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Research article

How does China's big data policy affect the digital economy of cities? Evidence from national big data comprehensive pilot zones

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ABSTRACT

Based on the panel data of 280 cities in China from 2011 to 2019, this paper examines the effects of big data policies on the digital economy development by using the national big data comprehensive pilot zones as a quasi-natural experiment. The findings of this paper are as follows. First, the big data policy significantly promotes China's digital economy development. Second, cities at a higher administrative level receive higher policy benefits than cities at a lower administrative level. Third, technological innovation and human capital are important ways for the big data policy to improve the development of the digital economy. The conclusions of this paper not only help to assess the effectiveness of big data policies and ensure the efficacy of policy implementation, but also provide policy support for local governments to fully explore the value of data elements and grasp the new opportunities for the digital economy development with the help of the pilot zones.

1. Introduction

The development of the digital economy is the result of the integration of modern information technology with human production and lifestyle. In recent years, developing digital economy has become the commanding height for countries all over the world to struggle for the international discourse right in the information age. Data is the production factor of the digital economy, and Big Data mining and applications can create significant value for the world economy. Therefore, in recent years, to promote the development of the digital economy, governments around the world have introduced policies related to big data, such as the *Big Data Research and Development Initiative* of the U.S. federal government, *Australian Public Service Information and Communications Technology Strategy 2012–2015*, *Seizing the Data Opportunity: A Strategy for UK Data Capability* and so on. China also kept pace with the times and released the *Action Outline for Promoting the Development of Big Data* in August 2015. To implement the outline, China has successively carried out the construction of national big data comprehensive pilot zones (hereinafter referred to as the pilot zones) since 2016, which is a new big data pilot policy issued by the Chinese government to promote the development of the digital economy. Its construction scope includes the Guizhou big data comprehensive pilot zone, two cross-regional comprehensive pilot zones (Beijing, Tianjin, Hebei, and the Pearl River Delta), four demonstration comprehensive pilot zones (Shanghai, Henan, Chongqing, and Shenyang), and one comprehensive pilot zone for overall development of big data infrastructure (Inner Mongolia). The pilot zones carried out systematic

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experiments around the seven main tasks (i.e., open data resource management and sharing, data center integration, data resource application, data element circulation, big data industrial agglomeration, big data international cooperation, and big data system innovation), and eventually form radiation effect and demonstration effects by constantly summarizing practical experience that can be used for reference, replication, and promotion.

However, government policy assessment has long been controversial in academia and practice. On the one hand, under the guidance of the government, all regions have good subjective initiative in economic development. Scholars have confirmed the positive effect of economic radiation, innovation-driven and sustainable development brought by the implementation of government policies [1,2]. On the other hand, government policies have been criticized for their subjectivity, resulting in improper allocation of resources and low investment efficiency [3]. Because of the uncertainty caused by government policies, countries will make targeted adjustments to relevant policies for the development of the digital economy in time.

The construction of pilot zones is a new pilot policy focusing on data resource management and application in China since 2016, and there is uncertainty about its policy effects. The level of digital economy development is the core competitiveness of a country and determines the sustainability of economic development. Currently, China's digital transformation is still in its infancy, with only 16 % of enterprises achieving significant results in digital transformation. Therefore, has the big data policy significantly improved China's digital economy development? If so, is there a significant difference in improvement between cities at different administrative levels? Mainly through which channels does the big data policy affect China's digital economy development?

To better reveal the overall impact and explore the function mechanism of big data policy on the development of the digital economy, we conduct a natural experiment study using the difference-in-differences (DID) method for China's first big data pilot policy, the National Big Data Comprehensive Pilot Zone (referred to as the Pilot Zone). The methodology has been widely used in the literature on policy effects assessment [4,5]. This paper utilizes panel data of 280 Chinese cities from 2011 to 2019 to first calculate the digital economy development index of cities by constructing an index system, and then estimate the impact of the big data policy on the digital economy based on the DID model. Chinese cities are categorized according to administrative levels to explore the heterogeneity of big data policy effects. From the perspectives of technological innovation and human capital, the channels of the big data policy to promote the digital economy development are examined.

The contributions in this paper include the following four points: First, this paper uses the data of 280 cities from 2011 to 2019 to construct a more scientific evaluation index system of digital economy development, and calculates the digital economy development index of cities over the years, which not only expands the sample size but also makes the conclusion more robust. Second, we use the natural experiment of the national big data comprehensive pilot zones to examine the effects of the big data policy on the development of the digital economy. Compared to other strategies or plans, the construction of pilot zones is a more targeted big data pilot policy that enriches research results on policies for the development of the digital economy. Given the specific construction objectives, using the DID method to examine the policy effects is both fitting and important. Third, this paper analyzes the regional heterogeneity in policy effects by grouping cities according to different administrative levels, which provides valid evidence for the rational layout of the pilot zones. Fourth, from the perspective of technological innovation and human capital, we analyze the transmission channels of big data policies promoting the digital economy development, deepening the understanding of the development issues of China's digital economy. Our findings are not only of significant policy value for understanding the policy effects and improving the policy design of big data pilot zones, but also inspirational for governments to formulate better big data policies to support the digital economy development.

The structure of this paper is as follows: The second part shows the literature review and hypothesis. The third part introduces the model, variable, and data. The fourth part provides the results and discussions. The fifth part presents the conclusion and policy recommendations. The sixth part is research limitations and future research.

2. Literature review and hypothesis

2.1. Literature review

The digital economy originates from networked intelligence, which can be related back to the 1990s [6]. It includes information and knowledge in a digital format, as the main production factor, computing and networking as an important communication and workspace, and Information and Communication Technologies (ICTs) as a productivity growth facilitator. The digital economy plays an important role in the national economy. It can promote the growth of total factor productivity in ICT industries [7], and the improvement of labor productivity through ICT capital deepening [8]. Therefore, most scholars have begun to measure the digital economy. First, after Machlup and Porat initiated the research method of measuring the value added to the knowledge economy and information economy [9,10], some scholars have calculated the real value added for the digital economy and its contribution to GDP in some countries [11]. Second, some studies have attempted to construct a new digital economy satellite account (DESA) for a comprehensive measure of the contribution of the digital economy to GDP [12,13]. Third, some scholars often compile the digital economy development index by constructing the index system, such as the ICT Development Index [14], Digital Economy and Society Index [15], Digital Knowledge Economy Index [16], Digital Economy Index [17] and so on. It shows that there has not been a unified standard for the evaluation of the development of the digital economy. Therefore, based on the combination of the existing research results of the same kind, this paper builds a digital economy development evaluation index system and then calculates the digital economy development index of Chinese cities, which provides data support for the correct judgment of the current situation of China's digital economy development and plays a guiding role in the subsequent similar quantitative research.

Data is the production factor of the digital economy [18]. Big data is bringing a revolution in science and technology. Big Data is the information assets that demand cost-effective, innovative forms of information processing that enable enhanced insight, decision-making, and process automation, characterized by 5Vs (i.e., volume, variety, velocity, veracity, and value) [19,20]. The impact of big data on the digital economy is mainly reflected in the following aspects. First, big data can unlock an organization's business value by unleashing new organizational capabilities and value. A 2011 McKinsey report shows that retailers can achieve up to 60 % increase in operating margins by putting big data into analytics [21]. Collecting, storing, and mining big data for insights can create significant value for the world economy, enhancing the productivity and competitiveness of companies and the public sector and creating a substantial economic surplus for consumers. Second, the ICT has greatly increased the amount of information people daily contact with, improving people's information processing capability and reducing the cost of releasing personal information and contacting others. People inject very rich relationship data such as contact, association, and group attachment into social networks. This makes digitization gradually permeate people's daily lives and provides the soil for the development of the digital economy. Third, big data shortens the space-time distance through efficient information transmission and enhances the breadth and depth of interregional economic activity linkages. Yilmaz et al. paid early attention to the spatial spillover effect brought by informatization by empirically testing the panel data of 48 states in the United States [22].

After realizing the importance of big data, many countries have successively introduced big data policies, which mainly refer to the strategies, plans, policies and pilot projects formulated by the government to ensure the promotion and application of big data, including national big data strategy or plan, data opening policy, data sharing policy, data security and privacy protection policy and so on [23–25]. Econometrics is widely used to analyze the impact of policies, because of the preciseness and intuitive nature of empirical analysis. However, few scholars have applied it to the study of big data policy. In China, the quantitative research on big data pilot projects mainly focuses on China's smart city pilot policy. It is a policy aimed at improving urban service quality with big data technology as the core. Most studies believe that smart cities incorporate information and communication technology into urban management, making cities more innovative, competitive, attractive, and flexible [26]. They pointed out the impact of smart cities on innovation, economy, society, and other aspects [27]. These works help assess the significance of big data policy, but few scholars have quantitatively analyzed the effect of the national big data comprehensive pilot zone, which is something we have included in the present study.

2.2. Hypothesis

In the mature period of the digital economy, data is the key factor of production. The pilot zones mainly carry out systematic experiments around data elements, and their mechanisms to drive the development of the digital economy are as follows. First, as a major measure to promote the development of big data, the establishment of the pilot zones is strongly supported by the government. Specifically, the government took the lead in carrying out big data legislation to provide legal protection for data financing and innovative applications. In addition, the government provided financial guarantees for the construction of digital economy infrastructure in the pilot zones. For example, the data show that after the establishment of the pilot zones, Guizhou has achieved full Internet coverage, and the development level of information infrastructure has risen from the 29th to the 15th in China. In 2020, 16330 5G base stations were built, with a total provincial bandwidth of 16700 Gbps and a total of 1689400 km of communication optical cables, 14 times and 3 times that in 2013 respectively. Second, data resources have strong liquidity, which can not only play a synergistic effect with other production factors such as capital, talent, and innovation but also have a multiplier effect on other factors [28,29]. The primary task of the pilot zones is to realize data sharing, including government data sharing, government data financing, and data-free flow between enterprises and governments. Data sharing is not only conducive to strengthening the ability of information acquisition, transmission, and value-added but also can effectively promote information flow, thus producing a knowledge spillover effect [30]. Third, the establishment of the pilot zones provides a space for the agglomeration of big data enterprises and related industries. On the one hand, enterprises effectively use data resources to develop industry chains and to form industrial clusters related to the digital economy. This is conducive to attracting big data innovation investment at home and abroad and promoting the exchange and cooperation of digital technology. On the other hand, it can improve the innovation ability, management ability, labor productivity, and market competitiveness of big data enterprises by reducing transaction costs, refining the division of labor, sharing infrastructures, and forming the scale effect [31]. For example, Intel, Microsoft, Apple, Qualcomm, and other world-famous enterprises have taken root in Guizhou. In 2020, the revenue of the software and information service industry in Guizhou increased by 26.3 % and the business revenue of the telecom industry increased by 5.6 %. The growth rate of the digital economy reached 22.1 %, ranking first in China for five consecutive years. Thus, we propose the following hypothesis.

Hypothesis 1. the big data policy can promote the development of the digital economy.

For China's high-tech industries, differences in factor endowment across regions will result in significant differences in R&D investment efficiency. Different initial factor endowments could lead to different effects of the same economic policy. Similarly, in terms of the development of China's big data industry, the different resource endowments, initial levels of economic development, and economic policies possessed by each region have led to large regional differences in digital development [32]. Some studies have shown that regions with poorer initial conditions also suffer from path dependence in the long run, resulting in lower policy effects than other regions [33]. In other words, developed regions can reap higher policy benefits by their initial advantages compared to lagging regions. In China's political and economic system, differences in factor endowments across cities are often correlated with administrative hierarchy. According to the administrative level of Chinese cities, cities can be broadly divided into municipalities directly under the central government, sub-provincial cities, provincial capitals, larger cities, and general prefecture-level cities. Generally speaking, cities with a higher administrative level are more advanced in terms of factor endowments and development conditions, the same policy preferences generate a greater boost to economic development. Thus, we propose the following hypothesis.

Hypothesis 2. Due to the long-term effect of path dependence, cities at a higher administrative level will receive higher policy benefits than cities at a lower administrative level.

The big data policy will reinforce its positive impact on the development of the digital economy through the technological innovation effect and the human capital effect. First, the flow of data and the application of information technology in the pilot zones accelerates technological innovation, which reinforces the positive impact of the big data policy. It is mainly reflected in the following aspects: (1) the widespread application of big data technology has broken the information gap in the market, making the market more transparent. The free flow of information forces the R&D department of enterprises to continuously develop new technologies, adapting to the complete competition in the market [34]. At the same time, the dissemination of information among enterprises can promote the spillover of technological innovation, which not only helps to improve the ability to obtain information and innovation performance of enterprises [35] but also accelerates the penetration of new technologies into traditional industries, realizing the technological innovation of traditional industries [36]. (2) To fully release data dividends and obtain potential profits, stakeholders often try new business models and allow low-cost innovation to realize potential business development [37]. For example, digital service trade boosts technological innovation [38]. (3) The information technology has a strong “link” integration capability. Under the multiplier effect of network links, it can realize the reorganization of cross-regional innovation elements and form a “positive feedback loop” innovation model that coordinates the development of manufacturing business and R&D ecosystems, thereby improving the level of cross-regional collaborative innovation [39].

Second, the pilot zones promote the development of the digital economy by improving the level of human capital. The key to yielding positive policy effects is the use of human capital, and high-quality human capital is in the form of increased knowledge, mastery of technology, innovation, and the ability to develop technology to encourage technology development [40,41]. On the one hand, the pilot zones can boost human capital quantitatively. It provides diversified opportunities to develop the great potential of human capital, which can greatly attract and retain talents. On the other hand, the pilot zones can improve the quality of human capital. The rigid demand for high-quality human capital makes the pilot zone become a gathering center for higher education talents, and it has been found that only highly skilled workers with a tertiary degree can effectively meet the demand for human capital brought about by ICT usage and digitalization [42]. The human capital effect brought by the establishment of the pilot zones at both quantitative and qualitative levels is conducive to accelerating the spatial diffusion and spillover of knowledge, information, innovation, and technology related to the digital economy, which further drives the development of the digital economy of cities. Thus, we propose the following hypothesis.

Hypothesis 3. The big data policy will strengthen its positive impact on the development of the digital economy through the technological innovation effect and the human capital effect.

3. Model, variable, and data

3.1. Difference in differences (DID) model

To quantitatively analyze the effect of the pilot zones and the development of the digital economy, this paper sets up a DID model. By comparing the different effects of an exogenous shock on the treatment group and the control group, the DID model is well-known for its effectiveness in identifying causal relationships and thus is widely used in causal inference and policy effect studies. Meanwhile, it helps avoid endogeneity problems in policy effect assessments and addresses the unobserved nature of virtual facts [43]. Because policies are generally exogenous relative to economic subjects, there is no reverse causality problem.

We define a time dummy variable to indicate whether the time is before (2011–2015) or after (2016–2019) the implementation of the pilot zones. We set $T_t = 1$ if $t \geq 2016$, and $T_t = 0$, otherwise. We divide our sample into two groups according to whether the city has established the pilot zones. If the city has established the pilot zones, it is classified into the treatment group, otherwise, the control group. Accordingly, we define a grouping dummy variable: $PZ_i = 1$ if city i belongs to the treatment group, and $PZ_i = 0$, otherwise. The equation is as follows:

$$DEDI_{it} = \alpha_0 + \alpha_1 T_t \times PZ_i + \sum \delta Z_{it} + \mu_i + \eta_t + \varepsilon_{it} \tag{1}$$

where $DEDI_{it}$ is the dependent variable for the digital economy development index of city i in year t. $T_t \times PZ_i$ is the interaction of the time dummy and the grouping dummy, and the corresponding coefficient α_1 is a DID estimator for the treatment effect, indicating the net impact of big data policy on the development of the digital economy. Z_{it} are other control variables and δ is the corresponding coefficients. To account for the potential unobserved heterogeneity, we also incorporate the city-fixed effect μ_i and the year-fixed effect η_t in the model. ε_{it} is the stochastic error term.

3.2. Variable description

This paper focuses on the effect of big data policy in the development of the digital economy and analyzes the regional differences in the effect. In addition, considering that other factors also affect the development of the digital economy, this paper introduces other control variables. Table 1 illustrates the summary of variable statistics.

3.2.1. Dependent variable

According to the above definition, the DEDI is a complex system for quantitatively evaluating the overall development of the digital economy. Based on the analytic hierarchy process (AHP[1]) and the indicator selection principle,[2] the indicator system was generated using elements of digital infrastructure, digital industrialization, and industry digitization, the three major areas of DEDI (see Table 1), according to the research of Pan et al. [44]. It is noted that all specific indicators have a positive (+) effect on the subsystems. Positive effect indicators will enhance the development of the digital economy with their values increasing. Based on all subsystems, the DEDI is a comprehensive indicator calculated by the Entropy-TOPSIS method.

The first step for the evaluation of DEDI is to conduct dimensionless standardization to remove the original data contamination issues. For the group of positive indicators, data is transformed by Eq. (2):

$$x_{ij} = \frac{X_j - \min\{X_j\}}{\max\{X_j\} - \min\{X_j\}} \tag{2}$$

Note that x_{ij} is the normalized value of indicator j for city i; $\min\{X_j\}$ and $\max\{X_j\}$ refer to the minimum and maximum value, respectively, of indicator j among all the cities.

The second step is to use Shannon's Entropy method for the relative weights of each indicator (occurrence probability, severity, and vulnerability). Based on the theory of information entropy, the index weight is determined according to the data provided by the amount of information and has a relatively objective and precise evaluation value. Next, we use Eq. (3) to Eq. (6) to determine the weight.

$$p_{ij} = \frac{x_{ij}}{\sum_i x_{ij}} \tag{3}$$

In this relation, p_{ij} is the proportion of indicator j on city i. Then, through the following relation, the entropy value is calculated.

$$e_j = -\frac{1}{\ln m}\sum_i \left(p_{ij} \times \ln p_{ij}\right) \tag{4}$$

where e_j is the entropy value of indicator j, and m is the total number of cities. Then the value of non-reliance or deviation d_j of indicator j is calculated. If the entropy value e_j is bigger, the deviation is smaller, and this index is less important. Finally, the weight w_j of indicator j is obtained in Eq. (6).

$$d_j = 1 - e_j \tag{5}$$

$$w_j = \frac{d_j}{\sum_j d_j} \tag{6}$$

The third step is to calculate the weighted normalized decision matrix R in Eq. (7), where $q_i\text{j} = w_j \times x_{ij}$.

$$R = (\text{qij})_{n\times m} \tag{7}$$

In the fourth step, positive ideal solution (Q_j^+) and negative ideal solution (Q_j^-) are obtained in Eq. (8) to Eq. (9).

$$Q_j^+ = (\max q_{i1}, \max q_{i2}, \cdots, \max q_{im}) \tag{8}$$

$$Q_j^- = (\min q_{i1}, \min q_{i2}, \cdots, \min q_{im}) \tag{9}$$

The fifth step is to calculate the separation measures, using the n-dimensional Euclidean distance. The separation of each observed object from the positive ideal solution is given in Eq. (10):

$$D_i^+ = \sqrt{\sum_{j=1}^{m}\left(Q_j^+ - q_{ij}\right)^2} \tag{10}$$

Similarly, the separation from the negative ideal solution is given in Eq. (11):

$$D_i^- = \sqrt{\sum_{j=1}^{m}\left(Q_j^- - q_{ij}\right)^2} \tag{11}$$

[1] The analytical hierarchical process (AHP) is structured hierarchically at different levels, with each level consisting of a finite number of decision elements. The top level of the hierarchy represents the overall goal, whereas the lowest level is composed of all possible alternatives. This method combines the qualitative and quantitative analyses and can provide a multi-dimensional and multi-criterion analysis.

[2] The indicator selection principle involves feasibility, scientificity, gradation and completeness.

Table 1
Indicator system of DEDI.

Primary indicators	Secondary indicators	Specific indicators (unit)
Digital Infrastructure	Traditional digital infrastructure	Internet penetration rate (%)
		Mobile phone penetration rate (%)
	New digital infrastructure	Mobile phone base station (10000 units)
		Fiber length (10000 km)
		Big data center (unit)
		Number of IPV4/IPV6 (10000 unit)
Digital industrialization	Telecommunications industry	Total telecommunications business/permanent population (%)
		Telecom business income/Tertiary sector of the economy added value (yuan/person)
	Digital product manufacturing industry	Number of listed companies in computer, communication, and other electronic equipment manufacturing (unit)
		Income from computer and other electronic equipment manufacturing/added value of Tertiary sector of the economy (%)
	Information technology service industry	Number of listed companies in the software and information technology service industry (unit)
		Revenue from software and information services/added value of Tertiary sector of the economy (%)
	Internet-related service industry	Number of Top 100 Internet Companies (unit)
		Income from Internet-related service industry/added value of Tertiary sector of the economy (%)
	Telecommunications, broadcasting, television, and satellite transmission industries	Number of listed companies in the broadcasting, television, film, and film recording production industries (unit)
	Digital Industry Patents	Patents for the digital economy of listed companies (unit)
	Digital industry practitioners	Number of employees in urban units/number of employees in information transmission, computer services, and software industries (%)
Industrial digitization	Digitization of the Secondary sector of the economy	The proportion of industrial application Internet (%)
		Number of computers per 100 people in industrial enterprises (%)
	Digitization of the Tertiary sector of the economy	China Digital Financial Inclusion Index (−)
		E-commerce transaction volume (billion yuan)
		Number of listed companies in e-commerce business (unit)

In these relations, q_{ij} is each of the entries of the weighted normalized decision matrix, is the positive ideal related to each column, and is the negative ideal related to each column.

In the last step, the relative closeness of each observed object to the positive ideal is calculated in Eq. (12).

$$DEDI_i = \frac{D_i^-}{D_i^+ + D_i^-} \tag{12}$$

where DEDI is between 0 and 1. If the value of DEDI is larger, the digital economy development index of the city i is bigger.

3.2.2. Core independent variable

$T_t \times PZ_i$ is the DID estimator indicated by the interaction between T_t and PZ_i. Its correlation coefficient of α_1 is expected to be positive, representing the rise of the development level of the digital economy since the big data policy was introduced.

3.2.3. Control variables

We focus on the following control variables that may affect the development of the digital economy. (1) The government scale (GS), which is measured by the proportion of government budget expenditure in regional GDP. The government plays a very important role in China's economic development. This variable can reflect the government's investments and consumption, or the expenditures on digital infrastructures and other input level areas [45]. (2) The foreign direct investment (FDI), which is the actual amount of foreign direct investment in the cities. FDI provides more financial funds for the development of the digital economy. In addition to the Chinese government's investment, the digital economy also relies on foreign investment in capital and technology. FDI plays an important role in digital infrastructure, digital business development and wider digital adoption [46]. (3) The urbanization rate (UR), which is represented by the proportion of the urban non-agricultural population in the total population. The impact of urbanization on China's society, economy, and environment cannot be ignored, and China's digital economy development is inevitably accompanied by the rapid advancement of urbanization [47]. (4) The industrial structure upgrading (ISU), which is measured by the proportion of the secondary industry and the tertiary industry value-added in GDP. The upgrading of industrial structure implies a shift from lower to higher levels of industrial structure, which brings about technological and institutional innovations, thus affecting the development of the digital economy. (5) The level of economic development (PCGDP), which is measured by real per capita GDP. A higher level of economic development corresponds to better technology and leading-edge facilities, thereby creating a favorable environment for the development of the digital economy.

3.3. Sample and data source

The data sample used in this paper is the panel data of 280 cities[3] in China from 2011 to 2019. Among them, 66 cities[4] in the Pilot Zone constitute the treatment group, and the other 214 cities constitute the control group.

The data mainly comes from the China Statistical Yearbook, China City Statistical Yearbook, EPS database, Local Statistical Yearbook, National Economic and Social Development Bulletin, Listed Company Database/Digital Economy Research Database on the China Research Data Service Platform, the website of the Bureau of Industry and Information Technology, Digital China Index report, China City Digital Economy Development Report, and China Digital Economy Development White Paper. China Digital Financial Inclusion Index adopts the Peking University Digital Financial Inclusion Index of China (PE-UDFIIC) which was produced by a research team from the Institute of Digital Finance at Peking University and Ant Financial Services Group. Some of the missing data are filled by moving smoothing.

4. Test results

4.1. Test results for Hypothesis 1

The validity of the DID model relies on the parallel trend assumption, i.e., that the treated and untreated groups have the same trend before the policy intervention. We first draw Fig. 1 to show the time trend of DEDI of treated and untreated cities and compare their difference intuitively. It shows that before the policy intervention of the pilot zone, the time trends of DEDI were parallel for the treatment group and control group. In contrast, after the publication of the big data policy, time trends for the two groups began diverging, as the DEDI of treated cities increased faster than those of untreated cities from 2017 to 2018. The intuition justifies the use of the DID method for policy evaluation.

[3] The Chinese mainland (excluding Hong Kong, Macao and Taiwan) has 293 prefecture-level cities and 4 municipalities directly under the Central Government (i.e.Beijing, Shanghai, Tianjin, and Chongqing) . Because of the limitations of data collection, we exclude 6 cities in Tibet Autonomous Region (i.e.Lhasa, Shigatse, Shannan, Changdu, Naqu and Nyingchi), 2 cities in Xinjiang Uygur Autonomous Region (i.e.Turpan and Hami), 2 cities in Guizhou Province (i.e.Tongren and Bijie), Hulunbuir in Inner Mongolia Autonomous Region, Pu'er in Yunnan Province, Sansha in Hainan Province, Bozhou in Anhui Province, Haidong in Qinghai Province, Suihua in Heilongjiang Province, and Xiangyang in Hubei Province.

[4] It includes 4 municipalities directly under the central government (i.e.Beijing, Shanghai, Tianjin, and Chongqing) , Shenyang in Liaoning Province, 4 cities in Guizhou Province, 11 cities in Hebei Province, 21 cities in Guangdong Province, 17 cities in Henan Province and 8 cities in Inner Mongolia Autonomous Region.

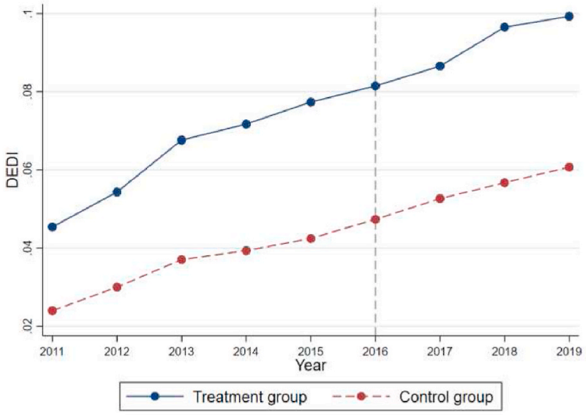


Fig. 1. Time trends DEDI for the full sample.

Then, we provide the regression-based DID estimation results of Eq. (1), which considers the city-fixed and year-fixed effects simultaneously (see Table 2). As shown in column (1), when the control variables are not added, the regression coefficient of T × PZ on DEDI is 0.037, which is significant at the 1 % levels, indicating that the big data policy significantly increases cities' development of the digital economy. As shown in column (2), when the control variable is taken into account, the net impact of the big data policy is still significantly positive, indicating that the introduction of the big data policy in 2016 improved the development level of the digital economy by 2.8 %. The results in Table 2 verify hypothesis 1 of this paper, that is, the big data policy does significantly promote the development of the digital economy.

We now discuss the results of other factors. The coefficient increases without the addition of control variables, while the coefficient decreases significantly after the addition of control variables, indicating that the control variables have a significant impact on the digital economy development level. Therefore, the government scale, foreign direct investment, urbanization rate, industrial structure upgrading, and economic development level of the region weaken the impact of the establishment of the pilot zone on the digital economy development level. Except for foreign direct investment, other control variables have a positive promoting effect on the digital economy development level. Therefore, the national big data comprehensive pilot zone needs to improve the policy environment, industrial structure, economic volume, and other policy conditions to effectively promote the development of the digital economy.

4.2. *Robust test*

To further test the robustness of the results, we conduct a counterfactual test by changing the policy implementation time. In addition to the policy change of the establishment of the pilot zones, some other policies or random factors that are not related to the pilot zones may also lead to differences in the development of cities' digital economy, which eventually leads to the failure of the previous regression results. To eliminate the influence of such factors, we assume that the year of setting up the pilot zones in each city is 1 year, 2 years, or 3 years ahead of schedule. If the core explanatory variable is significant at the assumed time, it indicates that the development of the digital economy is likely due to other policy changes or random factors. On the contrary, if the core explanatory variable is not significant at the assumed time, it shows that the incremental contribution of digital economy development comes from the establishment of the pilot zones. Columns (1) to (3) in Table 3 respectively indicate that the assumed establishment time of the pilot zones is 3 years, 2 years, or 1 year ahead of schedule. The counterfactual test shows that the core explanatory variable is not significant at the assumed time, indicating that the development of the digital economy is not caused by other factors, but by the establishment of the pilot zones.

In addition to using the counterfactual test to verify the parallel trend, we also use the single difference method to test the effect of the pilot zones on the development of the digital economy according to the traditional processing method. The regression results are shown in columns (4) and (5) of Table 3. Whether other variables are controlled or not, the estimation coefficients of T × PZ are significantly positive after the city-fixed effect is controlled. However, by observing the coefficients of T × PZ, it can be found that the coefficients obtained by the single difference method are higher than those obtained by the DID method in Table 2. It shows that although the traditional single difference method can explain some problems, this method overestimates the role of the pilot zones in the development of the digital economy. Therefore, the estimation results obtained by the DID method are more reliable.

4.3. *Test results for Hypothesis 2*

According to hypothesis 2, the difference between initial resource elements and economic development degree will lead to different effects of the pilot zones on the development of the digital economy. Due to the long-term impact of path dependence, the regions with better initial conditions will obtain higher benefits from the policy than the relatively backward regions. To test hypothesis 2, we first

Table 2
The DID estimation results of big data policy.

	(1)	(2)
T × PZ	0.037*** (0.004)	0.028*** (0.001)
GS		0.036*** (0.003)
FDI		−0.002 (0.002)
UR		0.003*** (0.001)
ISU		0.084*** (0.012)
PCGDP		0.017*** (0.003)
Cons	8.346*** (0.000)	6.246*** (0.000)
Year-fixed effect	Yes	Yes
City-fixed effect	Yes	Yes
Observations	2520	2520
R^2	0.613	0.424
Adj. R^2	0.608	0.415

Note: Standard errors in parentheses; *, **, *** indicate significance levels of 10 %, 5 %, and 1 %, respectively.

Table 3
The counterfactual test and single difference test.

	Counterfactual test			Single difference test	
	(1)	(2)	(3)	(4)	(5)
L3. T × PZ	0.012 (0.008)				
L2. T × PZ		0.010 (0.007)			
L1. T × PZ			0.009 (0.005)		
T × PZ				0.058*** (0.001)	0.045*** (0.004)
Control variables	Yes	Yes	Yes	No	Yes
Year-fixed effect	Yes	Yes	Yes	No	No
City-fixed effect	Yes	Yes	Yes	Yes	Yes
Observations	2520	2520	2520	2520	2520
R^2	0.657	0.657	0.656	0.529	0.556
Adj. R^2	0.651	0.651	0.651	0.520	0.551

Note: Standard errors in parentheses; *, **, *** indicate significance levels of 10 %, 5 %, and 1 %, respectively.

select four groups, namely, municipalities directly under the Central Government[5](MDUCG), sub-provincial cities (SPC), provincial capitals (PC), and larger cities[6] (LC), so we set 4 dummy variables. Then we multiply the 4 dummy variables by $T_t \times PZ_i$ to obtain 3 interactive items and redo the regression analysis.

The administrative level of cities is a key factor that cannot be ignored when exploring the differences in urban development in China. Unlike urbanization in western countries, which is a process of continuous expansion of the market economy, China's urbanization relies on a top-down political and administrative system. Under such a system, the important resources or production factors are distributed from cities with high administrative levels to those with low administrative levels. On the one hand, the higher the administrative level of a city, the broader its economic and social management authority, which helps it to seek more policy facilitation and strategic resources from the central government. On the other hand, under the "siphon effect", the profit-driven nature of production factors such as population, capital, and technology is constantly emerging, which is more conducive to the high-quality development of cities. Therefore, it is an appropriate perspective to investigate heterogeneity from the administrative hierarchy.

Drawing on Nie et al., the administrative hierarchy is used to classify cities [48]. First, MDUCG are administratively designated cities directly under the jurisdiction of the Central Government and the administrative level is highest. Second, SPC, including 10

[5] Beijing, Tianjin, Shanghai and Chongqing.
[6] Dalian, Benxi, Fushun, Jilin, Qiqihar, Baotou, Luoyang, Handan, Ningbo, Datong, Tangshan, Anshan, Qingdao, Zibo, Wuxi, Huainan, Suzhou and Xuzhou.

provincial capital cities[7] and 5 municipalities with independent planning status under the national social and economic development,[8] have part of the legislative power granted by the constitution due to their unique economic status. They also have greater advantages over other cities in terms of initial resources and policy preference and they are classified as the second category in this paper. Third, the PC, including 10 sub-provincial cities mentioned above and 17 general provincial capitals[9] of which the overall level is slightly lower than that of the SPC. Fourth, LC are other larger cities approved by the State Council. They have the same power to formulate local laws and regulations as the PC, but their administrative level is lower than that of the PC.

To further understand the absolute difference and spatial dynamic evolution characteristics of the four groups' DEDI, this part uses Kernel Density Estimation (KDE) to analyze the four groups' DEDI from 2011 to 2019 (See Fig. 2 and Table 4). First, in terms of the number of peaks, the transition of the kernel density curves from double-peak mode to single-peak mode in MDUCG, PC, and LC shows that the polarization of DEDI is gradually weakening in the 3 groups. SPC are always in the state of double peaks, which means that there is the Matthew effect and digital divide. Second, in terms of the distribution position, the kernel density curves of MDUCG and LC first move left and then right, which reflects that the two groups' DEDI first decreases and then increases over time. On the contrary, the curves of SPC and PC first shift right and then left, indicating a trend of rising first and then falling of the two groups' DEDI. Third, in terms of distribution, for MDUCG and LC, the peak height decreases and the wave width of a single peak widens, indicating that the absolute difference of DEDI increases. On the contrary, for SPC and PC, the peak height increases and the wave width of a single peak narrows, indicating that the absolute difference in DEDI decreases. Fourth, from the perspective of distribution ductility, the kernel density curves of MDUCG and LC show a "divergent" fluctuation trend, while those of SPC and PC show a "convergent" fluctuation trend. The curves of the four groups show a more significant state of the right tail, indicating that there are cities with relatively high DEDI in the four groups.

To test whether hypothesis 2 is true, we construct the following regression equation.

$$DEDI_{it} = \alpha_0 + \alpha_1 AL_{it} \times T_t \times PZ_i + \sum \delta Z_{it} + \mu_i + \eta_t + \varepsilon_{it} \tag{13}$$

where AL_{it} represents the administrative level of city i in year t. Specifically, it represents the dummy variable of MDUCG, SPC, PC, and LC in different equations. The meaning of other variables is the same as that in Eq. (1). The coefficient of the interactive item α_1 measures the effect of setting up the pilot zones in cities at different administrative levels on the development of the digital economy. Specifically, α_1 represents the impact of setting up the pilot zones in MDUCG, SPC, PC, and LC on the DEDI respectively. If hypothesis 2 is confirmed, then the estimated value should show an increasing trend with the rise of cities' administrative levels. The estimated results are shown in Table 5.

Table 5 shows that the coefficient of the interactive item of MDUCG, SPC, and PC is significantly positive, and the coefficient value decreases in turn, while the coefficient of the interactive item of LC is not significant. It shows that the establishment of pilot zones in cities with a high administrative level can promote the digital economy much more than that in cities with low administrative levels, which fully highlights a positive moderating role of the high administrative level in the relationship between big data policy and the development of the digital economy. Therefore, hypothesis 2 proposed in this paper is confirmed.

4.4. Test results for Hypothesis 3

Whether the promotion effect of big data policy on the development of the digital economy is mediated by the technological innovation effect and human capital effect needs to be tested by the mediating effect model [49]. We set the equations of the mediating effect model as follows:

$$DEDI_{it} = \alpha_0 + \alpha_1 T_t \times PZ_i + \sum \delta Z_{it} + \mu_i + \eta_t + \varepsilon_{it} \tag{14}$$

$$M_{it} = \beta_0 + \beta_1 T_t \times PZ_i + \sum \delta Z_{it} + \mu_i + \eta_t + \varepsilon_{it} \tag{15}$$

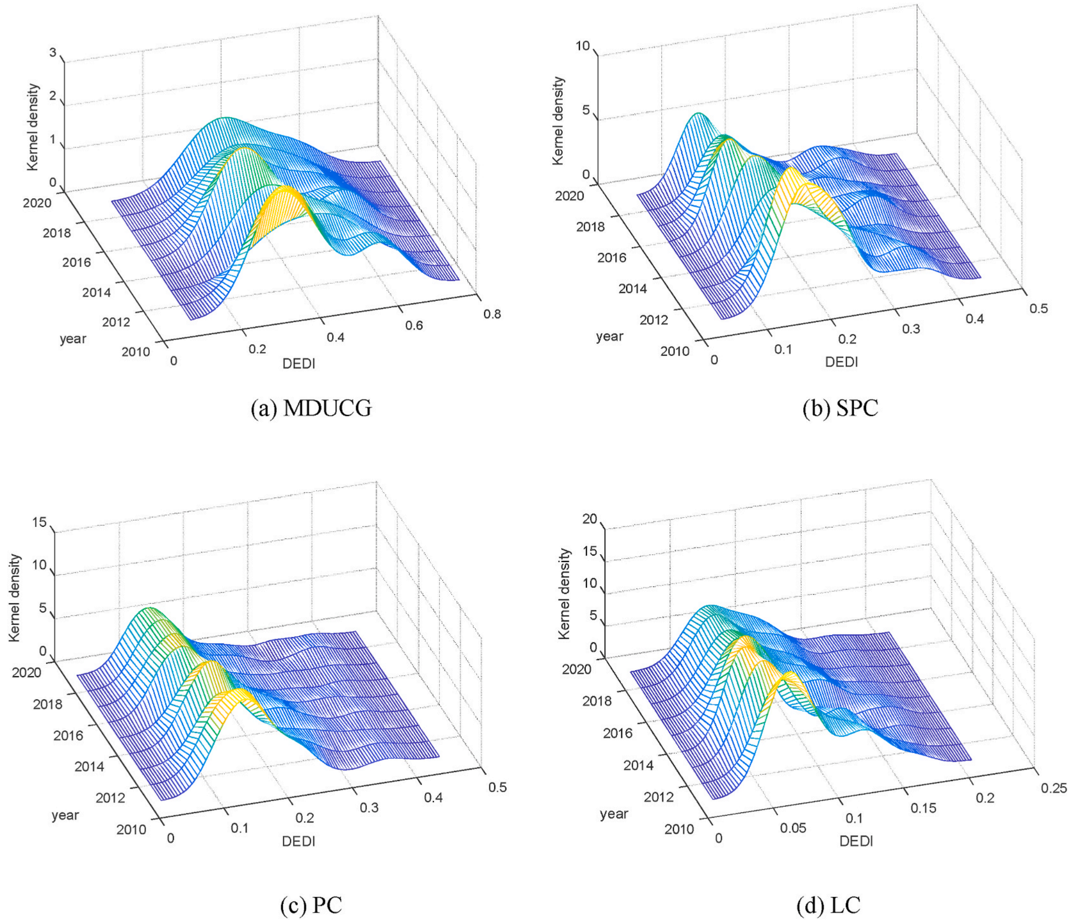
$$DEDI_{it} = \gamma_0 + \gamma_1 T_t \times PZ_i + \gamma_2 M_{it} + \sum \delta Z_{it} + \mu_i + \eta_t + \varepsilon_{it} \tag{16}$$

In these equations, M_{it} denotes mediators, including technological innovation (TI_{it}) and human capital (HC_{it}) of city i in year t. The meaning of other variables is the same as that in Eq. (1). α_1 is the total effect of big data policy on the DEDI; γ_1 is the direct effect of big data policy on the DEDI when the influence of the mediator and other control variables are controlled; $\beta_1 \times \gamma_2$ is the mediating effect that is also identical to an indirect effect. The relationship between total effect, direct effect, and mediating effect is as follows [50]:

$$\alpha_1 = \gamma_1 + \beta_1 \times \gamma_2 \tag{17}$$

If both β_1 and γ_2 in these equations are statistically significant, and $\gamma_1 < \alpha_1$, then the relationship between big data policy and the development of the digital economy is partially mediated by the mediating variable. If γ_1 is not statistically significant, then the

[7] Guangzhou, Wuhan, Harbin, Shenyang, Chengdu, Nanjing, Xi'an, Changchun, Jinan and Hangzhou.
[8] Dalian, Qingdao, Ningbo, Xiamen and Shenzhen.
[9] Taiyuan, Zhengzhou, Shijiazhuang, Hefei, Changsha, Nanchang, Nanning, Kunming, Xining, Fuzhou, Urumqi, Lhasa, Hohhot, Haikou, Yinchuan, Lanzhou and Guiyang.



(a) MDUCG (b) SPC

(c) PC (d) LC

Fig. 2. Kernel density estimation of the four groups.

Table 4
Distribution characteristics of kernel density curves of the four groups.

Group	Change in the number of peaks	Main peak movement	Main peak change	Ductility	Polarization characteristics
MDUCG	Double - Single	Left -Right	The height decreases and the width widens	Right tail, divergence	Polarization weakening
SPC	Double - double	Right-left	The height increases and the width narrows	Right tail, convergence	Polarization
PC	Double - Single	Right-left	The height increases and the width narrows	Right tail, convergence	Polarization weakening
LC	Double - Single	Left-right	The height decreases and the width widens	Right tail, divergence	Polarization weakening

relationship is totally mediated by the mediator.

TI is measured by the number of patent applications per 10,000 people in each city. Compared with the number of patent authorizations, the number of patent applications can objectively reflect the true level of a city's innovation capacity without being affected by man-made evaluation such as the ability of patent examination and patent judgment [51]. HC is measured by the proportion of students in colleges and universities. Relevant data comes from Chinese Research Data Services (CNRDS) and *China City Statistical Yearbook*. The estimation results of the mediating effect model are shown in Table 6. As can be seen from column (1), the total effect of big data policy on the development of the digital economy is 0.028 with a 1 % significance level. Columns (2) and (3) display that the coefficient of direct effect is 0.016 which is significant and slightly smaller than the total effect when controlling T $\times$ PZ and TI at the same time, suggesting that the relationship between big data policy on the development of the digital economy is partly mediated by technological innovation. The mediating effect is 0.012 (1.461 $\times$ 0.008), accounting for 41.7 % of the total effect, which means that the big data policy promotes the development of the digital economy by stimulating technological innovation. Similarly,

Table 5
Estimation results of heterogeneity.

	(1)	(2)	(3)	(4)
MDUCG × T × PZ	0.068*** (0.0044)			
SPC × T × PZ		0.046*** (0.0053)		
PC × T × PZ			0.021*** (0.0038)	
LC × T × PZ				0.001 (0.0047)
Control variables	Yes	Yes	Yes	Yes
Year-fixed effect	Yes	Yes	Yes	Yes
City-fixed effect	Yes	Yes	Yes	Yes
Observations	2520	2520	2520	2520
R^2	0.560	0.556	0.557	0.556
Adj. R^2	0.555	0.550	0.551	0.550

Table 6
Estimation results of mediating effect model.

	(1)	(2)	(3)	(4)	(5)
	DEDI	TI	DEDI	HC	DEDI
T × PZ	0.028*** (0.001)	1.461*** (0.2370)	0.016*** (0.002)	0.003*** (0.001)	0.025*** (0.004)
TI			0.008*** (0.000)		
HC					1.019*** (0.045)
Control variables	Yes	Yes	Yes	Yes	Yes
Year-fixed effect	Yes	Yes	Yes	Yes	Yes
City-fixed effect	Yes	Yes	Yes	Yes	Yes
Observations	2524	2524	2524	2524	2524
R^2	0.524	0.500	0.544	0.578	0.557
Adj. R^2	0.515	0.487	0.537	0.575	0.551

Columns (4) and (5) show that the coefficient of direct effect is 0.025 with a 1 % significance level when controlling T × PZ and HC at the same time, and the mediating effect is 0.003 (0.003 × 1.019), accounting for 10.9 % of the total effect, which means that the human capital plays a partial mediating role between the big data policy and the development of the digital economy. Overall, the big data policy can promote the development of the digital economy through the technological innovation effect and human capital effect, which verifies hypothesis 3.

5. Discussion

Plenty of theoretical and empirical research finds that Industry 4.0 is an era of using information technology to promote industrial change [52]. In this era, big data plays a significant role in promoting the growth of the digital economy [53]. Governments around the world have successively issued policies related to big data. Some scholars worry that the impact of government policies is uncertain [54,55]. Therefore, many countries will make targeted adjustments to the policies in time. The national big data comprehensive pilot zone is a new big data pilot policy issued by the Chinese government to adapt to Industry 4.0. However, few literatures discuss how big data policies affect the development of the digital economy. Therefore, one innovation of this paper is to use the natural experiment of the national big data comprehensive pilot zones to examine the effects of the big data policy on the development of the digital economy. Besides, unlike many previous studies [56,57], which divided China into East, Middle, and West regions to test spatial heterogeneity. This paper reclassified it to the MDUCG, SPC, PC, and LC according to different administrative levels of cities, which may maybe more scientific than just geographical division. Furthermore, this paper also deeply analyzes the function mechanism between big data policy and China's digital economy development from the perspective of the technological innovation effect and human capital effect. Based on the results in section 4, the following conclusion can be drawn to confirm or reject hypotheses:

First, our research shows that the introduction of a national big data comprehensive pilot zone in 2016 improved the development level of the digital economy by 2.8 %. At the same time, through the introduction of the counterfactual test and the single difference method for the robustness test, the conclusion was still valid. This confirms the hypothesis 1. At present, the literature on data-driven economy mostly focuses on the definition, application, and role of big data. The conclusion of this paper was complementary to the above literature, enriched the literature foundation of the digital economy research field, and provided a new interpretation of the development of the digital economy from the perspective of policy evaluation. It can be seen from China's case that the benefits of China's big data policy are obvious. This is an incentive for the Chinese government to further strengthen the construction of pilot zones. The US's *Big Data Research and Development Initiative*, the *Australian Public Service Information and Communications Technology Strategy*, *and* the EU's *General Data Protection Regulation* are important documents on big data strategies of countries all over the world. We support the integration of similar documents to implement a unified big data management system for various countries and create a "prosperous data-driven economy".

Second, our study finds that the effect of big data policy is the most evident in the MDUCG with the highest administrative level, followed by the SPC and PC with relatively high administrative level, while the effect is not significant in the LC with the lowest administrative level, which confirms the hypothesis 2. This is consistent with the path dependence theory [58,59]. Due to the long-term impact of path dependence, the regions with better initial conditions will obtain higher policy benefits than the relatively backward regions. Under the background of China, the initial conditions of a city are related to the administrative level of the city. The higher the administrative level of a city, the better its initial resources and economic conditions. Therefore, the establishment of pilot zones in cities with a high administrative level can promote the digital economy much more than that in cities with a low administrative level. This paper considers the heterogeneity of policy effects, more comprehensively reflects the relationship between the big data policy and the digital economy, and the empirical results have clearer policy implications.

Third, the relationship between big data policy on the development of the digital economy is partly mediated by technological innovation and human capital. The mediating effects are respectively 0.012 and 0.003, accounting for 41.7 % and 10.9 % of the total effects, indicating that the big data policy can promote the development of the digital economy through the technological innovation effect and human capital effect, which confirms hypothesis 3. On the one hand, the widespread application of information technologies such as the Internet and big data has broken the information gap in the market, to accelerate the dissemination of information among enterprises and the spread of new technologies between high-tech and non-high-tech industries. This forces the R&D department of enterprises to continue to develop new technologies, create new business models, and allow low-cost innovation. On the other hand, mastering information technology requires high-quality human capital, and industry labor capital directly determines the level of development of the digital economy. The improvement of labor literacy is a key factor in the rapid development of the digital economy. We agree with these views and this article provides a new internal theoretical mechanism for the relationship between the big data policy and the development of the digital economy from the perspective of technological innovation and human capital.

6. Conclusion, policy implications and limitation

6.1. Conclusion and policy implications

Based on the panel data of 280 cities in China from 2011 to 2019, this paper measures the digital economy development index by Entropy -TOPSIS method uses the DID model to evaluate the policy effect of the national big data comprehensive pilot zones on China's digital economy development and discusses the heterogeneity of policy effect from the perspective of cities' administrative level. In addition, from the perspective of technological innovation and human capital, the mediating effect model is used to empirically test the impact mechanism of big data policy on the development of the digital economy. The results show the following: (1) The big data policy significantly promotes China's digital economy development. (2) Cities at a higher administrative level receive higher policy benefits than cities at a lower administrative level. (3) The big data policy strengthens its positive impact on the development of the digital economy through the technological innovation effect and the human capital effect.

Based on the above conclusions, this paper proposes the following policy recommendations:

First, the construction of big data pilot zones should continue to be expanded, giving full play to the radiation-driven and demonstration-led effects of pilot zones on the digital economy. Since big data policies can effectively promote the digital economy development, it is necessary to actively utilize big data policies, efficiently use government digital subsidies, guide the flow of social capital to the key technological areas of the big data industry, and form a digital industry agglomeration.

Second, we suggest expanding the pilot area to cities with high administrative levels, which will maximize the total policy benefits in the short term. The results of the heterogeneity analysis suggest that the pilot zones in cities with higher administrative levels play a more positive role. However, the government also needs to pay attention to providing financial and technical assistance to cities at lower administrative levels to narrow the digital divide between regions.

Third, we should enhance the capacity for independent innovation in digital technology and strengthen the cultivation of digital talents. Mechanism analysis shows that technological innovation and human capital are important channels for the pilot zone to promote the development of the digital economy. Therefore, it is necessary to focus on the coordination of digital resources and encourage the R&D of basic digital technologies to realize technological breakthroughs in key areas and promote the transformation of scientific and technological achievements. Meanwhile, it is necessary to strengthen the training of digital talents and provide them with talent subsidies and a favorable innovation environment.

6.2. Limitations and future recommendations

However, there are still some limitations. On the one hand, the impact of big data pilot zones on the digital transformation of enterprises can be further explored, and spatial econometrics can be used to analyze the radiation effect of big data pilot zones on the digital economy of neighboring regions. On the other hand, due to the different stages and backgrounds in which each country finds itself, there may be limitations in extending the conclusions to a new context, location, or culture, and thus more cross-border data are needed for comparative studies. Therefore, the impact of big data pilot zones on the digital economy can be examined in the future in conjunction with other data and methods. In addition, in recent years, China has launched new digital policies, such as the "AI innovative development pilot zones", whose policy effects can be studied in depth.

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Consent to participate

Informed consent was obtained from all individual participants included in the study.

Consent to publish

Patients signed informed consent regarding publishing their data and photographs.

Data availability statement

Has data associated with your study been deposited into a publicly available repository? No.

Additional information

No additional information is available for this paper.

CRediT authorship contribution statement

Xinyun Hu: Writing – review & editing, Writing – original draft, Methodology, Data curation, Conceptualization. **Yanling Jiang:** Validation, Supervision. **Pengfei Guo:** Supervision, Resources, Funding acquisition. **Mingming Li:** Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

[1] B. Yuan, Q. Xiang, Environmental regulation, industrial innovation and green development of Chinese manufacturing: based on an extended CDM model, J. Clean. Prod. 176 (2018 Mar 1) 895–908.
[2] B. Yuan, Y. Zhang, Flexible environmental policy, technological innovation and sustainable development of China's industry: the moderating effect of environment regulatory enforcement, J. Clean. Prod. 243 (2020 Jan 10) 118543.
[3] S. Chen, Z. Sun, S. Tang, D. Wu, Government intervention and investment efficiency: evidence from China, J. Corp. Financ. 17 (2) (2011 Apr) 259–271.
[4] H. Wen, Z. Zhao, How does China's industrial policy affect firms' R&D investment? Evidence from 'Made in China 2025, Appl. Econ. 53 (55) (2020 Jan 21) 6333–6347.
[5] X. Tian, J. Zheng, L. Hu, Y. Liu, H. Wen, X. Dong, Impact of China's waste import policy on the scrap copper recovery pattern and environmental benefits, Waste Manage. (Tucson, Ariz.) 135 (2021 Nov) 287–297.
[6] D. Tapscott, Blueprint to the Digital Economy: Creating Wealth in the Era of E-Business, McGraw Hill, New York, 1999.
[7] H. Wen, C. Wen, C.C. Lee, Impact of digitalization and environmental regulation on total factor productivity, Inf. Econ. Policy 61 (2022 Dec) 101007.
[8] S. Md, L. Allan, A. Khorshed, On the contribution of information and communication technology to productivity growth in Australia, Econ. Chang. Restruct. 48 (2015 August 11) 281–304.
[9] F. Machlup, The Production and Distribution of Knowledge in the United States, Princeton university press, 1962.
[10] M.U. Porat, M.R. Rubin, The Information Economy, Department of Commerce, Office of Telecommunications, 1977.
[11] C. Watanabe, K. Naveed, Y. Tou, P. Neittaanmäki, Measuring GDP in the digital economy: increasing dependence on uncaptured GDP, Technol. Forecast. Soc. Chang. 137 (2018 Dec) 226–240.
[12] OECD, Measuring Digital Trade: towards a Conceptual Framework, OECD Publishing, Pairs, 2017.
[13] K. Barefoot, D. Curtis, W. Jolliff, J.R. Nicholson, R. Omohundro, Defining and Measuring the Digital Economy, vol. 15, US Department of Commerce Bureau of Economic Analysis, Washington, DC, 2018 Mar.
[14] M. Dobrota, V. Jeremic, A. Markovic, A new perspective on the ICT Development Index, Inf. Dev. 28 (4) (2012) 271–280.
[15] A. Stavytskyy, G. Kharlamova, E.A. Stoica, The analysis of the digital economy and society index in the EU, TalTech J. Eur. Stud. 9 (3) (2019 Sept) 245–261.
[16] S. Ojanperä, M. Graham, M. Zook, The digital knowledge economy index: mapping content production, J. Dev. Stud. 55 (12) (2019 Jan 30) 2626–2643.
[17] Q. Wang, J. Sun, U.K. Pata, R. Li, M.T. Kartal, Digital economy and carbon dioxide emissions: examining the role of threshold variables, Geosci. Front. (2023 June 5) 101644.
[18] M. Mueller, K. Grindal, Data flows and the digital economy: information as a mobile factor of production, Digit. Policy Regul. Gov. 21 (1) (2018 Dec) 71–87.
[19] S.F. Wamba, S. Akter, A. Edwards, G. Chopin, D. Gnanzou, How 'big data' can make big impact: findings from a systematic review and a longitudinal case study, Int. J. Prod. Econ. 165 (2015 July) 234–246.
[20] M.K. Saggi, S. Jain, A survey towards an integration of big data analytics to big insights for value-creation, Inf. Process. Manage. 54 (5) (2018 Sept) 758–790.
[21] J. Manyika, M. Chui, B. Brown, J. Bughin, R. Dobbs, C. Roxburgh, A. Hung Byers, Big Data: the Next Frontier for Innovation, Competition, and Productivity, McKinsey Global Institute, 2011.

[22] S. Yilmaz, K.E. Haynes, M. Dinc, Geographic and network neighbors: spillover effects of telecommunications infrastructure, J. Reg. Sci. 42 (2) (2002 Dec 17) 339–360.
[23] C.L. McNeely, J.O. Hahm, The big (data) bang: policy, prospects, and challenges, Rev. Policy Res. 31 (4) (2014 July 16) 304–310.
[24] I.A.T. Hashem, V. Chang, N.B. Anuar, K. Adewole, I. Yaqoob, A. Gani, .H. Chiroma, The role of big data in smart city, Int. J. Inf. Manage. 36 (5) (2016 Oct) 748–758.
[25] P. Casanovas, L. De Koker, D. Mendelson, D. Watts, Regulation of Big Data: perspectives on strategy, policy, law and privacy, Health Technol. 7 (4) (2017 May 08) 335–349.
[26] V. Albino, U. Berardi, R.M. Dangelico, Smart cities: Definitions, dimensions, performance, and initiatives, J. Urban Technol. 22 (1) (2015 Feb 04) 3–21.
[27] A. Visvizi, M.D. Lytras, E. Damiani, H. Mathkour, Policy making for smart cities: innovation and social inclusive economic growth for sustainability, J. Sci. Technol. Policy Manag. 9 (2) (2018 July 12) 126–133.
[28] S. Qureshi, L. Najjar, Information and communications technology use and income growth: evidence of the multiplier effect in very small island states, Inform. Technol. Dev. 23 (2) (2017) 212–234.
[29] I. Domazet, J. Zubović, M. Lazić, Driving factors of Serbian competitiveness: digital economy and ICT, Strateg. Manag. 23 (1) (2018 Jan) 20–28.
[30] C. Corrado, J. Haskel, C. Jona-Lasinio, Knowledge spillovers, ICT and productivity growth, Oxf. Bull. Econ. Stat. 79 (4) (2017) 592–618.
[31] Y. Lu, K. Cao, Spatial analysis of big data industrial agglomeration and development in China, Sustainability 11 (6) (2019 Mar 25) 1783.
[32] Z. Song, C. Wang, L. Bergmann, China's prefectural digital divide: spatial analysis and multivariate determinants of ICT diffusion, Int. J. Inf. Manage. 52 (2020 Jun) 102072.
[33] R. Jedwab, E. Kerby, A. Moradi, History, path dependence and development: evidence from colonial railways, settlers and cities in Kenya, Econ. J. 127 (603) (2017 Aug) 1467–1494.
[34] R.H. Lin, Z. Xie, Y. Hao, J. Wang, Improving high-tech enterprise innovation in big data environment: a combinative view of internal and external governance, Int. J. Inf. Manage. 50 (2020 Feb) 575–585.
[35] J.Q. Dong, J. Netten, Information technology and external search in the open innovation age: new findings from Germany, Technol. Forecast. Soc. Chang. 120 (2017 Jul) 223–231.
[36] H.M. Zhang, Industrial cluster innovation based on 5G network and internet of things, Microprocess. Microsyst. 83 (1) (2021 Jun) 103974.
[37] R. Howell, C. Beers, N. Doorn, Value capture and value creation: the role of information technology in business models for frugal innovations in Africa, Technol. Forecast, Soc. Chang. 131 (2018 Jun) 227–239.
[38] H. Wen, W. Chen, F. Zhou, Does digital service trade boost technological innovation?: international evidence, Socio-Econ, Plan. Sci. (2023 Aug) 101647.
[39] J. Liu, H. Chang, J.Y.L. Forrest, B. Yang, Influence of artificial intelligence on technological innovation: evidence from the panel data of China's manufacturing sectors, Technol. Forecast. Soc. Chang. 158 (2020 Sept) 120–142.
[40] M. Wang, M. Xu, S.J. Ma, The effect of the spatial heterogeneity of human capital structure on regional green total factor productivity, Struct. Change and Econ. Dyn. 59 (2021 Dec) 427–441.
[41] Q. Wang, F. Zhang, R. Li, Revisiting the environmental kuznets curve hypothesis in 208 counties: the roles of trade openness, human capital, renewable energy and natural resource rent, Environ. Res. 216 (2023 Jan 1) 114637.
[42] M. Falk, F. Biagi, Relative demand for highly skilled workers and use of different ICT technologies, Appl. Econ. 49 (9) (2016 Aug 21) 903–914.
[43] Y. Zhu, D. Xu, J. Cheng, S.H. Ali, Estimating the impact of China's export policy on tin prices: a mode decomposition counterfactual analysis method, Resour. Policy 59 (2018 Dec) 250–264.
[44] W. Pan, T. Xie, Z. Wang, L. Ma, Digital economy: an innovation driver for total factor productivity, J. Bus. Res. 139 (2022 Feb) 303–311.
[45] L. Liang, Y. Li, How does government support promote digital economy development in China? The mediating role of regional innovation ecosystem resilience, Technol. Forecast. Soc. Chang. 188 (2023 Mar) 122328.
[46] G. Zekos, Foreign direct investment in a digital economy, Eur. Bus. Rev. 17 (1) (2005 Feb 1) 52–68.
[47] Q. Wang, X. Wang, R. Li, Does urbanization redefine the environmental Kuznets curve? An empirical analysis of 134 Countries, Sustain. Cities Soc. 76 (2022 Jan) 103382.
[48] C. Nie, Z. Zhong, Y. Feng, Can digital infrastructure induce urban green innovation? New insights from China, Clean Techn Environ Policy 25 (Oct 13) (2023) 3419–3436.
[49] R.M. Baron, D.A. Kenny, The moderator–mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations, J. Pers. Soc. Psychol. 51 (6) (1986) 11–73.
[50] D.P. Mackinnon, G. Warsi, J.H. Dwyer, A simulation study of mediated effect measures, Multivariate Behav. Res. 30 (1) (1995) 41–62.
[51] E. Pelinescu, C. Pauna, C. Saman, T. Diaconescu, Human capital, innovation and economic growth the EU countries, Rom. J. Econ. Forecast 22 (4) (2019) 160–173.
[52] C.S. Tang, L.P. Veelenturf, The strategic role of logistics in the industry 4.0 era, Transp. Res. Pt. e-Logist. Transp. Rev. 129 (2019 Sept) 1–11.
[53] S.V. Novikov, Data science and big data technologies role in the digital economy, TEM J. 9 (2) (2020 May 27) 756–762.
[54] U. Bhattacharya, P.H. Hsu, X. Tian, Y. Xu, What affects innovation more: policy or policy uncertainty? J. Financ. Quant. Anal. 52 (5) (2017 Aug 29) 1869–1901.
[55] W. Drobetz, S. El Ghoul, O. Guedhami, M. Janzen, Policy uncertainty, investment, and the cost of capital, J. Financ. Stab. 39 (2018 Dec) 28–45.
[56] H. Daiyue, L. Chao, G. Puel, A study of new industrialization and foreign direct investment (FDI) based on China's East, Middle and West regions, Afr. J. Bus. Manag. 6 (27) (2012 Jul 11) 7931–7937.
[57] S. Wu, X. Zheng, C. You, C. Wei, Household energy consumption in rural China: Historical development, present pattern and policy implication, J. Clean. Prod. 211 (2019 Feb 20) 981–991.
[58] R. Martin, P. Sunley, Path dependence and regional economic evolution, J. Econ. Geogr. 6 (4) (2006 Aug) 395–437.
[59] R. Bohnsack, H. Kurtz, A. Hanelt, Re-examining path dependence in the digital age: the evolution of connected car business models, Res. Policy 50 (9) (2021 Nov) 104–328.