2. Core Explanatory Variable

The core explanatory variable is the DIGE. With regards to the measurement of the digital economy's development level, as officials have not yet disclosed a comprehensive index of concrete information for it, the calculation faces certain difficulties and challenges [44]. Based on the method of Huang et al. [45], the present study adopted the indicators of Internet penetration rate, relevant practitioners, relevant output, and mobile phone penetration rate. Based on the 2011–2018 panel data of 30 provinces, to build the digital infrastructure and digital industry variable, this study developed secondary indices where the secondary index of digital infrastructure corresponds to mobile telephone exchange capacity (10,000 families), optical fibre cable line length (km), number of Internet broadband access ports (10,000 units), number of websites (10,000 units), popularisation rate of mobile telephones (unit/100), and number of Internet broadband access users (10,000 units). The secondary index of digital industry is number of computers per 100 people in the enter-

prise, number of websites per 100 enterprises, proportion of enterprises with e-commerce transaction activities on the Internet per 100 enterprises, and proportion of e-commerce sales in the GDP. Using the entropy method, the data of these 10 indicators were processed to obtain the DIGE.

2.4.3. Intermediate Variable

Industrial structure (IS) is the intermediate variable. The proportion of the tertiary sector's output value indicates whether an economy has an advanced industrial structure [46]. The larger the value, the smaller the negative impact on haze pollution. Therefore, the sign of the coefficient is expected to be negative.

2.4.4. Control Variables

The control variables include the following:

Population structure (PS). Owing to livelihood pressures, young people are more willing to risk high pollution emissions to earn higher incomes, and an increase in the proportion of the labour population aggravates haze pollution [47]. In this study, the proportion of people aged 15–64 years in the total population was used to measure the influence of total regional population distribution on haze pollution. Therefore, this study expected the coefficient sign to be positive.

Fixed assets (FA). Following Li et al. [48], FA is expressed as the total investment in fixed assets. FA investment is positively correlated with digital economy development and is an essential source of funds for promoting technological innovation. Therefore, this study expected a negative coefficient sign.

Energy situation (ES). Burning fossil fuels, especially coal, is regarded as an important source of haze pollution [49], and China is among the few countries whose energy consumption structure is dominated by coal. Therefore, the total amount of energy consumption (tons of standard coal) is used. The higher the proportion of coal consumption, the less likely it is to decrease haze concentration. We expected a positive coefficient sign.

Innovation degree (IN). IN is the number of patents granted by each province. The larger its value, the stronger the technological innovation ability, which helps improve the factor utilisation efficiency and reduce pollution emission intensity. Therefore, we expected a negative coefficient sign.

The index data for the core explanatory variables are available from the *China Statistical Yearbook* [50]. The index data for the intermediary and control variables are from the WIND and China Stock Market Accounting Research databases.

2.5. Data Description

Table 1 shows the descriptive statistics. To reduce errors and heteroscedasticity caused by different units, each variable was treated logarithmically. The results show that haze pollution varies significantly among different regions. The development index of the digital economy (lnDIGE) has a small mean and large standard error, while the standard error of the industrial structure (the mediating variable) is relatively small. Clear differences among provinces exist in terms of PS, FA, ES, and IN.

Table 1. Descriptive statistics.

Type of Variable	Variable	Obs	Mean	SD	Min	Max
Dependent Variable	lnPM2.5	240	3.500	0.478	2.164	4.426
Independent Variable	lnDIGE	240	−1.80	0.665	−3.565	−0.114
Intermediate Variables	lnIS	240	3.804	0.190	3.391	4.419
	lnPS	240	−0.306	0.048	−0.409	−0.176
Control Variables	lnFA	240	9.451	0.782	7.219	10.941
	lnES	240	9.421	0.646	7.378	10.568
	lnIN	240	8.061	1.398	4.248	10.882

3. Results and Discussion

3.1. Spatio-Temporal Evolution of China's PM2.5 Concentration and Digital Economy

This study selected three cross sections of time—2011, 2014, and 2018. The spatial clustering characteristics of the digital economy development and haze pollution distribution in 30 Chinese provinces were analysed using the natural fracture method.

As illustrated in Figure 1a–c, for PM2.5 pollution, the 30 provinces showed an overall decline over the 8 years of the haze index. Maximum PM2.5 concentration by region was found in east-central China and the provinces of Shandong, Henan, Anhui, and Jiangsu, among others, in 2011, 2014, and 2018. The PM2.5 concentration in these regions was three times the smog concentration in the next highest echelon. In Hubei, Shanxi, Guangdong, Guizhou, and Chongqing provinces, PM2.5 pollution levels improved significantly, while they deteriorated in Xinjiang, Liaoning, and Gansu. This result was affected not only by geographical location and meteorological conditions but also by the provinces' social and economic development [51]. The possible reasons are as follows: (1) Most economically developed provinces have relatively high PM2.5 levels and have consequently witnessed greater efforts to control air pollution. (2) The industrial division of labour in the provinces is changing. An increase in the proportion of the tertiary sector improves air quality, while the transfer of the industrial structure aggravates haze pollution in the receiving province. (3) In the central and western regions, which have low population density, PM2.5 pollution is not quite as severe, and little attention is paid to, or investments made for, mitigating air pollution, causing a continuous deterioration of air quality.

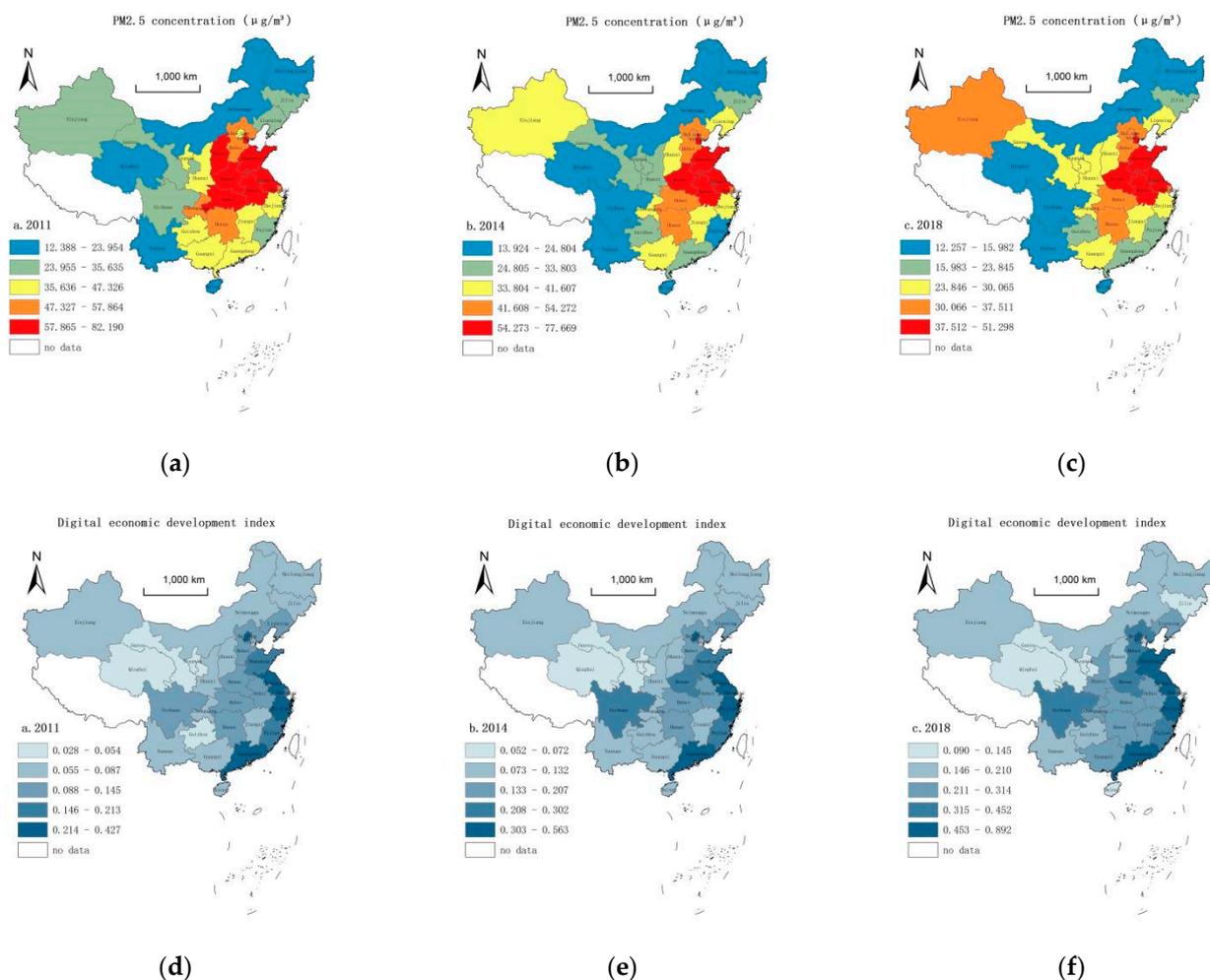


Figure 1. Spatio-temporal evolution of China's PM2.5 concentration levels (a–c) and digital economy (d–f) in 2011, 2014, and 2018.

Figure 1d–f show that, from 2011 to 2018, digital economy development was on the rise in all 30 provinces. China's three major economic belts are the bay area of the Yangtze River Delta, Guangdong province, and the Beijing–Tianjin–Hebei region, which witnessed substantial digital economy development in the first phase. Combined with other areas of the country, these form a clear core–periphery model wherein the eastern region's digital economy development index has leading areas, such as Guangdong, Jiangsu, Beijing, Shanghai, Zhejiang, Shandong, Shanxi, Shaanxi, and Guizhou. Moreover, Sichuan, Jiangxi, Anhui, Hubei, and other mid-west cities are catching up. Comparative advantage is implemented by digital economy development rotation. Simultaneously, the digital economy index reflects the imbalance and insufficiency among various regions in China [51]. The digital economy in Xinjiang, Gansu, Ningxia, and other regions in more remote areas is developing slowly, forming the bottom of the index. Thus, strengthening the Internet infrastructure construction in these areas is necessary.

3.2. Spatial Autocorrelation Analysis

To accurately understand the provincial-level digital economy and haze pollution agglomeration in the country, this study analysed the variables for the provinces with PM2.5 air pollution and digital economy development. Figure 2 shows the two indicators in the global Moran's I calculation formula: the 2011–2018 global Moran's I of the PM2.5 index, which is between 0.22 and 0.39 (p -value is 0.000–0.010, significant at 1%), with $Z(I)$ 2.6–3.4 ($Z > +2.58$); and the global Moran's I of the digital economy, which is between 0.28 and 0.37 (p -value is 0.000–0.004, significant at 1%), with $Z(I)$ 2.6–3.4 ($Z > +2.58$). Thus, the distribution of haze pollution and the digital economy presented significant spatial autocorrelation and had a geographical agglomeration feature. The more severe the haze pollution in the focal province, the higher the haze pollution in the neighbouring provinces. Moreover, the more advanced the digital economy in the focal province, the higher the degree of digital economy development in the neighbouring provinces.

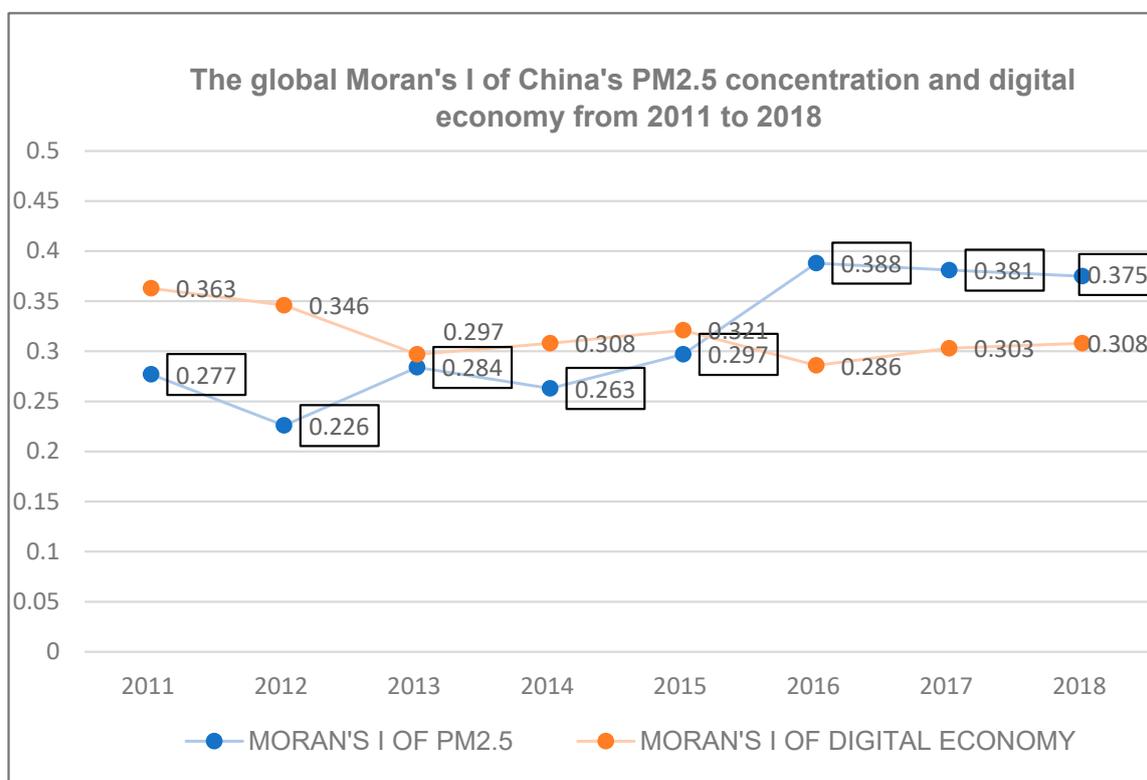


Figure 2. Global Moran's I of China's PM2.5 concentration levels and digital economy from 2011 to 2018.

Figure 3a–c show that haze pollution in 2011, 2014, and 2018 in the H–H agglomeration areas was mainly distributed in the Beijing–Tianjin–Hebei region and Yangtze River Delta; this includes the provinces that encompass Beijing, Tianjin, Shanghai, Jiangsu, and Zhejiang. The economically developed eastern region is the most populous province in China in terms of population density, urbanisation, industrialisation, new technology industry, and heavy industry base. Yunnan, Guizhou, and Sichuan in the west and Hunan, Hubei, and Hebei in the central region show an L–L agglomeration trend, while Gansu, Hainan, Hebei, Heilongjiang, and Jilin show an H–L agglomeration pattern. Haze pollution is geographically dispersed due to high pollution in this region [52].

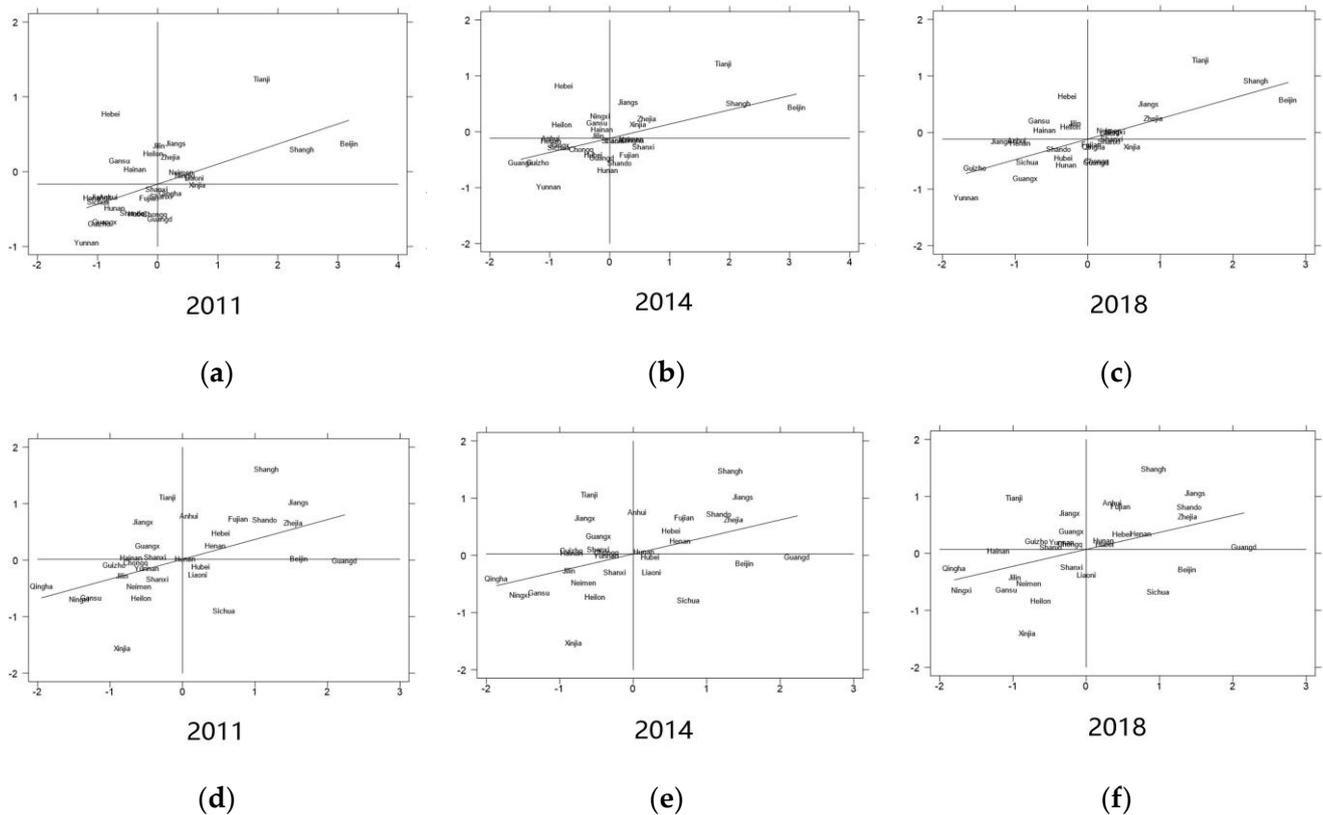


Figure 3. Local Moran's I of China's PM_{2.5} concentration levels (a–c) and digital economy (d–f) in 2011, 2014, and 2018.

Figure 3d–f show the relationship between the local space of the digital economy in 2011, 2014, and 2018. The Yangtze River Delta (Shanghai and Zhejiang in the east and Jiangsu), Shandong, Fujian, and Henan in central China, along with Hebei, all show H–H features. These are economically developed eastern coastal areas, with greater employment opportunities, strong talent agglomeration, and good development prospects, strengthening the development of the digital economy. However, the central region follows the existing trend, with an emerging digital economy. Tianjin, Jiangxi, and Guangxi all show the characteristics of the H–L agglomeration. Sichuan, Liaoning, and Hubei have an L–H agglomeration pattern. Compared with these three provinces, their neighbouring provinces are more attractive for developing the digital economy. Further, the remote western areas of Qinghai, Ningxia, Gansu, Xinjiang, Heilongjiang, and Inner Mongolia and the central areas of Shanxi and Hunan form an L–L agglomeration due to their low level of digital economy development and lack of a driving force in terms of digital economy development in neighbouring areas.

3.3. Spatial Panel Model Analysis

3.3.1. LM Test

Moran's I passed the significance test. The classical OLS regression had a significant spatial correlation; therefore, a spatial econometric model should be used for parameter estimation. As presented in Table 2, both LM-Lag and LM-Error passed the 1% significance level of the spatial dependence test. According to the criteria, LM-Lag and LM-Error should pass the significance test, and the lag and robust LM-Error should pass the 1% significance test. Thus, the spatial lag model and the SEM were used to estimate the regression. We introduced the neighbouring weighting matrix to the model and analysed the regression results.

Table 2. LM test.

Spatial Autocorrelation Text	Z-Value	p-Value
LM-lag	77.7777	0.000
Robust LM-lag	21.5651	0.000
LM-Error	105.2038	0.000
Robust LM-Error	48.9912	0.000

3.3.2. Regression Results and Discussion

As shown in Table 3, in the SAR estimation with a time fixed effect, the estimated value of ρ was 0.2, significant at the 5% level. This value indicates that neighbouring regions have a significant positive spatial spillover effect on PM2.5; an increase of 1% in PM2.5 concentration in neighbouring provinces leads to an increase of approximately 0.2% in PM2.5 concentration in the focal province. Thus, maintaining a province's particular approach to haze treatment cannot effectively solve inter-regional haze pollution. Consequently, transforming local treatment to regional joint prevention and control is necessary. In the SEM, the λ value was significant at the 10% level. This indicates that haze concentration is affected not only by observable factors such as population structure but also by observable factors in adjacent areas. The influencing factors are discussed below.

Table 3. Estimation results for different models (dependent variable is PM2.5).

Variables	OLS (FE) (1)		SAR (2)		SEM (3)	
	Estimate	T Value	Estimate	T Value	Estimate	T Value
(Intercept)	3.712 ***	5.55	0.010 ***	10.21	0.010 ***	10.21
lnDIGE	−0.263 **	−2.69	−0.216 ***	−3.44	−0.276 ***	−4.49
lnPS	0.064	0.10	−0.201	−0.36	−0.104	−0.19
lnFA	−0.021	−0.58	−0.030	−0.88	−0.038	−1.03
lnES	0.031 **	2.68	0.025 **	2.08	0.024 *	1.83
lnIN	−0.093 **	−2.32	−0.075 *	−1.91	−0.082 **	−2.08
ρ			0.200 **	2.39		
λ					0.172 *	1.78
R ²	0.663		0.666		0.662	

Note: ***, ** and * represent significance at 1%, 5% and 10% levels, respectively.

First, we focus on the effect and magnitude, of the core explanatory variable of the digital economy on haze pollution. The panel OLS, SAR, and SEM models showed that the digital economy development has a significantly negative effect on haze reduction, passing the significance test with a 99% confidence level. Every 1% increase in the development level of the digital economy reduces haze concentration in the region by approximately 0.2%. The possible reasons for this are as follows: (1) The digital economy promotes the construction of digital infrastructure through technological effects. (2) The digital economy, through structural effects, expands the proportion of digital industries, digitally empowers traditional industries, improves the energy efficiency and operational efficiency

of traditional industries, promotes the rapid and efficient transformation and upgrading of traditional industries, and finally achieves low energy consumption and low emissions [53].

Second, from the perspective of energy, in the OLS and SAR models, the total energy consumption was significantly positive at 5%, which is consistent with expectations. This indicator shows a significant promoting effect on haze pollution [54]. The secondary sector includes industry and construction; the industrial consumption of coal, oil, non-ferrous metals, and other raw materials creating fine dust, which is the leading cause of haze pollution. The energy structure is the key factor responsible for aggravating haze pollution. Therefore, accelerating the transformation and upgrade of this structure is urgently necessary.

The degree of innovation variable in the OLS and SEM models was significantly negative at the 5% level. The early stage of economic development involves resource consumption to expand production and satisfy people's material needs. Thus, economic development neglects environmental protection to a certain extent. Moreover, although living standards are widely improved, natural resources become constrained. These aspects of early development highlight the importance of environmental protection in the reversed transmission of technology innovation, transforming economic development patterns, and optimising economic structure adjustment [55].

The population structure variable in the three models showed inconsistencies; its coefficient was positive in the OLS model, confirming that young people are willing to accept high pollution emissions in exchange for high income; thus, an increase in the labour population can increase or aggravate haze pollution [47]. However, in the SAR and SEM models, the coefficient was negative, possibly because labour population agglomeration significantly reverses the transmission of regional environment improvement to reduce smog pollution.

The coefficients of fixed assets were all negative, indicating that fixed asset investment is positively correlated with the development of the digital economy and is an important source of funds to promote technological innovation. Among the control variables, population structure and fixed assets were statistically significant.

3.4. Test for Threshold Regression Model

From the analysis of the theoretical model (8), we observed the mechanism through which the digital economy affects haze pollution. Considering that the development of the digital economy acts on haze reduction through structural effects, this study introduced the mediation variable index of industrial structure as the threshold for a threshold effect analysis to examine the influence of different intervals of the industrial structure on haze. The form of the panel threshold model was tested first. Subsequently, we followed Hansen [56] and used the bootstrap sampling method to simulate a likelihood ratio statistic of 200, estimating the threshold value and relevant statistics. The results show that a single threshold of F statistic was significant at 5%, while the double and triple thresholds were not significant. Thus, to analyse the effect of the digital economy on haze pollution, we considered the industrial structure to be a single threshold effect and assumed that the industrial structure is the threshold variable. As shown in Table 4, the negative influence of the digital economy on haze pollution continued to weaken, and the non-linear characteristics of the negative and diminishing 'marginal effect' of the digital economy remained. This trend shows that the dynamic influence of the digital economy on haze pollution is affected not only by its development level but also by the regulating influence of the industrial structure, which is reflected in the positive interaction between the digital economy and industrial structure. However, this effect gradually weakens with the change of industrial structure.

Table 4. Estimation results for the threshold regression model.

Variables		Intermediate Variable
		lnIS
Threshold	q ₁	3.927
	q ₂	
	DIGE·I (Th ≤ q ₁)	0.302 **
	DIGE·I (q ₁ < Th < q ₂)	0.272 *
	Control variables	YES
	Number of periods	8
	Number of provinces	30
	R ²	0.6929

Note: **, * represent significance at 5%, 10% levels, respectively.

3.5. Heterogeneity Test

Owing to different resource endowments and stages of development, both the development level of the digital economy and haze pollution have noticeable heterogeneity in terms of their regional distribution. Therefore, regional differences may exist in the impact of the digital economy on haze pollution reduction, which are necessary to consider for an in-depth discussion.

First, a descriptive statistical explanation is provided for the differences in haze pollution and digital economy development levels in various regions. As shown in Table 5, in terms of PM_{2.5}, the logarithmic mean value of haze pollution is the lowest in western China and highest in eastern China. Thus, the eastern region is significantly ahead of the central and western regions in terms of digital economic development. The mean difference between the eastern and the middle and western regions is approximately 0.574 and 0.89, respectively, reflecting a first-mover advantage. This result sets the foundation for the regional heterogeneity test of the effects of the digital economy on haze pollution. The regression analysis of regional heterogeneity is shown in Table 6. The results of models (1), (2), and (3) show that the digital economy in eastern China has a significant effect on reducing haze pollution, while the effect is not significant in central and western China. In other words, considering regional heterogeneity, the digital economy in eastern China has a higher positive effect on haze pollution reduction. This result is possibly because the digital economy in eastern China developed earlier and was at a higher level, causing the dividend of the impact of the digital economy on environmental governance to be released more fully.

Table 5. Descriptive statistics (different regions).

lnPM _{2.5}					
Region	Obs	Mean	Std. Dev.	Min	Max
East	88	3.639	0.447	2.618	4.426
Middle	64	3.657	0.439	2.629	4.409
West	88	3.247	0.430	2.164	4.046
lnDIGE					
Region	Obs	Mean	Std. Dev.	Min	Max
East	88	−1.324	0.604	−2.760	−0.114
Middle	64	−1.898	0.454	−2.844	−0.929
West	88	−2.214	0.539	−3.565	−0.793

Table 6. Heterogeneity test (dependent variable is PM_{2.5}).

Variables	East (1)		Middle (2)		West (3)	
	Estimate	T Value	Estimate	T Value	Estimate	T Value
(Intercept)	3.614 ***	6.09	2.795	0.99	4.545 ***	5.62

Table 6. Cont.

Variables	East (1)		Middle (2)		West (3)	
	Estimate	T Value	Estimate	T Value	Estimate	T Value
lnDIGE	−0.324 **	−2.81	−0.323	−0.97	−0.187	−1.76
lnPS	−0.256	−0.27	−1.568	−0.58	0.759	0.51
lnFA	0.002	0.11	0.010	0.09	−0.117 **	−2.26
lnES	0.045	2.70	0.034	1.33	0.020	1.00
lnIN	−0.103 **	−1.76	−0.081	−0.59	−0.083	−2.18
Number of periods	8		8		8	
Number of provinces	11		8		11	
R ²	0.692		0.587		0.723	

Note: ** represent significance at 5% levels, respectively.

4. Robustness Test

4.1. Changing the Spatial Matrix

A spatial econometric model, which is highly dependent on the spatial weight matrix, was used to study the influence of the digital economy on haze pollution. First, the neighbouring spatial weight matrix (W1) was used to determine whether the provinces are adjacent. Adjacency was set to 1, and non-adjacency to 0. Second, the robustness of the regression results was tested using the geographical distance spatial weight matrix (W2), which was constructed using the reciprocal of the square deviation of the distance between provinces.

From the test results in Table 7, we inserted the weight matrix (W2) into the spatial lag model (4) and SEM (5). We observed that the coefficient of the core variable of the digital economy was significantly negative in the SEM model. The lnDIGE regression coefficient was the largest and was significant at 1%, indicating that the digital economy's spatial influence on haze pollution is more likely to be in the error term of undetectable than the spatial correlation between the two in time. Therefore, the development of the digital economy can effectively reduce haze pollution, which is consistent with the main research results and proves that the regression results are robust.

Table 7. Estimation results for different models (dependent variable is PM2.5).

Variables	SAR (4)		SEM (5)	
	Estimate	T Value	Estimate	T Value
(Intercept)	0.010 ***	10.21	0.010 ***	10.21
lnDIGE	−0.132 *	−1.83	−0.250 ***	−3.88
lnPS	−0.344	−0.62	−0.103	−0.19
lnFA	−0.042	−1.23	−0.052	−1.41
lnES	0.022 *	1.87	0.017 *	1.23
lnIN	−0.064	−1.64	−0.085 **	−2.11
ρ	0.415 ***	3.21		
λ			0.450 **	2.98
R ²	0.665		0.659	

Note: ***, ** and * represent significance at 1%, 5% and 10% levels, respectively.

4.2. Use of Instrumental Variable

Selecting appropriate instrumental variables for the core explanatory variables can resolve endogeneity problems. Following Huang et al. [45], this study adopts the 1984 volume of each province's post and telecommunications business as the core explanatory variable and the instrumental variable of the comprehensive index of digital economy development. The instrumental variables must satisfy exogeneity and correlation. On the one hand, with the continuous development of traditional communications technology, previous levels of the local telecommunications infrastructure affect the subsequent stage of application of Internet technology from the technical level perspective and usage habits.

On the other hand, the impact of the use of traditional telecommunications tools, such as the use of fixed-line telephones, on economic development should meet the exclusivity. As their usage frequency gradually declines with social and economic development, the instrumental variable must satisfy the conditions.

As the original data of the selected tool variable are in cross-sectional form, they cannot be used directly in the econometric analysis of panel data. Based on Nunn and Qian [57], a variable that changes over time is introduced to construct the panel tool variable. The interaction term is constructed by the number of Internet users in the last year and the number of telephones per 10,000 people in each province in 1984. This statistic is used as the instrumental variable of the digital economy index of the province in that year. The results in columns (1) and (2) of Table 8 show that the effect of the digital economy on reducing haze pollution remains valid after considering endogeneity, and the results are all significant at 1%. For the test of the null hypothesis of insufficient identification of instrumental variables, the LM statistic P values are all 0.000, which significantly rejects the null hypothesis. In the test for weak identification of instrumental variables, the Wald F statistic is greater than the threshold value above 10% of the weak identification test. In general, the tests illustrate the rationality of choosing the cross-term, between the historical postal and telecommunications volumes of various provinces, and the number of Internet users in China as the instrumental variable of digital economy development.

Table 8. Test of the instrumental variables.

Variable	Instrumental Variable	
	(1)	(2)
lnDIGE	−0.424 *** (−18.70)	−0.239 *** (−3.01)
Control variables	NO	YES
Province fixed effect	YES	YES
Year fixed effect	YES	YES
LM statistic	196.588 [0.0000]	122.964 [0.0000]
Wald F statistic	308.97 {16.38}	289.62 {16.38}
Number of periods	8	8
Number of provinces	30	30
R ²	0.6420	0.6634

Note: *** represents significance at 1% levels, respectively.

5. Conclusions

First, this study constructs an evaluation system for developing the digital economy at the provincial level in China from the two aspects of digital infrastructure (representing digital technology) and the digital industry (representing emerging industries). It calculates the development level of the digital economy in each province using the entropy weight method. Second, the spatial spillover effects of haze pollution and digital economy development are tested with the global and local spatial correlation indexes. Third, using the data of 30 provinces in China from 2011 to 2018, OLS regression and spatial SAR and SEM models were used to analyse the impact of digital economy development on haze pollution. Fourth, using the threshold model, the study discusses how the digital economy mechanism affects haze pollution through industrial structure change. Finally, the study divides the research samples into three regions (eastern, central, and western regions) to study the regional heterogeneity impact of digital economic development on haze pollution.

The findings of the present study are as follows: First, both haze pollution and digital economy distribution present significant global positive spatial spillover effects and local characteristics. Second, the digital economy has a positive impact on reducing smog. The development of the digital economy in neighbouring provinces has a significant positive spillover effect on reducing haze pollution in key provinces. The change of energy structure

and innovation degree can effectively restrain the aggravation of haze pollution, and the conclusion is still valid in the robustness test using the instrumental variable method and adjusting the spatial matrix. Third, the results of the transmission mechanism show that the development of the digital economy can affect haze pollution by changing the industrial structure, showing the non-linear feature that the influence of haze reduction continues to weaken. Finally, in terms of regional differences, the impact of the digital economy on haze pollution is most significant in eastern China, while not significant in central and western China. Based on this study, the following policy recommendations are put forward.

First of all, the penetration and application of digital technology in environmental governance should be accelerated. We would increase investment in digital technologies; pay attention to the breadth and depth of applications in advanced fields such as the Internet, 5G, artificial intelligence, and big data; promote the circulation and sharing of resources, knowledge, and capital; and promote the improvement of digital economy in environmental governance, such as energy conservation and emission reduction. Second, the transformation and upgrading of industrial structure should be promoted, encouraging enterprises to vigorously develop cutting-edge technologies and promoting the continuous progress of digital industry and digitization of industry. Third, it is necessary to understand further the positive impact of the digital economy on reducing haze pollution in central and western China, indicating that a dynamic and differentiated digital economy strategy should be implemented. Finally, haze reduction policies should take into account spatial spillover and decomposition boundaries of administrative areas.

Although this study supplements the relevant research on the impact of the digital economy on haze and provides some theoretical reference for the digital economy on environmental governance, there is still room for further research. First, this paper measures the digital economy from two aspects: digital infrastructure and digital industry. Because of the existing data, it may have measurement errors. The evaluation is conducted at the provincial level, and the sample size is limited. In the future, it can be more detailed and micro, which may be more accurate in exploring the relationship between the two from the city level. Second, this study empirically analyses the spatial impact of digital economy development on haze pollution. The mechanism part is only carried out from the perspective of industrial structure, and subsequent studies should further explore the multi-dimensional impact of different mechanisms on haze. Finally, the development of the digital economy is cyclical, and each stage has a different impact on haze levels. This should be further investigated in future studies.

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