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Convergence and Obstacles: Research on Regional of the Digital Economy Level in China

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ABSTRACT

The digital economy (DE) on China's regional economic equilibrium development strategy is evident. This study measures the DE development level in 30 Chinese provinces from 2007 to 2022 and analyzes its spatial-temporal pattern, transition probability, obstacles, and dynamic convergence. The result found that: (1) The level of China's DE development has significant polarisation characteristics, with the eastern part of the country significantly higher than the rest of the country and a multipolar phenomenon; (2) The DE in the northeastern region is experiencing a downward trend; (3) The regional disparity serves as the primary source of spatiotemporal differences in China's DE; (4) The main obstacles to the development of the DE include the primary operating income from the manufacturing of communication equipment, computers, and other electronic devices, revenue from software services, and the number of patent grants; (5) There is significant spatial β-convergence between regions and provinces in China. Building on these findings, this study enriches and enhances the measurement of China's digital economic level and spatial convergence research, offering valuable decision-making insights for China's DE and regional development.

KEYWORDS

DE; Dagum Gini coefficient; Barrier degree; Markov; Spacel convergence

1. INTRODUCTION

The Chinese government is committed to promoting economic growth while continuously addressing the issue of regional economic imbalances, aiming to achieve fairness through development. Currently, the new engine of China’s high-quality and rapid economic growth is the DE (Chen et al., 2019; Singhal et al., 2018). According to the China DE Development Report (2023), the scale of China's DE reached 50.2 trillion yuan in 2022, accounting for 41.5% of GDP. In 2021, the State Council issued the "14th Five-Year Plan" for the development of the DE, proposing to elevate the digital transformation of industries to a new level, strengthen the construction of digital infrastructure, and empower the transformation and upgrading of traditional industries. However, despite these efforts, regional economic imbalances remain a prominent feature of China's economic spatial pattern. In recent years, regional disparities in DE development have consistently narrowed, while the trend of overall high-quality DE economic has been expanding (Chen & Xin, 2023). As we promote the development of the DE to propel economic growth, how will China's DE landscape evolve spatially? What implications will it hold for the pattern of regional equitable development? Are we witnessing a narrowing or widening gap in the development level of the DE among different regions? This directly pertains to whether the overarching design principle of the policy advocated by the Chinese government, namely 'addressing imbalances through development,' is being adhered to (People's Daily, 2024).

The existing theoretical literature acknowledges that the DE has both positive and negative impacts on regional inequality. Firstly, digital technologies tend to favor highly skilled workers and are more beneficial to cities with strong agglomeration effects, thus widening the disparities between regions. Secondly, digital technologies also make the location of work less important, leading to richer information flows in remote areas and providing them with more abundant financial, logistical, and employment opportunities. Consequently, this scenario is more likely to promote the development of underdeveloped regions, narrowing the gap between regions (Li & Huang, 2022). The corresponding empirical studies often select various economic indicators, such as employment rates, wages, per capita GDP, etc., (Zhang, 2022; Wan & Feng, 2023) to investigate the relative changes in these indicators across regions influenced by the DE. Empirical evidence shows that there is evidence supporting both the positive and negative impacts (Zhang & Wan, 2016; Zhang et al., 2019; Cheng et al., 2022; Liu & Xu, 2024). Therefore, the relationship between the development of the DE and regional inequality still retains uncertainty. However, these studies actually raise a more important fundamental question: as the disruptive variable of the DE is poised to account for a significant portion of GDP, its large-scale development will have important implications for China's regional balanced development, beyond the various dimensions of economic indicators it impacts. Currently, there is a lack of literature that deeply investigates the uneven development of the DE itself within the theoretical framework of China's regional economic balanced development. Therefore, this paper will focus on studying the temporal and spatial evolution trends of the DE in China and its regional differentiation characteristics. It aims to provide scientific and objective decision-making references for the Chinese government in formulating policies related to the DE and regional balanced development.

2. EXISTING LITERATURE

The DE is a new form of economy driven by digital technology, following agricultural and industrial economies. It relies on data resources as a key production factor, modern information networks as important carriers, and the effective use of information and communication technology as a significant driver for efficiency improvement and economic structural optimization (Xu & Sun, 2023). The academic community has conducted extensive research in areas such as digital property rights (Liu et al., 2023; Chen et al., 2023), theoretical analysis, scale measurement (Xu & Zhang, 2020; Cai & Niu, 2021), and multi-dimensional impact mechanisms (Sun et al., 2023; Li et al., 2023). Among them, three specific documents closely relevant to this study are available.

The first citation discusses the polarization effect of the DE. There is evidence suggesting that the development of the DE benefits more from cities that are more developed and enriched with advanced digital technologies (Forman et al., 2012; Gaspar, 1998), as these cities have closer labor market connections and attract more skilled talent. Giannone (2017) found that since 1980, the convergence of wage disparities among different regions in the United States has gradually stopped, driven by skill-biased technological advancements, regions with concentrated technological enterprises experienced greater wage growth among high-skilled workers. Atkinson et al. (2019) also reported that from 2005 to 2017, 90% of the growth in the innovation sector in the United States was highly concentrated in the top five innovation hubs: Boston, San Francisco, San Jose, Seattle, and San Diego. These hubs saw their share of national innovation employment rise from 17.6% to 22.8%. Chen and Chen (2021) using macro data from 2011 to 2019 and employing a panel mediation effects model, found that inclusive digital finance widened the income gap between low-income rural groups and high-income groups through wage income channels. Similarly, research on macro data from 280 prefecture-level cities in China during the same period indicated that the DE significantly exacerbated urban economic imbalances (measured by the difference between urban per capita GDP and national

GDP during the same period) (Cheng et al., 2022). This conclusion is further supported by Fang and Tian (2021), whose study, based on microdata and employing the broadband China policy as an exogenous shock variable, demonstrated through a difference-in-differences method that the development of the DE widened income disparities between the eastern and western regions as well as between the central and western regions.

The second strand of literature is on the inclusive effects of the DE; theoretical analyses suggest that the DE also has the effect of narrowing the economic development gap between groups and regions. At the macro level, Song (2017) used the China Digital Inclusive Finance Index and the basic regression equation to test the theoretical hypothesis that the development of digital finance helps to narrow the urban-rural income gap; at the micro level, Zhang et al. (2019) and others, based on the 2011-2018 samples in the CFPS micro database, used quantile regression and subgroup regression to find that digital finance can effectively reduce the urban-rural income gap, in which promoting the entrepreneurial behaviour of low-income and high-skilled rural households is an important influence channel. In addition, Yao and Shen (2023) used a regression model to show that digital economic development can promote the accelerated development of regions with low economic levels by constructing the GDP per capita of prefecture-level cities in logarithmic form. The main existing features of the two aforementioned literatures are: first, the selected indicators to measure the degree of regional inequality are diversified, Long et al. (2022) found that digital inclusive finance has a contributing effect on the level of inclusive growth based on the innovation and entrepreneurship path from the dimensions of economic growth, income distribution and equality of opportunity; Yang and Li (2023) analysed the level of digital economic development from the eight dimensions, and found that there is a bifurcation in the level of development of the DE, and the conclusions of the study are subjective, so the relationship between the DE and the balanced growth of the regional economy is always unresolved; Second, it relies on causal measurement to test the effect of the DE on regional development, but ignores the fact that the heterogeneous level of development of the DE itself in different regions of China is a more essential motivation for the balance or otherwise of the region.

The third strand of literature is on the measurement and analysis of the DE level. In recent years, some scholars have also conducted research on the measurement of China's DE level and spatio-temporal patterns. However, the shortcomings of this branch of literature are: the sample period is short (Chen et al, 2023; He & Re , 2022), the temporal information is outdated and it fails to study and analyse the recent spatio-temporal development of the DE and the trend of regional differentiation in a long time scale (Pan et al. 2021; Hou et al. 2023; Cao et al. 2022), the indicator system is too general (Jiao Yong, 2021), the analytical framework is dimensionally incomplete (Han et al., 2021), and a lack of targeted policy insights (Li Yan, 2021).

At the current growth rate, the DE will soon exceed half of GDP, and its impact on the pattern of balanced regional economic development will become increasingly important. In response to the rapidly developing DE, the National Development and Reform Commission (NDRC) and the Data Bureau formulated the "Implementation Programme on DE for Common Wealth" in 2023, which initiated the strategy of solving the problem of unbalanced development by developing the DE from the national level. Therefore, it is necessary to comprehensively analyse its spatio-temporal changes and regional differentiation trends in a multi-dimensional way, based on the latest data and from a longer time period, and to propose targeted countermeasures. The marginal contributions of this paper may be: First, it places the DE in China's regional economic space-time, constructs a research framework from the five dimensions of spatio-temporal evolution, transfer probability, regional divergence, development obstacles and spatial convergence, and dynamically explores the regional characteristics of digital economic development in a multi-dimensional manner, so as to provide a better and more robust design basis for balanced regional development policies; and secondly, to adopt the latest 16-year panel data for the period of 2007-2022 to conduct the estimation, and then to conduct a comprehensive analysis of its spatial and temporal changes and regional divergence trends. Second, the latest panel data from 2007 to 2022 is used to measure the spatial and temporal development and regional development trend of the level of DE development in a longer period, which provides richer information for related research; third, countermeasures and proposals for the development of the DE to promote the balanced development of China's regions are put forward in a targeted manner.

This paper will construct a four-dimensional framework of regional DE level measurement, spatio-temporal heterogeneity analysis, relative level prediction and spatio-temporal convergence to analyse and study the spatio-temporal development of China's DE and regional divergence characteristics, and based on the results of the study, put forward countermeasures and suggestions to promote the balanced development of regional DE. The specific arrangement of the following chapters is as follows: The second part is the introduction of the main research techniques; the third part is the construction of the indicator system and level measurement; the fourth part is the study of regional differences in the DE based on Dagum's Gini decomposition technique; the fourth part is the spatio-temporal dynamic analysis of the level of the DE based on kernel density estimation; The fifth part is the analysis of the probability of the Markov transfer based on the Markov transfer; the sixth part is the measurement of the degree of obstacles and the main obstacle factors; Part VII is the study of spatial convergence; Part VIII is the conclusion of the study and suggestions for countermeasures.

3. METHODS AND MATERIALS

3.1. Constructing an Evaluation Index System for the DE

Currently, the DE's role in driving economic growth is primarily reflected in three key dimensions: industrial digitization, digital industrialization, and digital innovation. These dimensions not only reflect the depth of integration and innovation capacity of the DE with traditional economies but also provide the foundation for constructing a comprehensive indicator system to better measure and understand the level of digital economic development and its contribution to the overall economic ecosystem. Firstly, industrial digitization refers to the penetration of digital technology, especially Internet information technology, into traditional industries. This leads to internal process improvement and optimization, process design, and enhances their capabilities in big data processing and intelligent decision-making, thereby improving the production efficiency and output of traditional industries. Based on the objective availability of regional data and drawing from relevant practices (Liu et al., 2020; Lv et al., 2021), basic indicators such as Internet penetration rate and the number of regional information technology companies are selected to quantify the level of regional industrial digitization. Secondly, digital industrialization focuses on the growth of digital industries themselves as thriving clusters, including fields such as communication equipment, computers, and information services. In the indicator system of this dimension, indicators such as the scale of digital industries, digital infrastructure, and the number of employees in digital industries can be introduced to reflect the regional development level of digitalized industries as emerging economic forms. Lastly, a crucial function of the DE is to drive economic development through the innovation of new digital technologies and business models. This includes but is not limited to the application of cutting-edge technologies such as artificial intelligence, blockchain, and cloud computing. When constructing the indicator system for this dimension, factors such as the quantity, quality, and market activity of innovation activities can be considered. Therefore, based on the objective availability of data, a framework for measuring the level of digital economic development is constructed from the three major dimensions of digital industrialization, industrial digitization, and digital innovation (Table 1).

Table 1. DE development Index System

First-order index	Secondary index	Index attribute	Weight
Digital industrialization	Revenue generated from primary business activities in the manufacturing industry of communication equipment, computers, and other electronic devices X1	+	0.0566
	Total volume of telecommunication service X2	+	0.0847
	Software revenue X3	+	0.0948
	Length of long distance optical cable X4	+	0.0830
	Internet broadband access port X5	+	0.1171
	Employees in the industry of information and communication technology (ICT) X6	+	0.0714
Industry digitization	Number of regional information technology companiesX7	+	0.0933
	Internet penetration rate X8	+	0.0955
Digital innovation	R&D Input Intensity X9	+	0.0805
	R&D Personnel FTE X10	+	0.0962
	Technology market turnover X11	+	0.0503
	Number of patents granted X12	+	0.0766

Notes: The index weight is calculated by the vertical and horizontal grading method.

3.2. Data Source

The panel data in this paper mainly comes from theChina Science and Technology Statistical Yearbook (CSTSY), China Electronic Information Industry Statistical Yearbook (CEIISY), High-tech Industry Statistical Yearbook (HTISY) and Wind Data Services databases, etc. Interpolation is used to supplement missing data in the study. Due to limited data availability, the research sample in this paper excludes Hong Kong, Macao, Taiwan, and Tibet.

3.3. Data Methods

3.3.1. The vertical and horizontal grading method(VHGM)

Measuring the level of regional digital economic development is the core task of this study and also a prerequisite for analyzing spatio-temporal heterogeneity. The indicators we designed constitute a composite index system comprising three main dimensions and 12 sub-indicators. Scientifically and reasonably allocating the weights of each sub-indicator in the comprehensive index is the key technical aspect for calculating the composite index. Our dataset represents a typical multi-agent, multi-dimensional time-series indicator system. For such a data structure, the method of cross-sectional and longitudinal ranking is an appropriate technique for indicator weighting. The advantage of this method lies in its ability to simultaneously consider the dynamics and multidimensionality of the dataset. It allows for both cross-sectional comparisons of performance at a specific moment and longitudinal analysis of overall performance over the entire evaluation period (Guo, 2007). Therefore, it enables us to objectively and scientifically compare the relative spatio-temporal evolution characteristics of the DE in various regions. Its evaluation function is:

$$y_i\left(t_k\right)=\sum_{j=1}^{m}\omega_j x_{ij}\left(t_k\right) \tag{1}$$

$$\sigma^2 = \sum_{k=1}^{N}\sum_{i=1}^{n}\left(y_i\left(t_k\right)-\bar{y}\right)^2 \tag{2}$$

$$\bar{\mathrm{y}} = \frac{1}{\mathrm{N}}\sum_{\mathrm{k}=1}^{N}\left(\frac{1}{\mathrm{n}}\sum_{\mathrm{i}=1}^{\mathrm{n}}\sum_{\mathrm{j}=1}^{\mathrm{m}}\omega_{\mathrm{j}}\mathrm{x}_{\mathrm{ij}}\left(\mathrm{t}_{\mathrm{k}}\right)\right)=0 \tag{3}$$

$$\sigma^2 = \sum_{k=1}^{N}\sum_{j=1}^{n}\left(y_i\left(t_k\right)\right)^2 = \sum_{k=1}^{N}\left[\omega^T H_k \omega\right] = \omega^T\sum_{k=1}^{N}H_k\omega \tag{4}$$

Where w=(w_1, w_2, …, w_m) ^{T} in Eq. (4); $H=\sum_{K=1}^{N}$ is an m × m order symmetric matrix; $H_{\mathrm{k}}=A_K^T A\left(\mathrm{k}=1,2,\cdots,\ \mathrm{N}\right)$

$$A_k = \begin{bmatrix} x_{11}\left(t_k\right) & \cdots & x_{1m}\left(t_k\right) \\ \vdots & \ddots & \vdots \\ x_{n1}\left(t_k\right) & \cdots & x_{nm}\left(t_k\right) \end{bmatrix} \tag{5}$$

In this paper, in the research process, the original data are first standardised using the linear scaling method, and then by calculating the symmetric matrix H_K and its maximum eigenvalue λ' and the corresponding standard eigenvector; then, the standard eigenvector λ' is normalised to determine the combined weight vector w_{j}. Finally, the composite index is calculated using equation (1) above.

3.3.2. Obstacle degree model

Based on the measurement of the level of DE development, the factors affecting the level of DE development should be ranked according to the degree of influence, which is the basis for proposing effective countermeasures. This paper identifies the degree of influence of each factor on the level of development of the DE by using the obstacle degree model. The obstacle degree model quantifies the contribution or obstacle degree of each factor to the achievement of the goal, so as to reveal the key factors that have a significant impact on the development of the DE.

The calculation steps are as follows:

$$Z_{ij} = \frac{\left(1-X_{ij}^{`}\right)\times W_{ij}}{\sum\left(1-X_{ij}^{`}\right)\times W_{ij}}\times 100\% \tag{6}$$

Where Z_{ij} is the degree of obstacles of indicator i to the development of the DE, Wij is the weight value of indicator j at level i, and $X_{ij}^{`}$ is the standardised value of the indicator.

3.3.3. Dagum Gini coefficient and its decomposition method

An important element of this study is to examine the degree of spatial and temporal inequality in the level of DE development among Chinese provinces, and Dagum's Gini coefficient and its decomposition method provide a technique for measuring the inequality in the spatial and temporal distribution of the level of DE in this study. The method not only measures the overall level of inequality, but also analyses how much of the overall inequality is due to differences within regions and how much is due to differences between regions. This provides an in-depth perspective on the spatio-temporal heterogeneity of the DE. This paper draws on the Dagum Gini coefficient decomposition method (DagumC, 1997) to analyse regional distributional differences in China's DE development index. The coefficient is decomposed into intra-group disparity, net contribution to inter-group disparity and inter-group hypervariance density through the method of subgroup decomposition, and the larger its value, the greater the difference in its DE level. The methodology is specified in equations (7)-(14) below. Where G represents the overall Gini coefficient, k represents the number of regions, j and h are for the number of regional divisions, n represents the number of provinces, i and r are the number of provinces within the region, μ represents the average value of the efficiency of all the regions examined, n_j (n_h) is the number of provinces in the j_{th} (h) region, y_{ji}(y_{hr}) is the value of the digital efficiency measure of the provinces in the j_{th} (h) region, D_{hj} is the relative impact of the digital efficiency of the regional groups j and h between the indicated the difference in the composite index of the DE between regions, and at $\mu_j>\mu_h$, denotes the weighted average of all the differences in the composite index of the DE ,under the condition of y_{ji}- $y_{hr}>0$ is the hypervariable first-order distance, which at $\mu_j>\mu_h$, P_{hj} is the weighted average of all (y_{hr}-y_{ji}) under the y_{hr}-$y_{ji}>0$ condition.

$$G_{hh}=\frac{\sum_{i=1}^{n_h}\sum_{r=1}^{n_h}\left|y_{hi}-y_{hr}\right|}{2\bar{y}_h n_h^2} \tag{7}$$

$$G_w=\sum_{h=1}^{k}G_{hh}p_h s_h \tag{8}$$

$$G_{hj}=\frac{\sum_{i=1}^{n_h}\sum_{r=1}^{n_j}\left|y_{hi}-y_{jr}\right|}{n_h n_j\left(\bar{y}_h+\bar{y}_j\right)} \tag{9}$$

$$G_{rb}=\sum_{h=2}^{k}\sum_{j=1}^{h-1}G_{hj}\left(p_h s_j+p_j s_h\right)D_{hj} \tag{10}$$

$$G_t=\sum_{h=2}^{k}\sum_{j=1}^{h-1}G_{hj}\left(p_h s_j+p_j s_h\right)\left(1-D_{hj}\right) \tag{11}$$

$$D_{hj}=\frac{d_{hj}-p_{hj}}{d_{hj}+p_{hj}} \tag{12}$$

$$d_{hj}=\int_0^{\infty}dF_h(y)\int(y-x)dF_j(x) \tag{13}$$

$$p_{hj}=\int_0^{\infty}dF_j(y)\int(y-x)dF_h(x) \tag{14}$$

3.3.4. Kernel density estimation(KDE)

Kernel density estimation is a non-parametric estimation technique that essentially measures the state of spatially unbalanced distribution by estimating the probability of a random variable using a continuous density profile. Unconstrained by specific distributional assumptions, kernel density estimation can capture continuous trends in time and space, identifying high-density areas and potentially unbalanced distributions of digital economic development, thus providing a refined and dynamic research perspective.

In this paper, the spatial dynamic evolution of China's DE development is analysed by using the Gaussian kernel density (Chen & Qingi, 2022) with the following equation:

$$f(x)=\frac{1}{nh}\sum_{i=1}^{n}K(\frac{x_i-x}{h}) \tag{15}$$

$$K(x)=\frac{1}{\sqrt{2\pi}}e^{(-\frac{x^2}{2})} \tag{16}$$

Where f(x) is the kernel density estimate, h is the bandwidth, and K(x) is the kernel function.

3.3.5. Markov chain (MC)

Historical fluctuations in the relative levels of regional digital economies will influence and shape the future spatio-temporal pattern of China's DE. Therefore, constructing Markov transfer matrices from historical information to estimate the changes in the relative levels of future DE development in each region, with a focus on regions with declining relative levels, will provide valuable predictive information for the balanced regional development of the DE.

The Markov transfer matrix can calculate the probability of the distribution state of a random variable changing from one state to another, and discretise its periods. This paper focuses on predicting the regional development trend of the DE using Markov transfer evidence. The formula of its probability transfer is as follows:

$$P_{ij}^{t,t+d}=\frac{\sum_{t=T_0}^{T-d}n_{ij}^{t,t+d}}{\sum_{t=T_0}^{T-d}n_{i}^{t,t+d}}(i=1,2,...,r;j=1,2,...,r;t=T_0,...,T-d) \tag{17}$$

In the above formula, r indicates the number of grading levels in the DE, $n_{ij}^{t,t+d}$ indicates the number of provinces whose DE level is transferred from the i grade of year t to the j grade of year (t+d), and $n_{i}^{t,t+d}$ indicates the number of provinces whose DE level belongs to the grade i of year t. $r=4;d=1$

3.3.6. Space β convergence model

Will the interregional development gap in the DE widen indefinitely or is there an upper limit? This is an extremely important issue in the study of spatio-temporal development patterns, as it represents two system characteristics that are fundamentally different. Therefore, this study will use the spatial beta convergence model to determine whether there is a spatio-temporal convergence characteristic in the level of interregional digital economic development. The spatial β-convergence model is mainly used to analyse the convergence of serial data. In this paper, spatial β-convergence is used to analyse the degree of convergence of the DE between neighbouring regions. β-convergence includes two types: absolute β-convergence and conditional β-convergence, which mainly examines the trend change of the DE in each region in terms of the growth rate of digital economic development. If β is significantly negative, it proves that the spatio-temporal system has spatio-temporal convergence. The spatial econometric models include the spatial Durbin model (SDM), the spatial lag model (SAR) and the spatial error model (SEM), while their spatial relevance and model selection are assessed by the LM, Hausman, LR and Wald tests. The model settings are shown below:

$$\ln(\frac{DEDCI_{i,t}}{DEDCI_{i,t-1}})=\alpha+\beta\ln DEDCI_{i,t-1}+\rho\sum_{j\neq i}^{n}W_{i,j}\ln(\frac{DEDCI_{j,t}}{DEDCI_{j,t-1}})+\gamma x_{it}+\varphi_i+\pi_t+\mu_{it} \tag{18}$$

$$\ln\left(\frac{DEDCI_{i,t}}{DEDCI_{i,t-1}}\right)=\alpha+\beta\ln DEDCI_{i,t-1}+\gamma x_{it}+\varphi_i+\pi_t+\mu_{it},\ \mu_{it}=\lambda\sum_{j\neq i}^{n}W_{i,j}\mu_{jt}+\varepsilon_{it} \tag{19}$$

$$\ln\left(\frac{DEDCI_{i,t}}{DEDCI_{i,t-1}}\right)=\alpha+\beta\ln DEDCI_{i,t-1}+\rho\sum_{j\neq i}^{n}W_{i,j}\ln\left(\frac{DEDCI_{j,t}}{DEDCI_{j,t-1}}\right)+\theta\sum_{j\neq i}^{n}W_{i,j}\ln DEDCI_{j,t-1}+\gamma x_{it}+\psi\sum_{j\neq i}^{n}W_{i,j}x_{jt}+\varphi_i+\pi_t+\mu_{it} \tag{20}$$

In the above formulas, $\frac{DEDCI_{i,t}}{DEDCI_{i,t-1}}$ indicates the growth rate of DE index in the first year of the province i. $DEDCI_{i,t-1}$ is the DE index of the previous year, and β is the elasticity of the digital economic level to the initial regional economic level, which is a measure of the convergence of digital economic levels. When the value of β is significantly negative, it suggests that China's DE level is experiencing convergence (Chen and Li, 2006). Conversely, if the value of β is significantly positive, it indicates that China's DE level is diverging. $\sum_{j\neq i}^{n}W_{i,j}\ln\left(\frac{DEDCI_{j,t}}{DEDCI_{j,t-1}}\right)$ is the growth rate of the DE after weighting space. ρ is a spatial autoregressive coefficient, which is used to express the spatial interaction intensity of the DE across regions. x_{it} are a series of control variables. Based on data availability and previous research (Ding and Li, 2022), human capital, government management, city size, the degree of 'opening-up' and per capita GDP are chosen as control variables.

4. RESULTS

4.1. Analysis of the Measurement Levels of the DE

Based on the presented Fig.1, we can observe that from 2007 to 2022, national trend change of the DE development level of 30 provinces, calculated by the VHGM. The results show that China's regional DE development level has the characteristics of "overall growth, but the level in the east is high and the level in the west is low". Overall, the index of China's inter-provincial digital economy development level from 2007 to 2022 shows a general growth trend, the average value from 0.197 in 2007 to 0.239 in 2022, an increase of 21.32%; sub-regionally, the eastern region has a better DE development level, and its average value is much higher than that of the other three regions. Guangdong has always ranked first in the DE development index, Beijing and Zhejiang have always been in the top three despite fluctuations in individual years, followed by Jiangsu, indicating that the eastern region is leading in terms of the level of DE development. The provinces with the lowest rankings are Hainan, Qinghai, Ningxia and Guizhou, of which Qinghai, Ningxia and Guizhou are in the western region, indicating that the level of DE development in the western region is relatively weak. (as shown in Table 2).

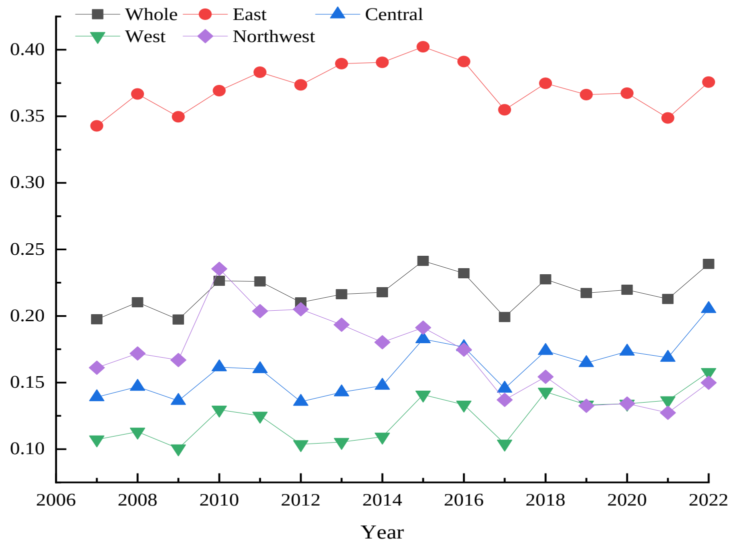


Figure 1. China's inter-provincial level of DE development

Table 2. DE Development Index of 30 Provinces

Province	2008	2010	2012	2014	2016	2018	2020	2022
Beijing	0.650	0.538	0.559	0.639	0.559	0.540	0.551	0.558
Tianjin	0.191	0.185	0.203	0.162	0.170	0.151	0.151	0.149
Hebei	0.167	0.193	0.175	0.175	0.202	0.193	0.194	0.224
Shanxi	0.137	0.148	0.116	0.097	0.107	0.111	0.106	0.126
InnerMongolia	0.112	0.150	0.094	0.103	0.155	0.158	0.125	0.158
Liaoning	0.235	0.296	0.307	0.311	0.239	0.199	0.186	0.171
Jilin	0.116	0.148	0.191	0.114	0.129	0.132	0.103	0.131
Heilongjiang	0.165	0.262	0.118	0.116	0.156	0.132	0.114	0.148
Shanghai	0.373	0.365	0.376	0.376	0.311	0.308	0.328	0.343
Jiangsu	0.513	0.589	0.629	0.675	0.674	0.615	0.585	0.614
Zhejiang	0.420	0.386	0.412	0.443	0.458	0.436	0.432	0.422
Anhui	0.113	0.140	0.132	0.150	0.191	0.185	0.184	0.231
Fujian	0.215	0.252	0.253	0.241	0.258	0.251	0.214	0.215
Jiangxi	0.094	0.092	0.070	0.080	0.108	0.115	0.121	0.135
Henan	0.332	0.373	0.354	0.406	0.466	0.406	0.389	0.384
Hubei	0.183	0.195	0.157	0.186	0.227	0.221	0.223	0.261
Hunan	0.188	0.214	0.190	0.213	0.245	0.228	0.210	0.231
Jiangxi	0.167	0.181	0.149	0.160	0.181	0.183	0.196	0.249
Guangdong	0.778	0.772	0.735	0.742	0.774	0.808	0.799	0.805
Guangxi	0.117	0.133	0.185	0.101	0.120	0.131	0.139	0.184
Hainan	0.030	0.039	0.040	0.045	0.038	0.040	0.038	0.044
Chongqing	0.104	0.121	0.127	0.151	0.156	0.156	0.159	0.169
Sichuan	0.262	0.266	0.221	0.278	0.314	0.360	0.350	0.350
Guizhou	0.073	0.086	0.048	0.068	0.088	0.114	0.111	0.118
Yunnan	0.100	0.107	0.067	0.080	0.133	0.135	0.118	0.150
Shaanxi	0.177	0.211	0.172	0.192	0.215	0.202	0.185	0.226
Gansu	0.080	0.097	0.057	0.078	0.091	0.099	0.088	0.101
Qinghai	0.066	0.085	0.049	0.034	0.062	0.075	0.058	0.081
Ningxia	0.032	0.037	0.038	0.052	0.049	0.060	0.052	0.063
Xinjiang	0.120	0.133	0.080	0.066	0.084	0.083	0.088	0.135

4.2. Analysis of Regional Disparities in the Development of DE

As measured, the level of development of China's DE is characterised by typical regional imbalances. It is then necessary to further investigate the spatial sources of this imbalance. This paper applies Dagum's Gini decomposition method to decompose into overall disparities, disparities within the four major regions (east, central, west and northeast), inter-regional disparities and sources of spatial disparities (as shown in Fig.2-3).

4.2.1. Overall variance analysis

The overall Gini coefficient of China's inter-provincial digital economy development level during the sample period shows a downward trend with repeated 'N-W' fluctuations (as shown in Fig. 2a). It decreases from 0.397 in 2007 to 0.352 in 2022, a decrease of 11.34%. Specifically, the overall gap has significant stage characteristics, with a 'rising-declining-rising-declining' trend from 2007 to 2015, with an overall decline of 2.14%; a stepped-up trend from 2015 to 2017, with the overall Gini coefficient rising from 0.388 in 2015 to 0.436 in 2017, and rising from 0.388 in 2015 to 0.436 in 2018, with a decline of 11.34%. It then falls from 0.436 in 2015 to 0.377 in 2018, followed by two consecutive years of fluctuating changes, from 0.377 in 2018 to 0.352 in 2022, a decrease of 6.61%.

4.2.2. Analysis of regional differences

Fig. 2a also shows the characteristics and evolutionary trends of the differences in the digital economy across China's four main regions. It is worth noting that there are 'two increases and two decreases' over the period. Among these, the intra-regional differences between the eastern and central regions show an increasing trend, rising from 0.325 and 0.112 in 2007 to 0.332 and 0.138 in 2022, or 1.96% and 23.73% respectively; while Intra-regional disparities in the West and North-East regions show a decreasing trend, from 0.269 and 0.133 in 2007 to 0.250 and 0.060 in 2022, or 7.05% and 55.19% respectively. In addition, compared with the other three regions, the intra-regional differences in the Gini coefficient of the DE are largest in the eastern region, while the intra-regional differences in the Gini coefficient of the DE are relatively small in the central, western and north-eastern regions. The above trends indicate to some extent that the level of the DE within the developed eastern region shows intra-regional polarisation, which further contributes to the sources of inequality.

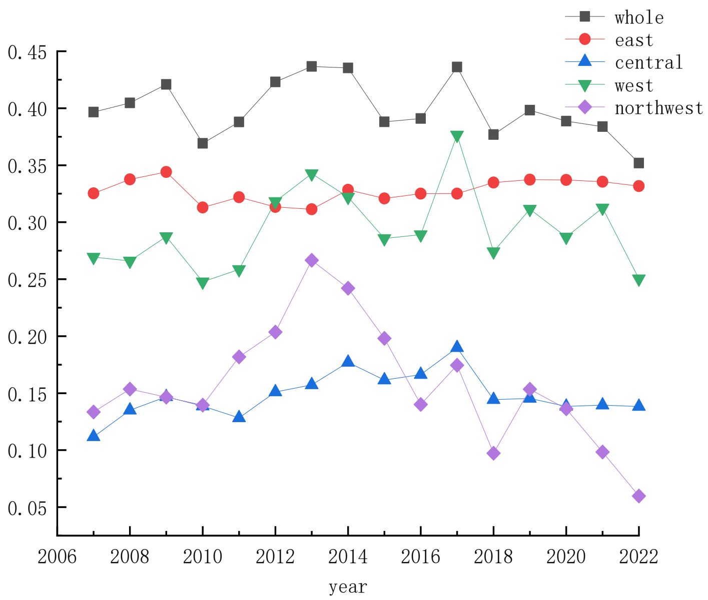


Figure 2(a). Regional differences of the DE

4.2.3. Analysis of regional disparities

The Inter-regional differences in China's digital economy and their evolutionary dynamics (as shown in Fig. 2b). Overall, the interregional differences show a trend of frequent fluctuations. Among them, the inter-regional differences in the East-West region are always at the highest level except in 2022, the inter-regional differences in the East-Central and East-Northeast regions are at the intermediate level, and the inter-regional differences in the Central-West, Central-Northeast and West-Northeast regions are at the downstream level. Over the period considered, interregional disparities in the East-Northeast, Central-West and Central-Northeast regions increased from 0.425, 0.235 and 0.144 in 2007 to 0.473, 0.244, 0.226 and 0.195 in 2022, or by 11.29%, 3.83% and 35.42% respectively, while the intraregional differences in the East-Northeast region increased from 0.526 in 2007 to 0.508 in 2022, a decrease of 3.4%, and the intra-regional differences of the East-Central, East-West and West-Northeast regions decrease significantly from 0.473, 0.565 and 0.273 in 2007 to 0.381, 0.472 and 0.182 in 2022, a decrease of 19.45%, 16.46% and 33.33% respectively. Such complex fluctuations reflect the fact that the level of DE development among regions in China is not yet clearly characterised by balanced development.

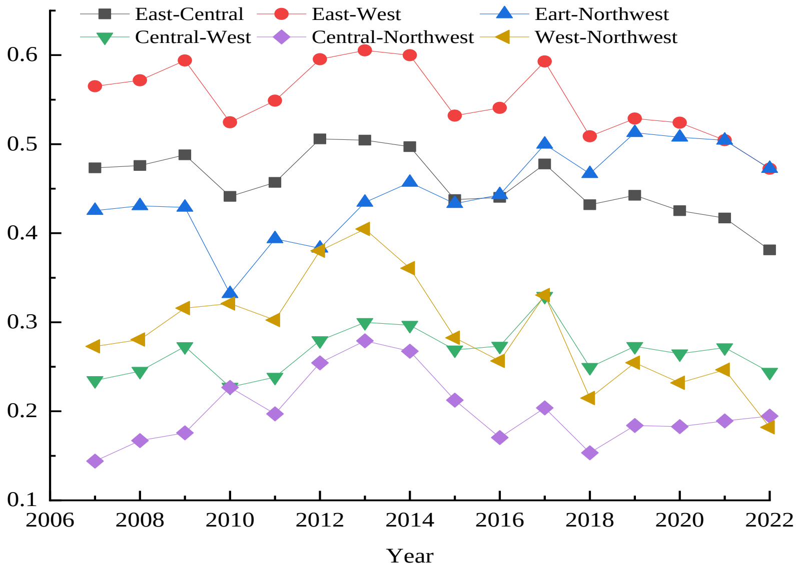


Figure 2(b). Regional differences in the DE

4.2.4. Sources of Regional Disparities

The evolution of the sources and contributions of regional differences in the level of development of the digital economy (as shown in Fig. 3). In terms of the degree of contribution of the sources of difference, the contribution rate of inter-regional differences is the largest, with an average value of 64.76%, the contribution rate of intra-regional differences has an average value of 22.55%, and the contribution rate of hypervariable density has the lowest average value of 12.69%, indicating that the contribution rate of inter-regional differences is the main source of the overall differences in China's DE, and the problem of sample overlap in the contribution rate of hypervariable density has a smaller impact on the overall differences in the DE. In terms of the development trend, the overall contribution rate of interregional differences shows a slow downward trend, from 67.91% in 2007 to 59.88% in 2022, with a decrease of 11.82%; the overall contribution rate of intraregional differences shows a slow upward trend, from 21.84% in 2007 to 24.21% in 2022, with an increase of 10.85%; the overall contribution rate of hypervariable density increases from 10.24% in 2007 to 15.90% in 2022, with an increase of 55.27%. The implication is that the promotion of balanced regional development of the DE should focus both on reducing interregional disparities and on preventing the beginnings of widening intraregional disparities.

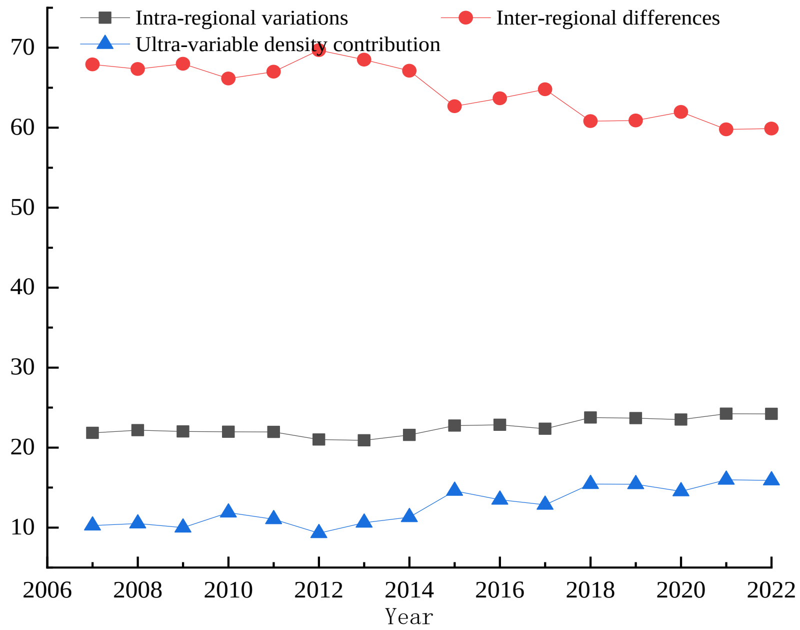


Figure 3. Sources of overall differences in the DEU

4.3. The Dynamic Evolution of DE

4.3.1. Distribution Dynamics and Evolution Analysis of DE

This study adopts KDE to examine the distribution position, shape, extensibility, and polarization of DE development across 30 provinces in four major regions of China, aiming to explore the evolution of DE development in China.

4.3.2. National level

The dynamic evolution of the distribution of the level of development of China's digital economy from 2007 to 2022 (as shown in Fig. 4). Overall, the regional DE level is mainly concentrated around 0.1, and the curve wave peak fluctuates with a rightward trend, while there is a small peak measurement phenomenon on the right. This means that the national base level fluctuates upwards and there is a degree of polarisation. In addition, there is a narrowing trend in the kernel density curve over the period, indicating that the overall national differences have all narrowed, which further confirms the conclusion of the Gini analysis.

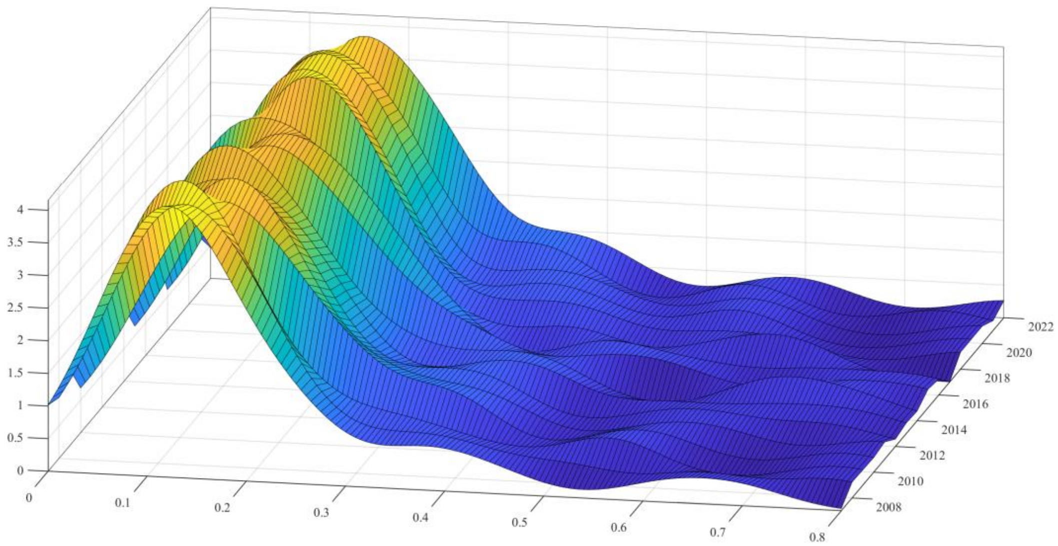
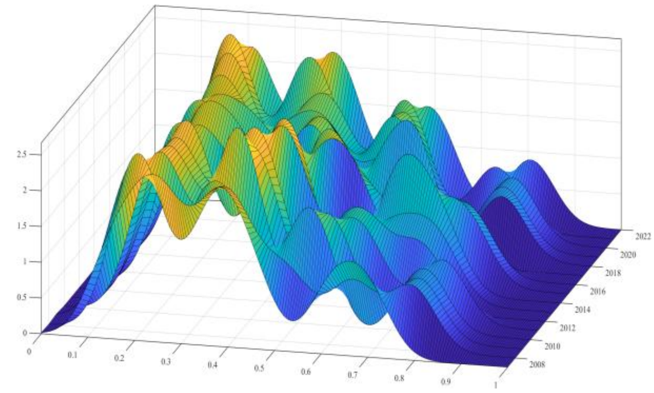


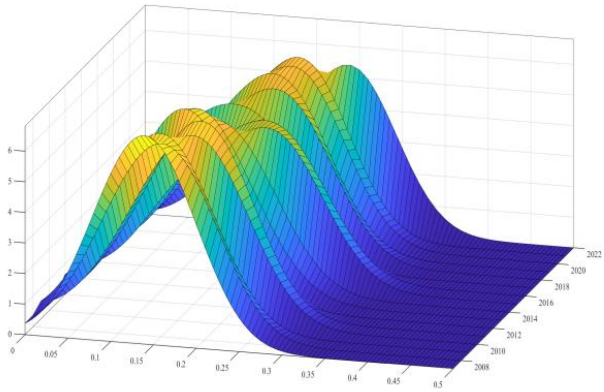
Figure 4. Composite index of the distribution and dynamics of development of the national DE

4.3.3. Four regional levels

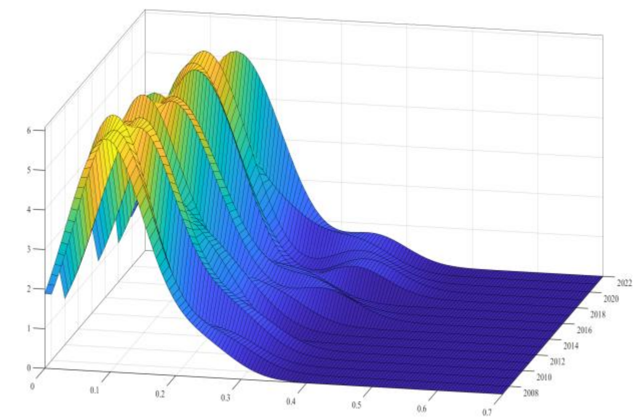
The dynamic development of the level of development of the digital economy in the eastern, central, western and north-eastern regions, respectively, over the period considered（as shown in Fig. 5). From the distribution position, the evolutionary trend of the level of DE development in the four regions is basically consistent with the country as a whole, with an overall rightward trend. From the distribution pattern, the height of the main peak distribution curve in the eastern and central regions shows a 'falling-rising-declining-rising-declining' trend, with an overall upward trend; the height of the main peak distribution curve in the western and northeastern regions shows a 'rising-declining-rising' trend. The height of the main peak distribution curve in the western and north-eastern regions shows a 'rising-declining-rising' trend. In terms of ductility, there is a significant right trailing phenomenon in the central, western and northeastern regions, but the ductility of the distribution curves is slightly different. The distribution curve of the northeastern region shows a broadening trend, indicating the beginning of differentiation within the region; the right trailing phenomenon of the eastern region is relatively insignificant, indicating that the level of DE development in the eastern region is still higher than that of the whole, and there are still some individual provinces with a leading level. The distribution curve of the northeast region has gone through a process of 'single peak - double peak - single peak': before 2010, it was a single peak, and a side peak was added in 2010-2015, and after 2016, it was a single peak with a high level of side peaks, indicating that the northeast region has a certain degree of bipolarity in the level of DE development. The level of DE development shows a certain polarisation phenomenon, the distribution curve in the Eastern region shows a clear multi-peak state, indicating that the level of DE development in the Eastern region shows a significant trend of high-level multi-polarisation. At the same time, further analysis of the gradual decline of the right peak in the eastern region suggests that its multi-polarisation began to decline at the end of the study.



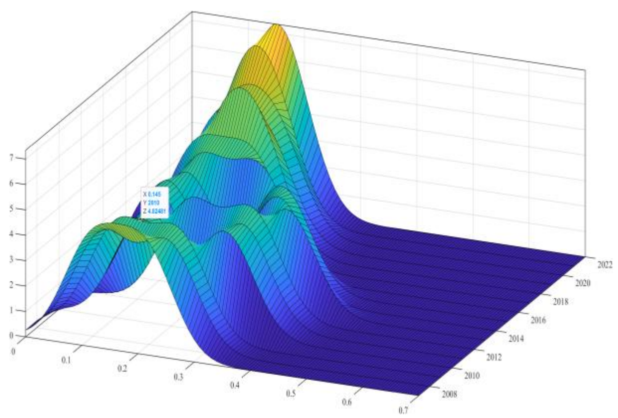
(a) East



(b) Central



(c) West



(d) Northeast

Figure 5. Distribution dynamics of the comprehensive index of digital economic development in the four major regions

4.4. Markov Analysis

In this research, China's digital economic index is divided according to a quartile method into four grades: low level, medium-low level, medium-high level and high level. Table 3 below is obtained by using Markov transition probability matrix.

Firstly, at the national level, the level of the regional DE shows a trend of steady improvement. The values on the diagonal are larger than those on the non-diagonal, and the probabilities of maintaining the original level at the low, medium-low, medium-high and high levels are 81.90%, 71.17%, 83.78% and 95.54%, respectively, which shows that the level of China's DE development has strong stability at different levels. At the same time, the probability of moving to the next level is 18.10%, 13.51% and 5.41% for low level, medium-low level and medium-high level, respectively, and there is a certain possibility of 'jumping' in the medium-low level with a probability of 0.9%. Observation of Table 3 also shows that the probability of moving to the next level of low, medium-high and high is low, 14.41%, 9.91% and 4.46% respectively, while the possibility of moving from medium-high to low is minimal, with a probability of 0.9%. Meanwhile, the probability of upward transfer of the regional DE is 37.92%, which is higher than the probability of downward transfer of 29.68%, indicating that the probability of overall progress in the level of the DE nationwide is higher.

Secondly, at the regional level, the probability values on the diagonal of the eastern, central and western regions are all greater than their non-diagonal probability values, and the future pattern of digital economic development in these three regions is stable; at the same time, the probability values of low and high levels on the diagonal are greater than the probability values of medium-low and medium-high levels, indicating that the future development of the DE will still maintain the 'pattern of inter-regional polarisation'. In addition, except for the northeast region, where the probability of downward transfer is higher than the probability of upward transfer, the probability of upward transfer is higher than the probability of downward transfer in the eastern, central and western regions, suggesting that the DE in the eastern, central and western regions is in a development trend and the level of the DE in the northeast region needs to be consolidated.

Table 3. Markov Transition Probability Matrix of the China DE Index from 2007 to 2022

	Rank	Low	Medium-low	Medium-high	High
Nationwide	Low	0.8190	0.1810	0	0
	Medium-low	0.1441	0.7117	0.1351	0.0090
	Medium-high	0.0090	0.0991	0.8378	0.0541
	High	0	0	0.0446	0.9554
East	Low	0.8684	0.1316	0	0
	Medium-low	0.1351	0.7297	0.1351	0
	Medium-high	0	0.1316	0.7895	0.0789
	High	0	0	0.0541	0.9459
Middle	Low	0.75	0.25	0	0
	Medium-low	0.2273	0.4545	0.2727	0.0455
	Medium-high	0	0.2083	0.5417	0.25
	High	0	0	0.15	0.85
Western	Low	0.7442	0.2326	0.0233	0
	Medium-low	0.1905	0.5238	0.2619	0.0238
	Medium-high	0.0244	0.1951	0.6098	0.1707
	High	0	0.0256	0.1026	0.8718
Northeast	Low	0.4167	0.4167	0.1667	0
	Medium-low	0.4545	0.3636	0.0909	0.0909
	Medium-high	0.2	0.2	0.6	0
	High	0	0	0.1667	0.8333

4.5. Obstacle Factor Analysis

In order to better develop the digital regional economy and optimise its spatial pattern, it is particularly important to identify the main factors that affect the development of the DE. The top five obstacle factors and the corresponding obstacle degrees of China's DE development level in the sample period (as shown in Table 4). First, the frequency statistics of the obstacle factors in each year show that there are major obstacle factors in the three guiding levels of digital industrialisation, industrial digitisation and digital innovation. Among them, the main business income of communication equipment, computer and other electronic equipment manufacturing industry appeared the highest frequency, a total of 16 times; followed by software business income (sales) and the number of patents granted 15 times, these three factors can be regarded as the main factors hindering the development of China's DE. These three factors can be regarded as the main factors hindering the development of China's DE. They are followed by the intensity of R&D investment, the number of legal entities and the length of long-distance fibre optic cables.

Table 4. Obstacles to China's Digital Economic Development from 2007 to 2022

Year	Project	Sort				
		1	2	3	4	5
2007	Obstacle factor (Degree of Obstacles)	X1 (5.3832)	X12 (4.1001)	X3 (3.5126)	X7 (3.3909)	X9 (3.2803)
2008	Obstacle factor (Degree of Obstacles)	X1 (5.5857)	X12 (4.0577)	X3 (3.7751)	X7 (3.3966)	X9 (2.9157)
2009	Obstacle factor (Degree of Obstacles)	X9 (17.8307)	X10 (2.9716)	X1 (2.0836)	X12 (1.6891)	X3 (1.3350)
2010	Obstacle factor (Degree of Obstacles)	X1 (5.4653)	X9 (5.0431)	X3 (3.5563)	X12 (3.4828)	X7 (2.6302)
2011	Obstacle factor (Degree of Obstacles)	X1 (5.1067)	X12 (4.3913)	X9 (4.1330)	X3 (3.4307)	X7 (2.6270)
2012	Obstacle factor (Degree of Obstacles)	X1 (4.6135)	X9 (4.1843)	X12 (4.0535)	X3 (3.2627)	X11 (2.5422)
2013	Obstacle factor (Degree of Obstacles)	X1 (4.3074)	X4 (3.8162)	X9 (3.7826)	X12 (3.7288)	X3 (3.1593)
2014	Obstacle factor (Degree of Obstacles)	X1 (4.8046)	X9 (4.1397)	X12 (3.7565)	X4 (3.3889)	X11 (2.5285)
2015	Obstacle factor (Degree of Obstacles)	X1 (4.9553)	X9 (4.1126)	X12 (3.8222)	X3 (3.4981)	X5 (2.6810)
2016	Obstacle factor (Degree of Obstacles)	X1 (4.7281)	X9 (3.9094)	X12 (3.6708)	X3 (3.5278)	X7 (2.6267)
2017	Obstacle factor (Degree of Obstacles)	X4 (5.2295)	X1 (4.1395)	X12 (3.1860)	X3 (3.1396)	X9 (2.5847)
2018	Obstacle factor (Degree of Obstacles)	X1 (4.9245)	X3 (3.5789)	X9 (3.4003)	X12 (3.2542)	X11 (2.9765)
2019	Obstacle factor (Degree of Obstacles)	X1 (4.8432)	X3 (3.5762)	X12 (3.3578)	X7 (3.0018)	X9 (1.4135)
2020	Obstacle factor (Degree of Obstacles)	X1 (4.7460)	X3 (4.2451)	X12 (3.1876)	X7 (2.9929)	X11 (2.9210)
2021	Obstacle factor (Degree of Obstacles)	X1 (4.2308)	X3 (4.0645)	X11 (3.0080)	X7 (2.7336)	X12 (2.9470)
2022	Obstacle factor (Degree of Obstacles)	X3 (4.6296)	X1 (4.1901)	X6 (3.4433)	X7 (3.2266)	X11 (3.0527)

4.6. Spatial Convergence Analysis of China's Digital Economic Development

Spatial convergence is a key element in studying long-term trends in the spatio-temporal pattern of China's DE. Whether regional differences in China's DE will continue to widen or converge to some limit corresponds to two spatio-temporal dynamical systems with different stability characteristics. In this section, the spatial model is used to test the spatio-temporal convergence characteristics of China's DE.

4.6.1. Absolute convergence

The results of the absolute β convergence test for the national DE under neighbourhood, economic and economic-geographic nested weights for the period under review are presented in Table 5. The results show that: first, the β values of absolute convergence are all significantly negative at the 1% level, indicating the existence of absolute β convergence in 30 provinces across the country. Second, the speed of β convergence under neighbourhood weights is 0.566, 0.635 and 0.654 for SAR, SEM and SDM models, respectively; under economic weights, the speed of β convergence under SAR, SEM and SDM models is 0.582, 0.677 and 0.724 for SAR, SEM and SDM models, respectively; under economic-geographical weights, the speed of β convergence under SAR, SEM and SDM models is 0.609, 0.618 and 0.616, respectively. Third, regardless of neighbourhood, economic or economic-geographical weights, the direct and total effects are significantly negative at the 1% level under the SAR and SDM models; while the spatial spillover effect is significantly negative under the SAR model.

4.6.2. Conditional convergence

Table 5. Absolute convergence in the DE

	Adjacent weight			Economic weight			Economic geographical weight		
	SAR	SEM	SDM	SAR	SEM	SDM	SAR	SEM	SDM
β	-0.432***	-0.470***	-0.480***	-0.441***	-0.492***	-0.515***	-0.456***	-0.461***	-0.460***
	(-11.16)	(-11.68)	(-11.65)	(-11.20)	(-11.97)	(-12.50)	(-11.47)	(-11.53)	(-11.48)
ρ	0.326***		0.391***	0.193***		0.285***	0.349***		0.371***
	(5.90)		(6.82)	(4.72)		(6.52)	(3.13)		(3.25)
λ		0.383***			0.274***			0.367***	
		(6.70)			(6.19)			(3.24)	
Direct effect	-0.443***		-0.470***	-0.446***		-0.498***	-0.460***		-0.460***
	(-10.89)		(-11.42)	(-10.91)		(-12.05)	(-11.08)		(-11.13)
Indirect effect	-0.198***		0.114	-0.099***		0.175***	-0.253**		-0.512
	(-4.05)		(0.98)	(-3.93)		(2.67)	(-2.008)		(-1.54)
Total effect	-0.641***		-0.356***	-0.544***		-0.323***	-0.714***		-0.524*
	(-8.61)		(-2.93)	(-9.96)		(-4.32)	(-4.98)		(-1.79)
N	450	450	450	450	450	450	450	450	450
r2	0.0313	0.0254	0.0209	0.027	0.0254	0.0203	0.0323	0.0254	0.0266

T statistics in parentheses * $P < 0.10$, ** $P < 0.05$, *** $P < 0.01$

According to the results of conditional β-convergence tests for the digital economy based on neighbourhood, economic and economic-geographical weights (as shown in Table 6). Firstly, the conditional convergence β values under the three weights are all significantly negative at the 1% level, implying that the gap in the level of digital economic development will gradually converge to a steady state over time; Secondly, under the neighbourhood weight, the β convergence speeds under the SAR, SEM, and SDM models are 0.629, 0.705, and 0.730, respectively; under the economic weight, the β convergence speeds under the SAR, SEM, and SDM models are 0.734, 0.759, and 0.681, respectively; and under the economic-geographic weight, the β convergence speeds under the SAR, SEM, and SDM models are 0.681, 0.685, and 0.683, respectively; Thirdly, regardless of neighbourhood, economic, or economic-geographical weights, the direct effects under the SAR and SDM models are significantly negative at the 1% level; Fourthly, the spatial autoregressive coefficients under all three weights are significantly positive, indicating that the DE is spatially interactive.

Table 6. Convergence of conditions in the DE

	Adjacent weight			Economic weight			Economic geographical weight		
	SAR	SEM	SDM	SAR	SEM	SDM	SAR	SEM	SDM
β	-0.467***	-0.506***	-0.518***	-0.520***	-0.532***	-0.494***	-0.494***	-0.496***	-0.495***
	(-11.93)	(-12.48)	(-12.41)	(-12.71)	(-12.90)	(-12.36)	(-12.36)	(-12.36)	(-12.33)
ρ	0.308***		0.375***	0.189***		0.274***	0.338***		0.312**
	(5.56)		(6.44)	(4.67)		(6.17)	(3.03)		(2.59)
λ		0.371***			0.265***			0.338**	
		(6.38)			(5.90)			(2.90)	
Direct effect	-0.478***		-0.508***	-0.483***		-0.519***	-0.498***		-0.499***
	(-11.79)		(-11.95)	(-11.86)		(-12.37)	(-12.09)		(-11.4)
Indirect effect	-0.199***		-0.126	-0.106***		-0.129*	-0.270*		-0.258
	(-377)		(1.06)	(-3.80)		(1.83)	(-1.80)		(-0.84)
Total effect	-0.677***		-0.381***	0.588***		-0.390***	-0.768***		-0.756***
	(-9.17)		(-2.98)	(-10.90)		(-4.72)	(-4.77)		(-2.40)
Control variable	control	control	control	control	control	control	control	control	control
N	450	450	450	450	450	450	450	450	450
r2	0.0383	0.0288	0.0262	0.0335	0.0290	0.0239	0.0384	0.0292	0.0463

4.6.3. Analysis of regional heterogeneity

Given the differences in regional resource conditions and levels of economic development, we further analyse regional heterogeneity by dividing the country into north-eastern, central, eastern and western regions. The results of the regional heterogeneity test based on geographical weights are presented in Table 7. It can be seen that not only β and the spatial autoregressive coefficient ρ of the four regions under the three models pass the significance test at the 1% level, but also are significantly negative; the direct effect of the northeastern, central, eastern and western regions is significantly negative and passes the test at the 1% level; under the SAR model, the indirect effect within the four regions is significantly positive, indicating that the level of the DE between provinces within the regions has a positive spatial spillover effect, which promotes the growth rate of the DE of neighbouring regions. neighbouring regions to increase the growth rate of the DE. However, under the three spatial models of SAR, SEM and SDM, the overall effect is significantly negative, indicating that the development of the DE within the region inhibits the rate of change of the level of the DE of each province at the spatial level of the whole region.

Table 7. Convergence results of four major regions of the DE

	Northeast			Middle		
	SAR	SEM	SDM	SAR	SEM	SDM
β	-0.592***	-0.978***	-0.795***	-0.319***	-0.391***	-0.416***
	(-5.72)	(-7.59)	(-2.89)	(-5.49)	(-5.79)	(-3.29)
ρ	-0.852***		-0.679***	-0.391***		-0.440***
	(-6.61)		(-3.67)	(-5.34)		(-4.49)
λ		-1.019***			-1.320***	
		(-8.48)			(-5.60)	
Provincial fixation	control	control	control	control	control	control
Year fixation	control	control	control	control	control	control
Control variable	yes	yes	yes	yes	yes	yes
Direct effect	-0.837***		-0.977***	-0.391***		-0.440***
	(-6.88)		(-5.32)	(-5.34)		(-4.49)
Indirect effect	0.516***		0.563	0.245***		0.0998
	(5.24)		(1.39)	(4.13)		(0.38)
Total effect	-0.321***		-0.414	-0.146***		-0.341
	(-4.38)		(-0.75)	(-4.06)		(-1.17)
N	45	45	45	90	90	90
r2	0.0445	0.0932	0.0329	0.00612	0.0275	0.0175
	East			Western		
	SAR	SEM	SDM	SAR	SEM	SDM
β	-0.524***	-0.576***	-0.655***	-0.604***	-0.648***	-0.734***
	(-9.08)	(-9.62)	(-9.28)	(-9.12)	(-9.41)	(-9.24)
ρ	-0.663***		-0.782***	-0.749***		-0.872***
	(-4.12)		(-4.44)	(-3.09)		(-3.23)
λ		-0.754***			-0.804***	
		(-4.26)			(-3.12)	
Direct effect	-0.559***		-0.643***	-0.632***		-0.722***
	(-8.99)		(-10.06)	(-8.87)		(-9.75)
Indirect effect	0.241***		-0.05	0.280**		-0.0685
	(4.68)		(-0.32)	(3.80)		(-0.24)
Total effect	-0.318***		-0.693***	-0.352***		-0.791***
	(-5.94)		(-3.92)	(-4.94)		(-2.66)
Provincial fixation	control	control	control	control	control	control
Year fixation	control	control	control	control	control	control
Control variable	yes	yes	yes	yes	yes	yes
N	150	150	150	165	165	165
r2	0.00702	0.0088	0.0109	0.049	0.0674	0.0385

5. CONCLUSIONS AND SUGGESTION

5.1. Conclusions

This paper constructs a DE development index system, firstly using the vertical and horizontal pull-out gearing method to measure China's inter-provincial DE development index, then using Dagum's Gini coefficient, kernel density estimation and Markov to analyse the regional differences and distribution dynamics of China's inter-provincial DE development, and introducing an obstacle degree model to identify the main obstacle factors affecting DE development, and finally using the spatial convergence β model to convergence analysis is carried out. The conclusions are as follows:

Firstly, the spatial and temporal pattern of China's DE has been relatively stable over the period. From the perspective of the four major regions, the development level of the eastern region is in the "leader" position, but the internal multipolar characteristics; the level of DE development in the central region as a whole is on the rise; the western region, except for Sichuan Province, the level of DE development is generally lagging behind, and the pace of development is relatively slow; the northeast region as a whole is declining in the level of DE development.

Secondly, the overall trend of the Gini coefficient of China's DE level is a fluctuating decline; from the perspective of intra-regional differences, the differences between the central and eastern regions are on the rise, and the western and northeastern regions are on the decline; from the perspective of inter-regional differences, the difference in annual average between the eastern and northeastern regions is the largest.

Thirdly, based on the kernel density estimates, it can be seen that there is a certain degree of dynamic polarisation in the country as a whole and in the western and north-eastern regions, and that multipolarity is prominent in the eastern region.

Fourthly, China's overall level of digital economic development reflects strong stability at different levels. At the same time, the overall probability of upward transfer of each region at the low level is relatively higher, reflecting a favourable trend of overall level improvement. Among the four regions, the eastern, central and western regions have strong stability in the internal levels of the DE. And only the northeast region, the level of DE downward slippage of higher probability on, need to pay close attention to.

Fifthly, the top three major factors affecting the level of development of China's DE are: software business revenue (X3), the main business revenue of the manufacturing industry of communications equipment, computers and other electronic equipment (X1), the number of patents granted (X12).

Sixthly, there are significant trends of spatial absolute β-convergence and conditional β-convergence in China as a whole and in the four major regions, and the overall system is a steady state system.

5.2. Suggestion

Based on the above analysis, the following recommendations are made: (1) given the significant spatial and temporal disparities in the level of development of China's DE, macroeconomic regulation should be carried out at the macroeconomic level, taking into account the relative backwardness of the central, western and northeastern parts of the country, Focus on the major obstacles and formulate a support policy that is in line with the reality of the foundation of different regions, and differentiated to promote the development of the DE of the region, so as to reasonably balance the excessive gap between the central, western and northeastern parts of China and the eastern regions; (2) it is necessary to further deepen the understanding of the dynamic law of DE development. The positive and negative effects of internal imbalances on the development of the DE must be studied simultaneously, and we should pay attention to the accumulation and intensification of the phenomenon of the digital divide between and within regions, and treat the relative differences in development levels scientifically on the basis of understanding the law; (3) in strengthening industrial and talent mobility policies and the adaptability of DE policies. It is necessary to consciously formulate industrial and talent policies that match the spatial and temporal patterns of the DE, so that the spatial and temporal flows of enterprises and talents can best respond to the regional characteristics of China's DE, in order to better bring into play the positive effects of the DE on balanced regional development.

DATA AVAILABILITY

The data used to support the findings of this study are included within the article.

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