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The Impact of the Digital Economy on Regional Economic Growth: Evidence of North–South Heterogeneity

Jing Wang[1,*]

[1] Applied Mathematics, School of Mathematical Science, University of Liverpool, Liverpool, United Kingdom

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ABSTRACT

The digital economy has become a core driver of economic growth; however, the regional heterogeneity of its economic effects has not been sufficiently examined. Using panel data from Hangzhou and Tianjin covering the period 2015–2024, this study investigates the impact of digital economy development on regional economic growth and explores potential north–south heterogeneity. A series of econometric models, including pooled ordinary least squares (OLS), individual fixed-effects models, and interaction term models, are employed. In addition, visualization analysis and robustness tests are conducted to ensure the reliability of the empirical results. The findings indicate that the digital economy exerts a significant positive effect on regional economic growth. This effect remains robust after controlling for city-specific fixed effects and demonstrates a short-term lagged growth effect. Furthermore, considerable north-south disparity is evident. Tianjin, in particular, experiences a notable immediate positive impact from the development of the digital economy, while Hangzhou displays a more substantial overall and delayed effect, implying that the digital economy's capacity to stimulate growth is more enduring in the southern region. The core findings are corroborated by robust checks, including the exclusion of the 2020 COVID-19 shock. Multicollinearity diagnostics also support the reliability of the estimated positive effects of the digital economy. This study provides dual-case empirical evidence on the heterogeneous regional growth effects of the digital economy and offers policy implications for designing differentiated digital economy development strategies and promoting balanced regional development between northern and southern China.

1. Introduction

Entering the new era, digital technologies represented by artificial intelligence, big data, and 5G have experienced rapid development. These technological advances have not only reshaped the allocation of global production factors but have also propelled the global economy into a critical stage of digital transformation. The emergence of the artificial intelligence era is injecting substantial momentum into economic development and generating significant economic value. According to

* *Corresponding author.*
E-mail address: Jing.Wang2403@student.xjtlu.edu.cn

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recent statistics, the digital economy has become a core pillar for stabilizing economic growth. In 2024, the digital economy worldwide hit a staggering USD 53.8 trillion. This represented a hefty 67.2% of the global GDP. The sector's year-on-year growth rate was a robust 8.1%. This was a significant leap, far outpacing the overall global GDP's 3.2% growth. Furthermore, the digital economy was responsible for over 65% of the world's economic expansion that year [1].

China's digital economy has experienced substantial growth. By 2024, it had achieved a value of RMB 58.9 trillion, representing 46.8% of the country's gross domestic product [2]. Furthermore, the digital economy's contribution to economic expansion surpassed 60%, thereby serving as a crucial element in stabilizing the macroeconomic environment and fostering enduring economic progress. Nevertheless, an examination of regional development patterns reveals considerable spatial disparities, both internationally and within China itself.

At the global level, the United Nations Conference on Trade and Development [3] pointed out that developed Western economies maintain a first-mover advantage in core digital technologies such as artificial intelligence and advanced semiconductor technology, enabling them to dominate the innovation and high value-added areas of the global digital economy. Their digital industrialization level exceeds 30% [4], and they dominate global digital trade. Conversely, digital infrastructure and fundamental technology capabilities remain limitations for developing economies.

While the effects of the digital economy on economic growth have been widely discussed, substantial gaps remain in the literature. Using a difference-in-differences framework, Aghion *et al.,* [5] analysed GDP data from 27 EU countries from 2018 to 2022 alongside national digital innovation policies. Their findings suggest that policies promoting digital research and development can significantly raise total factor productivity and support long-term economic growth. They further show that subsidies for innovation among small and medium-sized enterprises may amplify the spillover benefits of the digital economy for incumbent firms. Similarly, Goldfarb and Tucker (2022) [6] emphasise that coordinated regulation, when combined with interconnected national digital infrastructure, can stimulate GDP growth, reduce firms' digitalisation costs, and reinforce broader economic development. Although Han Jian *et al.,* [7] reach a broadly similar conclusion, they argue that the joint effects of integrated digital infrastructure and coordinated regulatory policies may be weaker than often assumed.

In sum, regional heterogeneity remains underexplored in the existing literature, which has largely concentrated on macro-level analyses at the national level. This limitation restricts the ability of existing research to provide precise policy guidance for regional development strategies. Therefore, the core question of this study is: What are the actual impacts of the digital economy on economic growth in different regions of China? Do these impacts exhibit significant regional heterogeneity?

2. Literature review

2.1 Macroeconomic growth effects: Penetration, substitution, and efficiency improvement

The digital economy is increasingly recognised as an important engine of global economic growth. From the perspective of technology penetration, Comin and Hobijn [8] developed a global technology diffusion model to analyse the spatial diffusion of digital technologies. Their findings suggest that a one-standard-deviation increase in the digital technology penetration rate in developed countries is associated with a 0.45 percentage-point increase in GDP growth in neighbouring developing economies. However, when the per capita GDP gap exceeds a ratio of 5:1, this positive effect declines sharply to 0.12 percentage points. Their study also shows that the global diffusion half-life of digital technologies, including the Internet and mobile communications, is approximately 6.8 years, which is substantially shorter than the 15.3-year diffusion cycle observed for traditional industrial technologies.

With regard to substitution effects, Hu Yongjun and Guan Lening (2025) [9] argue that the digital economy, through advances in automation and artificial intelligence, is increasingly generating structural shocks to employment by displacing conventional forms of labour. Between 2011 and 2020, the reduction of repetitive jobs in traditional manufacturing and service industries accounted for 23% of the total unemployment. Furthermore, this substitution effect shows a clear skill bias: the probability of low-skilled workers being replaced is as high as 38%, which is 3.2 times that of high-skilled workers. These findings highlight the potential for a “substitution gap” between different regions and labor groups. Moreover, Ni [10] performed an empirical analysis utilising panel data from 30 provinces in China, substantiating that the digital economy substantially fosters economic growth. In particular, the economic growth rate is projected to rise by 0.478% for each 1% increment in the digital economy development index. The study also points out that there are big differences between regions when it comes to the growth of the digital economy. The digital economy index in the western and northeastern regions is significantly lower than that in the eastern region, which has an average annual growth rate of 8% in its digital economy. These findings further highlight the persistent regional digital divide in China.

2.2 Regional heterogeneity: Evidence from cross-border and domestic studies

Regional heterogeneity is a key dimension for studying the economic effects of the digital economy. However, existing studies differ significantly in perspective and conclusion. Most of the research done in China is directed at differences between regions, especially between the east, central, and west, and between major urban areas. The Economic Research Center of Shanghai University of Finance and Economics [11] found that the digital economy had an effect on economic growth in the eastern, central, and western regions of China. The estimated coefficients were 0.518, 1.683, and 0.967, respectively. The central region exhibited the strongest marginal growth effect due to its “latecomer advantage,” while the western region, due to its relatively underdeveloped digital infrastructure, showed a weaker effect. At the urban cluster level, Mao Yanhua *et al.,* [12] analyzed the Yangtze River Delta, Beijing-Tianjin-Hebei, and Pearl River Delta urban clusters. Their findings indicate that the digital economy has a stronger impact on the rationalization of the manufacturing structure in the Pearl River Delta region than on industrial upgrading. Furthermore, cross-border digital economic cooperation, such as the integration of digital trade between Guangdong and Hong Kong, significantly improved regional economic performance. Institutional innovation, especially innovation related to “soft connectivity,” further amplified the spillover effects of the digital economy. By comparing the three major urban clusters in the Pearl River Delta, this study highlights how the institutional advantages of the Pearl River Delta region enhance the regional influence of digital economic development.

In contrast, international studies often emphasize differences between countries and regional digital divides. The World Bank [13] states that the internet penetration rate in high-income countries (92%) is almost four times that of low-income countries (23%). This shows that the global digital divide renders it significantly harder for developing economies to grow. Simione and Li [14] discovered that digital technology can confer significant advantages to latecomers. Their study of sub-Saharan Africa shows that for every 1% increase in internet penetration, per capita GDP increases by 0.37%, highlighting the huge growth potential of improved digital infrastructure in developing regions.

At the regional level, Wang and Lin [15] used a spatial econometric model based on a spatial weight matrix constructed from submarine cable connections. Their findings indicate the presence of a distance decay effect in the diffusion of digital technology. For example, the digital penetration efficiency of core EU city corridors (such as the Paris-Brussels-Amsterdam corridor) is 2.2 times that of peripheral regions. The digital spillover effect in Eastern Europe (0.36) was additionally significantly greater than the one in Southern Europe (0.20). The spillover effect between countries that are adjacent to each other was 3.8 times stronger than the one between countries that are not adjacent to each other.

While current studies validate that the digital economy can foster economic growth and demonstrate considerable regional diversity, certain research deficiencies persist. First, most international studies focus on cross-border comparisons, with less attention paid to multi-scale regional differences within a single country. Second, although domestic research has examined regional differences in eastern, central, and western China, as well as within urban agglomerations, it rarely explores the underlying mechanisms causing these differences, such as resource allocation efficiency and the distribution of digital infrastructure. Third, there remains a lack of long-term dynamic analyses examining how the digital divide influences regional economic convergence.

2.3 Literature review and research focus

A review of the existing literature provides an important foundation for this study in two main respects. First, prior research has theoretically confirmed the macroeconomic mechanisms through which the digital economy promotes economic growth, including channels such as technology penetration, substitution effects, and efficiency improvement. Second, empirical studies demonstrate that the economic effects of the digital economy display considerable regional variability, both among countries and within specific economies.

Despite these advances, some important research gaps remain. First, in terms of analytical scale, international research has primarily focused on cross-national comparisons. However, such analyses are often influenced by unobservable heterogeneity—such as institutional, cultural, and policy differences—which makes it difficult to accurately identify regional disparities within a single country caused by factors such as market segmentation and barriers to factor mobility. Although domestic studies have examined differences among the eastern, central, and western regions of China, as well as among major urban agglomerations, the identification of the core mechanisms underlying these differences remains insufficient. For example, the roles played by resource misallocation and the degree of market integration have not been systematically explored through comprehensive theoretical and empirical analysis. Secondly, regarding theoretical depth, current research on the distinctive benefits of the digital economy (specifically, its capacity to broaden market boundaries) frequently remains at a descriptive level, primarily concentrating on observable phenomena like the growth of e-commerce sales. These studies seldom incorporate this phenomenon with traditional economic frameworks, including transaction cost theory and the long tail theory, thereby constraining our comprehension of the conditions and parameters within which the digital economy exerts its economic impact across various regions. Third, with regard to dynamic evolution, current studies lack long-term tracking analyses examining how the digital divide influences the dynamic process of regional economic convergence or divergence.

To address these gaps, this paper uses provincial panel data from China and extends the existing literature in three aspects. First, this study develops a three-dimensional analytical framework that includes factor allocation efficiency, upgrading the industrial structure, and expanding the market. Second, it seems at how these mechanisms work differently in different regions with different types of infrastructure (including how developed the digital infrastructure is and how clustered the industries are), which allows one to find the root causes of regional differences. Third, this study offers empirical evidence for the formulation of digital economy policies designed to foster coordinated regional development through standardised econometric analysis.

2.4 Theoretical mechanisms and research hypotheses

2.4.1 The mechanism by which the digital economy promotes regional economic growth

Drawing on international literature and China's development experience, the digital economy is generally considered to influence regional economic growth through three main channels: improving the efficiency of factor allocation, promoting industrial upgrading, and expanding market boundaries. Due to differences in economic conditions and resource endowments, the effectiveness of these channels may vary from region to region. The specific mechanisms are described as follows.

(1) Improving Factor Allocation Efficiency

Data has increasingly become a new type of production factor. Due to its characteristics of replicability, scalability, and increasing marginal value, data can effectively alleviate the misallocation of traditional factors such as capital and labor [16]. Using provincial panel data from 2012–2018, Wang [17] employed a mediation effect model and found that the digital economy promotes both the rationalization and upgrading of industrial structures by improving the allocation efficiency of capital and labor. It is noteworthy that these impacts exhibit regional heterogeneity: the capital allocation effect is more pronounced in the eastern region, while the labor allocation effect plays a greater role in the central and western regions. These findings suggest that digital infrastructure and institutional frameworks should be improved based on local conditions to promote coordinated regional development.

(2) Optimization and upgrading of industrial structure

The digital economy also promotes industrial transformation through the process of "creative destruction." The combination of digital technology and traditional industries has led to new types of economic activity, including smart agriculture and intelligent manufacturing. This has made traditional industries more valuable [18]. On the other hand, digital technology has sped up the digital transformation of production and operation systems, made production more efficient overall, and increased the value creation of the whole industrial chain [19]. The digital economy encourages the transformation of industrial structure into a more advanced and logical form through these channels.

(3) Market Expansion and Transaction Cost Reduction

One of the most important things about the digital economy is that it can expand market boundaries and lower transaction costs, which is different from traditional economic models. Based on Coase's theory of the firm (1937) [20] and Anderson's long-tail theory [21], the platform-based and online nature of the digital economy significantly reduces cross-regional transaction costs and breaks geographical constraints on market activities. This mechanism is particularly valuable for regions with relatively underdeveloped markets, such as central and western China.

Specifically, this mechanism operates through three channels. First, digital platforms reduce intermediate trade links and significantly lower transaction costs. For instance, the costs of doing business the old-fashioned way typically consist of more than 30%, but with digital platforms, these costs can be decreased to less than 10%. In western China, Taobao sells RMB 40 billion worth of local speciality products every year [22]. Secondly, digital technology helps overcome geographical limitations. Applications such as remote work and online education enable talent in underdeveloped areas to provide services to enterprises in developed areas without actually relocating, thereby improving cross-regional resource allocation. Thirdly, the long tail effect enables digital platforms to activate niche markets. With zero marginal storage costs, almost unlimited shelf space, and algorithm-based recommendation systems, digital platforms reduce information search costs and match dispersed consumer demand, thereby expanding market boundaries and creating large-scale aggregated markets.

2.4.2 Research hypotheses under regional heterogeneity

Based on the theoretical mechanisms discussed above, this study proposes two testable research hypotheses.

First, through the synergistic interaction of factor allocation optimization, industrial structure upgrading, and market expansion, the digital economy can stimulate regional economic growth from multiple dimensions. Although short-term structural adjustments may occur due to the substitution effect, the long-term impact of the digital economy is expected to be dominated by improvements in total factor productivity. Accordingly, the following hypothesis is proposed:

H1: The development of the digital economy has a significant positive effect on regional economic growth in China.

Second, the strength of the above mechanisms is not uniform across regions but depends heavily on initial regional conditions, including resource endowment, digital infrastructure, and industrial structure. Specifically, the effectiveness of factor allocation efficiency improvements depends on the development level of local factor markets; the impact of industrial upgrading is conditioned by the existing industrial base; and the market expansion effect tends to be stronger in regions with relatively lower levels of marketization and heavier industrial structures. The empirical study by Liu *et al.,* [23] supports this view, showing that the impact of the digital economy on regional economic growth is stronger in the southern region (0.32) than in the northern region (0.18). Therefore, the growth effect of the digital economy is expected to show significant regional heterogeneity and be affected by regional basic conditions such as digital infrastructure, industrial agglomeration and market development level. Based on this, the following hypothesis is proposed:

H2: The impact of the digital economy on regional economic growth shows significant north-south heterogeneity, and this heterogeneity is moderated by regional characteristics such as digital infrastructure development, industrial agglomeration and marketization level.

3. Research design

3.1 Data source

The data used in this study primarily comes from the "China Statistical Yearbook", the "China Population and Employment Statistical Yearbook", and the annual statistical bulletins published by the Tianjin Municipal Bureau of Statistics and the Hangzhou Municipal Bureau of Statistics. In addition, supplementary data includes special statistical reports published by relevant government departments (including the Education Bureau and Finance Bureau) and information from other official sources.

The research period spans from 2020 to 2024, with Tianjin and Hangzhou designated as representative case cities. Tianjin is a traditional industrial city that is proceeding through a digital transformation. Hangzhou, on the other hand, is a model city for the growth of China's digital economy. The panel dataset created in this study comprises 120 observations, adequate for analysing the correlation between digital economy development and regional economic growth.

3.2 Variable definition and data processing

To guarantee the scientific rigour and robustness of the empirical analysis, this study develops an empirical model grounded in economic growth theory and existing empirical literature, while also taking into account data availability and continuity. Accordingly, the variables are categorized into explained variables, core explanatory variables, and control variables. The measurement methods, processing procedures, and selection rationale for each variable are described below.

(1) Explained Variable: Economic Growth Level

Following the common practice in the economic growth literature, the logarithm of real GDP per capita (ln(GDP_it)) is used to measure regional economic growth. To eliminate the impact of price fluctuations and improve comparability between years, nominal GDP per capita is deflated using 2015 as the base year to obtain real GDP per capita. The logarithmic transformation also helps reduce heteroscedasticity and allows the estimated coefficients to be interpreted as elasticity coefficients.

(2) Core explanatory variable: the level of development of the digital economy

The principal explanatory variable in this study is the degree of digital economy development (ln(DE_it)). It is very important to measure the digital economy correctly for empirical analysis. This study employs the measurement methodologies suggested by Huang *et al.,* [24] and Zhao *et al.,* [25], utilizing the number of broadband Internet access users as a proxy indicator for digital economy development.

This indicator effectively reflects the penetration of digital infrastructure and the adoption of digital technologies among residents, which are essential components of digital economy development. To further examine the dynamic effects of the digital economy on economic growth, the model also incorporates the lagged term of the digital economy variable, ln(DE_it−1).

(3) Control Variables

To mitigate potential bias from omitted variables, this study, based on economic growth theory and previous empirical research, included the following control variables:

i. Fixed Asset Investment Rate (ln(INV_it))

This variable is measured by the proportion of total social fixed asset investment to GDP, reflecting the contribution of physical capital accumulation to economic growth.

ii. Human Capital Level (ln(HUM_it))

Human capital level is measured by the proportion of the population aged 6 and above with a college degree or above, reflecting the region's human capital stock and innovation capacity.

iii. Government Intervention Level (ln(GOV_it))

This variable is measured by the proportion of local government general budget expenditure to GDP, reflecting the impact of government fiscal activities on resource allocation and economic development.

iv. Openness to the Outside World (ln(OPEN_it))

Openness to the outside world is measured by the proportion of total import and export volume to GDP, converted at the current exchange rate. This variable reflects the degree of a region's participation in the global economy and the role of international trade in promoting economic growth. All control variables in the regression model were logarithmically transformed to interpret the estimated coefficients as elasticity and to reduce potential heteroscedasticity.

3.3 Benchmark regression model specification

To empirically test the hypotheses proposed above (H1 and H2), this study adopts a stepwise empirical strategy consisting of benchmark analysis, core regression estimation, heterogeneity analysis, mechanism testing, and robustness checks. Based on this framework, this paper constructs a multilevel regression model system to systematically examine the relationship between digital economy development and regional economic growth.

3.3.1 Mixed OLS model

To preliminarily examine the overall relationship between the digital economy and economic growth, this study first estimates a mixed ordinary least squares (OLS) model as a benchmark reference. In this model, the panel dataset is treated as a mixed cross-sectional dataset, without explicitly controlling for potential unobserved heterogeneity between cities and over time.

The mixed OLS model provides a preliminary estimate of the average effect of digital economy development on sample economic growth. Although this method does not consider city characteristics or time effects, it serves as an important benchmark for comparison with more complex panel regression models (such as fixed effects and random effects models) estimated in subsequent analyses. The model is specified as follows in Eq. (1).

$$\ln(\mathrm{GDP_{it}}) = \alpha_0 + \alpha_1\ln(\mathrm{DE_{it}}) + \alpha_2\ln(\mathrm{DE_{it-1}}) + \sum_1^4\beta_k\ln(\mathrm{X_{kit}}) + \varepsilon_{it} \quad (1)$$

Where i represents the city (i=1 represents Tianjin, i=2 represents Hangzhou), and t represents the year. The explanatory variable ln(GDP_it) is the logarithmic form of GDP per capita, used to measure the level of regional economic growth. The core variables ln(DE_it) and ln(DE_(it-1)) are the logarithmic values of the current and lagged levels of digital economy development, respectively, with coefficients α_1 and α_2 measuring the current and lagged impacts of digital economy development, respectively. ln(X_kit) is the logarithmic value of the control variables (fixed asset investment rate, human resource level, government intervention level, and degree of openness to the outside world), covering other important factors affecting economic growth. β_k is the coefficient value for each control variable, used to determine the magnitude and direction of each variable's impact on GDP per capita. α_0 represents the basic starting point of the model, representing the initial level of economic growth when all variables are 0. ε_it is the random error term, used to represent other random factors included in the model and to absorb external disturbances.

3.3.2 Individual fixed effects model

To eliminate estimation bias caused by the inherent differences in endowments between Tianjin and Hangzhou, this paper constructs an individual fixed effects model as a core regression model to accurately identify the net effect of the digital economy on economic growth and to test research hypothesis H1 in Eq. (2).

$$\ln(\mathrm{GDP_{it}}) = \gamma_i + \alpha_1\ln(\mathrm{DE_{it}}) + \alpha_2\ln(\mathrm{DE_{it-1}}) + \sum_1^4\beta_k\ln(\mathrm{X_{kit}}) + \varepsilon_{it} \quad (2)$$

where, γ_i represents the fixed effect of individual cities, used to absorb and eliminate inherent characteristics at the city level that do not change over time, and to exclude the interference of non-observable factors such as geographical location, industrial structure, and development foundation on the estimation results, thereby more accurately identifying the net effect of the digital economy on economic growth. The definitions of the remaining contents are the same as above.

3.3.3 Fixed effects model with interaction term

To examine the regional differences in the impact of the digital economy on the North and South, this paper adds an interaction term between the digital economy and regional dummy variables to the core fixed effects model. This statistically tests whether regional heterogeneity is significant, thereby verifying the research hypothesis H2 in Eq. (3).

$$\ln(\mathrm{GDP_{it}}) = \gamma_i + \alpha_1\ln(\mathrm{DE_{it}}) + \delta_1(\ln(\mathrm{DE_{it}}) \times \mathrm{D_{NS,it}}) + \alpha_2\ln(\mathrm{DE_{it-1}}) + \delta_2(\ln(\mathrm{DE_{it-1}}) \times \mathrm{D_{NS,it}}) + \sum_1^4\beta_k\ln(\mathrm{X_{kit}}) + \varepsilon_{it} \quad (3)$$

where $D_{NS,it}$ represents the North-South dummy variable $D_{NS,it}$=0 represents Tianjin, and $D_{NS,it}$=1 represents Hangzhou), used to distinguish whether the model fits the characteristics of southern or northern cities. $\ln(DE_{it}) \times D_{NS,it}$ represents the interaction term between the digital economy and the dummy variable, used to capture whether there are significant differences in the impact of the digital economy on economic growth between the North and South, and to quantify the magnitude of this regional difference.

3.3.4 City-specific OLS model

To cross-validate the robustness of the North-South heterogeneity conclusion, OLS regression was performed on the subsamples of Hangzhou (South) and Tianjin (North). By directly comparing the magnitude and significance of the digital economy coefficients of the two cities, the regional differences are presented intuitively. The model is configured as follows in Eq. (4).

$$\ln(\mathrm{GDP_{it}}) = \alpha_0 + \alpha_1 \ln(\mathrm{DE_{it}}) + \alpha_2 \ln(\mathrm{DE_{it-1}}) + \sum_1^4 \beta_k \ln(\mathrm{X_{kit}}) + \varepsilon_{it} \quad (4)$$

Where i=1 represents Tianjin, i=2 represents Hangzhou, and the definitions of the other variables are the same as above.

3.3.5 Robust fixed effects model

To eliminate the interference of special events such as the 2020 pandemic on the empirical results, a robustness testing model was constructed. We removed the 2020 sample, re-estimated the individual fixed effects model, and tested the stability and reliability of the core conclusions. The model is specified as follows in Eq. (5).

$$\ln(\mathrm{GDP_{it}}) = \gamma_i + \alpha_1 \ln(\mathrm{DE_{it}}) + \alpha_2 \ln(\mathrm{DE_{it-1}}) + \sum_1^4 \beta_k \ln(\mathrm{X_{kit}}) + \varepsilon_{it} \quad (5)$$

The sample interval was adjusted to t=2015-2019, 2021-2024, and the definitions of other variables were the same as those in the core fixed effects model.

4. Empirical results and analysis

To comprehensively examine the impact of the digital economy on regional economic growth and its potential north–south heterogeneity, this study presents the empirical findings through a combination of quantitative regression results and visualization-based analysis. First, the core regression results—including estimated coefficients, standard errors, and statistical significance—are presented in the form of standardized regression tables, clearly quantifying the relationship between digital economy development and economic growth. Subsequently, a series of visualization tools are used to interpret the empirical results in depth. Specifically, the analysis unfolds across four key dimensions: descriptive statistics, baseline regression results, regional heterogeneity analysis, and model diagnostics and robustness tests. By integrating graphical methods such as correlation heatmaps, time-series trend comparisons, and coefficient distribution plots, the numerical information presented in the regression tables is transformed into more intuitive visual representations. This approach helps to more clearly understand the underlying relationships between variables and the empirical mechanisms driving regional economic growth.

4.1 Descriptive results

This section uses three visualization tools—correlation heatmaps, time-series trend plots, and box plots—to conduct a preliminary analysis of the statistical characteristics of the core variables. These graphical analyses explore the dataset from three complementary perspectives—variable associations, temporal dynamics, and regional distribution patterns—thus providing a solid empirical foundation for subsequent regression analysis. In particular, the descriptive analysis helps to preliminarily assess the potential relationship between digital economy development and economic growth, while also revealing regional disparities that may underpin north–south heterogeneity in the empirical results.

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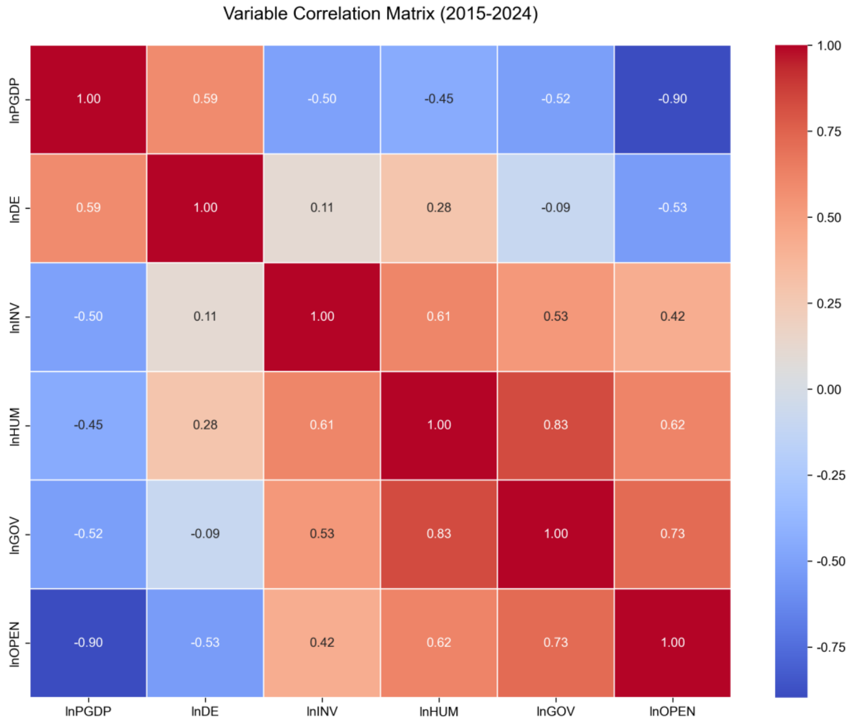

Fig. 1. Heatmap of the correlation matrix of variables

Figure 1 shows a heatmap of correlations among the core explanatory variables, control variables, and dependent variable. The correlation coefficient between the digital economy variable ln(DE_it) and GDP per capita ln(GDP_it) is 0.59, indicating a moderately strong positive correlation. This result preliminarily confirms the expected positive correlation between digital economy development and regional economic growth.

However, some of the control variables possess very high pairwise correlations. The correlation coefficients between human capital (ln(HUM_it)), government spending (ln(GOV_it)), and openness to the outside world (ln(OPEN_it)) specifically range from 0.73 to 0.83, indicating possible multicollinearity. Additionally, there is also a strong negative correlation of -0.90 between openness to the outside world and GDP per capita. These observations underscore the possibility of multicollinearity among certain explanatory variables, thereby validating the application of the variance inflation factor (VIF) test in forthcoming model diagnostics.

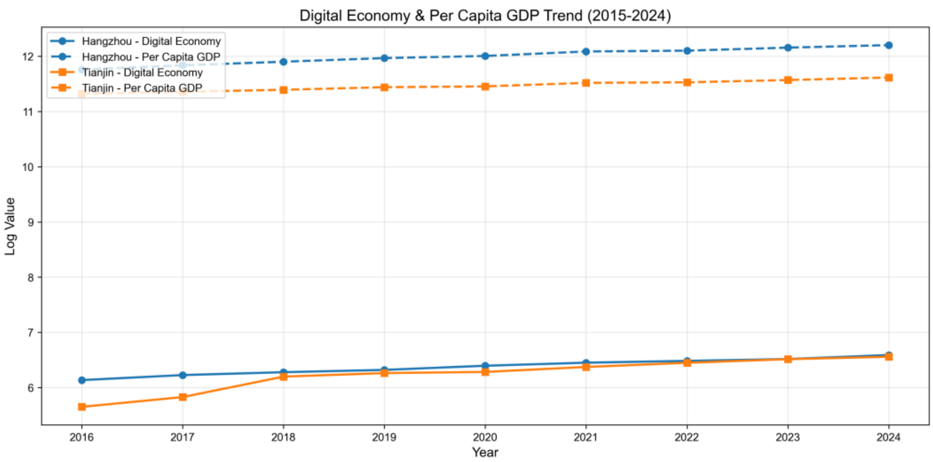

Fig. 2. Time series trends of digital economy and GDP per capita

Figure 2 shows how the digital economy level and GDP per capita in Tianjin and Hangzhou changed over time from 2015 to 2024. Both variables show a steady upward trend, which shows that digital infrastructure and the economy in the region have continued to become better over the course of the study. Hangzhou's digital economy level (ln(DE)) and GDP per capita (ln(GDP)) are consistently higher than Tianjin's. Hangzhou's digital economy index goes up by about 0.5 on a logarithmic scale, which is slightly higher than Tianjin's. The same corresponds to Hangzhou's GDP per capita growth, which is also greater. These simultaneous upward trends suggest a dynamic synergy between the advancement of the digital economy and overall economic growth, offering temporal validation for the positive correlation identified in the regression analysis. Moreover, the enduring disparity between the two cities underscores the structural distinctions in the developmental trajectories of the northern and southern regions, thereby offering an empirical foundation for subsequent regional heterogeneity analysis.

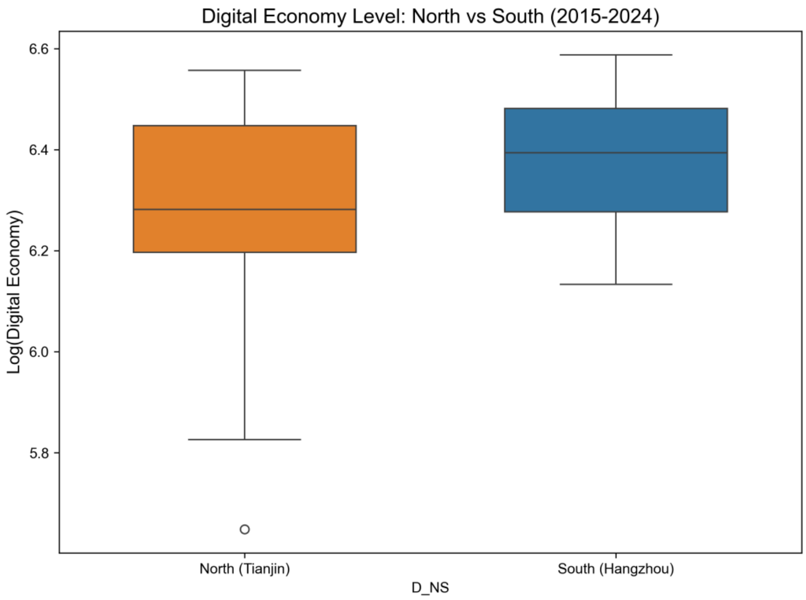

Fig. 3. Box plot of digital economy level in North and South China

Figure 3 presents the distribution of the digital economy variable $\ln(DE)$ for the two sample cities. The median, upper quartile, and lower quartile of Hangzhou (representing the southern region) are all substantially higher than those of Tianjin (representing the northern region). In contrast, Tianjin's digital economy level is more dispersed, with a wider interquartile range and several low-value outliers. These distribution characteristics indicate that southern cities, represented by Hangzhou, not only have a higher level of digital economy development but also a more stable digital development trajectory. This regional difference provides a structural explanation for the empirical results reported in the subsequent heterogeneity analysis, namely, that the digital economy has a stronger growth-promoting effect on Hangzhou than on Tianjin.

4.2 Visual analysis of benchmark regression results

Based on the descriptive analysis of variable characteristics and regional differences, this section will conduct a benchmark regression analysis. The quantitative results are initially presented in a standard regression table that shows the estimated coefficients, standard errors, and levels of statistical significance. To make it easier to understand, coefficient comparison plots and goodness-of-fit comparison plots are used to show the regression results in further detail. These charts demonstrate how significant and strong the estimated effects are in a visual way. These graphs add to the regression analysis table by showing the real-world results in a way that is easier to understand. Through this comprehensive analytical method, the benchmark regression analysis aims to verify the positive impact of digital economy development on regional economic growth and confirm the effectiveness of the selected core econometric model.

Table 1
Benchmark regression analysis

Variable name	Pooled OLS	Pooled OLS	Pooled OLS	FE	FE	FE
	coefficient	Standard error	Significance	coefficient	Standard error	Significance
$\ln(DE_{it})$	0.5607	0.3670	/	0.3217	0.0319	***
$\ln(DE_{it-1})$	-0.0117	0.1530	/	0.1085	0.0442	**
$\ln(INV_{it})$	-0.4878	0.1980	**	0.0916	0.0606	/
$\ln(HUM_{it})$	-1.3952	1.3410	/	-0.2748	0.0977	**
$\ln(GOV_{it})$	0.5240	0.4940	/	0.4111	0.0064	***
$\ln(OPEN_{it})$	-1.4217	0.4180	***	0.3076	0.1530	*
constant	16.3587	3.2170	***	5.2311	0.5043	***
N	/	/	18	/	/	18
R^2	/	/	0.9130	/	/	0.9788
Durbin-Watson statistic	/	/	0.813	/	/	1.98

Note: OLS-Ordinary Least Squares; FE-Fixed Effects; $\ln(DE_{it})$-Digital Economy; $\ln(DE_{it-1})$-The digital economy lags behind by one period; $\ln(INV_{it})$-Fixed asset investment rate; $\ln(HUM_{it})$-Human capital; $\ln(GOV_{it})$-Government spending scale; $\ln(OPEN_{it})$-Openness to the outside world; N-Sample size; R^2-Goodness of fit; ***-Significance level at 1%; **-Significance level at 5%; *-Significance level at 10%; /-No significance.

Table 1 reports the benchmark regression results. After controlling for city-specific fixed effects, the estimated coefficients of the digital economy variable $\ln(DE_{it})$ and its lagged term $\ln(DE_{i,t-1})$change substantially compared with the pooled OLS results. Specifically, in the mixed OLS model, the coefficients of both variables were insignificant (0.5607 and -0.0117, respectively); while in the fixed effects model, the coefficients of both variables became positive and statistically significant (0.3217 and 0.1085, respectively). This result shows that the positive impact of digital economy development on regional economic growth is more significant after adjusting for unobserved city-specific characteristics. Additionally, the lag coefficient indicates the presence of short-term dynamic effects in digital economy development. There are a number of significant changes with regard to the control variables. When unobserved heterogeneity is taken into account, the coefficients of the fixed asset investment rate and openness to the outside world change from negative to positive values, suggesting that their contributions to economic growth become more evident. In the meantime, government spending continues to have a significant positive impact across all model settings, while the negative impact of human capital has diminished. Regarding model performance, the fixed effects model's within-group R2 (0.9788) is much higher than the mixed OLS model's (0.913), suggesting that the fixed effects model has greater explanatory power and is better able to capture changes in economic growth.

Figure 4 visualizes the differences in estimated coefficients between the hybrid OLS model and the fixed effects model. The figure shows that, under the fixed effects model, the positive impact of digital economic development is more stable and statistically significant, indicating that the fixed effects model can effectively mitigate potential biases caused by unobserved city-specific characteristics. Figure 5 further compares the goodness-of-fit indices of the two models. The fixed-effects model demonstrates a noticeably higher R^2, confirming its superior explanatory performance relative to the pooled OLS model. Taking together, these results justify the selection of the fixed-effects model as the core benchmark specification in this study and provide a reliable empirical basis for the subsequent heterogeneity analysis.

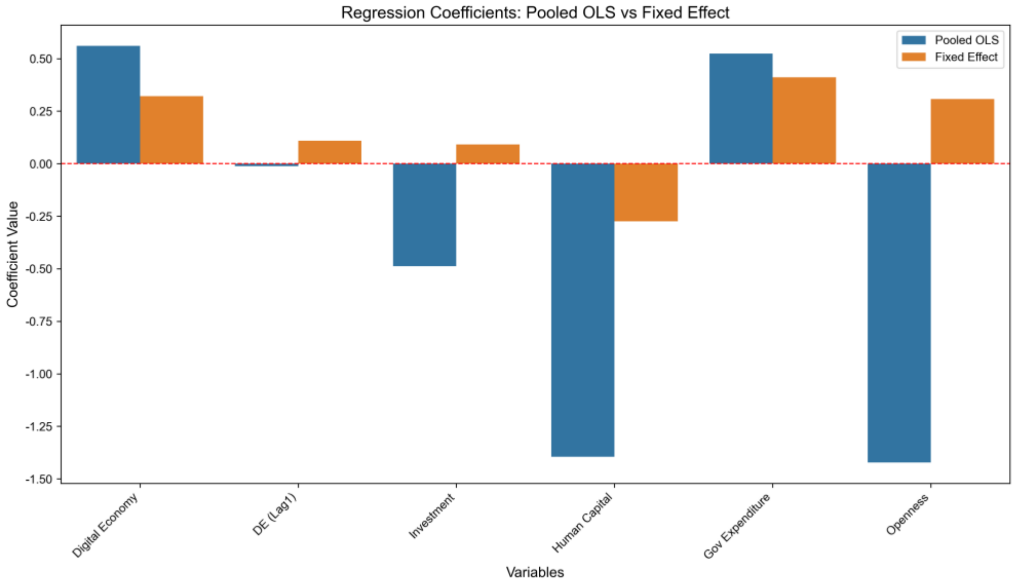

Fig. 4. Comparison of regression coefficients between mixed OLS and fixed effects models

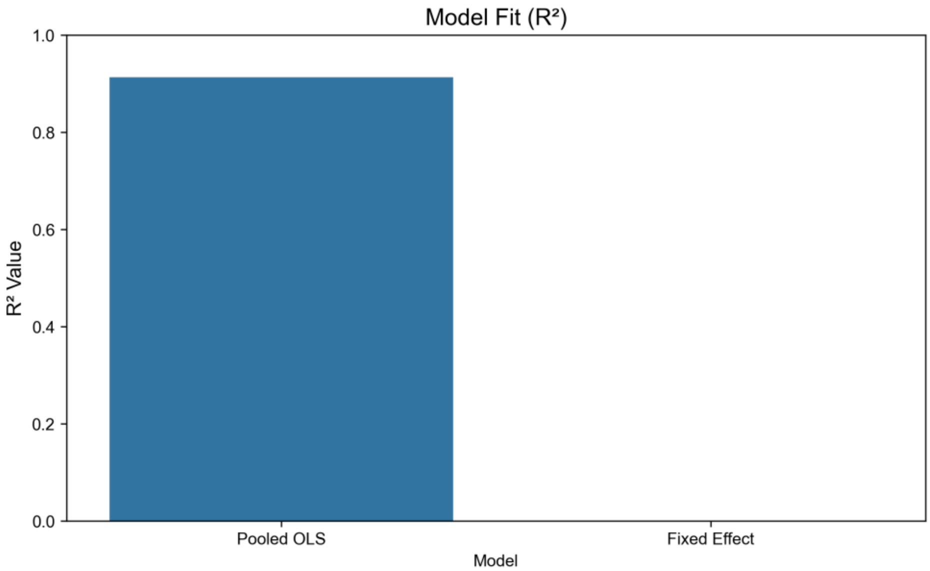

Fig. 5. Comparison of goodness of fit (R^2) between mixed OLS and fixed effects models

4.3 Visualization analysis of north-south heterogeneity results

The benchmark regression results above confirm that digital economy development exerts a significant positive effect on regional economic growth. To further investigate whether this effect varies across regions, this study conducts a north–south heterogeneity analysis. In particular, the quantitative findings of a regional heterogeneity regression model that assesses the varying effects of digital economic development on the northern and southern regions are first presented in this section. In order to visually interpret the empirical results, the analysis also uses visualisation techniques based on these regression results, such as a north-south coefficient comparison chart and a subsample coefficient comparison chart for Hangzhou and Tianjin. This section uses regression tables and visualisation comparison charts to show how the effects of digital economic development vary by region, emphasise how the impact of digital transformation differs in northern and southern cities, and clarify the regional transmission mechanism of digital economic development.

Table 2
Results of North-South Heterogeneity Regression

Variable name	Coefficient	Standard error	P-value	Significance
$\ln(\mathrm{DE_{it}})$	0.3198	0.0091	0.0000	***
$\ln(\mathrm{DE_{it}}) \times \mathrm{D_{NS,it}}$	0.1849	0.0879	0.0687	*
$\ln(\mathrm{DE_{it-1}})$	0.1315	0.0026	0.0000	***
$\ln(\mathrm{DE_{it-1}}) \times \mathrm{D_{NS,it}}$	0.6435	0.1453	0.0022	***
$\ln(\mathrm{INV_{it}})$	-0.1436	0.0252	0.0005	***
$\ln(\mathrm{HUM_{it}})$	-0.9684	0.0101	0.0000	***
$\ln(\mathrm{GOV_{it}})$	0.0856	0.0304	0.0226	**
$\ln(\mathrm{OPEN_{it}})$	-0.0672	0.0760	0.4022	/
Constant	9.8187	0.5570	0.0000	***
N	/	/	/	18
R2	/	/	/	0.9943

Note: $\ln(DE_{it})$-Digital Economy; $\ln(DE_{it}) \times D_{NS,it}$-Digital Economy × North-South Dummy Variables; $\ln(DE_{it-1})$-The digital economy lags behind by one period; $\ln(DE_{it-1}) \times D_{NS,it}$-Variables Lag by one period × North-South dummy variable; $\ln(INV_{it})$-Fixed asset investment rate; $\ln(HUM_{it})$-Human capital; $\ln(GOV_{it})$-Government spending scale; $\ln(OPEN_{it})$-Openness to the outside world; N-Sample size; R^2-Goodness of fit; ***-Significance level at 1%; **-Significance level at 5%; *-Significance level at 10%; /-No significance.

Table 2 lists the estimation results of the individual fixed effects interaction model. The results show that the growth effect of the digital economy exhibits significant regional heterogeneity between northern and southern China, particularly in terms of lag effects. The baseline coefficient of the digital economy variable for Tianjin, which is representative of the northern region, is 0.3198 and is statistically significant at the 1% level, suggesting that the development of the digital economy considerably boosts regional economic growth. The coefficient of the interaction term between the digital economy variable and the north–south dummy variable is 0.1849, which is significant at the 10% level. This result implies that the overall impact of the digital economy in Hangzhou, representing the southern region, reaches approximately 0.5047, suggesting that the growth-promoting effect of the digital economy is considerably stronger in southern cities. Regarding the dynamic lagged effects, the baseline coefficient of the one-period lagged digital economy variable for the northern region is 0.1315, which is statistically significant at the 1% level. In contrast, the interaction coefficient between the lagged digital economy variable and the north–south dummy variable is 0.6435, also significant at the 1% level. This finding indicates that the lagged growth-promoting effect of the digital economy in Hangzhou is substantially stronger than that in Tianjin, reflecting stronger persistence and spillover effects of digital development in the southern region. This model effectively accounts for time-invariant regional features and structural variations between the two cities by using an individual fixed effects framework. This method makes the possibility to identify the impact of the digital economy's regional heterogeneity more precisely. Overall, the estimation results demonstrate a high degree of statistical robustness and reliability.

Figure 6 compares the estimated values of the digital economy impact coefficients in the northern and southern regions in a visual manner. The figure shows that while Tianjin exhibits a significantly positive baseline effect, Hangzhou demonstrates a stronger overall impact, further confirming the presence of north–south heterogeneity in the growth effects of the digital economy. Figure 7 further illustrates the transmission dynamics of the digital economy's impact across the two cities. The results indicate that in Tianjin the digital economy exhibits both immediate and short-term lagged effects on economic growth. In contrast, Hangzhou's lag effect is much larger, indicating that the development of the digital economy in the southern region has a greater sustainability and cumulative growth effect.

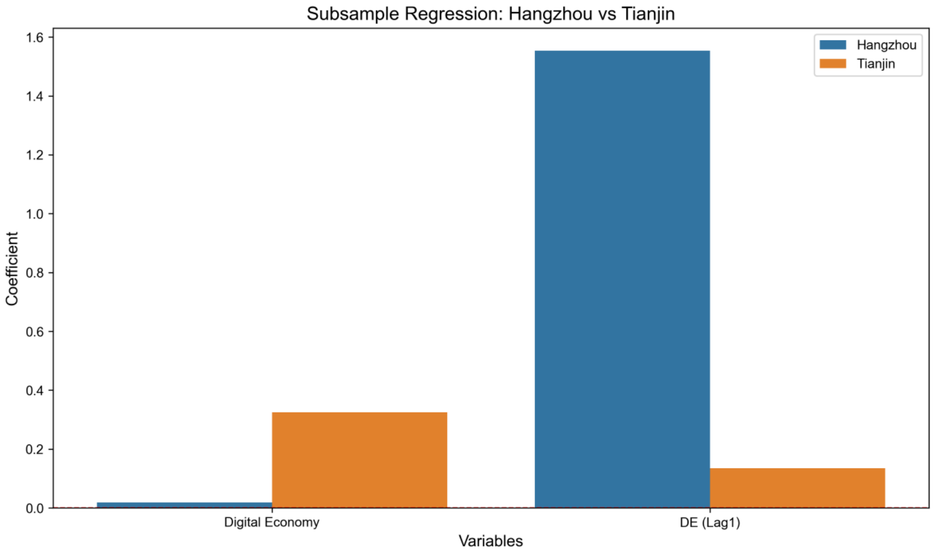

Fig. 6. Comparison of North-South Coefficients of the Impact of the Digital Economy

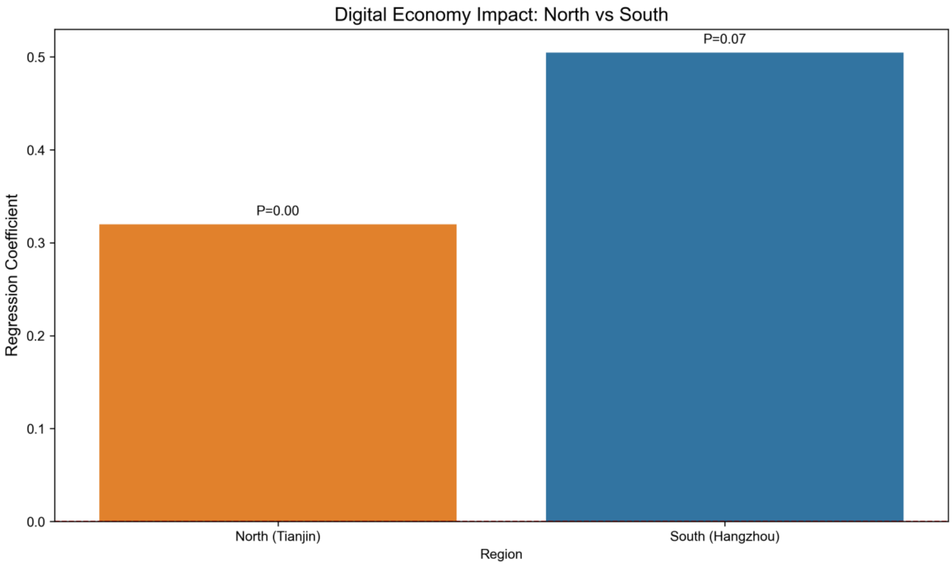

Fig. 7. Comparison of Digital Economy Impact Coefficients in Hangzhou Jinzi Sample

4.4 Model diagnosis and robustness visualization analysis

To ensure the reliability and stability of the empirical results, this study conducted a series of model diagnostics and robustness tests. First, after excluding samples affected by the 2020 pandemic (which could have led to abnormal fluctuations in economic indicators), robustness regression results were reported. The efficacy of the econometric model was then evaluated using a number of diagnostic techniques. In particular, the stability of the estimated coefficients under various model specifications was tested using a robustness coefficient comparison plot, and possible multicollinearity among explanatory variables was evaluated using the variance inflation factor (VIF) test. The robustness of the empirical results is confirmed, and the research conclusions are strengthened by the graphical results' strong agreement with the numerical results presented in the regression tables and diagnostic statistics.

Table 3
Robustness Test Regression Results (Excluding 2020 COVID-19 Samples)

Variable name	Coefficient	Standard error	P-value	Significance
$\ln(\mathrm{DE}_{\mathrm{it}})$	0.2308	0.0479	0.0013	***
$\ln(\mathrm{DE}_{\mathrm{it-1}})$	0.1032	0.0703	0.1803	/
$\ln(\mathrm{INV}_{\mathrm{it}})$	0.1338	0.0734	0.1059	/
$\ln(\mathrm{HUM}_{\mathrm{it}})$	-0.0332	0.1247	0.7966	/
$\ln(\mathrm{GOV}_{\mathrm{it}})$	0.3978	0.0134	0.0000	***
$\ln(\mathrm{OPEN}_{\mathrm{it}})$	0.0249	0.2186	0.9120	/
Constant	6.0026	0.7153	0.0000	***
N	/	/	/	16
R2	/	/	/	0.9821

Note: $\ln(DE_{it})$-Digital Economy; $\ln(DE_{it-1})$-The digital economy lags behind by one period; $\ln(INV_{it})$-Fixed asset investment rate; $\ln(HUM_{it})$-Human capital; $\ln(GOV_{it})$-Government spending scale; $\ln(OPEN_{it})$-Openness to the outside world; N-Sample size; R^2-Goodness of fit; ***-Significance level at 1%; **-Significance level at 5%; *-Significance level at 10%; /-No significance.

Further confirming the stability of the estimated relationship between digital economy development and regional economic growth, Table 3 presents the robustness test results after removing 2020, which was impacted by the pandemic. At the 1% significance level, the digital economy variable's coefficient, ln(DE_it), is still positive and statistically significant at 0.2308. The direction and statistical significance of this coefficient do not change, despite a slight decrease in absolute value when compared to the baseline regression, suggesting that the fundamental empirical conclusions are sound. After removing pandemic years, the coefficient of the lagged digital economy variable ln(DE_(i,t-1)) stays positive, but its statistical significance declines. The primary positive impact of the digital economy on economic growth is still statistically supported, so this modification possesses no significance on the study's main findings. Among the control variables, the scale of government spending still shows a significant positive impact on economic growth, while the signs and overall patterns of the remaining control variables are basically consistent with the baseline regression results. In addition, the degree of multicollinearity among explanatory variables is moderately alleviated in the robustness specification. The model goodness of fit was 0.9821 with a sample size of 16 observations, indicating strong explanatory power and supporting the validity of the empirical findings.

The variance inflation factor (VIF) test results are displayed in Figure 8, which shows that while there is some multicollinearity among the explanatory variables, the sign and statistical significance of the primary explanatory variables stay constant. Therefore, the validity of the empirical conclusions is not substantially affected. The regression coefficients from the full sample and the subsample that did not include the pandemic years are compared in Figure 9. The robustness of the empirical findings is confirmed by the results, which demonstrate that the digital economy's positive growth-promoting effect is still statistically significant.

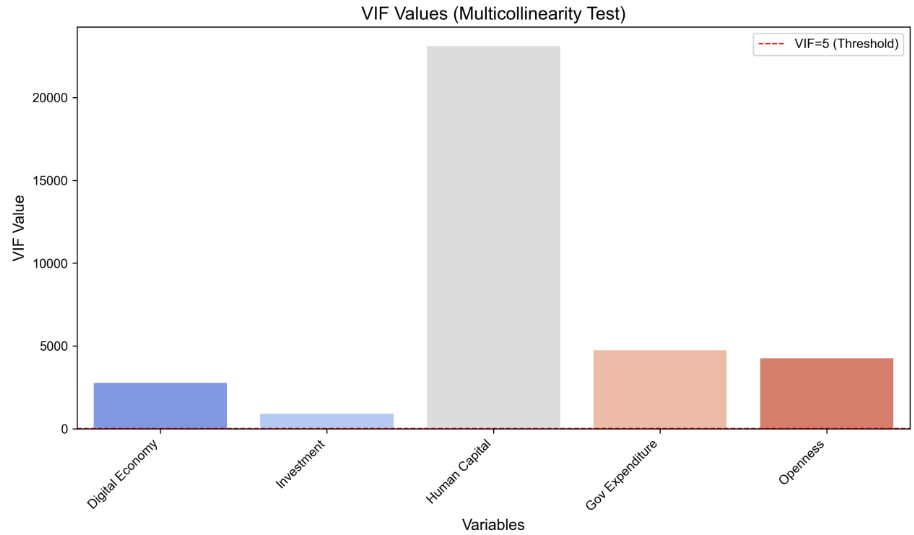

Fig. 8. Distribution of VIF values and multicollinearity test

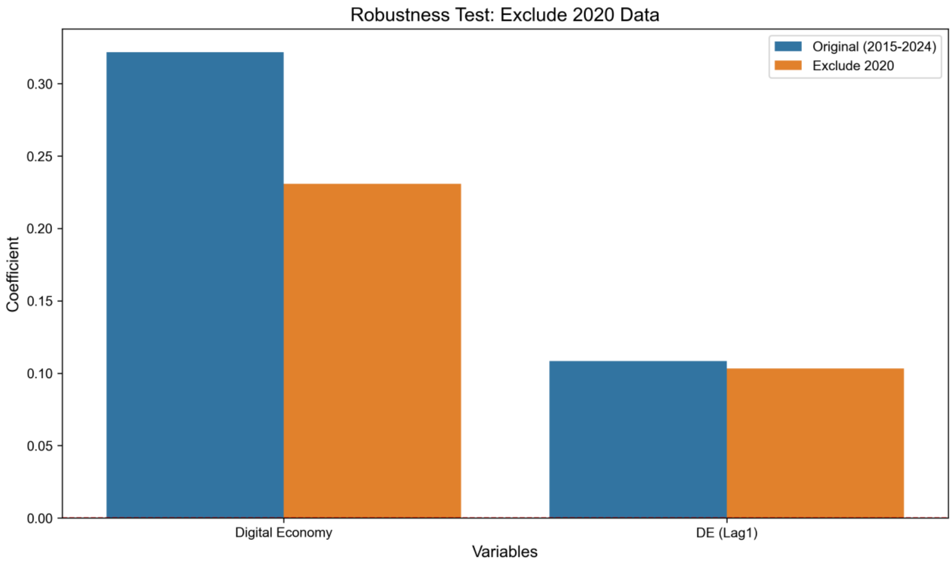

Fig. 9. Comparison of robust test coefficients after removing the 2020 COVID-19 sample

5. Conclusion and policy implications

5.1 Conclusions

Using panel data for Tianjin and Hangzhou from 2015 to 2024, this study constructs a multilevel econometric framework and integrates visualization analysis and robustness tests to empirically examine the impact of the digital economy on regional economic growth and its north–south heterogeneity. The main findings can be summarized as follows.

First, the digital economy exerts a significant and robust positive effect on regional economic growth. After controlling for city-specific fixed effects, the coefficients of the digital economy variable and its lagged term change from statistically insignificant to significantly positive, indicating that digital economy development has both direct growth-promoting effects and short-term dynamic spillover effects. Furthermore, the fixed effects model showed a significantly higher goodness of fit than the mixed OLS model, indicating stronger explanatory power. Secondly, the growth effect of the digital economy exhibited significant regional heterogeneity between the north and south, particularly in terms of lagged effects. Tianjin, a representative of northern cities, had a baseline coefficient for the digital economy of 0.3198, which was significant at the 1% significance level. This suggests that both direct and short-term lag effects of digital development contribute to economic growth. Hangzhou, on the other hand, had a greater lagged effect and a total growth effect of about 0.5047 as a representative of southern cities. This result implies that Hangzhou is experiencing a more long-lasting and cumulative economic impact from the digital economy. Thirdly, the empirical findings showed a high degree of robustness. The estimated coefficient for the digital economy only slightly decreased after the 2020 pandemic's effects were taken out, and it remained positive and statistically significant at the 1% significance level. Additionally, even though the model had some multicollinearity, this did not significantly alter the primary empirical findings or the sign or statistical significance of the key explanatory variables.

5.2 Policy suggestions

Based on empirical research findings and observed North-South differences, this study proposes differentiated policy recommendations to promote coordinated regional development of the digital economy. To expedite the digital transformation of traditional manufacturing, policymakers in the Northern region should make full use of the current industrial base. To support SMEs' digital transformation, the government can promote the creation of industrial digitalisation service platforms that are jointly run by businesses and public institutions. Additionally, enhancing industry-academia-research collaboration fosters the development of interdisciplinary talent with proficiency in both digital technology and manufacturing. The integration of digital technology with industrial production can be further encouraged by policy tools like targeted subsidies and tax incentives. To support industrial digitalisation, priority should be given to the deployment of specialised digital infrastructure, such as industrial computing centers and low-latency 5G networks. Policies should concentrate on developing new digital industries like artificial intelligence, digital trade, and data-driven services for the Southern region, which already has a solid foundation for the digital economy. The efficiency of digital economic activities can be further increased by creating regional data trading platforms and encouraging the market-based distribution of data resources. At the same time, targeted digital skills training should be conducted for different social groups (such as farmers, entrepreneurs, and technical professionals) to improve digital literacy and promote inclusive digital development. Furthermore, vigorous efforts should be made to promote the construction of green and energy-efficient data centers and 5G infrastructure to ensure the sustainable development of the digital economy. More generally, in order to encourage the cross-regional flow of talent, technology, and data resources, take advantage of complementary advantages, and promote a more balanced development of the digital economy, the northern and southern regions should set up cross-regional cooperation mechanisms using cities like Hangzhou and Tianjin as benchmarks.

5.3 Limitations and future recommendations

While this study has made contributions, it still has some limitations. First, the number of broadband internet users is the main proxy indicator used to measure the digital economy, which may not accurately reflect the multifaceted aspects of its growth. Second, only two representative cities—Hangzhou and Tianjin—are included in the empirical analysis, which results in a comparatively small sample size and may restrict how broadly the results can be applied. Third, the transmission channels through which the digital economy affects economic growth have not been empirically tested, so the analysis of possible mechanisms is still mainly conceptual. These shortcomings can be addressed in a number of ways by future research. For instance, researchers could create a multifaceted index of the digital economy that includes metrics for data resource utilisation, digital infrastructure, digital industry development, and digital innovation. A more thorough empirical analysis would also be made possible by extending the dataset to additional cities in both northern and southern China. The precise mechanisms by which the digital economy fosters regional economic growth, as well as the part played by regional infrastructure conditions and the institutional environment, could also be investigated using more rigorous econometric techniques, such as mediation effect models, moderating effect models, or spatial econometric techniques.

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Conflicts of Interest
The authors declare no conflicts of interest.

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