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Mechanisms Through Which China's Digital Economy Shapes Agricultural Export Trade

Meng-Qi Wang*, Zi-Yang Liu**

*PhD Student, Department of Global Business, Kyonggi University, Suwon, Korea
**Professor, Department of Global Business, Kyonggi University, Suwon, Korea

[Abstract]

This study investigates the mechanisms through which the digital economy affects China's agricultural export trade. Against the combined backdrop of global trade realignment and the rise of the digital economy, China's agricultural exports face structural challenges alongside opportunities for digital transformation. We construct a three-dimensional analytical framework—direct effects, indirect transmission, and spatial spillover effects—and, using province-level panel data for 2007–2023, conduct empirical tests based on a fixed-effects model, a panel threshold model, and a Spatial Durbin Model (SDM). The results show that the digital economy significantly promotes agricultural exports, with stronger effects in western provinces. Industrial agglomeration exhibits a nonlinear moderating pattern: it is positive at lower levels but turns negative at higher levels due to congestion effects, yielding an inverted-U relationship. Moreover, the digital economy generates positive spatial spillovers to neighboring regions. These findings provide theoretical support and actionable pathways for optimizing digital agriculture policy and advancing the high-quality development of foreign trade.

▸ **Key words**: digital economy, agricultural products, export trade

[요 약]

본 연구는 디지털 경제가 중국의 농산물 수출무역에 미치는 영향 메커니즘을 규명한다. 글로벌 무역 재편과 디지털 경제의 부상이라는 이중의 배경 속에서, 중국의 농산물 수출무역은 구조적 제약과 디지털 전환의 기회를 동시적으로 맞이하고 있다. 이를 위해 '직접효과–간접 전이–공간 파급효과'로 구성된 3차원 분석 틀을 구축하고, 2007–2023년 성(省) 단위 패널자료를 활용하여 고정효과 모형, 패널 임계값 모형, 공간 더빈 모형(SDM)으로 실증 분석을 수행하였다. 분석 결과, 디지털 경제는 농산물 수출무역을 유의하게 증진시키며 그 효과는 서부 지역에서 더욱 강하게 나타났다. 아울러 농업 산업집적은 비선형적 조절 특성을 보이며, 초기에는 정(+)의 조절효과가 존재하지만 집적도가 일정 수준을 초과하면 혼잡효과로 인해 부(−)의 조절효과로 전환되어 역(逆) U자형 관계가 형성된다. 또한 디지털 경제는 공간 파급효과를 통해 인접 지역의 수출 성과를 제고하는 것으로 확인되었다. 이러한 결과는 디지털 농업 정책의 최적화와 대외무역의 고품질 발전을 위한 이론적 근거와 실행 가능한 정책 경로를 제시한다.

▸ **주제어**: 디지털 경제, 농산물, 수출무역

• First Author: Meng-Qi Wang, Corresponding Author: Zi-Yang Liu
*Meng-Qi Wang (wmqwsx2025@gmail.com), Department of Global Business, Kyonggi University
**Zi-Yang Liu (victor@kgu.ac.kr), Department of Global Business, Kyonggi University
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I. Introduction

In the new era marked by the deep restructuring of the global trade architecture and the concurrent surge of the digital economy, China's export trade has continued to expand. by the end of 2023, total exports reached CNY 23,772.6 billion, over 200% higher than in 2006, becoming a major engine of economic growth. Yet, as a large agricultural country, China's agricultural export trade faces structural constraints. On the one hand, declining environmental carrying capacity, tightening resource constraints, and lagging production efficiency increasingly limit the realization of export potential; on the other, the export basket remains dominated by labor-intensive products, and the hallmark of "low quality-low price"—low value added and insufficient international competitiveness—has not been fundamentally reversed. Although the product structure has improved in recent years, deficiencies in quality and efficiency remain pronounced.

Against this backdrop, the Law of the People's Republic of China on the Quality and Safety of Agricultural Products (revised in 2022) explicitly advances the core policy orientation of "enhancing the quality of agricultural products and expanding sales channels," providing a policy lever for alleviating the impasse in agricultural exports. Meanwhile, the digital economy is reshaping the global economy at unprecedented speed. According to the China Digital Economy Development White Paper (2023), China's digital economy reached CNY 50.2 trillion in 2022, accounting for 41.5% of GDP and outpacing nominal GDP growth by 4.98 percentage points; during the COVID-19 pandemic, it served as a crucial stabilizer of economic growth. Beyond transforming traditional economic behaviors, digitalization is catalyzing broader changes in modes of production and everyday life. Its deep integration with agriculture has prompted extensive scholarly discussion over whether the digital economy can become a new engine for agricultural export trade.

In this context, we address three questions: (i) through what mechanisms and pathways the digital economy affects agricultural export trade; (ii) through which indirect effects these influences are transmitted; and (iii) how policy space for innovation can be expanded on the basis of digitalization.

This study overcomes the limitations of conventional research on the determinants of agricultural export trade. Prior studies have primarily focused on traditional factors—such as logistics performance, institutional quality, and trade barriers—while giving insufficient attention to the digital economy as an emerging driver. Compared with prior research, the theoretical contribution of this study lies in constructing a three-dimensional framework—direct effects, indirect transmission, and spatial spillover effects. It systematically shows how the digital economy affects agricultural export trade via several channels—lowering information costs, optimizing supply chain management, and raising product standards. This extends agricultural trade theory by clarifying the enabling role of digital factors. Methodologically, this study makes an important advance. Rather than relying on a single-model approach, we jointly employ fixed-effects, panel-threshold, and Spatial Durbin (SDM) models. This design identifies the net effect of the digital economy on agricultural export trade, tests the nonlinear moderating role of industrial agglomeration, and captures interregional spatial interactions. It thus moves beyond the traditional linear paradigm and provides more comprehensive evidence on the complex dynamics of agricultural export trade in the digital era.

This study employs empirical methods to quantify the dynamic relationship between the digital economy and agricultural export trade. We test the association with a fixed-effects model, examine the nonlinear moderating effect of industrial agglomeration using a panel-threshold model, and identify interregional spatial spillover effects via a Spatial Durbin (SDM) model. These steps establish a coherent logic chain of "problem diagnosis-mechanism analysis-policy recommendations." The findings provide an evidence base for differentiated digital agriculture policies and export-structure optimization. They offer practical guidance for advancing the high-quality development of foreign trade.

To our knowledge, this study is among the first to incorporate the digital economy into the analytical framework for the drivers of agricultural export trade. Through empirical tests, it quantifies the impact and addresses the literature's limited attention to emerging digital factors. Using a combined strategy—fixed-effects, panel-threshold, and Spatial Durbin (SDM) models—we confirm a linear association between the digital economy and agricultural export trade. We also identify the moderating role of industrial agglomeration and interregional spatial spillover effects, thereby strengthening the robustness and explanatory power of the findings. Building on the empirical results, the policy recommendations move beyond a single dimension to propose a three-part policy framework—digital infrastructure, industrial agglomeration, and regional coordination—offering actionable pathways for leveraging the digital economy to empower agricultural export trade.

II. Theoretical Foundations and Research Hypotheses

1. Pathways Through Which Digital-Economy Development Affects China's Agricultural Export Trade

Against the backdrop of deep integration between the digital economy and agriculture, digital-economy development has become a core driving force of China's agricultural export trade. A systematic review of its operative mechanisms indicates that the impact unfolds along four dimensions:

(1) In the domain of transaction cost optimization, the digital economy—through high-speed information dissemination—significantly lowers cross-border transaction costs. First, it builds a global, real-time information network that enables market participants to rapidly access international market dynamics and competitive intelligence; Pei et al. (2018) [1] document improved cross-border information-transmission efficiency. Second, it builds digital trade platforms that enable direct matching between producers and overseas buyers, thereby circumventing intermediary barriers in traditional trade. Third, it promotes the intelligent transformation of trade processes by deploying technologies such as blockchain and smart contracts to automate end-to-end workflows, thereby substantially reducing labor and time costs.

(2) In terms of connectivity facilitation, the digital economy has created virtual market spaces and driven innovation in cross-border trade infrastructure. On the one hand, virtual markets built on internet platforms give agricultural producers direct access to overseas consumers; the "disintermediation" trade model improves trade efficiency and product competitiveness [2]. On the other hand, the refinement of cross-border payment systems and smart logistics as digital infrastructure further enhances the security and convenience of cross-border trade, providing technical support for the internationalization of agricultural products.

(3) At the level of export competitiveness, digital technologies empower the entire agricultural value chain. IoT sensors, big-data analytics, and AI algorithms enable precision management—for example, soil-moisture monitoring and intelligent pest-and-disease early warning—thereby improving product quality and yields. Smart agricultural machinery—such as autonomous tractors and crop-protection drones—significantly increases production efficiency. Meanwhile, cross-border e-commerce platforms integrate logistics

information and quality-monitoring systems; by establishing quality inspection standards aligned with international norms, they support firms in expanding into overseas markets.

(4) At the level of structural change in market participants, digital platforms dismantle traditional trade barriers. SMEs gain global sales channels through cross-border e-commerce, overcoming constraints in finance and distribution and enabling direct overseas matching. On the consumer side, digital platforms deliver a convenient and secure cross-border shopping experience, creating a new "producer-consumer" direct-connection model that expands the scale of agricultural exports and accelerates industrial upgrading.

Compared with prior studies that typically assess the digital economy from a single dimension (e.g., information costs or platform effects), this study integrates four pathways—transaction costs, connectivity, competitiveness, and participant structure—to build a more systematic mechanism framework. This constitutes an important extension of existing theoretical explanations.

Based on the foregoing analysis, we advance the first core hypothesis.

Hypothesis 1(H1) : Development of the digital economy exerts a significantly positive impact on China's agricultural export trade.

2. Moderating Effect of Agricultural Industry Agglomeration

In the early stage of agglomeration, industrial agglomeration positively moderates the relationship between digital-economy development and agricultural export trade through two main channels.

(1) Knowledge and technology diffusion via factor pooling. By concentrating core factors—talent, knowledge, and technology—industrial agglomeration accelerates cross-firm flows and generates pronounced knowledge and technology spillovers. Classic theory holds that agglomeration fosters exchanges among specialized agricultural professionals, expedites interfirm learning and experience transfer, and facilitates the sharing of agronomic expertise and the diffusion of advanced equipment [3]. These processes reduce production costs, enhance innovation efficiency and productive performance, and ultimately strengthen firms' export propensity [4]. In parallel, the externalities of knowledge and information help lower innovation risk, optimize the network structure of digital technology innovation, and invigorate digital-economy dynamism, thereby promoting deeper application of digital solutions [5]. This virtuous interaction amplifies the pro-export effect of the digital economy and elevates international competitiveness.

(2) Competitive advantage through shared intermediates and specialized production. In agglomerated regions, dense supplier networks provide diverse, low-cost intermediate inputs, expanding firms' choice sets and lowering the relative domestic price of intermediates [6,7], which in turn strengthens exporters' international competitiveness. At the same time, the specialized production environment characteristic of clusters [8], when combined with deep adoption of digital-economy tools—such as e-commerce and cross-border e-commerce platforms—encourages firms to focus on niche agricultural products, forming scale and specialization advantages. This enables precise international marketing and sales expansion, thereby increasing the global visibility and market share of China's agricultural products.

However, as industrial agglomeration deepens, a negative moderating effect gradually emerges, driven by accumulating congestion effects. On the one hand, clustering of homogeneous firms intensifies product substitutability and competition; sustained exports of similar agricultural products encourage low-price competition [9]. Although the digital economy reduces transaction costs, compressed margins can undermine the healthy development of agricultural export trade. On the other hand, rising labor demand within clusters, coupled with the immobility of land, pushes factor prices above those in non-clustered regions [10], raising production costs and passing them through to export prices. Even when firms reach global consumers via cross-border e-commerce, higher pricing may weaken export competitiveness and erode export values.

Unlike prior research that typically treats agglomeration as a linear promoter, we show that industrial agglomeration exerts a nonlinear moderating role in the relationship between digital-economy development and agricultural export trade. It exhibits a staged pattern—shifting from promotion to inhibition—thereby deepening understanding of their complex interaction. Accordingly, we propose Hypothesis 2.

Hypothesis 2(H2) : Industrial agglomeration exerts a nonlinear moderating effect on the impact of digital-economy development on China's agricultural export trade.

3. Spatial Spillover Effects of Digital-Economy Development on China's Agricultural Export Trade

With digital knowledge and information as core production factors, the digital economy diffuses rapidly and penetrates across regions via modern information networks. It is characterized by openness and sharing. Its development can transcend traditional geographic constraints, enhance the convenience of interregional information exchange, and reduce cross-regional communication and learning costs [11]. This property fosters interregional knowledge-sharing mechanisms, improves the efficiency of division of labor and coordination among agricultural actors, and generates spillover effects in technology and managerial experience. Through cross-regional learning of new technologies and methods, agricultural actors can raise production efficiency and product quality, thereby directly boosting agricultural exports.

Meanwhile, digital platforms and information networks provide agricultural firms with efficient bridges for cooperation, expanding the space for interregional firm-to-firm exchange [12]. Through digital-economy platforms, resource aggregation facilitates partner matching among firms, strengthens trade linkages, and fosters agricultural alliances, thereby advancing collaborative R&D and information sharing. This cooperative mechanism integrates multi-party resource advantages, reduces coordination and transaction costs, promotes cross-regional division of labor and technological collaboration, accelerates talent mobility and upgrades innovation capacity, and—through higher agricultural productivity and improved product quality—ultimately generates sustained momentum for agricultural exports.

This discussion of spatial spillover effects goes beyond the limits of traditional trade theory, which primarily focuses on geographic proximity or infrastructure connectivity. It highlights the cross-spatial penetration and sharing mechanisms of digital knowledge and information as core factors, offering a new theoretical lens on the drivers of agricultural export trade in the digital economy. Accordingly, we propose Hypothesis 3.

Hypothesis 3(H3): Digital-economy development exerts spatial spillover effects on China's agricultural export trade.

III. Research Methodology

1. Model Specification

1.1 Baseline Regression Model

Drawing on panel data for 30 provincial-level regions in mainland China over 2007-2023, we estimate a two-way fixed-effects model to empirically assess the impact of digital-economy development on the scale of China's agricultural exports. The specific model is given by Equation (3-1).

$$lny_{it} = \beta_0 + \beta_1 dei_{it} + \beta_2 lnX_{it} + \mu_i + \delta_t + \epsilon_{it} \quad (3\text{-}1)$$

1.2 Moderation Model

To reveal how industrial agglomeration moderates the impact of the digital economy on agricultural export trade, we extend the baseline model (3-1) by adding an interaction between the digital-economy index and the industrial-agglomeration indicator. We then estimate a moderating-effects model. (3-2).

$$lny_{it} = \beta_0 + \beta_1 dei_{it} + \beta_2 aic_{it} + \beta_3 dei_{it} \times aic_{it} + \beta_4 X_{it} + \mu_i + \delta_t + \epsilon_{it} \quad (3\text{-}2)$$

To examine whether this moderating effect exhibits nonlinear structural changes, we follow Hansen's (1999) threshold-effect framework [13]. Using the interaction term between the digital-economy index and agricultural industry agglomeration as the core explanatory variable and treating agglomeration level as the threshold variable, we specify a nonlinear panel threshold model as Equation (3-3).

$$lny_{it} = \rho_0 + \rho_1 dei_{it} \times aic_{it} \cdot I(aic_{it} \le \tau) + \rho_2 dei_{it} \times aic_{it} \cdot I(aic_{it} > \tau) + \rho_3 X_{it} + \mu_i + \delta_t + \epsilon_{it} \quad (3\text{-}3)$$

1.3 Spatial Panel Model

To capture the spatial spillover effects of the digital economy on China's agricultural export trade, we introduce a spatial econometric (spatial panel) framework.

(1) Spatial weight matrix specification

We adopt a geographic distance-decay weight matrix, in which each element is defined as the inverse of the squared geographic distance between provincial capital cities. The specific form is given in Equation (3-4).

$$W_{ij} = \begin{cases} \dfrac{1}{d_{ij}^{l}} & if\ \ i \ne j \\ 0 & if\ \ i = j \end{cases} \quad (3\text{-}4)$$

(2) Spatial autocorrelation tests

In the spatial autocorrelation stage, we employ both Global Moran's I and Local Moran's I (LISA) for two-tier testing. The relevant formula for Global Moran's I is given in equation (3-5).

$$I = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}(X_i - \overline{X})(X_j - \overline{X})}{S^2 \sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}} \quad (3\text{-}5)$$

In the formula, Wij denotes the economic-distance matrix; Xi and Xj denote the attribute values of city$i$ and cityj, respectively; n denotes the number of cities. The interpretation of Local Moran's I is essentially the same as that of Global Moran's I; it allows testing the spatial clustering of a given area i. The corresponding formula is shown in equation (3-6).

$$I_i = \frac{(X_i - \overline{X})}{s^2} \sum_{j=1}^{n} W_{ij} LEFT(X_j - \overline{X}) \quad (3\text{-}6)$$

(3) Specification of the spatial econometric model

Under the geographic-distance matrix, to identify the spatial spillover effects of digital-economy development on China's agricultural export trade, we employ the Spatial Durbin Model (SDM). Its specification is given in equation (3-7).

$$lny_{it} = \beta_0 + \rho \Sigma_{j=1}^{n} W_{ij} \cdot \ln y_{jt} + \beta_1 dei_{it} + \beta_2 X_{it} + \theta_1 \Sigma_{j=1}^{n} W_{ij} dei_{jt} + \theta_2 \Sigma_{j=1}^{n} W_{ij} X_{jt} + \mu_i + \delta_t + \epsilon_{it} \quad (3\text{-}7)$$

2. Variable Selection

2.1 Dependent Variable

Agricultural export trade (ln y). Following Ma and Guo (2023) [14], we use each province's agricultural export value as a proxy for agricultural export trade. To eliminate exchange-rate effects, export values are first converted using the annual average RMB-USD exchange rate for the corresponding year; the series—denominated in RMB after conversion—is then log-transformed to obtain ln y.

2.2 Core Explanatory Variable

Digital-economy development (dei). Following Chen and Zhou (2024) [15], we measure provincial digital-economy development for 2007-2023 using the entropy-weight method, constructing a composite index that reflects the relative development level of the digital economy across provinces.

2.3 Moderating Variable

Agricultural industry agglomeration (aic). Following Wang et al.(2023), agricultural industry agglomeration is measured as follows, see Equation (3-8):

$$aic_{ij} = \frac{\frac{a_{ij}}{g_{ij}}}{\frac{a_i}{g_i}} \tag{3-8}$$

In this formulation, aic_{ij} denotes the agricultural industry agglomeration level of region (i) in year (j); a_{ij} and g_{ij} denote, respectively, the gross output of agriculture, forestry, animal husbandry, and fishery and the regional gross domestic product (RGDP) of region (i) in year (j). a_i and g_j denote, respectively, the national gross output of agriculture, forestry, animal husbandry, and fishery in year (i) and the regional gross domestic product in year (j). If an agricultural firm is located in region (i), then its agricultural industry agglomeration in year (j) equals aic_{jj}

2.4 Control Variables

Following Ma & Guo (2023) and Jia (2023) [16], we include the following controls: industrial structure (stru), government regulation (gov), agricultural product price level (appi), degree of openness (open), and population size (labor). These variables account for compositional shifts in the economy, policy intensity, price dynamics, external openness, and labor endowment that may confound the relationship between digital-economy development and agricultural export performance.

Industrial structure (stru), Measured by the share of gross output of agriculture, forestry, animal husbandry, and fishery in GDP.

Government regulation (gov), Proxied by government fiscal expenditure as a share of GDP.

Agricultural product price level (appi), Proxied by the agricultural producer price index (PPI).

Degree of openness (open), Measured by the ratio of total imports and exports to GDP.

Population size (labor), Measured by the year-end resident population. Population size serves as an indicator of domestic market scale and labor endowment.

3. Data Sources

This study uses a sample of 30 provincial-level administrative regions in mainland China and analyzes data for 2007-2023. Data are primarily drawn from the China Statistical Yearbook; the Statistical Report on China's Internet Development; the National Bureau of Statistics (NBS) website; the Department of Foreign Trade, Ministry of Commerce (MOFCOM); and provincial and municipal statistical yearbooks. To address missing data, we impute missing values using linear interpolation.

It should be noted that the province-level macro data used in this study have certain limitations in revealing micro-level mechanisms and structural details. First, due to the aggregated nature of province-level data, this study cannot fully examine heterogeneous firm characteristics or household behavior, nor the differentiated responses of micro actors to the digital economy. Second, measuring agricultural exports in the aggregate may mask structural differences across product categories—for example, primary products versus processed (including deep-processed) products—within the digital value chain. These limitations leave room for future research to deepen the analysis using firm-level or product-level data. Even so, province-level panel data effectively capture the overall association, regional heterogeneity, and spatial effects between the digital economy and agricultural exports at the macro level, providing reliable empirical evidence for the core questions of this study.

IV. Empirical Analysis

1. Descriptive Statistics

As summarized in Table 4.1, the dependent variable—agricultural export trade (lny) has a mean of 4.101, standard deviation of 1.423, maximum of 7.248, and minimum of −0.742, indicating substantial interprovincial heterogeneity over the study period. The core explanatory variable—digital-economy development (dei) has a mean of 0.085, standard deviation of 0.099, maximum of 0.711, and minimum of 0.004, likewise reflecting pronounced province-level divergence in digital-economy development.

Table 4.1. Descriptive Statistics

Variable	Obs	Mean	Std	Min	Max
ln y	510	4.101	1.423	-0.742	7.248
dei	510	0.085	0.099	0.004	0.711
aic	510	1.210	0.639	0.031	3.263
stru	510	0.107	0.057	0.002	0.309
gov	510	0.242	0.108	0.095	0.758
appi	510	1.053	0.072	0.864	1.315
open	510	0.194	0.298	0.001	1.500
labor	510	0.454	0.280	0.055	1.268

2. Baseline Regression Results

Prior to estimation, Hausman tests are conducted; the p-values are < 0.01, rejecting the null of random effects. Accordingly, Models 1 and 2 are estimated using fixed effects. In Model 1 (without controls), the coefficient on dei is 2.853 (1% significance). After adding controls for industrial structure, government regulation, agricultural product prices, openness, and population size in Model 2, the coefficient on dei remains 2.050 (1% significance). These results confirm a significant positive effect of digital-economy development on agricultural exports, consistent with prior evidence, and support Hypothesis 1.

Table 4.2. Baseline Regression Results

	(1)	(2)
dei	2.853***	2.050***
	(0.246)	(0.415)
stru		-8.135***
		(0.887)
goV		1.994***
		(0.356)
appi		-0.346*
		(0.200)
open		0.263
		(0.161)
labor		-0.545
		(0.997)
constant	3.859***	4.880***
	(0.026)	(0.532)
fixed effects	Yes	Yes
Observations	510	510
R-squared (R^2)	0.219	0.430
Number of IDs	30	30

Note : *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Values in parentheses are robust standard errors; the same applies below.

3. Endogeneity Tests

To mitigate endogeneity arising from reverse causality, we first lag the core explanatory variable by one period (Model 1), The coefficient on L.dei is 2.095 (1% significance), indicating that the lagged term continues to have a positive effect. Second, we estimate a GMM dynamic panel model (Model 2), The coefficient on dei is 0.316 (10% significance), and the results remain robust under this specification, suggesting that endogeneity is not severe.

Table 4.3. Endogeneity Tests

	(1)	(2)
	core explanatory variable (lagged one period)	gmm
L.lny		0.915***
		(0.019)
L.dei	2.095***	
	(0.405)	
dei		0.316*
		(0.167)
stru	-7.743***	0.544*
	(0.972)	(0.278)
gov	1.685***	-0.466***
	(0.394)	(0.170)
appi	-0.432**	0.103
	(0.205)	(0.151)
open	0.327*	0.069
	(0.176)	(0.050)
labor	-0.332	0.131**
	(1.009)	(0.055)
constant	4.917***	0.255
	(0.546)	(0.203)
AR(1)		-5.56***
AR(2)		0.24
hansen		28.93
fixed effects	Yes	Yes
Observations	480	480
R-squared (R^2)	0.386	
Number of IDs	30	30

4. Robustness Tests

We verify robustness using two approaches. First, we reduce the sample size (Model 1); the coefficient on dei is 1.722 (5% significance). Second, we apply a log transformation to the core variable (Model 2); the coefficient on ln(dei) is 0.439 (1% significance). Both adjustments yield results consistent with the baseline, further supporting the reliability of the findings.

Table 4.4. Robustness Tests

VARIABLES	(1) reduced sample size	(2) log transformation of the core explanatory variable
dei	1.722**	
	(0.709)	
indei		0.439***
		(0.033)
stru	-3.933*	-2.338**
	(2.349)	(0.907)
gov	-1.769***	-0.115
	(0.581)	(0.354)
appi	-0.308	-0.281
	(0.223)	(0.175)
open	-0.673	0.306**
	(0.596)	(0.136)
labor	-5.404*	0.141
	(2.818)	(0.667)
constant	5.952***	5.839***
	(0.611)	(0.436)
fixed effects	Yes	Yes
Observations	210	510
R-squared (R^2)	0.986	0.566
Number of IDs	30	30

5. Tests of the Moderating Mechanism

5.1 Moderation Test

Model 1 (Table 4.5) verifies the moderating effect of industrial agglomeration on the relationship between the digital economy and agricultural export trade. The results show that the interaction between industrial agglomeration and the digital economy (aic × dei) has a coefficient of 1.811, significant at the 1% level, confirming a significant positive moderating effect of industrial agglomeration in the impact of the digital economy on agricultural export trade.

Table 4.5. Moderation Test

	(1)
dei	1.882***
	(0.636)
stru	-12.555***
	(1.596)
gov	0.751**
	(0.369)
appi	-0.183
	(0.189)
open	-0.008
	(0.153)
labor	1.466
	(0.955)
aic	0.876***
	(0.133)
aic×dei	1.811***
	(0.693)
constant	3.625***
	(0.509)
fixed effects	Yes
Observations	510
Number of IDs	30
R-squared (R^2)	0.519

5.2 Test for the Existence of Threshold Effect

Using 500 bootstrap replications, we test for the existence of threshold effects (Table 4.6). The single-threshold test yields an F-statistic p-value of 0.096 (< 0.10), significant at the 10% level, confirming the presence of a single threshold in industrial agglomeration. The estimated threshold value is 1.628.

Table 4.6. Test for the Existence of Threshold Effect

number of thresholds	F-statistic	p-value	threshold (R)	95% CI	bootstrap replications (BS)
single threshold	39.91	0.096	1.626	[1.624, 1.628]	500

5.3 Estimation Results of the Panel-Threshold Model

The panel-threshold model (Table 4.7) shows that when (aic < 1.626), the coefficient on the interaction term ((dei \times aic)) is 1.972 (significant at the 1% level); when (aic \ge 1.626), the coefficient turns −8.336 (significant at the 1% level). This indicates that agricultural industry agglomeration positively moderates the relationship between the digital economy and agricultural export trade at lower levels of agglomeration, but as agglomeration intensifies the moderating effect becomes negative, yielding an inverted-U pattern—thereby supporting Hypothesis 2(H2).

Table 4.7. Estimation Results of the Panel-Threshold Model

	(1)
dei×aic(aic<1.626)	1.972***
	(0.671)
dei×aic(aic≥1.626)	-8.336***
	(1.882)
dei	1.713***
	(0.616)
stru	-15.508***
	(1.626)
gov	0.684*
	(0.358)
appi	-0.029
	(0.185)
open	-0.054
	(0.148)
labor	1.510
	(0.924)
aic	0.829***
	(0.129)
constant	3.782***
	(0.493)
fixed effects	Yes
Observations	510
Number of IDs	30
R-squared (R^2)	0.551

6. Tests for Spatial Spillover Effects

6.1 Moran's I Tests

(1) Global Moran's I Test

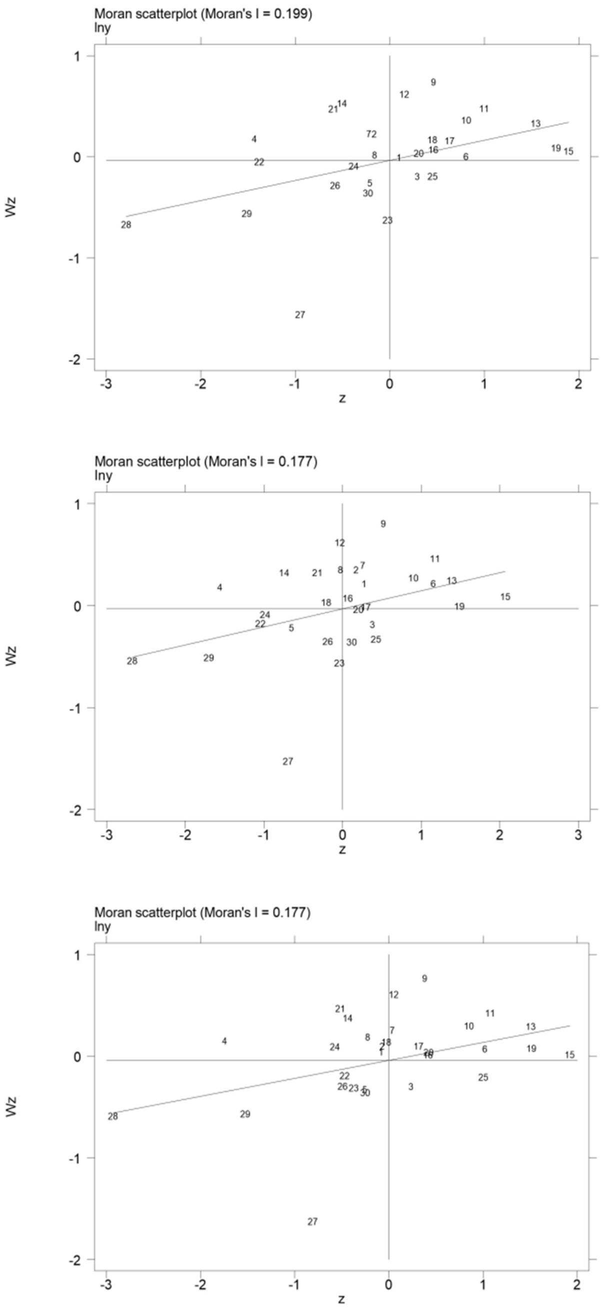
During 2007-2023, the Global Moran's I for agricultural export trade ranges from 0.167 to 0.207, with all p-values < 0.01, indicating significant spatial dependence and a deviation from complete spatial randomness in China over the period.

Table 4.8. Global Moran's I Test

year	I	p
2007	0.207	0.005
2008	0.205	0.005
2009	0.177	0.011
2010	0.180	0.011
2011	0.177	0.012
2012	0.171	0.015
2013	0.168	0.016
2014	0.190	0.009
2015	0.185	0.009
2016	0.167	0.016
2017	0.177	0.011
2018	0.183	0.011
2019	0.194	0.007
2020	0.187	0.009
2021	0.184	0.010
2022	0.202	0.006
2023	0.199	0.006

(2) Local Moran's I

We examine local spatial features using Moran scatterplots (Figure 4.1) for 2007, 2011, 2017, and 2023. The results indicate that agricultural export trade exhibits "high-high" and "low-low" clustering patterns across all selected years, confirming the presence of positive spatial autocorrelation.



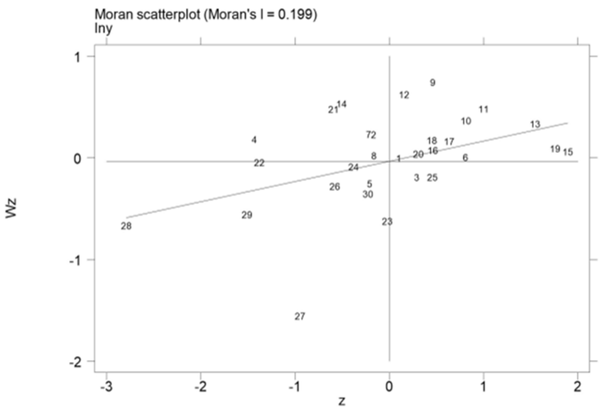


Fig. 4.1. Local Moran Scatterplots of Agricultural Export Trade for Four Sample Years

6.2 Model Selection

Based on the LR, Wald, and Hausman tests (Table 4.9), the spatial Durbin model (SDM) outperforms the SEM and SAR alternatives, and fixed effects are more appropriate for this study. We therefore adopt the fixed-effects SDM to analyze the spatial spillover effects of the digital economy on agricultural export trade.

Table 4.9. Model Selection

	Test type		Result
LM tests	Spatial error	LM statistic	7.456***
		Robust LM statistic	13.514***
	Spatial lag	LM statistic	4.141**
		Robust LM statistic	10.199***
Wald tests	Wald test(SAR)		156.47***
	Wald test(SEM)		147.87***
LR tests	LR test(SAR)		156.47***
	LR tests(SEM)		147.87***
Hausman	Chi-square (χ^2)		36.43***

Notes: LM = Lagrange Multiplier; Robust LM denotes robust versions of LM tests. SAR = Spatial Autoregressive model; SEM = Spatial Error model. LR = Likelihood Ratio. Reported values are test statistics; p-values in parentheses.

6.3 Analysis of Spatial Regression Results

The Spatial Durbin Model (SDM) results (Table 4.10) show that the spatial autoregressive coefficient is 0.174 (5% significance), indicating positive spatial spillovers from local agricultural export trade to neighboring regions. The coefficient on local digital-economy development (dei) is 1.331 (5% significance), which confirms Hypothesis 1 (H1). The spatial interaction term W×dei is 6.776 (1% significance), suggesting that local digital-economy development significantly promotes agricultural export trade in adjacent regions, thereby supporting Hypothesis 3 (H3).

Table 4.10. Estimation Results of the Spatial Durbin Model

	(1)
dei	1.331**
	(0.525)
stru	7.614***
	(0.869)
gov	-8.041***
	(0.560)
appi	0.429
	(0.863)
open	1.236***
	(0.146)
labor	1.347***
	(0.175)
Wx×dei	6.776***
	(1.262)
Wx×stru	6.233***
	(2.121)
Wx×gov	3.446**
	(1.499)
Wx×appi	-0.606
	(1.941)
Wx×open	2.487***
	(0.351)
Wx×labor	-3.979***
	(0.528)
ρ (rho)	0.174**
σ^2_e	0.495***
Observations	510
R-squared (R^2)	0.634
Number of IDs	30

6.4 Decomposition of Spatial Spillover Effects

The effect decomposition (Table 4.11) shows that the digital economy exhibits significantly positive impacts at the 1% level in both the direct effect and the indirect effect. This indicates that digital-economy development not only promotes local agricultural export trade but also stimulates neighboring regions' trade through channels such as information diffusion.

Table 4.11. Spatial Effect Decomposition of the Spatial Durbin Model

	Direct	Indirect	Total
dei	1.555***	8.412***	9.968***
	(0.532)	(1.602)	(1.729)
stru	7.763***	8.730***	16.493***
	(0.737)	(2.285)	(2.152)
gov	-7.925***	2.458*	-5.468***
	(0.595)	(1.436)	(1.441)
appi	0.477	-0.642	-0.166
	(0.934)	(2.366)	(2.343)
open	1.291***	3.195***	4.486***
	(0.161)	(0.481)	(0.539)
labor	1.245***	-4.440***	-3.195***
	(0.171)	(0.697)	(0.753)

7. Heterogeneity Analysis

Model 1 (Table 4.12) shows that the coefficient on digital-economy development for the eastern-central region is 1.998 (1% significance). Model 2 shows that the coefficient for the western region is 5.978 (1% significance). Thus, digital-economy development has a significant positive effect in both regions, with a stronger impact in the west. A plausible explanation is that the west's abundant agricultural resources can leverage the digital economy to optimize logistics and supply chains, lower transportation costs, and improve circulation efficiency; by contrast, the more mature markets in the eastern-central region yield smaller marginal gains from further digitalization.

Table 4.12. Heterogeneity Analysis

	(1)	(2)
	eastern-central region	western region
dei	1.998***	5.978***
	(0.337)	(1.994)
stru	-7.750***	-6.292**
	(0.749)	(2.922)
gov	1.493***	2.019***
	(0.469)	(0.571)
appi	-0.236	-0.475
	(0.212)	(0.372)
open	0.203	-2.876***
	(0.130)	(0.992)
labor	-0.777	4.031
	(0.799)	(4.291)
Constant	4.086***	-0.105
	(0.306)	(0.693)
fixed effects	Yes	Yes
Observations	323	187
Number of IDs	19	11

V. Conclusions and Policy Recommendations

1. Conclusions

This study yields three core conclusions.

(1) Digital-economy development has a significant positive effect on China's agricultural export trade. From a regional perspective, advances in the digital economy promote local agricultural exports in both the eastern-central and western regions, with a stronger effect in the west.

(2) The moderating effect of industrial agglomeration is nonlinear: in the early stage of agglomeration, it positively moderates the relationship between the digital economy and agricultural export trade; once agglomeration exceeds a threshold, the moderating effect turns negative, yielding an inverted-U pattern.

(3) Beyond local effects, the digital economy generates positive spatial spillover effects on the agricultural export trade of neighboring regions.

2. Recommendations

(1) Strengthen the strategic layout of digital infrastructure and promote balanced regional development of the digital economy. Build a systematic development framework, create an institutional environment suited to the digital economy, and prioritize digital technology support. Specific pathways include forward-looking planning for next-generation digital infrastructure and expanded investment in big data centers and the industrial internet. Advance the digital transformation of traditional infrastructure to achieve deep integration of agriculture, energy, and environmental facilities with digital technologies. To address regional imbalances, increase policy support for the central and western regions. Through mechanisms such as interregional allocation of computing power and guided technology spillovers from the east, establish an "east-led, central-west coordinated" development pattern, thereby maximizing the digital economy's positive effect on agricultural export trade.

(2) Optimize patterns of industrial agglomeration in agriculture to unlock its positive moderating potential. Curb the negative effects of over-agglomeration through spatial-layout optimization. Specific measures include: promoting diversified spatial layouts in agriculture to avoid single-industry overconcentration and the resulting "siphon-congestion" effects; fostering new agricultural business entities and building a farmer-enterprise-government collaborative innovation network to improve the allocation efficiency of digital resources; and implementing strict ecological-resource governance to ensure the sustainable use of resources in agglomeration areas. Through institutional innovation, build an industrial ecosystem of "orderly agglomeration and stable development," fully unlocking economies of scale, knowledge spillovers, and demonstration effects, thereby advancing the high-quality development of agricultural export trade.

(3) Deepen interregional coordination in the digital economy to activate spatial spillover effects. Prioritize the development of regional digital-innovation platforms to facilitate the free flow of technology, talent, capital, and data across neighboring regions, thereby forming a cooperative network of complementary advantages and shared outcomes. Establish regularized coordination mechanisms to strengthen industry matching and market-development cooperation, enabling the interregional transfer and application of innovation outcomes. Place special emphasis on leveraging major export provinces as demonstrative leaders. Through a "point-to-surface" (pilot-to-scaling) strategy, expand the agricultural export scale of surrounding regions, thereby achieving nationwide coordinated growth and quality upgrading in agricultural export trade.

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Authors

Meng-Qi Wang, Ph.D., is a faculty member at Inner Mongolia Medical University and holds a doctorate in International Business from Kyonggi University, South Korea. She also serves as a council member of the Inner Mongolia Psychological Consultant Association. Her research and teaching focus on career planning education, and she developed the award-winning "Domino Triple-Driven Dual-Track" instructional method. Her academic contributions include one SSCI-indexed article and three textbooks

Zi-Yang Liu received the B.A. degree in Management from the Army Command College of Shijiazhuang, China PLA, China, in 2006, and the M.A. and Ph.D. degrees in Management from Kyonggi University Korea, in 2010 and 2013, respectively. Dr. Liu joined the faculty of Global Business at Kyonggi University, Korea, in 2015. He is currently a Professor of Global Business at Kyonggi University. His research interests include quality management, management information systems, international economics, and e-business.