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Assessing the growth and spatial-temporal evolution of China's digital economy

Lin Li[1,2]
Le Xiaobing[2]
Brahim Chekima[1+]

[1]*Faculty of Business, Economic and Accounting, Univertiti of Malasia Sabah, Jalan UMS, 88400 Kota Kinabalu, Sabah, Malaysia.*
[1,2]*Email: LIN_LI_DB21@iluv.ums.edu.my*
[1]*Email: bchekima@ums.edu.my*
[2]*School of Management, WuZhou University, WuZhou Guangxi, 543002, China.*
[2]*Email: 176337361@qq.com*

(+ Corresponding author)

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ABSTRACT

This research examines the assessing growth and spatial-temporal evolution of China's digital economy. There exists a notable imbalance in the advancement of the digital economy across different districts in China. To gain a comprehensive understanding of China's digital economy's development, this study establishes an evaluation system to assess the level of digital economic growth. By employing metrics such as the difference coefficient, Moran's I, and Moran scatter plot, the research delves into the spatial distribution characteristics of China's regional digital economy using provincial panel data from 2013 to 2020. The findings reveal a consistent alignment between the distribution of the regional digital economy and the country's geographical layout, with the development level regularly decreasing from east to west. The decreasing overall difference coefficient indicates a gradual convergence in the development level of the regional digital economy. Moreover, substantial spatial autocorrelation is observed, suggesting the formation of a relatively stable spatial pattern in the development of the digital economy.

Contribution/ Originality: This study introduces a novel evaluation system for China's digital economy and uses provincial data from 2013 to 2020 to analyze its regional disparities and spatial distribution. It finds significant spatial autocorrelation and convergence in development levels, highlighting the digital economy's geographic influence from east to west.

1. INTRODUCTION

The unexpected COVID-19 pandemic outbreak in 2020 had a major impact on the global economy, revealing increasing destabilizing factors and uncertainties. The current global economic condition is characterized by a state of pessimism and uncertainty. In response to these complex circumstances, the Government of China introduced the 'Double Cycle' concept on May 14, 2020. Subsequently, the Fifth Session of the 19th Communist Party of China (CPC) proposed boosting the deep integration of the digital economy (DE) and the real economy, accelerating digital progress, and providing substantial support for building an innovative development framework. The DE, as a crucial engine of technological progress, encompasses various aspects of the social economy, such as production, circulation, distribution, and consumption. It creates new growth drivers for high-quality economic development and significantly impacts consumption enhancement. According to a white paper by the China Academy of Information and Communication Technology (CAICT) on China's digital economy development (DED), the value-added of China's DE showed significant growth from 2005 to 2020, reaching 39.2 trillion Yuan in 2020 (refer to Figure 1). The DE accounted for approximately 38.6% of the nation's Gross Domestic Product (GDP), showing a rate of expansion that surpasses that of the GDP by more than three times. This emerging economic paradigm has become a significant catalyst for fostering economic growth, permeating various sectors and daily life. It has inspired the creation of new products, industries, business structures, and models, offering innovative concepts to drive high-quality economic growth.

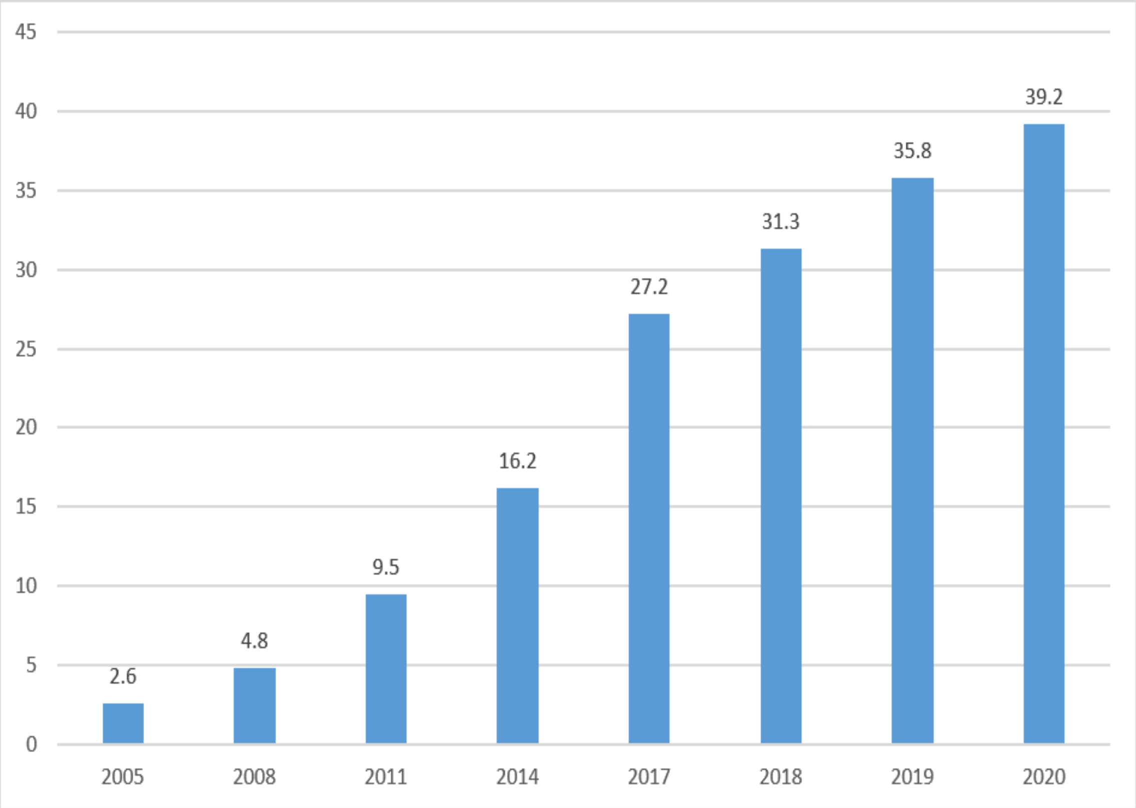

Figure 1. The value-add of the DE in China.

Source: China academy of information and communication technology.

Moran's I is a statistical assessment that is frequently used in geographic information systems and spatial analysis to assess spatial autocorrelation (Moran, 1950). Researchers employ it to identify and quantify spatial relationships or patterns within geographic data.

Currently, numerous researchers have applied the Moran's I method to investigate and assess regional economic disparities, economic growth and CO_2 emissions, urban economic activity concentration and dispersion effects, ecological footprint, and economic development studies, among others (Andrews et al., 2020; Chen, Madni, & Shahzad, 2023; Kavousi, Sabri, Momeni, & Alhosseini, 2022; Kozonogova & Dubrovskaya, 2020; Sari, Frananda, & Fransiska, 2020). Notably, there is a gap in the existing literature regarding the utilization of the Moran's I to assess the correlation between the DE and spatial aspects.

This study introduces an evaluation index system designed to assess the advancement level of Digital Economy (DE). This study analyzes the development of DE in various provinces in China, using provincial panel data from 2013 to 2020.

It employs difference coefficients, Moran's I, Moran scatter diagrams to analyze the spatial distribution characteristics of regional DE development levels in China. Furthermore, optimization strategies for DED are suggested, aiming to offer insights for choosing evaluation methods and crafting DE policies.

2. LITERATURE REVIEW

During the 1990s, several governments began exploring the concept of the DE, initially introduced by Tapscott (1996). In 2018, the U.S. Bureau of Economic Analysis (BEA) defined the DE to encompass digital infrastructure, e-commerce, and sectors related to digital technologies. Similarly, China has issued a series of policy documents aimed at fostering the development of the DE. Following the 18th National Congress of the CPC, the country has implemented various policies to promote industry digitization and overall growth in the DE.

Scholars have extensively investigated the DE as it evolves. Xu and Zhang (2020) defined the DE as a range of economic activities carried out through digital technologies, platforms, and infrastructure. Zhang, Liu, and Chen (2018) described it as a unique economic structure centered on digital information. Li, Guo, and Zhou (2022) identified digital knowledge and information as key production components in the DE, highlighting the essential role of the modern information network. Jing and Sun (2019) suggested that internet technology strengthens the connection between supply and demand, expanding the DE's reach. Xiong and Guo (2023) emphasized the importance of information and communication technology in driving the DE forward, citing its potential to boost labor productivity and foster economic growth.

Zhang et al. (2018) conducted an empirical study to explore how the expansion of the DE impacts China's inclusive growth through a transmission mechanism. They developed an index system for digital financial analysis. Jing and Sun (2019) identified digital foundation, application, innovation, and transformation as key components in constructing an evaluation system for DE indicators. Their empirical analysis focused on assessing the DE 's influence on upgrading industrial structure. Gao, Zhao, Zhang, and Li (2021) define the DE as a new economic paragon that integrates intelligentization, informatization, and digitalization.

Scholars use variety of perspectives to create assessment indices for measuring DE. Mu and Ma (2021) conducted a study on the rural DE, focusing on digital infrastructure, agricultural digitalization, and rural digital industrialization. Researchers have developed assessment systems for the DE development index, incorporating indicators like digital financial index, digital technology, and information and communication technology. These studies explore the impact of the DE on economic growth and consumption enhancement (Ahmed, 2021; Qian, Tao, Cao, & Cao, 2020; Shen, Zhao, & Zhu, 2021; Syuntyurenko & Dmitrieva, 2019). Katz, Koutroumpis, and Martin Callorda (2014) proposed a comprehensive assessment framework for the DE, covering dimensions such as affordability, infrastructure investment, network access, capacity, usage, and human capital.

Billon, Lera-Lopez, and Marco (2016) emphasized that the successful adoption of advanced information and communication technologies (ICTs) requires local government support for ICT development, the presence of knowledge-intensive service industries, the level of economic growth, and the per capita education level in the region. Mu and Ma (2021) concluded that the development of DE is likely to significantly influence future economic growth, suggesting the incorporation of economic indicators such as GDP into the DED assessment framework. Lastly, Kotarb (2017) stressed the importance of enhancing information and communication technology (ICT) in the DE.

In addition, scholars have primarily focused on using Moran's I to analyze regional economic disparities, economic development, CO_2 emissions, urban economic activity concentration and dispersion effects, and the relationship between ecological footprint and economic development. There is a lack of research on utilizing the Moran's I to study the advancement relationship between the DE and spatial factors. Kozonogova and Dubrovskaya (2020) utilized the inverse distance weight matrix and weight boundary matrix to calculate the Moran's I results in Russian districts, establishing a spatial development index system to provide recommendations for enhancing the spatial organization of the national economy. Chen et al. (2023) employed a spatial dependence model to evaluate the spatial impact of the ecological footprint and its influencing factors, aiming to advocate for policies promoting environmental sustainability, particularly focusing on enhancing production capacity and green investment. Andrews et al. (2020) utilized the Moran's I for mapping and analysis to develop a Neighborhood Deprivation Index (NDI) for community-based research and to guide the allocation of public health resources. Sari et al. (2020) utilized the Moran's

I to examine the spatial autocorrelation of poverty levels in West Pasaman Regency. Kavousi et al. (2022) utilized the Moran spatial index to analyze the impact of creative tourism on urban development, using Izeh City as a case study.

Researchers have used various assessment indices to evaluate the progress of the DE and have conducted thorough investigations in this field. However, it is crucial to identify the key characteristics of the DED in China. What are the disparities in the DE 's growth among different provinces? This study aims to create an assessment system for DE to gauge its development level. By utilizing the difference coefficient, Moran's I, and Moran scatter plot, this research analyzes the spatial distribution patterns and dynamic evolution process from 2013 to 2020. The goal is to explore both similarities and differences in the DE's progress within different geographical contexts, with the intention of establishing a theoretical framework that can guide sustainable development, tailored management approaches, and policy-making. The findings of this study offer valuable insights for achieving a well-rounded development of the DE in China while also supplying a framework that may be applicable to other countries with similar aspirations by using Moran's I.

3. METHODS

This study utilized provincial panel data from 2013 to 2020 and applied statistical techniques including the coefficient of variation, Moran's I, and Moran scatter plot. Compared to other spatial measurement tools at the economic level, Moran's I provides a comprehensive perspective and helps researchers quickly understand the overall spatial autocorrelation of the data. For example, Geary's C (Haining, 1990) is more suitable for identifying local spatial heterogeneity. Conversely, Moran's I facilitates a rapid comprehension of the spatial aggregation or dispersion of the data. While the CRITIC method (Diakoulaki, Mavrotas, & Papayannakis, 1995) is not specifically designed for spatial data analysis, it is used for a thorough evaluation of multiple indicators to determine the weight of each indicator.

3.1. Constructing Index

Drawing on existing scholarly literature, this study establishes an assessment system for assessing for the DE's level. Key indicators within this framework include informatization, internet usage, and digital transactions. Table 1 provides a comprehensive depiction of these indicators.

Table 1. Assessment system of DED and weight.

Primary index	Subsidiary index	Label	Definition	Weight
Information	Density of cable	A1	The ratio of cable length to population	0.034
	Density of cell phone base station	A2	The ratio of mobile phone base stations to the population	0.064
	Information employment personnel	A3	The ratio of urban employment in software and information technology services to total urban employment	0.149
	Telecommunications service	A4	Revenue from telecommunications business	0.054
	Software revenue	A5	Actual revenue from software business	0.186
Internet	Mobile internet penetration	A6	Number of mobile phones per 100 people	0.041
	Number of broadband internet users	A7	The ratio of broadband internet access users to the total population	0.043
	Number of mobile internet users	A8	The ratio of mobile Internet users to total population	0.045
	Number of websites	A9	Number of websites per 100 enterprises	0.021
Digital transaction	E-commerce sales	A10	The actual transaction volume of e-commerce	0.127
	Online retail sales	A11	Retail sales of goods and services realized by public online trading platforms	0.174
	Digital inclusive finance	A12	Digital inclusive finance index	0.063

3.2. Measurements

This study utilizes the entropy and linear weighting approaches to evaluate the progress of China's regional DE. All empirical techniques were conducted using Stata 15 software. The evaluation index weights (refer to Table 1) and the DED index in China from 2013 to 2020 (refer to Annexed Table 1) were calculated using the specified evaluation index system and methodology. The study focuses on the evaluation of 31 provinces in China (excluding Hong Kong, Macao, and Taiwan) during the period of 2013-2020. Data sources include the official website of the National Bureau of Statistics, provincial statistical yearbooks, and the Peking University Digital Finance Research Center. However, data from the past four years is currently unavailable. In order to clearly show the distribution characteristics of the DE in China, this study determined the mean of the DE index from 2013 to 2020 using the data in annex table and drew the cluster diagram through Stata15 (refer to Figure 2).

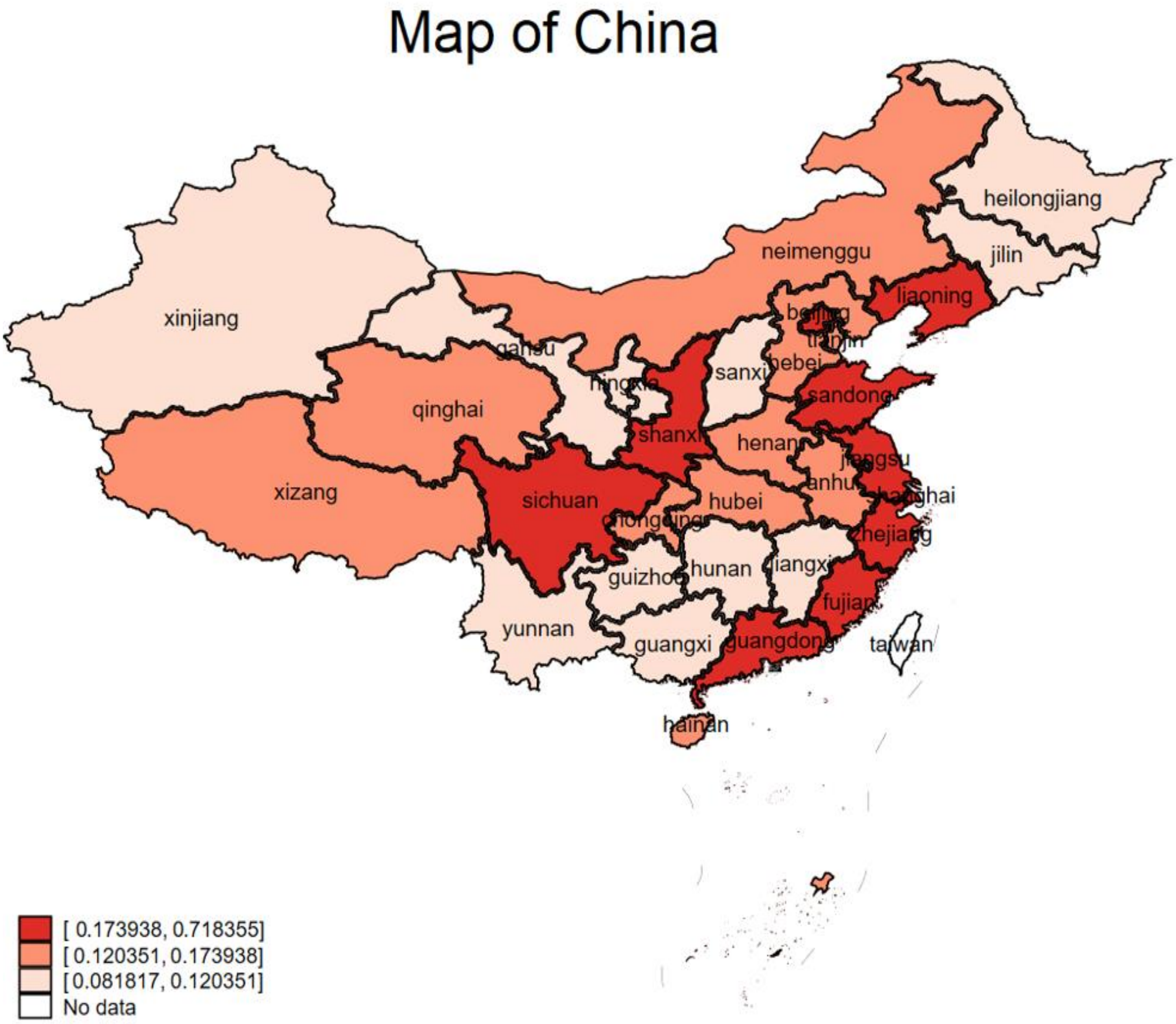

Figure 2. Cluster analysis of DED.

Figure 2 highlights significant variations in the advancement of China's DE. The geographical distribution of DE growth follows a consistent trend, showing a decline from the eastern to the western districts of China.

Furthermore, Table 2 illustrates the classification of Chinese provinces into three distinct categories based on their average DE index values. These categories consist of highly developed, moderately developed, and less developed districts, as illustrated in Table 2.

Table 2. Regional disparity distribution of DED from 2013 to 2020.

Type	Province	DE index	Province	DE index
Districts with developed DE	Beijing (2)	0.718	Shandong (21)	0.287
	Guangdong (5)	0.713	Fujian (3)	0.282
	Zhejiang (30)	0.538	Sichuan (25)	0.226
	Shanghai (24)	0.522	Liaoning (17)	0.213
	Jiangsu (15)	0.506	Shaanxi (23)	0.195
Districts with moderately developed DE	Hubei (12)	0.174	Anhui (1)	0.134
	Chongqing (31)	0.174	Hebei (9)	0.131
	Tianjin (26)	0.171	Henan (10)	0.122
	Tibet (27)	0.147	Qinghai (20)	0.121
	Hainan (8)	0.141	Shanxi (22)	0.120
	Neimengu (18)	0.138		
Districts with underdeveloped DE	Hunan (13)	0.116	Ningxia (19)	0.103
	Xinjiang (28)	0.115	Heilongjiang (11)	0.095
	Jilin (14)	0.106	Gansu (5)	0.095
	Jiangxi (16)	0.106	Guizhou (7)	0.088
	Yunnan (29)	0.103	Guangxi (6)	0.082

Note: The number in parentheses represents the code of the province

4. RESULTS

4.1. Research on the Difference of Regional DED

Equation 1 further investigates the unbalanced development of China's regional DE by determining the overall difference using the coefficient of variation.

$$DF = \frac{1}{\overline{D}}\left(\frac{1}{n}\sum_{i=1}^{n}(D_i - \overline{D})^2\right)^{1/2} \quad (1)$$

Where DF is the difference coefficient, $\overline{D}$ is the mean of the digital economic index. The larger the DF value is, the greater the difference in the development of the regional DE is. *The* results are shown in Table 3.

Table 3. Difference coefficient of DED from 2013 to 2020.

Year	2013	2014	2015	2016	2017	2018	2019	2020	Mean
DF	0.848	0.838	0.848	0.998	0.814	0.797	0.796	0.789	0.841

The coefficient of variation for China's DED remained broadly consistent between 2013 and 2020, as indicated by the data presented in Table 3. Since 2016, there has been a progressive reduction in the overall disparity in China's regional DED. To elucidate the discrepancies in the growth of the DE across various provinces, the difference coefficient of each region has been ascertained and presented in Table 4. As depicted in Figure 3, a cluster graph has been generated to represent these differences visually.

Table 4. The difference coefficient of DED among provinces in China from 2013 to 2020.

Area	Province	DF	Province	DF	Province	DF
Eastern region	Beijing	0.024	Guangdong	0.030	Hebei	0.131
	Tianjin	0.137	Shandong	0.065	Liaoning	0.156
	Shanghai	0.044	Hainan	0.044	Jiangsu	0.065
	Fujian	0.074	Zhejiang	0.043		
Central region	Shanxi	0.055	Jiangxi	0.116	Hubei	0.058
	Jilin	0.093	Henan	0.086	Hunan	0.081
	Heilongjiang	0.061	Anhui	0.141		
Western region	Neimenggu	0.033	Gansu	0.097	Yunnan	0.041
	Guangxi	0.174	Qinghai	0.080	Shaanxi	0.038
	Sichuan	0.060	Ningxia	0.039	Xinjiang	0.096
	Guizhou	0.108	Chongqing	0.065	Tibet	0.039

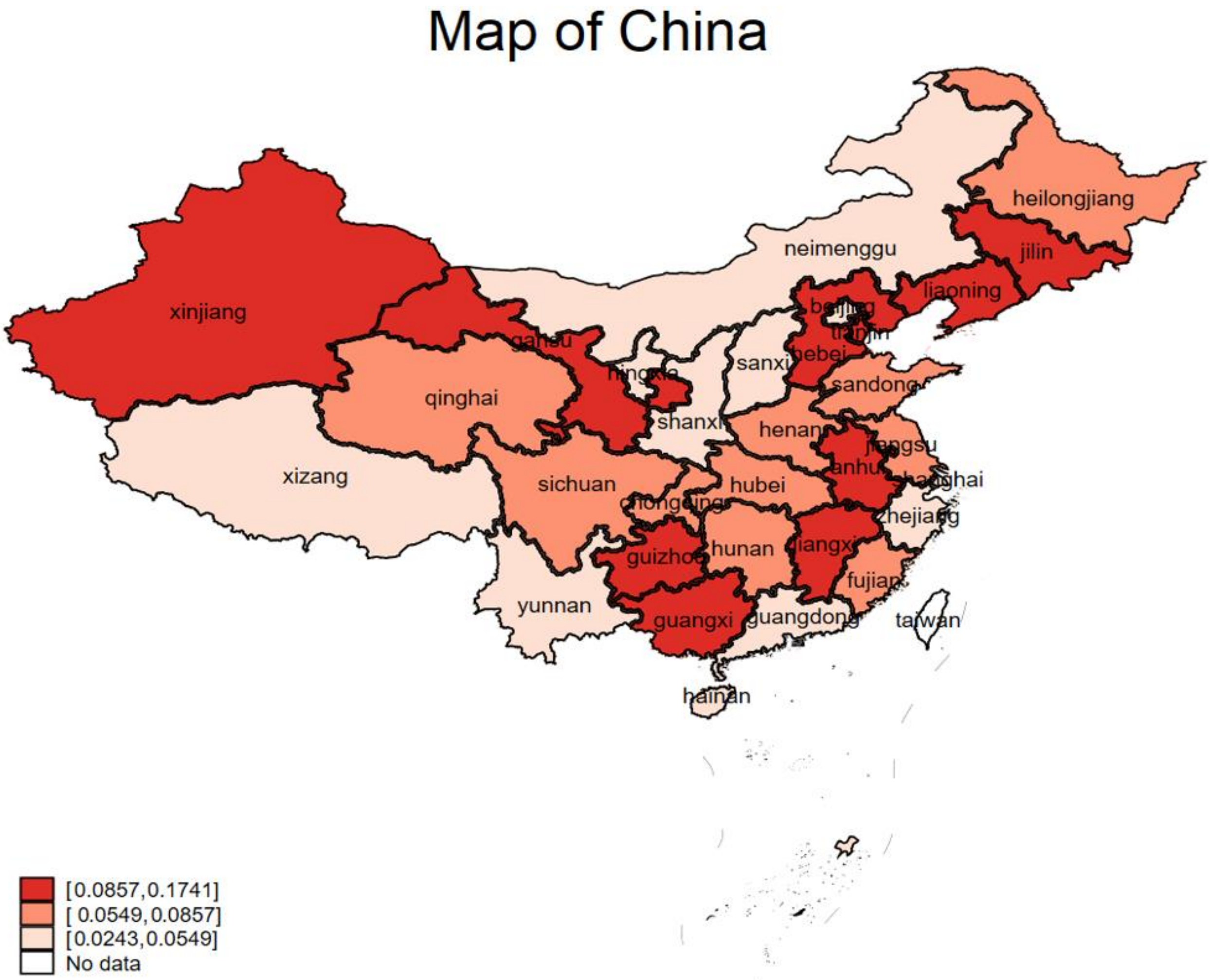

Figure 3. Cluster diagram of the difference coefficient of DED in China's provinces.

Table 4 and Figure 2 analysis reveals that from 2013 to 2020, the volatility of indices in the eastern provinces generally remains low, with the exception of Liaoning and Hebei. This indicates a steady level of progress in the DE of the eastern region. In contrast, the Western area shows more variability in DED, with Guangxi experiencing the most notable fluctuations.

4.2. Spatial Statistical Analysis of China's Regional DED

4.2.1. Global Spatial Correlation

The difference coefficient is an index independent of geographical location. This study introduced Moran's I to test the global spatial autocorrelation to study further the imbalance and global spatial autocorrelation of Chinese regional DED. *Moran's I* can reflect the degree of spatial agglomeration. Equations 2 and 3 determine it (refer to Table 5).

$$W_{ij} = \begin{cases} \frac{1}{d_{ij}}, & i \neq j \\ 0, & i = j \end{cases} \qquad (2)$$

$$I = \frac{n\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(x_i-\overline{x})(x_j-\overline{x})}{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}\sum_{i=1}^{n}(x_i-\overline{x})^2}, \quad -1 < I < 1 \qquad (3)$$

In this study, i and j represent different provinces, with dij being the geographical distance matrix calculated using Stata 15 based on the longitude and latitude of each province. Wij is the spatial weight matrix, while xi and x

denote observations in districts and their mean values, respectively. A positive spatial correlation is indicated by I>0, a negative spatial correlation by I<0, and no spatial correlation by I=0.

Based on the observations shown in Table 5, it is evident that all Moran's I indexes exceed zero. For most of the years, a significance level of 10% rejects the null hypothesis, which posits the absence of a spatial correlation. This outcome indicates the presence of spatial correlation.

Table 5. Moran's I of DE from 2013 to 2020.

Year	2013	2014	2015	2016	2017	2018	2019	2020
Moran's I	0.017	0.025	0.022	0.028	0.020	0.023	0.033	0.033
Z-value	1.567	1.802	1.690	1.893	1.641	1.734	2.045	2.068
P-value	0.117	0.072	0.091	0.058	0.101	0.083	0.041	0.039

4.2.2. Local Spatial Correlation

To comprehensively examine the local geographical correlation, this study employs the Moran scatterplot to analyze the spatial differentiation and distribution of spatial patterns in China's DE. Scatter plots of Moran's I for 2013 and 2020 are used to visually depict the spatial clustering features of China's DE (refer to Figure 4 and Figure 5). The analysis of these figures reveals that most provinces fall within the 'low-high (LH)' and 'low-low (LL)' quadrants. The 'high-high (HH)' quadrant includes Shanghai, Zhejiang, Jiangsu, Shandong, Fujian, and other eastern districts, forming an 'efficient circle' within the DE. Conversely, many western provinces such as Shaanxi, Qinghai, Gansu, Xinjiang, and Guizhou are clustered in the 'LL' category, often referred to as 'underdeveloped areas' in terms of DE progress. This observation indicates a significant disparity in DED across different districts of China.

After comparing the Moran scatter plots from 2013 and 2020, it is clear that China's DE has a high degree of spatial aggregation stability. Only two provinces experienced notable changes during this period. Specifically, Sichuan shifted from the third quadrant ('LL') to the fourth quadrant ('HL'), while Liaoning moved from the intersection of the first and fourth quadrants to the intersection of the second and third quadrants. Overall, a majority of Chinese provinces remain in areas with low-level agglomeration, showing a consistent spatial distribution over time. This disparity highlights varying growth rates in China's DE across districts.

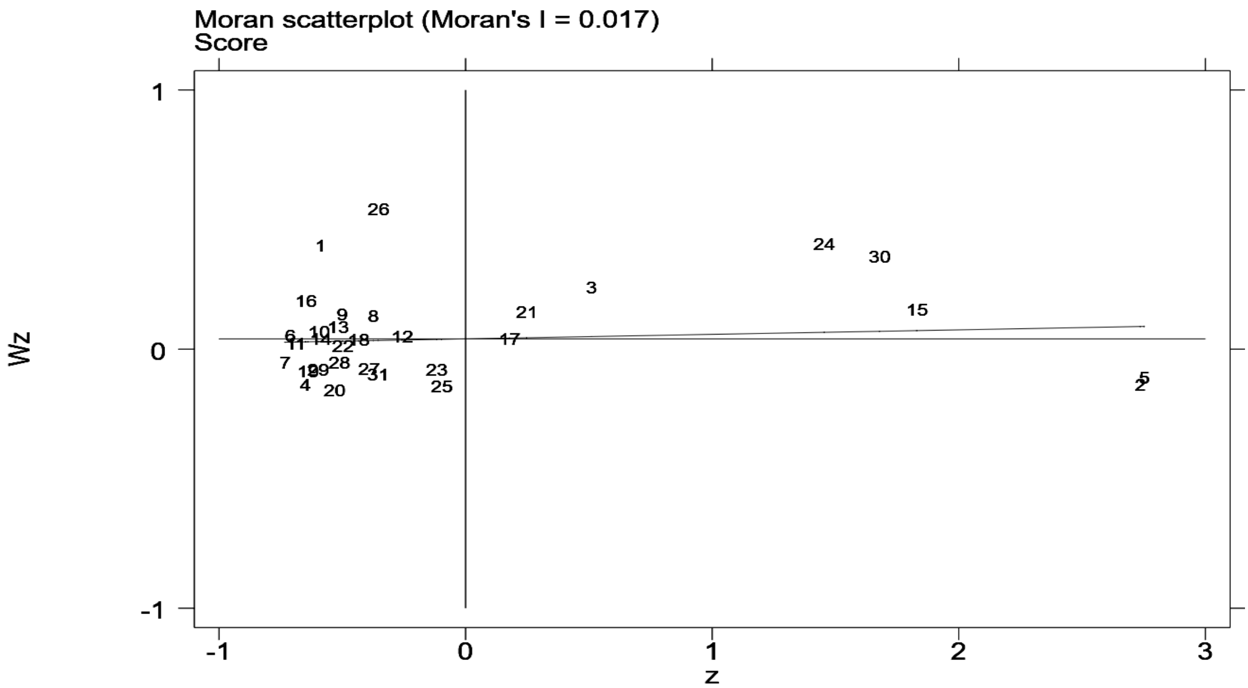

Figure 4. Moran's I Scatter chart of China's DED in 2013.

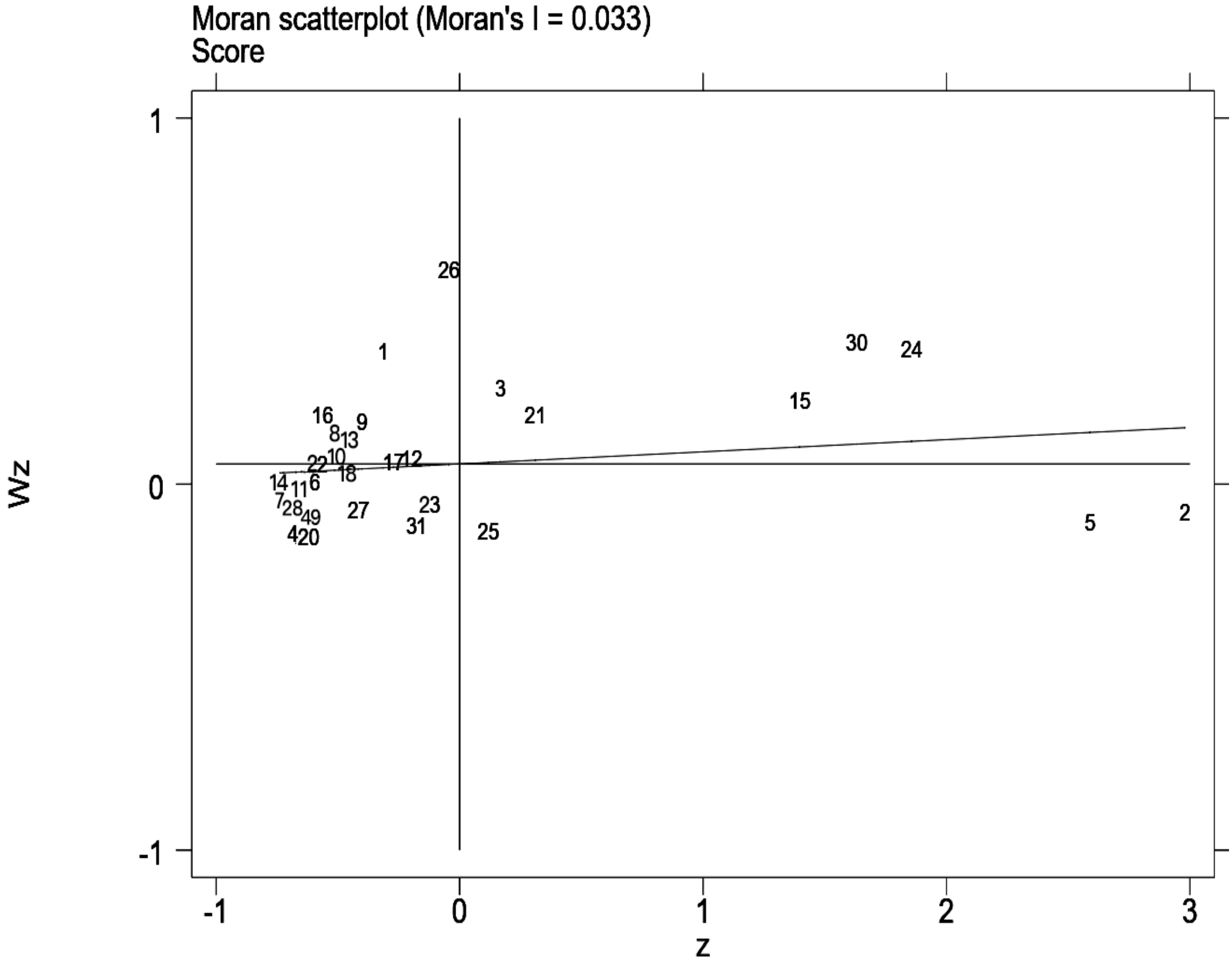

Figure 5. Moran's I Scatter chart of China's DED in 2020.

This study investigates the spatial and temporal dynamics of the DE by analyzing its evolution path from 2013 to 2020, as illustrated in the Moran scatter plot (refer to Table 6). The provinces' stability within each quadrant is evident as per the data presented in Table 6.

The analysis clearly places Shanghai, Jiangsu, Zhejiang, Shandong, and Fujian are positioned in the first quadrant (HH) during the period under review, suggesting that the eastern districts, known for their advanced DE growth, predominantly occupy this quadrant.

Conversely, Chongqing, Guizhou, Yunnan, Tibet, Shaanxi, Gansu, Qinghai, Ningxia, and Xinjiang are located in the third quadrant (LL) throughout the observed period, highlighting that the western areas generally exhibit lower levels of digital economic development. This spatial distribution underscores the presence of spatial polarization within the DE. Beijing, Guangdong, and Sichuan districts exhibit notable economic growth and demonstrate a relatively advanced level of DED.

However, the progress in the DE of neighboring provinces such as Guangxi, Hebei, Qinghai, and Yunnan lags behind in comparison. During the specified period, Beijing, Guangdong, and Sichuan occupy the fourth quadrant (HL).

Table 6. Temporal and spatial evolution path of China's regional DED.

Year	First quadrant (HH)	Second quadrant (LH)	Third quadrant (LL)	Fourth quadrant (HL)
2013	Shanghai, Fujian, Shandong, Jiangsu, Zhejiang, Liaoning	Hubei, Hunan, Jiangxi, Anhui, Guangxi, Henan, Hebei, Hainan, Neimenggu, Jilin, Heilongjiang, Tianjin	Guizhou, Ningxia, Tibet, Qinghai, Gansu, Yunnan, Xinjiang, Chongqing, Shanxi	Beijing, Guangdong, Sichuan, Shaanxi
2014	Shanghai, Fujian, Shandong, Jiangsu, Zhejiang, Liaoning	Hubei, Hunan, Jiangxi, Anhui, Guangxi, Henan, Hebei, Hainan, Neimenggu, Jilin, Heilongjiang, Tianjin	Guizhou, Ningxia, Tibet, Qinghai, Gansu, Yunnan, Xinjiang, Chongqing, Shanxi	Beijing, Guangdong, Sichuan, Shaanxi
2015	Shanghai, Fujian, Shandong, Jiangsu, Zhejiang, Liaoning	Hubei, Hunan, Jiangxi, Anhui, Guangxi, Henan, Hebei, Hainan, Neimenggu, Jilin, Heilongjiang, Tianjin	Guizhou, Ningxia, Tibet, Qinghai, Gansu, Yunnan, Xinjiang, Chongqing, Shanxi, Shaanxi	Beijing, Guangdong, Sichuan
2016	Shanghai, Fujian, Shandong, Jiangsu, Zhejiang, Liaoning	Hubei, Hunan, Jiangxi, Anhui, Guangxi, Henan, Hebei, Hainan, Neimenggu, Jilin, Heilongjiang, Tianjin	Guizhou, Ningxia, Tibet, Qinghai, Gansu, Yunnan, Xinjiang, Chongqing, Shanxi, Shaanxi, Heilongjiang	Beijing, Guangdong, Sichuan
2017	Shanghai, Fujian, Shandong, Jiangsu, Zhejiang, Liaoning	Hubei, Hunan, Jiangxi, Anhui, Guangxi, Henan, Hebei, Hainan, Neimenggu, Jilin, Heilongjiang, Tianjin	Guizhou, Ningxia, Tibet, Qinghai, Gansu, Yunnan, Xinjiang, Chongqing, Shanxi, Shaanxi, Heilongjiang	Beijing, Guangdong, Sichuan
2018	Shanghai, Fujian, Shandong, Jiangsu, Zhejiang	Hubei, Hunan, Jiangxi, Anhui, Guangxi, Henan, Hebei, Hainan, Neimenggu, Jilin, Heilongjiang, Tianjin, Liaoning	Guizhou, Ningxia, Tibet, Qinghai, Gansu, Yunnan, Xinjiang, Chongqing, Shanxi, Shaanxi, Heilongjiang	Beijing, Guangdong, Sichuan
2019	Shanghai, Fujian, Shandong, Jiangsu, Zhejiang, Tianjin	Hubei, Hunan, Jiangxi, Anhui, Guangxi, Henan, Hebei, Hainan, Neimenggu, Jilin, Heilongjiang, Liaoning	Guizhou, Ningxia, Tibet, Qinghai, Gansu, Yunnan, Xinjiang, Chongqing, Shanxi, Heilongjiang	Beijing, Guangdong, Sichuan, Shaanxi
2020	Shanghai, Fujian, Shandong, Jiangsu, Zhejiang, Tianjin	Hubei, Hunan, Jiangxi, Anhui, Guangxi, Henan, Hebei, Hainan, Neimenggu, Jilin, Heilongjiang, Liaoning	Guizhou, Ningxia, Tibet, Qinghai, Gansu, Yunnan, Xinjiang, Chongqing, Shanxi, Heilongjiang	Beijing, Guangdong, Sichuan, Shaanxi

Note: HH reflects a high level of DED in the region and its surrounding areas with a small difference between them. LL signifies a low level of DED in the region and its surrounding areas with a slight difference. HL denotes a high level of DED in the region compared to lower development in the surrounding areas, with a significant difference. LH represents a low level of DED in the region and higher development in the surrounding areas, with a large difference between them.

5. CONCLUSIONS AND IMPLICATIONS

The study findings indicated a spatial distribution of China's DE aligned with geographical location classifications. The shift of the DE from eastern to western districts corresponded to a decline in development. These results are in line with previous studies by Wei, Wang, and Ma (2024) and Wang, Teng, Hu, and Li (2024). Wei et al. (2024) utilized the TOPSIS method and the CRITIC weight gray correlation TOPSIS method to estimate the digital economy's development in 31 Chinese provinces from 2015 to 2020. Wang et al. (2024) modified the CRITIC evaluation method to assess China's provincial DED from 2013 to 2020 and applied social network analysis methods to investigate the evolution characteristics and causes of the spatial network structure of the DE.

Since 2016, the gap coefficient in China's regional digital economic development levels has gradually decreased. The differences in coefficients between provinces reveal a consistent growth pattern in the DED of the eastern region, while the western districts show more noticeable fluctuations. A key observation is the vital spatial correlations within China's regional DE, characterized by a 'high-high' clustering pattern predominantly in eastern provinces and a corresponding 'low-low' clustering pattern mainly in the western districts. Interestingly, despite being located in the western districts, Sichuan sticks out as a relatively developed region with a higher level of DED compared to previous studies by Wei et al. (2024) and Wang et al. (2024).

The study proposes a series of policy recommendations based on the analysis results. The policymakers should prioritize the coordinated growth of the DE across all provinces. It is suggested to actively cultivate inter-regional information resource sharing systems and platforms to facilitate the smooth exchange of information, technology, and skilled talents among districts. Furthermore, focusing on strengthening the development of the DE in the third quadrant provinces (LL) is recommended. By implementing preferential policies and incentives, we can bridge the gap between these districts and those with well-established digital economies. These measures aim to foster sustainable growth and progress in each district. To further forester the development of the DE, enhancing cooperation between developed areas in the fourth quadrant (HL) and less developed areas in the second quadrant (LH) is essential.

Pursuant to the above conclusions, balancing China's digital economic advancement requires efforts to make breakthroughs in the following three aspects.

Firstly, it is highlighted the importance of coordinating the digital economy, clarifying regional division of labor by focusing on new information infrastructure to overcome administrative obstacles, avoiding resource fragmentation, and enhancing network spillover effects. While the spillover intensity of various subgroups within China's digital economic network has increased, significant regional disparities persist, necessitating strengthened exchanges in western and peripheral areas. It is important to improve the regulatory and spillover effects of each subgroup in the network. To do this, the digital economic strengths of the southeast coastal areas and Beijing-Tianjin-Hebei region should be used to their full potential. Through new infrastructure projects and targeted transfer of digital technology, the development of regional informatization infrastructure can be advanced to ensure equitable development of new infrastructure, with a focus on preventing marginalization in central and western regions and fostering the coordinated growth of provincial digital economies.

Besides, administering authority should enhance the supportive environment for digital economy growth by implementing dual-track industrial development and talent nurturing. Suitable efforts are emphasizing the advancement of e-commerce and Internet sectors, facilitating the convergence of digital economy with the real economy, fostering talent platforms, and driving industrial progress. Policy backing drives rapid advancement and inter-regional collaboration in the digital economy sphere. Eastern coastal districts should innovate in new digital economy models, whereas central and western districts should enhance current industry infrastructure, leveraging their strengths to steadily advance industrial digitization.

Furthermore, it is recommended that by promoting the digital economy through technological innovation we achieve the seamless integration of the 'innovation-driven' and 'Digital China' development strategies. The inherent characteristics of the digital economy create a natural synergy between these two strategies. The eastern districts should focus their scientific and technological innovation efforts on digital technology research, platform development, and fostering the digital economy's growth through innovation. This, in turn, will drive further scientific and technological innovation, creating a mutually beneficial cycle. Meanwhile, the central, western, and northeastern regions should leverage the transfer of digital industries and technology from the east to elevate their own digital economic capabilities. By strengthening inter-regional economic ties through industrial transfer and technology diffusion, they can contribute to the development of a national digital economic network.

Advancements in transportation and information and communication technology have weakened the impact of geographical distance, indicating a need for future research that incorporates time or information distance into the assessment to enhance research accuracy. It is crucial to explore the driving factors of digital economic development within a single region from an attribute perspective, warranting further in-depth research.

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Annexed Table 1. DED index of China's provinces from 2013 to 2020.

Province/Year	2013	2014	2015	2016	2017	2018	2019	2020
Anhui	0.109	0.117	0.113	0.132	0.137	0.144	0.158	0.163
Beijing	0.745	0.709	0.722	0.703	0.696	0.702	0.733	0.738
Chongqing	0.154	0.168	0.163	0.174	0.176	0.178	0.189	0.189
Fujian	0.320	0.301	0.289	0.287	0.272	0.271	0.270	0.247
Gansu	0.098	0.087	0.076	0.091	0.101	0.102	0.105	0.101
Guangdong	0.748	0.722	0.699	0.719	0.729	0.712	0.708	0.670
Guangxi	0.086	0.073	0.067	0.069	0.071	0.084	0.095	0.110
Guizhou	0.082	0.070	0.077	0.096	0.095	0.097	0.096	0.089
Hainan	0.150	0.144	0.142	0.143	0.135	0.142	0.145	0.128
Hebei	0.126	0.118	0.105	0.132	0.134	0.137	0.148	0.148
Heilongjiang	0.090	0.098	0.088	0.089	0.105	0.094	0.099	0.100
Henan	0.108	0.109	0.110	0.131	0.132	0.123	0.129	0.134
Hubei	0.173	0.171	0.158	0.167	0.173	0.173	0.194	0.183
Hunan	0.123	0.121	0.102	0.104	0.113	0.110	0.120	0.131
Jiangsu	0.572	0.526	0.509	0.521	0.499	0.474	0.482	0.462
Jiangxi	0.098	0.094	0.086	0.099	0.118	0.114	0.119	0.119
Jilin	0.110	0.118	0.110	0.106	0.099	0.120	0.094	0.091
Liaoning	0.256	0.253	0.250	0.211	0.198	0.180	0.184	0.170
Neimenggu	0.139	0.129	0.136	0.143	0.142	0.138	0.143	0.134
Ningxia	0.100	0.097	0.101	0.101	0.101	0.111	0.105	0.105
Qinghai	0.120	0.126	0.138	0.133	0.111	0.121	0.113	0.109
Shanxi	0.127	0.129	0.123	0.127	0.117	0.114	0.111	0.115
Shandong	0.269	0.267	0.271	0.317	0.312	0.298	0.287	0.272
Shanghai	0.500	0.555	0.514	0.525	0.485	0.509	0.546	0.542
Shaanxi	0.200	0.199	0.182	0.196	0.187	0.194	0.208	0.196
Sichuan	0.203	0.213	0.217	0.227	0.226	0.233	0.249	0.238
Tianjin	0.154	0.152	0.153	0.165	0.152	0.174	0.209	0.210
Xinjiang	0.124	0.118	0.125	0.131	0.106	0.117	0.097	0.103
Xizang	0.147	0.155	0.149	0.149	0.151	0.134	0.146	0.145
Yunnan	0.108	0.104	0.110	0.099	0.096	0.099	0.104	0.104
Zhejiang	0.543	0.546	0.568	0.573	0.533	0.513	0.528	0.503

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