Digital Economy Empowering New Quality Productivity: Theoretical Logic, Spatio-temporal Evolution and Empirical Analysis

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Keywords: Digital Economy; New Quality Productivity; Spatio-Temporal Evolution; Panel Data Model

Abstract: With the rapid development of IT, the digital economy has become a key driver of global growth, changing traditional models via advanced tech. Using 2013 - 2022 data of 30 Chinese provinces, this study constructs index systems by entropy weight CRITIC - TOPSIS and projection pursuit model. It analyzes spatio - temporal evolution through kernel density estimation, Moran's index and Dagum Gini coefficient decomposition. A two - way fixed effects panel data model tests the digital economy's empowerment mechanism. Results show new quality productivity grows but with regional differences, spatial agglomeration exists, and the digital economy has a positive impact, emphasizing its role in reducing disparities and promoting growth.

1. Introduction

The digital economy has undeniably become a dominant force propelling global economic growth. New quality productivity, which stems from technological breakthroughs, innovative resource allocation, and industrial transformation, represents the vanguard of modern production. In China's pursuit of strategic economic transformation towards high-quality development and modernization, nurturing new quality productivity is of paramount significance. The digital economy, leveraging data as a vital production factor, plays a pivotal role in enhancing resource allocation efficiency and empowering this new form of productivity[1].

However, existing research in this domain has several notable limitations. Xiao and Fan primarily centered on theoretical conjectures regarding the relationship between the digital economy and new quality productivity. However, the absence of substantial empirical evidence made it arduous to truly fathom the practical workings of how the digital economy drives new quality productivity in real economic landscapes[2]. In the measurement aspect, Li and Gao's study adopted a rather narrow index system for the digital economy. It overly emphasized elements such as the quantity of digital products while disregarding the crucial importance of digital infrastructure development[3]. Similarly, Han, Li, and Lu selected a limited set of indicators for new quality productivity, failing to comprehensively encapsulate all the essential elements[4]. In terms of analysis, Liu, Wang, and Tang merely considered a short-term perspective and completely overlooked the disparities among regions with varying economic structures and digital development levels[5].

To address these deficiencies, this study proposes a method for constructing comprehensive measurement index systems for both the digital economy and new quality productivity. By integrating the entropy weight method and the CRITIC method for calculating weights and subsequently employing the Topsis method to derive the comprehensive score, it ensures a more scientifically sound measurement process. Moreover, it divides the 30 Chinese provinces into eastern, central, and western regions to conduct an in-depth analysis of regional heterogeneity. This approach provides highly valuable insights and a solid foundation for the government to formulate effective strategies aimed at promoting balanced regional development.

  DOI: 10.25236/icssem.2025.063

2. Methodology

2.1. Model Construction and Data Integration for Analyzing Digital Economy and New Quality Productivity

To analyze the digital economy and its impact on new quality productivity, a comprehensive approach is used. Index systems for both are constructed. For the digital economy, four first-level indicators are chosen: digital infrastructure (like mobile phone and internet penetration rates), digital industrialization (including employment and business volumes), industrial digitization (such as enterprise websites and e-commerce metrics), and digital finance index (with components like coverage breadth and usage depth).For new quality productivity, three first-level indicators are selected based on labor, means, and objects of labor upgrading. New quality laborers involve human capital input and output. New quality means of labor are described by energy consumption, digital infrastructure, robot application, and digital innovation. New quality objects of labor focus on science and technology-empowered natural object utilization[6].

Data from 30 Chinese provinces (2013 - 2022) come from various yearbooks and databases. Missing data are filled.

2.2. Model Methods

2.2.1. Entropy Weight CRITIC-TOPSIS Method

The Entropy Weight and CRITIC methods are used to determine objective weights by evaluating the contrast intensity and conflict among indicators. The entropy method gauges indicator dispersion, while the CRITIC method measures variability and correlation. Combining these ensures comprehensive weight calculation[7]. Key formulas include:(1) Entropy Weights:

$$e_j = \frac{1}{\ln m}\sum_{i=1}^{m} h_{ij}\ln(h_{ij}),\quad h_{ij} = \frac{X_{ij}^*}{\sum_{i=1}^{m} X_{ij}^*},\quad W_j = \frac{1-e_j}{\sum_{j=1}^{n}(1-e_j)} \tag{1}$$

where X_{ij} represents the value of the j-th indicator in the i-th province.

(2) CRITIC Weights:

$$R_j = \sum_{i=1}^{n} A\,(1-r_{ij}),\quad C_j = \delta_j R_j,\quad W_j = \frac{C_j}{\sum_{j=1}^{m} C_j} \tag{2}$$

where r_{ij} is the negative correlation coefficient, and δ_j is the standard deviation of the j-th indicator.

The final weights are normalized using:

$$W_{\text{new}} = \frac{W_1 \times W_2}{\sum (W_1 \times W_2)} \tag{3}$$

Using the calculated weights, indicators are scored across development, sharing, and sustainability factors. The TOPSIS method is then applied to evaluate the closeness of samples to the ideal solution, determining the comprehensive scores for digital economy measurement.

2.2.2. Projection Pursuit Model Based on Genetic Algorithm

The projection pursuit model effectively reduces dimensionality by mapping high-dimensional data into a one-dimensional space through a projection function. This method enhances the robustness of data analysis, revealing internal data structures and providing reliable evaluation results[8].

To eliminate the dimension difference between different indicators and unify the change range of each indicator value within a certain fixed range, an extreme value normalization method is adopted.

For indicators that are better when larger and smaller:

$$M(i,j)=\frac{M^*(i,j)-M_{\min}}{M_{\max}-M_{\min}},\quad M(i,j)=\frac{M_{\max}-M^*(i,j)}{M_{\max}-M_{\min}} \tag{4}$$

where $M_{\max}$ is the maximum value of the j-th indicator, and $M_{\min}$ is the minimum value of the j-th indicator. $M(i,j)$ is the normalized sequence of indicator characteristic values.

Construct a projection index function $G(d)$, and comprehensively generate a one-dimensional projection value $w(i)$ with $a=\{a(1),a(2),a(3),\cdots,a(q)\}$ as the projection direction from the q-dimensional data $\{M^*(i,j)\mid i=1,2,\cdots,p;j=1,2,\cdots,q\}$:

$$w(i)=\sum_{j=1}^{q}a(j)M(i,j),\quad G(d)=D_w\cdot S_w \tag{5}$$

where D_w is the standard deviation of the projection value $w(i)$, $E(w)$ is the expected mean of the projection value $w(i)$, S_w is the local density of the projection value $w(i)$, R is the local density window radius, and can be determined by experiments, for example, $R=0.1D_w r(i,j)=|w(i)-w(j)|$, and $f(x)$ is a unit step function. When $x<0, f(x)=0$ and when $x>0, f(x)=1$.

$$D_w=\sqrt{\frac{\sum_{i=1}^{n}[(w(i)-E(w))^2]}{n-1}},\quad S_w=\sum_{i=1}^{n}\sum_{j=1}^{n}[(R-r(i,j))f(R-r(i,j))] \tag{6}$$

The genetic algorithm identifies the optimal projection direction by simulating natural genetic variations. This approach maximizes the projection index function, providing a robust evaluation of data structures[9].

2.2.3. Kernel Density Estimation

Kernel density estimation, which is developed from histograms, is a non-parametric method and is especially suitable for estimating probability density functions. This method does not need to know the specific form of the distribution function in advance but estimates the distribution completely based on sample data. Compared with parametric density estimation, non-parametric density estimation can more accurately describe the density function form of continuous variables and obtain accurate density estimation results[10]. Let $X_i(i=1,2,\cdots,n)$ be the observed values from the population X, and the expression of kernel density estimation is:

$$f(x)=\frac{1}{nr}\sum_{i=1}^{n}K\left(\frac{x-X_i}{r}\right) \tag{7}$$

where $f(x)$ is the density function; r is the sample size; $K(x)$ is the window; $u=\frac{x-X_i}{r}$ is the kernel function. Let $K(u)$ then satisfies: $\int_{-\infty}^{\infty}K(u)\,du=1$, $\int_{-\infty}^{\infty}uK(u)\,du=0$, $\int_{-\infty}^{\infty}K^2(u)\,du<\infty$

3. Results and Discussion

3.1. Growth Trends and Regional Disparities

The digital economy and new quality productivity both exhibit an upward trend from 2013 to 2022. However, significant regional differences exist. The scatter plot in Figure 1 clearly indicates a positive correlation between the two, suggesting that the development of the digital economy has a promoting effect on new quality productivity.

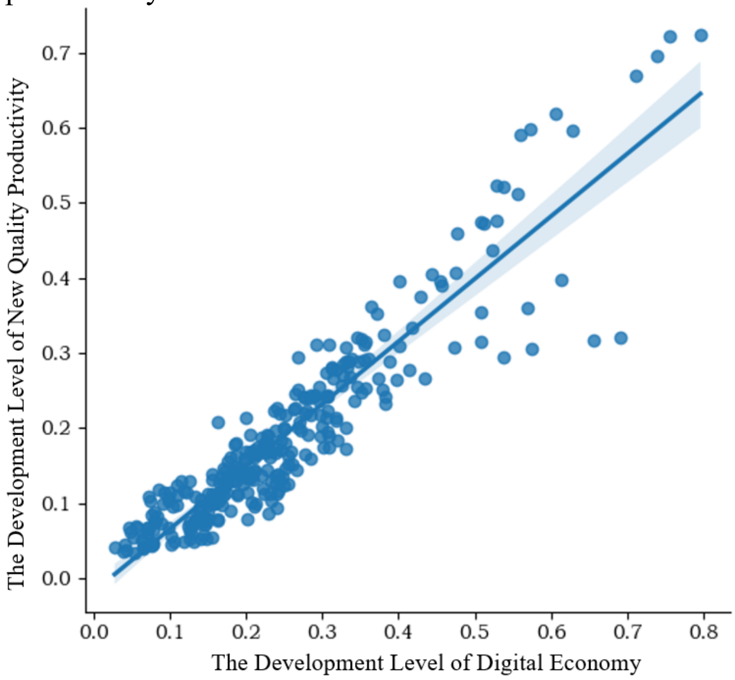


Figure 1. Scatter Plot of the Relationship between the Development Level of New Quality Productivity and the Development Level of Digital Economy

3.2. Dynamic Evolution of New Quality Productivity

Nationally, the kernel density curve of new quality productivity shifts to the right from 2013 to 2022, as demonstrated in Figure 2, indicating development. But the curve height decreases, width widens, and right tail lengthens, signifying increasing regional differences and a slowing growth rate in the later stage. In the eastern region (Figure 3), the curve is "fat and short", showing inconsistent development levels among provinces. In the western region (Figure 4), the curve is "thin and tall", with relatively small differences. In the central region (Figure 5), the curve shift is accompanied by a decrease in peak height and an increase in width, indicating expanding regional differences.

3.3. Spatial Agglomeration and Heterogeneity

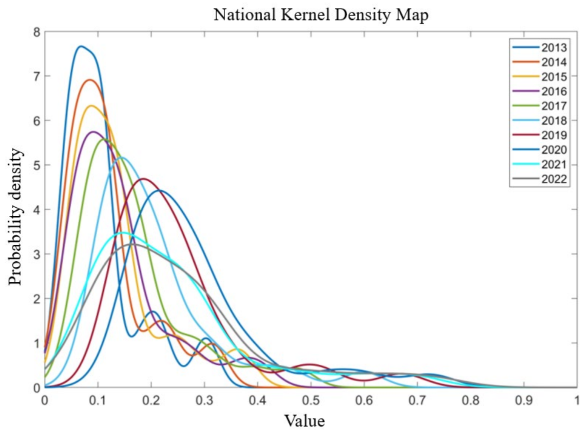
The Moran index fluctuates from 2013 to 2022, mostly between 0.15 and 0.22, as shown in Figure 6, indicating spatial agglomeration of new quality productivity. The local Moran scatter plot further confirms this, with most provinces in the first and third quadrants. Provinces like Shanghai and Zhejiang are in the high-high agglomeration area, while Xinjiang and Qinghai are in the low-low agglomeration area. Some provinces like Anhui and Sichuan have changed positions over the years.

3.4. Sources of Differences

The Dagum Gini coefficient decomposition shows that regional differences contribute the most to new quality productivity differences, followed by regional internal differences, and super-variable density contributes the least. As shown in Figure 7 and Figure 8, the Gini coefficients within regions and between regions have specific evolution trends.

3.5. Empirical Analysis Results

Through model testing, the fixed effects model is determined. In this model, the digital economy has a significant positive impact on new quality productivity, with a regression coefficient of 0.74 significant at the 1% level. Government innovation support and urbanization level also have positive effects. In different regions, the digital economy's promoting effect on new quality productivity is stronger in the central and western regions than in the eastern region.



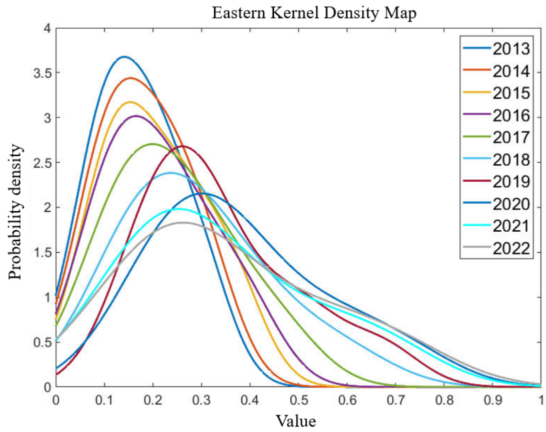
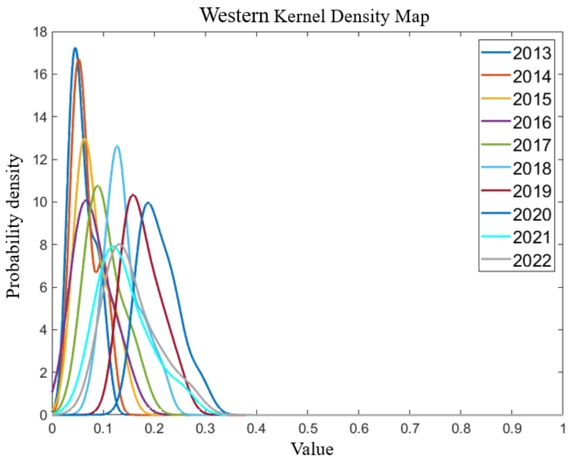


Figure 2. Kernel Density Dynamic Evolution Distribution Maps: National Region (Left)

Figure 3. Kernel Density Dynamic Evolution Distribution Maps: Eastern Region (Right)



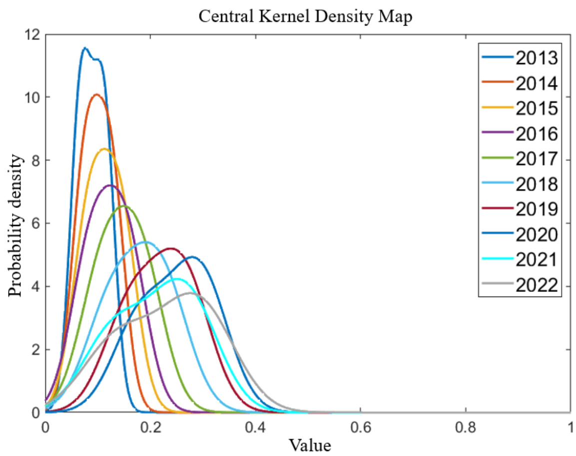


Figure 4. Kernel Density Dynamic Evolution Distribution Maps: Western Region (Left)

Figure 5. Kernel Density Dynamic Evolution Distribution Maps: Central Region (Right)

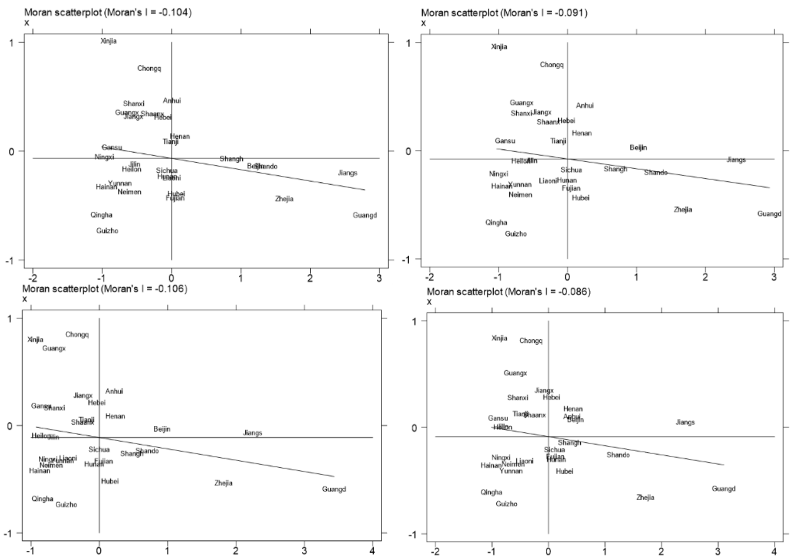
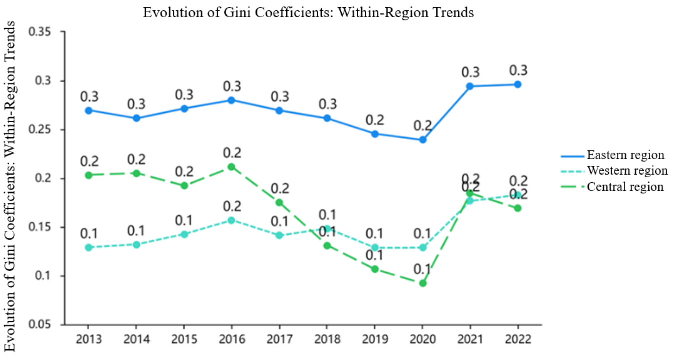


Figure 6. The Local Moran Scatter Plot in 2013, 2016, 2019 and 2022



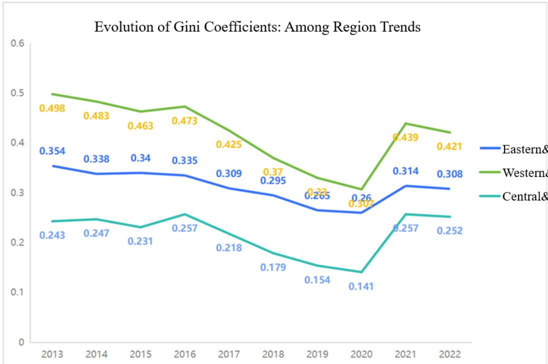


Figure 7. Evolution of Gini Coefficients: Within-Region Trends (Left)

Figure 8.Evolution of Gini Coefficients: Among -Region Trends (Right)

4. Conclusion

This study offers a comprehensive and innovative exploration of the digital economy's influence on new quality productivity. Through the construction of index systems and application of multiple model methods, it is found that both the digital economy and new quality productivity have shown growth trends over time, yet with significant regional differences. Importantly, the digital economy has a significant positive impact on new quality productivity across different regions, with a relatively stronger effect in the central and western regions. This research enriches the theoretical understanding and provides practical guidance for economic development. Future research can focus on further improving the index system and expanding the research scope.

References

[1] Zheng M, Yan S, Xu S. Digital Economy, Industry–Academia–Research Collaborative Innovation, and the Development of New-Quality Productive Forces. Sustainability. 2025;17(1):318.

[2] Xiao W, Fan D. The “Simultaneous Development of Quantity and Quality”: Research on the Impact of the Digital Economy in Enabling Manufacturing Innovation. Systems. 2024;12(11):470.

[3] Li Y, Gao P. Research on Measurement and Index System Design of Digital Economy Development. Int J Res Soc Sci Econ. 2023;5(3):320-325.

[4] Han Z, Li X, Lu Y. New quality productivity enabling high-quality economic development: a case study in China. J Econ Bus Manag. 2024;12(4):240-253.

[5] Liu X, Wang Z, Tang Y. The Impact of the Digital Divide on Labor Mobility and Sustainable Development in the Digital Economy. Sustainability. 2024;16(22):9944.

[6] Li Q, Zhao S. The impact of digital economy development on industrial restructuring: Evidence from China. Sustainability. 2023;15(14):10847.

[7] Mukhametzyanov R. Entropy method and CRITIC method for objective criteria weights determination. Decis Mak Appl Manag Eng. 2021;4(2):76-105.

[8] Ding C, He X, Zha H. A probabilistic framework for projection pursuit. IEEE Trans Neural Networks. 2004;15(3): 513-526.

[9] Etschera R. A study of the genetic algorithm in optimizing binary data and enhancing data structures. Comput Oper Res. 1998;25(12):1091-1099.

[10] Smith A, Zhao M, Choi J. Kernel density estimation: A nonparametric method for estimating probability density functions. J Stat Methods. 2021;10(3):415-421.