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Research on the impact of the digital economy on haze pollution: evidence from prefecture-level cities in China

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Lately, the ongoing issue of haze pollution in multiple cities across China has had a profound impact on the residents' wellbeing and overall health. The urgent necessity to address haze pollution is undeniable. Meanwhile, the rapidly evolving digital economy has sprung up as a pivotal driver for China's economic growth, providing innovative approach to tackle haze pollution. This research explores the impact of the digital economy on haze pollution through utilizing the big data pilot zone as a quasi-natural experiment. Panel data from 280 prefecture-level cities in China is adopted, covering the period from 2011 through 2020. This analysis incorporates various models, namely, difference-in-differences model (DID), mediation effect model, and difference-in-differences spatial Durbin model. The findings highlight the substantial contributions of digital economy in alleviating haze pollution. Furthermore, these findings hold true even after a series of rigorous robustness checks. The constraint influence of the digital economy on haze pollution is particularly prominent in metropolitan areas, cities with elevated administrative levels, primary environmental protection cities, as well as economically developed cities. Financial development and technological innovation serve as important mechanisms through which the digital economy suppresses haze pollution. After accounting for spatial factors, the digital economy exhibits consequential spillover effects, leading to substantial inhibition of haze pollution in surrounding cities as well as locally. The novel aspects of this paper are as follows: Firstly, it regards the establishment of big data experimental zones as the exogenous policy shock of digital economy and employs a multi period DID model to evaluate the impact of the digital economy on haze pollution. Secondly, it explores the transmission pathways through which the digital economy affects haze pollution from the perspectives of financial development and technological innovation. Thirdly, it investigates the heterogeneous characteristics of the impact of the digital economy on haze pollution. Fourthly, it examines the spatial spillover effects of the digital economy on haze pollution from the perspective of spatial econometrics.

KEYWORDS

digital economy, haze pollution, heterogeneity, mechanism, spatial spillover effect

1 Introduction

Throughout the last 40 years of reform and opening up, China has made impressive progress in economic growth, characterized by a substantial rise in its gross domestic product (GDP) and cementing its position as the world's second-largest economy. Nevertheless, this advancement has been accompannied by severe ecological and environmental harm, with air pollution manifesting in frequent hazy weather patterns. This issue has become a major concern as it adversely affects the country's economic performance (Wang F et al., 2021). The 2022 Environmental Performance Index (EPI) Report positions China 160th among 180 major economies concerning overall environmental performance, with a score of 28.4. In relation to air quality specifically, China ranks 157th with a score of 20.6 (Wolf et al., 2022). Moreover, the 2021 World Air Quality Report indicates that the average concentration of PM2.5 in 143 cities out of 1,347 cities in East Asia is seven times upper than the target recommended by the World Health Organization (WHO). Importantly, all the 143 cities with excessively high PM2.5 levels are located in China (Tan and Chen, 2022).To address this pressing issue, the Chinese government has implemented targeted procedures since 2013, including the Air Pollution Prevention and Control Action Plan, the Three-Year Action Plan for Winning the Battle for Blue Sky, and the Central Ecological and Environmental Protection Inspection Work Regulations. Through relentless efforts, the annual average concentration of PM2.5 has been steadily decreasing. The 2022 China Ecological Environment Report revealed that 37.2% of the 339 prefecture-level cities in China have air quality exceeding standards, affecting 126 cities. Additionally, 86 cities have PM2.5 level that exceed standards, making up 25.4% of the total. The issue of hazy pollution not only degrades air quality but also adversely affects urban traffic, daily living, and public health, posing a significant challenge to China's sustainable development goals (Zhao et al., 2021).

Research on haze pollution has significant increased owing to its profound harmful impact. An detailed analysis of the available literature on haze pollution indicates that recent studies predominantly revolve around its measurement (Yu and Wang, 2023), spatio-temporal evolution analysis (Zeng and Li, 2019; Zhang et al., 2022a), population migration, health effects (Nguyen et al., 2023; Wang K et al., 2021, Wang et al., 2023b), and influencing factors (Liu and Xia, 2019; Wu and Zhang, 2019). Furthermore, the investigation of factors influencing haze pollution has become the focal point of extensive research within the field. In addition to natural factors such as temperature (Zhang et al., 2015), wind direction, and humidity, economic factors are significantly correlated with haze pollution. The Environmental Kuznets Curve (EKC) theory posits that environmental pollution varies with *per capita* income. Specifically, in the early stages of economic development, lower income levels are associated with higher pollution levels, whereas higher income levels correlate with lower pollution levels. This relationship creates an inverted "U" shape between income and environmental pollution (Grossman and Krueger, 1995). Building on the EKC theory, an increasing number of scholars have integrated economic factors into its framework and have empirically validated the existence of this inverted "U" relationship between economic development and haze pollution (Gan et al., 2021; Wang, 2023). Presently, studies have identified several critical factors that contribute to haze pollution, including population density and agglomeration (Wu and Yu, 2022; Zhu and Zhao, 2021), technological innovation (Chen, 2022a; Liu, 2018), industrial structure (Chen, 2022b; Ma and Cao, 2022), urbanization (Li L et al., 2022; Yang et al., 2023), environmental regulation (Li J et al., 2022), foreign investment (Guan et al., 2022; Li et al., 2016), government support (Pang et al., 2020), and financial development (Wang, 2023; Guo and Liu, 2021). Furthermore, due to the strong diffusiveness and externality of haze pollutants, various factors may have spatial spillover effects on haze pollution. For instance, Yufeng Chen et al. investigated the spillover effects of industrial agglomeration on haze pollution and further explored whether industrial agglomeration could achieve a balanced development between economic growth and environmental quality. The results indicate that there is an inverted "U" relationship between industrial agglomeration and haze pollution, with the indirect effects of spatial spillover dominating this influence (Chen et al., 2022).

The essence of environmental issues can be distilled into the challenges associated with production methods and lifestyle. The digital economy, fueled by 5G, big data, and artificial intelligence, transforms and enhances societal production, lifestyles, and governance across multiple dimensions. It has increased the efficiency of resource allocation throughout society, fostered high-quality economic development, and emerged as a vital engine of the modern economic system. To capitalize on the considerable opportunities arising from the development of the digital economy and to advance a data-centric digital economy, major industrial nations worldwide have progressively implemented big data development strategies. For example, the United States issued its "Big Data Research and Development Strategic Plan" as early as 2011, and Australia followed in 2013 with its "Public Service Big Data Strategy". Subsequently, both the United Kingdom and France introduced their own big data development strategies to further advance the digital economy (Liang and Shen, 2023). In August 2015, China released the "Action Plan for Promoting Big Data Development," which specifically outlined the establishment of national-level comprehensive big data pilot zones (hereinafter referred to as big data pilot zones). The construction of the big data pilot zone in Guizhou Province officially began in September 2015. In 2016, a second batch of pilot zones was established in the Beijing-Tianjin-Hebei region, the Pearl River Delta, as well as in Shanghai, Henan Province, Chongqing, and Shenyang. The primary objective of these pilot zones is to foster industrial innovation and development by fully utilizing data as a vital resource to facilitate economic transformation and upgrading, which is regarded as a crucial pathway for advancing the development of China's digital economy (Li and Liu, 2023).

The incorporation of the digital economy into economic prosperity, industrial advancement, as well as societal life has underscored the importance of harnessing its potential to support environmental conservation and foster sustainable development, which has garnered increasing attention in research. Therefore, exploring the extent to which the digital economy contributes to deterring air pollution caused by haze is paramount. If such a deterrent role exists, exploring potential heterogeneity effects is also necessary. Understanding the underlying mechanisms behind the effects is imperative. Additionally, studying whether the impact of the digital economy on haze pollution demonstrates spatial spillover effects would be meaningful. Research on these questions can provide theoretical and practical sustenance for evaluating the environmental effect of the digital economy on mitigating haze pollution and designing relevant policies, which holds notable theoretical and practical implications.

Drawing on the aforementioned information, the study utilizes a quasi-natural experiment in the National Big Data Comprehensive Pilot Zone, commonly referred to as the Big Data Experimental Area, to probe the policy implications of the digital economy on haze pollution utilizing the multi period Difference-in-Difference (DID) model according to panel data from 280 prefecture-level cities in China, covering the period from 2011 through 2020. Subsequently, the research examines the heterogeneous effects of the digital economy on haze pollution, considering various dimensions including city size, administrative level, environmental protection type, and level of economic development. Additionally, the study analyzes the mediation mechanism of the digital economy's impact on haze pollution by incorporating two mediating variables: financial development and technological innovation. Spatial econometrics techniques are then applied to investigate the spatial spillover effect of the digital economy on haze pollution.

This article makes significant contributions in several aspects: Firstly, it utilizes big data experimental areas as exogenous policy shocks to the digital economy and employs the multi period DID model to evaluate the impact of the digital economy on environmental pollution. This approach effectively alleviates endogeneity issues caused by measurement errors in the digital economy, providing a novel research direction for assessing the haze pollution effects of the digital economy. Secondly, the paper explores the transmission pathways of how the digital economy impacts environmental pollution from the lenses of financial development and technological innovation. The exploration helps uncover the intrinsic mechanisms through which the digital economy influences haze pollution, thus expanding the depth and breadth of research in this field. Thirdly, the study examines the heterogeneity of the digital economy's impact on environmental pollution considering city size, administrative level, environmental protection type, and economic development level. This provides a more comprehensive analytical perspective and policy insights on the connection between the digital economy and haze pollution. Fourthly, this paper examines the spatial spillover effects of the digital economy on haze pollution from the viewpoint of spatial econometrics, expanding the application field of the Difference in Differences model. The research conducted by Zhao et al. (2023) and Zhou et al. (2021) relates closely to the topic of this paper; however, the aforementioned studies measure the digital economy using indicators such as internet penetration rate, relevant employment, related output, and mobile phone penetration rate, which may inevitably introduce some measurement errors. In contrast, this paper employs a DID model for causal effect identification, providing a more accurate assessment of the impact of the digital economy on haze pollution. Furthermore, the mechanism analysis and heterogeneity analysis presented in this paper differ significantly from those in the previous studies. Additionally, while those studies also examined spatial spillover effects, this paper employs the Difference-in-Difference Spatial Durbin Model (DIDSDM). This model extends the traditional DID model to a spatial DID framework, enhancing the understanding of the digital economy's impact on haze pollution and providing valuable insights for policymakers. The structure of this study is organized as follows: the second section entails a theoretical analysis and research hypotheses; the third section adumbrates research design; the fourth section encompasses empirical testing; and the fifth section conducts an examination of the mechanisms involved. The sixth section addresses expand research, specifically an analysis of spatial spillover effects. Finally, the seventh section consists of conclusions, policy implications and further research.

2 Theoretical analysis and research hypothesis

2.1 The digital economy and haze pollution

The digital economy fundamentally refers to the utilization of the internet and information communication technology to facilitate the modernization of both the economy and society. The digital economy has propelled the growth of digital industries, like information and communication, as well as the infiltration of digital technologies into traditional industries (Song et al., 2022), which have improved the networked, digital, and intelligent aspects of society (Guo B et al., 2022). Furthermore, while fostering high-quality economic growth, the digital economy has also exhibited a certain restrictive effect on haze pollution.

From the perspective of an enterprise, in alignment with the boundaryless organization theory, the furtherance of the digital economy facilitates rapid inter-enterprise exchange of information, resources, creativity, and energy. The acceleration of flow and production of diverse components allows enterprises to respond promptly to environmental variations, expedite the digitization of production, operation, and management processes in a more energy-efficient manner, ultimately saving energy consumption related to temporal and spatial factors (Zhu et al., 2022). This is beneficial for significantly enhancing energy efficiency and helping to curb haze pollution (Ashkenas et al., 2002). Furthermore, the digital economy has propelled the application of cutting-edge digital technologies in energy companies (Chen and Xu, 2023). Energy enterprises have the capability to implement real-time collection of production data, as well as scheduling and distribution of energy. This functionality serves to alleviate the challenges associated with regulating conventional energy peak demand. Moreover, it promotes the advancement of new energy sources, optimizes energy operations, and contributes to a substantial increase in energy efficiency while simultaneously reducing reliance on traditional fossil fuels (Hao et al., 2022). Therefore, these advancements lead to energy savings and further mitigation of haze pollution.

From the perspective of local residents, technological advancements involving big data and "Internet+" e-commerce platforms, resulting from the growth of the digital economy, have significantly influenced their daily lives. These advancements have not only significantly transformed their lifestyles, but also served as catalysts for adopting more environmentally-friendly sustainable practices (Wu et al., 2023; Yin et al., 2019). The advancement of internet technology has propelled the ongoing growth of e-commerce and smart logistics (Yang and Jia, 2022), rendering online shopping, e-learning, virtual tourism, and web conferencing more accessible and trendy. To a certain extent, it has decreased energy consumption and pollutant emissions. Furthermore, as Internet technology continues to mature and Internet platforms grow stronger, employees have the flexibility to work remotely from their homes. This not only helps to save energy consumption in office spaces but also contributes to a reduction in energy consumption generated by commuting, thereby alleviating haze pollution (Wang and Li, 2022). In addition, digital economy-based shared mobility and intelligent transportation systems also contribute to reducing haze pollution. By utilizing the Internet, these systems can help lower vehicle energy consumption, enhance the quality of public transportation services, and significantly improve vehicle utilization and sharing rates (Yi et al., 2022). Simultaneously, the real-time sharing of traffic information can reduce energy consumption caused by traffic congestion, thereby helping to alleviate haze pollution.

From the perspective of government regulation, the digital economy has enhanced the oversight capabilities of environmental regulatory authorities (Wu et al., 2023) and has prompted the development of new strategies for haze pollution management. Digital economy enable the dynamic and automatic collection of data at every stage of the energy sector, allowing for synchronized analysis. This facilitates the government's understanding of trends and price fluctuations in the energy market (Bhattacharya et al., 2015). By implementing measures such as pricing mechanism and subsidy programs, the government effectively regulate energy consumption and reduce the release of various air pollutants (Miao et al., 2022), thereby curbing haze pollution. Additionally, the digital economy can leverage information technology for real-time monitoring of a wide range of pollutants, tracing their sources, and establishing collaborative prevention and control measures. This strengthens the supervision and regulation of enterprises' daily production and operations throughout the entire process and timeframe. Consequently, it reduces the occurrence of companies concealing pollution data to evade penalties and compels them to engage in clean production activities, effectively curbing haze pollution (Sun et al., 2022). Buiding upon the aforementioned analysis, the current study posits the hypothesis below:

H1: The digital economy can substantially suppress haze pollution.

2.2 Digital economy, financial growth and haze pollution

Within the digital economy, businesses are able to leverage digital information to rapidly match the supply and demand of funds, thus enhancing the efficiency of the financial supply-demand matching (Shi and Sun, 2022), accelerating the flow of funds, reducing transaction time and costs, and thus benefiting financial development (Dong et al., 2022). Additionally, the digital economy also utilizes artificial intelligence and big data to eliminate the ethical hazards and adverse selection issues inherent in conventional financial systems, enhancing the allocation of financial resources and accelerating financial development. Following the reform and amelioration of the financial sector, financial development has emerged as a crucial component in the governance of regional environmental pollution. Financial activities, particularly the development of green finance, facilitates the effective transfer of social resources between various sectors of society. It plays a critical part in directing resources from high-pollution, high-energy consumption industries to the environmental protection sector, thereby becoming an important factor in restraining environmental pollution (Nasir et al., 2019; Ren and Zhu, 2017). Digital platforms are vital in assisting financial institutions to identify companies and allocate financial resources towards enterprises actively engaged in green research and development. These platforms aid in excluding enterprises that have excessive energy use and pollution, encouraging the adoption of clean energy sources, decreasing reliance on coal, and enhancing energy and industrial structures, ultimately contributing to the mitigation of haze pollution (Teng and Ma, 2020; Zhu and Jing, 2020). Meanwhile, financial development, especially in digital finance, has broadened the coverage of financial services. By lowering the threshold required for enterprises to access financing from traditional financial institutions and markets, a large number of customers previously excluded by traditional finance are now integrated into the financial services system (Liu et al., 2021). This inclusion facilitates enterprises in pursuing research and development investments to enhance production processes, thus assisting in the reduction of haze pollution through the adoption of energy-saving technological advancements (Wan et al., 2023; Wu et al., 2022) Based on the aforementioned information, a hypothesis can be established:

H2: The digital economy can help mitigate haze pollution by promoting financial development.

2.3 Digital economy, technological innovation and haze pollution

The digital economy serves a pivotal part in boosting technological innovation, particularly in the realm of green technology (Hu, 2023). Specifically, it expands market boundaries, stimulates the generation of novel ideas, fosters the growth of emerging industries, services, and business strategies, and accelerates the dissemination for fresh and explicit knowledge to drive the rapid progress of technological innovation. In addition, traditional economic forms have been ineffective in organizing individuals' scattered "tacit knowledge". However, digital economy offers an effective avenue for the dissemination of this fragmented "tacit knowledge", allowing more individuals to develop new "tacit knowledge" and engage in technological innovation (Wu et al., 2022). Alternatively, technological innovation can boost productivity and resource employment efficiency, lessening the input of production factors and mitigating the negative environmental impacts of production (Lv et al., 2022). Simultaneously, technological innovation can meliorate the processing efficiency of contaminants through bolstering end-of-pipe procedures. Overall, digital economy improves supply chain efficiency, optimize resource allocation, incentivize enterprises to allocate more resource for autonomous research and development, accelerate the transformation of the industrial chain towards a low-carbon and environmentally friendly green chain, and thereby promote technological innovation while indirectly curbing haze pollution (Wang et al., 2022; Yu et al., 2021). Given the aforementioned reasons, this paper posits the ensuing research hypothesis:

H3: The digital economy can efficiently curb haze pollution through the facilitation of technological innovation.

3 Research design

3.1 Model setting

In February 2016, the National Development and Reform Commission, the Ministry of Industry and Information Technology, and the Cyberspace Administration of China jointly issued an approval letter for the establishment of a big data pilot zone in Guizhou Province. Subsequently, in October of the same year, approval was granted to initiate a second round of big data pilot zones. The primary objective of setting up these big data pilot zones is to expedite the implementation of the national big data strategy, enhance coordination among regional big data infrastructures, and promote the concentrated development of digital industrialization and industrial digitalization, thereby allowing for an objective assessment of the digital economy. In addition, the establishment of big data experimental zones serves as a "natural experiment" in the field of economics, which can alleviate potential endogeneity issues and accurately identify the net effect of the digital economy on haze pollution. Therefore, the study views the foundation of the big data experimental zones as a quasi-natural experiment that can be utilized to validate the effectiveness of the data-driven digital economy in mitigating urban haze pollution in China. Drawing on the research by Qiu and Zhou (2021) and Guo Y et al. (2022), and considering that Guizhou Province officially launched the construction of its big data pilot zone in September 2015, a multi period DID model can be constructed to assess the net impact of the digital economy on haze pollution. The specific baseline regression model is described below:

$$\mathrm{Ln\,PM2.5}_{it} = \beta_0 + \beta_1 \mathrm{DIG}_{it} + \gamma Z_{it} + \eta_i + \delta_t + \varepsilon_{it} \tag{1}$$

In this model, the subscript "i" denotes various cities, while the subscript "t" specifies the corresponding years. The variable $\mathrm{LnPM2.5}_{it}$ represents the magnitude of haze pollution in city i during year t. DIG_{it} represents a virtual variable signifying whether city i has established a big data pilot zone in year t. The variable Z_{it} signifies a collection of control variables influencing urban haze pollution and change with city i and time t. The variables η_i and δ_t indicate city fixed effects and year fixed effects, respectively. The symbol ε_{it} represents the residual term. The estimated coefficient β_1 represents the policy impact of the big data pilot zone on haze pollution. If β_1 is substantially negative, it implies that the digital economy has a substantial suppressive effect on haze pollution.

Building upon the baseline regression, we adopt the mediation effect testing method proposed by Wen and Liu (2020) to explore the influence of the digital economy on haze pollution across the pathways of financial development and technological innovation. The following test equation is constructed:

$$M_{it} = \alpha_0 + \alpha_1 \mathrm{DIG}_{it} + \gamma Z_{it} + \eta_i + \delta_t + \varepsilon_{it} \tag{2}$$

$$\mathrm{Ln\,PM2.5}_{it} = \varphi_0 + \varphi_1 \mathrm{DIG}_{it} + \varphi_2 M_{it} + \gamma Z_{it} + \eta_i + \delta_t + \varepsilon_{it} \tag{3}$$

The mediating variable, denoted as M, comprises financial development LnFIN and technological innovation LnPAT. The remaining variables are explained as previously mentioned. If both coefficients α_1 and φ_2 are significantly different from zero, this implies that the validation of a mediation effect. If either α_1 or φ_2 is not significant, a Bootstrap test is conducted to ascertain whether the equation $\alpha_1 \times \varphi_2 = 0$ holds true. If $\alpha_1 \times \varphi_2$ is significantly not equal to zero, the mediation effect is established. Otherwise, the mediation effect is not supported.

3.2 Variable setting

3.2.1 Explained variable

The explained variable in this study is haze pollution (LnPM2.5). Common indicators used to measure haze pollution include SO_2, CO_2, CO, TSP, API, PM2.5, or PM10. However, in the real scenario, PM2.5, owing to its smaller diameter compared to PM10 and other pollutants, is less likely to settle and is easier to observe using remote sensing techniques (Song and Bian, 2019). It is also widely recognized as a major contributor to haze pollution. Therefore, this study selects PM2.5 as the measurement indicator for haze pollution. Given the limited availability of comprehensive data on PM2.5 concentrations in all prefecture-level cities in China and the fact that the existing data only starts from 2012, it does not meet the research requirements. Following the approach of Chen and Chen (2018), this study utilized grid data on annual average PM2.5 concentration in China from 2011 to 2020, as supplied by the Atmospheric Composition Analysis Group at Washington University in St. Louis. The data source can be accessed at the following link: https://sites.wustl.edu/acag/datasets/surface-pm2-5/#V5.GL.04. The data were then processed using ArcGIS software to derive the annual average PM2.5 concentrations at the surface level for 280 prefectural cities in China from 2011 to 2020.

3.2.2 Core explanatory variable

The core explanatory variable in this research is identified as the big data pilot zone (DIG), where $\mathrm{DIG}_{it} = \mathrm{treat}_i \times \mathrm{period}_{it}$. In this equation, treat_i stands for a virtual variable for the experimental group, and period_{it} represents a virtual variable indicating the establishment time of the big data pilot zone. If a city is founded as a big data experimental zone, the variable treat_i is set to a value of 1; otherwise, it is set to 0. Given the actual construction progress of the big data pilot zone, this paper assigns the policy time point for Guizhou Province to 2015 and for other pilot provinces to 2016. Consequently, the time dummy variable period_{it} for cities in Guizhou Province is set to 1 for the year 2015 and subsequent years, while the same variable for cities in other pilot provinces is set to 1 starting in 2016 and thereafter. For all remaining cities, period_{it} is assigned a value of 0.

3.2.3 Control variables

The pollution of urban haze is also influenced by various other factors. To address the potential bias arising from omitted variables in empirical studies and drawing from prior research, the following control variables are selected: (1) economic development (LnGDP),

TABLE 1 Definition of related variables.

Types of variables	Variable name	Variable symbol	Variable description
Explained variable	Haze pollution	LnPM2.5	The average concentration of PM2.5
Explanatory variable	Digital economy	DIG	Big data pilot zone
Control variable	Economic development	LnGDP	The *per capita* GDP of a city
	Population density	LnPOP	The ratio of total urban population to the administrative area
	Industrial structure	LnIND	The ratio of value added from the tertiary industry to that of the secondary industry
	Government support	LnGOV	The ratio of government public fiscal expenditure to GDP
	Urbanization	LnURB	The ratio of urban population to total population
	Openness to international trade	LnTRD	The city's total imports and exports of goods
Mediator variable	Financial development	LnFIN	The year-end balance of RMB loans from financial institutions
	Technological innovation	LnPAT	The total number of patent applications

assessed by the ratio of *per capita* GDP to total population in cities; (2) population density (LnPOP), calculated by dividing the entire urban population by the administrative area; (3) Industrial structure (LnIND), quantified by the ratio of value added from the tertiary industry to the secondary industry; (4) Government support (LnGOV), assessed by the proportion of government public fiscal expenditure to GDP; (5) Urbanization (LnURB), gauged by the ratio of urban population to the total population; and (6) Openness to international trade (LnTRD), measured by the overall value of goods imported and exported by the city, converted into Chinese Yuan based on the annual average exchange rate.

3.2.4 Mediator variables

According to the action mechanism theory, the study incorporates two mediating variables: financial development (LnFIN) and technological innovation (LnPAT). Financial development is measured by analysing the year-end balance of various RMB loans extended to financial institutions within the city, while technological innovation is determined by the total number of patent applications in the city.

The definitions of the aforementioned variables are illustrated in Table 1.

3.3 Data sources and processing

Considering the availability of data, the research sample utilized in this study consisted of panel data encompassing 280 prefecture-level cities, covering the period from 2011 to 2020. The data employed in this study mainly originated from various sources, including the annual "China City Statistics Yearbook," provincial statistical yearbooks, certain cities' National Economic and Social Development Statistical Bulletins. Missing data were treated with linear interpolation to supplement and complete the data. To address data dispersion and minimize the detrimental effects of heteroscedasticity on equation assessment, a logarithmic transformation was implemented for all variables except the core explanatory variables. On one hand, the Box-Cox test is utilized to evaluate the appropriateness of applying a logarithmic transformation to the dependent variable. In this test, the parameter θ has specific interpretations: a value of 1 indicates that no transformation is applied; a value of 0 signifies that a logarithmic transformation is used; and a value of −1 implies that a reciprocal transformation is applied to the dependent variable. The Box-Cox test rejects both $\theta = -1$ and $\theta = 1$ while failing to reject $\theta = 0$, thus supporting the validity of taking a logarithmic transformation to the dependent variable. On the other hand, the choice between a logarithmic and a linear form for the right-hand side variables in the model primarily depends on the goodness of fit, favoring the model that exhibits a higher adj. R^2. The regression results reveal that when the right-hand side variables are not transformed logarithmically, the adj. R^2 is 0.9411. Conversely, when a logarithmic transformation is applied, the adjusted R^2 rises to 0.9466. This suggests that employing the logarithmic transformation for the right-hand side variables (excluding DIG) is more appropriate.

4 Empirical test

4.1 Descriptive statistics

Following the defined variable settings mentioned above, the experimental group comprised 57 prefecture-level cities in China that established big data testing zones in 2016, while the control group was composed of the remaining prefecture-level cities in the research sample. Table 2 displays descriptive statistics for both the explanatory and control variables. In the entire research sample, consisting of 2,800 observations, there are 570 observations within the experimental group and 2,230 observations within the control group. Due to the substantial variations in city characteristics between the two study samples, it is imperative to incorporate control variables in the regression model to control these discrepancies.

4.2 Parallel trend test and dynamic effects analysis

The primary requirement for applying the DID model is to meet the parallel trends assumption, which stipulates that the trends of

TABLE 2 Descriptive statistics for the grouping of explained and control variables.

Variable	Experimental group			Control group			Comparison of mean difference
	N	Mean	SD	N	Mean	SD	
LnPM2.5	570	3.7461	0.4084	2,230	3.6045	0.3131	−0.1416***
LnGDP	570	10.8290	0.5508	2,230	10.6986	0.5319	−0.1304***
LnPOP	570	5.9910	1.1267	2,230	5.7112	0.8371	−0.2798***
LnIND	570	−.0565	0.4972	2,230	−.0805	0.4730	−0.0240
LnGOV	570	2.8368	0.3791	2,230	2.9252	0.4396	0.0884***
LnURB	570	4.0159	0.3247	2,230	3.9598	0.2590	−0.0561***
LnTRD	570	14.4768	2.3375	2,230	13.8275	2.0417	−0.6493***

Note: *** represent significance at the 1% level.

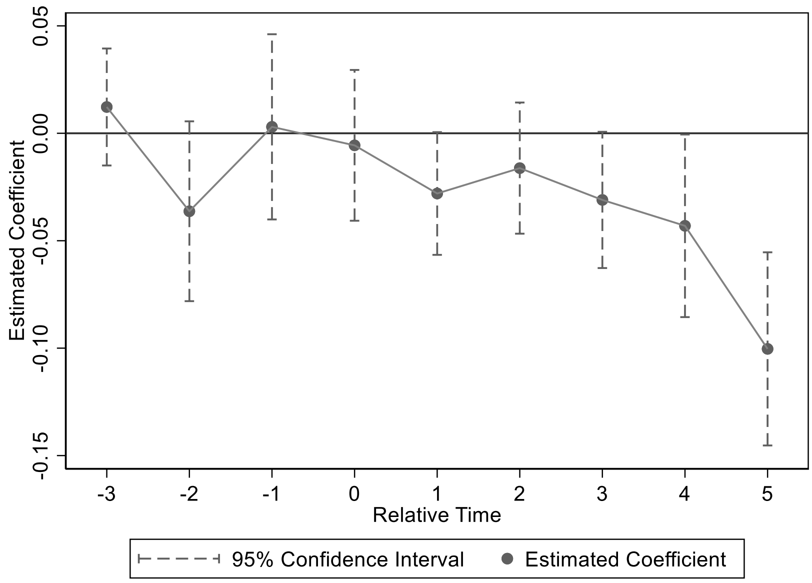

FIGURE 1
Parallel trend and dynamic effect.

the explanatory variables for both the experimental and control groups should be consistent before policy implementation Deng and Zhang (2017). To investigate parallel trends and analyze dynamic effects, we adopt the event study approach recommended by Jacobson et al. (1993) and Lyu et al. (2019). Here is the explicit model setting:

$$LnPM2.5_{it} = \beta_0 + \sum_{k=-3}^{5} \theta_k treat_i \times year_k + \gamma Z_{it} + \eta_i + \delta_t + \varepsilon_{it} \quad (4)$$

In this model, the variable $year_k$ serves as a virtual variable representing the year, where k is relative time of the big data pilot zone establishment. The symbol θ_k represents the estimated coefficient for the interaction term in the big data pilot area, while the definitions of the remaining variables remain coherent with those previously stated. Model (4) decomposes the interaction term DIG in model (1) into the interaction between the experimental group virtual variable "treat" and "year" for each year within the study period. The coefficient θ_k captures the differential effects between the treatment and control groups in the big data pilot area compared to the base period. The coefficients θ_{-1} to θ_{-3} indicate the effects from period 1 to period 3 prior to policy implementation, θ_0 represents the effect in the current period of policy implementation, while θ_1 to θ_5 represent the effects from period 1 to period 5 following policy implementation. According to Equation 4, the parallel trend test, as depicted in Figure 1, was conducted using regression analysis. The test uses the year 2011, which represents the period prior to the establishment of the big data experimental zone, as the base period. From Figure 1, it can be observed that none of the evaluated coefficients of the interaction terms θ_k before 2015 are statistically significant, revealing that prior to the foundation of the big data pilot zone, the experimental and control groups exhibited consistent trends in the explained variable, without significant differences. Building upon the findings of the

TABLE 3 Stationarity test.

Variables	ADF	P-value	Is it stable
LnPM2.5	1,698.9688	0	YES
LnGDP	1,062.1089	0	YES
LnPOP	1,099.6317	0	YES
LnIND	1,224.2821	0	YES
LnGOV	1,163.3743	0	YES
LnURB	1,040.6075	0	YES
LnTRD	1,362.4680	0	YES

parallel trend test, it can be inferred that the research sample has met the necessary requirement for the DID model. This outcome allows for the opportunity to conduct further regression analysis. Furthermore, the significance test revealed that the impact of haze pollution in the year of the establishment of the big data experimental zone, as well as in the subsequent 3 years, did not reach statistical significance. This suggests that the suppressive effect of the big data pilot zone on haze pollution may be delayed or have a time lag. The estimated coefficient stabilized after 2018, suggesting that the inhibition of haze pollution should have dynamic sustainability.

4.3 Baseline regression

Before conducting regression analysis, it is essential to test the stability of the sample data to avoid spurious regression. Table 3 displays the results of the ADF Fisher PP test for the variables. All variables, except for the policy dummy variable DIG, are significant at the 1% level, which indicates the data is stationary. Furthermore, this study utilizes Hausman test to determine whether a fixed effects model or a random effects model is more appropriate. The test results reveal that the Sargan-Hansen statistic is 174.602, with a corresponding P-value less than 0.01. This allows for the rejection of the null hypothesis in favor of the random effects model at the 1% significance level. Therefore, this study opts for the fixed effects model for the regression analysis.

Based to Equation 1, the regression results provided in columns (1) to (7) of Table 4 showcase the assessment of the influence of the digital economy on urban haze pollution using the DID model. These columns consist of two cases: one case excludes control variables, while the other employs a stepwise approach to gradually incorporate control variables. To eliminate individual and time variations, the DID model incorporates fixed effects for cities and years. Moreover, cluster-robust standard errors are employed to account for potential autocorrelation in the panel data during the estimation of standard errors. In column (1), which presents the estimation results without control variables, the coefficient for the digital economy (DIG) is −0.0242. This coefficient is statistically significant at the 5% level, which implies that the decrease in haze pollution in the pilot cities is higher compared to non-pilot cities. To ensure the robustness of the findings, control variables including economic development level (LnGDP), population density (LnPOP), industrial structure (LnIND), government support (LnGOV), urbanization (LnURB), and Openness to international trade (LnTRD) are gradually added in columns (2) to (7). The DIG coefficient remains stable with minimal variation and continues to be significantly negative.

TABLE 4 Baseline regression results on the influence of digital economy on haze pollution.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
DIG	−0.0242** (0.0118)	−0.0283*** (0.0099)	−0.0193** (0.0096)	−0.0189* (0.0097)	−0.0191** (0.0096)	−0.0211** (0.0094)	−0.0210** (0.0094)	−0.0198** (0.0090)
LnGDP		−0.1448*** (0.0172)	−0.1301*** (0.0174)	−0.1463*** (0.0188)	−0.1884*** (0.0274)	−0.1961*** (0.0270)	−0.1942*** (0.0279)	−0.1930*** (0.0274)
LnPOP			−0.2852*** (0.0566)	−0.3077*** (0.0553)	−0.3207*** (0.0556)	−0.3198*** (0.0561)	−0.3187*** (0.0556)	−0.3563*** (0.0608)
LnIND				−0.0343*** (0.0123)	−0.0323*** (0.0120)	−0.0341*** (0.0120)	−0.0344*** (0.0120)	−0.0357*** (0.0120)
LnGOV					−0.0691** (0.0327)	−0.0717** (0.0326)	−0.0717** (0.0324)	−0.0750** (0.0329)
LnURB						0.0550 (0.0352)	0.0563 (0.0348)	0.0579* (0.0342)
LnTRD							−0.0030 (0.0052)	−0.0030 (0.0049)
Constant	3.6358*** (0.0012)	5.1890*** (0.1845)	6.6756*** (0.3368)	6.9764*** (0.3456)	7.7047*** (0.4507)	7.5702*** (0.4722)	7.5811*** (0.4696)	7.7893*** (0.4893)
N	2,800	2,800	2,800	2,800	2,800	2,800	2,800	2,767
Adj. R^2	0.940	0.9428	0.9438	0.9441	0.9445	0.9446	0.9446	0.9466

Note: *** indicates statistical significance at the 0.01 level, ** at the 0.05 level, and * at the 0.1 level. Robust standard errors are provided in parentheses. Subsequent tables are the same as this one.

Additionally, the DID model may encounter issues of sample selection bias, leading to biased estimation results. To enhance the comparability between the treatment group and the control group, we utilized propensity score matching (PSM), inspired by the research ideas of Chen et al. (2024). This approach aimed to eliminate sample selection bias, followed by regression analysis using a multi period DID model (Zhang et al., 2022b). In this analysis, control variables were treated as covariates, and the sample data underwent caliper matching with a 1:2 ratio through PSM. After the matching process, the bias rates for all covariates were reduced to within 10%, demonstrating a robust matching effect. Column (8) reports the regression results of the PSM-DID model, showing that the estimated coefficient for DIG closely aligns with the findings in column (7), and its significance remains unchanged. Moreover, the application of the PSM method can lead to a reduced sample size, potentially resulting in unbalanced panel data, which may complicate further analyses. Thus, the subsequent research utilizes a multi period DID model for the regression analysis. The above results demonstrate that the growth of the digital economy substantially suppresses urban haze pollution to some extent, thereby confirming research hypothesis H1.

The regression analysis results in column (7) for the control variables reveal the estimation coefficient for LnGDP is significantly negative, providing evidence that as the level of regional economic development rises, the public's environmental awareness strengthens. This finding aligns with the research conducted by Deng and Zhang (2022). This, in turn, leads to constraints on corporate pollution emissions through activities such as purchasing green products and reporting environmental pollution incidents. It also encourages government efforts in environmental pollution control, thereby aiding in the mitigation of urban haze pollution. Furthermore, the coefficient of estimation for LnPOP is substantially negative, aligning with the findings reported by Liang et al. (2017). This implies that increasing population density promotes the positive externality of population agglomeration effects, resulting in a decrease in urban haze pollution by means of cost-saving measures and technological spillovers (Deng and Zhang, 2022). The coefficient of estimation for LnIND is substantially negative, suggesting that the technological spillover effects resulting from the upgrading of industrial restructure can foster energy efficiency and drive industries towards intelligent and green development, ultimately contributing to the mitigation of haze pollution. The estimated coefficient of LnGOV is significantly negative, disclosing that government support plays a crucial role in mitigating haze pollution. One plausible explanation for this occurrence is that government support, under the constraint of environmental performance assessment targets, has a discernible effect in suppressing haze pollution. The coefficient of estimation for LnURB is positive, but it does not reach statistical significance, which suggests that increasing level of urbanization is linked to aggravated haze pollution. However, whether urbanization development can effectively mitigate haze pollution relies heavily on the quality of urbanization. The long-standing characteristic of urban industrial structure, which is predominantly composed of secondary and heavy industries, remains challenging to completely transform completely in the short term (Deng and Zhang, 2022). The coefficient of estimation for LnTRD is negative, yet it is also not statistically significant, which may be attributed to the possibility that increasing foreign trade leads to an economic "lock-in effect", where urban economies remain stagnant in a cycle of processing imported materials and exporting labor-intensive products (Zha et al., 2022). Consequently, the slow progress in upgrading the industrial structure inadequately alleviate urban haze pollution.

Linear regression predicts the mean of the dependent variable given the independent variables. However, since the mean cannot capture the properties of the entire distribution, modeling the mean fails to adequately reflect the nonlinear relationships between the independent and dependent variables. Furthermore, it cannot account for how the influence of the independent variables on the dependent variable varies across the overall distribution of the dependent variable (Lee et al., 2023). Building on the preceding analysis, this study further utilizes a panel quantile regression model to investigate the nonlinear effects of the digital economy on haze pollution. Table 5 presents the estimated results for various quantiles within the distribution of haze pollution. The estimated coefficients for DIG are significantly negative across the 30th to 90th quantiles of LnPM2.5, with their absolute values increasing as the LnPM2.5 quantiles rise. This suggests that in regions with more severe haze pollution, the digital economy has a stronger effect on mitigating haze pollution.

4.4 Robustness test

4.4.1 Other matching methods

The results of the PSM-DID model estimation have been reported in the baseline regression. However, variations in estimated results may arise from the use of different matching methods. To verify the robustness of the baseline regression findings, we employ various matching methods for re-examination. Given that PSM is ideal for cross-sectional data and DID is more suitable for panel data, we follow the methodology introduced by of Bai J et al. (2022), sequentially utilizing cross-sectional matching and period-by-period matching to conduct propensity score matching before estimating the DID model. The cross-sectional matching method involves considering panel data as cross-sectional data and directly matches the experimental cities with the optimum control group that meets the shared sustainability requirements, thereby creating a new dataset. Alternatively, the technique of period-by-period matching matches the original sample for each period and subsequently combines the matched data vertically to generate a new panel dataset. Under the aforementioned two matching methods, six new datasets are obtained by using radius caliper matching, kernel matching, and Mahalanobis distance matching. Using these datasets, the DID model is estimated, and the PSM-DID regression results from column (1) to column (6) in Table 6 are obtained. The findings manifest that the DIG estimation coefficients under different matching methods remain significantly negative, with only minor differences compared to the baseline regression results. Thus, the core conclusions remain robust.

4.4.2 Placebo test

According to counterfactual ideas, two placebo tests were conducted. One approach entailed randomly assigning 57 cities as the pseudo-experimental group, corresponding to the 57 pilot

TABLE 5 The results of panel quantile regression.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Q10	Q20	Q30	Q40	Q50	Q60	Q70	Q80	Q90
DIG	−0.0161 (0.0146)	−0.0175 (0.0117)	−0.0188* (0.0097)	−0.0198** (0.0084)	−0.0210*** (0.0079)	−0.0221*** (0.0083)	−0.0234** (0.0098)	−0.0246** (0.0118)	−0.0261* (0.0148)
Control variables	YES	YES	YES	YES	YES	YES	YES	YES	YES
City FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
N	2,800	2,800	2,800	2,800	2,800	2,800	2,800	2,800	2,800

TABLE 6 PSM-DID robustness test results.

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	Cross-sectional matching			Period-by-period matching		
	Radius caliper matching	Kernel matching	Mahalanobis distance matching	Radius caliper matching	Kernel matching	Mahalanobis distance matching
DIG	−0.0198** (0.0090)	−0.0195** (0.0090)	−0.0287** (0.0116)	−0.0189** (0.0090)	−0.0216** (0.0091)	−0.0237** (0.0096)
Constant	7.7893*** (0.4893)	7.7908*** (0.4891)	8.0724*** (0.8581)	7.3488*** (0.4817)	7.5704*** (0.4833)	7.8714*** (0.5667)
Control variables	YES	YES	YES	YES	YES	YES
City FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
N	2,767	2,760	1,228	2,620	2,728	1,761
Adj.R^2	0.9466	0.9467	0.9551	0.9476	0.9468	0.9508

cities, while assigning the remaining cities as the control group. Subsequently, a regression analysis was performed to estimate the coefficient of DIG for the pseudo-treatment group. To improve the efficacy of the placebo test, the procedure was iterated 500 times, yielding 500 estimated coefficients of DIG for the pseudo-treatment group and their corresponding P-values.

This allowed for the illustration of Figure 2, which depicts the placebo test outcomes for the random pilot cities. From Figure 2, it can be observed that the estimated coefficients of DIG for the random pilot cities conform to a normal distribution, centered around zero. The majority of the pseudo-treated cities show non-significant DIG estimated coefficients. Additionally, the estimated coefficients for DIG in column (7) of Table 4 are positioned at the lower end of the distribution among the random pilot cities, indicating a rare occurrence. Moreover, the baseline regression model does not demonstrate significant issues related to omitted variables, and the core conclusions remain robust. The other approach is to randomly generate pilot cities and the corresponding time when these cities are established. To delve deeper into whether the outcomes of the baseline regression are influenced by imperceptible factors, we followed the approach of Lu et al. (2021) and randomly generated pilot cities along with their corresponding establishment times. Through simulating the randomization process of pilot cities as in the second approach, we acquired the placebo test results depicted in Figure 3, mirroring those in Figure 2. This suggests that the baseline regression model is unaffected by unobservable factors, and the core conclusions remain robust.

4.4.3 Addressing endogeneity concerns

To address potential endogeneity concerns, this study employs instrumental variable method for analysis. Drawing on the existing literature, urban topographical relief is selected as the instrumental variable. Cities with more pronounced relief encounter elevated costs and increased challenges in broadband deployment and 5G base station construction, leading to weaker network signals and diminishing the likelihood of the city evolving into a prominent data experimental area.

However, topographical relief is a geographical condition not directly related to haze pollution, meeting the exogeneity requirement. Since topographical relief data is cross-sectional, estimating model parameters is complex due to fixed effects. Hence, the interaction term of topographical relief and year is utilized as the instrumental variable for the big data experimental

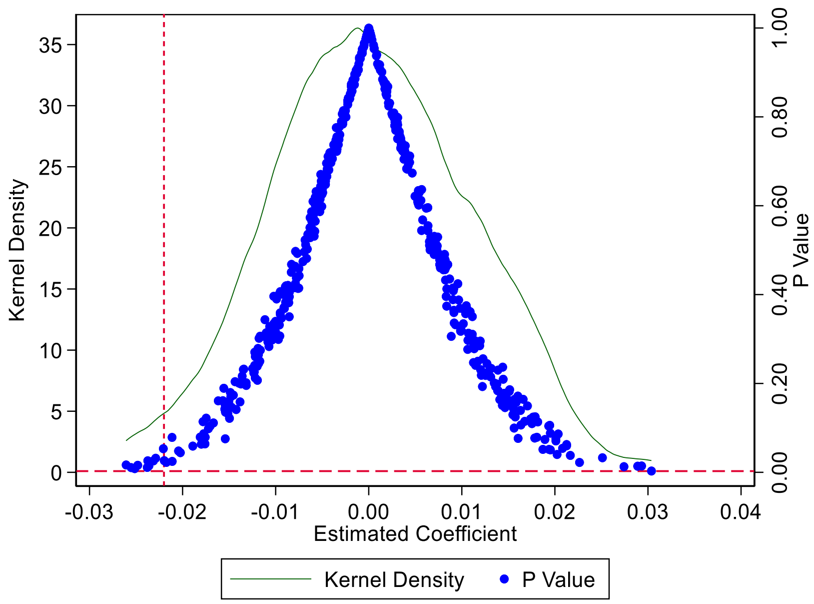

FIGURE 2
Placebo test chart for random pilot city.

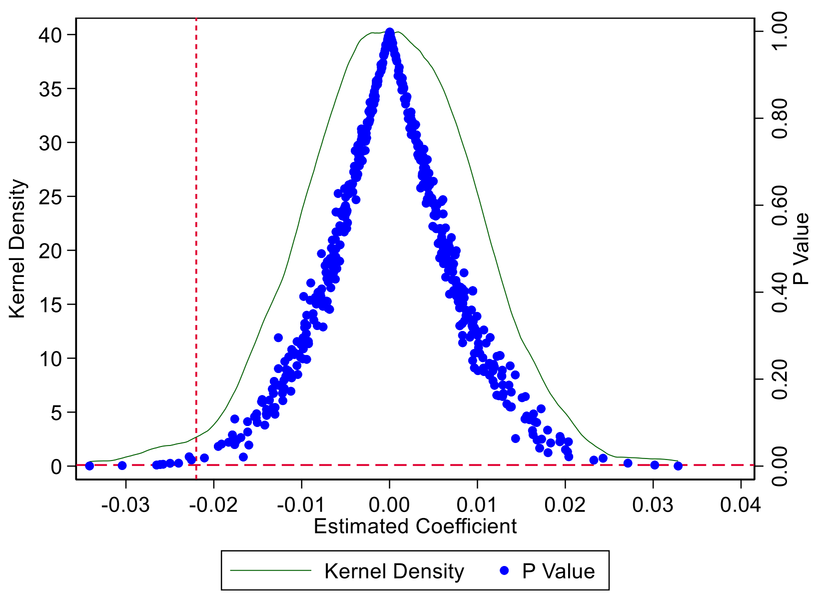

FIGURE 3
Placebo test chart for random pilot city and random pilot time.

area or digital economy. Estimation is carried out using 2SLS, with regression outcomes detailed in Table 7.

The F statistic for the first-stage regression is 17.98, which exceeds 10, suggesting a vigorous correlation between the selected instrumental variables and the endogenous variables, excluding the weak instrumental variables problem. In the second-stage regression, the estimated coefficient for DIG is −0.2453, significant at the 5% level.

Furthermore, the P-value of the Kleibergen-Paap rk LM statistic is 0.001, indicating no issue of weak instrument identification. The Kleibergen-Paap rk Wald F statistic is 13.2210, exceeding the threshold value of 8.96 at the 15% significance level, further confirming the vacancy of weak instrumental variables. Based on these results, after considering endogeneity issues, it is evident that the digital economy still exhibit a significant inhibitory effect on haze pollution. Additionally, the inhibitory effect is stronger compared to the benchmark regression, suggesting that neglecting endogeneity issues may underestimate the inhibitory effect of digital economy on haze pollution.

TABLE 7 Endogeneity estimation results.

Variables	(1)	(2)
	First-stage	Second-stage
IV	−0.0070*** (0.0019)	
DIG		−0.2453** (0.1159)
Constant	4.6417* (2.6696)	6.1411*** (0.5740)
Control variables	YES	YES
City FE	YES	YES
Year FE	YES	YES
Kleibergen-Paap rk LM statistic		14.7060 [0.0001]
Kleibergen-Paap rk Wald F statistic		13.2210 {8.96}
N	2,800	2,800
Adj.R^2	0.5350	0.9230

Note: The P-value for the Kleibergen-Paap rk LM, statistic is shown in square brackets, and the 15% critical value for the Stock-Yogo weak identification test is shown in curly brackets for the Kleibergen-Paap rk Wald F statistic.

4.4.4 Testing for heterogeneous treatment effects

Recent research has identified that the estimation coefficients derived from two-way fixed effects in multi period DID demonstrate heterogeneous treatment effects. When treatment effects exhibit heterogeneity, even if the parallel trend assumption is met, the estimated results of the treatment effects may still be biased. In recent years, several estimation methods have been developed to address heterogeneous treatment effects. This paper builds on the research of de Chaisemartin and D'Haultfoeuille (de Chaisemartin and D'Haultfœuille, 2020) by designating individuals whose policy treatment status changes before and after the implementation of the policy as the treatment group, while those whose treatment status remains unchanged are classified as the control group. By comparing the actual outcomes of the treatment group after receiving the treatment with their counterfactual outcomes, we can derive the treatment effect. Following a weighting average, this analysis yields an unbiased estimate of the policy switching effect (Xu and Sun, 2023). Utilizing the methods of de Chaisemartin and D'Haultfoeuille, the average treatment effect of the policy switch in the big data experimental zone is estimated to be −0.0291, which is statistically significant. Figure 4 illustrates the dynamic treatment effects of the big data experimental zone policy across three periods preceding the pilot phase, the current period, and the five subsequent periods. It is observed that the DIG estimated coefficients are not significant prior to the implementation of the policy; however, the effects of the policy gradually emerge following its enactment. These findings are consistent with the magnitude of the estimated coefficients obtained in the baseline regression. Moreover, the dynamic effect graph of the estimated coefficients largely aligns with the previously presented parallel trend graph, indicating the robustness of the conclusions derived from the baseline regression.

4.4.5 Excluding the impacts of interference principles

Other principles associated with the digital economy during the observed period may have additionally influenced the haze pollution in the pilot cities, thereby causing interference in the identification of the haze pollution reduction effect in the big data experimental zones. In addition to the big data pilot zones, the Smart City established between 2012 and 2014, and the Broadband China program executed in China between 2014 and 2016 is intricately connected to the research. According to the methodology of Zhi and Lu (2023), we simultaneously incorporate Smart City and Broadband China experimental principles in the baseline regression model and re-estimate the model parameters, as demonstrated in the column (1) of Table 8. The coefficient of estimation for DIG remains substantially negative at the 5% level, while the estimated coefficients for the experimental principles of Smart City and Broadband China are non-significant. This finding suggests that the implementation of Smart City and Broadband China pilot principles did not effectively reduce the impact on haze pollution during the sample period.

4.4.6 Other robustness tests

This study categorizes other robustness tests into four aspects. Firstly, we incorporate interaction terms between provincial fixed effects and year fixed effects into the baseline regression to control for the potential impact of imperceptible factors at the provincial level that may vary over time and affect haze pollution. After accounting for the potential impact of imperceptible elements at the provincial level that may fluctuate with time, the outcomes of estimation are presented in column (2) of Table 8. Secondly, we adjusted the study interval to mitigate the potential influence of data anomalies caused by the COVID-19 pandemic on our study findings. Specifically, we narrowed the study period to cover the years 2011–2019. The outcomes of estimation are exhibited in the column (3) of Table 8. Thirdly, to further eliminate the impact of outlier values of variables on the regression analysis, a two-tailed winsorization was performed on the main variables, by truncating them at the top and bottom 1% levels. The regression outcomes, after applying winsorization to variables, are presented in column (4) of Table 8. Fourthly, in light of the potential presence of weak pre-existing parallel trends, we employ the synthetic control

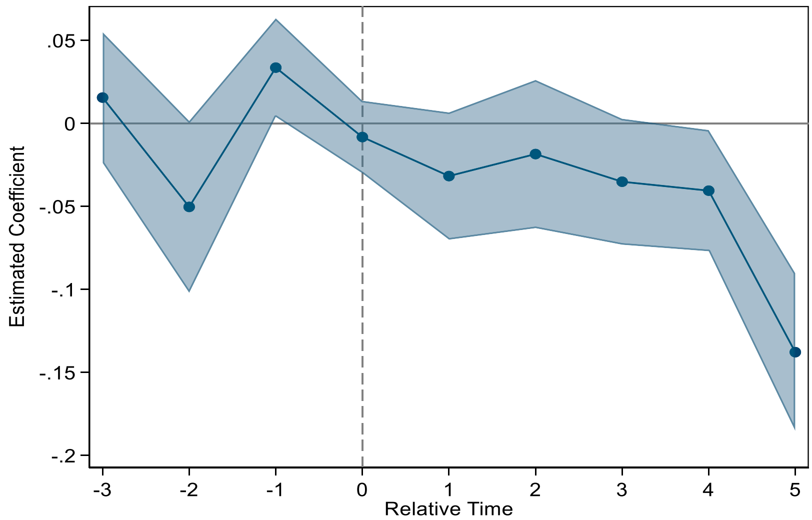

FIGURE 4
Dynamic effect graph of the estimated coefficients.

TABLE 8 Elimination of simultaneous interference policies and other robustness test results.

Variables	(1)	(2)	(3)	(4)	(5)
	Excluding interference policies	Controlling provincial time trends	Changing research period	Two-sided winsorization	SC-DID
DIG	−0.0204** (0.0094)	−0.0188* (0.0107)	−0.0174** (0.0086)	−0.0195** (0.0096)	−0.0232*** (0.0079)
Smart City	−0.0176 (0.0151)				
Broadband China	0.0019 (0.0094)				
Constant	7.5894*** (0.4715)	3.8277*** (0.4272)	7.1788*** (0.4748)	7.5051*** (0.4993)	
Control variables	YES	YES	YES	YES	YES
City FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
N	2,800	2,800	2,520	2,800	2,800
Adj. R^2	0.9446	0.9823	0.9440	0.9429	

difference-in-differences (SC-DID) model introduced by Arkhangelsky et al. (2021). This model incorporates individual and time weights to match the pre-trends of both the treatment and control groups while simultaneously accounting for both pre- and post-treatment periods. This approach mitigates the dependence on the parallel trends assumption. The estimation results from the SC-DID model can be found in column (5) of Table 8. Fifthly, we replaced the dependent variable. Considering that the causes of haze pollution and other pollutants share common origins, the digital economy should also have similar policy effects on the emissions of pollutants other than PM2.5. To further ensure the robustness of the baseline regression, Table 9 presents the regression results regarding the impact of the digital economy on various indicators: industrial sulfur dioxide (LnSO2), carbon dioxide (LnCO2), industrial smoke (LnSmoke), inhalable particulate matter PM10 (LnPM10), and the air quality index (AQI) (LnAQI). It is noteworthy that data for the air quality index (AQI) is relatively complete only after 2015; therefore, the regression results in column (5) of Table 9 are based on sample data from 2015 to 2020. The coefficient of estimation for DIG in the regression results still remains significantly negative, providing further evidence of the robustness of the baseline regression outcomes.

4.5 Heterogeneity analysis

The aforementioned baseline regression outcomes reveal that the digital economy substantially suppresses urban haze pollution.

TABLE 9 Replacing the dependent variable.

Variables	(1) LnSO2	(2) LnCO2	(3) LnSmoke	(4) LnPM10	(5) LnAQI
DIG	−0.3680*** (0.0929)	−0.0210** (0.0094)	−0.2851*** (0.1047)	−0.0267** (0.0114)	−0.0253* (0.0152)
Constant	10.2350*** (2.4872)	7.5811*** (0.4696)	10.4605*** (3.7083)	6.3274*** (0.4770)	3.1456*** (0.7920)
Control variables	YES	YES	YES	YES	YES
City FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
N	2,800	2,800	2,800	2,800	1,680
Adj. R^2	0.8700	0.9446	0.7970	0.9554	0.9219

TABLE 10 Outcomes for heterogeneity analysis.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	City size		Administrative level of city		City environmental protection type		Level of city economic development	
	Large	Medium-small	High-level	Low-level	Key	Non-key	Developed	Underdeveloped
DIG	−0.0298** (0.0128)	−0.0208 (0.0134)	−0.0586** (0.0259)	−0.0163* (0.0096)	−0.0203* (0.0107)	−0.0177 (0.0220)	−0.0286*** (0.0105)	−0.0160 (0.0150)
Constant	8.0699*** (0.8681)	7.4699*** (0.4989)	9.6205*** (1.8831)	7.7324*** (0.4632)	7.2753*** (0.7294)	7.8877*** (0.6236)	7.4843*** (0.5608)	8.2232*** (0.7994)
Control variables	YES	YES	YES	YES	YES	YES	YES	YES
City FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
N	1,310	1,490	350	2,450	1,660	1,140	1,318	1,482
Adj. R^2	0.7942	0.7821	0.7866	0.7921	0.9407	0.8975	0.7938	0.7856

However, the influence caused by the digital economy on haze pollution may differ according to city size, administrative level, environmental preservation type, and degree of economic growth.

4.5.1 City size

Indeed, city size may indeed influence the suppressive effect exerted by the digital economy on haze pollution. According to the median population size of the cities in our sample, we categorize cities with a population size above the median as large cities, and those below the median as medium-small cities. Separate econometric regressions were conducted for each category, and the outcomes are demonstrated in columns (1) and (2) of Table 10. According to the regression outcomes, the estimated coefficient for DIG in large cities is substantially negative. However, in small and medium-sized cities, the coefficient is negative but not statistically significant. This implies that the suppressive effect of the digital economy on haze pollution is more pronounced in large cities when compared to small and medium-sized cities. These findings can be attributed to the actuality that larger cities possess inherent advantages in view of technological innovation, institutional environment, and technical support (Wang et al., 2023a), which facilitate greater economies of scale and agglomeration effects. The expeditious growth of the digital economy has consequently enabled larger cities to avail themselves of enhanced digital infrastructure and a heightened degree of networked and intelligent systems. This facilitates the exchange and distribution of diverse data and information within the urban environment, promoting continuous improvements in environmental governance, and ultimately suppressing haze pollution (Bai F et al., 2022).

4.5.2 Administrative level of city

The administrative level of a city reflects, to some degree, the level of advancement in the digital economy. Considering the considerable discrepancies in economic growth, industrial structure, and technological innovation among municipalities directly under the central government, provincial capitals, vice-provincial cities, and regular cities (Guo B et al., 2022), the strength of the influence exerted by the digital economy on haze pollution may differ in view of the city's administrative level. In this context, regular cities are categorized as low-level cities, whereas the other cities are categorized as high-level cities. The outcomes from the grouped regression analysis based on city administrative level are demonstrated in columns (3) and (4) of Table 10. The regression analysis reveals that the coefficient of estimation for DIG in high-level and low-level cities is significantly negative. However, the estimated coefficients for the digital economy in higher-level cities are more significant. Moreover, the absolute magnitude of the estimation coefficient for high-level cities is much greater than that for low-level cities. This indicates that the inhibitory impact exerted by the digital economy on haze pollution is likely to be stronger in high-level cities rather than low-level cities. One possible reason is that higher-level cities enjoy more favorable conditions and support, including preferential policies from the central government, the ability to integrate and aggregate data resources to boost the growth of big data experimental zones. Therefore, they are more conducive to the release of the suppressing effect exerted by the digital economy on haze pollution.

4.5.3 City environmental preservation type

In 2018, the Chinese government released the Three-Year Action Plan for Winning the Blue Sky Defense Battle. This action plan identified 168 primary environmental protection cities and developed a series of initiatives aimed at significantly reducing PM2.5 concentrations, decreasing the number of heavily polluted days, and improving the overall air quality within 3 years. In light of this action plan, the question arises: Can the digital economy efficiently decrease haze pollution in these primary environmental preservation cities? In light of the action plan, the research sample cities were classified into primary environmental preservation cities and non-primary environmental preservation cities. Columns (5) and (6) of Table 10 exhibit the outcomes of heterogeneity regression in light of the environmental preservation types of these cities. The results reveal that the estimation coefficient for DIG in primary environmental preservation cities is substantially negative, while in non-primary environmental preservation cities, although the estimation coefficient for DIG is negative, it is statistically non-significant. These findings demonstrate that the digital economy can significantly mitigate haze pollution in primary environmental preservation cities. However, its influence may not be statistically significant in non-primary environmental preservation cities. The possible explanation for these findings is that primary environmental preservation cities have intensified efforts in regional industrial layout adjustments, promoting industrial transformation and upgrading. Consequently, the synthesis of the digital economy with the growth of these new industries is higher, facilitating the release for the inhibiting effects on haze pollution caused by the digital economy.

4.5.4 Degree of city economic growth

Variations in the degree of urban economic growth can lead to varying effects exerted by the digital economy on haze pollution. For the purpose of this study, the sample cities were categorized into two groups: economically developed cities and underdeveloped cities. This categorization was in light of the median *per capita* gross domestic product of each city. Cities with a *per capita* GDP above the median were classified as economically developed cities, while those below the median were classified as underdeveloped cities. Separate regression analyses were performed for each category, and the corresponding outcomes are demonstrated in columns (7) and (8) of Table 10. The estimation coefficients for DIG in economically developed cities are substantially negative, implying that the digital economy significantly decreases haze pollution in these cities. However, the coefficients for underdeveloped cities, although negative, do not demonstrate statistical significance, suggesting that it is insignificant for the digital economy to decrease haze pollution in underdeveloped cities. One plausible explanation for these findings is that well-established digital infrastructure and advanced technological capabilities in economically developed cities enable them fully harness the inhibiting impacts of the digital economy on haze pollution. This is especially evident when these cities have ample access to abundant digital innovation talents and capital. On the other hand, underdeveloped cities have relatively limited digital infrastructure and a slower pace of industrial structure upgrading. They are more dependent on resource-intensive economic development and often bear the burden of high-energy-consuming and polluting industries transferred from economically developed regions. The combination of these multiple detrimental factors results in the failure of the digital economy to efficiently curb haze pollution in underdeveloped areas (Kong et al., 2022).

5 Test of action mechanism

To further explore the underlying reasons for the haze pollution mitigation effect achieved by the digital economy, an action effect model was employed to probe the mechanisms by which the digital economy influences haze pollution in cities, building upon the theoretical framework proposed earlier. Specifically, we explored two pathways: financial development and technological innovation.

The action mechanism of how the digital economy affects haze pollution through financial development was tested according to Equations 2, 3. The test outcomes were provided in columns (1) and (2) of Table 11. The estimation coefficient for DIG in column (1) is substantially positive at the 10% level, which implies that the digital economy has the potential to significantly enhance financial development. In the past few years, cutting-edge science and technologies like big data, artificial intelligence, and cloud computing have facilitated the expansion for financing channels for businesses, reduced financing costs, and greatly accelerated financial development. The coefficient estimate for LnFIN in column (2) is substantially negative at the 5% level, implying that a higher degree of financial growth has a positive fluence for decreasing haze pollution. Furthermore, the coefficient estimate for DIG in column (2) remains substantially negative at the 5% level and exhibits the consistent sign with the product term between the estimated coefficient for DIG in column (1) and LnFIN in column (2). These findings suggest a significant partial mediation effect of financial development between the digital economy and haze pollution. Given these findings, hypothesis H2 is validated, further bolstering the claim that the digital economy can effectively decrease haze pollution through the facilitation of financial development.

Similarly, Table 11 depicted the test results in columns (3) to (4), which examine the usage of technological innovation as mediating

TABLE 11 Test outcomes of action mechanism.

Variables	(1)	(2)	(3)	(4)	(5)
	LnFIN	LnPM2.5	LnPAT	LnPM2.5	LnPM2.5
DIG	0.0390* (0.0236)	−0.0197** (0.0095)	0.1239*** (0.0469)	−0.0169* (0.0098)	−0.0159** (0.0076)
LnFIN		−0.0344** (0.0173)			−0.0295*** (0.0107)
LnPAT				−0.0338*** (0.0078)	−0.0326*** (0.0055)
Constant	10.3386*** (1.1490)	7.9372*** (0.4858)	−7.6960*** (2.2582)	7.3213*** (0.4653)	7.6353*** (0.3354)
Controls variables	YES	YES	YES	YES	YES
City FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
N	2,800	2,800	2,800	2,800	2,800
Adj R^2	0.9836	0.9448	0.9670	0.9454	0.9456

variables to investigate the potential of technological innovation in acting as a mediation for the fluence of the digital economy on haze pollution. The estimation coefficients for DIG in columns (3) is substantially positive severally at the 1% level, reflecting that the digital economy has a beneficial influence on technological innovation. The estimation coefficients for LnPAT in column (4) is substantially negative at the 1% levels, reflecting that an increment in technological innovation is beneficial for suppressing haze pollution. Further analysis reveals that the estimation coefficient for DIG in column (4) is substantially negative at the 10% level, and it is consistent with the sign of the product term between the estimation coefficient of DIG in column (3) and LnPAT in column (4). These findings suggest a significant partial mediation effect of technological innovation. Therefore, hypothesis H3 is validated, supporting the claim that the digital economy can effectively repress haze pollution through boosting technological innovation.

Given that financial growth and technological innovation are not entirely independent, there may be a certain correlation between them. Therefore, conducting separate examinations for the mediation effects of these two variables may lead to the contamination of the mediating effect of the other variable. To enhance the precision of testing the net mediating effects of financial growth and technological innovation, financial growth and technological innovation are included in Equation 3 for estimation. The outcomes can be observed in columns (5) of Table 11. In column (5), both the estimation coefficients of LnFIN and LnPAT are substantially negative at the 1% level. Additionally, the DIG coefficient is also substantially negative at the 5% level. These outcomes imply that in the context of a multiple mediating effects model, the action mechanism by which the digital economy curb haze pollution via financial growth and technological innovation still holds true, further confirming research hypotheses H2 and H3.

6 Further research: analysis of spatial spillover effects

Existing studies have indicated that there are significant spatial correlation characteristics linking haze pollution and the digital economy driven by Internet development (Li and Wang, 2022; Zhao, 2021). Neglecting spatial factors may incur biased estimation results. Accordingly, the study further applies a spatial econometric model to inspect the impact of the digital economy on the spread of haze pollution within the spatial domain. Considering that the spatial correlation of haze pollution and digital economy development may result from either the variables themselves or the error term of the estimation outcomes, following Xu et al. (2022), we employ a difference-in-difference spatial Durbin model (DIDSDM) to test local and spatial spillover effects exerted by the digital economy on haze pollution. The DIDSDM is illustrated below:

$$\begin{aligned} \text{Ln PM2.5}_{it} = \beta_0 + \rho W \times \text{Ln PM2.5}_{it} + \beta_1 \text{DIG}_{it} + \gamma Z_{it} \\ + \theta_1 W \times \text{DIG}_{it} + \theta_2 W \times Z_{it} + \eta_i + \delta_t + \varepsilon_{it} \end{aligned} \tag{5}$$

In the above equation, W depicts the spatial weight matrix, comprising the neighbor weight matrix W_1, geographic distance weight matrix W_2, economic distance weight matrix W_3, and the nested weight matrix that combines geographic distance and economic distance, denoted as W_4. The symbol ρ denotes the spatial regression coefficient for the explanatory variable, haze pollution, while θ_1 and θ_2 respectively stands for the spatial regression coefficients for the DIG and the control variables. All remaining symbols adhere to the previously described notation.

In general, the presence of spatial correlation in the explained variable is a fundamental prerequisite for adopting a spatial econometric model. In view of this, we initially verify the existence of spatial correlation for haze pollution. The global Moran's I for haze pollution obtained using the W_1 neighbor weight matrix can be seen in Table 12. The data in Table 12 pinpoints a substantially spatial positive correlation in annual haze pollution. For a more in-depth exploration of the spatial correlation characteristics for haze pollution, scatter plots depicting the Moran's I for haze pollution in 2011 and 2020 were generated, as exhibited in Figures 5, 6. The scatter plots indicate that the majority of cities in China are concentrated in the 1st and 3rd quadrants, while just a minority are in the 2nd and 4th quadrants. This suggests the existence of spatial dependence and heterogeneity

TABLE 12 The global Moran's I for haze Pollution.

Year	Moran's I	E(I)	Sd(I)	Z	P-value
2011	0.7939	−0.0036	0.0406	19.6394	0.0000
2012	0.7663	−0.0036	0.0406	18.9556	0.0000
2013	0.7943	−0.0036	0.0406	19.6375	0.0000
2014	0.7431	−0.0036	0.0406	18.3816	0.0000
2015	0.7878	−0.0036	0.0406	19.4737	0.0000
2016	0.7908	−0.0036	0.0406	19.5483	0.0000
2017	0.7590	−0.0036	0.0406	18.7706	0.0000
2018	0.7801	−0.0036	0.0406	19.2847	0.0000
2019	0.7850	−0.0036	0.0406	19.4004	0.0000
2020	0.7670	−0.0036	0.0406	18.9603	0.0000

in haze pollution, highlighting the necessity of considering spatial factors and utilizing spatial econometric models for analysis.

Owing to the regression coefficients for the DIDSDM not capturing the marginal effects of the explanatory variable or the spatial spillover effects, interpreting these coefficients directly is deemed meaningless. It is crucial to decompose the regression coefficients into local effects, spatial spillover effects, and overarching effects by adopting partial differential equations. In line with this, the study does not discuss the regression coefficient for the DIDSDM. Instead, based on the estimates from Equation 5 it provides the decomposition results of the DIG estimation coefficients as exhibited in Table 13, highlighting that irrespective of the sort of spatial weight matrix utilized, the impact of the big data experimental zone on urban haze pollution is markedly negative. This finding implies that the local digital economy has a considerable suppressing effect on haze pollution in the local city, which aligns with the baseline regression outcomes mentioned earlier. Concurrently, the spatial spillover effects are also significantly negative, implying that the digital economy has a notable suppressing effect on haze pollution in neighboring cities. Moreover, the overarching effects are substantially negative as well, signifying that the digital economy helps to curb regional haze pollution as a whole.

7 Research conclusions, policy implications and further research

7.1 Research conclusions

This study utilizes panel data from 280 prefecture-level cities in China spanning from 2011 to 2020 to empirically explore the impact and action mechanism caused by the digital economy on haze pollution. Furthermore, it also investigates the spatial spillover effects exerted by the digital economy on haze pollution.

On the basis of the study conducted, the following conclusions can be drawn: Firstly, research findings have demonstrated that the digital economy plays a fundamental part in significantly inhibiting haze pollution. The above research findings still hold true after an array of robustness examinations. Secondly, the influence caused by the digital economy in descending haze pollution is more pronounced in large cities, high-level administrative cities, key environmental protection cities, and economically developed cities. Thirdly, the digital economy can mitigate haze pollution through two pathways: financial development and technological innovation. Fourthly, in addition to its local reduction of haze pollution, the digital economy also exhibits spatial spillover effects, which implies that it considerably contributes to declining haze pollution in neighboring cities. Accordingly, it plays a pivotal part in diminishing regional haze pollution as a whole.

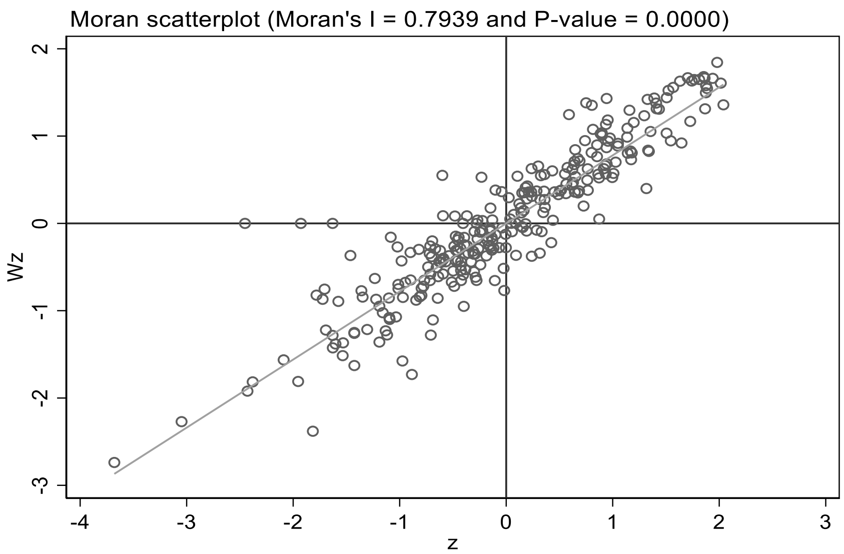

FIGURE 5
2011 years.

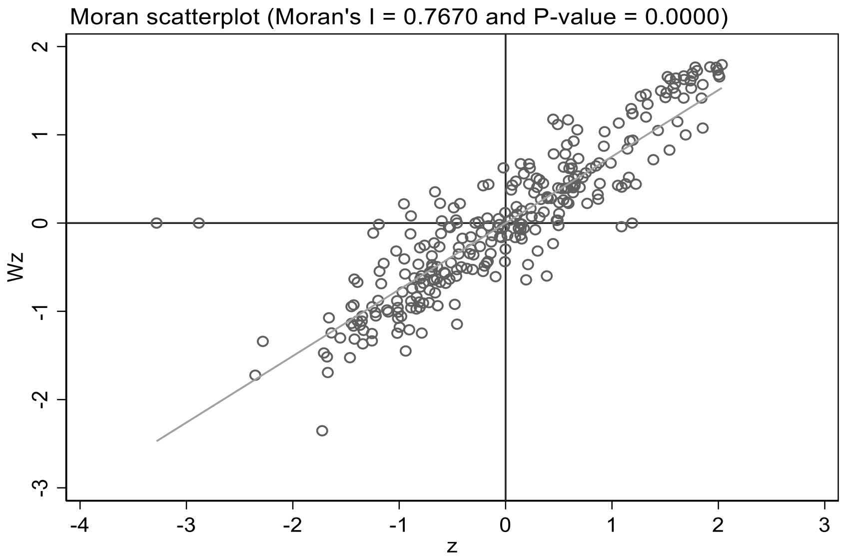

FIGURE 6
2020 years.

TABLE 13 Decomposition of marginal effects in the difference-in-difference spatial Durbin model.

Variables	(1)	(2)	(3)	(4)
	W_1	W_2	W_3	W_4
Local effect	−0.0112** (0.0052)	−0.0289*** (0.0076)	−0.0207*** (0.0077)	−0.0297*** (0.0076)
Spatial spillover effect	−0.1131*** (0.0410)	−0.0964** (0.0395)	−0.0240** (0.0101)	−0.1088** (0.0446)
Total effect	−0.1243*** (0.0431)	−0.1253*** (0.0417)	−0.0447*** (0.0121)	−0.1386*** (0.0468)
Control variables	YES	YES	YES	YES
City FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
N	2,800	2,800	2,800	2,800
R^2	0.0574	0.0015	0.0378	0.0018

7.2 Policy implications

In accordance with the aforementioned findings, the following policy implication can be drawn.

Firstly, the potential of the digital economy for lessening haze pollution should be fully leveraged. Consolidating the foundation for the development of the digital economy, it is vital to accelerate the development of new infrastructures like big data centers, 5th generation base stations, artificial intelligence, and the industrial internet. Accelerating the pace of digital industrialization and the digitalization of industries provides a strong guarantee for harnessing the benefits of the digital economy to abate haze pollution.

Secondly, due to the heterogeneity in the action of the digital economy on haze pollution influenced by urban characteristics, the Chinese government should focus on tailored measures in the follow-up support for the development of the digital economy, marked by the construction of big data experimental zones. Based on comprehensive considerations of multiple factors such as city size, administrative level, environmental protection type, and economic development level, appropriate strategies and models for reducing haze pollution for the digital economy should be cultivated building upon local conditions and unique characteristics.

Thirdly, it is crucial to establish a multidimensional and multi-level financial support system. This will expedite the development of resource-efficient and environmentally friendly societies. Additionally, the government should foster a conducive atmosphere for intellectual property protection, provide tax incentives and financing channels for companies' research and development investments. These measures will incentivize enterprises to increase their research, development, application, and promotion of clean production technologies, thus leading to the evident manifestation of haze pollution reduction effects through technological innovation driven by the digital economy.

Finally, given the considerable spatial spillover effects generated by the digital economy, there is a critical need to enhance communication and cooperation among cities through convenient and efficient digital platform. This can facilitate the transfer of funds, technology, knowledge, and experiences, harnessing the spatial spillover effect of the digital economy to mitigate haze pollution.

7.3 Further research

While this study offers several valuable policy insights, it also has space for further research. Firstly, this study considers the establishment of big data pilot zones as a quasi-natural experiment, but it does not measure the digital economy levels in the cities. Future research should develop a scientifically sound indicator system and evaluation methods to assess the digital economy in these urban areas and validate the conclusions drawn in this study. Secondly, this study explores the mechanisms by which the digital economy mitigates haze pollution, focusing on financial development and technological innovation. However, other transmission pathways may also exist. Future research could investigate additional alternative mechanisms through which the digital economy influences haze pollution. Finally, this study utilizes panel data at the urban level in China as the research subject, which limits its ability to reveal the mechanisms and heterogeneity of the digital economy's impact on haze pollution at the micro-enterprise level. Future research could attempt to conduct relevant studies from the perspective of micro-enterprises.

Data availability statement

Publicly available datasets were analyzed in this study. This data can be found here: https://sites.wustl.edu/acag/datasets/surface-pm2-5/#V5.GL.04.

Author contributions

ML: Conceptualization, Data curation, Formal Analysis, Investigation, Methodology, Project administration, Software, Validation, Writing–original draft, Writing–review and editing. CL: Writing–review and editing. YZ: Writing–review and editing. YH: Writing–review and editing. YF: Writing–review and editing. GL: Conceptualization, Formal Analysis, Funding acquisition, Methodology, Project administration, Writing–original draft, Writing–review and editing, Investigation.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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References

Arkhangelsky, D., Athey, S., Hirshberg, D. A., Imbens, G. W., and Wager, S. (2021). Synthetic difference-in-differences. *Am. Econ. Rev.* 111, 4088–4118. doi:10.1257/aer.20190159

Ashkenas, R., Ulrich, D., Jick, T., and Kerr, S. (2002). *The boundaryless organization: breaking the chains of organizational structure*. San Francisco: Jossey-Bass.

Bai, F., Huang, Y., Shang, M., and Ahmad, M. (2022) Modeling the impact of digital economy on urban environmental pollution: empirical evidence from 277 prefecture-level cities in China. *Front. Environ. Sci.* 10, 991022. doi:10.3389/fenvs.2022.991022

Bai, J., Zhang, Y., and Bian, Y. (2022). Does innovation-driven policy Increase entrepreneurial activity in cities—evidence from the national innovative city pilot policy. *China Ind. Econ.* 6, 61–78. doi:10.19581/j.cnki.ciejournal.2022.06.016

Bhattacharya, M., Rafiq, S., and Bhattacharya, S. (2015) The role of technology on the dynamics of coal consumption—economic growth: new evidence from China. *Appl. Energy* 154, 686–695. doi:10.1016/j.apenergy.2015.05.063

Chen, G. (2022a). Misallocation of regional land resources, technological innovation and haze pollution. *Econ. Surv.* 39, 13–21. doi:10.15931/j.cnki.1006-1096.2022.04.005

Chen, G. (2022b). Land resource misallocation, industrial structure and haze pollution: an empirical study based on spatial econometrics and dynamic panel threshold model. *China Soft Sci.* 12, 143–152. doi:10.3969/j.issn.1002-9753.2022.12.014

Chen, S., and Chen, D. (2018). Air pollution, government regulations and high-quality economic development. *Econ. Res. J.* 53, 20–34.

Chen, Y., Chen, S., and Miao, J. (2024). Does smart city pilot improve urban green economic efficiency: accelerator or inhibitor. *Environ. Impact Assess. Rev.* 104, 107328. doi:10.1016/j.eiar.2023.107328

Chen, Y., and Xu, J. (2023). Digital transformation and firm cost stickiness: evidence from China. *Financ. Res. Lett.* 52, 103510. doi:10.1016/j.frl.2022.103510

Chen, Y., Zhu, Z., and Cheng, S. (2022). Industrial agglomeration and haze pollution: evidence from China. *Sci. Total Environ.* 845, 157392. doi:10.1016/j.scitotenv.2022.157392

de Chaisemartin, C., and D'Haultfœuille, X. (2020). Two-way fixed effects estimators with heterogeneous treatment effects. *Am. Econ. Rev.* 110, 2964–2996. doi:10.1257/aer.20181169

Deng, R., and Zhan, J. (2017). Does two low carbon pilot policy promote the performance of carbon emissions reduction in pilot cities—based on difference in difference method. *Syst. Eng.* 35, 68–73.

Deng, R., and Zhang, A. (2022). Research on the impact of urban digital economy development on environmental pollution and its mechanism. *South China J. Econ.* 2, 18–37. doi:10.19592/j.cnki.scje.390724

Dong, F., Hu, M., Gao, Y., Liu, Y., Zhu, J., and Pan, Y. (2022) How does digital economy affect carbon emissions? Evidence from global 60 countries. *Sci. Total Environ.* 852, 158401. doi:10.1016/j.scitotenv.2022.158401

Gan, T., Yang, H., Liang, W., and Liao, X. (2021) Do economic development and population agglomeration inevitably aggravate haze pollution in China? New evidence from spatial econometric analysis. *Environ. Sci. Pollut. Res. Int.* 28, 5063–5079. doi:10.1007/s11356-020-10847-4

Grossman, G. M., and Krueger, A. B. (1995). Economic growth and the environment. *Q. J. Econ.* 110, 353–377. doi:10.2307/2118443

Guan, Y., Zhai, Z., Wang, Y., Wu, D., Yu, L., and Lei, Z. (2022). Foreign direct investment, environmental regulation, and haze pollution: empirical evidence from China. *Environ. Sci. Pollut. Res. Int.* 29, 27571–27584. doi:10.1007/s11356-021-17841-4

Guo, B., Wang, Y., and Zhang, H. (2022). Does digital economy Improve urban air quality: quasi natural experiment based on national big data comprehensive pilot zone. *J. Guangdong Univ. Finance and Econ.* 37, 58–74.

Guo, L., and Liu, F. (2021). Research on the relationship among scientific and technological Innovation, financial development and haze pollution in provinces and cities—based on spatial econometric model. *Soft Sci.* 35, 31–36. doi:10.13956/j.ss.1001-8409.2021.10.05

Guo, Y., Guo, B., and Zhang, R. (2022). Research on the impact of digital economy on carbon emission intensity under the background of double carbon-based on the test of moderated mediating effect. *Mod. Manag. Sci.* 6, 138–147. doi:10.3969/j.issn.1007-368X.2022.06.016

Hao, X., Wen, S., Li, Y., Xu, Y., and Xue, Y. (2022) Can the digital economy development curb carbon emissions? Evidence from China. *Front. Psychol.* 13: 938918. doi:10.3389/fpsyg.2022.938918

Hu, J. (2023). Synergistic effect of pollution reduction and carbon emission mitigation in the digital economy. *J. Environ. Manage* 337, 117755. doi:10.1016/j.jenvman.2023.117755

Jacobson, L. S., Lalonde, R. J., and Sullivan, D. G. (1993). Earnings losses of displaced workers. *Am. Econ. Rev.* 83, 685–709.

Kong, L., Dong, Y., and Zhao, X. (2022). The impact of digital economy development on carbon emission: based on the test of intermediary effect and threshold effect. *Urban Dev. Stud.* 22, 42–49. doi:10.3969/j.issn.1006-3862.2022.09.006

Lee, C., Yuan, Z., and Lee, C. (2023). A nonlinear analysis of the impacts of information and communication technologies on environmental quality: a global perspective. *Energy Econ.* 128, 107177. doi:10.1016/j.eneco.2023.107177

Li, J., Li, F., and Li, J. (2022). Does new-type urbanization help reduce haze pollution damage? Evidence from China's county-level panel data. *Environ. Sci. Pollut. Res. Int.* 29, 47123–47136. doi:10.1007/s11356-022-19272-1

Li, J., and Liu, Q. (2023). How digital economy empowers urban green total factor productivity - based on the empirical evidence of national big data comprehensive experimental zone construction. *Mod. Manag. Sci.* 5, 33–42. doi:10.3969/j.issn.1007-368X.2023.05.015

Li, L., Sun, J., Jiang, J., and Wang, J. (2022). The effect of environmental regulation competition on haze pollution: evidence from China's province-level data. *Environ. Geochem Health* 44, 3057–3080. doi:10.1007/s10653-021-00854-w

Li, L., Tang, D., Kong, Y., Liu, D., and Yang, Y. (2016). A spatial econometric analysis of impact of FDI on urban haze pollution—case of the pearl river delta region. *Manag. Rev.* 28, 11–24. doi:10.14120/j.cnki.cn11-5057/f.2016.06.002

Li, Z., and Wang, J. (2022) How does the digital economy affect spatial carbon emissions under economic agglomeration? *J. Xi'an Jiaot. Univ. Soc. Sci.* 42, 87–97. doi:10.15896/j.xjtuskxb.202205009

Liang, H., and Shen, D. (2023). The policy effects of digital economic development strategy on industrial structure upgrading - based on quasi-natural experiment of national big data comprehensive pilot zones. *Mod. Manag. Sci.* 1, 46–55. doi:10.3969/j.issn.1007-368X.2023.01.007

Liang, W., Yang, M., and Li, X. (2017) Interaction between agglomeration and haze pollution in Chinese cities. *Urban Probl.* 9, 83–93. doi:10.13239/j.bjsshkxy.cswt.170912

Liu, S., Luo, W., and Wang, Y. (2021). On the digital finance development and the smog pollution control: evidence from the counties of China. *J. Ningde Normal Univ. Philosophy Soc. Sci.* 4, 61–67.

Liu, X. (2018). Dynamic evolution, spatial spillover effect of technological innovation and haze pollution in China. *Energy Environ.* 29, 968–988. doi:10.1177/0958305X18765249

Liu, X., and Xia, H. (2019) Empirical analysis of the influential factors of haze pollution in China—based on spatial econometric model. *Energy Environ.* 30, 854–866. doi:10.1177/0958305X18813648

Lu, S., Dong, R., and Ye, C. (2021) Does "the belt and road initiative" promote high-quality exports—evidence from firms in China. *China Ind. Econ.* 3, 80–98. doi:10.19581/j.cnki.ciejournal.2021.03.012

Lv, C., Song, J., and Lee, C. (2022). Can digital finance narrow the regional disparities in the quality of economic growth? Evidence from China. *Econ. Anal. Policy* 76, 502–521. doi:10.1016/j.eap.2022.08.022

Lyu, Y., Lu, Y., Wu, S., and Wang, Y. (2019). The effect of the belt and road initiative on firms' OFDI: evidence from China's greenfield investment. *Econ. Res. J.* 54, 187–202.

Ma, T., and Cao, X. (2022). The effect of the industrial structure and haze pollution: spatial evidence for China. *Environ. Sci. Pollut. Res. Int.* 29, 23578–23594. doi:10.1007/s11356-021-17477-4

Miao, L., Chen, J., Fan, T., and Lv, Y. (2022). The impact of digital economy development on carbon emission: a panel data analysis of 278 prefecture-level cities. *South China Finance* 2, 45–57. doi:10.3969/j.issn.1007-9041.2022.02.004

Nasir, M. A., Duc Huynh, T. L., and Xuan Tram, H. T. (2019) Role of financial development, economic growth and foreign direct investment in driving climate change: a case of emerging ASEAN. *J. Environ. Manage* 242, 131–141. doi:10.1016/j.jenvman.2019.03.112

Nguyen, T. H., Nagashima, T., Doan, Q., Khan, A., and Niyogi, D. (2023) Source apportionment of pm2.5 and the impact of future pm2.5 changes on human health in the monsoon-influenced humid subtropical climate. *Atmos. Pollut. Res.* 14, 101777. doi:10.1016/j.apr.2023.101777

Pang, Y., Liu, Z., and Pan, Y. (2020). Spatial relevance effect of fiscal technology and education expenditure on haze pollution. *Econ. Surv.* 37, 128–138. doi:10.15931/j.cnki.1006-1096.2020.06.008

Qiu, Z., and Zhou, Y. (2021). Development of digital economy and regional total factor productivity: an analysis based on national big data comprehensive pilot zone. *J. Finance Econ.* 47, 4–17. doi:10.16538/j.cnki.jfe.20210119.103

Ren, L., and Zhu, D. (2017). Is China 's financial development green—also on the hypothesis of China 's environmental kuznets curve. *Econ. Perspect.* 11, 58–73.

Shi, D., and Sun, G. (2022) Digital economy, financial efficiency and high-quality economic development of China. *Enterp. Econ.* 41, 5–16. doi:10.13529/j.cnki.enterprise.economy.2022.01.001

Song, B., Shi, H., Wang, M., and Gu, R. (2022). The research on the effect of digital economy development on urban air quality. *Front. Environ. Sci.* 10. doi:10.3389/fenvs.2022.993353

Song, K. Y., and Bian, Y. C. (2019). Dose financial openness aggravate smog pollution. *J. Shanxi Univ. Finance Econ.* 41, 45–59. doi:10.13781/j.cnki.1007-9556.2019.03.004

Sun, X., Chen, Z., and Loh, L. (2022). Exploring the effect of digital economy on pm2.5 pollution: the role of technological innovation in China. *Front. Environ. Sci.* 10, 904254. doi:10.3389/fenvs.2022.904254

Tan, J., and Chen, L. (2022) Spatial effect of digital economy on particulate matter 2.5 in the process of smart cities: evidence from prefecture-level cities in China. *Int. J. Environ. Res. Public Health* 19, 14456. doi:10.3390/ijerph192114456

Teng, L., and Ma, D. (2020) Can digital finance help to promote high-quality development? *Stat. Res.* 37, 80–92. doi:10.19343/j.cnki.11-1302/c.2020.11.007

Wan, J., Pu, Z., and Tavera, C. (2023). The impact of digital finance on pollutants emission: evidence from Chinese cities. *Environ. Sci. Pollut. Res. Int.* 30, 42923–42942. doi:10.1007/s11356-021-18465-4

Wang, F., Liu, X., Zhang, L., and Cheng, W. (2022) Does digitalization promote green technology innovation of resource-based enterprises? *Stud. Sci. Sci.* 40, 332–344. doi:10.16192/j.cnki.1003-2053.20210824.001

Wang, F., Ren, J., Liu, J., Dong, M., Yan, B., and Zhao, H. (2021) Spatial correlation network and population mobility effect of regional haze pollution: empirical evidence from pearl river delta urban agglomeration in China. *Environ. Dev. Sustain.* 23, 15881–15896. doi:10.1007/s10668-021-01326-y

Wang, K., Zhao, B., Ding, L., and Wu, G. (2021). Fiscal decentralization, government innovation preference and haze pollution. *China Popul. Resour. Environ.* 31, 97–108. doi:10.12062/cpre.20201218

Wang, L., Li, X., and Dong, W. (2023a) Digital economy, urban innovation and smog pollution. *World Surv. Res.* 3, 11–21. doi:10.13778/j.cnki.11-3705/c.2023.03.002

Wang, L., Zhao, Y., Shi, Y., Liu, H., Li, H., Liu, J., et al. (2023b). The interaction effects between exposure to ambient pm2.5 and economic development on the settlement intention for floating population in China. *Environ. Sci. Pollut. Res. Int.* 30, 67217–67226. doi:10.1007/s11356-023-27043-9

Wang, R. (2023). Is the development of digital finance conducive to reducing haze pollution? Empirical evidence from 284 cities in China. *Environ. Sci. Pollut. Res. Int.* 30, 53478–53491. doi:10.1007/s11356-023-25652-y

Wang, X., and Li, J. (2022). Did the digital economy effectively promote energy conservation and co2 reduction? *China Popul. Resour. Environ.* 32, 83–95. doi:10.12062/cpre.20221022

Wen, Z., and Liu, H. (2020). *Analyses of mediating and moderating effects: methods and applications*. Beijing: Educational Science Press, 103–106.

Wolf, M., Emerson, J., Esty, D., de, S., and Wendling, Z. (2022). 2022 environmental performance index. Available at: https://epi.yale.edu/epi-results/2022/component/epi (Accessed September 23, 2023).

Wu, L., Wan, X., Jahanger, A., Li, M., Murshed, M., and Balsalobre-Lorente, D. (2023) Does the digital economy reduce air pollution in China? A perspective from industrial agglomeration. *Energy Rep.* 9, 3625–3641. doi:10.1016/j.egyr.2023.02.031

Wu, S., and Yu, W. (2022). The effects of population and economic agglomeration on haze pollution—an empirical analysis based on spatial panel date model. *J. Univ. Electron. Sci. Technol. China* 24 (Social Sciences Edition), 57–69. doi:10.14071/j.1008-8105(2022)-5016

Wu, X., Wu, X., Qin, Y., Xie, Q., and Zhang, Y. (2022) The mediating and moderating effects of the digital economy on PM2.5: evidence from China. *Sustainability* 14, 16032. doi:10.3390/su142316032

Wu, Z., and Zhang, S. (2019) RETRACTED ARTICLE: study on the spatial–temporal change characteristics and influence factors of fog and haze pollution based on GAM. *Neural Comput. Appl.* 31, 1619–1631. doi:10.1007/s00521-018-3532-z

Xu, L., Hou, L., and Cheng, G. (2022). Innovation effect of national big data comprehensive pilot zone. *Sci. and Technol. Prog. Policy* 39, 101–111. doi:10.6049/kjjbydc.2021080751

Xu, W., and Sun, L. (2023). Market-incentive environmental regulation and energy consumption structure transformation. *J. Quantitative and Technol. Econ.* 40, 133–155.

Yang, S., and Jia, J. (2022) Digital economy, technological innovation, and environmental quality improvement. *Sustainability* 14, 15289. doi:10.3390/su142215289

Yang, S., Liu, S., Wu, T., and Zhai, Z. (2023). Does new-type urbanization curb haze pollution? A case study from China. *Environ. Sci. Pollut. Res. Int.* 30, 20089–20104. doi:10.1007/s11356-022-23379-w

Yi, M., Liu, Y., Sheng, M. S., and Wen, L. (2022) Effects of digital economy on carbon emission reduction: new evidence from China. *Energy Policy* 171, 113271. doi:10.1016/j.enpol.2022.113271

Yin, Z., Gong, X., Guo, P., and Wu, T. (2019) What drives entrepreneurship in digital economy? *Evid. china. Econ Model.* 82, 66–73. doi:10.1016/j.econmod.2019.09.026

Yu, S., Fan, X., and Jiang, H. (2022). Research on the impact of digital economy development on carbon productivity improvement. *J. Statistics Inf.* 37, 26–35. doi:10.3969/j.issn.1007-3116.2022.07.003

Yu, S., and Wang, C. (2023). Research on pm2.5 concentration prediction algorithm based on temporal and spatial features. *Comput. Mater. and Continua* 75, 5555–5571. doi:10.32604/cmc.2023.038162

Zeng, H., and Li, Y. (2019). Study on the temporal and spatial evolution of haze pollution in Yangtze River economic belt and its governance strategies. *J. East China Univ. Technol. Soc. Sci.* 38, 120–126. doi:10.3969/j.issn.1674-3512.2019.02.005

Zha, Q., Huang, C., and Kumari, S. (2022) The impact of digital economy development on carbon emissions—based on the Yangtze River Delta urban agglomeration. *Front. Environ. Sci.* 10, 1028750. doi:10.3389/fenvs.2022.1028750

Zhang, G., Wen, J., and Lin, W. (2022b). Does urban agglomeration construction improve or deteriorate urban air quality? —an empirical test based on the difference-in-difference model. *Syst. Engineering-Theory and Pract.* 42, 1245–1259. doi:10.12011/SETP2021-1288

Zhang, H., Wang, Y., Hu, J., Ying, Q., and Hu, X. M. (2015). Relationships between meteorological parameters and criteria air pollutants in three megacities in China. *Environ. Res.* 140, 242–254. doi:10.1016/j.envres.2015.04.004

Zhang, Y., Wang, T., and Zhang, H. (2022a). Non-linear impact and spillover effects of industrial agglomeration on haze and ecological efficiency. *Acta Ecol. Sin.* 42, 6656–6669. doi:10.5846/stxb202105201317

Zhao, B. (2021). The impact of digital economy on regional innovation performance and its spatial spillover effect. *Sci. and Technol. Prog. Policy* 14, 37–44. doi:10.6049/kjjbydc.2020120488

Zhao, R., Zhao, L., and Liu, Z. (2021). Fiscal decentralization, marketization, and haze pollution. *East China Econ. Manag.* 35, 1–10. doi:10.19629/j.cnki.34-1014/f.200519016

Zhao, T., Jiao, F., and Wang, Z. (2023). The impact of the digital economy development on haze pollution: evidence from the perspective of factor marketization. *Environ. Sci. Pollut. Res.* 30, 35478–35491. doi:10.1007/s11356-022-24706-x

Zhi, Y., and Lu, X. (2023) Establishment of national big data comprehensive pilot zone and urban entrepreneurship activity—based on empirical evidence from 284 cities. *China Bus. Mark.* 37, 84–96. doi:10.14089/j.cnki.cn11-3664/f.2023.03.007

Zhou, J., Lan, H., Zhao, C., and Zhou, J. (2021). Haze pollution levels, spatial spillover influence, and impacts of the digital economy: empirical evidence from China. *Sustainability* 13, 9076. doi:10.3390/su13169076

Zhu, D., and Jing, W. (2020). Financial development, spatial spillover and haze pollution—an empirical research based on generalized space two-stage least square method. *Inq. Into Econ. Issues* 8, 134–143.

Zhu, Y., and Zhao, J. (2021). Agglomeration and haze pollution: from the perspective of subsistence consumption. *Ecol. Econ.* 37, 167–175.

Zhu, Z., Liu, B., Yu, Z., and Cao, J. (2022). Effects of the digital economy on carbon emissions: evidence from China. *Int. J. Environ. Res. Public Health* 19, 9450. doi:10.3390/ijerph19159450