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The Digital Economy, Spatial Spillovers and New Qualitative Productivity--Empirical Study Based on the Yangtze River Delta Region

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Abstract: Drawing upon panel data from 41 prefecture-level cities in the Yangtze River Delta region spanning 2013 to 2022, this research employs a spatial Durbin model to examine how the digital economy affects new quality productivity. The results demonstrate that the digital economy substantially boosts local new quality productivity while simultaneously generating beneficial spillover effects for adjacent cities. Heterogeneity analysis indicates these positive impacts are particularly pronounced in both economically advanced areas and those receiving limited government financial support. Mechanism analysis further confirms that the digital economy drives new quality productivity growth and creates spatial spillovers through elevating regional innovation capacity. These findings elucidate the digital economy's operational mechanisms and practical impacts on new quality productivity enhancement, offering valuable insights for the Yangtze River Delta region to achieve high-quality development through digital economic advancement.

Keywords: digital economy, new quality productivity, spatial Durbin model, regional innovation level.

1. Introduction

With China's economic transition into a high-quality development phase, innovative productivity has emerged as a pivotal engine for overcoming the constraints of conventional growth paradigms [1]. New Quality Productivity (NQP) is fundamentally characterized by enhanced labor competency, breakthroughs in production technology, the diversification of labor inputs, and the synergistic evolution of these elements—collectively embodying cutting-edge innovation, superior efficiency, and exceptional output quality [2].

The exponential growth of the Digital Economy (DE) has created transformative opportunities for enhancing New Quality Productivity (NQP). Empirical data reveals that China's DE reached a staggering 53.9 trillion yuan in 2023, representing over two-fifths of the nation's GDP [3]. DE, with data, information, and knowledge as its core production factors, transcends the temporal and spatial constraints of traditional economic activities. By incorporating data elements into the production function system, it demonstrates exponential growth characteristics that enhance resource allocation efficiency [3] and boost productivity.

Academic discourse in recent years has increasingly focused on examining how DE advancements influence NQP development. Existing literature demonstrates that DE fundamentally

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aligns with NQP's growth requirements by facilitating optimal allocation of digital human capital, innovative technologies, and data resources[4]. Complementary research further establishes that DE expansion enhances total factor productivity through dual mechanisms: accelerating technological innovation and optimizing efficiency parameters [5]. Technological innovation and regional entrepreneurship also play significant mediating roles in the process of DE empowering NQP[6] .

Research suggests digital infrastructure and services enable cross-regional collaboration across development gradients, strengthening economic synergies [7]. Yet current literature primarily investigates DE's local NQP stimulation or measures spillover effects using regional indices [8], with scant spatial econometric analysis of DE's NQP influence or examination of its spatial mechanisms. Given the Yangtze River Delta's (YRD) pivotal role in national development, systematically examining DE's NQP impacts and economic implications in this region is crucial for maximizing DE's potential.

2. Theoretical analysis and research hypothesis

2.1. Analysis of the impact of the DE on NQR

DE develops NQP through data-driven technological innovation. Relying on technologies such as cloud computing, big data and artificial intelligence, DE promotes technological innovation in the productivity system, improves efficiency and gives rise to new business models [9]. New industries further lower the threshold of innovation and accelerate the diffusion of knowledge, forming a positive feedback loop of "technology-knowledge-innovation"[5].

DE restructures production factors, where data-traditional factor synergy enables nonlinear value creation. The introduction of data elements enables decision makers to access real-time market information, empowering precise decision-making and optimizing the efficiency of resource allocation [4], and its "non-competitive" characteristic breaks through the constraints of resource scarcity and promotes the productivity leap by relying on the incremental returns to scale [10].

DE fundamentally reshapes industrial chains through vertical integration (advancing smart transformation of conventional sectors) and horizontal expansion (transcending industrial boundaries to foster collaborative growth) [11], thereby crucially enabling NQP. This leads to our first hypothesis:

Hypothesis 1: DE positively influences regional NQP enhancement.

2.2. Analysis of spatial spillovers of the impact of the DE on NQP

A defining characteristic of DE lies in its pervasive nature, creating interregional spillovers via knowledge transfer, industrial interdependencies, and factor mobility. Firstly, DE reshapes industrial network structures, enabling digital resources from advanced regions to extend into adjacent areas [7], thereby enhancing operational efficiency across supply chains[12]. Secondly, leveraging data elements' fluidity and low transmission costs, DE mitigates information disparities through shared platforms, facilitates optimal distribution of capital and human resources, and expedites innovation dissemination across regions. This leads to our second hypothesis:

Hypothesis 2: DE has spatial spillover effects on the level of development of NQP in other neighboring cities.

2.3. Analysis of the mechanism of action of DE in influencing the level of regional NQP

DE empowers regional innovation through the two-way paths of digital industrialization and industrial digitization [13]. Digital industrialization directly promotes technological innovation by improving infrastructure and accelerating the deployment of digital technologies [14] while

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industrial digitization facilitates the technological upgrading of conventional industries through digital solutions and data assets to enhance R&D productivity [15]. The sharing characteristic of digital economy also strengthens the knowledge spillover effect and accelerates the diffusion of innovation factors among regions.

Technological advancement constitutes a fundamental pillar of NQP. Consequently, innovation capacity directly determines NQP's growth trajectory, which transcends conventional productivity's reliance on basic inputs (labor, capital, land) and transitions toward knowledge-driven factors (data, smart technologies), enabling qualitative productivity leaps. This leads to:

Hypothesis 3: DE accelerates NQP development in focal and adjacent urban areas through innovation diffusion, demonstrating both catalytic and spatial spillover effects.

3. Research design

3.1. Model building

Building upon prior findings [16], this study employs spatial econometrics to analyze DE's influence on NQP development. The spatial Durbin model (SDM) is initially adopted as the preferred specification, given its dual incorporation of SAR and SEM features, with final model selection contingent on diagnostic tests. The SDM specification follows:

$$\mathrm{Produ}_{it} = \alpha_0 + \rho \mathrm{WProdu}_{it} + \alpha_1 \mathrm{Die}_{it} + \beta X_{it} + \delta \mathrm{WDie}_{it} + \theta \mathrm{WX}_{it} + \mu_i + \lambda_t + \varepsilon_{it} \tag{1}$$

Where, i represents the city, t indicates the year, Produ reflects the city's new quality productivity level; Die corresponds to the degree of digital economy advancement; X stands for a group of control variables; W denotes the spatial weight matrix; μ_i and λ_t capture the fixed effects for city and time, respectively; and ε_{it} signifies a stochastic disturbance component.

Following the methodology outlined in prior literature [17], this study constructs a spatial weight matrix based on geographic distance, defined as follows:

$$W_{ij} = \begin{cases} \frac{1}{d_{ij}}, i \neq j \\ 0, i = j \end{cases} \tag{2}$$

Where, d_{ij} represents the separation between the geographic central points of the two cities.

3.2. Variable measurement

3.2.1. Dependent variable: extent of NQP (Produ)

Referencing prior research [18], this study formulates an indicator system encompassing two dimensions: physical components—including laborers, labor materials, and objects of labor—and permeable factors such as advanced technologies, organizational forms of production, and data-related elements. The entropy weighting method is utilized to determine indicator weights, thereby assessing the NQP level across prefecture-level cities within the YRD region. Owing to space limitations, the detailed structure of the specific indicators used to evaluate NQP is not included in this paper.

3.2.2. Key independent variable: degree of DE advancement (Die)

Drawing on the research methodology of existing literature [19], this paper identifies five indicators—including Internet penetration rate, employment in Internet-related sectors, Internet-driven production, mobile Internet user base, and the digital financial inclusion index—to

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develop a city-level DE evaluation framework (see Table 1). Principal component analysis is then employed to quantify the level of DE development across prefecture-level cities in the YRD region.

Table 1: Framework for constructing indicators of DE development

Target Layer	First-Level Indicators	Second-Level Indicators
Degree of DE development	Internet penetration	Internet users per 100 population
	Employment in Internet-related sectors	Proportion of employees in computer services and software
	Internet-related production	Per-capita telecom expenditure
	Mobile Internet user base	Mobile subscribers per 100 inhabitants
	Digital inclusive financial development	China's Digital Inclusive Finance Index

3.2.3. Mechanism variable: regional level of innovation (Ric)

In view of the complete collection of patent information in China and the comparability between regions, this paper adopts patent indicators to measure regional innovation levels. Furthermore, given the inherent latency between patent grants and their subsequent innovation impact, patent application volumes offer a more immediate, precise, and holistic measure of innovative activity. Consequently, this study adopts standardized patent application counts as a proxy for regional innovation capacity.

3.2.4. Control variable

To precisely isolate DE's true impact on NQP, this study refers to existing researches and controls for the following variables: (1) the tertiary-to-secondary industry output ratio for industrial structure (Ind), (2) regional higher education enrollment relative to household population for human capital level (Hc), (3) the urban population proportion for urbanization level (Urb), (4) regional import-export volume as a percentage of GDP for the level of openness (Tra), and (5) general government expenditure-to-GDP ratio for government intervention (Gov).

3.3. Data sources

This paper analyzes panel data covering 41 YRD prefecture-level cities (2013-2022), sourced primarily from from China Urban Statistical Yearbook, statistical yearbooks of provinces, National Bureau of Statistics, and annual reports of enterprises, etc., and missing values are addressed through interpolation. Variable summaries are presented in Table 2.

Table 2: Summary statistics of the measured variables

variant	sample size	average value	standard deviation	minimum value	maximum values
Produ	410	0.093	0.111	0.007	0.620
Die	410	0.6	0.078	0.477	0.877
Ric	410	27564.15	35697.6	902	228161
Ind	410	1.133	0.343	0.557	2.888
Hc	410	0.022	0.021	0.002	0.127
Urb	410	0.632	0.116	0.344	0.896
Tra	410	0.301	0.306	0.019	1.733
Gov	410	0.167	0.062	0.079	0.356

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4. Empirical findings and interpretation

4.1. Spatial autocorrelation examination

This study employs Moran's index to examine spatial dependence in NQP across YRD prefecture-level cities. Table 3 reveals significantly positive Moran's I values ($p<0.01$) throughout the study period, confirming strong regional spatial autocorrelation in NQP. These findings substantiate the necessity of spatial econometric modeling for analyzing DE's impact on NQP.

Table 3: Moran's index of NQP levels in cities

particular year	Moran's I	particular year	Moran's I
2013	0.369	2018	0.424
2014	0.365	2019	0.432
2015	0.378	2020	0.454
2016	0.382	2021	0.423
2017	0.420	2022	0.368

4.2. Regression results and analysis

Prior to spatial econometric estimation, Lagrange Multiplier (LM) tests verified the presence of both spatial lag and error terms (Table 4). The consistently significant LM statistics initially justified adopting the spatial Durbin model (SDM). Subsequent LR and Wald tests confirmed SDM's superiority over pure spatial lag or error specifications. Hausman test results further established fixed effects' dominance over random effects, leading to our final selection of a two-way fixed effect SDM for analysis.

Table 4: Results of diagnostic tests of spatial econometric models

diagnostic test	statistic	P-value
LM-error	150.699***	0.000
Robust LM-error	282.303***	0.000
LM-lag	10.470***	0.001
Robust LM-lag	142.074***	0.000
Hausman test	26.51***	0.0002

Note: ***, **, * indicate 1%, 5% and 10% significance levels, respectively. Same as below.

Table 5 presents the SDM estimation results. The analysis reveals three key findings: First, the spatial lag term coefficient demonstrates statistically significant positivity ($p<0.01$) when applying the geographic distance weight matrix W, providing robust evidence for the existence of spatial spillover effects in NQP. Second, DE exhibits a significantly positive regression coefficient, confirming its substantial role in promoting local NQP development. Third, and most notably, the spatial interaction term for DE reaches 0.793 with statistical significance, indicating that DE development not only enhances NQP within a given region but also generates positive spillover effects that benefit neighboring cities' NQP levels. These empirical findings collectively provide strong support for both Hypothesis 1 and Hypothesis 2.

Since the SDM incorporates spatial lags of explanatory variables, direct interpretation of coefficient estimates would yield biased spillover assessments. We therefore employ partial differential decomposition to distinguish direct, indirect, and total effects. As Table 5 demonstrates, DE’s both direct and indirect effects show statistically significant positive impacts ($p<0.01$),

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confirming its dual role in enhancing local NQP and generating cross-regional spillovers. Notably, indirect effects account for 86.78% of total effects under the distance weight matrix, revealing DE-driven spatial spillovers as a predominant force behind NQP advancement across the YRD region.

Table 5: Spatial Durbin model estimation results

variant	main effect	direct effect	indirect effect	total effect
Die	0.251*** (5.15)	0.3005*** (5.66)	1.970*** (3.84)	2.270*** (4.25)
W × Die	0.793*** (3.45)			
ρ	0.535*** (5.95)			
urban fixed effect	be	be	be	be
time fixed effect	be	be	be	be
observed value	410	410	410	410
R^2	0.180	0.180	0.180	0.180

Note: t-values are in parentheses. Same as below.

4.3. Robustness check

Given that variable measurement errors, special city samples, and model settings may cause bias in regression results, this paper conducts robustness tests by replacing variable measurement methods, excluding special samples, and replacing estimation methods to ensure the accuracy and reliability of the research findings. The regression models all use two-way fixed effects spatial Durbin model.

4.3.1. Substitution of variable measures

As column (1) of Table 6 demonstrates, the entropy weighting approach (substituted for principal component analysis) yields consistent regression outcomes with baseline results when measuring the DE's development level.

4.3.2. Excluding special sample cities

To address potential bias from Shanghai's outsized economic and digital advantages within the YRD's 41 cities, we conduct robustness checks by excluding this outlier. Column (2) of Table 6 confirms DE's persistent positive significance ($p<0.01$) in the trimmed sample, reinforcing our baseline findings' robustness.

4.3.3. Replacement of estimation methodology

As a robustness check, we substituted the SDM with a spatial autoregressive (SAR) specification. Table 6 column (3) reveals: (1) a positive, statistically significant spatial lag coefficient ($p<0.01$); and (2) persistently significant positive direct, indirect, and total effects of DE - aligning with prior findings. This consistency across model specifications confirms the robustness of DE's positive spatial spillovers on NQP.

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Table 6: Robustness test results

variant	(1) Entropy weight method to measure Die	(2) Excluding special sample cities	(3) Replace with SAR for estimation
Die	0.130***	0.227***	0.354***
	(5.2)	(5.02)	(7.18)
W × Die	0.360***	0.814***	
	(2.94)	(3.98)	
ρ	0.558***	0.631***	0.823***
	(6.38)	(8.13)	(18.11)
direct effect	0.155***	0.299***	0.405***
	(5.57)	(5.78)	(6.76)
indirect effect	0.968***	2.579***	1.779***
	(3.37)	(3.92)	(2.17)
aggregate effect	1.123***	2.878***	2.184***
	(3.75)	(4.21)	(2.56)
Other control variables	be	be	be
observed value	410	410	410
R^2	0.1673	0.0823	0.3231

4.4. Heterogeneity analysis

Given varying economic development stages and government financial support (GFS) across YRD cities - leading to divergent DE infrastructure costs and maturation - DE's NQP impacts likely exhibit regional heterogeneity. We therefore examine spatial variations through dual lenses: economic development tiers and GFS levels, employing two-way fixed effects SDM throughout.

4.4.1. Heterogeneity analysis based on level of economic development

This paper analyzes the heterogeneity of the sample cities by dividing them into the economically developed regions of Jiangsu, Zhejiang and Shanghai and the economically underdeveloped regions of Anhui Province. Table 7 presents the regression outcomes. Effect decomposition reveals significantly positive direct and indirect DE impacts on NQP in developed regions, confirming strong spatial spillovers. For less-developed areas, while both effects remain positive, neither achieves statistical significance. This primarily stems from Jiangsu, Zhejiang, and Shanghai's well-established Internet infrastructure. As a national pilot zone for digital economy innovation, these regions exhibit advanced DE development, enabling more precise assessment of market fluctuations and resource needs. Moreover, robust economic growth facilitates talent attraction and fosters digital-physical integration, creating synergistic effects across urban clusters that elevate NQP levels in nearby cities. In contrast, Anhui Province—compared to other YRD areas—faces delayed economic development, inadequate digital literacy among its workforce, and challenges in corporate digital transformation, hindering economies of scale. Furthermore, Anhui's urban clusters remain underdeveloped in YRD integration, characterized by limited bidirectional collaboration and constrained data element mobility.

4.4.2. Heterogeneity analysis based on the level of GFS

This paper conducts a heterogeneity analysis of sample cities based on GFS levels. Table 7 shows that regions with high GFS exhibit a DE coefficient of 0.126 (significant at 5%), whereas low-GFS

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areas demonstrate a stronger coefficient of 0.461 (significant at 1%). Effect decomposition reveals that DE's direct impact on NQP is significantly positive in high-GFS regions, while its indirect effect, though positive, lacks statistical significance. Conversely, both direct and indirect effects are strongly positive in low-GFS regions. This divergence may arise because DE, as an emerging economic model, remains market-driven. Excessive government intervention can disrupt market mechanisms that optimize factor allocation efficiency [20], potentially crowding out market-based innovation. Additionally, high-support regions risk developing policy dependence, impeding cross-regional flows of technology, knowledge, and data. In contrast, the market-oriented approach in low-support areas fosters greater technology diffusion and knowledge sharing.

Table 7: Heterogeneity test results

variant	(1) Level of economic development		(2) Level of GFS	
	developed area	less developed area	high level	low level
Die	0.324***	0.0468	0.126**	0.461***
	(4.35)	(0.81)	(2.09)	(5.60)
W × Die	0.648***	0.121	0.221	0.871***
	(1.84)	(0.45)	(0.65)	(2.76)
ρ	0.356***	0.0490	0.006	0.373***
	(3.39)	(0.19)	(0.02)	(3.60)
direct effect	0.366***	0.050	0.130**	0.519***
	(4.36)	(0.80)	(2.13)	(5.84)
indirect effect	1.177***	0.145	0.241	1.645***
	(2.10)	(0.41)	(0.60)	(3.11)
aggregate effect	1.543***	0.195	0.370	2.164***
	(2.55)	(0.5)	(0.88)	(3.83)
Other control variables	be	be	be	be
observed value	410	410	410	410
R^2	0.4635	0.6672	0.0915	0.4373

5. Mechanism testing and analysis

To examine the underlying mechanisms through which DE influences and generates spillover effects on cities' NQP, this study adopts a methodological approach aligned with prior research [21], employing a two-way fixed-effects spatial Durbin model for empirical analysis.

$$M_{it} = \alpha_0 + \rho WM_{it} + \alpha_1 Die_{it} + \beta X_{it} + \delta WDie_{it} + \theta WX_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (3)$$

Here, M represents the mechanism variable, which corresponds to regional innovation level (RIL) based on the preceding theoretical framework. Table 8 presents the mechanism test results, revealing significantly positive coefficients for both DE's direct effect on RIL and its spatial impact. This demonstrates DE's capacity to substantially enhance innovation capabilities in both local and adjacent cities. The findings indicate that DE elevates local NQP by boosting RIL while simultaneously generating beneficial spillover effects on neighboring cities' NQP development. Effect decomposition analysis confirms that DE's direct and indirect impacts on RIL are both statistically significant, providing empirical support for Hypothesis 3. These results collectively verify that DE facilitates NQP advancement in local and surrounding areas through RIL improvement, creating positive spatial spillovers.

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Table 8: Mechanism test results

variant	main effect	direct effect	indirect effect	aggregate effect
Die	3.349*** (3.98)	3.805*** (4.23)	19.209*** (2.71)	21.014*** (3.11)
W × Die	8.862** (2.24)			
ρ	0.471*** (4.87)			
Other control variables	be	be	be	be
observed value	410	410	410	410
R^2	0.3005	0.3005	0.3005	0.3005

6. Conclusion

Utilizing spatial econometric modeling with panel data from 41 YRD prefecture-level cities (2013-2022), this study examines DE's influence on NQP and its cross-regional diffusion effects. Three key findings emerge: (1) DE substantially enhances local NQP while generating beneficial spillovers to adjacent areas; (2) Heterogeneity analysis reveals stronger impacts in economically advanced regions and more pronounced effects in areas receiving limited financial support; (3) The research confirms that DE facilitates NQP advancement both within cities and their neighbors through regional innovation capacity building.

Based on the above findings, this paper makes the following policy recommendations:

Firstly, strengthen digital infrastructure in advanced economic regions while implementing tax incentive schemes to facilitate digital transformation of specialized sectors in less-developed cities. Simultaneously, avoid excessive government intervention in market mechanisms, and instead stimulate corporate innovation vitality through government guidance and market-driven approaches.

Secondly, focus on establishing a cross-regional collaborative development mechanism. Break down administrative barriers, establish an industrial ecological community and improve the "R&D-transformation-production" whole-chain synergistic network. Simultaneously, develop digital innovation consortiums to promote the sharing of digital resources and innovation outcomes, which will collectively enhance NQP across the YRD region.

Thirdly, strengthen the sci-tech innovation ecosystem. Focus on building a quintuple-helix innovation community integrating "government-industry-university-research-application" and establish digital innovation incubation platforms. Concurrently, Foster a culture that encourages innovation which thereby fully unleashes the innovation vitality of market entities.

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