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The Structural Transformation, Driving Mechanisms, and Enhancement Pathways of Aggregate Productivity in the Era of Digital Economy

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ABSTRACT

Based on multi-source data and econometric modeling, this paper systematically analyzes the characteristics of structural transformation, key driving factors, and optimization pathways of macro-level productivity in the era of the digital economy. Firstly, by employing the Solow residual method and the Malmquist index approach to measure trends in total factor productivity (TFP), we find that China's macro productivity has exhibited a U-shaped change—rising initially and then slowing down—since 2010, with significant regional and sectoral disparities. Secondly, in terms of structural transformation, industrial upgrading, labor resource reallocation, capital deepening, and innovation agglomeration have emerged as typical patterns, with the digital economy exerting a particularly pronounced amplifying effect on high-value-added industries. Thirdly, empirical analysis reveals that digital infrastructure development, the expansion of digital penetration, and policy support are the core drivers of TFP growth, with resource allocation efficiency playing a significant mediating role.

KEYWORDS

Digital economy; Macro productivity; Total Factor Productivity (TFP); Driving mechanisms; Enhancement pathways

1 Introduction

As the global technological revolution and industrial transformation continue to deepen, the digital economy is reshaping the world economic landscape at an unprecedented pace, emerging as a core driving force behind macro-level productivity transformation. According to the China Digital Economy Development Research Report, by 2024, the scale of China's digital economy had exceeded 60 trillion yuan, accounting for more than 45% of GDP, highlighting its increasingly prominent role in the national economy. Against this backdrop, traditional models of economic growth and analytical frameworks of productivity are facing new challenges.

Macro productivity, as a key indicator reflecting the efficiency and growth potential of a country or region's economic operations, is typically centered on Total Factor Productivity (TFP) as its core measurement criterion. In traditional theory, TFP growth mainly stems from technological progress, institutional optimization, and improvements in resource allocation efficiency. However, in the era of the digital economy, the emergence of new production factors such as data, algorithms, and platforms has led to structural adjustments in the traditional production function. The widespread application of artificial intelligence has significantly enhanced information processing and decision-making efficiency, while cloud computing and big data technologies have substantially reduced enterprise operating costs and improved the precision of resource allocation.

2 Theoretical framework and analytical model

2.1 Conceptual definition and measurement of macro productivity

As a core indicator for measuring economic efficiency and growth potential, the concept of macro productivity has evolved significantly across different theoretical stages, leading to variations in both its conceptualization and measurement methods. Traditionally, Total Factor Productivity (TFP) has been widely accepted as a proxy for macro productivity. It captures the portion of output growth that cannot be explained by conventional inputs such as capital and labor under given production conditions (Solow, 1957).

In terms of specific measurement methodologies, current mainstream approaches include parametric estimation based on production functions, non-parametric methods such as Data Envelopment Analysis (DEA), and fixed-effects or random-effects modeling using panel data. Among these, the Olley-Pakes (OP) method proposed by Olley and Pakes (1996) and the Levinsohn-Petrin (LP) method introduced by Levinsohn and Petrin (2003) are widely used in micro-level TFP estimation due to their ability to address endogeneity at the firm level.

2.2 Transmission mechanisms of the digital economy's impact on productivity

The development of the digital economy exerts profound impacts on macro productivity through multiple pathways, which can be categorized into three main mechanisms: technological diffusion, institutional adaptation, and resource allocation optimization. Understanding these transmission channels is essential for uncovering how the digital economy reshapes the drivers of economic growth.

The technological diffusion effect represents the most direct pathway through which the digital economy enhances macro productivity. Digital technologies such as artificial intelligence, cloud computing, and blockchain significantly improve resource allocation efficiency by reducing information processing costs, enhancing decision-making capabilities, and fostering innovation. Acemoglu and Restrepo (2020) argue that the introduction of automation and intelligent systems not only increases the marginal output of high-skill labor but also boosts overall labor productivity by substituting low-skill labor.

3 Empirical analysis of structural transformation and driving factors

3.1 Description of data sources

3.1.1 Data sources

To ensure comprehensiveness and representativeness, this study integrates data from the following authoritative databases:

Table 1 Data Sources

Data Type	Source Institution	Time Span (Year)	Characteristics
Macroeconomic Data	National Bureau of Statistics (NBS), World Bank	2000–2024	Includes GDP, employment, capital stock, etc.
Digital Economy Indicators	China Digital Economy Development Report (Ministry of Industry and Information Technology), Alibaba Research Institute, IDC	2010–2024	Covers digital infrastructure, digital penetration rate, etc.
Input-Output Tables	Input-Output Survey Office of the National Bureau of Statistics	2002–2020	Reflects inter-industry input-output relationships
Institutional and Policy Variables	Government Work Reports, PKU Law Database, Local Government Information Disclosure Platforms	2005–2024	Quantified through policy text mining
Micro-level Firm Data	Annual Reports of Listed Companies, CNIPA Patent Database (National Intellectual Property Administration of China)	2010–2024	Captures firm-level innovation behavior and financial performance

3.1.2 Variable definitions and calculation methods

Aggregate Total Factor Productivity (TFP)
Calculation Method:
Solow Residual Method:

$$TEP = \frac{Y}{K^{\alpha} L^{1-\alpha}}$$

Where: Y denotes GDP;
K represents capital stock;
L indicates labor input;
α is the capital income share.

$$\text{Malmquist TFP Index} = \left(\frac{D_t(x_{t+1}, y_{t+1})}{D_t(x_t, y_t)} \right)^{1/2}$$

The Malmquist TFP index is calculated under two specifications: Constant Returns to Scale (CRS) and Variable Returns to Scale (VRS) . The final result is obtained by taking the average of the two estimates.

Table 2 Core Explanatory Variables

Variable Name	Construction Method	Data Source
Digital Infrastructure Level (DI)	Number of 5G base stations per 10,000 people + Data center capacity per 100 million yuan of GDP	Ministry of Industry and Information Technology (MIIT), National Bureau of Statistics (NBS)
Digital Penetration Rate (DP)	E-commerce transaction volume / GDP + Online service coverage rate	Alibaba Research Institute, China Internet Network Information Center (CNNIC)
Share of Digital Industry Value Added (DIG)	Value added of digital industries / GDP	NBS industry classification data

Table 3 Control Variables

Variable Name	Construction Method	Data Source
Education Input (EDU)	Average years of schooling per capita, higher education enrollment rate	Statistical Yearbook of the Ministry of Education
R&D Intensity (RD)	R&D expenditure / GDP	Science and Technology Statistical Yearbook of the NBS
Urbanization Rate (URB)	Urban population / Total population	Population Census Data of the NBS
Degree of Openness (OPEN)	Total import and export volume / GDP	General Administration of Customs, Ministry of Commerce
Policy Support Index (POL)	Keyword frequency extraction from government work reports, weighted synthesis	Government publications, NLP processing

3.2 Trend analysis of aggregate productivity changes

3.2.1 Time series trend analysis

The growth rate of China's aggregate Total Factor Productivity (TFP) from 2000 to 2024 was calculated using the Solow residual method. The results are as follows:

Table 4 China's Aggregate TFP Growth Rate (2000–2024)

Year	TFP Growth Rate (%)	Year	TFP Growth Rate (%)
2000	0.7	2013	1.9
2005	1.1	2016	2.1
2010	1.3	2020	1.6
2012	1.8	2024	1.4

Trend Characteristics:2000–2010: A period of slow growth, with an average annual growth rate of approximately 1.0% . 2011–2017: Driven by the "Internet Plus" strategy, TFP growth rose to around 2.0% per year. After 2018: The growth rate slowed down, possibly due to changes in the external economic environment.

3.2.2 Regional disparity analysis

TFP growth rates were calculated separately for three major regions—Eastern, Central, and Western China:

Table 5 China's Aggregate TFP Growth Rate by Region (2000–2024)

Region	Average (2000–2010)	Average (2011–2020)	Average (2021–2024)
Eastern	1.1%	2.3%	1.9%
Central	0.9%	1.6%	1.3%
Western	0.6%	1.2%	1.0%

Conclusion: The eastern region has consistently led in TFP growth, and the regional gap has been widening over time.

3.2.3 Industry-level decomposition perspective

Taking 2023 as an example, the TFP growth rates across industries are as follows:

Table 6 Industry-Level TFP Growth Rates in China (2023)

Industry Category	TFP Growth Rate (%)	Industry Category	TFP Growth Rate (%)
Information Transmission, Software, and IT Services	3.8	Manufacturing (Overall)	1.5
Scientific Research and Technical Services	3.2	Wholesale and Retail Trade	1.1
Education	0.8	Agriculture, Forestry, Animal Husbandry, and Fisheries	0.6
Real Estate	0.5	Transportation and Warehousing	0.7

Implications: Industries related to the digital economy exhibit significantly higher TFP growth compared to traditional sectors.

3.3 Stylized facts of structural transformation

3.3.1 Industrial structure upgrading

Trend: The tertiary industry has established its dominant position in the economy, with the information services sector emerging as a new growth engine.

Table 7 Sectoral Composition of GDP

Year	Share of Secondary Industry (%)	Share of Tertiary Industry (%)	Share of Information Services (%)
2000	45.9	33.2	1.2
2010	46.2	43.3	2.8
2020	37.8	54.5	7.3
2024	35.6	55.8	9.1

3.3.2 Optimization of Labor Resource Allocation

Table 8 Employment Absorption by the Digital Economy

Year	Number of Employees in the Digital Economy (100 million)	Share of Total Employment (%)
2014	0.8	11.2
2020	2.1	27.5
2024	2.5	32.8

Conclusion: The digital economy has become a major channel for employment absorption.

3.3.3 Capital Deepening and Digital Investment

Table 9 Digital Capital Formation

Year	Digital Capital Formation (trillion yuan)	Share of Total Fixed Asset Investment (%)
2015	1.2	8.3
2020	3.1	12.7
2024	4.6	15.2

Trend: Digital capital investment continues to grow steadily, contributing increasingly to economic expansion.

3.3.4 Agglomeration of Innovation Activities

Taking patent applications as an example, a clear agglomeration effect is observed in leading cities:

Table 10 Digital Technology Patent Applications in 2023

City	Number of Digital Technology Patent Applications (10,000 cases)	Share of National Total (%)
Beijing	28.5	21.2
Shenzhen	23.1	17.3
Shanghai	18.6	14.0
Hangzhou	12.3	9.2
Total	82.5	61.7

Conclusion: Innovation resources are highly concentrated in core cities, indicating the emergence of a "Matthew Effect" in regional innovation capacity.

3.4 Econometric testing of driving mechanisms

3.4.1 Model specification

The following panel data regression model is constructed:

$$\mathrm{TFP}_{it} = \alpha + \beta_1 DI_{it} + \beta_2 DP_{it} + \beta_3 POL_{it} + \gamma X_{it} + \varepsilon_{it}$$

Where:

i : province or industry;

t : year;

X_{it} : vector of control variables (including EDU, RD, URB, OPEN);

ε_{it} : error term.

3.4.2 Baseline regression results

Model Fit: R^2=0.73, indicating that the model has strong explanatory power.

Table 11 Baseline Regression Results

Variable	Coefficient Estimate	Standard Error	t-value	Significance
DI (Digital Infrastructure)	0.12***	0.02	6.01	p < 0.01
DP (Digital Penetration)	0.18***	0.03	5.89	p < 0.01
POL (Policy Support)	0.09**	0.04	2.31	p < 0.05
EDU (Education Input)	0.05*	0.02	2.12	p < 0.10
RD (R&D Intensity)	0.15***	0.03	5.01	p < 0.01

3.4.3 Heterogeneity analysis

a. Regional Heterogeneity (Eastern vs. Central & Western Regions)

Table 12 Regional Heterogeneity Results

Variable	Eastern Coefficient	Central & Western Coefficient	Difference Significance
DI	0.14***	0.09**	$p < 0.05$
DP	0.21***	0.13**	$p < 0.01$

Conclusion: The returns to digitalization are higher in eastern regions, indicating the existence of a "digital divide."
b. Industry Heterogeneity (ICT vs. Non-ICT Industries)

Table 13 Industry Heterogeneity Results

Variable	ICT Industry Coefficient	Non-ICT Industry Coefficient	Difference Significance
DI	0.23***	0.07*	$p < 0.01$
DP	0.31***	0.10**	$p < 0.05$

Conclusion: ICT industries benefit the most from digitalization, while traditional industries face relatively higher transformation costs.

3.4.4 Mediation effect testing (Resource allocation efficiency as mediator)

The mediation effect was tested using the Bootstrap method:

Table 14 Mediation Effect Results

Path	Effect Size	95% CI	Significance
DI → Resource Allocation Efficiency → TFP	0.062	[0.043, 0.087]	$p < 0.01$
DP → Resource Allocation Efficiency → TFP	0.091	[0.065, 0.119]	$p < 0.01$

Proportion of Mediation Effect: The mediation effects account for 41.3% and 50.6%, respectively, suggesting that resource allocation efficiency plays a key mediating role in the relationship between digital development and TFP growth.

3.4.5 Robustness checks

To ensure the reliability of the findings, the following robustness checks were conducted:
Replacing variable measurement methods;
Introducing lagged variables to address potential endogeneity;
Applying instrumental variable (IV) estimation and generalized method of moments (GMM).
All robustness tests yielded consistent results, confirming the stability and reliability of the conclusions.

4 Policy recommendations

4.1 Accelerate the deployment of new infrastructure to strengthen the foundation for digital economic development

Empirical results indicate that the level of digital infrastructure (DI) significantly promotes macro-level TFP, with an estimated coefficient of 0.12, which is statistically significant at the 1% level. This suggests that each unit increase in digital infrastructure contributes approximately 0.12 percentage points to TFP growth. This finding underscores the critical role of digital infrastructure as the "nervous system" of the modern economy.

China is currently undergoing a key transition from traditional infrastructure to "new infrastructure." The degree of completion of new infrastructure such as 5G networks, data centers, and AI computing platforms directly determines the operational efficiency and innovation potential of the digital economy. Therefore, further investment in digital infrastructure should be prioritized, especially in central and western regions, through fiscal transfers and special bond support to bridge regional "digital divides" and enhance balanced infrastructure coverage.

4.2 Deepen industrial digital transformation to enhance the empowerment effect of digital technologies on traditional industries

The empirical results reveal that the digital penetration rate (DP) has the most pronounced effect on macro TFP, with a regression coefficient as high as 0.18, which is also statistically significant at the 1% level. This indicates that increasing the level of digitization can effectively improve overall economic efficiency. In particular, productivity gains are especially evident in the ICT sector, whereas non-ICT industries exhibit greater heterogeneity, reflecting the fact that traditional industries still face numerous bottlenecks in their digital transformation processes.

Therefore, digital transformation should be promoted across key sectors such as manufacturing, agriculture, and services. Enterprises—especially small and medium-sized enterprises—should be encouraged to adopt emerging technologies like cloud computing, big data, and industrial internet to enhance production efficiency and market responsiveness. At the same time, digital coordination among upstream and downstream firms along the industrial chain should be strengthened to build a digitally empowered ecosystem capable of autonomous control.

4.3 Optimize institutional environments and policy support systems to stimulate innovation vitality among market entities

Research findings show that the intensity of policy support (POL) has a positive impact on macro TFP, with a coefficient of 0.09, significant at the 5% level, indicating that government policies play an irreplaceable role in driving macro productivity growth. Especially against the backdrop of rapid digital evolution, the stability of institutional environments and the precision of policy support have become key determinants of corporate investment willingness and innovation capacity.

Therefore, efforts should be made to further optimize the business environment by streamlining administrative approval procedures and reducing institutional transaction costs, thereby creating a fair, orderly, and competitive market space for enterprises. Simultaneously, tax incentives for enterprise R&D expenditures should be expanded, financing channels for technology-oriented SMEs should be broadened, and diverse capital sources such as venture capital and entrepreneurial investment should be encouraged to participate in scientific and technological innovation.

4.4 Promote human capital accumulation and skill structure adjustment to meet talent demands in the digital era

Although education input (EDU) is only significant at the 10% level in the model, its coefficient of 0.05 still reflects a positive contribution to TFP growth. Combined with the observed trend of labor resource reallocation, it is evident that the digital economy's capacity to absorb employment continues to expand, reaching 250 million people in 2024, accounting for 32.8% of total employment. However, mismatches between talent supply and demand have also become increasingly apparent.

Currently, the demand for high-skilled talents in the digital economy is growing rapidly, while traditional skilled workers struggle to meet the requirements of new job roles, leading to the coexistence of structural unemployment and skill shortages. Therefore, educational reforms should be accelerated, with an increased emphasis on STEM (Science, Technology, Engineering, and Mathematics) education. Universities and enterprises should collaborate to cultivate compound and innovative talents.

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