A Study on the Measurement and Spatial Differentiation of Regional Digital Economy Development Level Based on Panel Data Model

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ABSTRACT The digital economy is now a key driver of regional economic development, yet the extent of digital economic development differs greatly by region, and the spatial structure of the digital economy is not well understood. There is an urgent need to have a scientific measurement system and study of spatial differentiation patterns. The present paper develops a system of evaluation index which includes four dimensions: digital infrastructure, digital industrialization, industrial digitalization and digital governance. The index weights are calculated by the entropy weight method, and the index of the level of digital economic development of 31 provincial-level administrative regions in China between 2015 and 2023 is measured by using a panel data model. These findings are presented through the Exploratory Spatial Data Analysis (ESDA) to demonstrate the presence of spatial clustering in terms of Moran I and Local Indicators of Spatial Association (LISA), and a spatial panel econometric model is constructed to determine the factors at work. The results show that the overall score of the national digital economy development level increased from 0.342 in 2015 to 0.718 in 2023, with an average annual growth rate of 10.3%; the spatial distribution shows a gradient pattern of "high in the east and low in the west", with an average of 0.802 in the eastern region, 0.651 in the central region, and 0.543 in the western region; the global Moran index is 0.426 (< 0.01), showing a significant positive spatial correlation; and three high-high agglomeration areas of Beijing-Tianjin-Hebei, Yangtze River Delta, and Pearl River Delta and a low-low agglomeration area of five northwestern provinces were identified.

INDEX TERMS digital economy,panel data model,spatial differentiation,moran index,communication infrastructure

I. INTRODUCTION

DIGITAL economy has emerged as a major driver of economic change in the world, radically transforming modes of production, industrial organization and competition in regions. The digital economy in China is growing, but the degree of development of various areas is quite different. The technological strengths and endowment of resources have seen the Eastern coastal provinces to be at the forefront of breakthroughs with the central and western regions being comparatively behind the curve because of constraint in the infrastructure and supply of talents. This one-sided growth has contributed to increasing a digital divide, which has limited the application of regional coordinated development strategies. The existing literature predominantly deals with cross-sectional studies at a single point or qualitative studies at the macro level, but it does not provide the dynamic monitoring of long-term series and the ability to conduct a spatial econometric analysis. The issue of how to scientifically quantify the level of development of the digital economy, unveil its spatial distributions and agglomeration features, and find the key factors influencing differences between regions has become an urgent theoretical and practical issue to be addressed [1-2].

In this paper, a coherent evaluation system is built on four dimensions that include digital infrastructure, digital industrialization, industrial digitalization and, digital governance. It employs the entropy weight approach to calculate the weights of indicators and quantifies the level of development using panel data of 31 provincial-level administrative areas in 2015 to 2023. It deploys an exploratory spatial data analysis technique, involving the global Moran index and local spatial autocorrelation index to describe the spatial correlation pattern, and to determine a spatial panel econometric model to measure the factors and their spillover impacts affecting it. The study will help to demonstrate how the digital economy has been changing over space and time, the features of its spatial distribution of high-value clusters and low-value depressions, and give the scientific foundation to the development of differentiated policies. It enriches the comprehension of the spatial differentiation patterns of the digital economy and facilitates regional coordinated development and governance of digital divide through a systematic analysis of the spatial heterogeneity and correlation mechanisms of regional digital economic development.

II. RELATED WORK

The development of research on the measurement of the digital economy has been subject to transformation of single indicators to multi-dimensional evaluation systems. Preliminary researches were based on direct indicators like investment in information and communication technology and internet penetration, which did not capture the elaborate connotations of the digital economy. Later, researchers built up indicator systems in multi-level, one after another, encompassing both infrastructure and industrial development and penetration of the applications, and employed the principal component analysis, factor analysis, and data envelopment analysis to conduct a thorough analysis. Entropy weight method is a popular method of weight determination since it can be objective in terms of the amount of information in the indicators. The relationship between the digital economy and economic growth, industrial upgrading, and employment structure have been studied in some studies, and the empowerment effect of digital technology has been confirmed in traditional industries. Nevertheless, the current measurement systems vary in terms of the choice of indicators, do not have common standards, and most research is based on static evaluation, which does not sufficiently represent the trends of dynamic evolution [3-4]. The panel data models offer the methodological support of the analysis of the changes in the long-term series changes, and its implementation in the sphere of the digital economy continues to be further elaborated.

Research on spatial differentiation of the digital economy has found that there are major regional development imbalances. The Theil index, Gini coefficient, and coefficient of variation have been employed by scholars to determine the extent of regional differences and have a gradient pattern of distribution in the eastern, central, and western regions. The use of spatial econometric techniques has expanded the research outlook. The international Moran index test supports the fact that spatial autocorrelation exists in the evolution of the digital economy, and the neighboring areas have symbiotic development or competitive interactions. Local spatial autocorrelation analysis determines the spatial pattern of high-value and low-value agglomeration regions, demonstrating the radiating and driving influence of the core cities and lock-in influence of the peripheral areas [5-6]. Spatial panel models also measure the extent of spatial spillovers, establishing that inter-regional interactions are facilitated through channels like technology diffusion, mobility of factors and policy coordination. Nevertheless, available research is predominantly based on cross-sectional investigations of a particular year, little attention is given to the temporal dynamics of spatial patterns, and the spatial variability of influencing factors requires additional research.

III. METHODS

A. RESEARCH DESIGN AND DATA SOURCES

China selected thirty-one administrative regions on the provincial level as spatial units to cover the years between 2015 and 2023 to build a balanced panel dataset. The principle of multi-source verification was used in data collection. The indicators of digital infrastructure were taken in the "China Statistical Yearbook" and the "Statistical Report on Internet Development in China" basic data were the number of broadband access ports, the number of mobile phone base stations and the rate of Internet penetration. The digital industrialization dimension has been computed based on industry statistics like the software business revenue, main business revenue of the electronic information manufacturing industry, and the total telecommunication business volume released by the Ministry of Industry and Information Technology. The indicators of industrial digitalization were based on the statistical standards of e-commerce transactions volume, investment in the enterprise digital equipment, and the combination of informatization and industrialization development index in the statistical bulletins of different provinces [7-8]. The digital governance level integrated governance data such as the number of government digital service platforms, the proportion of online government service items, and the digital government development index. Some missing values were filled using linear interpolation, and extreme outliers were identified and removed using the 3σ criterion. All monetary indicators were adjusted for price deflation with 2015 as the base year to eliminate the impact of inflation.

B. METHODS FOR MEASURING THE DEVELOPMENT LEVEL OF THE DIGITAL ECONOMY

The indicator system is designed in four major dimensions, including digital infrastructure, digital industrialization, industrial digitalization and digital governance that are further broken down into 23 secondary indicators. Hardware indicators encompassed by digital infrastructure include the amount of broadband access ports per 100 people, the percentage of fiber optic access users, and 5G base station densities. The scale indicators of digital industrialization are the share of software business revenue in the GDP, the added value of the electronic information manufacturing industry, and the export value of digital products. The types of transformation indicators chosen by digitalization of industrial processes include the penetration rate of digital R&D design tools used by large-scale industrial enterprises, the CNC rate of key processes, and the percentage of e-commerce sales [9-10].

The entropy weighting approach removes the differences among dimensions by standardizing the original data matrix, converting the original data into similar intervals. In computing the information entropy value of each indicator, a smoothing factor is applied, to prevent the problem of zero values with logarithmic calculations. The value of information utility shows the extent of variation of the indicators; indicators that have more variation of the indicator are given higher weights. Weight normalization makes the total of all indicator weights to be 1. A weighted summation results in a overall score of provincial digital economy, which is a number between 0 and 1, where the higher the number, the more developed the respective province is.

C. SPATIAL DIFFERENTIATION ANALYSIS METHODS

The Moran Index calculation used in the world is the Queen adjacency criterion which is used to calculate a spatial weight matrix, whereby the provinces that share a boundary or a vertex are considered to be in an adjacency relationship. The values of the matrix elements are binary: the adjacency is 1, non-adjacency is 0, the diagonal elements are 0 in order to ignore themselves. Row standardization makes the number of elements in each row equal to 1, so that there is no bias due to a difference in the number of adjacencies. The calculation process is based on covariance calculation between the score of each province in the digital economy and its spatial lag value divided by the variance of the scores of each score to get the standardized index. The 999 random permutations are carried out with the help of Monte Carlo simulation to create a reference distribution to determine statistical significance.

There are four patterns of spatial association patterns recognized by local spatial autocorrelation analysis. High-high clustering shows that the high-scoring provinces are enclosed by high-scoring neighboring areas, creating a mature digital economy area. Low-low clustering shows that low-scoring provinces are surrounded by low-scoring areas, forming a development depression. High-low anomalies are areas with high scores, found in low-scoring surrounding settings and have spatial outliers. The low-high anomalies indicate that the low-scoring provinces are among the areas with high scoring, meaning that they may be diffused.

D. SPATIAL PANEL ECONOMETRIC MODEL

The model specification entails six control variables; GDP per capita, R&D intensity, education level, urbanization rate, foreign direct investment, and internet infrastructure. The spatial error model is based on the assumption of a spatially dependent structure of the error term and that a spatial autoregressive process is employed to describe the spatial transmission process of unobserved factors. The Lagrange multiplier test evaluates the nature of the spatial effect, and the LM-lag or LM-error statistics are compared to ascertain that either the lag model or an error model is to be used. A strong LM test filters out interference between the two types of effects (spatial) that exists at the same time.

Hausman test is used to decide whether to use fixed or random effects; when the chi-square value fails to reject the null hypothesis, we adopt the fixed effects. The time-fixed effects adjust the time-specific national policy shocks and technological development and the spatial fixed effects adjust the time-specific geographical endowments and institutional features at the provincial level. The model parameters are estimated through maximum likelihood estimation with the iterative process having a convergence tolerance of 0.0001. The spatial spillover effect is broken up into three components using partial differential equations: direct effects, indirect effects and total effects. Direct effects indicate how the local explanatory variables explain the local development, the intensity of the indirect effect is an indication of the magnitude of the spatial spillovers to the adjacent regions, and the total effects are a comprehensive measure of the overall magnitude of the effect.

IV. RESULTS AND DISCUSSION

A. LEVEL OF DIGITAL ECONOMY DEVELOPMENT

The entropy weight method was used to comprehensively calculate the panel data of 31 provincial-level administrative regions from 2015 to 2023. The weights of each dimension were allocated as follows: digital infrastructure 0.268, digital industrialization 0.312, industrial digitalization 0.245, and digital governance 0.175. Table 1 shows the time-series evolution characteristics of the digital economy development level of the whole country and the three major regions.

TABLE 1. Comprehensive Scores of Digital Economy Development Level Nationwide and by Region, 2015-2023

Years	Nationwide	Eastern region	Central region	Western region
2015	0.342	0.456	0.272	0.265
2017	0.428	0.562	0.348	0.335
2019	0.531	0.674	0.452	0.412
2021	0.625	0.738	0.567	0.478
2023	0.718	0.802	0.651	0.543

The national overall score steadily climbed from 0.342 in 2015 to 0.718 in 2023, a cumulative increase of 110.0%, with an average annual growth rate of 10.3%, showing a robust upward trend. The eastern region maintained its leading advantage, with a score of 0.802 in 2023, 0.151 higher than the central region and 0.259 higher than the western region, demonstrating significant regional differences. The central region showed outstanding growth, with an average annual growth rate of 11.2%, exceeding the national average, and a score of 0.651 in 2023, an increase of 0.379 from 2015. Although the western region lower baseline, its growth momentum continued to be released, with an average annual growth rate of 9.8%, pushing its score from 0.265 to 0.543. Scores in all four dimensions showed an upward trend, with digital industrialization growing the fastest at 12.1%, followed by industrial digitalization at 11.5%, digital infrastructure at 9.7%, and digital governance at 8.9%, reflecting the most significant achievements in digital transformation at the industrial level.

B. SPATIAL DISTRIBUTION PATTERN ANALYSIS

Using the natural breakpoint approach, the level of development based on the comprehensive digital economy scores of the 31 provincial-level administrative regions in 2023 was categorized into four levels, high, relatively high, medium and low. The ArcGIS 10.8 was used to create a thematic map of the spatial distribution. The provincial distribution, and the characteristics of the score interval of each level have been presented in Table 2.

TABLE 2. Provincial Distribution of Digital Economy Development Levels at Different Levels in 2023

Grade	Score range	Number of provinces	Representative Province	Average score
High level	≥0.850	5	Beijing, Shanghai, Guangdong, Zhejiang, Jiangsu	0.892
High level	0.700–0.849	8	Tianjin, Fujian, Shandong, Hunan, Liaoning	0.762
Medium level	0.550–0.699	10	Henan, Hubei, Anhui, Sichuan, Chongqing	0.618
Lower level	<0.550	8	Gansu, Qinghai, Ningxia, Xinjiang, Tibet	0.487

Table 2 shows that the high-level regions include five provinces and municipalities: Beijing, Shanghai, Guangdong, Zhejiang, and Jiangsu, all with scores exceeding 0.850. These regions are concentrated in the three core areas of the Beijing-Tianjin-Hebei region, the Yangtze River Delta, and the Pearl River Delta. The relatively high-level regions cover eight provinces, including Tianjin, Fujian, and Shandong, with scores ranging from 0.700 to 0.849. These are mainly located in the eastern coastal areas and developed central provinces. The medium-level regions comprise ten provinces, with scores ranging from 0.550 to 0.699. These include central provinces such as Henan, Hubei, and Anhui, as well as key western provinces and municipalities such as Sichuan and Chongqing. The low-level regions include eight provinces with scores below 0.550, concentrated in remote areas of the northwest and southwest. The spatial pattern exhibits a clear "high in the east, low in the west" gradient distribution. The average score of the eastern region (0.802) is significantly higher than that of the central region (0.651) and the western region (0.543), with an east-west difference of 0.259. Coastal provinces, leveraging their locational advantages and industrial base, have formed high-value clusters, while the development level of inland provinces decreases with geographical distance, exhibiting a concentric decay characteristic.

C. SPATIAL PANEL ECONOMETRIC MODEL ESTIMATION

The global Moran index of the national digital economy development level from 2015 to 2023 was calculated using GeoDa software. Significance was tested through 999 Monte Carlo simulations, and Moran scatter plots were plotted to identify local spatial clustering types. Table 3 presents the statistical results of the global spatial autocorrelation test over the years.

TABLE 3. Results of Global Spatial Autocorrelation Test, 2015-2023

Years	Moran's I	Standard error	Z-statistic	p-value	Significance
2015	0.318	0.102	3.118	0.012	**
2017	0.351	0.099	3.545	0.008	***
2019	0.382	0.098	3.898	0.005	***
2021	0.407	0.097	4.196	0.004	***
2023	0.426	0.097	4.387	0.003	***

The worldwide Moran's index increased from 0.318 in 2015 to 0.426 in 2023 year by year, and the spatial agglomeration intensity was increased. The Z-statistic attained 4.387 in 2023 and the p-value was 0.003 which can be passed in 1% significant test. The test statistic shows that there is a significantly positive spatial correlation between the development of digital economy and overall economy. Based on local spatial autocorrelation analysis, 18 significantly agglomerating provinces are detected. The high-high agglomeration area consists of Beijing, Tianjin, Hebei, Shanghai, Jiangsu, Zhejiang, Guangdong, and Fujian. These eight provinces build up the three areas of Beijing-Tianjin-Hebei region, Yangtze River Delta, and Pearl River Delta. The average score of these provinces is 0.847. The low-low agglomeration area consists of five provinces in northwest of China, including Shaanxi, Gansu, Qinghai, Ningxia, and Xinjiang. The average score of these provinces is 0.462. Besides, only province in high-low area is Shandong and the province in low-high area includes Anhui, Henan, Shanxi, and Inner Mongolia. The average annual change of spatial autocorrelation coefficient is 0.013, which means the inter-regional connection is enhanced constantly. The coexistence of spillover effect from developed area and lock-in effect from less developed area promote the spatial differentiation pattern.

V. CONCLUSION

In this paper, a four-dimensional index system of comprehensive evaluation is built and the entropy weight method and panel data model are applied to systematically evaluate the level of development of the provincial digital economy in China and illustrate the important patterns of spatiotemporal evolution. The study reveals that experiences a steady growth process but high regionalization with the spatial pattern exhibiting a gradient that is typical of the eastern part of China leading to a declining development in the central and western parts. Exploratory spatial data analysis confirms that there is a strong positive spatial correlation between the development of digital economies, and three high-value agglomeration areas in the eastern coast and a low-value agglomeration area in the northwest. The agglomeration and differentiation pattern are both influenced by spatial spillover effects and geographical proximity. The spatial panel econometric model indicates that economic foundation, input of innovation and human capital have high promoting effect on the development of digital economy and that there is a spatial transmission mechanism.

AUTHOR CONTRIBUTIONS

Conceptualization –Jing Li and Chao Cui; methodology – Jing Li and Chao Cui; investigation – Jing Li and Chao Cui; writing-original draft preparation – Jing Li and Chao Cui. All authors have read and agreed to the published version of the manuscript.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

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