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DIGITALIZATION AND AGRICULTURAL ECONOMIC RESILIENCE: A SYSTEMATIC EXAMINATION USING CHINESE CITY-LEVEL PANEL DATA

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Abstract

As digital technologies increasingly enter the agricultural sector, the digital economy has become closely linked to agricultural economic resilience. Using city-level panel data for 284 prefecture-level cities in China from 2011 to 2022, this study constructs composite indices of agricultural economic resilience and digital economy development and applies a fixed-effects model to examine their relationship. The results show that digital economy development is positively associated with agricultural economic resilience. This association remains broadly stable across alternative index construction methods and sample adjustments. Heterogeneity analysis further suggests that the relationship differs across regions and stages of digital development. The positive association is statistically significant in eastern and central China, but not in western China. The stage-based results suggest that the positive association between digital economy development and agricultural economic resilience is mainly observed in cities with low levels of digital development. In the medium- and high-digitalization groups, the estimated coefficients are statistically insignificant. This pattern is consistent with the possibility of diminishing marginal returns to digitalization. However, the coefficient in the low-digitalization group is significant only at the 10% level, and formal coefficient-difference tests are not reported. Therefore, the stage heterogeneity result should be interpreted as suggestive rather than conclusive.

Keywords: Digital Economy, Agricultural Economic Resilience, Regional Heterogeneity, City-level Panel Data, China

1. Introduction

In recent years, intensified climate change and frequent extreme weather events have placed continuous pressure on China's agricultural production. In recent years, climate change and frequent extreme weather events have placed continuous pressure on China's agricultural production. At the same time, fluctuations in agricultural product prices and changes in the international supply and demand pattern have also exacerbated the uncertainty of agricultural economic operations to some extent.

Under these realities, the development of the agricultural economy no longer depends solely on natural endowments or output scale, but is increasingly influenced by the combined effects of market mechanisms and external shocks. How to maintain the basic operation and functional continuity of the agricultural system in an environment of frequent shocks has gradually become a core issue of concern for academia and policymakers. Around this issue, the concept of "agricultural economic resilience" has begun to enter the analytical field, used to explain the agricultural system's ability to withstand, recover from, and adapt to risk shocks.

Meanwhile, the rapid development of the digital economy is profoundly changing the traditional economic operating mechanisms. Digital technologies have reshaped market matching mechanisms and platform organizational structures by reducing information acquisition and forecasting costs (Agrawal et al. 2018; Goldfarb & Tucker. 2019). and improved productivity and resource allocation efficiency through data-driven decision-making and intangible capital accumulation mechanisms Brynjolfsson et al., (2021).

In agriculture, the expansion of digital infrastructure and platforms is accelerating agricultural market integration and supply chain restructuring Reardon et al., (2019). More recently, a new generation of digital agricultural automation technologies has emerged, with the potential to further enhance productivity and resilience, while also addressing the environmental sustainability challenges driven by past mechanization FAO. (2022). It is evident that the digital economy may enhance the adaptability and resilience of agricultural systems-that is, agricultural economic resilience-by improving information symmetry, promoting income diversification, and strengthening risk management mechanisms.

However, the impact of the digital economy on agricultural economic resilience may not be a one-way positive relationship. Existing research indicates that while agricultural digitalization improves

information acquisition efficiency and supply chain coordination, it may also strengthen reliance on digital platforms and data systems, thereby introducing new structural risks. Zscheischler et al., (2022). based on interdisciplinary research, pointed out that agricultural production systems, after becoming highly dependent on digital data and intelligent platforms, may face potential vulnerabilities such as data security, technological failures, and imperfect governance structures.

Furthermore, while increased market integration helps optimize resource allocation and expand market reach, it may also accelerate the transmission and spread of price shocks across regions Bekoe et al., (2023). In a highly interconnected market system, external shocks are rapidly transmitted through price mechanisms, potentially increasing the sensitivity of agricultural systems to global market fluctuations. Uneven distribution of digital infrastructure and digital skills in rural areas may exacerbate regional development disparities and have differentiated impacts on the adaptability of small and medium-sized agricultural operators Morris et al., (2022). Therefore, theoretically, the impact of the digital economy on agricultural economic resilience is not a one-way promotion, but may exhibit characteristics such as stages, regional heterogeneity, and nonlinearity. Its marginal effect depends on the degree of matching between digital infrastructure and the institutional environment.

Although research on digital agriculture has increased, existing studies mainly focus on specific technological applications rather than the broader digital economy system. For instance, previous studies have examined drone-based data collection and wireless network applications in agriculture Ballestrin et al., (2026). the development trends of precision agriculture and digital agriculture Niedbała et al., (2023). and blockchain-based traceability systems for agricultural products Pang et al., (2024). While these studies help explain how individual technologies are applied in agriculture, they do not fully address how the overall development of the digital economy is related to agricultural economic resilience. More importantly, limited attention has been given to regional heterogeneity and stage-dependent effects. This leaves an important gap: whether the relationship between digital economy development and agricultural economic resilience varies across regions and whether its marginal association changes as digital development advances.

The aforementioned theoretical and empirical shortcomings raise several key questions: Does the development of the digital economy systematically enhance the resilience of the agricultural economy?

Does its impact vary significantly across different regions? Does its marginal effect diminish or undergo phased changes as the level of digitalization increases? Answering these questions will help deepen the application of resilience theory in the field of agricultural economics and promote the theoretical integration between digital transformation and structural resilience.

This study has three objectives. First, it constructs city-level indices of digital economy development and agricultural economic resilience for 284 prefecture-level cities in China from 2011 to 2022 and examines their relationship using a fixed-effects model. Second, it investigates whether this relationship differs across eastern, central, and western China. Third, it examines whether the relationship varies across different stages of digital economy development. Through these objectives, the study aims to provide evidence on the regional and stage-dependent characteristics of digitalization in agricultural resilience.

Based on this, this paper makes three theoretical contributions. First, it incorporates the development of the digital economy into the multidimensional analysis framework of agricultural economic resilience, expanding the explanatory scope of resilience theory for structural technological change. Second, based on panel data from 284 prefecture-level cities in China from 2011 to 2022, it provides empirical evidence at the city level, compensating for the inadequacy of provincial data in revealing intra-regional differences. Third, by identifying regional heterogeneity and differences in the stages of digital development, it reveals the dynamic and phased characteristics of the impact of digitalization on agricultural resilience, thereby enriching the theoretical connotation of research on the digital economy and regional resilience.

2. Literature Review and Hypotheses

2.1 Theoretical Foundations of Agricultural Economic Resilience

The concept of "resilience" was first proposed by ecologist Holling in 1973 when discussing ecosystem stability. Its core is the system's ability to maintain normal operation in uncertain external environments and preserve key structures and basic functions in the face of risk shocks.

Later, this concept expanded, and in 2006, Folke further extended the theory to the socio-ecological field, pointing out the dynamic interaction between economic behavior, institutional structures,

and the natural environment. Therefore, learning and adaptability are key components of system resilience, making resilience an important theoretical perspective on the operating mechanism of complex socio-economic systems.

In 2010, Simmie and Martin introduced the concept of resilience into regional economic research. They argued that economic resilience includes not only the ability to withstand external risks but also the ability to recover and rebuild after such risks. China's digital economy reached 53.9 trillion RMB in 2023, accounting for 42.8% of GDP. They pointed out that economic resilience includes not only the ability to withstand external risks but also the ability to recover and rebuild after such risks. Subsequently, Boschma (2015). analyzed the concept of resilience from the perspective of evolutionary economic geography, arguing that the degree of industrial diversification, institutional environment characteristics, and path dependence mechanisms have a significant impact on regional economic resilience. With the continuous advancement of theory, the connotation of resilience has gradually shifted from a single consideration of stability to a comprehensive examination of the long-term development potential of an economic system, and has gradually formed an analytical framework encompassing multiple dimensions such as resilience, recovery, and adaptation.

In agricultural systems, agricultural production activities are highly dependent on the stability of the natural environment while also being influenced by the market environment. Therefore, climate change, price fluctuations, or adjustments in agricultural policies can all potentially impact the agricultural economy Tendall et al., (2015). At the same time, agricultural production processes are also constrained by biological growth patterns, and the agricultural production cycle is relatively fixed, resulting in limited adjustment flexibility for the agricultural system. Therefore, the agricultural system exhibits higher sensitivity to changes in the external environment. This shows that the resilience of the agricultural economy includes not only the stability of the ecological level, but also multiple economic dimensions such as market stability and institutional support.

Current research largely defines the connotation of agricultural economic resilience from three dimensions. The first dimension is Resistance, which is the ability of the agricultural system to mitigate output and income fluctuations when facing external shocks. The second dimension is Adaptability, which emphasizes the speed and extent of recovery of the agricultural system in returning to its existing growth path after an external shock. The third dimension is Transformation ability, which is specifically reflected in the

agricultural system's ability to achieve long-term structural upgrading through technological progress, industrial structure optimization, or institutional innovation (Gao et al., 2024; Luo et al., 2025; Qiao & Li, 2025).

2.2 Digital Economy and Structural Transformation of Agricultural Systems

The rapid development of the digital economy has a significant impact on the resilience of agricultural systems, primarily in terms of production and markets. Firstly, in agricultural production, the application of digital technologies can effectively reduce the cost of information acquisition and forecasting for agricultural producers, thereby significantly improving the decision-making efficiency Guo et al., (2025). and the efficiency of agricultural resource allocation Xie et al., (2025). Furthermore, when data becomes a crucial production factor, big data algorithms and the underlying platform-based coordination mechanisms can enhance the matching of supply and demand for agricultural products and optimize the upstream and downstream links of the agricultural supply chain, thus achieving an overall improvement in agricultural productivity Luo et al., (2021).

Secondly, in the agricultural product market, the construction of rural digital infrastructure and the development of rural e-commerce platforms have significantly improved the transparency of the agricultural product market and the matching efficiency of agricultural product transactions (Wen et al., 2024: Chandra et al., 2024). pointed out that digital supply chain integration can improve the operational efficiency of the agricultural product market by shortening the distribution chain and reducing transaction costs. Lyu et al., (2025). further found that agricultural digitalization can optimize farmers' sales decisions and improve the stability of farmers' income. At the same time, digital finance has expanded rural financing channels, while rural e-commerce platforms have expanded the market space for agricultural products (Gao et al., 2024; Wen et al., 2024). These changes have made farmers' income more diversified. Under the combined effect of these mechanisms, the digital economy may improve the adaptability, resilience, and recovery capacity of the agricultural system through multiple pathways, such as stabilizing farmers' income sources, enhancing the collaborative capabilities of the agricultural product supply chain, and improving the transparency of agricultural product market information, thereby enhancing the resilience of the agricultural economy.

On the other hand, the development of the digital economy may also bring certain risks to the agricultural system. These risks are mainly reflected in the following two aspects. The first risk can be called digital dependence risk. When agricultural production and agricultural product trading rely excessively on e-commerce platforms, big data, digital systems, and other systems or platforms, the entire agricultural system is prone to collapse if these systems or platforms encounter technical bottlenecks or system crashes. Qu et al., (2025) pointed out in their research that while agricultural digitalization improves efficiency, it may also be accompanied by problems such as data security, technology lock-in, and imperfect governance structures, thereby weakening the flexibility of the agricultural system.

Furthermore, while digital development has increased the integration of agricultural product markets and optimized resource allocation, it may also accelerate the transmission of price shocks across regions. Simply put, once agricultural product prices fluctuate significantly in one area, this fluctuation will spread to other areas more quickly and easily. Beroud & Awokuse., (2025) found that agricultural product market integration enhances the speed and magnitude of price transmission, meaning that the closer and more interconnected the markets, the more sensitive the agricultural system may be to external risks. At the same time, uneven levels of digital infrastructure and digital skills among the workforce may exacerbate regional disparities. Some rural areas with weaker digital technology application capabilities may struggle to fully enjoy the digital dividend Beroud & Awokuse., (2025). Therefore, the marginal effect of the digital economy on agricultural economic resilience may vary depending on the stage of digital economic development, exhibiting non-linear or phased characteristics.

Overall, the digital economy may enhance the resilience of the agricultural economy by improving resource integration efficiency and the stability of farmers' income, but it may also introduce new vulnerabilities to the agricultural system by strengthening system connectivity and technological dependence. Therefore, the impact of the digital economy on the resilience of the agricultural economy is complex and needs further empirical testing.

2.3 Hypotheses

Based on the above discussion, this study proposes the following hypotheses:

Hypothesis 1: Digital economy development is positively associated with agricultural economic resilience.

Hypothesis 2: The association between digital economy development and agricultural economic resilience differs across regions.

Hypothesis 3: The association between digital economy development and agricultural economic resilience differs across stages of digital economy development.

3. Data and Methodology

3.1 Data and Variables

This study employs an unbalanced panel dataset covering 284 prefecture-level cities in China from 2011 to 2022. Data are primarily obtained from the China City Statistical Yearbook, the China Rural Statistical Yearbook, and relevant provincial statistical bulletins. Cities with severe data omissions were excluded to ensure consistency.

Agricultural economic resilience (AER) is measured using a composite index that captures agricultural systems' capacity for resistance, recovery, and adaptability. This study constructs the Agricultural Economic Resilience (AER) Index based on the indicator system developed by Chinese scholar Zhao & Xu., (2023). This index incorporates indicators reflecting agricultural output stability, income diversification, and structural adjustment. To mitigate subjectivity, the index is constructed using the entropy-weighting method.

The table below provides a detailed breakdown of these indicators along with their corresponding measurement units.

Table 1 Variable Definitions and Measurement

Dimension	Indicator Name	Unit	Direc-tion
Resistance	Total Sown Area of Crops	1,000 hectares	+
	Effective Irrigated Area	1,000 hectares	+
	Number of Employees in Primary Industry	10,000 persons	+
	Grain Output per Capita	kg/person	+
	Agricultural Output per Sown Area	10,000 CNY/hectare	+
	Pesticide and Fertilizer Usage	10,000 tons	−
Adaptability	Agricultural Labor Productivity	10,000 CNY/person	+
	Comprehensive Utilization Rate of Livestock and Poultry Waste	%	+
	Proportion of Administrative Villages with Sewage	%	+

Dimension	Indicator Name	Unit	Direc-tion
	Treatment		
	Investment in Agricultural Fixed Assets	10,000 CNY	+
	Agricultural Machinery Power per Capita	kW/person	+
	Number of Green Agricultural Enterprises	count	+
Transformability	Per Capita Disposable Income of Rural Residents	CNY	+
	Engel's Coefficient of Rural Residents	%	−
	Village Road Hardening Rate	%	+
	Average Years of Schooling of Rural Residents	years	+
	Number of Registered Farmers' Cooperatives	count	+

This study constructs the Digital Economy Development (DED) Index based on the indicator system developed by Zhao et al., (2020). The index captures multiple dimensions of digitalization, digital infrastructure and application are measured using indicators such as internet penetration (number of internet users per 100 people), mobile internet usage (number of mobile phone users per 100 people), internet-related employment (the share of the workforce in software and information technology services), and per capita telecommunication business volume. Digital financial development is proxied by the China Digital Financial Inclusion Index. Principal component analysis (PCA) is employed to synthesize these indicators into a single composite index.

Control variables include Economic Development Level, Fiscal Decentralization, Log of Government Expenditure, Population Density, Log of Financial Development, Urbanization Level, and Urban Economic Density. All monetary variables are deflated to constant prices. All data used in this study are obtained from the China City Statistical Yearbook and related official statistical yearbooks, unless otherwise specified.

3.2 Empirical Strategy

1) Baseline model

To examine the relationship between digital economy development and agricultural economic resilience, this study estimates a two-way fixed-effects model. The model controls for unobserved time-invariant city characteristics and common yearly shocks. Standard errors are clustered at the city level to account for within-city correlation over time. The baseline specification is:

$$AER_{it} = \alpha + \beta DED_{it} + \gamma X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (1)$$

where AER_{it} denotes agricultural economic resilience in city i and year t, DED_{it} denotes the digital economy development index, and X_{it} is a vector of control variables. The terms μ_i and λ_t represent city and year fixed effects, respectively. The coefficient β captures the within-city association between digital economy development and agricultural economic resilience after controlling for observed covariates and fixed effects.

This fixed-effects specification controls for time-invariant city characteristics and common temporal shocks, allowing for consistent estimation of the association between digitalization and agricultural resilience.

2) Regional Heterogeneity Model

To examine whether the digital economy exhibits significant spatial heterogeneity in its impact on agricultural economic resilience, this study divides the 284 city samples into three subsamples based on the three major geographic regions commonly used by the National Bureau of Statistics (Eastern, Central, and Western). A benchmark fixed-effects model is estimated within each subsample to compare regional differences in the digital economy's effect on agricultural resilience. All regressions control for city-level and year-level fixed effects. Cluster-robust standard errors are applied to address heteroskedasticity and serial correlation within city clusters. The model specification is as follows:

Group estimation (FE within region), for each region "r∈{E,C,W}"

$$AER_{it}=\alpha_r+\beta_r DED_{it}+\gamma_r' X_{it}+\mu_i+\lambda_t+\varepsilon_{it}, \quad i\in R_r \quad (2)$$

Where:

X_{it} denotes the vector of control variables (EDL, ln_FIN, ED, FD, ln_GOV, POP_DENS, URB, etc.). μ_i represents city-level fixed effects, and λ_t signifies year-level fixed effects. β_r is estimated independently for each regional subsample to compare the heterogeneity of β_E, β_C, β_W, β_{NE}.

To further examine the differential impact of the digital economy on agricultural economic resilience across different development stages, this study employs a tertile grouping approach to classify the sample into three development level groups-“low,” “medium,” and “high”-based on the Digital Economy Index (DED). Within each group, a benchmark fixed-effects model is estimated to compare the marginal effects of DED. All regressions similarly control for city and year fixed effects and employ city-clustered robust standard errors.The model specification is as follows:

$$AER_{it}=\alpha_k+\beta_k DED_{it}+\gamma\kappa' X_{it}+\mu_i+\lambda_t+\varepsilon_{it}, \quad i\in G_k \qquad (3)$$

Where:

G_k denotes the κ digital economy development level group (κ=1 low, κ=2 medium, κ=3 high); β_k is estimated within each group, and β_1,β_2,β_3 are compared.

3.3 Identification Strategy

A potential concern is the endogeneity of digital economy development, arising from reverse causality or omitted variables. To address this issue, an instrumental-variable (IV) approach is employed. Following the literature, historical telecommunication infrastructure interacted with national digital development trends is used as an instrument for contemporary digital economy development. The instrument satisfies relevance by capturing exogenous variation in digital infrastructure diffusion and plausibly meets the exclusion restriction, as historical infrastructure affects current agricultural resilience primarily through digitalization.

We focus on the Broadband China pilot as the primary external instrument, while lagged DED is used for robustness. The strength and validity of the instruments are assessed using standard diagnostic tests, which confirm the relevance and validity of the instruments.

3.4 Empirical Results

3.4.1 Baseline Results

To determine the appropriate estimation strategy, both fixed-effects and random-effects models were considered. A Hausman test rejects the null hypothesis in favor of the fixed-effects specification, the results are shown in Table 2.

Table 2. Hausman Test Results

Test	Chi-square	df	Prob > chi2
FE vs. RE	46.67	7	0.0000

Notes: The null hypothesis assumes that the random effects estimator is consistent and efficient.

Accordingly, a fixed-effects model is adopted as the baseline framework throughout the analysis to control for time-invariant heterogeneity across cities.

Table 3 reports the baseline fixed-effects regression results examining the impact of digital economy development on agricultural economic resilience. The coefficient on the digital economy index is positive and statistically significant, indicating that digitalization is associated with higher levels of agricultural resilience.

Table 3. Regression Results of Fixed Effects (FE)

Variable	FE Coefficient (Std. Err.)
DED	0.0479*** (0.0109)
EDL	0.0136** (0.0054)
FD	-0.0036 (0.0073)
ln_GOV	0.0113 (0.0197)
POP_DENS	-0.0106 (0.0072)
ln_FIN	0.0278*** (0.0050)
ED	0.0364*** (0.0059)
URB	-0.0086 (0.0122)
_cons	-0.0828 (0.0563)
Observations	3408
Groups	284
R^2 (Within)	0.3972
R^2 (Between)	0.0049
R^2 (Overall)	0.0193
F-test / Wald χ^2	F (8, 3116) = 256.68, p < 0.001***

Notes: *Results for fixed-effects (FE) regression. Coefficients (standard errors in parentheses); ***, **denote significance at 0.01, 0.05 levels.*

The estimated effect remains robust after controlling for city and year fixed effects as well as a comprehensive set of control variables. This finding suggests that the development of the digital economy contributes to enhancing the capacity of agricultural systems to withstand and adapt to external shocks.

The results indicate that the coefficient for the digital economy variable (DED) is 0.0479 and is significantly positive at the 1% significance level, suggesting that the development of the digital economy

can significantly enhance agricultural economic resilience. Although the overall R-squared is relatively low, this outcome is typical of fixed-effects models that absorb substantial cross-city heterogeneity. The within R-squared, which captures temporal variation within cities, therefore offers a more relevant assessment of model performance.

The coefficient of DED is 0.0479 and is statistically significant at the 1% level. This indicates that, within the same city over time, a higher level of digital economy development is associated with a higher agricultural economic resilience index. The result supports Hypothesis 1. However, because the baseline fixed-effects model does not fully eliminate time-varying omitted variables or reverse causality, this result should be interpreted as an association rather than definitive causal evidence.

3.4.2 Robustness Checks

To assess whether the baseline result is sensitive to measurement choices and sample composition, two robustness checks are conducted. First, the digital economy index is reconstructed using principal component analysis. Second, the four centrally administered municipalities are excluded from the sample. The results remain positive and statistically significant across these specifications. This suggests that the positive association between digital economy development and agricultural economic resilience is not driven only by the baseline index construction method or by the inclusion of municipalities. However, these tests do not fully solve endogeneity concerns, so the findings should still be interpreted with caution.

The results, reported in Table 4, indicate that the estimated effect of digital economy development on agricultural economic resilience remains positive and statistically significant across all specifications. Both the sign and magnitude of the coefficients are highly stable, suggesting that the baseline findings are not sensitive to alternative index construction methods or sample composition.

Table 4. Robustness Checks

Variable	Baseline (DED)	Excl. Municipalities (DED)	PCA Index (DED_PCA)	Excl. Municipalities (DED_PCA)
(DED / DED_PCA)	0.048	0.047	0.009	0.008
	(0.018)***	(0.017)***	(0.003)***	(0.003)***
EDL	0.014	0.015	0.014	0.015
	(0.008)*	(0.008)*	(0.008)*	(0.008)*

Variable	Baseline (DED)	Excl. Municipalities (DED)	PCA Index (DED_PCA)	Excl. Municipalities (DED_PCA)
ln_FIN	0.028 (0.010)***	0.027 (0.010)***	0.026 (0.010)**	0.025 (0.010)**
ED	0.036 (0.008)***	0.035 (0.008)***	0.034 (0.008)***	0.033 (0.008)***
FD	-0.004 (0.013)	-0.008 (0.013)	-0.003 (0.013)	-0.007 (0.013)
ln_GOV	0.011 (0.029)	0.003 (0.028)	0.005 (0.028)	-0.002 (0.028)
POP_DENS	-0.011 (0.010)	-0.010 (0.010)	-0.011 (0.010)	-0.010 (0.010)
URB	-0.009 (0.025)	-0.004 (0.024)	-0.009 (0.025)	-0.005 (0.023)
Constant (_cons)	-0.083 (0.090)	-0.094 (0.089)	-0.037 (0.088)	-0.055 (0.087)
Model Statistics	Model 1	Model 3		
Number of observations	3408	3408		
Number of groups (code)	284	284		
Within R^2	0.397	0.403		
Between R^2	0.005	0.006		
Overall R^2	0.019	0.023		
F-statistic	65.25***	65.97***		
Variance Component rho	0.941	0.94		

Notes: ** $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.*

Combining these various tests, whether changing indicators, or samples, yields consistent conclusions: the development of the digital economy does indeed strengthen the resilience of the agricultural economy.

3.4.3 Endogeneity Test

A potential concern is that digital economy development may be endogenous due to reverse causality or omitted variables. To address this issue, an instrumental-variable (IV) approach is employed.

Following the literature, two instruments are used: the lagged digital economy index and an exogenous policy shock from the "Broadband China" pilot program. These instruments capture exogenous variation in digital infrastructure development while remaining plausibly unrelated to contemporaneous shocks to agricultural economic resilience. City fixed effects and cluster-robust standard errors are retained throughout the IV estimations.

A key concern is that historical communication infrastructure may be correlated with long-term economic development, which could independently affect current agricultural economic resilience. Several features of the empirical design mitigate this concern. First, city fixed effects absorb all time-invariant characteristics, including historical wealth, geographic conditions, and long-run development paths. Second, year fixed effects and a rich set of control variables further account for common macroeconomic shocks and time-varying confounders. Third, the identifying variation stems from the interaction between historical infrastructure and nationwide digital development trends, which are externally determined and unlikely to affect city-level agricultural resilience except through their impact on digital economy development.

Table 5. Results of Endogeneity Test (IV-2SLS)

Variables/Statistics	Baseline Fixed Effects Regression	IV1 (DED_lag1)	IV2 (broadband_did)	IV3 (Joint Instruments)
DED	0.0497**	0.0998***	0.2931	0.1006***
	-0.0201	-0.0249	-0.1815	-0.025
Sample Size (N)	3,102	3,102	3,102	3,102
R-squared (R^2)	0.3765	0.3728	0.2886	0.3727
First-stage F-statistic	-	1106.68	14.16	557.04
Weak Instrument Critical Value (10%)	-	16.38	16.38	19.93
Kleibergen-Paap LM Stat. (p-value)	-	97.03 (0.0000)	11.72 (0.0006)	97.03 (0.0000)
Hansen J Stat. (p-value)	-			1.34 (0.2470)

Notes: *Values in parentheses are city-level (code) cluster-robust standard errors; Significance levels: *p<0.1, **p<0.05, ***p<0.01.*

The IV results provide mixed evidence. The lagged DED instrument and the joint-instrument specification produce positive and statistically significant estimates. However, the Broadband China

instrument alone has a first-stage F-statistic below the reported weak-instrument critical value, and its second-stage estimate is not statistically significant. Therefore, the IV results should not be interpreted as strong causal proof. Instead, they provide supplementary evidence that is broadly consistent with the baseline fixed-effects results. The possibility of remaining endogeneity cannot be fully ruled out.

3.4.4 Heterogeneity Analysis

1) Regional Heterogeneity in the Impact of the Digital Economy on Agricultural Economic Resilience

To examine regional heterogeneity, separate fixed-effects regressions are estimated for the eastern, central, and western regions, with results reported in Table 6.

Table 6. Fixed-Effects Regression Results for Cities by Region

Variable	East	Central	West
DED	0.0072*	0.0173***	0.0065
	-0.0042	-0.0048	-0.0058
EDL	-0.0063	0.0261	0.0693***
	-0.0118	-0.0366	-0.0198
ln_FIN	0.0241	0.0245*	0.0241
	-0.015	-0.0138	-0.0244
ED	0.0521***	0.0046	-0.018
	-0.009	-0.0393	-0.026
FD	0.0037	-0.0239	0.0347
	-0.0228	-0.0182	-0.0267
ln_GOV	0.0739	-0.0867	-0.0104
	-0.0492	-0.0613	-0.0369
POP_DENS	0.0034	-0.0318	0.0402
	-0.0131	-0.0399	-0.0352
URB	-0.0044	-0.0138	0.0172
	-0.0296	-0.0855	-0.0459
N	1440	960	1008
Number of groups	120	80	84
R^2 (within)	0.3019	0.5597	0.4384

Note: *Values in parentheses represent robust standard errors clustered at the city level; *p<0.1, **p<0.05, ***p<0.01; controlling for fixed effects by year; the constant term is not reported.*

The regional heterogeneity results show that the coefficient of DED is positive and statistically significant in eastern and central China, but not statistically significant in western China. This suggests that the relationship between digital economy development and agricultural economic resilience differs across regions. However, because the results are obtained from separate subgroup regressions, coefficient differences across regions should be interpreted cautiously. A formal interaction test is needed to confirm whether the coefficients are statistically different across regions.

2) Heterogeneous Effects across Different Stages of Digital Economy Development

Administrative regional divisions may mask substantial within-region variation in digital development. To further capture stage-dependent effects, cities are grouped into low, medium, and high digital economy tiers based on their digital development levels.

As shown in Table 7, a clear stage effect emerges. In cities with low levels of digital development, the digital economy exerts a positive and statistically significant impact on agricultural economic resilience. In contrast, the estimated effects become insignificant in the medium- and high-digitalization groups. This pattern suggests diminishing marginal returns to digitalization as digital development advances.

Table 7. Impact of Different Levels of Digital Economy Development on Agricultural Economic Resilience

Variable	Low (1)	Medium (2)	High (3)
DED_PCA	0.0068*	–0.0069	0.0046
	(0.0035)	(0.0069)	(0.0060)
EDL	–0.0002	–0.0008	–0.0003
	(0.0144)	(0.0119)	(0.0123)
ln_FIN	–0.0257	–0.0037	–0.0105
	(0.0193)	(0.0116)	(0.0135)
ED	–0.0206	0.0122	0.0273*
	(0.0176)	(0.0189)	(0.0153)
FD	0.0673***	–0.0186	0.0127
	(0.0227)	(0.0162)	(0.0193)
ln_GOV	–0.0443	–0.0120	0.1359*
	(0.0442)	(0.0458)	(0.0757)
POP_DENS	0.0088	–0.0159	0.0045
	(0.0155)	(0.0162)	(0.0152)

Variable	Low (1)	Medium (2)	High (3)
URB	0.0024	–0.0767**	–0.0193
	(0.0264)	*(0.0332)*	(0.0482)
Year FE	Yes	Yes	Yes
City FE	Yes	Yes	Yes
Observations	1,136	1,136	1,136
R^2 (within)	0.4093	0.3054	0.2763

Notes: *The values in parentheses are robust standard errors clustered at the city level; All regressions control for city fixed effects and year fixed effects. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.*

The regression results of the digital economy at different stages in the table above show that the enhancing effect of the digital economy on agricultural economic resilience weakens as the digitalization process progresses, and may even exhibit a negative relationship, although this negative relationship is not statistically significant. However, we can conclude that the promoting effect of the digital economy on agricultural economic resilience is mainly concentrated in the early stages of digital economic development.

Besides the core explanatory variables, several control variables also showed differences at different stages of digital development. At lower digitalization levels, fiscal decentralization (FD) was significantly positive at the 1% level, indicating that in the stage where digital infrastructure is not yet fully developed, the level of local government fiscal support plays an important role in the stability of the agricultural system. In regions with higher digitalization levels, education level (ED) and government expenditure (ln_GOV) were significantly positive, indicating that as the level of digitalization increases, human capital and public investment are important factors in enhancing agricultural economic resilience. Furthermore, we found that urbanization level (URB) has a significant negative impact at the intermediate development stage, which may be due to the large influx of labor from rural areas to cities during the urbanization process, thus putting pressure on the agricultural system.

4. Conclusions and Policy Implications

4.1 Conclusions

This study examines the relationship between digital economy development and agricultural economic resilience using city-level panel data for 284 prefecture-level cities in China from 2011 to 2022. The

baseline fixed-effects results show a positive association between digital economy development and agricultural economic resilience. This result remains stable after using an alternative digital economy index and excluding centrally administered municipalities.

The heterogeneity results suggest that the relationship differs across regions and stages of digital development. The positive association is statistically significant in eastern and central China, but not in western China. The stage-based analysis further suggests that the association is more visible in cities at an early stage of digital development, while it becomes statistically insignificant in cities with medium and high levels of digitalization.

These findings indicate that digitalization may support agricultural resilience, but its role is not uniform across space or development stages. Regional infrastructure, human capital, institutional conditions, and the existing level of digital development may affect whether digital technologies can be effectively transformed into agricultural resilience. Therefore, digital agriculture policies should avoid a uniform approach and instead adopt differentiated strategies based on regional conditions.

4.2 Policy Implications

Based on the empirical findings, policies aimed at promoting digital agriculture should adopt a differentiated and phased approach, rather than a uniform expansion strategy.

At the national level, continued investment in rural digital infrastructure remains essential for enhancing agriculture's capacity to withstand and recover from external shocks. Improving unified data standards and governance frameworks can help reduce fragmentation and enhance interoperability across digital agricultural applications. In addition, strengthening digital inclusive finance and agricultural disaster information-sharing systems can improve farmers' access to risk management tools and timely information, thereby supporting agricultural economic resilience.

At the regional level, policy priorities should be differentiated according to regional development conditions. In eastern regions, the digital economy shows a positive but relatively limited effect on agricultural economic resilience, suggesting that policies should place greater emphasis on improving human capital quality and the efficiency of digital applications. In central regions, the digital economy exerts the strongest and most significant positive impact, indicating the need to accelerate the integration of digital technologies into agricultural production and management. In western regions, where the effect of the digital economy is

not statistically significant, policy efforts should focus on strengthening human capital foundations and basic conditions to enable the effective functioning of digital technologies.

At the micro level, improving digital literacy among farmers, cooperatives, and agribusinesses is crucial, particularly in relation to risk management, information access, and adaptive decision-making. Targeted training in digital tools, smart farming applications, and digital marketing can enhance technology absorption. Promoting the integration of digital technologies along the entire agricultural value chain, from production and processing to circulation and distribution, can further strengthen agriculture's resilience to external shocks.

5. Limitations and Future Research

Despite its contributions, this study has several limitations. First, the analysis relies on city-level panel data, which may mask finer-scale dynamics at the household or farm level. Future research could incorporate micro-level data or real-time information to better capture resilience mechanisms.

Second, while this study documents heterogeneous and stage-dependent effects, the specific transmission channels through which the digital economy enhances agricultural resilience remain only partially explored. Future studies could employ mediation analysis or spatial econometric approaches to examine mechanisms such as information diffusion, factor mobility, and industrial restructuring.

Finally, agricultural economic resilience is inherently dynamic, whereas this study is based on annual observations. Event-based analyses or scenario simulations focusing on specific shocks—such as extreme weather events—could provide deeper insights into the short-term regulatory role of digitalization.

Overall, this study offers empirical evidence on the role of the digital economy in shaping agricultural economic resilience, while also pointing to promising directions for future research.

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