Empirical Study on the Dynamic Interaction between China's Digital Industry Development and Economic Growth: Evidence from Panel Data Using the EWM-PVAR Approach

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Abstract:
This research explores the mutual influence between China's digital industry expansion and its economic growth, employing an EWM-PVAR model based on panel data analysis. The rapid growth of China's digital economy significantly impacts global resource allocation and reshapes industrial structures, driving national economic development. Utilizing datasets sourced from the National Bureau of Statistics of China and the China Urban Statistical Yearbook, the study evaluates digital industry development through eight indicators, including telecommunications volume, internet penetration, and IT sector employment. Analytical methods include the ADF unit root test, Johansen cointegration test, and Granger causality test to investigate the dynamics between digital industry development (LNDID) and economic growth (LNGDP). Results indicate a notable bidirectional causality between digital industry development and economic growth. Further analysis using impulse response functions demonstrates that the digital industry's short-term effect on economic growth is significantly positive, though this impact diminishes and ultimately reverses into a negative influence in the long run. Variance decomposition reveals a declining explanatory capacity of digital industry growth on overall economic performance over time, whereas the economic growth itself progressively gains a stronger explanatory role. The findings emphasize the interdependent relationship between digital industry development and economic growth, highlighting the necessity for coordinated strategies to achieve sustainable economic advancement.

Keywords: digital industry development, economic growth, interactive relationship, EWM-PVAR model

INTRODUCTION

As a highly dynamic segment of the contemporary global economy, the digital economy is rapidly transforming worldwide resource distribution patterns and industrial frameworks, exerting profound and extensive impacts. In the context of China, the digital economy has emerged as a pivotal engine propelling both economic development and societal advancement. China benefits from a substantial population of online consumers, providing it with notable competitive advantages, particularly in fields such as online retail and digital financial services. Nonetheless, the accelerated growth of the digital economy has simultaneously introduced significant challenges, including the widening digital gap and adverse environmental effects. Given the intricate interactions between these emerging issues and established economic structures, policymakers and researchers increasingly prioritize understanding and fostering positive synergies between digital economic innovation and sustainable growth.

Pfriemer (2017) examined the role of intelligent mobility within the digital economy, highlighting emerging trends, conceptual frameworks, and practical guidelines. The study emphasizes digital technologies' capacity to redefine mobility and connectivity[1]. Milošević et al. (2018) evaluated European countries' digital economy performances, identifying key strengths and weaknesses to guide policy formulation[2]. Jiang and Murmann (2022) detailed China's growing prominence in the digital economy, assessing its developmental trajectory, current achievements, and potential future directions, underscoring China's influential position globally[3].Tapscott (1999) addressed both opportunities and threats inherent in the digital economy era, stressing how network intelligence could drive substantial economic growth but also present significant risks[4]. Belk (2013) examined how digital technologies transform individuals' self-perception and self-expression, subsequently influencing consumer behavior and marketing strategies[5]. Shkarlet et al. (2020) analyzed shifts in business paradigms resulting from digitalization, proposing innovative strategies and models for adaptation to the new economic environment[6]. Purnomo et al. (2022) conducted a comprehensive review of 35 years of research on the digital economy, outlining historical developments and suggesting future research pathways[7]. Litvishko et al. (2020) investigated the digital economy's influence on banking, illustrating significant changes to business practices and efficiency driven by digital technologies[8]. Murthy et al. (2021) analyzed global disparities in digital economic development, specifically highlighting issues related to the digital divide across different nations and regions[9]. Li et al. (2021) explored the relationship between the digital economy and carbon emissions, presenting theoretical and empirical evidence suggesting that digital technologies promote carbon reduction through enhanced efficiency and innovation[10]. Xu et al. (2022) assessed regional differences in the impact of digital economic growth on environmental pollution, providing spatially contextualized evidence of varying environmental outcomes[11]. L'Hoest (2001) discussed policy-driven dimensions of Europe's digital economy, examining relevant European practices and policy responses[12]. Schmid (2001) identified fundamental transformations driven by the digital economy, arguing that these changes transcend mere technological advancements and reshape business models and social structures comprehensively[13]. Jiang (2020) explored the accelerating effect of the COVID-19 pandemic on digital economic growth and examined potential long-term implications and trajectories[14]. Miao (2021) introduced and analyzed the digital economy value chain concept, highlighting its significance as an analytical tool for understanding digital economic dynamics[15]. Vatamanescu et al. (2017) investigated shifts in market competition and consumer behavior resulting from digitalization, highlighting digital technologies' profound effect on competitive environments and consumer decision-making processes[16].

The digital economy represents a transformative economic phenomenon, significantly reshaping resource allocation, industry patterns, and broader societal dynamics. Its expanding interaction with economic growth is particularly evident in China, where it has become instrumental in fostering sustainable economic advancement and societal transformation. Recognizing the growing interdependence between digital industry development and broader economic performance, this study employs empirical analysis to investigate their mutual relationship within the Chinese context. Additionally, it proposes targeted policy recommendations designed to support theoretical understanding and practical guidance for policymakers to sustain robust and balanced economic growth.

DATA PROCESSING AND VARIABLE SELECTION

Data Selection

The data utilized in this research are primarily sourced from official statistics published by China's National Bureau of Statistics and the China Urban Statistical Yearbook, compiled and processed by the research team.

Considering the multifaceted nature of digital industry development, it is essential to integrate diverse indicators for accurate assessment. Drawing upon existing academic frameworks, this study evaluates China's digital industry through eight specific dimensions: total telecommunications business, per capita telecommunications activity, employment figures in information transmission and software services, percentage of employees in computer services and software sectors, broadband internet subscriptions, year-end mobile phone subscriptions, internet penetration per 100 inhabitants, and mobile phone subscriptions per 100 inhabitants. Detailed indicators and their measurement criteria are presented in Table 1.

Table 1. Indicators of China's digital industry development level

Primary Indicator	Secondary Indicator	Unit	Attribute	Code
China's Digital Industry Development	Total Telecom Business Volume	100 million yuan	Positive	DID1
	Per Capita Telecom Business Volume	10,000 yuan	Positive	DID2
	Employment in Information Transmission, Software, and IT Services in Urban Units	10,000 persons	Positive	DID3
	Proportion of Computer Services and Software Practitioners	%	Positive	DID4
	Broadband Internet Access Users	10,000 households	Positive	DID5
	Year-end Number of Mobile Phone Users	10,000 households	Positive	DID6

	Number of Internet Users per 100 People	units	Positive	DID7
	Number of Mobile Phone Users per 100 People	units	Positive	DID8

Data Processing

Based on the constructed indicator system, this study performs dimensionless processing on the secondary indicator data, determines the weights of each indicator through the entropy method, and calculates the comprehensive score to represent the development of the digital economy, as shown in Table 2.

Table 2. Calculation results of the weight of China's digital industry development

Entropy Method			
Item	Information Entropy Value (e)	Information Utility Value (d)	Weight (%)
DID1	0.887	0.113	20.1
DID2	0.886	0.114	20.264
DID3	0.901	0.099	17.676
DID4	0.918	0.082	14.538
DID5	0.941	0.059	10.569
DID6	0.956	0.044	7.826
DID7	0.971	0.029	5.206
DID8	0.979	0.021	3.821

As shown in Table 2, the entropy method's weight calculation results indicate that the weights are as follows: DID1 at 20.1%, DID2 at 20.264%, DID3 at 17.676%, DID4 at 14.538%, DID5 at 10.569%, DID6 at 7.826%, DID7 at 5.206%, and DID8 at 3.821%. Among these, the highest weight is for DID2 (20.264%) and the lowest is for DID8 (3.821%). Figure 1 presents the importance ranking of the indicators in the form of a histogram.

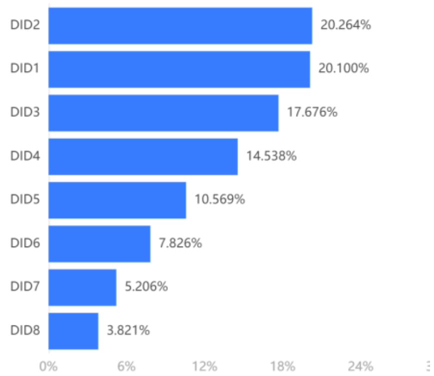

Figure 1. The importance of indicators for the development level of China's digital industry

Table 3. General description of LNDID and LNGDP data

Variable Name	LNDID	LNGDP
Mean	0.167991865	16.31774341
Median	0.128241951	18.60168781
Maximum	0.744102353	20.73347306
Minimum	0.008313582	7.399398083
Std. Dev.	0.123481613	4.069063595
Skewness	1.44463612	-0.907732868
Kurtosis	5.495256971	2.135524846
Jarque-Bera	207.0751119	57.44760406
Probability	1.08E-45	3.35E-13
Sum	57.28522604	5564.350501
Sum Sq. Dev.	5.184220994	5629.474705
Observations	341	341

This study selects DID to represent the comprehensive score of China's digital industry development level, as the independent variable representing the level of China's digital industry development. Meanwhile, GDP is selected to represent China's per capita gross domestic product, as the indicator of economic growth (dependent variable); to explore the interactive relationship between China's digital industry development and economic growth. To avoid heteroscedasticity, this study uses LNGDP and LNDID to represent the natural logarithms of the respective variables, as shown in Table 3.

EMPIRICAL TEST OF THE PVAR MODEL

Panel Data Adf Stationarity Test

The unit root test is commonly used to check whether a time series is stationary; if a unit root exists, it implies that the series is non-stationary. The stationarity of LNGDP and LNDID time series can be tested using the ADF unit root test.

From the results in Table 4: The value of the ADF - Fisher Chi-square statistic is 4.598945794, with a corresponding p-value (i.e., probability) of 0.33097575. This p-value is far above the commonly used significance level (e.g., 0.05), so we cannot reject the null hypothesis of the presence of a unit root, which means the time series is non-stationary.

The value of the ADF - Choi Z-stat statistic is -0.303033177, with a corresponding p-value of 0.380932289. Similarly, this p-value is also far above the commonly used significance level, indicating that we cannot reject the presence of a unit root. Based on the results of these two ADF tests, we cannot reject the null hypothesis that the time series has a unit root, meaning the series is non-stationary.

The ADF values for the first-order differenced series are 170.94472431 and 36.841361487, with corresponding p-values of 0.0000, both of which are less than the critical value at the 5% significance level, indicating stationarity. Therefore, a VAR model based on the first-order differenced variables is established.

Table 4. ADF Unit Root Test for Variables

Method	Variables	Statistic	Prob.**
ADF - Fisher Chi-square	LNGDP、LNDID	4.598945794	0.33097575
ADF - Choi Z-stat	LNGDP、LNDID	-0.303033177	0.380932289
ADF - Fisher Chi-square	D(LNGDP)、D(LNDID)	170.94472431	0.0000
ADF - Choi Z-stat	D(LNGDP)、D(LNDID)	36.841361487	0.0000

Panel Data Cointegration Test

The Johansen cointegration test is commonly used to determine whether a set of time series variables has a long-term stable relationship. From Table 5:

For the hypothesis of "None" (i.e., no cointegration relationship), the Trace statistic is 19.02320383, which exceeds the critical value of 15.49471288, and the p-value is 0.014069511, which is less than 0.05. Therefore, we reject the hypothesis of "no cointegration relationship."

Table 5. Johansen cointegration test results

Unrestricted Cointegration Rank Test (Trace)				
Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.** Critical Value
None *	0.054149392	19.02320383	15.49471288	0.014069511
At most 1	0.000945588	0.317867976	3.841465498	0.57289004
Trace test indicates 1 cointegrating equation(s) at the 0.05 level				
* denotes rejection of the hypothesis at the 0.05 level				
**MacKinnon-Haug-Michelis (1999) p-values				

For the hypothesis of "At most 1" (i.e., at most one cointegration relationship), the Trace statistic is 0.317867976, below the critical value of 3.841465498, and the p-value is 0.57289004, which is much greater than 0.05. Therefore, we cannot reject the hypothesis of "at most one cointegration relationship."

The results of the Trace test indicate the presence of one cointegration equation. This means that there is a long-term stable equilibrium relationship between the LNGDP and LNDID series in the examined time series data, allowing for the establishment of a PVAR model.

Model Identification and Construction

PVAR models with different lag orders, as shown in Table 6, when the lag order is 2, the FPE, AIC, SC, and HQ all reach their optimal values (marked by asterisks), indicating that according to these criteria, the optimal lag order for the model should be 2. Meanwhile, it is noted that the LR test also selects the model with a lag order of 2 (the LR value marked with an asterisk), further supporting the choice of a lag order of 2. Therefore, it can be concluded that the optimal lag order for this PVAR model is 2. We select the PVAR model with a lag order of 2 as the optimal model and establish the PVAR (2) model.

Table 6. Comparison of PVAR Models with Different Lag Orders

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-693.8189616	NA	0.207915	4.105127	4.127699	4.114122
1	-214.382025	950.3883	0.012581	1.300189	1.367906	1.327174
2	-177.0660156	73.53125*	0.010336*	1.103634*	1.216496*	1.148610*

* indicates lag order selected by the criterion

Table 7. Parameter estimation of PVAR (2) model

Parameter	LNDID	LNGDP
LNDID(-1)	0.251654047	-1.807290345
	0.057694235	0.723040672
	[4.36186]	[-2.49957]
LNDID(-2)	0.234482727	-2.497650665
	0.057329374	0.718468133
	[4.09010]	[-3.47636]
LNGDP(-1)	0.001603252	0.610608976
	0.004536486	0.05685254
	[0.35341]	[10.7402]
LNGDP(-2)	-0.010803983	0.294584927
	0.004571693	0.057293765
	[-2.36323]	[5.14166]
C	0.236990746	2.233921563
	0.03218119	0.403303888
	[7.36426]	[5.53905]
R-squared	0.414607342	0.915528569
Adj. R-squared	0.407596652	0.914516935
Sum sq. resids	3.021424582	474.5395057
S.E. equation	0.095111416	1.191963491
F-statistic	59.13930178	904.9998901
Log-likelihood	319.0658856	-538.0306004
Akaike AIC	-1.85289608	3.203720356
Schwarz SC	-1.7964654	3.260151036
Mean dependent	0.168084189	16.30354174
S.D. dependent	0.123573086	4.076832905

Table 7 presents the parameter estimation results of the PVAR (2) model. The R-squared and Adj. R-squared reflects the model's goodness of fit to the data. The R-squared of the LNDID equation is 0.4146, indicating the model explains approximately 41.46% of the variation in LNDID. The R-squared of the LNGDP equation is

0.9155, indicating the model explains approximately 91.55% of the variation in LNGDP. The F-statistic is used to test the overall significance of the model. The F-statistics for both equations indicate the model is statistically significant. The Akaike AIC and Schwarz SC are used for model selection, with smaller values being preferable. Based on the model parameter estimation results, the following equations can be established:

$$LNDID = C(1,1)*LNDID(-1) + C(1,2)*LNDID(-2) + C(1,3)*LNGDP(-1) + C(1,4)*LNGDP(-2) + C(1,5) \quad (1)$$

$$LNGDP = C(2,1)*LNDID(-1) + C(2,2)*LNDID(-2) + C(2,3)*LNGDP(-1) + C(2,4)*LNGDP(-2) + C(2,5) \quad (2)$$

Model Stability Test

In the stability test, the modulus of the eigenvalues is a crucial indicator. As shown in Figure 2, if the modulus of all eigenvalues is less than 1 (i.e., the absolute value is less than 1), then the time series can be considered stable. From Table 8, it can be seen that the modulus of the first root is 0.98912093, close to but less than 1. The modulus of the second root is 0.514317533, much less than 1. The modulus of the third root is 0.462146174, much less than 1. The modulus of the fourth root is 0.179029266, much less than 1. Since the modulus of all roots is less than 1, this indicates that the corresponding time series is stable, all characteristic indices are within the unit circle, and the PVAR model is stable.

Table 8. Results of Stability Tests

Root	Modulus
0.989121	0.98912093
0.514318	0.514317533
-0.462146	0.462146174
-0.179029	0.179029266

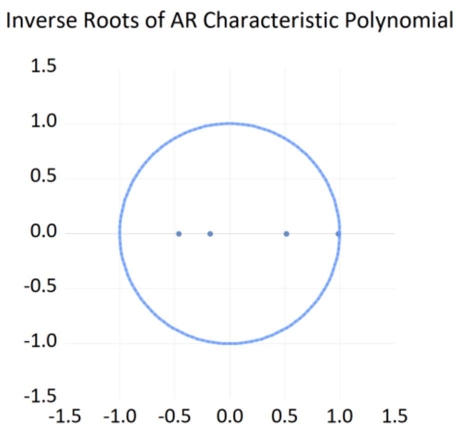

Figure 2. AR unit root stability test

Granger Causality Test

The Granger Causality Test is a statistical method used to determine whether one time series can help predict another time series. The core idea is: if past values of variable X can help predict future values of variable Y, then we can say that X is a Granger cause of Y.

As shown in Table 9, when LNDID is the dependent variable, excluding LNGDP leads to a significant Chi-square statistic (36.58) with 2 degrees of freedom and a corresponding p-value of 0.0000. This indicates that LNGDP has a significant Granger causal relationship with LNDID.

When LNGDP is the dependent variable, excluding LNDID also leads to a significant Chi-square statistic (36.34) with 2 degrees of freedom and a corresponding p-value of 0.0000. This indicates that LNDID also has a significant Granger causal relationship with LNGDP.

In short, there is a bidirectional Granger causal relationship between these two variables.

Table 9. Granger Causality Test

Dependent variable: LNDID			
Excluded	Chi-sq	df	Prob.
LNGDP	36.58023684	2	0.0000
All	36.58023684	2	0.0000
Dependent variable: LNGDP			
Excluded	Chi-sq	df	Prob.
LNDID	36.3385612	2	0.0000
All	36.3385612	2	0.0000

Impulse Response Function Analysis

Impulse Response Function (IRF) analysis is commonly used in time series analysis to illustrate the reaction of other variables in the model when one variable experiences a unit shock (or "impulse"). Figure 3 presents the reaction results of LNGDP to shocks in LNGDP and LNDID.

The response of LNGDP to its own shocks: In the 1st period, the response of LNGDP to its own shocks is 1.05338307, indicating that LNGDP significantly increases immediately when it experiences a positive shock. This significant initial positive response reflects the intrinsic momentum of economic growth and the self-reinforcing mechanism. In the 2nd period, the response value decreases to 0.643205158, indicating that the positive shock effect on LNGDP weakens in the short term. The 3rd period sees a slight increase in the response value to 0.700005395, showing some fluctuation. From the 4th period onwards, the response value gradually decreases and stabilizes, from 0.630626461 to 0.580929895 in the 10th period, indicating that the positive shock effect on LNGDP gradually weakens in the long term but remains positive.

The response of LNGDP to LNDID shocks: In the 1st period, the response of LNGDP to LNDID is 0.557818134, indicating that LNGDP increases immediately when it experiences a positive shock from LNDID. This shows that the development of the digital industry has a positive promoting effect on economic growth in the short term. However, from the 2nd period onwards, the response value decreases to 0.168714816, showing that the impact of LNDID shocks on LNGDP gradually weakens. From the 3rd period onwards, the response value turns negative (-0.015085604). It remains negative in subsequent periods, gradually increasing to -0.144765667 in the 10th period, indicating that the positive effect of LNDID shocks on LNGDP turns negative in the long term.

In summary, the response of LNGDP to its own shocks is initially strong and positive, then gradually weakens but remains positive. The response of LNGDP to LNDID shocks is initially significant and positive but gradually weakens and turns negative. These results indicate that LNGDP exhibits different dynamic response patterns when subjected to its own shocks and LNDID shocks, reflecting the complex interactive relationship between economic growth and the level of digital industry development.

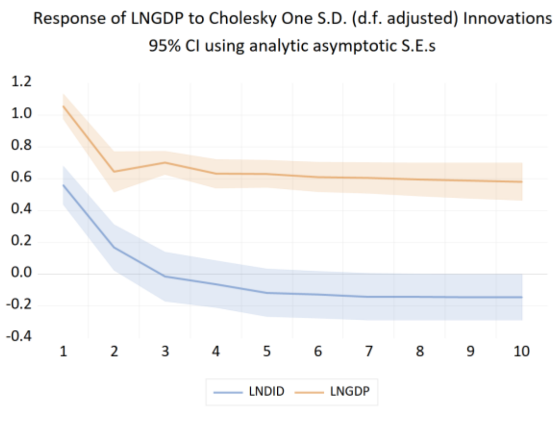

Figure 3. Response of LNNGDP to innovations

As shown in Figure 4, the responses of LNDID to shocks in LNGDP and LNDID can be observed.

The response of LNDID to its own shocks, in the 1st period, the response of LNDID to its own positive shock is 0.095111416, indicating that LNDID will increase significantly immediately when receiving a positive shock to itself. This significant initial positive response reflects the inherent momentum of digital industry development. In the 2nd period, the response value decreases to 0.024829496, indicating that the positive shock effect of LNDID significantly weakens in the short term. From the 3rd period onwards, the response value gradually decreases but remains positive, reaching 0.002867127 in the 10th period, indicating that the positive shock effect of LNDID tends to stabilize in the long term but remains positive.

The response of LNDID to shocks in LNGDP, in the 1st period, the response of LNDID to LNGDP is 0, indicating that LNDID is not directly affected by LNGDP in the 1st period. In the 2nd period, the response value is 0.001688839, showing that the influence of LNDID to LNGDP shocks begins to appear, but is very weak. From the 3rd period onwards, the response value turns negative (-0.009924509). It remains negative in the subsequent periods, gradually increasing in magnitude, reaching -0.010757651 in the 10th period, indicating that the positive effect of LNDID to LNGDP shocks turns negative in the long term.

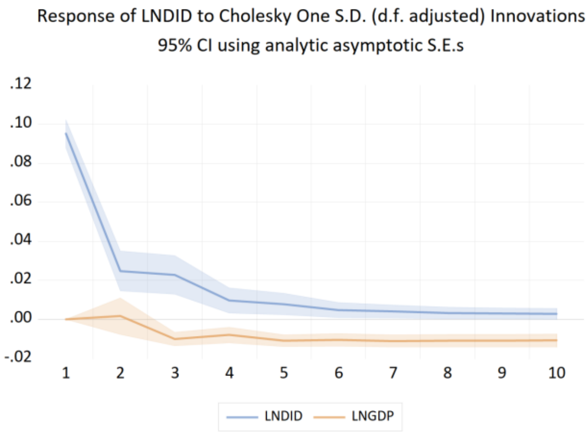

Figure 4. Response of LNDID to innovations

Variance Decomposition Analysis

Variance decomposition is a method that measures how much each variable contributes to prediction errors within a time-series framework. This approach helps identify the extent to which individual variables influence overall variations in the model's forecasts.

Table 10. Variance Decomposition of LNGDP

Period	S.E.	LNDID	LNGDP
1	0.095111416	21.90076826	78.09923174
2	0.098313465	18.2304911	81.7695089
3	0.101408144	14.44224157	85.55775843
4	0.102180148	12.47951529	87.52048471
5	0.103056639	11.29294622	88.70705378
6	0.103688408	10.5223073	89.4776927
7	0.104350537	9.999908438	90.00009156
8	0.104963008	9.608973224	90.39102678
9	0.105570458	9.306699117	90.69330088
10	0.106155872	9.060595299	90.9394047

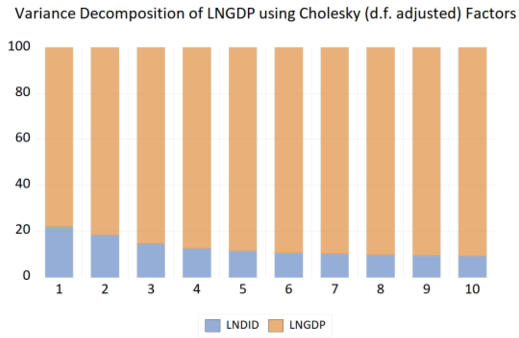

Figure 5. Analysis of variance decomposition LNGDP

According to Table 10 and Figure 5, in the 1st period, the variance contribution rate of LNDID to LNGDP is 21.90076826%, and the variance contribution rate of LNGDP itself is 78.09923174%. This indicates that in the short term, the development of the digital industry has an important explanatory power for economic growth, accounting for about 1/5 of the total variance.

In periods 2-5, the variance contribution rate of LNDID gradually decreases from 18.2304911% to 11.29294622%, while the variance contribution rate of LNGDP itself continuously increases from 81.7695089% to 88.70705378%. This suggests that with the passage of time, the explanatory power of digital industry development for economic growth gradually weakens, and economic growth is more dependent on its own factors.

In periods 6-10, the variance contribution rate of LNDID continues to decline from 10.5223073% to 9.060595299%, and the variance contribution rate of LNGDP itself further increases from 89.4776927% to 90.9394047%. This indicates that in the long run, the explanatory power of digital industry development for economic growth is very limited, and economic growth is more dependent on its own driving forces.

Table 11. Variance Decomposition of LNDID

Period	S.E.	LNDID	LNGDP
1	0.095111416	100	0
2	0.098313465	99.97049127	0.029508726
3	0.101408144	99.01447024	0.985529763
4	0.102180148	98.42724361	1.572756394
5	0.103056639	97.34051633	2.659483671
6	0.103688408	96.36715525	3.632844748
7	0.104350537	95.30208663	4.697913372
8	0.104963008	94.29225192	5.707748076
9	0.105570458	93.29578536	6.704214644
10	0.106155872	92.34258021	7.657419787

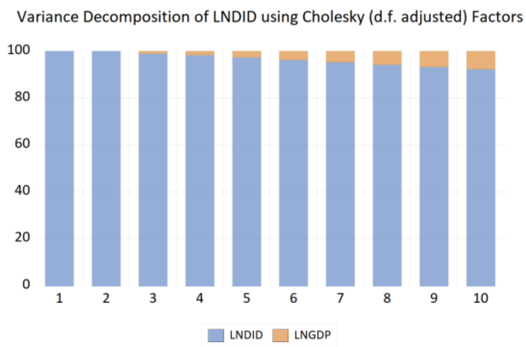

Figure 6. Analysis of variance decomposition LNDID

As shown in Table 11 and Figure 6, in the first period, the variance contribution rate of LNDID is 100%, and the variance contribution rate of LNGDP (China's economic growth) is 0%. This indicates that in the short term, the fluctuations in LNDID are determined entirely by its own factors, and are not affected by LNGDP.

In periods 2-5, the variance contribution rate of LNDID gradually decreases, from 99.97049127% to 97.34051633%. Meanwhile, the variance contribution rate of LNGDP continues to rise, from 0.029508726% to 2.659483671%. This suggests that with the passage of time, LNDID begins to be influenced by LNGDP, but the degree of influence is still relatively small.

In periods 6-10, the variance contribution rate of LNDID continues to decline, from 96.367155525% to 92.34258021%. The variance contribution rate of LNGDP further increases, from 3.632844748% to 7.657419787%. This indicates that in the long term, the fluctuations in LNDID are influenced not only by its own factors, but also by LNGDP, and there is a specific degree of mutual interaction between them.

In the short term, the fluctuations in LNDID are mainly determined by its own factors, and the impact of economic growth (LNGDP) on it is very small. Over time, LNDID begins to be influenced by LNGDP, and the interaction between them gradually strengthens. In the long run, the fluctuations in LNDID are influenced by both its own factors and LNGDP, and the exhibit a dynamic balance. This indicates that the development of the digital industry and economic growth are closely interdependent, and they should develop in coordination to jointly promote high-quality economic growth.

CONCLUSIONS AND RECOMMENDATIONS

Research Conclusions

This study employs the EWM-PVAR model based on panel data to analyze the interactions between China’s digital industry and economic growth. The key findings are summarized as follows:

Firstly, a significant bidirectional causality exists between the development of the digital industry and economic growth in China. Granger causality tests confirmed reciprocal influences between the digital industry (LNDID) and economic growth (LNGDP), highlighting their complex and interdependent relationship across different developmental stages. This relationship manifests not only in short-term impacts but also in long-term dynamics. Specifically, digital industry development significantly stimulates short-term economic expansion, while in the long term, digital industry growth and overall economic development increasingly align, jointly facilitating structural optimization and upgrading.

Secondly, impulse response analysis clarifies the dynamic interactions. When economic growth faces a self-generated shock, it demonstrates a strong initial positive reaction, which gradually diminishes yet remains positive over time. Conversely, when economic growth encounters a shock originating from the digital industry, an initial significant positive response gradually weakens and eventually turns negative. This indicates that while the digital industry initially drives economic growth positively, its long-term impact weakens or may even become adverse. Meanwhile, the digital industry's response to shocks from economic growth is relatively weak and predominantly negative in the long run, suggesting that economic growth directly exerts limited influence on the digital industry.

Further, variance decomposition reinforces these insights. Initially, digital industry development considerably contributes to fluctuations in economic growth, emphasizing its substantial short-term influence. Over time, however, this impact decreases, with economic growth itself increasingly explaining its fluctuations. In the long term, economic fluctuations primarily depend on inherent factors, with the digital industry maintaining a reduced yet still notable role. These results underscore the evolving nature of the interactive relationship over different time horizons.

In conclusion, the interaction between China’s digital industry and economic growth is mutually reinforcing. Although digital industry development initially drives economic growth significantly, this impact gradually diminishes as the economy matures, with growth becoming more dependent on intrinsic mechanisms. Policymakers should thus carefully consider these dynamic interactions when formulating strategies to ensure sustainable and balanced economic development.

Policy Recommendations

Drawing on the empirical findings regarding interactions between China's digital industry and economic growth, the following policy suggestions are proposed:

Strengthen infrastructure and technological innovation

Accelerate investments in advanced digital infrastructure, including the deployment of 5G networks, Internet of Things (IoT), and big data centers. Intensify support for research, development, and practical application of critical technologies such as artificial intelligence and blockchain. Additionally, efforts should be directed toward enhancing the efficiency of information transmission and facilitating the secure and efficient flow and sharing of data, thus establishing a robust foundation to accelerate digital industry growth.

Promote industrial digital transformation

Implement targeted initiatives to drive digitalization across traditional sectors, including financial incentives and technical assistance for enterprises adopting digital solutions. Encourage widespread use of emerging technologies such as cloud computing and big data analytics to optimize operational processes. Such measures aim to boost overall industrial productivity, decrease operational costs, and significantly enhance enterprises' global competitiveness.

Optimize digital governance and regulation

Establish a regulatory framework that adapts to the digital economy, adopting flexible approaches such as sandbox regulation and tiered management to protect consumer rights and prevent systemic risks. Promote innovation and compliance in parallel, maintain market order, and enhance public trust in the digital economy.

Strengthen digital talent cultivation

Enhance digital skills education, promote school-enterprise cooperation, and provide lifelong learning opportunities, especially increasing investment in remote areas. Alleviate the digital skills gap, improve digital literacy for all, and promote employment and entrepreneurship.

Promote green digital development

Establish clear standards for sustainable growth within the digital economy, promoting eco-friendly practices such as the establishment of energy-efficient data centers. Encourage initiatives aligned with the circular economy, introduce systems for monitoring carbon emissions, and actively minimize the ecological footprint of digitalization. These measures aim to foster a green, low-carbon transition within the broader economic system.

Support SMEs and innovation ecosystem

Establish special funds to support the digital transformation of startups and small and micro enterprises, build open innovation platforms, and promote industry-university-research cooperation. Stimulate market vitality, promote the deep integration of innovation and industrial chains, and foster emerging business models.

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