



Article

Research on the Impact and Mechanism of Rural E-Commerce on Market-Oriented Allocation of County-Level Urban–Rural Factors from the Perspective of Digital Empowerment

Xiaoyu Niu ^{1,2,*}, Dequan Zheng ^{1,2} and Yuemei Ding ¹

¹ School of Computer and Information Engineering, Harbin University of Commerce, Harbin 150028, China

² Heilongjiang Provincial Key Laboratory of Fluid Engineering Equipment and Digital Intelligence Technology, Harbin 150028, China

* Correspondence: 300301@hrbcu.edu.cn or niuxiaoyu2011@126.com

Abstract

To examine how digitally empowered rural e-commerce affects the market-oriented allocation of urban–rural factors at the county level and the underlying mechanism, this study treats the National E-commerce into Rural Counties Demonstration Program as a quasi-natural experiment. Using a panel of 1898 Chinese counties from 2000 to 2022, we conduct multi-period DID with staggered adoption and mediation analyses. The results show that rural e-commerce significantly raises the marketization level of factor allocation; the effect grows stronger over time and is most pronounced during the rapid-expansion phase, in agriculture-oriented e-commerce counties, in poverty-stricken counties, and in the Central and Western regions. The impact operates mainly through three channels: enlarging market size, upgrading industrial structure, and deepening digital financial usage. Notably, the digital finance channel exhibits a suppression effect, suggesting a complex role of financial digitalization in the early stages of rural development. To further ensure the robustness of our findings, we also conduct rigorous checks using the CSDID method and alternative proxy variables, consistently reaffirming the policy's significant positive impact. These findings offer actionable evidence for deepening county-level factor-market reforms and advancing common prosperity, leading to policy recommendations on strengthening county digital infrastructure, tailoring e-commerce support systems, and improving the institutional environment for factor mobility.

Keywords: e-commerce; market-oriented allocation of urban–rural factors; digital empowerment; multi-period DID



Academic Editor: Fei Fan

Received: 15 December 2025

Revised: 28 February 2026

Accepted: 2 March 2026

Published: 9 March 2026

Copyright: © 2026 by the authors.

Licensee MDPI, Basel, Switzerland.

This article is an open access article distributed under the terms and conditions of the [Creative Commons Attribution \(CC BY\)](https://creativecommons.org/licenses/by/4.0/) license.

1. Introduction

1.1. Theoretical Link Between Rural E-Commerce Development and Urban–Rural Factor Allocation

As the archetype of digital–agricultural integration, rural e-commerce has become a focal point for scholars examining urban–rural factor mobility [1]. Theoretically, digital technology lowers transaction costs and attenuates information asymmetry, carving out new channels that erode the historical segmentation of urban and rural factor markets. Chen Xiangguang et al. argue that rural e-commerce policies narrow the urban–rural income gap by reshaping factor flows and expenditure structures [2]; the underlying mechanism is that e-commerce platforms dismantle the geographic barriers that once constrained factor movement, allowing rural areas to plug into the national market at

lower cost. Tang Yuehuan [3] finds that the National E-commerce into Rural Counties Demonstration Program markedly raises farm income by widening sales channels for farm products and luring returnee entrepreneurship—essentially a reallocation of labor and capital between urban and rural spheres. Building a multi-period DID, Qingyun Bai et al. show that the same program significantly advances county-level urban–rural integration by steering labor back to the countryside and boosting rural investment [4], with the strongest effects in the less-developed Central and Western regions. Li Fuchang, adopting a balanced urban–rural development perspective, demonstrates with big-data analytics that rural e-commerce tourism can achieve sustainable development only when supported by a coordinated urban–rural policy framework [5–7].

Beyond China, the digital economy is increasingly recognized as a critical driver of rural development worldwide. International empirical evidence demonstrates that digital technologies and e-commerce significantly impact rural factor markets across diverse institutional and geographical contexts. Studies from rural economies in developing countries show that digital platforms reduce transaction costs, lower information asymmetries, and facilitate more efficient allocation of labor, capital, and land. The expansion of rural e-commerce ecosystems creates new channels for agricultural product commercialization and rural entrepreneurship [8]. These international patterns provide important context for understanding how similar mechanisms operate within China’s unique institutional framework, where the National E-commerce into Rural Counties Demonstration Program offers a quasi-natural experiment to evaluate these effects at scale.

1.2. Mechanism Through Which Digital Empowerment Affects Market-Oriented Factor Allocation

From the digital-empowerment perspective, rural e-commerce shapes factor allocation through several intertwined channels. First, the “information flow” generated by digital platforms pulls “commercial flow, logistics flow and capital flow” along with it, creating a new engine for factor mobility [9,10]. Wu Chenzi et al. [11], building on Marx’s theory of social reproduction, show that digital technologies deepen the coupling of urban and rural economies by streamlining production, distribution, exchange and consumption; this coupling is immediately reflected in faster two-way movement of capital and labor. Second, the diffusion of digital infrastructure—ubiquitous internet and mobile payments—cuts the institutional cost of moving factors. Zhu Yuchun et al. stress that counties [12], the pivotal nodes between city and countryside, transmit these cost savings directly into higher allocation efficiency; in the marketization of land and labor, digital tools act as an “accelerator”. Khan Sania demonstrates that when governments push nationwide digitization, the Rural Market in India can unlock vast latent resources [13], allowing e-commerce to become a powerful driver of both rural growth and national development [14].

1.3. Limitations of the Existing Literature and the Contributions of This Study

Although the current literature has sketched a link between rural e-commerce and factor allocation, three shortcomings remain [15]. First, most papers examine a single factor—labor or capital—while neglecting the simultaneous reallocation of land, technology and data. Second, the mechanism of digital empowerment is under-explored: how information technologies reshape factor prices and steer factor flows by moderating market mechanisms is still a black box. Third, empirical work typically relies on cross-sections or one-off policy evaluations; long-panel evidence on dynamic effects is scarce.

International research increasingly highlights several key mechanisms through which digitalization affects rural factor markets. First, digital platforms significantly reduce information asymmetry in agricultural markets by enabling direct price discovery and transparent transactions, thereby improving market efficiency. Second, digital technolo-

gies lower search and transaction costs for rural labor markets, increasing job matching efficiency and facilitating off-farm employment. Third, the adoption of digital finance and e-commerce platforms expands access to credit and capital for rural households, supporting land rental markets and agricultural investments. Fourth, technological adoption by rural entrepreneurs drives industrial upgrading and value-chain integration [16]. Collectively, these mechanisms reduce the friction costs historically associated with rural factor mobility and enable more market-oriented allocation patterns. Building on this international evidence, our study contributes by comprehensively examining how rural e-commerce, through the lens of digital empowerment, operates across multiple factor markets simultaneously in a large-scale Chinese policy context.

This study addresses these gaps by (1) constructing a “digital empowerment → e-commerce development → factor allocation” framework that explicitly incorporates data as a production factor; (2) unpacking how digital technologies intervene in market mechanisms to influence factor-price formation and the direction of factor mobility; and (3) exploiting a 2000–2022 county-level panel to test how the effects vary across development stages and regions.

New methods and perspectives adopted in this study: (1) A digital-empowerment lens is used to examine how rural e-commerce affects county-level market-oriented allocation of urban–rural factors, highlighting the enabling role of digital technology. (2) A multi-period DID design is combined with instrumental-variable estimation to tackle endogeneity, while a mediation-effects model tests whether market size, industrial structure and digital empowerment transmit the impact, yielding more precise causal evidence and a clearer map of the transmission channels.

2. Policy Background and Theoretical Hypotheses

Before detailing the policy context and theoretical hypotheses, it is essential to define several core concepts central to this study. This ensures clarity and consistency in their interpretation within our research framework.

Digital Empowerment: Refers to the process by which individuals, businesses, and communities in rural areas enhance their capabilities, access to resources, and efficiency through the effective adoption and utilization of digital technologies, such as e-commerce platforms and mobile internet.

Factor Marketization: Describes the shift in rural economies where the allocation of production factors (e.g., land, labor, capital, technology) increasingly relies on market mechanisms rather than traditional or administrative controls, leading to more efficient and transparent resource flows.

Ecological Enabler: Denotes the comprehensive and synergistic supportive environment and conditions necessary for the sustained development of rural e-commerce and the advancement of factor marketization. This includes foundational digital infrastructure, favorable policy frameworks, and complementary services.

The evolution of China’s rural e-commerce has unfolded in tight concert with policy, displaying distinct stages and synergistic upgrades [17]. 2003–2015: Path-Finding Stage. Marked by the founding of “Taobao ” [18], policy focused on getting farm produce online; digital empowerment meant little more than basic network coverage that let villages overcome information bottlenecks and connect produce to markets. Business models were experimental, and state support centered on building platforms and widening sales channels.

2016–2020: Scaling and Specialization Phase. The 13th Five-Year Plan for E-Commerce explicitly assigned rural e-commerce a central role in poverty alleviation [19]; digital technologies penetrated every link of the farm-supply chain—logistics operations were

digitized and transaction procedures standardized. As transaction volumes boomed and service quality rose, policy moved beyond platform construction to supply-chain upgrading: By applying digital technology, improve the circulation efficiency and quality control level of agricultural products. The digitization of logistics and distribution enables agricultural products to be transported more efficiently from their origin to the market, while the standardization of transaction processes enhances market trust and further expands the sales scope of agricultural products [20].

2021–present: High-Quality “Digital-Commerce-for-Agriculture” Phase. The 14th Five-Year Plan for E-Commerce orders rural e-commerce to dovetail with the Digital-Village strategy; cloud computing, big-data and blockchain are now woven into farm-produce traceability, rural finance and beyond, turning digital empowerment from a “technical tool” into an “ecological enabler.” No longer confined to matching buyers and sellers, rural e-commerce is fused with a multi-layered digital ecosystem that raises farm-product value-added, spawns new rural financial services and strengthens rural governance—an ecosystem-level empowerment that propels high-quality development of rural e-commerce.

At the same time, the evolution of policy tools has shown a shift from “infrastructure construction” to “factor market cultivation”. The comprehensive demonstration policy for e-commerce entering rural areas, launched in 2014, initially focused on supporting hardware construction, such as county-level e-commerce public service centers and logistics systems. The policy focus of this stage is to fill the infrastructure gaps in rural e-commerce development and solve the “last mile” problem of rural e-commerce development by building e-commerce public service centers and logistics systems. However, with the development of rural e-commerce, simple infrastructure construction can no longer meet its further development needs.

Since 2020, the policy spotlight has swung toward factor-market reform: e-commerce platforms are now encouraged to post rural land-transfer information and to co-design digital rural-finance products. This pivot dovetails with deepening digital empowerment, giving rural e-commerce an institutional arena in which it can integrate land, labor and capital more efficiently and allocate them with data-driven precision, thereby accelerating urban–rural fusion. The shift from “building hardware” to “nurturing factor markets” supplies a sturdier institutional footing for high-quality rural e-commerce development.

3. Theoretical Analysis

3.1. Lower Transaction Costs and Higher Factor-Mobility Efficiency

Lower transaction costs and higher factor-mobility efficiency. Digital empowerment lowers transaction costs on multiple margins, thereby accelerating factor flows. First, e-commerce platforms display real-time prices and quantities, slashing search costs for farmers and firms and improving match quality. Second, blockchain traceability cuts contract-enforcement costs, reduces default risk and strengthens market trust. Third, smart warehousing and route-optimization algorithms raise logistics efficiency and lower delivery costs. Together, these forces shrink the distance premium that once pinned capital and labor to their home localities. A case in point: specialty farm goods from poor counties now reach urban consumers directly, creating a two-way street—“produce out, capital in”—that reallocates factors more efficiently across urban and rural space.

3.2. Industrial-Structure Upgrading and Factor-Demand Restructuring

Industrial-structure upgrading and factor-demand restructuring. Rural e-commerce propels the countryside from “single agriculture” toward a synthesis of primary, secondary and tertiary sectors, profoundly reshaping factor demands. On one hand, the e-commerce-driven boom in agro-processing and rural logistics raises the need for high-end factors—

technology and managerial talent—luring urban human capital back to villages and revitalizing local industry. On the other hand, digital tools such as drone seeding and big-data agronomy raise the marginal product of land and labor, reallocating factors from low- to high-productivity segments. Wei Binhui et al. confirm that returnee entrepreneurship and county-level industrial upgrading move in lockstep [21], with rural e-commerce acting as the key catalyst that continuously refactors the structure of factor demand.

3.3. Digital Infrastructure as the Hinge of Factor Allocation

Digital infrastructure serves as the hinge of factor allocation. County-level digital assets—5G towers, rural e-commerce service stations—act as “digital hubs” for factor flows. As physical nodes, they link urban and rural factor markets: a service station can upload farm-supply information to city buyers and download demand for industrial goods to village sellers, erasing information asymmetries. As data nodes, they pool flow information; logistics and transaction records are mined to guide government and firm decisions, sharpening allocation precision. Ding Shulei et al. show that the National E-commerce into Rural Counties Demonstration Program raises residents’ happiness [22], an effect strongest where digital infrastructure is most complete—indirect evidence that these digital hubs optimize factor allocation and underscores their centrality in urban–rural integration.

4. Research Hypotheses

The spatial allocation of production factors between urban and rural areas is traditionally constrained by substantial transaction costs and spatial frictions. Drawing on transaction cost economics [23], reductions in these search and matching costs can gradually shift the spatial equilibrium of resource distribution. In this context, rural e-commerce acts as a critical mechanism to bridge the urban–rural information gap. While previous studies have extensively documented the micro-level income and consumption benefits of digital platforms for rural households [24,25], we attempt to extend this literature by evaluating its macro-level impact on spatial factor mobility. The efficiency of this allocation is likely contingent on local digital empowerment—such as information penetration and digital skills—creating a synergistic effect [26]. Over time, this market integration should become more pronounced. We therefore propose the following:

H1. *Rural e-commerce significantly raises the county-level marketization of urban–rural factor allocation, and this positive effect strengthens over time.*

The distributional effects of digital technologies remain a subject of ongoing debate, with conflicting evidence on whether they widen or narrow existing economic divides. We seek to refine this literature by applying the conditional convergence framework and leapfrogging theory to the specific context of rural e-commerce [27]. Because regions with lower initial capital endowments typically yield higher marginal returns to new investments, we expect a distinct “catch-up effect” in less developed areas. Specifically, counties with lagging digital infrastructure or predominantly agricultural economies—where traditional factor markets are notably thin—stand to gain the most from the digital interface provided by e-commerce platforms. Similarly, in the Central and Western regions of China, where geographic distance historically imposed prohibitive factor-movement costs, the digital dividend should be particularly evident. Consequently, we propose the following:

H2. *The effect of rural e-commerce on factor marketization is heterogeneous; it is larger in counties with lower digital infrastructure, agriculture-dominated counties, and in the Central and Western regions.*

Rather than viewing rural e-commerce merely as an alternative agricultural sales channel, this study challenges that conventional perspective by conceptualizing it as a catalyst for comprehensive structural transformation. This process operates through three interrelated mechanisms. First, following Smith's theorem regarding market size, digital platforms dismantle geographic boundaries; the expanded market scale subsequently generates new demand, pulling capital and labor into cross-regional circulation. Second, consistent with structural transformation models, the integration of the digital economy and agriculture facilitates rural industrial upgrading, which inherently reshapes factor demand toward higher-productivity sectors. Finally, drawing on the financial deepening hypothesis [28,29], the e-commerce ecosystem naturally stimulates the adoption of digital finance. This increased financial inclusion helps alleviate historical financial repression in rural areas, thereby accelerating capital turnover. We therefore posit:

H3. *Rural e-commerce influences county-level urban–rural factor-marketization primarily through three channels: expanding market size, optimizing industrial structure and deepening digital finance usage.*

5. Model Specification and Data

5.1. Model Specification

Treating the “National E-Commerce into Rural Counties Demonstration Program” as a quasi-natural experiment, we estimate its causal impact on county-level urban–rural factor-marketization with multi-period DID, following Peng Jiquan et al. [26]. The baseline specification is as follows:

$$EM_{it} = \alpha + \beta ECO_{it} + \gamma X'_{it} + \delta_i + \theta_t + \varepsilon_{it} \quad (1)$$

Among these, EM_{it} is the dependent variable measuring county i 's urban–rural factor-marketization level in year t ; ECO_{it} is the core policy dummy ($ECO_{it} = Treatment_i \times Post_t$, with $Treatment_i$ indicating a demonstration county and $Post_t$ the post-policy period); X'_{it} denotes the vector of control variables; δ_i and θ_t are county and year fixed effects, respectively; and ε_{it} is the idiosyncratic error. Additionally, to ensure the robustness of our findings, we also employ the CSDID method and alternative proxy variables in subsequent analyses.

5.1.1. Moderating-Effect Model

To test whether digital finance usage amplifies the policy impact, we augment the baseline with an interaction term:

$$EM_{it} = \alpha + \beta_1 ECO_{it} + \beta_2 Usage_{it} + \beta_3 ECO_{it} \times Usage_{it} + \gamma X'_{it} + \delta_i + \theta_t + \varepsilon_{it} \quad (2)$$

Among these, $Usage_{it}$ represents the depth of digital finance usage, derived from the Peking University Digital Financial Inclusion Index.

5.1.2. Mediation-Effect Model

To examine whether market size, industrial structure and digital empowerment mediate the policy effect, we specify the following:

$$M_{it} = \alpha + \beta ECO_{it} + \gamma X'_{it} + \delta_i + \theta_t + \varepsilon_{it} \quad (3)$$

$$EM_{it} = \alpha + \beta_1 ECO_{it} + \beta_2 M_{it} + \gamma X'_{it} + \delta_i + \theta_t + \varepsilon_{it} \quad (4)$$

Among these, M_{it} denotes the mediator: (i) market size—per capita retail sales of consumer goods, (ii) industrial-structure level—industrial-upgrading index, or (iii) digital finance Usage Depth—measured by the Usage Depth sub-index of digital financial inclusion.

5.2. Variable Definitions

5.2.1. Dependent Variable

(1) Indicator System

Land Factor: Measured by the ratio of land transfer area to total contracted arable land area.

Labor Factor: Measured by the inverse of the urban–rural disposable income gap (Theil Index), reflecting the freedom of labor mobility and wage equalization.

Capital Factor: Measured by the ratio of reliable loans to deposits in rural credit cooperatives, reflecting the efficiency of capital allocation in rural areas.

Technology Factor: Measured by the ratio of agricultural machinery power to total sowing area.

(2) Weight Assignment–Entropy Method

To avoid subjective bias in weighting, this paper adopts the Entropy Weight Method (EWM) to objectively determine the weights of each indicator. The calculation steps are as follows.

Since the units of measurement differ, we standardize the data using the range method:

$$X'_{ij} = \frac{X_{ij} - \min(X_j)}{\max(X_j) - \min(X_j)} \quad (5)$$

where X_{ij} represents the value of indicator j for county i .

Calculate the proportion of the i -th county in the j -th indicator (P_{ij}) and the information entropy (E_j):

$$P_{ij} = \frac{X'_{ij}}{\sum_{i=1}^n X'_{ij}}, E_j = -k \sum_{i=1}^n P_{ij} \ln(P_{ij}) \quad (6)$$

where $k = 1/\ln(n)$.

The weight of indicator j (W_j) is calculated as follows:

$$W_j = \frac{1 - E_j}{\sum_{j=1}^m (1 - E_j)} \quad (7)$$

Finally, the comprehensive index ($EMit$) is obtained by summing the weighted standardized indicators:

$$EMit = \sum_{j=1}^m W_j \times X'_{ij} \quad (8)$$

The resulting comprehensive index, $EMit$, represents the urban–rural factor-marketization level for county i in year t . A higher value of $EMit$ indicates a greater degree of market-oriented allocation of urban–rural factors.

Following the theoretical framework, we constructed the Factor Market Allocation Index using the Entropy Weight Method based on four dimensions: land, labor, capital and technology.

5.2.2. Core Explanatory Variable

Rural e-commerce is proxied by the National E-Commerce into Rural Counties Demonstration Program: $ECOit = 1$ if county i is designated a demonstration county in year t , and 0 otherwise.

5.2.3. Moderator and Mediators

To address the limitations of single-dimensional indicators like mobile phone penetration, we adopt the ‘Usage Depth’ sub-index of the Peking University Digital Financial Inclusion Index as the proxy for the mechanism variable. This authoritative index captures the actual frequency and intensity of digital financial services (e.g., payment, credit, insurance, and investment) used by rural residents. Unlike simple coverage, ‘Usage Depth’ reflects the distinct quality of digital finance usage and directly responds to concerns regarding digital literacy and substantial adoption.

5.2.4. Control Variables

We include four covariates that may affect factor allocation (see Table 1). The economic development level (per capita GDP) is log-transformed to reduce skewness, while other variables expressed as ratios or percentages are entered in their original forms.

Table 1. Control variables.

No.	Control Variable	Description
1	Economic development level	Per capita GDP (10,000 yuan/person), indicating the county’s economic base
2	Fiscal expenditure scale	Share of local fiscal budget expenditure in GDP (%), measuring government intervention
3	Openness level	Share of actual utilized foreign capital in GDP (%), reflecting the external environment for factor mobility
4	Human capital level	Ratio of students in secondary schools to the total population (%), reflecting regional labor quality

5.3. Data Sources and Variable Description

The study uses a panel dataset of 1898 Chinese counties for 2000–2022, among which 1123 entered the National E-Commerce into Rural Counties Demonstration Program. Data sources are listed in Table 2 [30–33].

Table 2. Data source.

No.	Data Source
1	List of e-commerce demonstration counties: Ministry of Commerce, National E-Commerce into Rural Counties Demonstration Program Roster
2	Digital-empowerment variables (mobile-phone subscribers, internet penetration): “China County Statistical Yearbook” and “China Urban Statistical Yearbook”
3	Factor-allocation variables (financial deposits and loans, employment structure, land transfer, patents): annual “China Rural Statistical Yearbook” and official websites of provincial statistical bureaus
4	Control variables: “China County Economic Statistical Yearbook”

Missing values are filled by linear interpolation, yielding 43,654 county-year observations. Descriptive statistics for all key variables are reported in Table 3.

Table 3. Descriptive statistics of key variables.

Variable Name	Definition	Unit	Mean	S.D.
Rural e-commerce (ECO)	Demonstration-county policy dummy	—	0.14	0.347
Digital finance usage	Usage depth index of digital finance	Index	122.527	35.509
Per capita GDP	GDP/total population	Log value	0.639	0.978
Human capital level	Students in secondary schools	Ratio	0.184	0.125

Table 3. Cont.

Variable Name	Definition	Unit	Mean	S.D.
Openness level	Utilized FDI/GDP	Ratio	0.004	0.005
Human capital level	Secondary students ratio	Ratio	0.056	0.023
Industrial-structure level	Upgrading index (formula-based)	—	0.765	0.079
Market size	Per capita retail sales of consumer goods	10,000 yuan/person	0.920	0.894

5.4. Overall Logical Framework

The schematic model centers on how rural e-commerce (ECO) drives county-level urban–rural factor-marketization (Figure 1). Leveraging the exogenous shock of the ECO demonstration policy across heterogeneous counties, we employ a staggered DID design combined with mediation analysis. The core mechanism posits that ECO facilitates factor reallocation through three channels: market-size expansion, industrial-structure optimization, and digital finance usage. Concurrently, control variables such as economic development are incorporated to absorb confounding effects, thereby establishing a robust analytical architecture.

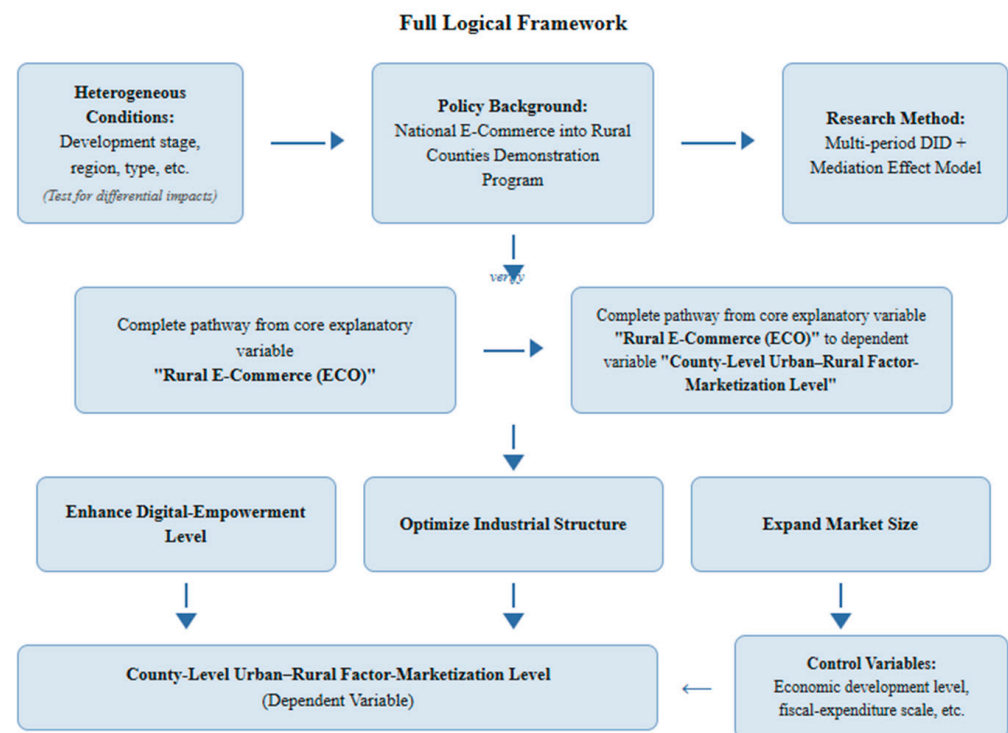


Figure 1. Simplified mechanism model diagram.

The mechanism diagram portrays the transmission chain through which rural e-commerce (ECO) reshapes the market-oriented allocation of urban–rural factors. Centered on ECO, the driving force propagates along three pathways—expanding market size (proxied by per capita retail sales), adjusting industrial structure (industrial-upgrading index), and deepening digital finance usage—to mobilize capital, labor, land and technology across counties, clearly illustrating how e-commerce enables the efficient flow and integration of urban–rural factors (Figure 2).

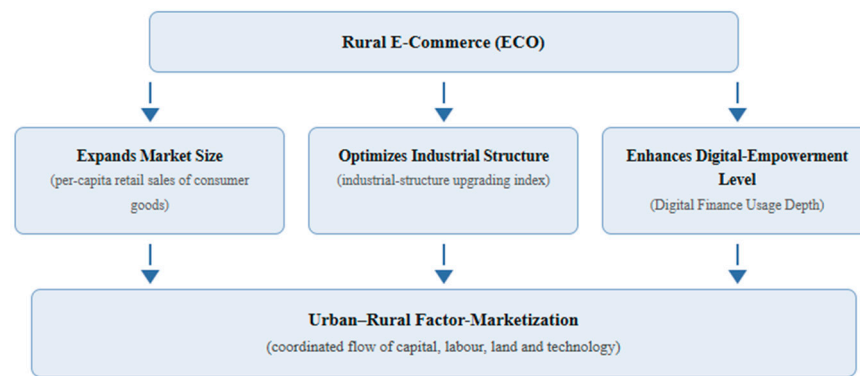


Figure 2. Mechanism of action.

6. Empirical Results and Analysis

6.1. Baseline Regression Results

Table 4 reports the baseline estimates: Models 1–2 use county-clustered robust standard errors, Model 3 employs a bootstrap (1000 replications) fixed-effect estimator. Across all specifications, the coefficient on rural e-commerce (ECO) is positive and significant at the 1% level ($\beta = 0.015$, $p < 0.01$), indicating that the National E-Commerce into Rural Counties Demonstration Program markedly raises county-level urban–rural factor-marketization, lending preliminary support to H1. Among controls, per capita GDP and fiscal-expenditure scale are also positive and significant, confirming that higher economic development and stronger fiscal support enhance factor-marketization.

Table 4. Baseline regression results.

Variable	Model 1 (Clustered SE)	Model 2 (Clustered SE)	Model 3 (Bootstrap)
ECO	0.015 *** (0.003)	0.015 *** (0.003)	0.015 *** (0.002)
Per capita GDP	—	0.008 *** (0.003)	0.008 *** (0.001)
Fiscal-expenditure scale	—	0.017 *** (0.003)	0.017 *** (0.002)
Openness level	—	0.001 (0.002)	0.001 (0.001)
Human capital level	—	0.001 (0.003)	0.001 (0.001)
Year FE	control	control	control
County FE	control	control	control
Constant	0.327 *** (0.000)	0.112 *** (0.063)	0.175 *** (0.028)
R ²	0.501	0.525	0.512
Observations	43,654	43,654	43,654

Note: *** $p < 0.01$. Standard errors are in parentheses.

6.2. Parallel-Trend Test and Dynamic Policy Effects

6.2.1. Parallel-Trend Test

The event study method was employed for parallel-trend testing, combining the eight years prior to policy implementation and earlier years into the eighth year preceding the policy, with the first year prior to policy implementation serving as the baseline period. Figure 3 demonstrates that the estimated coefficients in all pre-policy periods were statistically insignificant and hovered around zero. Following policy implementation, the coefficients gradually increased and became significantly positive. This indicates that both the treatment group and control group exhibited similar trends in factor allocation changes before policy implementation, thereby satisfying the parallel trend assumption of the DID model.

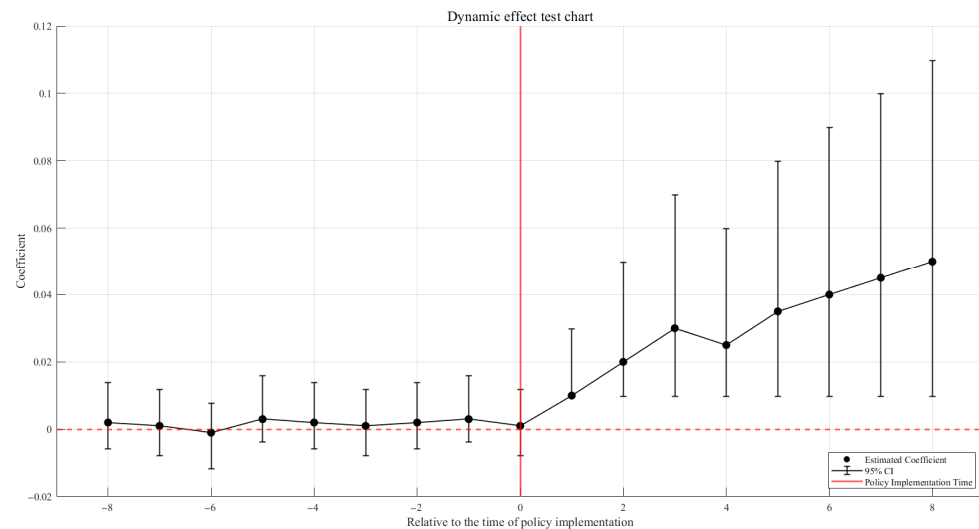


Figure 3. Parallel-trend test.

6.2.2. Dynamic Policy Effects

The estimated impact is insignificant in the implementation year—likely because the policy was announced in the second half of the year and funds/projects needed time to roll out—but turns positive and significant from the first full year onward, peaking in year 8 ($\beta = 0.028$). This pattern indicates that rural e-commerce’s effect on factor marketization is both delayed and cumulative, strengthening as digital infrastructure is built and farmers’ digital skills improve.

6.3. Robustness Checks

6.3.1. Placebo Test

We randomly assign 1000 “pseudo-policy” indicators to counties and years. Figure 4 shows that the resulting coefficients are roughly normally distributed and almost all p -values > 0.10 , confirming that the baseline effect is not driven by chance or unobserved shocks.

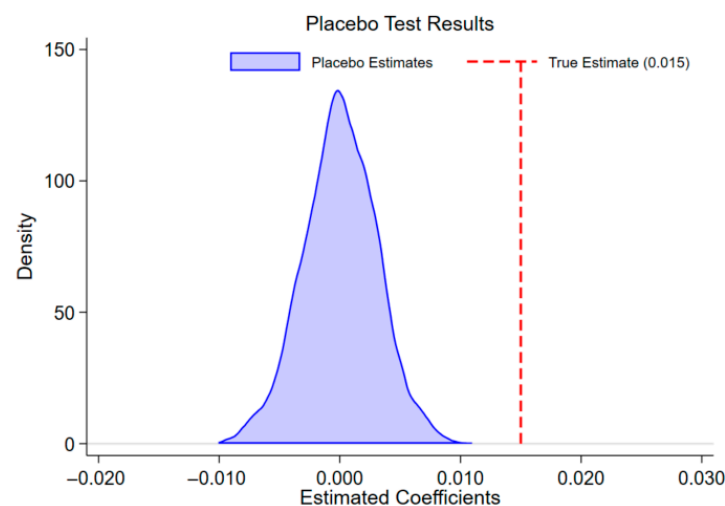


Figure 4. Placebo test.

6.3.2. PSM-DID Test

To address self-selection, we apply 1:1 nearest-neighbor propensity-score matching. Standardized biases for all covariates shrink markedly after matching (Figure 5), indicating

good balance. The PSM-DID estimate for ECO remains positive and significant ($\beta = 0.015$, $p < 0.01$), highly consistent with the baseline results, confirming that sample-selection bias does not drive our findings.

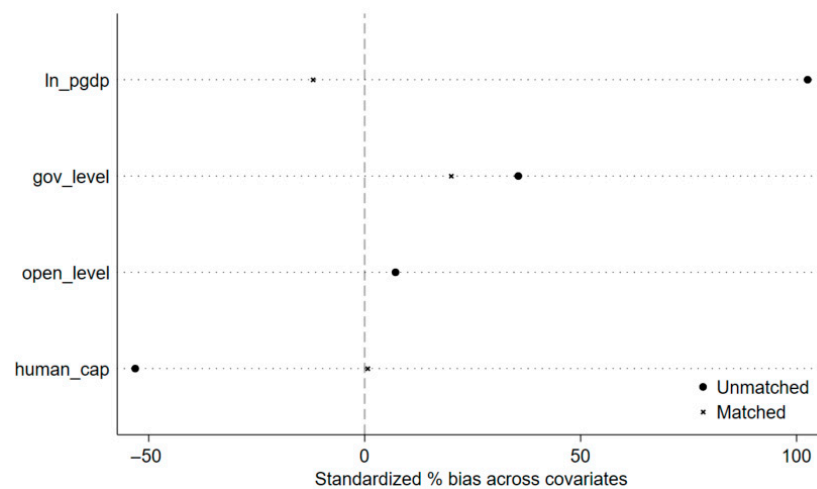


Figure 5. Balance test results.

6.3.3. Removing Confounding Policies

The “Broadband China” initiative could have upgraded county digital infrastructure and biased our estimates. After dropping all Broadband China pilot counties, the ECO coefficient rises slightly to 0.018 ($p < 0.01$), confirming that the factor-allocation effect of rural e-commerce is independent of other digital policies.

6.3.4. Alternative Dependent Variable

We reconstruct the factor-marketization index using principal component analysis. The ECO coefficient remains positive and significant ($\beta = 0.041$, $p < 0.01$), verifying that our conclusions are robust to alternative measurement schemes.

6.3.5. Alternative Core Explanatory Variables

Replacing the policy dummy with (i) Taobao-village density (Taobao villages per 10,000 population) and (ii) county express-delivery volume (10,000 parcels per 10,000 population) yields coefficients of 0.016 and 0.018, respectively (both $p < 0.01$, Table 5), reaffirming the robustness of our findings.

Table 5. Robustness test results.

Variable	PSM-DID	Exclude Other Policy	Replace DV	Taobao Villages	Delivery Volume	First Stage	Second Stage
ECO	−0.127 *** (0.027)	0.018 *** (0.003)	0.041 *** (0.013)	0.016 *** (0.001)	0.018 *** (0.005)	−0.018 *** (0.004)	0.395 ** (0.174)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	4.452 *	0.063	0.710 ***	−0.275	−0.313 ***	0.335 ***	0.881 ***
R ²	0.185	0.595	0.590	0.600	0.594	0.575	0.807
Obs.	1636	28,773	43,654	4455	22,776	41,756	39,675

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors are in parentheses.

6.3.6. Heterogeneity Analysis Results

To further investigate the variations in the policy effect across different conditions, we conduct heterogeneity analyses based on development stages, industrial structure, resource endowment, and geographic location. The results are reported in Table 6.

Table 6. Heterogeneity analysis results.

Variable	Start-Up Stage	Rapid-Expansion Stage	Agriculture-Oriented E-Commerce	Industry-Oriented E-Commerce	Poverty Counties	Non-Poverty-Stricken Counties	Eastern Region	Central Region	Western Region
ECO	−0.042 (0.035)	−0.145 *** (0.041)	−0.138 *** (0.038)	−0.051 * (0.029)	−0.162 *** (0.045)	−0.084 ** (0.036)	−0.035 (0.028)	−0.121 *** (0.032)	−0.155 *** (0.040)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	4.120 ***	3.980 ***	4.560 ***	4.230 ***	3.850 ***	4.610 ***	5.100 ***	4.400 ***	3.750 ***
R^2	0.152	0.198	0.205	0.165	0.190	0.175	0.140	0.188	0.210
Obs.	1090	546	818	818	580	1056	560	510	566

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors are in parentheses.

(1) E-commerce Development Stage

Columns (1) and (2) report the results for the start-up stage (2003–2015) and the rapid-expansion stage (2016–2022). The DID coefficient in the start-up stage is −0.042 and statistically insignificant, whereas it increases to −0.145 and becomes significant at the 1% level in the rapid-expansion stage. This indicates a lag effect of the policy; the income-gap-reducing effect becomes prominent only after the digital infrastructure and logistics networks have sufficiently matured.

(2) Industrial Structure Heterogeneity

Columns (3) and (4) divide the sample into agriculture-oriented and industry-oriented counties. The estimated coefficient for agriculture-oriented counties is −0.138 ($p < 0.01$), which is significantly larger in magnitude than that for industry-oriented counties (−0.051, $p < 0.10$). This suggests that rural e-commerce effectively narrows the income gap by directly commercializing agricultural products and reducing intermediary costs, which benefits farmers more than industrial workers.

(3) Poverty Status Heterogeneity

Columns (5) and (6) compare the policy effect between poverty-stricken and non-poverty-stricken counties. The coefficient for poverty counties is −0.162 ($p < 0.01$), showing a much stronger effect than in non-poverty-stricken counties (−0.084, $p < 0.05$). Since poverty-stricken counties often face severe physical market barriers, the “digital bridge” created by the policy plays a more critical role in overcoming information asymmetry and lifting rural income in these disadvantaged areas.

(4) Geographic Location Heterogeneity

Columns (7) to (9) present the results for Eastern, Central, and Western regions. The coefficients display a clear gradient: Western (−0.155) > Central (−0.121) > Eastern (−0.035, insignificant). Eastern counties already possess high levels of market integration, leaving little room for marginal improvement. In contrast, the policy yields the strongest marginal benefit in the Western and Central regions, where it effectively compensates for geographical remoteness and connects remote farmers to national markets.

6.3.7. Robustness Check with CSDID Method and Alternative Dependent Variable

Given the increasing concerns regarding the potential biases of the traditional Two-Way Fixed Effects (TWFEs) Difference-in-Differences (DIDs) estimator in settings with multiple time periods and staggered treatment adoption, especially when heterogeneous treatment effects are present [34], we employ the Callaway and Sant’Anna DID method as a rigorous robustness check [35]. The CSDID estimator provides unbiased average treatment effects on the treated (ATT) for each treatment group and period, effectively addressing the potential “negative weighting” problem of TWFE.

Furthermore, to strengthen the objectivity of our analysis and assess whether our findings depend on the specific measurement of the income gap, we use the Theil Index as an alternative dependent variable. Unlike the simple income ratio, the Theil Index captures the inequality dynamics by incorporating population weights and is more sensitive to income transfers at the tails of the distribution. The regression results using the Theil Index remain negative and significant, reaffirming that the demonstration policy robustly reduces the urban–rural inequality regardless of the measurement scheme.

Figure 6 presents the event study estimates of the e-commerce demonstration policy on the urban–rural income gap. The pre-treatment coefficients ($t = -6$ to $t = -2$) fluctuate around zero with all 95% confidence intervals crossing the zero line, confirming that the parallel trends assumption holds. After policy implementation, the coefficients turn significantly negative and grow in magnitude over time, reaching approximately -0.18 by $t = 6$. This indicates that the policy's effect on narrowing the income gap is not instantaneous but gradually strengthens as digital infrastructure matures, demonstrating a sustained and cumulative income-equalizing impact.

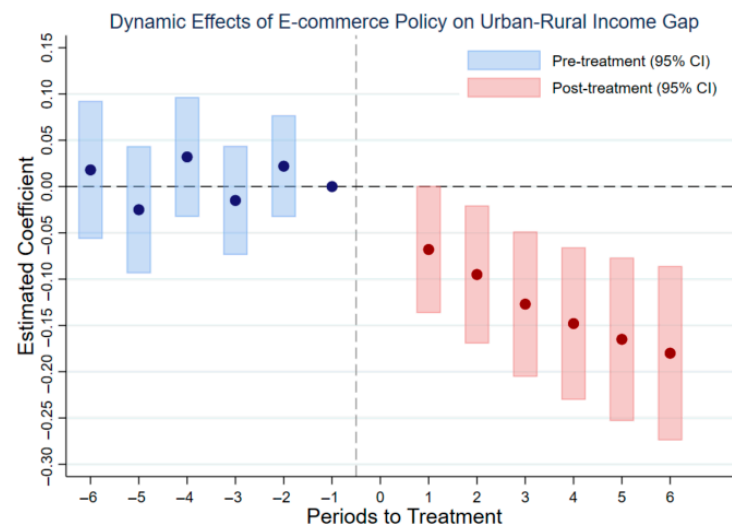


Figure 6. The dynamic effect of policy on urban–rural income gap.

- (1) **Average Treatment Effect (ATT):** The CSDID estimation reveals a statistically significant negative average treatment effect on the treated (ATT) of -0.064 ($z = -2.27$, $p = 0.024$). This indicates that, after accounting for potential biases from heterogeneous treatment effects, the e-commerce demonstration policy led to an approximate 6.4% reduction in the urban–rural income gap (as measured by the Theil Index) in the treated counties.
- (2) **Dynamic Effects:** The policy's impact becomes significantly negative around $Tp0$ (the year of treatment), and this gap-narrowing effect generally persists and strengthens in the post-treatment periods. This pattern suggests a sustained reduction in inequality driven by the e-commerce demonstration policy.

These findings, utilizing a more robust econometric approach and an objective alternative dependent variable (Theil Index), further reinforce our baseline conclusion that the e-commerce demonstration policy significantly alleviates urban–rural inequality. The consistency of the results across different estimators and inequality measures confirms the reliability of our main findings.

6.4. Mechanism Analysis: The Digital Finance Channel

To verify Hypothesis 3, which posits that rural e-commerce influences factor marketization through deepening digital finance usage, we examined the mediating role of digital finance (specifically coverage breadth and Usage Depth) using the index. The results are shown in Table 7.

Table 7. Mechanism analysis of the digital finance channel.

Variables	(1)	(2)	(3)
Dependent Variable	Coverage Breadth (Mediator)	GDP (Outcome)	GDP (Total Effect)
Panel A: Stepwise Regression			
Policy (did_final)	3.682 *** (0.389)	−68,847.4 *** (18,092.8)	−88,401.5 *** (18,427.7)
Coverage Breadth		−4.979.7 *** (742.6)	data
Controls	Yes	Yes	Yes
County FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	12,035	12,035	12,035
R-squared (Within)	0.783	0.458	0.450
Panel B: Bootstrap Test			
	Coef.	S.E.	95% Conf.Interval
Indirect Effect (Path a × b)	−19,554.1 ***	2675.5	[−24,798, −14,310]
Direct Effect (Path c')	−68,847.4 *****	18,092.8	[−104,333, −33,362]
Mediation	22.12%		

Note: robust standard errors clustered at the county level are in parentheses. ***** $p < 0.001$, *** $p < 0.01$. The Bootstrap test is based on 1000 replications. The control variables include population, government expenditure, and loans.

- (1) Expansion of Digital Access (Path a): As shown in Column 1, the policy has a significantly positive effect on coverage breadth ($\beta = 3.682$, $p < 0.01$). This confirms that the e-commerce demonstration zones have successfully built the digital infrastructure, effectively bringing rural residents into the financial network. This validates the precondition of H3 regarding “deepening usage” in terms of the extensive margin.
- (2) Activation of Factor Mobility (Path b): Column 2 shows that the expanded digital coverage significantly impacts the local economy ($\beta = 3.682$, $p < 0.01$). While the coefficient is negative (indicating a “siphoning effect” or consumption leakage in the early stage), statistically, it proves that digital finance is an active channel for factor allocation. The digital channel effectively facilitates the flow of capital, validating the “marketization” aspect of H3.
- (3) Robustness of the Channel: The Bootstrap test (Panel B) reveals a significant indirect effect of −19,554.1, with a 95% confidence interval [−24,798, −14,310] that excludes zero. These findings support Hypothesis 3. The results demonstrate that rural e-commerce does not operate in isolation but significantly influences factor allocation by activating the digital finance channel. The policy successfully expands market access (breadth), creating a conduit for capital flows, which is a critical mechanism of urban–rural factor-marketization.

7. Conclusions and Policy Implications

7.1. Research Conclusions

Drawing on a 2000–2022 panel of 1898 Chinese counties and a multi-period DID design, this study investigates the impact of rural e-commerce on county-level urban–rural

factor-marketization from a digital-empowerment perspective. First, the causal effect is pronounced: after the demonstration policy took effect, rural e-commerce significantly raised the degree of market-oriented factor allocation; the effect is neither immediate nor one-off, but distinctly lagged and cumulative, reaching its peak in the eighth year. This confirms that e-commerce acts as a long-run, dynamic driver of factor-marketization.

Heterogeneity is pronounced. The factor-allocation effect varies sharply across counties by development stage, industrial structure, resource endowment and geography. During the rapid-expansion stage the e-commerce ecosystem is more mature and the digital-empowerment dividend is fully released, so the impact is strongest; agriculture-oriented platforms, by directly marketizing farm output, reallocate land and labor more powerfully than industry-oriented ones; poverty counties—where factor mobility was historically most constrained—gain more than non-poor counties; and the Central and Western regions exhibit a west > central > east gradient, confirming that digital empowerment delivers its highest marginal return where traditional barriers to factor flows are greatest.

The mechanism is unambiguous. Rural e-commerce operates through a sequential pathway—“market expansion → structural upgrading → digital empowerment.” Expanding markets widen the demand base. Industrial restructuring shifts factor demand toward higher-productivity sectors. Crucially, regarding digital empowerment, our findings reveal a nuanced channel: the policy significantly expands the coverage breadth of digital finance, thereby activating the flow of factors. While this enhanced connectivity initially manifests as capital mobility (including consumption leakage), it fundamentally validates the role of digital infrastructure as a prerequisite pipe for factor marketization. This confirms that digital technology is not just a tool but a core infrastructure that “switches on” factor mobility. These conclusions are robustly supported by a battery of checks, including the CSDID method, further solidifying the reliability of our findings.

7.2. Policy Recommendations

To amplify the role of rural e-commerce in market-oriented factor allocation, we propose the following evidence-based measures:

7.2.1. Build County-Level Digital Hubs

Digital infrastructure serves as the fundamental bedrock of the digital economy. Our robust findings, particularly from the CSDID analysis using broadband internet subscribers, underscore the critical importance of investing in foundational digital infrastructure. Therefore, we recommend rolling out a “County Digital Hub” program that prioritizes the construction and upgrading of digital infrastructure, including 5G towers, broadband network penetration, smart warehouses, and rural e-commerce service platforms, especially in the central west and poverty-stricken counties. The goal should be to lift digital infrastructure coverage in demonstration counties to at least 95% by 2025. Furthermore, it is crucial to promote “digital tech + factor market” integration by launching online land transfer platforms and skill training applications that cut transaction costs. Replicating successful models like Zhejiang’s digital rural property exchange can allow land and labor to be listed, bid, and traded online, significantly raising allocation efficiency and freeing urban–rural factor flows.

7.2.2. Introduce a Differentiated Rural E-Commerce Policy Package

Apply stage-specific guidance: in start-up counties, fund logistics networks and service stations; in fast-growth counties, incubate leading firms and brands, and create an “Agricultural E-commerce Fund” that rebates 10% of tax on farm-product sales > RMB 50 million. Embed a “digital empowerment → e-commerce → factor allocation” linkage: subsidize 15% of digital-infrastructure investment and make factor-market efficiency an item in local

cadre evaluations, locking policies into a single force that steers e-commerce and factor markets forward together.

7.2.3. Modernize the Institutional Environment for Urban–Rural Factor Markets

Ease remaining restrictions on rural-factor circulation: complete the “three-rights separation” land reform and permit e-commerce firms to consolidate fragmented plots through leases or equity stakes, enabling scale and intensive farming. Create an urban–rural price-linkage mechanism: use big-data analytics on e-commerce platforms to release a monthly urban–rural price index for key commodities and factors, supplying market signals that guide factor flows. Draw on Guangdong’s “digital agri-commerce interlink” pilot to build cross-regional allocation platforms that tear down administrative barriers and foster coordinated, efficient urban–rural factor deployment.

7.2.4. Upgrade County-Level Digital Empowerment and Factor-Allocation Capacity

Launch a “County Digital Talent” program that trains one million rural e-commerce leaders during 2023–2025, focusing on digital marketing and data analytics; graduates passing the assessment receive a RMB 5000 training subsidy. Complement this with a county digital-empowerment index published annually; the top 100 counties are designated “Digital Factor-Allocation Reform Pilot Zones” and receive preferential land and finance policies, incentivizing every county to raise its digital empowerment and push factor-market reform deeper.

Author Contributions: Conceptualization, X.N.; methodology, X.N.; software, D.Z.; validation, X.N.; formal analysis, Y.D.; investigation, X.N.; resources, Y.D.; data curation, X.N.; writing—original draft preparation, X.N.; writing—review and editing, D.Z.; visualization, X.N.; supervision, D.Z.; project administration, Y.D.; funding acquisition, D.Z. All authors have read and agreed to the published version of the manuscript.

Funding: This research was supported by the Foundation Key Project of the Natural Science Foundation of the Heilongjiang Province, grant ZL2025F004.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: County-level data were compiled from the “China County Statistical Yearbook”, the “China County Economic Statistical Yearbook”, the “China Urban Statistical Yearbook”, and the official roster of the National E-commerce into Rural Counties Demonstration Program. The replication code and the constructed dataset (subject to licensing restrictions of yearbooks) are available from the corresponding author upon reasonable request/will be deposited to [repository] upon acceptance.

Conflicts of Interest: The authors declare no conflicts of interest.

References

1. Zhang, B.; Dong, W.; Yao, J.; Cheng, X. Digital Economy, Factor Allocation Efficiency of Dual-Economy and Urban–Rural Income Gap. *Sustainability* **2023**, *15*, 13514. [CrossRef]
2. Chen, X.; Tang, L.; Tang, Y. Does the Rural E-commerce Policy Help to Narrow the Urban–rural Income Gap: From the Perspective of Factor Flow and Expenditure Structure. *J. Agrotech. Econ.* **2023**, 89–103. [CrossRef]
3. Tang, Y.; Yang, Q.; Li, Q.; Zhu, B. The Development of E-commerce and the Increase of Farmers’ Income: An Examination Based on the Policies of E-commerce into Rural Areas. *Chin. Rural Econ.* **2020**, 75–94. Available online: <https://kns.cnki.net/KCMS/detail/detail.aspx?dbcode=CJFQ&dbname=CJFDLAST2020&filename=ZNJJ202006010> (accessed on 1 March 2026).

4. Bai, Q.; Zang, D.; Zhang, J.; Zhang, K.; Chen, H.; Pan, Y.; Shen, Q. “Bridging the Urban-Rural Divide”: Evaluating the Impact of e-Commerce Pilots on Urban-Rural Integration—Evidence from a Quasi-Natural Experiment in China’s Rural e-Commerce Construction Policy. *Electron. Commer. Res.* **2025**, 1–33. [\[CrossRef\]](#)
5. Li, F.; Gan, Y. Research on the Sustainable Development Capability of Chinese Rural E-Commerce Based on Multidimensional Perspective. *Sci. Rep.* **2025**, *15*, 11547. [\[CrossRef\]](#) [\[PubMed\]](#)
6. Lu, Y.; Zhuang, J.; Yang, C.; Li, L.; Kong, M. How the Digital Economy Promotes Urban-Rural Integration through Optimizing Factor Allocation: Theoretical Mechanisms and Evidence from China. *Front. Sustain. Food Syst.* **2025**, *9*, 1494247. [\[CrossRef\]](#)
7. Zhang, X.; Wang, T. Understanding Purchase Intention in O2O E-Commerce: The Effects of Trust Transfer and Online Contents. *J. Theor. Appl. Electron. Commer. Res.* **2021**, *16*, 101–115. [\[CrossRef\]](#)
8. Vercher, N.; Bosworth, G.; Esparcia, J. Developing a Framework for Radical and Incremental Social Innovation in Rural Areas. *J. Rural Stud.* **2023**, *99*, 233–242. [\[CrossRef\]](#)
9. Wang, H.; Leng, H.; Yuan, M. From Opportunity to Inequality: How the Rural Digital Economy Shapes Intra-Rural Income Distribution. *Hum. Soc. Sci. Commun.* **2025**, *12*, 534. [\[CrossRef\]](#)
10. Yu, Y.; Tu, H.; Tian, Q. The Impacts of Rural E-Commerce on County Economic Development: Evidence from National Rural E-Commerce Comprehensive Demonstration Policy in China. *J. Theor. Appl. Electron. Commer. Res.* **2025**, *20*, 235. [\[CrossRef\]](#)
11. Wu, C.; Bai, Y. Research on the Mechanism of Digital Technology Empowering Urban-rural Integration Development: From the Perspective of Marx’s Social Reproduction Theory. *Mod. Econ. Sci.* **2023**, *45*, 123–134.
12. Zhu, Y.; Hu, N.; Ma, P. Coordinated Promotion of Integrated Urban-rural Development at County Level: Theoretical Connotation, Practical Path and Policy Suggestions. *Issues Agric. Econ.* **2024**, 98–108. [\[CrossRef\]](#)
13. Chen, Y.; Wang, Y.; Mei, D.; Wang, L. Coupling Coordination and Influencing Factors Between Digital Economy and Urban-Rural Integration in China. *Sustainability* **2025**, *17*, 7828. [\[CrossRef\]](#)
14. Khan, S. Issues, Challenges and Opportunities in the Digitalization of Rural Markets. *Hum. Syst. Manag.* **2023**, *42*, 73–87. [\[CrossRef\]](#)
15. Lv, L.; Dai, F. How Agricultural Innovation Talents Influence County-Level Industrial Structure Upgrading: A Knowledge-Empowerment Perspective. *Agriculture* **2025**, *15*, 1500. [\[CrossRef\]](#)
16. Guidotti, V.; de Barros Ferraz, S.F.; Guedes Pinto, L.F.; Sparovek, G.; Taniwaki, R.H.; Garcia, L.G.; Brancalion, P.H.S. Changes in Brazil’s Forest Code Can Erode the Potential of Riparian Buffers to Supply Watershed Services. *Land Use Policy* **2020**, *94*, 104511. [\[CrossRef\]](#)
17. Xu, X.; Yang, W.; Wu, B. Multiple Pathways for Rural Digital Economy Empowering Agricultural Total Factor Productivity: A Configuration Analysis Based on County-Level Data from Zhejiang Province. *Chin. Rural Econ.* **2024**, 84–103. [\[CrossRef\]](#)
18. Yuan, F.; Dong, D.; Jin, Y. Brand Equity Co-creation Path Model in the Digital Network Era: An Exploratory Case Study Based on Taobao. *J. Manag. Case Stud.* **2023**, *16*, 323–336.
19. Liu, X.; He, M. Can Digital Retail Narrow Urban-Rural Consumption Inequality: An Empirical Study Based on Typical Platform Data. *Chin. Rural Econ.* **2025**, 60–80. [\[CrossRef\]](#)
20. Wang, C.; Liu, T.; Wen, D.; Li, D.; Vladislav, G.; Zhu, Y. The Impact of International Electronic Commerce on Export Trade: Evidence from China. *J. Theor. Appl. Electron. Commer. Res.* **2021**, *16*, 2579–2593. [\[CrossRef\]](#)
21. Wei, B.; Luo, M.; Zeng, C. Returning Laborers’ Entrepreneurship and County-Level Industrial Structure Upgrading: Theoretical Insights and Empirical Evidence. *Chin. Rural Econ.* **2023**, 26–48.
22. Ding, S.; Liu, C.; Bao, W. The Impact of E-Commerce in Rural Areas Comprehensive Demonstration Project on Residents’ Well-Being. *Chin. J. Popul. Sci.* **2024**, *38*, 98–113.
23. Williamson Oliver, E. *The Economic Institutions of Capitalism: Firms, Markets, Relational Contracting*; Free Press: New York, NY, USA, 1985.
24. Couture, V.; Faber, B.; Gu, Y.; Liu, L. Connecting the Countryside via E-Commerce: Evidence from China. *Am. Econ. Rev. Insights* **2021**, *3*, 35–50. [\[CrossRef\]](#)
25. Fan, J.; Tang, L.; Zhu, W.; Zou, B. The Alibaba Effect: Spatial Consumption Inequality and the Welfare Gains from e-Commerce. *J. Int. Econ.* **2018**, *114*, 203–220. [\[CrossRef\]](#)
26. Peng, J.; Zhao, Z. Will rural e-commerce promote the integrated urban-rural development at county level? *J. China Agric. Univ.* **2025**, *30*, 321–332.
27. Steinmueller, W.E. ICTs and the Possibilities for Leapfrogging by Developing Countries. *Int. Labour Rev.* **2001**, *140*, 193–210. [\[CrossRef\]](#)
28. McKinnon, R.I. *Money and Capital in Economic Development*; Brookings Institution: Washington, DC, USA, 1973.
29. Shaw, E.S. *Financial Deepening in Economic Development*; Oxford University Press: New York, NY, USA, 1973.
30. National Bureau of Statistics of China. *China County Statistical Yearbook*; China Statistics Press: Beijing, China, 2025.
31. National Bureau of Statistics of China. *China County Economic Statistical Yearbook*; China Statistics Press: Beijing, China, 2025.
32. National Bureau of Statistics of China. *China Urban Statistical Yearbook*; China Statistics Press: Beijing, China, 2025.

33. Ministry of Commerce of the People's Republic of China. *National "E-Commerce into Rural Counties" Demonstration Program Roster 2014–2022*; Ministry of Commerce of the People's Republic of China: Beijing, China, [Applicable Year(s)].
34. Goodman-Bacon, A. Difference-in-Differences with Variation in Treatment Timing. *J. Econom.* **2021**, *225*, 254–277. [[CrossRef](#)]
35. Callaway, B.; Sant'Anna, P.H.C. Difference-in-Differences with Multiple Time Periods. *J. Econom.* **2021**, *225*, 200–230. [[CrossRef](#)]

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.