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Original Research

Will Mismatched New Infrastructure Investment Cause Air Pollution Crisis? Environmental Impact Analysis Based on the Coupling Degree of Digital Economy and New Infrastructure Investment

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Abstract

Although new infrastructure investment is generally considered to have a high environmental improvement expectation, mismatched new infrastructure investment still has the potential to damage the environment. This study examines the environmental impact of the matching degree (NDC) between new infrastructure investment (NII) and digital economy (DECO), using comprehensive economic theory and the panel data of 30 provinces from 2011 to 2019 in China. We employ a range of models including fixed effect, lag effect, threshold effect, and spatial autoregressive models, as well as regional heterogeneity tests. Our results indicate that NII, DECO, NDC, and $PM_{2.5}$ all have significant spatial spillover effects. In addition, our results indicate that both NII and NDC significantly promote the weakening of haze concentration, and NDC has a strong hysteresis effect. Moreover, the significant single-threshold effect reveals structural mutations in the environmental impact of NII and NDC in air pollution. All the results remained valid under a series of robustness tests. Based on these empirical results, we provide a theoretical and empirical basis about environmental protection for the government to implement new infrastructure investment and digital economy, and the research has implications for other developed or developing countries as well.

Keywords: new infrastructure investment, digital economy, air pollution, threshold regression, fixed effect, spatial spillover effect, coupling coordination

Introduction

As a major industrial country, China has long faced criticism for the negative environmental impact caused by traditional infrastructure [1], which formed the backbone of the country's industrialization. In response, China has been actively seeking a more environmentally friendly solution to governance. On December 26, 2022, China released the "China's Carbon Neutrality and Clean Air Cooperative Path (2022)" report was officially released, which set ambitious targets for the country to reduce major air pollutants by over one-third by 2030,

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and for more than 80% of cities to meet national air quality standards. The establishment of these goals during a period of relative economic depression reflects the Chinese government's strong determination in environmental governance. However, it may not be practical to wait for the inflection point effect of the Environmental Kuznets Curve [2] to achieve these targets in the post-epidemic period, given the unique circumstances of the country.

The rise of the digital economy, industrial upgrades, and macro policy direction have all contributed to the growing importance of new infrastructure in national strategic planning. As the world enters a new era of technological revolution, the digital economy has become a key global economic driver, and traditional industries have undergone a more profound phase of digital transformation. Correspondingly, infrastructure for these industries has been upgraded and iterated, and traditional infrastructure has gradually been replaced by new infrastructure. In this context, new infrastructure has become the new cornerstone of high-quality economic development, replacing traditional infrastructure that was the foundation of China's rapid economic growth in the past. However, the scale of new infrastructure investment is over massive. CCID Consulting predicts that China's county-level new infrastructure investment will reach 1.7 trillion yuan in 2022, a year-on-year increase of 7%, and exceeding 2 trillion yuan in 2024. This investment is expected to have a knock-on effect that will impact the environment. Therefore, it is essential to investigate whether the impact of new infrastructure on environmental pollution differs from that of traditional infrastructure, a matter of concern.

Compared to traditional infrastructure which is known for its high energy consumption and emissions, new infrastructure exhibits the distinct characteristics of a digital economy. On April 20, 2020, the National Development and Reform Commission (NDRC) of China provided a comprehensive definition of new infrastructure: it is guided by new development concepts, driven by technological innovation, based on information networks, oriented towards high-quality development, and providing digital transformation, intelligent upgrades, and integrated innovation services for the infrastructure system. Specifically, new infrastructure is comprised of three key aspects: information infrastructure, integrated infrastructure, and innovation infrastructure. Information infrastructure pertains to infrastructure generated by the new generation of information technology. Integrated infrastructure refers to the application of digital technology to transform and upgrade traditional infrastructure into a more integrated technology system. Finally, innovation infrastructure mainly refers to public welfare infrastructure that supports scientific research and development. The official definition highlights the digital economy characteristics of new infrastructure and its goal for future-oriented infrastructure that meets the needs of high-quality development.

The close association between new infrastructure and the digital economy has led to high expectations for the impact of new infrastructure investments on environmental protection. In the post-epidemic era, many governments are implementing policies to stimulate economic recovery, which could involve relaxing environmental regulations. Therefore, the environmental impact of new infrastructure investment, which plays a crucial role in the new economy, is undoubtedly of profound significance to achieve sustainable development. New infrastructure investment is a large-scale, future-oriented project whose influence will last for several years. Whether new infrastructure investment has a positive or negative impact on air pollution, it requires the attention of local governments and environmental protection agencies alike.

The coupling and coordination of new infrastructure investment and the digital economy may have environmental repercussions. Apart from the direct environmental impact of new infrastructure investment, there may also be detrimental environmental effects from poorly planned integration between the digital economy and new infrastructure investment. For instance, in regions where digital economy is lacking, large-scale infrastructure investment may result in more environmental harm than economic benefits. This could be due to factors such as a mismatch between industrial structure and the potential threshold effect. As a major social infrastructure investment, it's important to assess whether it's aligned with the local digital economy's current level. Therefore, this paper presents an innovative exploration of the coupling and coordination between new infrastructure investment and the digital economy, including its impact and mechanism on air pollution, to investigate the coupling mechanism and environmental impact of these two domains.

Literature Review and Hypothesis

This section provides a conceptual comparison between new and traditional infrastructure and clarifies their relationship between new infrastructure and the digital economy. Then, from the perspective of environmental protection, it highlights the potential environmental benefits of new infrastructure investment with digital features as the primary driver, while also discussing the possible environmental impacts resulting from the coupling relationship between this type of infrastructure and the digital economy. This article draws upon four key literatures: firstly, the dual impact of traditional infrastructure on air quality; secondly, the difference and correlations between new infrastructure and traditional infrastructure; thirdly, the correlation and coupling impact of new infrastructure investment and digital economy; fourthly, literature examining the impact of new infrastructure investment on air quality. Finally, the research hypothesis of this paper is put forward.

Studies indicate that traditional infrastructure has a dual impact on air quality. On the one hand, industrialization-based traditional infrastructure has caused significant harm to the environment. In particular, the construction industry is a major contributor to smog. China's industrialization and urbanization have led to the creation of numerous high-energy-consuming buildings, which have been a significant factor in the current smog crisis. According to the "2021 Global Status Report for Buildings and Construction" compiled by the United Nations Environment Program (UNEP) and the Global Construction Alliance (Global ABC) shows that construction activities have decreased due to the COVID-19 pandemic in 2020 and global greenhouse gas emissions are expected to decrease. However, global greenhouse gas emissions are still expected to be as high as 11.7 billion tons, accounting for 37% of global carbon dioxide emissions. Besides the construction industry, transportation infrastructure is also a significant contributor to smog pollution. Studies demonstrate that highway traffic can lead to both short- and long-term haze pollution [3-5]. The undesirable consequences of industrial infrastructure in raising smog levels are widely acknowledged. Much literature has confirmed the role of the local industrial level and local industrial structure in haze pollution. Numerous studies have examined the empirical relationship between industrial output value, industrial structure differences, and haze levels [6-10]. The majority of these studies confirm the adverse effects of industrialization on air quality.

On the other hand, traditional infrastructure can also contribute to the improvement of air quality. For instance, high-speed rail is considered a cleaner transportation infrastructure, and numerous studies have demonstrated its positive environmental impact. Although high-speed rail does not directly improve the environment, it indirectly enhances it through various effects , such as technical, distribution, and substitution effects [11]. From the quantitative effect level of atmospheric improvement, Liu et al. [12] research proves that the opening of high-speed rail in Chinese cities has led to a significantly improve urban air quality by reducing the Air Quality Index (AQI) by an average of 4%. In addition to high-speed rail, traditional information infrastructure is also regarded as one of the environmental protection infrastructures. Zhang et al. [13] discovered that information infrastructure can effectively enhance air quality by improving the industrial structure, but the spatial spillover effect is not obvious. Similarly, Qiao et al. [14] found that information infrastructure can reduce air pollution by improving traditional infrastructure quality and energy efficiency. Furthermore, extensive research has been conducted on the atmospheric environmental protection of network infrastructure-related information infrastructure. Niu et al. [15] and Zou & Pan [16] adopted the "Broadband China" pilot policy as a quasi-natural experiment, and confirmed that network infrastructure construction can reduce pollution. All these research results demonstrate that certain elements of traditional infrastructure have a positive impact on air quality improvement.

The research findings above indicate that certain infrastructure activities within traditional infrastructure have a positive impact on improving air quality. There is an interconnected relationship between new infrastructure and traditional infrastructure. It can be argued that new infrastructure represents an informatization extension of traditional infrastructure [17]. The concept of traditional infrastructure is constantly evolving in response to changing times. Generally, it refers to railways, highways, airports, water conservancy construction, power grid transformation, and so on [18], while new infrastructure is primarily focused on the foundation of the new generation of information technology facilities construction [19]. Traditional and new infrastructures are both products of economic and technological development, but at different stages. Traditional infrastructure has made indelible contributions during rapid economic development [18], while new infrastructure represents the infrastructure for future-oriented high-quality economic development in the new era of tremendous economic scale. Despite the relative decline in economic activities brought about by the pandemic, China still adheres to environmental protection and low-carbon policies. For example, the Chinese government work report during the pandemic included the "two constructions," which refers to new infrastructure construction and new urbanization construction, both of which are highly consistent with green and low-carbon recovery concepts. Combined with the vigorous development of the digital economy during the new round of technological revolution, the new infrastructure projects the underlying foundation of the digital economy have received unprecedented attention and expectations. It is difficult for traditional infrastructure to improve the environment and upgrading the industrial structure simultaneously. Whether the new infrastructure can gently protect or even improve environmental protection without harming the economy is a critical question that has garnered significant research interest in both industry and academia.

There have been limited studies on the coupling of new infrastructure investment and the digital economy. As an emerging concept, new infrastructure is still in the early stages of development. This paper studies the coupling and coordination relationship between new infrastructure investment and the digital economy, with a focus on the correlation between local new infrastructure investment and the corresponding level of the digital economy. If new infrastructure investment does not align with the local development level, excessive investment of infrastructure may result in resource waste and environmental damage [18]. While the uncoordinated degree of infrastructure investment is not unique to either traditional infrastructure or new infrastructure, it is natural to think that new infrastructure investments may not be at the same level as the local digital economy. There has been extensive literature on measuring and researching the level of the digital economy. Wang et al. [20] constructed an evaluation index system for the development level of the digital economy in 30 provinces in China, and found that insufficient and unbalanced digital economy development is a severe problem in China. In addition, the digital economy exhibits significant heterogeneity both between and within regions. Some research on new infrastructure investment has also explored tentative index construction. For instance, Jiang et al. [21], Wang et al. [22] and Du et al [23] calculated the new infrastructure investment index using the total new fixed assets related to information technology. Comparing data from various indicators, it is indicated that there is indeed a mismatch between China's local new infrastructure and the level of the digital economy. However, there is a lack of research on the coupling and coordination of the digital economy and new infrastructure investment, which is one of the innovations of this paper.

Based on the above literature review and research status, this paper makes the following hypotheses:

Hypothesis (H1). New infrastructure investment will affect local smog levels.

Hypothesis (H2). The degree of coupling and coordination between new infrastructure investment and the digital economy will affect the local air pollution levels.

The main logical framework of this paper is shown in Fig. 1.

Methods

Global Principal Component Analysis (GPCA)

To ensure the comparability of data at the global sequence level, this paper utilizes the global principal component analysis (GPCA) method to calculate the new infrastructure investment index (NII). Compared with traditional principal component analysis (PCA), GPCA uniformly processes the whole panel data, calculates the contribution rate and principal component coefficient of each component based on a global perspective, and aims to capture the original information as accurately as possible [24]. This method can effectively reflect the dynamic characteristics and change trajectory of all objects [25].

If M regions are counted in the sample, the same N index variables $X_1, X_2, ..., X_n$ are described. From an overall perspective, each year's data becomes a panel data with n sample points and m variables. In year t, $X_t = (X_{mn})_{M*N}$. Where a data table is in each year, there are a total of t data tables in the t years, which is the time series solid data table after adding the time series. Next, arrange T tables from top to bottom into a row T*M row N column matrix, and define this matrix as a global data table, which is denoted as $X = (X_{mn})_{TM*N}$. Finally, global principal component analysis is carried out [26-29].

To better capture the information of multidimensional indicators, this paper utilizes the time-series global principal component analysis (GPCA) method in constructing specific indices. This method is more effective in reflecting the overall characteristics of the indicators. Specific practices refer to previous literature [27-29]. Through the global processing and calculation of ten third-level indicators, the new infrastructure investment index of the corresponding province in a certain year is obtained. Firstly, the three-level original indicators are standardized and the time-series global principal component analysis is used to reduce the dimension. Firstly, the three-level original index is standardized and the dimension is reduced by time-series global principal component analysis. Then, according to the principle that the cumulative variance contribution rate is not less than 85%, the number of principal components is determined and the score of each component is calculated. Finally, the final regional new infrastructure investment index is obtained by weighted summation of the principal component scores. In the part of digital economy (DECO), this paper first standardizes the four secondary indicators under the digital economy and then conducts global principal component analysis, and then uses the cumulative

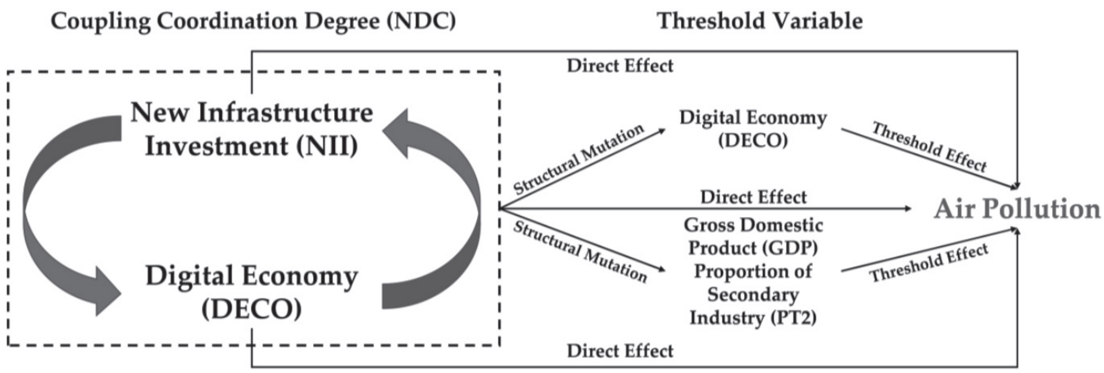

Fig. 1. Main logical framework.

contribution rate of 85% to perform principal component screening and score calculation, and finally obtains the global data of the digital economy index.

The Coupling Coordination Degree Model (CCDM)

The calculation of coupling degree refers to the concept of capacity coupling in physics and the capacity coupling coefficient model. The specific formula of coupling coordination degree is shown below:

$$C_n = 2 \times \left[\frac{U_{NII} \cdot U_{DECO}}{(U_{NII} + U_{DECO})^2}\right]^{1/2} \tag{1}$$

$$T = \alpha U_{NII} + \beta U_{DECO} \; (\alpha + \beta = 1) \tag{2}$$

$$\mathrm{D} = \sqrt{C \cdot T} \tag{3}$$

C_n represents the degree of coupling, U_{NII} and U_{DECO} represents the new infrastructure investment index and the digital economy index, respectively. The coordination degree is expressed by the coordination index T, which reflects the process of continuous harmony between the whole system or subsystems. D reflects the degree of coupling coordination between NII and DECO. The higher the T-value of a region, the higher the level of coupling coordination between new infrastructure investment and digital economy in that region, in other words, the higher the level of matching between new infrastructure investment and digital economy in that region. This article uses the coupling coordination degree model to compare the matching degree of new infrastructure investment between different regions in China, and explore the air pollution situation in various regions under different coupling coordination levels.

Global Spatial Autocorrelation Analysis

Spatial statistics generally use the spatial autocorrelation index to reflect spatial dependence, and the research on the spatial dimension of coupling is gradually being valued by more and more environment-related research [30, 31]. By studying the spatial relationship of coupling coordination degree between new infrastructure investment and digital economy, this paper will help to observe the overall trend and dynamic distribution of coupling data across time and space. The specific operation mainly reflects the degree of aggregation through Moran Index calculation, and its calculation formula is shown below.

$$Moran's\ I = \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} W_{ij}(x_i - \bar{x})(x_j - \bar{x})}{S^2 \sum_{i=1}^{n} \sum_{j=1}^{n} W_{ij}} \tag{4}$$

$$S^2 = \frac{1}{n} \sum_{i=1}^{n} (x_i - \bar{x})^2 \tag{5}$$

MI (*Moran's I*) represents Moran index, and the value range of MI is [−1,1]. MI>0 indicates that the attribute values of spatial units are clustered and present as spatial positive autocorrelation; MI<0 indicates that the attribute values of spatial units are scattered and present as spatial negative autocorrelation; MI = 0 indicates that the attribute values of spatial units present as spatial random distribution. W_{ij} is a spatial weight matrix constructed based on spatial distance by using Geoda or Stata software. N represents the total number of regional spatial units, x_i and x_j represent the attribute values of random variable x in geographic unit i and j, and is the average value of attribute values. S^2 represents the variance of the independent variable. If the value of the Moran's Index is close to zero, it indicates that the values in the spatial dataset are distributed randomly, with no apparent spatial correlation. A positive Moran's Index value suggests an aggregation trend, meaning that similar values are more likely to occur in adjacent areas. Conversely, a negative Moran's Index value indicates a dispersion trend, where similar values are more likely to occur in distant regions.

Threshold Regression Model (TR)

In order to test the phased effect of new infrastructure investment on local haze level under the condition of heterogeneity, the threshold model proposed by Hansen [32] is used for further analysis and research. The specific threshold regression model is set as follows:

$$y_{it} = \beta_0 + \beta_1 x_{it} \times I(q_{it} \leqslant \gamma) + \beta_2 x_{it} \times I(q_{it} > \gamma) + \varepsilon_{it} \tag{6}$$

In the formula, $I(\cdot)$ is the indicative function, which takes the value of 1 when the conditions in the brackets hold, and 0 when the conditions in the brackets do not hold; q_{it} is the threshold variable; y_{it} represents the unknown threshold value. In this paper, the expression can be rewritten as:

$$y_{it} = \begin{cases} \beta_0 + \beta_1 x_{it} + \varepsilon_{it},\ q_{it} \leq \gamma \\ \beta_0 + \beta_2 x_{it} + \varepsilon_{it},\ q_{it} > \gamma \end{cases} \tag{7}$$

Based on the above threshold regression idea, the threshold regression model of new infrastructure investment and local haze level is established, and the proportion of the output value of the secondary industry (*pt2*), the level of digital economy (*deco*) and the total local output value (*gdp*) are respectively taken as threshold variables. When threshold variables are in different value ranges, the coefficients of explanatory variables are therefore different. The specific model is as follows:

$$(PM_{2.5})_{it} = \alpha_0 + \alpha_1 \times M_{it} \times I(pt2_{it} \leqslant q) + \alpha_2 \times M_{it} \times I(pt2_{it} > q) + \alpha_3 X_{it} + \varepsilon_{it} \quad (8)$$

$$(PM_{2.5})_{it} = \beta_0 + \beta_1 \times M_{it} \times I(deco_{it} \leqslant q) + \beta_2 \times M_{it} \times I(deco_{it} > q) + \beta_3 X_{it} + \varepsilon_{it} \quad (9)$$

$$(PM_{2.5})_{it} = \gamma_0 + \beta_1 \times M_{it} \times I(gdp_{it} \leqslant q) + \gamma_2 \times M_{it} \times I(gdp_{it} > q) + \gamma_3 X_{it} + \varepsilon_{it} \quad (10)$$

M can be represented by NII and NDC. As shown in the model above, it only assumes the presence of a single threshold *q*. However, in reality, there are often double or triple thresholds, and the method for setting up the model is similar to the one used in this paper. The specific model design should be based on the specific situation. This paper chose a more suitable single-threshold model after multiple threshold regression attempts. If the empirical results of the above formula are significant, it suggests the presence of a threshold effect within the specified range. This finding can be used to some extent to demonstrate the process by which new infrastructure investment transforms from a quantitative change to a qualitative change in terms of pollution control efficacy. For example, when the threshold effect of the variables related to new infrastructure investment in this paper is significant for $PM_{2.5}$, it proves that the new infrastructure investment and its matching degree do have a nonlinear impact on local air pollution. This will help the government better achieve environmental protection in the implementation of new infrastructure construction or corresponding digital economic development activities.

Data Series and Sources

The New Infrastructure Investment Index (NII)

The calculation method of the new infrastructure investment index is detailed in the methods section. According to the official definition[1], the index comprises three secondary indicators, namely investment in information infrastructure, integrated infrastructure investment, and investment in innovative infrastructure. Investment in information infrastructure is indicated by per capita fixed asset investment in information technology services. The proportion of information and innovation investment in new infrastructure investment (PII) is computed by determining the proportion of investment in information infrastructure and innovative infrastructure of total new infrastructure investment. Integrated infrastructure investment is calculated by multiplying the portion of traditional infrastructure related to new infrastructure by PII. Investment in innovative infrastructure is represented by per capita fixed asset investment in scientific research and technology services. In this paper, PII is innovatively used to calculate the relevant fixed asset investment share in the aspect of integrated infrastructure investment. This calculation method provides a more intuitive reflection of the investment proportion of the integration of traditional and new infrastructure.

The data used in this paper are annual, and the sample includes 30 provinces in mainland China (excluding Hong Kong, Macao, Taiwan, and Tibet), covering the period from 2011 to 2019. The selected data A1~A10 are obtained from the China Statistical Yearbook (2012~2020), annual statistical report on investment in fixed assets (2013), and China Fixed Assets Statistical Yearbook (2012~2013 & 2015~2020). To eliminate the impact of price factors, the fixed asset investment index is deflated using the fixed asset investment index of each province based on 2010.

Table 2 shows the top 15 regions in terms of investment in new infrastructure in 30 provinces in China from 2011 to 2019. Firstly, judging from the average value of the statistical year, the investment levels of new infrastructure in Tianjin, Qinghai, Inner Mongolia, Beijing, and Heilongjiang are relatively advanced, and there is a big gap with the following provinces. Secondly, judging from the changes in the ranking of new infrastructure investment, Beijing and Tianjin are in the leading position in the first half of the statistical year. However, after 2015, Beijing's new infrastructure investment level has regressed considerably. Qinghai has maintained a high level of new infrastructure investment since 2014. Cities such as Guangdong and Shanghai, traditionally big economic provinces, are not on the list, which may be related to their high level of new infrastructure and macro policy focus.

The Digital Economy Index (DECO)

This paper's measurement method of the digital economy level also uses the global principal component analysis (GPCA) method mentioned above. At the level of specific index construction, this paper refers to the various index construction standards of the digital economy by Zhao et al. [33], Wang et al. [20], and Yang et al. [34]. Finally, this paper measures from four perspectives: Internet penetration rate, Internet employment rate, Internet-related output, and mobile Internet users.

Table 4 illustrates the top 15 regions with the highest digital economy ranking among the 30 provinces in China from 2011 to 2019. Firstly, based on the average statistical year value, Beijing, Shanghai, Zhejiang, Guangdong, Fujian, and Jiangsu occupy the top tier with a significant lead over the following provinces.

[1] Explanation from China's National Development and Reform Commission. https://baijiahao.baidu.com/s?id=1664652607899867736&wfr=spider&for=pc

Table 1. Composition of core explanatory variable.

Variable	Level I indicators	Level II indicators	Level III indicators	Sym.
Core explanatory variable	New infrastructure investment (NII)	Investment in information infrastructure	(A1) Per capita fixed asset investment in information technology services	+
		Integrated (converged) infrastructure investment	(A2) Per capita fixed asset investment in mining industry * PII	+
			(A3) Per capita investment in manufacturing fixed assets * PII	+
			(A4) Per capita investment in fixed assets in construction * PII	+
			(A5) Per capita investment in fixed assets of health and social work * PII	+
			(A6) Per capita fixed asset investment in transportation, storage, and postal services * PII	+
			(A7) Per capita fixed asset investment in water conservancy, environment, and public facilities management industry * PII	+
			(A8) Per capita investment in fixed assets in the production and supply of electricity, heat, gas, and water * PII	+
			(A9) Per capita investment in fixed assets of public administration, social security, and social organizations * PII	+
		Investment in innovative infrastructure	(A10) Per capita fixed asset investment in scientific research and technology services	+

Table 2. Top 15 of China's NII index (2011-2019).

City	2011	City	2012	City	2013	City	2014	City	2015	Rank
Beijing	2.96	Beijing	3.81	Beijing	3.44	Inner Mongolia	5.37	Qinghai	5.31	1
Inner Mongolia	2.87	Tianjin	2.94	Tianjin	3.21	Tianjin	4.01	Tianjin	2.46	2
Tianjin	2.79	Inner Mongolia	2.30	Inner Mongolia	3.06	Shaanxi	2.73	Jilin	1.72	3
Shaanxi	1.42	Shaanxi	2.29	Heilongjiang	2.02	Beijing	1.25	Shandong	1.49	4
Gansu	1.39	Heilongjiang	1.59	Shaanxi	1.72	Jiangsu	1.24	Jiangsu	1.43	5
Liaoning	1.11	Liaoning	1.58	Shandong	1.55	Jilin	1.09	Shaanxi	1.08	6
Xinjiang	1.08	Jiangsu	0.87	Jiangsu	1.20	Gansu	1.01	Inner Mongolia	0.78	7
Shanghai	0.90	Jilin	0.75	Gansu	1.17	Heilongjiang	0.94	Ningxia	0.69	8
Hainan	0.53	Gansu	0.67	Liaoning	0.85	Liaoning	0.85	Beijing	0.58	9
Jiangsu	0.48	Shandong	0.54	Jilin	0.60	Shandong	0.66	Xinjiang	0.42	10
Ningxia	0.38	Shanghai	0.40	Fujian	-0.14	Xinjiang	0.13	Heilongjiang	0.40	11
Heilongjiang	0.25	Xinjiang	0.18	Shanghai	-0.29	Ningxia	-0.02	Liaoning	0.33	12
Fujian	0.23	Fujian	0.02	Xinjiang	-0.32	Qinghai	-0.27	Hunan	0.26	13
Shandong	-0.03	Hainan	-0.17	Anhui	-0.54	Anhui	-0.43	Gansu	0.13	14
Hunan	-0.28	Guangdong	-0.43	Hunan	-0.58	Hunan	-0.46	Fujian	0.12	15
City	2016	City	2017	City	2018	City	2019	City	Mean	Rank
Qinghai	4.98	Tianjin	5.51	Qinghai	3.93	Qinghai	5.79	Tianjin	3.08	1
Tianjin	3.37	Qinghai	3.26	Jilin	2.97	Heilongjiang	3.25	Qinghai	2.07	2
Jilin	1.95	Jilin	2.69	Heilongjiang	2.49	Hunan	2.61	Inner Mongolia	2.02	3
Heilongjiang	1.12	Ningxia	2.13	Tianjin	1.93	Tianjin	1.46	Beijing	1.48	4
Ningxia	1.01	Inner Mongolia	1.67	Hunan	1.81	Hebei	0.87	Heilongjiang	1.47	5
Inner Mongolia	0.97	Heilongjiang	1.18	Fujian	1.05	Beijing	0.75	Jilin	1.27	6
Shandong	0.86	Xinjiang	0.99	Beijing	0.90	Inner Mongolia	0.55	Shaanxi	1.13	7
Shaanxi	0.75	Jiangsu	0.40	Xinjiang	0.82	Jilin	0.33	Jiangsu	0.73	8
Xinjiang	0.62	Hunan	0.36	Ningxia	0.65	Shandong	0.28	Shandong	0.69	9
Jiangsu	0.59	Shandong	0.33	Inner Mongolia	0.62	Fujian	0.12	Xinjiang	0.42	10
Gansu	0.54	Hainan	0.19	Shandong	0.50	Jiangsu	0.11	Hunan	0.35	11
Hainan	0.28	Beijing	0.14	Shaanxi	0.40	Guangxi	0.05	Ningxia	0.32	12
Fujian	0.13	Fujian	0.07	Jiangsu	0.26	Ningxia	-0.02	Gansu	0.14	13
Hunan	0.10	Shaanxi	0.04	Hebei	-0.05	Xinjiang	-0.18	Fujian	0.11	14
Anhui	-0.13	Hebei	-0.45	Guangxi	-0.19	Jiangxi	-0.19	Hainan	-0.27	15

Table 3. Composition of explanatory variable DECO.

Variable	Level I indicators	Level II indicators	Basis of calculation
Core explanatory variable	The digital economy (DECO)	Internet penetration rate	(B1) Number of Internet broadband users per capita
		Internet employment rate	(B2) Proportion of employees in information transmission, computer services and software industries
		Internet related output	(B3) Total amount of telecommunications services per capita
		Mobile Internet users	(B4) Per capita year-end mobile phone users

Notably, these provinces are also traditional economic powerhouses in China. Secondly, the ranking of the digital economy changes less rapidly than that of new infrastructure investment. Beijing maintained its first-place position throughout the statistical year, followed by Zhejiang and Shanghai. While many inland regions already show a substantial gap in the digital economy compared to coastal provinces and cities, some provinces and cities in the northeast and northwest regions did not appear on the list. The information in Table 4 highlights a significant developmental gap in the digital economy across provinces. The country's increased investment in new infrastructure aims to promote the overall development of the digital economy and reduce economic development inequality. Therefore, this paper aims to explore the coupling and coordination of the digital economy and new infrastructure investment, by examining the degree of inconsistency between these two areas.

The Coupled Coordination Index of NII and DECO

Table 5 depicts the degree of local coupling and coordination between new infrastructure investment and the digital economy. This paper categorizes the coupling coordination level into five standards: high misalignment (0-0.2), moderate misalignment (0.2-0.4), basic

Table 4. Top 15 of China's DECO index (2011-2019).

City	2011	City	2012	City	2013	City	2014	City	2015	Rank
Beijing	5.65	Beijing	5.48	Beijing	5.36	Beijing	5.57	Beijing	5.18	1
Shanghai	2.96	Shanghai	2.94	Shanghai	3.04	Shanghai	2.94	Zhejiang	2.57	2
Zhejiang	1.90	Zhejiang	1.89	Guangdong	2.08	Guangdong	1.89	Shanghai	2.56	3
Guangdong	1.77	Guangdong	1.76	Zhejiang	1.95	Zhejiang	1.88	Guangdong	1.74	4
Fujian	1.16	Fujian	1.40	Fujian	1.59	Fujian	1.46	Jiangsu	1.38	5
Tianjin	0.81	Liaoning	0.78	Jiangsu	0.84	Jiangsu	0.75	Fujian	1.24	6
Liaoning	0.80	Jiangsu	0.71	Liaoning	0.69	Liaoning	0.60	Liaoning	0.34	7
Jiangsu	0.65	Tianjin	0.59	Inner Mongolia	0.16	Jilin	0.06	Shaanxi	0.08	8
Inner Mongolia	0.31	Inner Mongolia	0.30	Tianjin	0.01	Shaanxi	0.04	Tianjin	-0.04	9
Jilin	0.03	Jilin	0.01	Shaanxi	-0.02	Tianjin	0.00	Shanxi	-0.12	10
Shaanxi	-0.04	Shaanxi	-0.04	Jilin	-0.09	Inner Mongolia	-0.03	Chongqing	-0.13	11
Hainan	-0.21	Xinjiang	-0.10	Xinjiang	-0.16	Shanxi	-0.13	Shandong	-0.18	12
Xinjiang	-0.26	Shanxi	-0.16	Hainan	-0.16	Hainan	-0.19	Hainan	-0.22	13
Shandong	-0.29	Hainan	-0.25	Shanxi	-0.20	Chongqing	-0.29	Jilin	-0.33	14
Shanxi	-0.30	Qinghai	-0.31	Shandong	-0.23	Shandong	-0.30	Sichuan	-0.38	15
City	**2016**	**City**	**2017**	**City**	**2018**	**City**	**2019**	**City**	**Mean**	**Rank**
Beijing	4.77	Beijing	4.33	Beijing	4.08	Beijing	3.93	Beijing	4.93	1
Zhejiang	2.64	Zhejiang	2.58	Zhejiang	2.37	Zhejiang	2.32	Shanghai	2.58	2
Shanghai	2.55	Shanghai	2.03	Shanghai	1.94	Shanghai	2.23	Zhejiang	2.23	3
Jiangsu	1.42	Jiangsu	1.46	Jiangsu	1.40	Jiangsu	1.35	Guangdong	1.56	4
Guangdong	1.38	Guangdong	1.39	Guangdong	1.22	Fujian	0.94	Fujian	1.21	5
Fujian	1.14	Fujian	1.01	Fujian	0.97	Tianjin	0.92	Jiangsu	1.11	6
Liaoning	0.42	Ningxia	0.49	Ningxia	0.85	Ningxia	0.86	Tianjin	0.36	7
Shaanxi	0.16	Liaoning	0.26	Tianjin	0.61	Guangdong	0.79	Liaoning	0.31	8
Tianjin	0.14	Hainan	0.23	Qinghai	0.44	Chongqing	0.36	Shaanxi	0.08	9
Hainan	0.02	Tianjin	0.22	Chongqing	0.40	Qinghai	0.21	Inner Mongolia	-0.02	10
Chongqing	-0.06	Shaanxi	0.12	Shaanxi	0.30	Hainan	0.11	Ningxia	-0.04	11
Shandong	-0.07	Chongqing	0.12	Hainan	0.16	Shaanxi	0.11	Hainan	-0.06	12
Sichuan	-0.21	Qinghai	-0.02	Inner Mongolia	0.08	Gansu	-0.04	Chongqing	-0.12	13
Ningxia	-0.23	Inner Mongolia	-0.13	Sichuan	-0.11	Inner Mongolia	-0.06	Jilin	-0.25	14
Jilin	-0.30	Jilin	-0.26	Gansu	-0.25	Sichuan	-0.31	Qinghai	-0.26	15

Table 5. Top 15 of the coupled coordination index of NII and DECO in China (2011-2019).

City	2011	City	2012	City	2013	City	2014	City	2015	Rank
Beijing	0.90	Beijing	0.93	Beijing	0.91	Beijing	0.81	Beijing	0.76	1
Shanghai	0.71	Shanghai	0.68	Inner Mongolia	0.63	Inner Mongolia	0.67	Jiangsu	0.66	2
Tianjin	0.68	Tianjin	0.66	Shanghai	0.63	Tianjin	0.64	Qinghai	0.60	3
Inner Mongolia	0.64	Liaoning	0.63	Tianjin	0.62	Jiangsu	0.61	Tianjin	0.60	4
Liaoning	0.61	Inner Mongolia	0.62	Jiangsu	0.62	Shaanxi	0.61	Fujian	0.59	5
Fujian	0.59	Jiangsu	0.59	Liaoning	0.59	Liaoning	0.59	Zhejiang	0.56	6
Guangdong	0.58	Shaanxi	0.59	Fujian	0.59	Shanghai	0.57	Shaanxi	0.56	7
Zhejiang	0.57	Fujian	0.59	Shaanxi	0.57	Jilin	0.56	Shandong	0.55	8
Jiangsu	0.57	Guangdong	0.57	Guangdong	0.56	Fujian	0.55	Shanghai	0.54	9
Shaanxi	0.56	Jilin	0.54	Shandong	0.55	Zhejiang	0.54	Liaoning	0.54	10
Xinjiang	0.53	Zhejiang	0.52	Zhejiang	0.54	Guangdong	0.54	Jilin	0.54	11
Hainan	0.51	Heilongjiang	0.50	Jilin	0.52	Heilongjiang	0.51	Guangdong	0.50	12
Ningxia	0.48	Xinjiang	0.50	Heilongjiang	0.52	Shandong	0.51	Inner Mongolia	0.50	13
Shandong	0.47	Shandong	0.50	Xinjiang	0.47	Xinjiang	0.47	Ningxia	0.48	14
Jilin	0.46	Hainan	0.47	Shanxi	0.45	Ningxia	0.47	Xinjiang	0.47	15
City	2016	City	2017	City	2018	City	2019	City	Mean	Rank
Beijing	0.66	Beijing	0.71	Beijing	0.75	Beijing	0.73	Beijing	0.79	1
Tianjin	0.64	Tianjin	0.70	Qinghai	0.68	Qinghai	0.71	Tianjin	0.65	2
Jiangsu	0.62	Ningxia	0.63	Tianjin	0.63	Tianjin	0.63	Hebei	0.42	3
Qinghai	0.60	Qinghai	0.62	Fujian	0.62	Jiangsu	0.59	Shanxi	0.39	4
Fujian	0.58	Jiangsu	0.61	Jiangsu	0.60	Zhejiang	0.58	Inner Mongolia	0.58	5
Zhejiang	0.56	Jilin	0.58	Ningxia	0.59	Fujian	0.57	Liaoning	0.45	6
Jilin	0.55	Fujian	0.57	Jilin	0.55	Ningxia	0.56	Jilin	0.53	7
Shaanxi	0.55	Inner Mongolia	0.56	Shaanxi	0.54	Shanghai	0.52	Heilongjiang	0.49	8
Shandong	0.53	Zhejiang	0.54	Inner Mongolia	0.54	Inner Mongolia	0.52	Shanghai	0.57	9
Ningxia	0.53	Hainan	0.53	Zhejiang	0.53	Shaanxi	0.49	Jiangsu	0.61	10
Shanghai	0.52	Shaanxi	0.51	Shanghai	0.50	Hainan	0.48	Zhejiang	0.55	11
Hainan	0.52	Heilongjiang	0.50	Heilongjiang	0.48	Hebei	0.48	Anhui	0.28	12
Inner Mongolia	0.51	Shanghai	0.50	Hainan	0.47	Heilongjiang	0.47	Fujian	0.58	13
Heilongjiang	0.49	Shandong	0.48	Shandong	0.45	Sichuan	0.46	Jiangxi	0.23	14
Xinjiang	0.47	Guangdong	0.47	Hebei	0.45	Guangdong	0.44	Shandong	0.49	15

coordination (0.4-0.6), moderate coordination (0.6-0.8), high coordination (0.8-1). At the overall level, Beijing, Tianjin, Hebei, Shanxi, and Inner Mongolia comprise the first echelon of coupling coordination, which differs from the digital economy and new infrastructure investment index. Regarding annual changes in indicators, Beijing and Tianjin are in the first echelon of coupling and coordination between new infrastructure investment and the digital economy, but they are only at the moderate coordination standard, indicating room for improvement. Except for Beijing and Tianjin, most provinces and cities in the former middle ranking are still in the moderate imbalance stage, highlighting that China's local new infrastructure investment level has yet to match the digital economy's development. From the experience of traditional infrastructure construction, a low coordination level may cause certain resource waste and environmental pollution. Regarding annual index changes, the coupling coordination degree of leading cities such as Beijing, Shanghai, and Tianjin displays a downward trend. While inland provinces such as Inner Mongolia, Qinghai, Ningxia, and Xinjiang have an overall low coupling coordination level, they have experienced a certain upward trend throughout the statistical period.

Variable Distribution and Control Variable Selection

The $PM_{2.5}$ data comes from the global annual average concentration data of $PM_{2.5}$ provided by the Socioeconomic Data and Application Center of

Table 6. Descriptive statistics.

Variable	Obs	Mean	Std.Dev.	Min	Max
Lnnii	270	1.320	0.358	0.519	2.281
Lntech	270	1.029	0.408	0.329	2.049
ndc	270	0.450	0.150	0.000	0.930
Lndeco	270	1.011	0.403	0.344	2.158
$LnPM_{2.5}$ (g1)	270	3.618	0.387	2.260	4.450
Lnpt2	270	3.702	0.231	2.773	4.127
Lnqgt	270	0.168	0.222	0.010	1.426
Lnrgdp	270	10.299	0.404	9.532	11.377
Lnpop	270	7.881	0.410	6.639	8.669
Lngdp	270	9.293	0.868	7.089	10.912

Columbia University. This paper selects the proportion of secondary industry (*pt2*), quality of green technology innovation (*qgt*), gross domestic product (*gdp*) and population density (*pop*) as control variables, and logarithmizes each control variable to stabilize data. The quality of green technology innovation (*qgt*) is represented by the number of local green innovation patents granted. The distribution of variables involved in this paper is as follows (Table 6).

Empirical Results and Discussion

Global Spatial Autocorrelation Analysis of NII, DECO, NDC & $PM_{2.5}$

Considering the extensive body of literature available on the spatial nature of the digital economy and smog concentration, this section will refrain from reviewing them again. To demonstrate the spatial attributes of new infrastructure investment and its coupling coordination with the digital economy, this study employs spatial

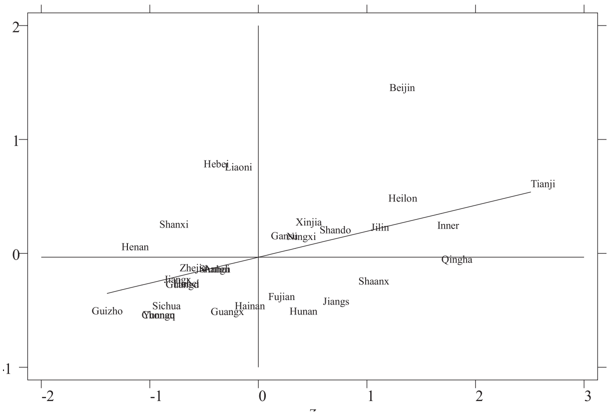

Fig. 2. Moran index scatterplot for NII.

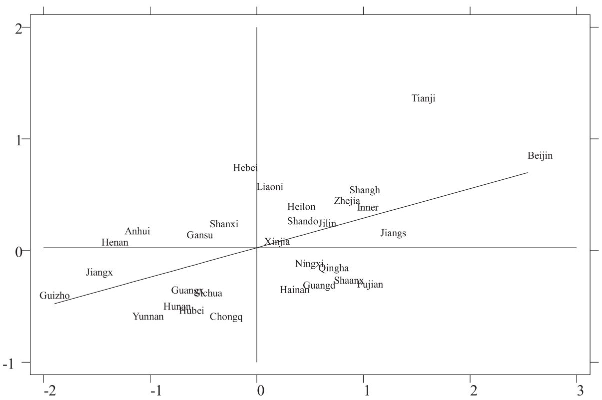

Fig. 4. Moran index scatterplot for NDC.

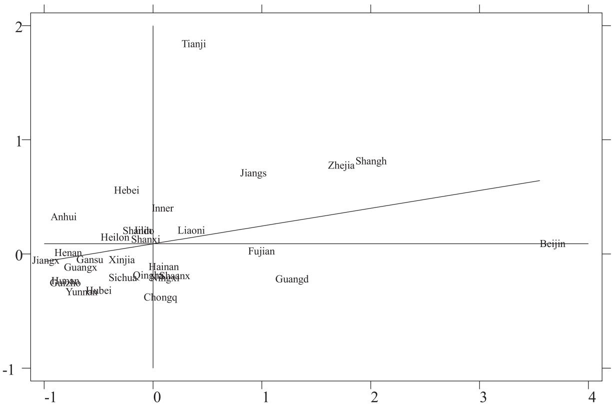

Fig. 3. Moran index scatterplot for DECO.

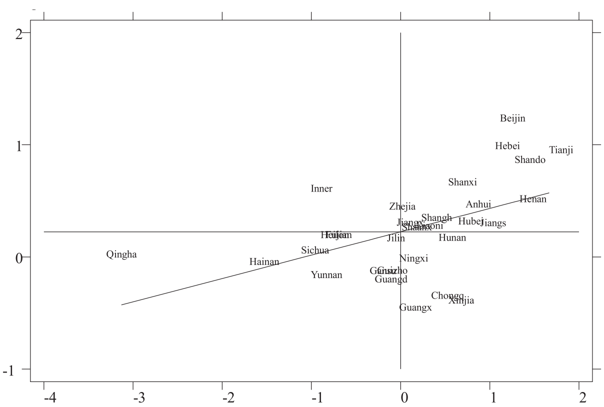

Fig. 5. Moran index scatterplot for $PM_{2.5}$

Table 7. Spatial Moran Index of NII, DECO, NDC & $PM_{2.5}$

Variables	2011	2012	2013	2014	2015	2016	2017	2018	2019	Mean
nii	0.199*** (2.876)	0.281*** (3.895)	0.303*** (4.151)	0.185*** (2.835)	0.097** (1.718)	0.01 (0.57)	0.004 (0.501)	0.009 (0.535)	-0.024 (0.143)	0.228*** (3.22)
deco	0.189*** (3.036)	0.169*** (2.727)	0.114** (1.973)	0.103** (1.865)	0.13** (2.199)	0.167*** (2.64)	0.148*** (2.36)	0.169*** (2.6)	0.225*** (3.314)	0.156*** (2.536)
ndc	0.233*** (3.306)	0.243*** (3.466)	0.222*** (3.21)	0.268*** (3.704)	0.23*** (3.25)	0.215*** (3.048)	0.186*** (2.67)	0.1** (1.643)	0.151** (2.275)	0.264*** (3.682)
$LnPM_{2.5}$	0.194*** (2.919)	0.147*** (2.33)	0.211*** (3.093)	0.252*** (3.644)	0.26*** (3.725)	0.237*** (3.425)	0.206*** (3.095)	0.186*** (2.756)	0.177*** (2.692)	0.208*** (3.092)

The content in parentheses is the Z value. *** p<.01, ** p<.05, * p<.1

Table 8. The fixed effect regression of the impact of NII on the haze.

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	FE	IV-GMM	FE	IV-GMM	FE	IV-GMM
Lnnii	-.099**	-.11**	-.117**	-.145***		
	(.044)	(.055)	(.044)	(.054)		
Lnpt2	1.035***	1.147***				
	(.186)	(.132)				
Lnqgt	-.364**	-.318**				
	(.144)	(.138)				
Lnrgdp	-1.21***	-1.358***				
	(.198)	(.171)				
Lnpop	-.096	-.062				
	(.087)	(.065)				
L_Lnnii					-.102**	-.11**
					(.046)	(.043)
L_Lnpt2			.887***	.89***	.898***	1.033***
			(.174)	(.139)	(.173)	(.122)
L_Lnqgt			-.737***	-.75***	-.726***	-1.001***
			(.175)	(.171)	(.172)	(.134)
L_Lnrgdp			-.739***	-.738***	-.774***	-.703***
			(.232)	(.155)	(.249)	(.178)
L_Lnpop			-.058	-.058	-.066	-.052
			(.076)	(.051)	(.073)	(.051)
Individual	Fixed	Fixed	Fixed	Fixed	Fixed	Fixed
_cons	13.195***		8.642***		9.011***	
	(2.291)		(2.295)		(2.381)	
Observations	270	240	240	240	240	210
R-squared	.585	.593	.582	.581	.575	.743

Based on robust standard error. *** p<.01, ** p<.05, * p<.1

autoregression to analyze new infrastructure investment, digital economy level, coupling coordination between new infrastructure investment and digital economy, and smog concentration. The analysis reveals significant spatial spillover effects among these variables, as indicated by Moran's I greater than 0. Moreover, the global Moran's I indicates a positive spatial correlation among new infrastructure investment, digital economy, coupling coordination between the two, and $PM_{2.5}$. Figs 2-5 demonstrate that these four variables exhibit mainly "high-high" and "low-low" clustering. The findings suggest that, in addition to the well-known positive spatial correlation between China's digital economy and smog levels, there exists a positive spatial correlation between China's new infrastructure investment and the coupling coordination between new infrastructure investment and the digital economy.

The Impact of New Infrastructure Investment (NII) on $PM_{2.5}$

Table 8 displays the individual fixed effect results[2] of the impact of new infrastructure investment on haze and a series of robustness testing processes[3]. Regression (1) indicates that a 1% increase in new infrastructure investment (NII) leads to a 0.1% reduction in $PM_{2.5}$ concentration, with statistical significance at the 5% level. Meanwhile, the proportion

[2] This article uses the xtivreg2 command and xtivreg2 does not estimate or report a constant with the fixed effects model fe. Source: Schaffer, M.E., 2010. xtivreg2: Stata module to perform extended IV/2SLS, GMM and AC/HAC, LIML and k-class regression for panel data models.

[3] Since there are explanatory and control variables that are completely collinear with time, the fixed effects model does not include time fixed effects. To address endogeneity issues, this paper employs robustness tests such as IV-GMM, core variable substitution, and lag regression.

Table 9. The fixed effect regression of the impact of Tech on the haze.

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	FE	IV-GMM	FE	IV-GMM	FE	IV-GMM
Lntech	-.244***	-.246***	-.215***	-.275***		
	(.069)	(.073)	(.074)	(.075)		
Lnpt2	.986***	1.104***				
	(.157)	(.132)				
Lnqgt	-.268**	-.223				
	(.126)	(.141)				
Lnrgdp	-1.017***	-1.145***				
	(.202)	(.192)				
Lnpop	-.067	-.035				
	(.085)	(.063)				
L_Lntech					-.208***	-.263***
					(.068)	(.065)
L_Lnpt2			.873***	.872***	.867***	1.018***
			(.149)	(.134)	(.151)	(.119)
L_Lnqgt			-.602***	-.579***	-.629***	-.88***
			(.163)	(.17)	(.157)	(.131)
L_Lnrgdp			-.59**	-.547***	-.633**	-.514***
			(.246)	(.179)	(.241)	(.18)
L_Lnpop			-.045	-.041	-.047	-.032
			(.079)	(.052)	(.079)	(.056)
Individual	Fixed	Fixed	Fixed	Fixed	Fixed	Fixed
_cons	11.271***		7.102***		7.576***	
	(2.222)		(2.406)		(2.389)	
Observations	270	240	240	240	240	210
R-squared	.603	.597	.583	.581	.581	.73

Based on robust standard error. ***p<.01, **p<.05, *p<.1

of the secondary industry (*pt2*) has a positive effect on haze concentration at the 1% significance level. This finding is consistent with the fact that the secondary industry is a major contributor to smog. Additionally, the quality of green technology innovation (*qgt*) can suppress regional $PM_{2.5}$ concentration, while per capita gross regional product has an inhibitory effect on $PM_{2.5}$ increase with a 1% significance level, which is consistent with previous studies. Regression (2) employs IV-GMM with the lagged first-order variable of new infrastructure investment as an instrumental variable, and the results are largely consistent with those of regression (1), indicating the robustness and credibility of the model. Considering the lag effect of control variables, regression (3) includes the lagged control variables in the regression, and the original conclusion still holds, as confirmed by the IV-GMM test of regression (4). Furthermore, regression (5) lags both the new infrastructure investment variables and control variables, and the results remain significant, passing the robustness test of regression (6). These results suggest that the positive impact of new infrastructure investment on smog reduction is robust.

Considering the contingency of the possible results of the core explanatory variable new infrastructure investment, Table 9 uses the proportion of local fiscal science and technology expenditure to replace new infrastructure investment for further testing. Both local science and technology expenditure and new infrastructure investment are part of local generalized emerging construction investment, and both are different from traditional infrastructure investment. The

Table 10. The fixed effect regression of the impact of NDC on the haze.

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	FE	IV-GMM	FE	IV-GMM	FE	IV-GMM
ndc	-.282**	-.315*	-.369***	-.487***		
	(.126)	(.164)	(.134)	(.163)		
Lnpt2	1.019***	1.128***				
	(.178)	(.136)				
Lnqgt	-.379**	-.335**				
	(.143)	(.141)				
Lnrgdp	-1.179***	-1.323***				
	(.21)	(.18)				
Lnpop	-.093	-.055				
	(.089)	(.065)				
L_ndc					-.355**	-.279**
					(.129)	(.139)
L_Lnpt2			.859***	.853***	.866***	.998***
			(.163)	(.142)	(.166)	(.118)
L_Lnqgt			-.766***	-.793***	-.763***	-1.024***
			(.171)	(.176)	(.177)	(.141)
L_Lnrgdp			-.669***	-.645***	-.736***	-.661***
			(.233)	(.166)	(.257)	(.177)
L_Lnpop			-.062	-.063	-.065	-.045
			(.078)	(.051)	(.077)	(.053)
Individual	Fixed	Fixed	Fixed	Fixed	Fixed	Fixed
_cons	12.916***		8.074***		8.763***	
	(2.406)		(2.36)		(2.535)	
Observations	270	240	240	240	240	210
R-squared	.581	.584	.582	.579	.578	.743

Based on robust standard error. *** p<.01, ** p<.05, * p<.1

signs of the results in Table 9 are basically the same as those in Table 8, and they are basically significant at the 1% significance level. Since the scope of technology expenditure is wider than that of new infrastructure investment, it is understandable why the impact coefficient of technology expenditure on $PM_{2.5}$ is greater than that of new infrastructure investment, which is also in line with the actual situation. From this, it can be considered that new infrastructure investment does play a certain role in weakening the local $PM_{2.5}$ level.

The Impact of Coupling Degree of NII and DECO on $PM_{2.5}$

In this section, the Table 10 presents the results of a fixed effect regression analysis on the coupling coordination degree of new infrastructure investment and digital economy level on local $PM_{2.5}$ index, which is a measure of haze pollution. The results of the regression analysis indicate that the coupling coordination degree has a significant negative effect on haze pollution, and the effect is significant at the 5% level. Specifically, every 1 unit increase in the coupling coordination degree will reduce the haze pollution level by 28.2%. The regression analysis also considers the impact of other control variables, such as the proportion of the secondary industry, per capita GDP, and quality of green innovation, and their effects on the level of haze pollution. The results of the robustness test based on IV-GMM also confirm the negative impact of the coupling coordination degree on haze pollution, even when considering the lag of the control variable.

Table 11. Threshold regression results of NII and NDC.

Threshold	Lnpt2	Lndeco	Lngdp	Lnpt2	Lndeco
Variables	(1)	(2)	(3)	(4)	(5)
	TR	TR	TR	TR	TR
Lnpt2	1.236***	1.073***	1.135***	1.289***	1.067***
	(.149)	(.188)	(.118)	(.142)	(.185)
Lnqgt	-.235	-.555***	-.359***	-.206	-.524***
	(.144)	(.146)	(.106)	(.152)	(.154)
Lnrgdp	-1.162***	-1.314***	-1.047***	-1.182***	-1.295***
	(.162)	(.189)	(.207)	(.173)	(.202)
Lnpop	-.099	-.073	-.1	-.092	-.074
	(.082)	(.085)	(.088)	(.084)	(.087)
0bn._cat#c.Lnnii	.048	-.071*	-.053		
	(.057)	(.035)	(.041)		
1._cat#c.Lnnii	-.113**	-.34***	-.183***		
	(.043)	(.041)	(.05)		
0bn._cat#c.ndc				.176	-.185*
				(.168)	(.098)
1._cat#c.ndc				-.29***	-.735***
				(.093)	(.106)
_cons	11.962***	13.966***	11.226***	11.876***	13.781***
	(1.872)	(2.27)	(2.075)	(2.058)	(2.369)
Observations	270	270	270	270	270
R-squared	.616	.628	.618	.625	.618

Based on robust standard error. *** p<.01, ** p<.05, * p<.1

Further analysis of the hysteresis effect of the coupling coordination degree on haze suppression shows that the lagging effect is greater than that of the current period. These findings suggest that the coupling coordination degree of new infrastructure investment in the digital economy has a high inhibitory effect on the local $PM_{2.5}$ level, and this result is robust after multiple tests.

Heterogeneity Test Based on Threshold Effect

The heterogeneity testing in this paper is focused on exploring the existence of threshold effects for new infrastructure investment and its coupling coordination with the digital economy on the impact of smog. It is recognized that the impact of new infrastructure investment on the environment is not a simple linear relationship, and that a threshold point may exist, beyond which the investment has a significant effect on reducing smog. The same is true for the degree of coupling and coordination between the digital economy and new infrastructure investment. The paper examines the potential threshold variables of industrial level, digital economy level, and economic level and conducts threshold regression to test whether there is a significant threshold value that affects the environmental protection effect of new infrastructure investment. The results of the regression indicate that there are indeed threshold values for each of these variables, beyond which new infrastructure investment has a significant inhibitory effect on smog.

Table 11 presents the threshold regression results of the impact of new infrastructure investment and its coupling coordination with the digital economy on smog. Fig. 6, combined with regression (1), reveals that when the proportion of the secondary industry is below the threshold value, the impact coefficient of new infrastructure investment on smog is not significant. However, when the proportion of the secondary industry reaches the threshold, new infrastructure investment has a significant inhibitory effect on smog, which is significant at a level of 5%. Additionally, when the new infrastructure investment is higher than the threshold, every 1% increase in the investment level will decrease the smog level by 11.3%. Fig. 7, combined

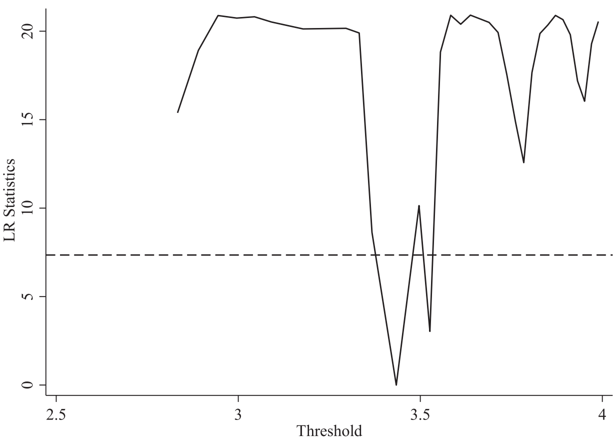

Fig. 6. Threshold regression results on PT2 for NII.

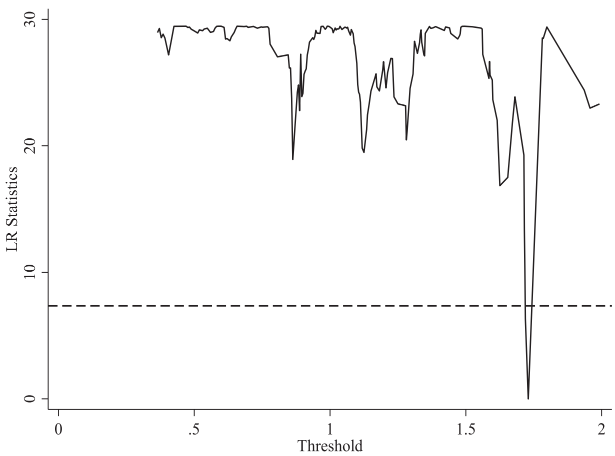

Fig. 7. Threshold regression results on DECO for NII.

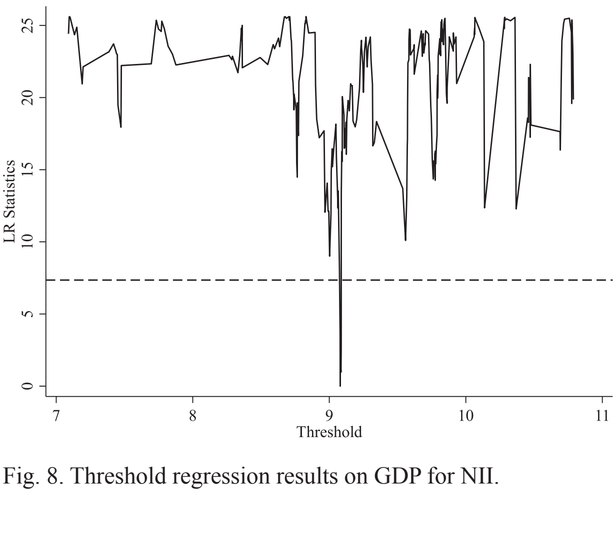

Fig. 8. Threshold regression results on GDP for NII.

with regression (2), shows that when the proportion of the digital economy level is below the threshold value, the impact coefficient of new infrastructure investment on smog is only significantly negative at the 10% level. However, when the level of the digital economy reaches the threshold, new infrastructure investment has a strong inhibitory effect on smog, which is significant at

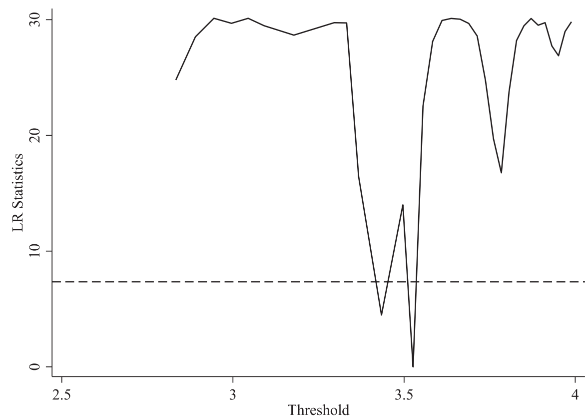

Fig. 9. Threshold regression results on PT2 for NDC.

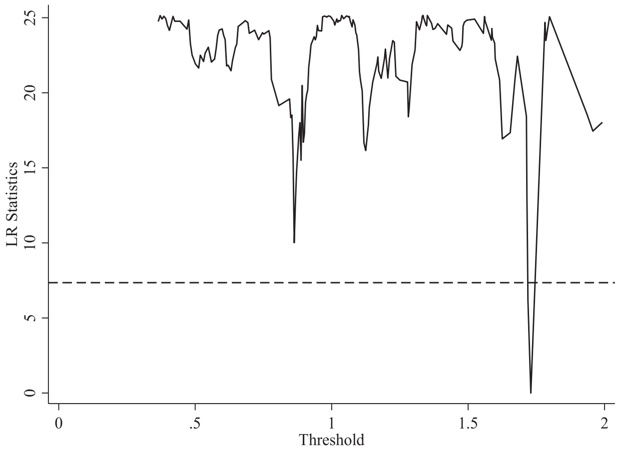

Fig. 10. Threshold regression results on DECO for NDC.

a level of 1%. Furthermore, when the investment in new infrastructure is higher than the threshold, the smog level will decrease by 0.34% for every 1% increase in new infrastructure investment. Fig. 8, combined with regression (3), indicates that when the proportion of the local economic level is below the threshold value, the impact coefficient of new infrastructure investment on smog is not significant. When the local economic level reaches the threshold, new infrastructure investment has a significant inhibitory effect on smog, which is significant at a level of 1%. Additionally, when the investment in new infrastructure is higher than the threshold, the smog level will decrease by 0.18% for every 1% increase in new infrastructure investment. Fig. 9, combined with regression (4), demonstrates that when the proportion of the secondary industry is below the threshold value, the influence coefficient of the coupling coordination degree of new infrastructure investment and the digital economy on smog is not significant. However, when the proportion of the secondary industry reaches the threshold value, the degree of coupling coordination has a significant inhibitory effect on smog, which is significant at a level of 1%. Moreover, when the coupling coordination degree is higher than the threshold value, the haze level will be reduced by 29% for each unit increase in the coupling coordination degree. Fig. 10, combined with regression (5), reveals that when the proportion of the digital economy level is below the threshold value, the influence coefficient of the degree of coupling coordination on smog is only significantly negative at the 10% level. However, when the level of the digital economy reaches the threshold, the degree of coupling coordination has a strong inhibitory effect on smog, which is significant at a level of 1%. Furthermore, when the coupling coordination degree is higher than the threshold value, the haze level will be reduced by 73.5% for every unit increase in the coupling coordination degree.

Conclusion and Policy Implications

While traditional infrastructure has brought significant economic achievements to China, it has also brought unprecedented problems to the current environmental pollution. In the new era of advocating a green economy and high-quality economic development, China's new infrastructure has become a policy choice that aims to achieve a win-win situation for economic growth and environmental protection. Consequently, economic, and environmental research on new infrastructure has gradually become a hot topic, and new infrastructure has a more future-oriented technical vision than traditional information infrastructure.

Therefore, from the perspective of air pollution, this study explores the effect of new infrastructure investment and the digital economy on $PM_{2.5}$. Based on the data from 30 provinces in China from 2011 to 2019, this paper constructs the new infrastructure investment index (NII) and the digital economy index (DECO) through the GPCA method. It uses the CCDM method to construct the new infrastructure investment and digital economy coupling coordination index (NDC). In the empirical part, based on the spatial autoregressive model, this paper finds that NII, NDC, DECO, and $PM_{2.5}$ have positive spatial spillover effects. Then through the individual fixed effect model, it was found that NII and NDC had a significant inhibitory effect on $PM_{2.5}$. Finally, using the threshold regression model, it is found that there are three single threshold variables in the action path of NII inhibiting $PM_{2.5}$, and the threshold variables are PT2, DECO, and GDP, respectively. At the same time, there are two single threshold variables in the action path of NDC inhibiting $PM_{2.5}$ The variables are PT2 and DECO, respectively. The study results show that although both NII and NDC can reduce the concentration of haze, their significant effect requires other macro variables to reach a certain threshold to appear.

Based on the research results presented above, this paper proposes puts forward the following policy recommendations: 1. Given the current emphasis on driving the digital economy in the post-epidemic era, it is crucial for local governments to prioritize the promotion of new infrastructure investment. Such investment has a dual positive impact on both the local economy and the environment, which aligns with the macro requirements and realistic development needs of the green economy and low-carbon transformation. 2. It is essential to ensure that the scale of local new infrastructure investment matches the level of the local digital economy. New infrastructure serves as the fundamental support for the digital economy, and investing without coordination can lead to resource wastage and environmental pollution. 3. Local governments must adopt a long-term perspective when making new infrastructure investments and promoting the growth of the digital economy. This is because both new infrastructure investment and the environmental benefits of the digital economy require a certain level of economic development or industrial structure to be effective. Therefore, local governments should consider the long-term impact of their actions and prioritize sustainable and strategic investments in infrastructure and digital development. 4. The development of new infrastructure investment should prioritize environmental protection. This paper finds that new infrastructure investment has a significant inhibitory effect on smog when it reaches a certain threshold level. Therefore, local governments should give priority to the development of environmentally friendly and low-carbon new infrastructure, such as green transportation and clean energy infrastructure. 5. To ensure sustainable environmental protection and reduction of smog levels, local governments must strengthen their monitoring and enforcement efforts. Despite the promotion of new infrastructure investment and digital economy development, it is crucial to maintain robust monitoring and enforcement measures to protect the environment. By doing so, local governments can ensure that their efforts to reduce smog levels and promote sustainable development are effective and long-lasting.

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Conflict of Interest

The authors declare no conflict of interest.

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