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Modelling economic policy issues

Effect of digital economy on air pollution in China? New evidence from the "National Big Data Comprehensive Pilot Area" policy☆

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ABSTRACT

This paper, based on the panel data of 284 Chinese prefecture level and above cities span 2010 to 2019, systematically investigated the relationship between digital economy and air pollution, with introducing difference-in-differences model, mediating effect model, and spatial difference-in-differences model, as well as treating the "National Big Data Comprehensive Pilot Area" policy as a quasi natural experiment. Finally, results show that:(1) Digital economy does negatively affect air pollution, in particular the industrial dust, followed by industrial sulfur dioxide and carbon dioxide. All these benchmark results have withstood the robustness test. (2) Almost all the mediating roles of industry structure upgrading, industry intensive development, and online life in the relationship between digital economy and air pollution have been confirmed, except it is partly absent in the digital economy-industrial dust nexus and the digital economy-industrial sulfur dioxide linkage. (3) Negative spatial spillover effect is evident between digital economy and air pollution, regardless of involving the neighboring pilot cities or the non pilot cities. (4) The passive air pollution effect of digital economy varies with the regional distribution, administrative scale, marketization level, and government competitiveness. All these findings shed new lights on government intervention.

1. Introduction

In recent years, the frequent outbreak of extreme weather, especially caused by air pollution, is challenging the bottom line of people's survival (Evans and Smith, 2005; Chen et al., 2013; He et al., 2016; Fan et al., 2020), as well as warning that the previous efforts in environmental governance fails to at least keep space with the environmental pollution (Zhang et al., 2022; Zhou et al., 2022). As The United Nations Environment Program (UNEP) and The World Health Organization (WHO) have repeatedly called for, human beings are asked to end the suicide war against nature before it is too late. Given this backdrop, China, a typical developing country used to exchange environment for economic growth, has attached growing concerns and investments to air pollution since the 1970s. Also, to shoulder the responsibility of a large country, China has solemnly announced its determination to combat air pollution in the world. Nonetheless, according to the latest data, in 2021, 35.7% of China's 339 prefecture level and above cities still face the dilemma of unqualified air quality. If sandstorms are considered, this proportion will increase to 43.1%. Assessing the performance of 11.9 billion tons of total

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0313-5926/

emission, 25.9% growth rate, and 33% global share, China remains the world's largest carbon emitter. The overall air quality of China ranks 22nd in the world, with 34% of cities not showing a significant decline in PM2.5 concentration. China has not yet escaped the plight of air pollution (Reis, 2001; Qiao et al., 2022); worse still, these toughest issues began to evolve towards localization and complexity without ready-made reference answers, calling for more independent exploration or will yield an ill influence on green transformation and even high-quality development of China in the new era. Hereby, discussing the causes of air pollution and seeking scientific ways for air pollution governance seem to be the main practical directions and hot research topics in China during the 14th Five Year Plan period.

Meanwhile, the booming digital economy injects new impetus into China's economic development by providing new economic growth points and setting off all-around socioeconomic changes (Sorescu and Schreier, 2021). As a consequence, in 2021, the scale of the digital economy of China has reached 45.5 trillion yuan and accounted for 39.8% of GDP, coupled with spawning new forms of the best practice of production and life (Bastida et al., 2019; Anser et al., 2021; Yuan et al., 2021), which further be proved to simultaneously bring opportunities and challenges to economic growth (Nambisan et al., 2017; Lange et al., 2020). Taken together, relying on the inseparable correlation between economic growth and environmental pollution (Lu et al., 2017; Liang and Yang, 2019; Irfan et al., 2021), we cannot help thinking that whether digital economy may exert an impact on air pollution while affecting economic growth? If so, to what extent and how does the digital economy acts on air pollution? As readily seen, compared with the clear and excellent performances of the digital economy in the economic field, we know little about the role of the digital economy in the environmental field, notably the entanglement of the digital economy and air pollution, which elicit our initiative to bridge this gap by delivering this study. In general, focusing on the aforementioned questions may help perfect the theoretical framework of current studies and facilitate the practice design of digital schemes involving air pollution.

Although existing advances in our confusion have offered valuable references and inspirations for this study, there is still inevitably left rooms for improvement to infinitely approaching the truth. For this reason, we try to make the following updates, which correspond well to this paper's marginal contributions. (1) We schedule to directly investigate the potential linkage between the two keywords "digital economy" and "air pollution", rather than others with similar expressions (e.g., ICT, Internet, Sulfur dioxide emission, or Environmental pollution), as well as spare no effort to select the indicators that best fit the connotation of keywords as the proxy variables (e.g., while the development of the digital economy has progressively transitioned from the stage of knowledge dissemination and infrastructure construction to the phase of deep integration with the real economy, we prefer to use the "National Big Data Comprehensive Pilot Area" policy with multi-attributes of digital economy replace the other policies emphasizes one-dimensional attribute of the digital economy as the agent of the digital economy), to correct the deviation of the result caused by the above two types of factors. (2) Different from regarding production factors as the only route through which digital economy affects air pollution, we creatively take life factors into account, thereby capturing ample evidence for better uncovering the mechanisms of digital economy-air pollution linkage. (3) To curb the source of endogenous problems in current studies, we introduce DID model to finish the baseline regression analysis. Subsequently, we further deliver a series of robustness checks, including a parallel trend hypothesis test, placebo test, PSM-DID test, and policy interference test, to minimize the subjective and objective influences on baseline results, thus sharply increasing the reliability of our conclusions as a whole. (4) We also incorporate the spatial spillover effect and heterogeneity into research. Specifically, the former analysis is responsible for the fundamental role of the digital economy on air pollution by making up for the neglect of spatial effect in well-established studies. In contrast, the latter analysis contributes to the insurance of applicability involving our findings via considering the inherent differences between cities, which indeed offer new evidence for the effectiveness and necessity of regional joint prevention and control as well as regional precision governance.

The rest of this article is designed as follows: Section 2 clearly delineate the implementation motivation and purpose behind the "National Big Data Comprehensive Pilot Area" policy and puts forward the main hypothesis of this paper. Section 3 variable description, data source, and model construction, are described in detail. All the findings related to DID analysis and robustness test are outlined in Section 4. In Section 5, we can see all the empirical results and judging process of mediating effect. Section 6, *Further analysis*, is subdivided into *Spatial spillover effect* and *heterogeneity*. Conclusions, implications, and prospects of this paper are simultaneously depicted in Section 7. The flow chart of this study is shown in Fig. 1.

2. Policy background and research hypothesis

2.1. Policy background

Data, born from the digital economy, is attracting global concern and progressively becoming a new competition target. To address the pressure of gaining a first-mover advantage in the digital economy era, most developed countries have regarded the layout of data strategy as their top priority. Correspondingly, a series of policy documents have been issued successively. To name a few, The Office of Administration and Budget (OMB) of the White House announced the Federal Data Strategy and 2020 Action Plan[1] in 2019, endeavoring to describe the data vision of the Federal Government of the United States for the next ten years from 2020, as well as determines 20 burning actions that government agencies are

[1] https://strategy.data.gov/assets/docs/2020-federal-data-strategy-action-plan.pdf.

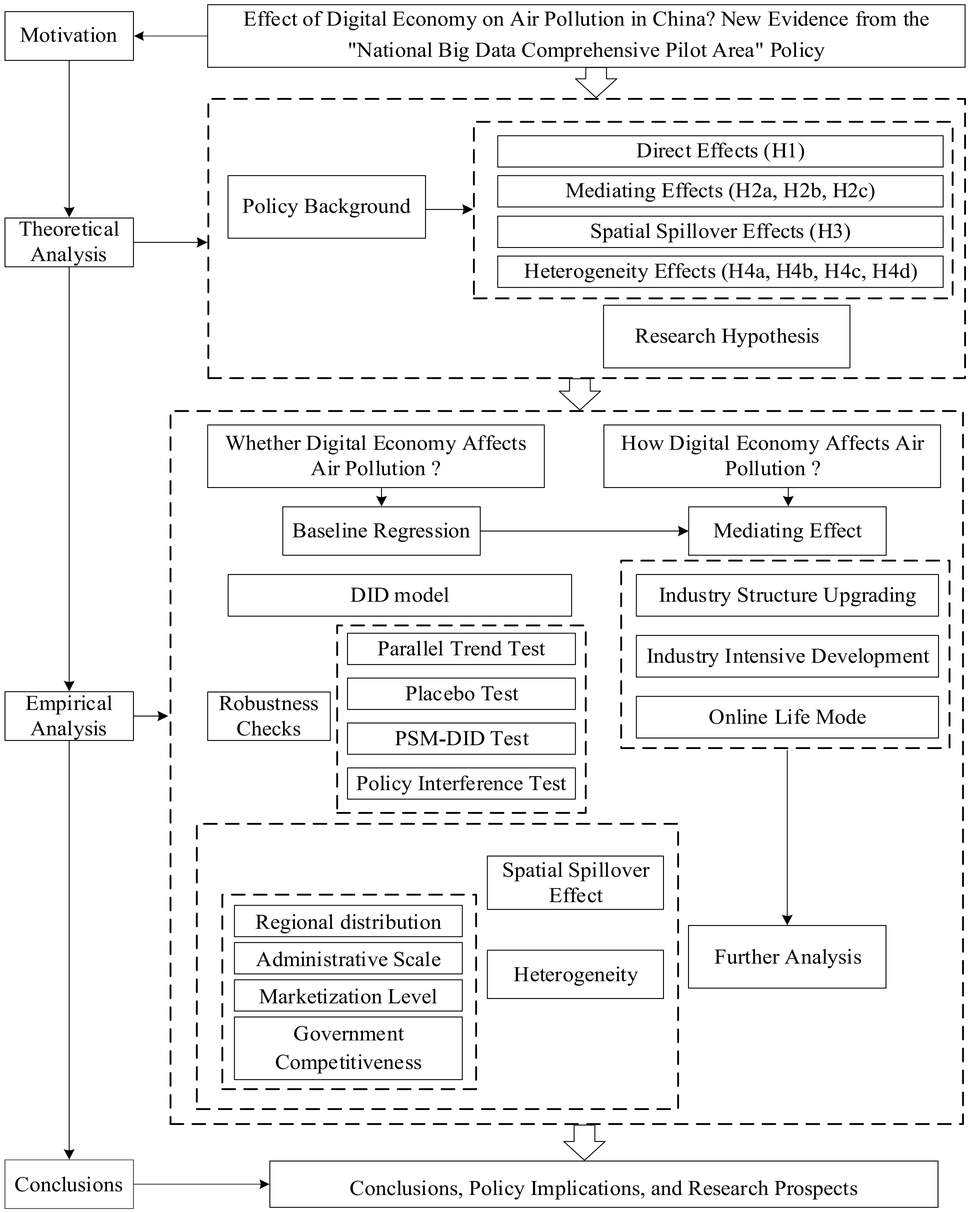


Fig. 1. Flowchart of research steps.

required to take in 2020. The National Data Strategy,[2] promulgated by the UK Department of Digital, Culture, Media, and Sports (DCMS) in 2020, both witnessed the establishment of a framework involving the promotion effect of data investment on economic development and the formation of the determination being a leader in data-driven innovation. In 2020, The European Commission put forward the common digital vision and goals of the European Union through orderly published two documents, encompassing A European Strategy for Data[3] and Shaping Europe's Digital Future.[4] Additionally, all the above expectations were further transformed into concrete actions in 2030 Digital Compass: The European way for the Digital Decade.[5]

2 https://www.gov.uk/government/publications/uk-national-data-strategy/national-data-strategy.
3 https://www.docin.com/p-2322519105.html.
4 https://ec.europa.eu/commission/presscorner/detail/en/ip_20_273.
5 https://eufordigital.eu/wp-content/uploads/2021/03/2030-Digital-Compass-the-European-way-for-the-Digital-Decade.pdf.

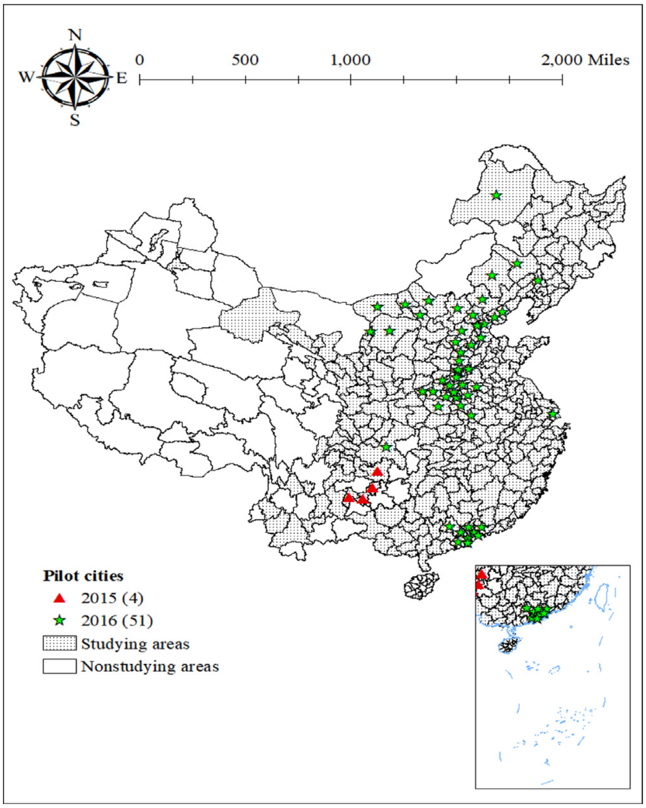


Fig. 2. Spatial distribution of sample cities.

Consistent with the above international trend, China has attached increasing energy to data strategy at the national level, as the data value has already radiated to all socioeconomic fields. During this process, China began to prepare to construct the National Big Data Comprehensive Pilot Area in 2015 for form demonstration and leading effect of the pilot area in the development of big data by continuously summarizing practical experiences that can be used for reference, copied, and promoted. Up to now, China possesses eight pilot areas, including two cross-regional pilot areas (i.e., Beijing-Tianjin-Hebei and the Pearl River Delta), five regional demonstration pilot areas (i.e., Guizhou, Shanghai, Henan, Chongqing, and Shenyang), and one infrastructure overall development pilot area (i.e., Inner Mongolia). These areas cover almost the whole country and then help to build a "three-dimensional skeleton" of big data development practice; more details of their spatial distribution are shown in Fig. 2. In addition, Guizhou, as the sole target of the first batch of pilot zone construction plans, was officially recognized by the State Council in August 2015, even if it was approved authoritatively in February 2016. Subsequently, in October 2016, the pilot roles of the rest test areas were officially recognized.

Since pilot areas undertake seven types of tasks, encompassing open data resource management and sharing, data center integration, data resource application, data element circulation, big data industry aggregation, big data international cooperation, and big data system innovation, we can easily conclude that the establishment of National Big Data Comprehensive Pilot Area both concentrates in digital industrialization and industrial digitalization, which is accompanied by technology renewal, infrastructure perfection, and data application. All these changes involve almost all the digital economy's potential attributes that have been mined. Therefore, it can be inferred that the "National Big Data Comprehensive Pilot Area" policy performs a very similar effect to the digital economy, supporting the suitability of utilizing the "National Big Data Comprehensive Pilot Area" policy as the proxy for the digital economy.

2.2. Research hypothesis

2.2.1. Direct effects

For a long time, it has been common to omit the role of endogenous technological progress in the economic growth-environmental pollution linkage until scholars checked the biased estimations caused by this behavior in their research (Manne and Richels, 2004; Kemfert, 2005). Then, a growing number of studies taking technological factors into account have emerged (Grossman and Krueger, 1995; Antweiler et al., 2001; Levinson, 2009), and almost all of them confirmed the technological effect of environmental pollution (Anderson, 2001; Li et al., 2022), no matter whether the technology is clean or not (Acemoglu et al., 2012, 2014). On this basis, extensive studies associated with the digital economy-environmental pollution nexus, from the perspective of digital technology, have been carried out, with inconclusive findings. On the one hand, the emergence, application, and maintenance of a new kind of technology may require extra resource input and release excess pollution (Kenny, 2003; Cheng et al., 2019), thereby aggravating environmental pollution via significantly increasing the emission scale of pollutants (Jiang and Liu, 2015; Shahnazi and Dehghan, 2019). On the other hand, digital technology may contribute to redundant links reduction, dematerialization, and environmental supervision or governance capabilities improvement (Toffel and Horvath, 2004; Moyer and Hughes, 2012; Ishida, 2015; Cheng et al., 2019; Yang et al., 2020a), thus helps to decouple economic growth from environmental pollution, ultimately preventing or even reducing the pollutants.

However, the third view holds that the above two opposing opinions exist in the whole life cycle of digital economy development at the same time, illustrating that the linkage between the digital economy and environmental pollution is far more complex than previous stated. Borrowing a mainstream point of view, in the birth stage of digital technology, a large amount of infrastructure investment and the very small application scale are culprits for the situation that the environmental deterioration effect exceeds the environmental improvement effect. Conversely, in the mature application stage of digital technology, as the marginal input of resources is significantly less than the marginal substitution of resources, the environmental improvement effect equals or exceeds the ecological deterioration effect. Accordingly, when China's digital economy development is stepping into a high-level phase, emphasizing the deep integration with the real economy, we have reasons to infer that the digital economy may improve the environmental quality (Qiao et al., 2022). The speculation that air pollution, as one of the main contents of environmental pollution, is negatively affected by the digital economy has been widely confirmed, For example, Che and Wang (2022) and Zhao et al. (2023) all found that digital economy had a significant negative impact on urban haze pollution by promoting industrial structure upgrading, technological innovation, resource allocation optimization, etc. when exploring the relationship between the digital economy and haze pollution, and the above passive impact has significant heterogeneity; Liu and Hao (2023), used a spatial simultaneous equation model, has confirmed the bidirectional causal relationship between regional digital economy coordinated development and air quality, that is, regional digital economy coordinated development improves air quality, and better air quality also facilitates regional digital economy coordinated development. This relationship is influenced by spatial spillover effects. Correspondingly, we propose the following hypothesis.

Hypothesis 1 (H1): Digital economy negatively affects air pollution.

2.2.2. Mediating effects

After confirming the existence of the Environmental Kuznets Curve, scholars further turned their eyes to the formation mechanism of environmental pollution and finally put forward a basic theoretical framework consisting of scale effect, structure effect, and technology effect (Antweiler et al., 2001; Levinson, 2009; Hao et al., 2020; Tian and Liu, 2021). Also, there exhibit an interesting phenomenon that both scale effect and technology effect may eventually cause an equivalent structure effect (Khan et al., 2019), according to which structure effect always be regarded as the most crucial impact path of environmental pollution (Oosterhaven and Broersma, 2007). Against this background, there abundant literature emerged to uncover the impact of the digital economy on environmental pollution from the perspective of the structure effect. Reviewing this literature, the structure effect can be roughly divided into the industry structure effect and the element structure effect. As far as industry structure effect, there is a consensus that the digital economy may change the industry structure, in particular resulting in the industry structure upgrading (Grossman and Krueger, 1995; Kohli and Melville, 2019; Chen and Yang, 2021; Wu et al., 2021), through industrial digitalization and digital industrialization (Cheng et al., 2019), thereby promoting the green transformation of the economy by significantly weakening the dependence of production on natural resources and fossil energy (Ishida, 2015). In light of the element structure effect, scholars insist that the digital economy subverts the existing structure of production elements by adding data as a new production element, notably as the major production element, and then all these changes may ultimately improve the total factor productivity via substitution effect and integration effect (Berkhout and Hertin, 2004; Moyer and Hughes, 2012; Qiu and Zhou, 2021; Pan et al., 2021), which facilities to shift the economy mode to a more intensive direction. To sum up, we put forward the hypothesis H2a and H2b.

Environmental pollution is both a by-product of people's production and living activities, rather than only coming from the process of production like most previous researchers insisted, so a growing number of studies have joined the ranks of testing the specific effects of life path in digital economy-environmental pollution nexus (Bastida et al., 2019). As a result, the passive environmental pollution effect of the digital economy has also been proved from the perspective of life, especially well explained by the online life mode accelerated by the digital economy (Blum and Goldfarb, 2006). Hence, we propose hypothesis H2c.

Hypothesis 2a (H2a): Industry structure upgrading mediates the negative impact of the digital economy on air pollution.

Hypothesis 2b (H2b): Industry-intensive development mediates the negative impact of digital economy on air pollution.

Hypothesis 2c (H2c): Online life mode mediates the negative impact of the digital economy on air pollution.

2.2.3. Spatial spillover effects

The first law of geography told that any event might have a spatial correlation. According to this, from three viewpoints, current studies may have offered indirect clues about the existence of the spatial spillover effect of digital economy-air pollution linkage. First, as the most mobile pollutant, air pollution is very vulnerable to natural factors (e.g., temperature, weather, and wind). That is, as long as the conditions are suitable, air pollution will flow between regions or countries (Poon et al., 2006), adhering to the diminishing marginal distance effect. As a result, air pollution, compared with other public goods, has a stronger externality. Second, relying on breaking through the constraints of space and time (Sorescu and Schreier, 2021; Ma and Zhu, 2022), the new best socioeconomic practice model brought by the digital economy has greatly accelerated the development of market integration, thus normalizing the regional cross division of labor, cooperation, imitation, and competition, eventually strengthening the spatial correlation of air pollution. Third, driven by the promotion tournaments, any policy representing the national strategic proposition promulgated will cause the "race to the bottom" or "race to the up" of local governments (Esty, 1996; Konisky, 2007; Kunce and Shogren, 2008; Hou et al., 2018), even if only part of cities are selected as the initial target of policy. Also, the convenience of people's supervision in the digital economy era aggravated these behaviors. Besides, some direct evidence are offered by introducing the spatial econometric model in research, such as Cheng et al. (2019), Shahnazi and Shabani (2019), respectively found that internet technological progress or digital economy can affect surrounding areas environmental pollution via spatial spillover effects. To sum up, we put forward the following hypothesis.

Hypothesis 3 (H3): Digital economy not only negatively affects local air pollution but also suppresses the adjacent air pollutant emissions; namely, the passive air pollution effect of digital economy has a negative spatial spillover effect.

2.2.4. Heterogeneity effects

Unbalanced regional development in China caused by multi types of factors has persuaded researchers to incorporate heterogeneity analysis into their research; in turn, they offered equally statistical evidence for this phenomenon (Zhang and Liu, 2015; Chen et al., 2019; Li and Wang, 2022). Especially due to the difference in resource endowment, industry structure, informatization level, and pollution tolerance (Chen and Zhou, 2017), cities located in different geographical directions differ in the initial conditions and development potentials of the digital economy and air pollution, which complicates the relationship between the two. Similarly, urban administrative level has also witnessed heterogeneity (Ma and Zhu, 2022). Scholars insisted that cities with high administrative level have priority to obtain government support under the rule of authoritative resources will be orderly allocated from high administrative levels to low; namely, cities with high administrative level have many natural development advantages, which in turn helps to obtain more advantages via enhancing the attractiveness of the city, eventually, forming a virtuous circle, according to which the gap between cities with different administrative levels is widened. As we all know, element distortion is accused of environmental pollution, mainly because element distortion hinders the accurate matching of supply and demand, terminates the intensive development mode formation, inhibits technological innovation, and interrupts pollution industries' timely withdrawal from the market. Meanwhile, whereas element distortion is inseparable from the marketization level, we can infer that the marketization level will determine the environmental pollution through the path of element distortion. As such, marketization level may be a potential heterogeneity factor in this study.

As many researchers proved, fiscal decentralization and promotion tournaments are the two crucial factors to induce local government competition (Blanchard and Shleifer, 2001). In the process of this normalized competition, government competitiveness greatly guides the final direction of government behavior. Generally speaking, if the local government has strong competitiveness, it will escape from the pressure of economic growth, make more achievements in green strategy, and have more patience in advanced technological innovation, which undoubtedly favors the local environmental pollution governance. Conversely, if the government has weak competitiveness, it is bound to concentrate on economic growth, particularly short-term economic growth, rather than on others. Therefore, it may sacrifice the environment and abandon long-cycle innovation projects (Buchanan and Musgrave, 2001), ultimately worsening urban environmental pollution. To sum up, the differentiation of government competition accompanying the economic growth difference may inhibit the narrowing of urban pollution gap or technological gap, namely, the digital economy-air pollution nexus may has a heterogeneity on government competitiveness. In summary, we propose the following hypothesis.

Hypothesis 4a (H4a): The negative effect of digital economy on air pollution varies with the regional distribution.

Hypothesis 4b (H4b): The negative effect of digital economy on air pollution varies with administrative levels.

Hypothesis 4c (H4c): The negative effect of digital economy on air pollution varies with the marketization level.

Hypothesis 4d (H4d): The negative effect of digital economy on air pollution varies with government competitiveness.

Following the logic mentioned above, we draw the theoretical mechanisms of this study, and illustrate it in Fig. 3.

3. Methodology and data

3.1. Variable description

3.1.1. Explained variable

Air pollution is the explained variable, which usually is measured by the emission of one or more pollutants. This paper, constrained by data availability and integrity, learning from Chen et al. (2017) and Feng and Wang (2021), select

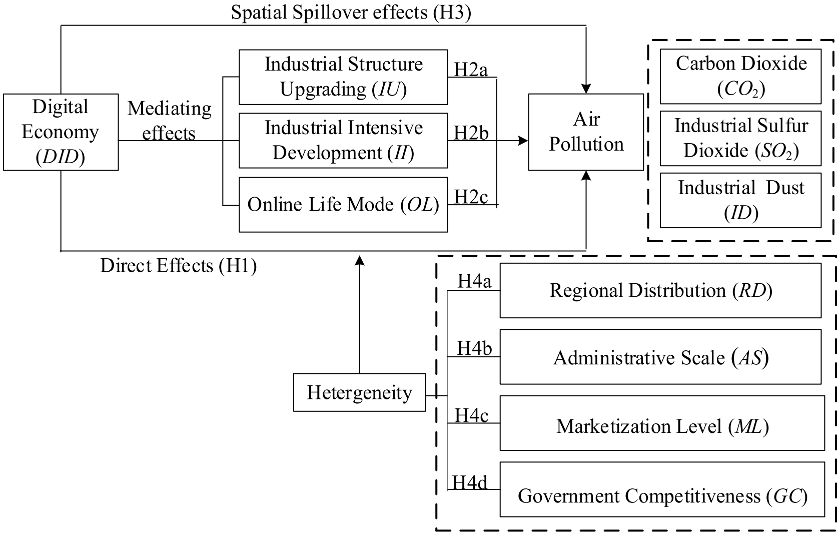


Fig. 3. Theoretical mechanisms.

the emission of industrial sulfur dioxide (SO_2) and industrial dust (*ID*) to reflect the level of air pollution. Also, considering the severe greenhouse effect and China's dual carbon emission targets, we include carbon dioxide (CO_2) emission as an air pollution indicator in this study. To exclude the influence of unit and population size, all thees above variables have been treated by per capita (i.e., emissions per 10000 people) and logarithm.

3.1.2. Explanatory variable

Treating the "National Big Data Comprehensive Pilot Area" policy as a quasi-natural experiment and introducing a multi-period difference-in-differences model as our benchmark regression model, a dummy variable *DID*, representing the digital economy, is employed as the core explanatory variable. In detail, *DID* equal one after enacting the "National Big Data Comprehensive Pilot Area" policy in the corresponding city, and zero otherwise. Noteworthily, to truly reflect the policy effect, we set the "National Big Data Comprehensive Pilot Area" implementation time in the Guizhou pilot area as 2015 rather than 2016. However, all pilot areas were officially approved in 2016.

3.1.3. Mediating variable

As mentioned above, the air pollution effect of the digital economy may come from industrial structure upgrading (*IU*, referring to Xu et al. (2021) and Feng and Wang (2021), measured by the ratio of the added value of the tertiary industry to the added value of secondary industry), industry intensive development (*II*, mainly represented by total factor productivity), and online life mode (*OL*, measured by the number of mobile phones per capita in the region at the end of the year). Among them, industrial structure upgrading (*IU*) and intensive industrial development (*II*) belong to the production mediating mechanism, whereas online life mode (*OL*) belongs to the life mediating mechanism.

3.1.4. Control variable

In addition to the aforementioned core variables, many other factors, especially those involving urban characteristics, may interfere with research results. So, to address this problem, we seriously selected financial decentralization (*FD*, following Feng et al. (2021), calculated by the proportion of regional financial expenditure in total financial revenue), urbanization rate (*UR*, referring to Yang et al. (2020b) and Zhang et al. (2021), calculated by the shares of urban population to total population at the end of the year), external openness (*EO*, drawing on Antweiler et al. (2001) and Qiu et al. (2021), is measured by the ratio of actual foreign direct investment of GDP, the applied foreign capital is converted into RMB utilizing the average exchange rate of RMB to USD in that year), and green innovation (*GI*, according to Wagner (2007) and Hsu et al. (2014), calculated by the number of green innovation patents) as the control variables of this study.

3.2. Data source

Since we took cities as the sample body and selected 2010–2019 as the observation period, the balanced panel data of 284 prefecture-level cities and above (including 67 pilot cities and 217 non-pilot cities) span 2010–2019 were used for empirical analysis in this paper. The list of cities selected as the National Big Data Comprehensive Pilot Area comes from the official website of the Ministry of Industry and Information Technology of the People's Republic of China. Some explanatory variables (SO_2 and *ID*) and control variables (*FD*, *EO*, *UR*), as well as all mediating variables (*IU*, *II*, *OL*) are

Table 1
Summary descriptive statistics of core variables (2010–2019).

Variables		N	Mean	Std.Dev.	Min	Max
Dependent variable	CO_2	2840	1.897	0.801	−1.699	4.857
	SO_2	2840	3.748	1.083	−2.110	7.707
	ID	2840	5.390	1.362	−3.380	9.070
Key explanatory variable	*DID*	2840	0.096	0.294	0	1
Control variable	*FD*	2840	2.389	1.853	0	35.953
	UR	2840	0.570	0.262	0.046	1
	EO	2840	0.022	0.037	0.000	0.775
	GI	2840	2.643	1.306	0	5.050

collected from the China Urban Statistical Yearbook. Carbon dioxide emission is taken from the China Emission Accounts and Datasets. Green patent information is got from the serious match of the green patent details shown in the State Intellectual Property Office (SIPO) of China, the green patent list published by WIPO, and the IPC green list provided by the Organization for Economic Cooperation and Development (OECD). It should be noted that we have filled in the missing data by using the interpolation method. Table 1 is the descriptive statistics results of core variables.

3.3. Model construction

3.3.1. DID model

To answer the question of whether the digital economy affects air pollution, we first treat the "National Big Data Comprehensive Pilot Area" policy as a quasi-natural experiment and introduce DID model to delve into the direct impact of the digital economy on air pollution. Since the pilot policy cycle lasted for two years, we eventually employed the multi-period difference- in-differences model to act as our benchmark regression model.

$$Emission_{\mathrm{it}} = \beta_0 + \beta_1 DID_{it} + \beta_2 X_{it} + \gamma_i + \mu_t + \varepsilon_{it} \tag{1}$$

where $Emission_{it}$ represents the emission of air pollutants of city I in t year, which consists of variable SO_{2it}, ID_{it}, and CO_{2it}. DID_{it} reflects the big data development level of city i in year t, which equals one if city i is selected as the pilot city to implement the "National Big Data Comprehensive Pilot Area" policy at the certain year t, and zero otherwise. X_{it} refers to a vector of control variables, including fiscal decentralization (*FD*), urbanization rate (*UR*), external openness (*EO*), and green innovation (*GI*). γ_i and μ_t respectively depicts the fixed effect of city and time, which can effectively avoid the result deviation caused by the change of relevant factors. ε_{it} is the residual term. β_0 stands for the coefficients of the constant term, while β_1 and β_2 separately are the coefficients of explanatory variable and control variable.

As we all know, the premise of using DID model is to pass the parallel trend hypothesis test, that is, before implement the "National Big Data Comprehensive Pilot Area" policy, it is imperative to have a consistent evolution trend of air pollution between pilot cities and non pilot cities. Referring to Zhang et al. (2022) we complete this test by constructing a dynamic DID model (detailed in Eq. (2)). By the way, we also use this model to finish the exploration of the dynamic effect of "National Big Data Comprehensive Pilot Area" policy on air pollution.

$$Emission_{it} = \beta_0 + \sum_{k \geq -6}^{k=4} \delta_k D_{it}^k + \beta_2 X_{it} + \gamma_i + \mu_t + \varepsilon_{it} \tag{2}$$

Where the new variable *Dk it*, as a dummy variable, denotes whether city i in k year is before/after the implementation of "National Big Data Comprehensive Pilot Area" policy in t year. In more details, *Dk it* equals to one if t-f_i=k, otherwise zero, f_i represents the year of pilot city i implement the "National Big Data Comprehensive Test Area" policy, K ranges from −6 to 4 in this paper. Correspondingly, δ_k is the coefficient of *Dk it*, and the rest parameters in Eq. (2) show no difference with that in Eq. (1).

3.3.2. Mediating effect model

To answer the question of how digital economy affects air pollution, this paper employed causal steps approach supplemented by a bootstrap test to uncover the embodied path of digital economy on air pollution. Generally speaking, the causal steps approach totally have three steps. The first step is to check the linkage between the digital economy and air pollution, the second step is to analyze the relationship between the digital economy and mediating variables, the third step is to observe the correlation between the digital economy, mediating variables, and air pollution. Noteworthily, the completion of all the above steps depends on the benchmark model of this study, and finally obtains three mediating effect test equations correspondingly (i.e., Eq. (1), Eq. (3), and Eq. (4)).

When judging the existence of mediating effect via statistical results, we are required to concentrate on the coefficients of variable *DID* and *M*, including β_1, ω_1, α_1, and α_2. If β_1, ω_1, and α_2 are all significant, we can say yes to the existence of mediating effect; further, if α_1 happened to significant, it is partial mediating effect, otherwise is complete mediating effect (Baron and Kenny, 1986). Conversely, if at least one of ω_1 and α_2 is insignificant, the judgement process will be hindered

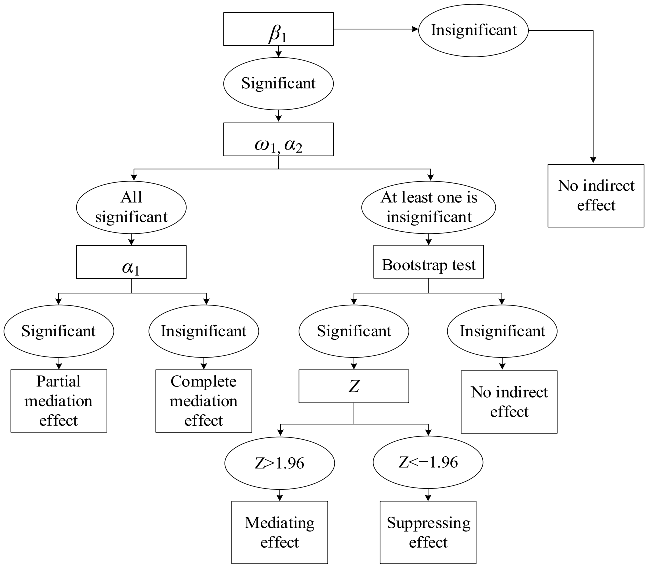


Fig. 4. Flow chart of mediating effect test.

until further verification with bootstrap rest. According to the results reported by bootstrap test, if a 95% confidence interval contains zero, there is no indirect effect between digital economy and air pollution, otherwise, it does exist. Notably, when Z > 1.96 the positive mediating effect is proved, whereas when Z < -1.96 the suppressing effect is proved. Fig. 4 is the flow chart of mediating effect test.

$$M_{it} = \omega_0 + \omega_1 DID_{\mathrm{it}} + \omega_2 X_{\mathrm{it}} + \gamma_i + \mu_t + \varepsilon_{it} \tag{3}$$

$$Emission_{it} = \alpha_0 + \alpha_1 DID_{\mathrm{it}} + \alpha_2 M_{it} + \alpha_3 X_{it} + \gamma_i + \mu_t + \varepsilon_{it} \tag{4}$$

where M_{it} denotes the mediating variables, including industry structure upgrading (IU), industry intensive development (II), and online life mode (OL). ω_0 and α_0 are the coefficients of constant term. ω_1 and α_1 are the coefficients of DID in different equations. α_2 is the coefficient of mediating variable. ω_2 and α_3 represent the coefficients of control variables. The rest parameters in Eqs. (3) and (4) are the same as those in Eq. (1).

3.3.3. SDID model

As described before, it is necessary to incorporate the spatial spillover effects into this study. Referring to Delgado and Florax (2015) and Chagas et al. (2016), we construct the following spatial difference-in-differences model (SDID).

$$Emission_{it} = \beta_0 + \beta_1 DID_{\mathrm{it}} + \beta_2 X_{it} + \varphi_1 W_{T,T} D_{it} + \varphi_2 W_{NT,T} D_{it} + \varphi_3 WX_{it} + \gamma_i + \mu_t + \varepsilon_{it} \tag{5}$$

where W denotes the spatial weight matrix, including the first-order adjacency weight matrix and the squared inverse distance weight matrix. $W_{T,T}D_{it}$ stands for the spatial spillover effects between pilot cities, while $W_{NT,T}D_{it}$ describes the spatial spillover effects between pilot cities and non pilot cities. Correspondingly, φ_1 and φ_2 are the coefficients of $W_{T,T}D_{it}$ and $W_{NT,T}D_{it}$. φ_3 is the spatial coefficient of control variable. The meaning of other parameters and variables in Eq. (5) are consistent with that in Eq. (1).

4. Baseline regression

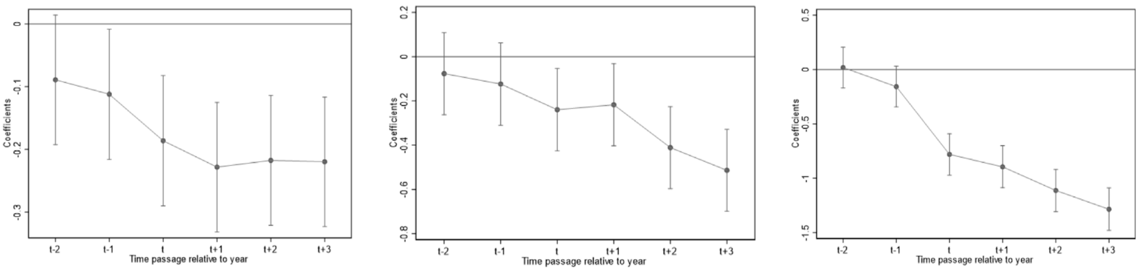
4.1. Results and analysis of DID model

As indicated in Table 2, columns (1)–(2), (3)–(4), and (5)–(6) respectively depict the impact of the digital economy on CO_2, SO_2, and ID. Among them, all the odd series are the results without control variables, whereas all the even series are the results added control variables. By comparison, the absolute values of DID coefficient decreased slightly after taking control variables into account. At the same time, R^2 showed an upward trend, implying that incorporating control variables in research is entirely justified and the digital economy-air pollution nexus gained a better portrayal. Focusing on the first line of Table 2, we observed that all the coefficients of DID are winsorized at the 1% level, no matter the presence or absence of control variables, indicating that the digital economy has an inhibitory effect on three types of air pollutants emissions. H1 is proved. Further, with each unit increase in the digital economy, CO_2 will be reduced by 17.4%, SO_2 will be reduced by 25.9%, and ID will be reduced by 55.6%.

Table 2
Results of the DID model.

Variables	CO_2		SO_2		ID	
	(1)	(2)	(3)	(4)	(5)	(6)
DID	−0.185*** (−5.963)	−0.174*** (−5.612)	−0.264*** (−4.782)	−0.259*** (−4.673)	−0.571*** (−10.474)	−0.556*** (−10.181)
FD		−0.009 (−1.533)		0.036*** (3.252)		0.018* (1.691)
UR		0.204*** (4.753)		0.011 (0.148)		0.267*** (3.527)
EO		0.583*** (2.593)		−0.503 (−1.250)		0.762* (1.922)
GI		0.004 (0.597)		0.014 (1.121)		0.006 (0.452)
Constant	1.738*** (84.904)	1.613*** (41.865)	3.877*** (106.261)	3.782*** (54.882)	6.033*** (167.518)	5.796*** (85.293)
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2840	2840	2840	2840	2840	2840
R-squared	0.109	0.119	0.225	0.230	0.595	0.598

Notes: t-statistics in parentheses; *** $p < 0.01$, * $p < 0.1$.



(A) (B) (C)

Fig. 5. Parallel trend test. Notes: diagrams A, B, and C respectively represents the parallel trend hypothesis test results of CO_2, SO_2, and *ID*.

4.2. Robustness checks

4.2.1. Parallel trend test

As shown in Fig. 5, diagrams A, B, and C are used to describe the coefficient change trend of variable CO_2, SO_2, and *ID* during the two years before and three years after the implementation of "National Big Data Comprehensive Pilot Area" policy. Results showed that the coefficients of variable CO_2, SO_2, and *ID* are distributed around zero in $t-2$ and $t-1$, illustrating that the pilot cities and non-pilot cities have the same change trend before executing the "National Big Data Comprehensive Pilot Area" policy. In addition, the obvious fluctuation of the correlation coefficient trend in t, $t+1$, and $t+2$, compared with $t-1$, $t-2$, proves that the "National Big Data Comprehensive Pilot Area" policy is to blame for the interruption of consistency between pilot cities and non-pilot cities. As such, the parallel trend hypothesis is satisfied, and we are fully qualified to use the DID model.

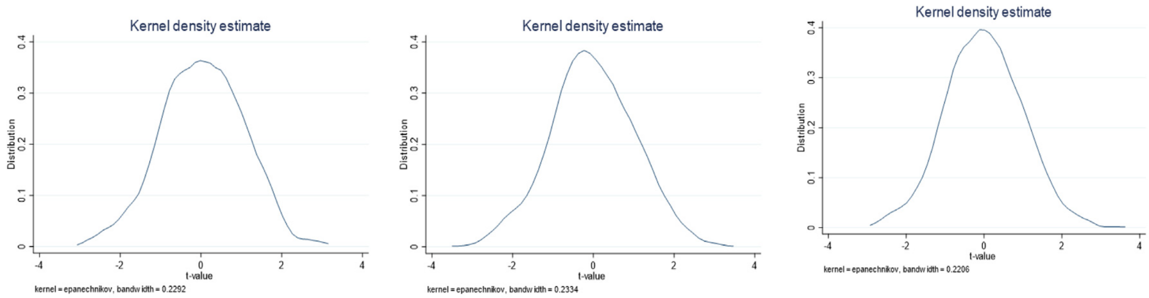
4.2.2. Placebo test

To escape from the influence of other potential factors on the benchmark regression results, this paper, referring to Li et al. (2016) and Cantoni et al. (2017), introduces the placebo test by randomly generating the experiment group. Specifically, we randomly selected 67 pilot cities from the whole samples as the pseudo experiment group, while the other cities as the control group, in this process, the number of pilot cities in each year is equal to the real station. Finally, we gained a new explanatory variable and all corresponding empirical results based on the new samples. After repeating the above process 1000 times, we got the following results.

As shown in Fig. 6, the kernel density estimations of CO_2, SO_2, and *ID*, displayed in diagrams A, B, and C in turn, conform to the normal distribution centered on 0, with the absolute values of almost all t-value (which reflected in the X-axis) are less than 2 and their corresponding p-values (which reflected in the Y-axis) are greater than 0.1. Hence, we can infer that the baseline above results are hardly or even not disturbed by other factors; that is, the placebo test is perfectly passed.

4.2.3. PSM-DID test

Following Rosenbaum and Rubin (1984), we further introduced the PSM-DID test. Finally, by comparing the regression results before and after using the PSM-DID model, we are expected to judge whether the benchmark regression results



(A) (B) (C)

Fig. 6. Placebo test. Notes: diagrams A, B, and C represent the placebo test results of CO_2, SO_2, and *ID*.

Table 3
Matching and balance test results.

Variables	Type	Mean		Reduction		T-test	
		Treated	Control	Bias(%)	|bias| (%)	t	p > |*t*|
FD	Unmatched	2.023	2.428	−27.8	87.5	−3.44	0.001
	Matched	2.023	2.073	−3.5		−0.67	0.501
UR	Unmatched	0.479	0.581	−36.3	96.8	−6.09	0.000
	Matched	0.479	0.482	−1.2		−0.14	0.889
EO	Unmatched	0.029	0.021	23.5	42.0	3.70	0.000
	Matched	0.029	0.024	13.7		1.42	0.156
GI	Unmatched	3.442	2.558	72.4	93.5	10.82	0.000
	Matched	3.442	3.499	−4.7		−0.63	0.530

Table 4
The pseudo R^2 and joint statistical significance of the covariate propensity score.

Sample	PseudoR^2	LR chi2	p > chi2
Unmatched	0.101	181.73	0.000
Matched	0.003	2.56	0.634

are robust. In Table 3, the mean value of covariates increases significantly after PSM matching, and all the standardized deviations after PSM matching are sharply decreased, accompanied by an entirely reversal of significance. All these changes proved the improvement of systematic difference between the experiment group and the control group. As we can see from Table 4, the pseudo R^2 decreases from 0.063 to 0.003 and the corresponding significance shifts from yes to no, supporting the PSM's effectiveness. Table 5 exhibits all PSM-DID test results, and after compare with Table 2, we can easily find that the sign of all DID coefficients remains stable, but their absolute value has decreased in Table 5. In the meantime, all the values of R^2 in Table 5 are larger than those in Table 2. All these comparisons demonstrate that the baseline regression results withstand checks.

4.2.4. Policy interference test

In reality, policies usually interfere with each other. Given this, other policy effects are often excluded to capture the net effect of a certain policy. A substantial number of studies have stated that the relationship between digital economy and air pollution may be related to three types of policies, encompassing the policies of digital economy development, environmental pollution governance, and environmental supervision. On this basis, referring to Li and Wang (2022), we respectively selected the "Broadband China" policy (*BC*), "Ten Measures for Air Pollution Prevention and Control" policy (*TA*), and "Central Environmental Protection Supervision" policy (*CS*) as our main elimination objects. In more details, the "Broadband China" strategy proposed in 2011 is committed to promoting the development of digital economy by increasing the construction of information infrastructure. The Notice on Printing and Distributing the Action Plan for the Prevention and Control of Air Pollution, referred to as the "Ten Measures for Air Pollution Prevention and Control" policy, issued by State Council in September 2013, is considered as the strictest air pollution control policy, and its purpose is to cut down the air pollution via increasing pollution costs. The Environmental Protection Supervision Plan, as the direct result of the reform of China's ecological environment supervision system since 2015, is facilities to improve environmental regulation's implementation effect through breaking the local protectionism. What should be pointed out is that we only put the first round of central environmental protection supervision action into our research, because the second round of plan began in 2019, the last year of our observation period.

Table 5
Results of the DID model.

Variables	CO_2		SO_2		ID	
	(1)	(2)	(3)	(4)	(5)	(6)
DID	−0.170*** (−5.218)	−0.163*** (−5.021)	−0.234*** (−3.584)	−0.227*** (−3.485)	−0.554*** (−10.682)	−0.542*** (−10.510)
FD		−0.038*** (−3.275)		0.064** (2.424)		0.048* (1.826)
UR		0.172*** (4.118)		−0.051 (−0.532)		0.257** (2.333)
EO		0.718** (2.347)		−1.205*** (−2.902)		0.766** (2.201)
GI		0.010 (1.475)		0.015 (1.135)		0.001 (0.080)
Constant	1.937*** (259.597)	1.878*** (46.557)	3.789*** (288.869)	3.663*** (41.604)	5.416*** (428.313)	5.148*** (58.849)
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2636	2636	2636	2636	2636	2636
R-squared	0.834	0.837	0.708	0.710	0.824	0.826

Notes: Robust t-statistics in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 6
Results of the policy interference test.

Variables	CO_2				SO_2				ID			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
DID	−0.137*** (−4.442)	−0.174*** (−5.636)	−0.171*** (−5.492)	−0.135*** (−4.344)	−0.226*** (−4.042)	−0.258*** (−4.666)	−0.256*** (−4.610)	−0.223*** (−3.972)	−0.530*** (−9.620)	−0.557*** (−10.220)	−0.560*** (−10.214)	−0.535*** (−9.691)
BC	−0.228*** (−7.912)			−0.228*** (−7.901)	−0.208*** (−3.996)			−0.209*** (−4.016)	−0.161*** (−3.136)			−0.159*** (−3.104)
TA		−0.076*** (−2.954)		−0.075*** (−2.929)		−0.080* (−1.723)		−0.081* (−1.760)		−0.156*** (−3.426)		−0.154*** (−3.389)
CS			−0.044 (−0.967)	−0.048 (−1.078)			−0.034 (−0.416)	−0.033 (−0.415)			−0.067 (−0.845)	−0.061 (−0.774)
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2840	2840	2840	2840	2840	2840	2840	2840	2840	2840	2840	2840
R-squared	0.141	0.122	0.120	0.144	0.234	0.231	0.230	0.235	0.600	0.600	0.598	0.602

Notes: t-statistics in parentheses; *** $p < 0.01$, * $p < 0.1$.

After adding these dummy variables (i.e. *BC*, *TA*, and *CS*) to the benchmark regression model sequentially, we gained the following results. Concentrating on the first row of Table 6, we can see that all DID coefficients are significant at the 1% level, even if their values of them have changed compared with those in Table 2, implying that the influence of other policies is too small to change the basic conclusion of this paper; namely, H1 is still valid. In the result area of variable CO_2, the first three columns (i.e., columns (1)–(3)) respectively describe the independent interference effects of three types of policies, while column (4) portrays their joint interference effect. The coefficients of *BC*, *TA*, and *CS* are negative, a couple with *BC* and *TA* passed the significance test. These phenomena illustrate that all three types of policies benefit carbon emissions reduction. Also, relying on the absolute value changes of DID coefficient, we can observe that the "Broadband China" policy is accused of baseline regression results overestimation, while the "Ten Measures for Air Pollution Prevention and Control" policy and "Central Environmental Protection Supervision"policy are to blame for the baseline regression results underestimation. Similarly, all these laws mentioned above are also suitable for the other two types policies results.

5. Mediating effect

When closely adhering to the test steps of mediating effect, we are asked to observe the empirical results of relevant variables embedded in Eq. (1), Eq. (3), and Eq. (4). But, because the effects of Eq. (1) has detailed in Table 2, we only exhibit the rest two equations results in this chapter.

5.1. Mediating effect of industry structure upgrading

In Table 7, we can first deduce from the DID coefficient in column (1) that the digital economy favors industry structure upgrading. Then, when concentrating on the last three columns results corresponding to Eq. (4), we next judged that industry structure upgrading plays a mediating role in the relationship between the digital economy and air pollution, in particular plays a partly mediating role, since all *IU* coefficients in column (2)–(4) are significantly negative. Thereby, H2a, H2b and H2c are verified.

Table 7
Mediating effect results of industry structure upgrading.

Variables	IU	CO_2	SO_2	ID
	(1)	(2)	(3)	(4)
DID	0.213***	−0.185***	−0.152**	−0.527***
	(4.968)	(−3.544)	(−2.22)	(−6.369)
IU		−0.075***	−0.413***	−0.745***
		(−3.073)	(−12.38)	(−19.315)
FD	0.044***	−0.119***	−0.079***	0.007
	(6.735)	(−14.659)	(−7.10)	(0.538)
UR	−0.176***	0.535***	−0.129	1.071***
	(−3.566)	(8.934)	(−1.63)	(11.297)
EO	3.079***	0.560	0.040	0.137
	(9.362)	(1.377)	(0.08)	(0.213)
GI	0.101***	0.053***	0.012	−0.136***
	(10.446)	(4.409)	(0.75)	(−7.129)
Constant	0.670***	1.620***	4.408***	5.946***
	(13.615)	(26.158)	(53.55)	(60.673)
Fixed effects	Yes	Yes	Yes	Yes
Observations	2480	2480	2840	2480
R-squared	0.126	0.147	0.082	0.274

Notes: t-statistics in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 8
Mediating effect results of industry intensive development.

Variables	II	CO_2	SO_2	ID
	(1)	(2)	(3)	(4)
DID	0.237***	0.221***	−0.118	−0.691***
	(4.440)	(4.225)	(−1.559)	(−7.794)
II		−0.081***	−0.162***	0.023
		(−4.133)	(−5.731)	(0.684)
FD	0.013	−0.115***	−0.095***	−0.026*
	(0.042)	(−14.395)	(−8.187)	(−1.928)
UR	−0.009	0.521***	0.006	1.202***
	(−0.148)	(8.738)	(0.070)	(11.852)
EO	0.724*	0.849**	−0.854	−2.172***
	(1.770)	(2.127)	(−1.479)	(−3.203)
GI	0.011	0.062***	−0.030*	−0.212***
	(0.888)	(5.229)	(−1.752)	(−10.577)
Constant	1.562***	1.796***	4.328***	5.412***
	(25.515)	(26.806)	(44.612)	(47.515)
Fixed effects	Yes	Yes	Yes	Yes
Observations	2480	2480	2480	2480
R-squared	0.011	0.150	0.044	0.165

Notes: t-statistics in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

5.2. Mediating effect of industry-intensive development

As shown in Table 8, *DID* coefficient in column (1) is significantly positive, indicating that the digital economy is conducive to industry-intensive development, supporting us to continuously observe the results of Eq. (4) listed in columns (2)–(4). Specifically, except in column (4), all coefficients of industry intensive development are winsorized at the 1% level, illustrating that the digital economy does affect carbon dioxide emissions and industrial sulfur dioxide emissions through industry intensive development, and *DID* coefficients further help to subdivided these mediating effects into partly mediating effect and completely mediating effect in turn.

With respect to the insignificant II coefficient in column (4), we utilize bootstrap test to supplement our judgment on whether industry intensive development mediates the digital economy-industrial dust relationship. Consequently, 0 is included in the 95% confidence interval, proving that the aforementioned mediating effect fails to pass the check. Hence, H2b is not confirmed.

5.3. Mediating effect of online life

In Table 9, we can easily find that the digital economy accelerates the online transfer of lives, rely on the results in column (1). Subsequently, the *OL* coefficients in column (2) and (4) are significantly positive and negative, respectively, supporting the existence of mediating effect in the corresponding two relations. Also, their coefficient sign difference tells that online life intensifies carbon dioxide emissions but curbs industrial dust emissions. In addition, since the *OL* coefficient

Table 9
Mediating effect results of online life.

Variables	OL	CO_2	SO_2	ID
	(1)	(2)	(3)	(4)
DID	0.302***	0.100**	−0.142*	−0.574***
	(6.503)	(1.991)	(−1.861)	(−6.567)
OL		0.335***	−0.047	−0.370***
		(15.614)	(−1.433)	(−9.903)
FD	−0.054***	−0.097***	−0.098***	−0.046***
	(−7.521)	(−12.539)	(−8.265)	(−3.421)
UR	0.747***	0.272***	0.042	1.478***
	(13.989)	(4.579)	(0.470)	(14.308)
EO	1.572***	0.263	−0.898	−1.573**
	(4.408)	(0.686)	(−1.540)	(−2.358)
GI	0.076***	0.035***	−0.028	−0.183***
	(7.192)	(3.100)	(−1.619)	(−9.247)
Constant	0.461***	1.515***	4.097***	5.618***
	(8.645)	(26.142)	(46.450)	(55.662)
Fixed effects	Yes	Yes	Yes	Yes
Observations	2480	2480	2480	2480
R-squared	0.146	0.221	0.033	0.197

Notes: t-statistics in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 10
The estimation results of the *SDID* model.

Variables	First-order adjacency weight matrix			Squared inverse distance weight matrix		
	CO_2	SO_2	ID	CO_2	SO_2	ID
	(1)	(2)	(3)	(4)	(5)	(6)
DID	−0.212***	0.080	−0.302**	−0.186**	0.187	−0.338***
	(−2.739)	(0.576)	(−2.219)	(−2.534)	(1.428)	(−2.607)
$W_{\mathrm{T,T}}$D	0.043	−0.459***	−0.356**	0.004	−0.606***	−0.301*
	(0.438)	(−2.646)	(−2.091)	(0.041)	(−3.820)	(−1.918)
$W_{\mathrm{NT,T}}$D	−0.137	0.058	−0.291*	−0.132	0.088	−0.074*
	(−1.515)	(0.361)	(−1.829)	(−1.459)	(0.547)	(−0.463)
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2840	2840	2840	2840	2840	2840
R-squared	0.126	0.235	0.605	0.129	0.236	0.600

Notes: t-statistics in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

in column (3) is insignificant, we reevaluated this kind of correlation by introducing the bootstrap test method. Finally, new test results did not bring any different findings, the assumption that *OL* mediates the relationship between the digital economy and industrial sulfur dioxide emissions is not correct.

6. Further analysis

6.1. Spatial spillover effect

In Table 10, we utilize the first three columns to list the results involving the first-order adjacency weight matrix while use the rest to display the results rely on the squared inverse distance weight matrix. As we can see, *DID* coefficients are insignificantly positive in columns (2) and (5), which are entirely contrary to those in benchmark regression results, illustrating that the objective existence of the spatial spillover effect may lead to the overestimation of policy results. As far as other *DID* coefficients, all their absolute values have changed, proving that ignoring the spatial spillover effect may lead to result deviation. Additionally, the majority of $W_{T,T}D$ coefficients are significantly negative indicating that local digital economy development in pilot cities can inhibit the industrial sulfur dioxide emissions and industrial dust emissions of the neighboring pilot cities. Still, this passive effect is not reflected in carbon dioxide emissions; instead, it even performs a promotion trend. In light of $W_{NT,T}D$ coefficients, they only significant in columns (3) and (6), as well as only positive in columns (2) and (5). All these phenomena shows that local digital economy development in pilot cities has an ill effect on carbon dioxide emissions and industrial dust emissions in neighboring non pilot cities, particularly the industrial dust emissions, whereas showing a promoting trend on industrial sulfur dioxide emissions in non-pilot neighboring towns.

6.2. Heterogeneity analysis

This part aims to check whether the benchmark analysis results have heterogeneity at four types of urban characteristics. To do this, we adopt the grouping regression method to deliver relevant checks based on the benchmark model. Before

Table 11
Regional heterogeneity results of benchmark regression.

Variables	CO_2			SO_2			ID		
	Eastern	Central	Western	Eastern	Central	Western	Eastern	Central	Western
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
DID	−0.175*** (−4.658)	−0.228*** (−4.546)	0.564*** (5.475)	−0.348*** (−4.598)	0.089 (1.087)	0.054 (0.266)	−0.367*** (−4.111)	−0.799*** (−9.822)	−0.388** (−2.181)
FD	0.121*** (3.806)	−0.036*** (−3.761)	0.009 (1.097)	0.057 (0.891)	0.026* (1.675)	0.041** (2.457)	−0.064 (−0.850)	0.059*** (3.792)	−0.010 (−0.688)
UR	0.141*** (2.734)	0.238*** (3.156)	0.339*** (3.264)	−0.275*** (−2.642)	0.139 (1.134)	0.161 (0.781)	0.175 (1.427)	0.199 (1.628)	0.632*** (3.522)
EO	1.672*** (2.586)	0.081 (0.305)	0.092 (0.148)	−1.076 (−0.828)	−0.534 (−1.244)	0.161 (0.131)	−2.540* (−1.655)	0.955** (2.237)	0.976 (0.909)
GI	0.003 (0.325)	−0.002 (−0.207)	0.010 (0.697)	−0.010 (−0.548)	0.023 (1.271)	0.024 (0.848)	−0.008 (−0.381)	−0.025 (−1.388)	0.062** (2.522)
Constant	1.892*** (27.520)	1.508*** (22.900)	1.088*** (13.863)	4.278*** (30.939)	3.736*** (34.837)	3.242*** (20.871)	5.961*** (36.530)	5.873*** (55.090)	5.669*** (41.845)
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1000	1090	750	1000	1090	750	1000	1090	750
R-squared	0.087	0.148	0.408	0.236	0.271	0.350	0.599	0.647	0.574

Notes: t-statistics in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

that, we divided the above four types of urban characteristics into groups. Especially referring to the relevant authoritative regulations and most current studies (Zhang et al., 2021), regional distribution is commonly subdivided into three categories (i.e., Eastern, Central, and Western), administrative scale is roughly divided into Top cities (including first-tier cities) and Tail cities (encompassing second tier and lower cities), marketization level and government competitiveness are respectively divided into two groups: High and Low, Strong and Weak, with treating their average value as the criterion. Additionally, marketization level (*ML*) is measured by the China marketization index. At the same time, government competitiveness (*GC*) is calculated by urban per capita GDP because government competitiveness is greatly determined by economic prosperity under the background of economic performance is still the main assessment standard.

As readily seen, Table 11 shows all the regional heterogeneity results of the benchmark regression in the order of carbon dioxide (columns (1)–(3)), industrial sulfur dioxide (columns (4)–(6)), and industrial dust (columns (7)–(9)). Overall, the digital economy-air pollution nexus varies with the types of region. DID coefficients fluctuate with region type changes, involving significance, sign, and absolute values. Accordingly, H4a is proved. Furthermore, considering all the aforementioned coefficient characteristics comprehensively, we also found some other laws. First of all, as we gleaned from the DID sign, digital economy increased carbon dioxide and industrial sulfur dioxide emissions in the western region, which runs counter to our expectations and other results. Hence, compared with others, we may conclude that the western region has not yet fully enjoyed the digital dividend of air pollution control. Secondly, focusing on the absolute values of *DID* coefficients, it is easy to observe that the passive air pollution effect of the digital economy is more prominent in eastern and central regions than in the western region, notably in the east region, which proves the first law again. In short, a regional gap exists in the digital control of air pollution.

6.2.1. Regional distribution

6.2.2. Administrative scale

In Table 12, all *DID* coefficients in top cities are insignificantly positive while significantly negative in tail cities, illustrating that the air pollution suppression effect of digital economy only occurs in cities with low administrative scales. Conversely, the digital economy intensifies air pollution in cities with high administrative scales. This phenomenon may be ascribed to the rule of diminishing marginal utility, wherein development advantages of cities with high administrative scales are also obstacles to pollution control. Finally, the severe differentiation of benchmark results in administrative scale supports us to judge that there indeed exists administrative heterogeneity, H4b is proved.

6.2.3. Marketization level

As shown in Table 13, *DID* coefficients are significantly negative in all analysis, indicating that the basic conclusion in this paper, namely, digital economy has a passive influence on air pollution, remains steady regardless of whether marketization level is high or low. Further, the absolute values of *DID* coefficient exhibits obvious differences even in a certain research, which can be used to confirm the existence of heterogeneity on marketization level, that is, the effect of digital economy on air pollution is affected by urban marketization level, according to which H4c is verified. Also, we found that the aforementioned heterogeneity varies with the types of air pollutant. Specifically, the inhibition effect of digital economy on carbon dioxide is stronger in the low marketization level group, whereas this effect of industrial sulfur dioxide an industrial dust are stronger in high marketization level groups, all these appearances remind us of the complexity of reality.

Table 12
Administrative heterogeneity results of benchmark regression.

Variables	CO_2		SO_2		ID	
	Top City	Tail City	Top City	Tail City	Top City	Tail City
	(1)	(2)	(3)	(4)	(5)	(6)
DID	0.005	−0.186***	0.149	−0.282***	0.016	−0.614***
	(0.089)	(−5.377)	(1.017)	(−4.803)	(0.130)	(−10.244)
FD	0.002	−0.012*	−0.026	0.036***	−0.067	0.019*
	(0.091)	(−1.923)	(−0.506)	(3.248)	(−1.548)	(1.654)
UR	−0.053	0.266***	−1.314***	0.214***	−0.714***	0.410***
	(−0.504)	(5.669)	(−5.107)	(2.679)	(−3.291)	(5.031)
EO	0.089	0.588**	−1.011	−0.490	−0.626	0.823*
	(0.209)	(2.342)	(−0.967)	(−1.147)	(−0.710)	(1.888)
GI	−0.009	0.005	−0.014	0.014	0.038	−0.000
	(−0.592)	(0.670)	(−0.372)	(1.125)	(1.176)	(−0.014)
Constant	2.164***	1.536***	4.418***	3.738***	5.959***	5.821***
	(20.518)	(37.401)	(17.146)	(53.427)	(27.413)	(81.647)
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	350	2490	350	2490	350	2490
R-squared	0.080	0.142	0.179	0.279	0.751	0.584

Notes: t-statistics in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 13
Marketization level heterogeneity results of benchmark regression.

Variables	CO_2		SO_2		ID	
	High	Low	High	Low	High	Low
	(1)	(2)	(3)	(4)	(5)	(6)
DID	−0.138***	−0.155***	−0.251***	−0.171*	−0.635***	−0.472***
	(−3.261)	(−3.742)	(−3.546)	(−1.883)	(−9.411)	(−4.696)
FD	−0.014**	0.003	0.039***	−0.005	0.011	0.049
	(−2.033)	(0.029)	(3.278)	(−0.160)	(0.993)	(1.479)
UR	0.422***	−0.092	0.191*	−0.307**	0.140	0.451***
	(7.153)	(−1.590)	(1.930)	(−2.411)	(1.483)	(3.206)
EO	0.481*	0.398	−0.511	−0.782	0.941**	0.287
	(1.753)	(1.103)	(−1.109)	(−0.987)	(2.145)	(0.328)
GI	0.011	0.004	0.026*	−0.010	0.015	0.003
	(1.197)	(0.392)	(1.728)	(−0.463)	(1.049)	(0.115)
Constant	1.340***	2.151***	3.697***	4.044***	6.009***	5.386***
	(27.702)	(35.407)	(45.502)	(30.342)	(77.656)	(36.621)
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1887	953	1887	953	1887	953
R-squared	0.180	0.054	0.285	0.173	0.603	0.591

Notes: t-statistics in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

6.2.4. Government competitiveness

See from Table 14, *DID* coefficients show serious differentiation in columns (1)–(6), involving significance, sign, or value. In more details, *DID* coefficient is negative in column (1), insignificant in columns (2) and (3), and has completely different values in all columns, reflecting that the effect of digital economy on air pollution may be affected by government competitiveness, that is, our baseline regression results have heterogeneity on government competitiveness, thereby H4d is confirmed. Additionally, by seriously comparing the heterogeneity results of three types of air pollutants, we found that in the digital economy-industrial sulfur dioxide linkage and digital economy-industrial dust linkage, the weaker the government competitiveness, the more likely the negative air pollution effect of digital economy will appear, which runs counter to the relevant results in the digital economy-carbon dioxide nexus. The possible reason is that the popularization and implementation of the concept of green development (such as incorporating green development performance into the assessment) may bring more economic growth disconnected from air pollution, even though this behavior will aggravate the short-term promotion pressure of local governments by increasing costs and delaying growth. At the same time, the outstanding performance of digital economy may helps to strengthen the confidence of local governments to do so.

7. Conclusions, policy implications, and research prospects

7.1. Conclusions

To answer the questions whether and how digital economy affect air pollution, this paper strive to design a systematic research framework, which can be roughly divided into theoretical analysis and empirical analysis. In general, all these

Table 14
Results of Government competitiveness heterogeneity analysis of benchmark regression.

Variables	CO_2		SO_2		ID	
	Strong	Weak	Strong	Weak	Strong	Weak
	(1)	(2)	(3)	(4)	(5)	(6)
DID	0.444*** (4.782)	−0.015 (−0.268)	−0.161 (−1.221)	−0.270*** (−2.682)	−0.668*** (−5.008)	−0.670*** (−5.271)
FD	−0.028*** (−2.691)	−0.171*** (−6.925)	−0.095*** (−6.349)	−0.091** (−2.053)	−0.074*** (−4.882)	−0.007 (−0.122)
UR	0.814*** (8.564)	−0.170** (−2.255)	0.638*** (4.724)	−0.679*** (−5.038)	1.986*** (14.561)	0.734*** (4.309)
EO	0.878* (1.655)	−0.676 (−1.090)	−0.198 (−0.263)	−2.897*** (−2.616)	0.255 (0.335)	−4.716*** (−3.373)
GI	0.040** (2.182)	−0.040** (−2.549)	−0.020 (−0.769)	−0.044 (−1.550)	−0.112*** (−4.289)	−0.192*** (−5.374)
Constant	0.871*** (9.556)	2.566*** (26.506)	3.664*** (28.295)	4.696*** (27.181)	5.130*** (39.210)	5.816*** (26.667)
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1464	1376	1464	1376	1464	1376
R-squared	0.165	0.170	0.084	0.040	0.280	0.147

Notes: t-statistics in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

analysis are completed under the premise of introducing a series of models, encompassing DID model, mediating effect model (i.e. causal steps approach supplemented by bootstrap test), and SDID model, selecting 284 prefecture level and above cities from 2010 to 2019 as samples, as well as treating the "National Big Data Comprehensive Pilot Area" policy as a quasi natural experiment and utilizing the corresponding dummy variable represent digital economy. Besides, to make conclusions more complete and applicable, this paper also delivered extra analysis including spatial spillover effect and heterogeneity on the basis of baseline regression. Finally, all the conclusions we gained are summarized as follows.

First, digital economy has a significant passive impact on three types of air pollutants, in particular industrial dust, followed by industrial sulfur dioxide and carbon dioxide. All these findings are remain valid after a series of robustness tests. In short, digital economy may be an modern weapon to improve the air quality via curbing the emission of air pollutants.

Second, digital economy may helps to decouple life and production activities from air pollution through promoting industry structure upgrading, stimulating industry intensive development, and accelerating online transfer of lives. However, when facing of different air pollutants, the above generally mediating effect law will be break. Such as, industry intensive development failed to mediate the digital economy-industrial dust nexus. The assumption that online life mediate the digital economy-industrial sulfur dioxide nexus did not pass the bootstrap test. Moreover, in contrast, online life has been proved to increase carbon dioxide emissions, which entirely runs counter to other mediating effect results.

Third, the relationship between digital economy and air pollution does has spatial spillover effect, and ignoring this effect is to blame for the baseline regression results overestimation or underestimation. Although there is a negative spatial spillover effect on the whole, the passive effect of digital economy on air pollution in neighboring pilot cities is only occurs in industrial sulfur dioxide as well as industrial dust, while the same effect in surrounding non pilot cities mainly reflected in industrial dust, followed by carbon dioxide.

Last but not the least, the relationship between digital economy and air pollution is greatly affected by four kinds of urban characteristics (i.e. regional distribution, administrative scale, marketization level, and government competitiveness). Generally speaking, the baseline regression results of this paper are stronger in advanced areas (mainly including the eastern area and the central area), tails cities (namely the second tier and lower cities), high marketization level cities, and strong government competitiveness groups. But, it should also be pointed out that the heterogeneity of the digital economy-carbon dioxide nexus is completely opposite to the above general law.

7.2. Policy implications

Based on the aforementioned conclusions, several policy implications can be drawn as follows: (1) In order to fully tap up the positive role of digital economy in environmental field, governments are encouraged to vigorously promote the development of digital economy, so as to guarantee the lockstep of economic and environmental development. Moreover, since the development of digital economy has shifted from the phrase of knowledge popularization and infrastructure construction to the stage of emphasizing close integration with the real economy in China, actions delivered by governments should better concentrate on the latter matters rather than the former. Meanwhile, considering the interference effect between polices, government are expected to plan or design solutions to problems from a more overall perspective. (2) Inspired by the mediating effect results, governments actually have two type of ways to stimulate the negative effect of digital economy occur, rather than just from the perspective of production. In contrast, a lot of attentions and supports have gathered in production field in the past, as well as have made many outstanding advances, thereby, next, governments are required to take the digitalization of life as a new breakthrough point in environmental governance. (3) Relying on spatial spillover effect, governments may effectively achieve the air pollution control via fully utilizing the demonstration and leading effect of the pilot areas, and how to reasonably deployment pilot cities are the key of government efforts. In a meantime, the existence of urban heterogeneity urge governments to take more localization actions according to its own development endowment.

7.3. Research prospects

Although we have spared no effort to perfect this study, it still suffers from several limitations, which leaves some possible rooms for the follow-up research. First, although we have creativityly incorporated life factors into the mechanism research, compared with the achievements in production mechanism, we still know little about it, like the potential types and effects of life factors, thus more relevant research deserve delivered in the future. Second, constrained by taking "National Big Data Comprehensive Pilot Area" policy as the measurement basis for digital economy, this paper only selects Chinese cities as sample. However, as digital economy and air pollution are two crucial topics accepted global concern, it is worthwhile to reexamined the relationship between them by broaden the international sources of samples.

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