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Coupling Digital Inclusive Finance and Rural E-Commerce: A Systems Perspective on China's Urban–Rural Income Gap

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Abstract

Using a balanced provincial panel of 31 Chinese regions (2014–2022), this study examines how Digital Inclusive Finance (DIF) and Rural E-Commerce (RE) jointly shape the urban–rural income gap. Two-way fixed effects and instrumental-variable estimators mitigate confounding. Both DIF and RE are associated with narrower gaps, and the interaction term is negative and robust across specifications. Mechanism evidence indicates that the coupling operates through higher Agricultural Green Total Factor Productivity, expanded rural credit supply, and stronger entrepreneurship. Effects are larger in Central/Western provinces and are most pronounced when DIF's usage-depth and digital-support components are salient. For policymakers and managers, the findings support bundled investments in digital rails, platform logistics, and e-commerce-linked credit, with priority to lagging regions and programs that deepen usage. Overall, the results provide a tractable systems approach to aligning finance and markets for inclusive rural transformation.

Keywords: digital inclusive finance; rural e-commerce; subsystem coupling; systems perspective; urban–rural income gap; AGTFP; credit supply; entrepreneurship; two-way fixed effects; instrumental variables



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1. Introduction

China's eradication of extreme poverty during 2013–2020 has not extinguished concerns over a persistent urban–rural income divide that now sits at the center of the “common prosperity” agenda [1]. The policy shift reorients growth toward inclusivity and balanced distribution, casting inequality as a first-order systems challenge rather than a residual social issue [2]. Within this context, the income gap—measured using decomposable indices such as the Theil index—emerges as a stubborn, structural feature of China's development path that demands new forms of coordination across finance, markets, and production. Recent empirical work underscores the salience of the gap and the potential for digital development to influence it, while also documenting substantial spatial and structural heterogeneity that policy must address [3].

Digital Inclusive Finance (DIF) and Rural E-commerce (RE) are modeled as interacting subsystems of a broader regional development system that shapes China's urban–rural income distribution. A “subsystem” denotes a coherent set of functions—actors, technologies, and institutions—whose internal linkages are denser than their cross-boundary linkages within the larger system. Within this architecture, DIF (digital financial rails) and RE (platform-enabled rural market access) form two coupled subsystems. DIF, measured by the Peking University Digital Inclusive Finance Index (coverage breadth, usage depth, and digitalization support), expands access to payments, credit, and insurance and thereby influences household and firm decisions in rural areas [4]. Consistent global

evidence on digital payments and accounts shows that transactional access catalyzes saving, borrowing, and financial resilience, enabling low-cost participation in formal finance even where branch networks are thin [5]. Complementing this, China's Rural E-commerce Demonstration Program and the rapid diffusion of Taobao Villages/Towns reduce search costs, expand markets for both agricultural and non-agricultural products, and generate local employment and entrepreneurship opportunities in previously lagging regions [6,7]. Rather than assuming independence between DIF and RE, the analysis allows for interdependence and evaluates whether their joint variation and complementarity are empirically distinguishable.

A systems perspective clarifies why DIF and RE may exhibit a synergistic effect on the urban–rural gap. By compressing transaction, search, and verification costs, complementarities between finance and markets can unlock produce–finance–market feedback loops that isolated policies cannot achieve. The logic draws on transaction-cost economics and organization theory—treating transactions as the unit of analysis and governance structures as cost-minimizing arrangements—and on the notion of synergy from complex systems, in which subsystem cooperation generates order parameters that shape macro-outcomes [8–10]. In rural China, DIF stabilizes cash-flow timing and risk management while RE expands buyer access and information, jointly enabling productivity-enhancing and income-diversifying adjustments whose diffusion is uneven across places.

The empirical record is mixed and context dependent: many studies document sizable inclusion gains, while others identify conditions under which digital tools deliver limited or even adverse distributional effects—underscoring the value of a mechanisms-first, critical synthesis. At the macro- and meso-levels, digital financial inclusion in China is associated with poverty reduction, with spatial spillovers and salient nonlinearities for policy design [11]; cross-province and household evidence points to reduced inequality and disproportionate benefits for lower-income and rural groups, tempered by digital-divide risks for elderly or remote populations [12]. Provincial panel analyses further suggest that DIF narrows the urban–rural gap through labor-market channels, including shifts in employment structure. At the micro level, digitally enabled credit and payments strengthen household resilience and reduce vulnerability to income shocks, complementing entrepreneurship-based pathways out of poverty [13,14]. Energy deprivation also responds: digital finance alleviates rural energy poverty by improving access, affordability, and uptake of clean household technologies [15]. Consumption patterns tilt toward higher-quality goods and services, and county-level “common prosperity” metrics improve [16]. On the firm side, DIF is linked to higher innovation output and R&D investment, with marked sectoral and regional heterogeneity [17,18], and it stimulates entrepreneurial entry and activity where human-capital complements and household digital capabilities are stronger [19,20].

Despite broad progress, the evidence is not uniformly convergent. Several studies report digital-divide risks for older, remote, or low-literacy groups; selection into platforms can concentrate gains among households or firms with stronger skills, capital, or social networks; and platform concentration may shift surplus away from late-entering regions. A growing set of papers also documents nonlinear or threshold responses—where benefits emerge only after basic digital infrastructure, logistics density, and digital literacy clear minimum levels—and sizable regional heterogeneity. These tensions imply that finance and market digitization can either compress or entrench gaps depending on local absorptive capacity, making it essential to analyze their joint operation and boundary conditions rather than assume monotonic, uniform effects.

Parallel literature on rural e-commerce document sizable income effects for participating households and villages, including robust gains in Taobao Village/Town settings

where network externalities, logistics density, and product standardization coevolve [21]. Regional analyses indicate that RE can reduce intra-provincial inequality by raising the floor in lagging counties, although impacts depend on digital infrastructure, supply-chain readiness, and the tradability and branding of local products [22]. Policy evaluations of the nationwide demonstration program suggest improvements in household consumption and opportunities for vulnerable groups when e-commerce is bundled with training, logistics, and public-service support [23]. New evidence on the evolution from villages to Taobao Towns highlights multi-product clusters and live-streaming channels, with benefits extending beyond early coastal hubs [7,24]. Distributional analyses within rural populations also show uneven gains; participation costs, product characteristics, and social capital condition returns, strengthening the case for complementary finance and capability investments [25].

Despite these advances, three gaps persist. Many studies estimate the effects of DIF or RE in isolation, leaving their interaction under-identified. Proposed mechanisms are frequently examined one at a time, without tracing a closed evidence chain from finance to productivity to market outcomes. Heterogeneous and threshold-type responses across regions and along DIF subdimensions remain under-mapped in terms of where and how marginal returns are highest. The present study foregrounds three mediating channels consistent with a systems view: (i) Agricultural Green Total Factor Productivity (AGTFP) as a joint outcome of technology adoption and environmental performance; (ii) rural credit supply as the financing backbone for adoption and scale-up; and (iii) rural entrepreneurship as the organizational vehicle that translates financial access and market reach into diversified income. AGTFP is now routinely measured using DEA-based methods that incorporate undesirable outputs via the Malmquist–Luenberger index and slack-based measures, enabling green-growth accounting suitable for provincial panels [26–29]. On the finance and organization sides, digital credit alleviates income vulnerability and relaxes borrowing constraints that bind rural producers, while return-migrant entrepreneurship responds measurably to improvements in digitally enabled finance and information [30,31].

Methodologically, synergy is estimated as the coefficient on the interaction term $DIF \times RE$ in a two-way fixed-effects model on a balanced provincial panel, and endogeneity is addressed through 2SLS using lagged infrastructure-based interactions as instruments. The dependent variable is the urban–rural income gap measured by the Theil index, whose decomposability permits a direct systems interpretation of within- and between-region contributions [32]. Heterogeneity is examined across China’s macro-regions (East/Central/West) and along DIF subdimensions (coverage, usage depth, digitalization support), consistent with the policy imperative to target contexts where returns to coupling finance and markets are largest.

Recent county-level evidence shows that digital inclusive finance plays a vital role in narrowing the urban–rural income gap, with rural e-commerce acting as an intermediary. Another study finds that disparities in digital usage can diminish or even distort the convergence benefits of digital finance, highlighting the need to jointly develop digital infrastructure and digital literacy.

This study adopts a systems lens over plausible alternatives for three reasons. First, transaction-cost economics aligns with the measurable cost compressions induced by digital inclusive finance (payments, screening, monitoring) and rural e-commerce (search, matching, logistics), directly mapping to the variables and identification strategy employed. Second, the complementarity/supermodularity perspective yields a transparent, testable implication—a negative cross-partial of the urban–rural income gap with respect to DIF and RE—rather than a generic interaction. Third, complex-systems synergy captures feedback among production efficiency, formal credit, and entrepreneurship that single-channel models overlook, generating falsifiable predictions: (i) the cross-partial is negative; (ii) effects

exhibit thresholds and heterogeneity consistent with absorptive-capacity constraints; and (iii) mechanism coherence, whereby agricultural green total factor productivity (AGTFP), rural credit, and rural entrepreneurship move in directions required by the coupling logic. Building on prior research that typically investigates digital finance (DIF) or rural e-commerce (RE) in isolation, the analysis conceptualizes DIF and RE as complementary subsystems whose coupling structures flows of information, capital, and productivity within rural economies. From this systems perspective, coupling is expected to narrow the urban–rural income gap through direct market and information effects and through reinforcing feedback loops that enhance AGTFP, expand access to formal credit, and foster rural entrepreneurship. Empirically, coupling effects are estimated using province–year two-way fixed effects and instrumental-variables approaches, and the mechanism loop is closed by tracing how AGTFP, loan supply, and the rural entrepreneurial ecosystem (REP) co-move with the DIF $\times$ RE interaction in theoretically consistent and policy-relevant ways. Heterogeneity across regions and across DIF subdimensions is further examined to identify where complementarities are most pronounced. By reframing the problem as subsystem coupling and validating the associated feedback channels, the study explains why the joint development of digital financial infrastructure and platform markets can yield inequality reductions greater than the sum of their individual effects, providing a tractable, evidence-based roadmap for policy design. Section 2 develops the systems-based conceptual framework and testable hypotheses; Section 3 introduces the data, variable construction, and identification strategy; Section 4 presents baseline two-way fixed-effects and instrumental-variable estimates with diagnostic checks; Section 5 examines mechanism channels (AGTFP, rural credit, and entrepreneurship); and Section 6 reports heterogeneity, robustness, and policy implications.

2. Conceptual Framework & Hypotheses

2.1. Systems View and Theoretical Background

Digital Inclusive Finance (DIF) and Rural E-commerce (RE) are conceptualized as two coupled subsystems embedded within China’s regional development framework. Drawing on synergy theory, factor endowment theory, and transaction cost theory, these subsystems are expected to co-evolve. DIF expands access to affordable financial services and alleviates information friction, while RE broadens market access and reorganizes value chains. Their joint operation reallocates factors of production, reduces transaction costs, and contributes to a synergistic narrowing of the urban–rural income gap.

In functional terms, DIF integrates payment, credit, and risk-management services whose data footprints are inherently digital, whereas RE integrates search, matching, and logistics functions that diminish spatial and informational segmentation. Treating them as subsystems is not a rhetorical device but a modeling assumption: intra-links within financial rails and within platform commerce are stronger than their cross-links to other policy domains, conditional on controls. Under this assumption, coupling is expected to compress transaction and verification costs and to align incentives across producers, intermediaries, and consumers in ways that isolated interventions cannot achieve.

DIF represents the digital transformation of inclusive finance, extending coverage, lowering service costs, and overcoming persistent barriers to financial access for rural households and smallholders. By improving the allocation of capital toward rural economic activities, it strengthens scale economies, enhances operational efficiency, and supports risk sharing, thereby reducing income disparities. RE complements this process by mitigating spatial and informational segmentation, shortening producer–consumer chains, widening product markets, and stabilizing price formation. Through improved information sym-

metry, expanded market reach, and more efficient resource reallocation, RE raises rural earnings relative to urban incomes, further contributing to the narrowing of the gap.

2.2. Conceptual Mechanism

The coupling of Digital Inclusive Finance (DIF) and Rural E-commerce (RE) constitutes a mutually reinforcing mechanism. DIF supplies payment systems, credit rails, and risk-management tools tailored to the data streams generated by e-commerce, while RE produces rich behavioral records and commercially viable use-cases that enable fintech intermediaries to assess risk and extend finance at scale. This co-evolution promotes productive investment, eases financing constraints, and stimulates employment and entrepreneurship in rural areas, ultimately narrowing the urban–rural income gap. The systems view provides the ex-ante rationale for analyzing DIF and RE jointly rather than as unrelated covariates, and it yields testable implications for both the interaction term and the transmission channels—agricultural green total factor productivity (AGTFP), rural loan supply, and rural entrepreneurship—that are evaluated in the empirical sections.

Three measurable channels operationalize this mechanism. First, AGTFP—computed using the SBM–GML approach—captures technological progress and efficiency improvements under environmental constraints. Both DIF and RE are expected to raise AGTFP through greener inputs, digital infrastructure, and managerial upgrading; higher AGTFP then reduces the gap by boosting rural operating income and enabling structural upgrading. Second, rural loan supply (Loan) is shaped by the $DIF \times RE$ interaction: digital scoring and platform data reduce information asymmetry, lower monitoring costs, and encourage financial institutions to expand credit, thereby relaxing liquidity constraints on production and self-employment and compressing the gap. Third, rural entrepreneurial activity (REP) increases when platform-enabled commerce and digital finance lower entry barriers and transaction costs for household businesses, generating new ventures, non-farm employment, and higher rural incomes.

2.3. Hypotheses

Grounded in this systems perspective, six testable hypotheses are formulated to align with the direct effects and the three transmission channels evaluated in the empirical analysis.

H1: *Digital Inclusive Finance reduces the urban–rural income gap. Broader and lower-cost digital financial services improve rural households' access to payments, savings, and credit, thereby enhancing productivity and incomes.*

H2: *Rural E-commerce reduces the urban–rural income gap. Greater information symmetry, wider market access, and higher rural value-added narrow income differentials.*

H3: *The interaction of DIF and RE reduces the urban–rural income gap beyond their separate effects. Platform data and fintech rails reinforce one another, lowering transaction and financing costs and amplifying inclusion.*

H4: *The gap-reducing effect of the $DIF \times RE$ interaction is mediated by improvements in agricultural green total factor productivity. Joint increases in AGTFP are expected to be negatively associated with the income gap.*

H5: *The gap-reducing effect of the $DIF \times RE$ interaction is mediated by increases in rural loan supply. Expanded credit availability is expected to be negatively associated with the gap.*

H6: *The gap-reducing effect of the DIF $\times$ RE interaction is mediated by greater rural entrepreneurial activity. Increased entrepreneurship expands non-farm employment and income sources, thereby narrowing the gap.*

These hypotheses correspond directly to the empirical design, which begins with a two-way fixed-effects baseline including the DIF $\times$ RE interaction, followed by mediation tests for AGTFP, Loan, and REP, consistent with the variable definitions and identification strategy described in Section 3.

3. Data and Methods

3.1. Data Sources and Sample Construction

A balanced provincial panel for Mainland China was constructed using annual data from 2014 to 2022. Rural E-commerce (RE) is proxied by the number of Taobao Villages reported in the Ali Research Institute's Taobao Village Research Report, while Digital Inclusive Finance (DIF) is measured using the Peking University Digital Finance Index. Additional macroeconomic controls are drawn from the China Statistical Yearbook, provincial statistical yearbooks, and the Wind database. Estimations are conducted in Stata 16, yielding an effective empirical sample of 279 province-year observations.

Descriptive statistics indicate that the dependent variable is the log income ratio between rural and urban residents, $gap_{it} = \ln(income_{rural}/income_{urban})$, which ranges from -4.068 to -1.726 (sd = 0.515). Because rural incomes are typically lower, gap_{it} is negative; values closer to zero indicate a smaller gap. For ease of interpretation in regression tables, we also report $gap_{it}^* \equiv -gap_{it}$, so that larger values denote a wider gap (range 1.726–4.068). Other variables retain the units described above.

3.2. Measures

The dependent outcome is the log income ratio between rural and urban residents, defined as

$$gap_{it} = \ln\left(\frac{\text{mean income}_{rural,it}}{\text{mean income}_{urban,it}}\right) \quad (1)$$

Because rural incomes are typically lower, the ratio of rural to urban income (gap_{it}) is negative, with more negative values indicating a wider urban–rural gap. We adopt this measure for interpretability and to align with the distributional properties of the data, noting that results are monotonic with conventional inequality indices such as the Theil index. Logging the rural-to-urban income ratio further allows coefficients to be interpreted as elasticities with respect to the gap, stabilizes variance in panels with heterogeneous scales across provinces and years, and preserves a monotonic mapping to standard inequality measures, ensuring that coefficient signs and relative rankings remain consistent with established indices.

The key regressors include:

Digital Inclusive Finance (dif): the logarithm of the Peking University DIF index.

Rural e-commerce (RE) is measured by the number of Taobao Villages reported by the Ali Research Institute. To address right-skewness and zero observations, the transformation $\ln(1 + RE)$ is applied. This approach preserves zeros, reduces skewness and heteroskedasticity typical of count data, and attenuates province-specific surges from discrete infrastructure upgrades, thereby limiting the leverage of extreme observations in panel estimation. These adjustments are particularly important when comparing macro-regions with intrinsically different market depths. Digital Inclusive Finance (DIF) is measured using the Peking University Digital Inclusive Finance Index, which aggregates 33 indicators into three subdimensions—coverage breadth, usage depth, and digitalization support. Because

the index is multiplicative across dimensions and levels, its natural logarithm is taken. This transformation yields semi-elasticities that can be interpreted as percentage responses of the income gap to proportional changes in inclusive finance, while compressing the right tail and mitigating the influence of outliers in fixed-effects estimation. Descriptive statistics for all variables are reported in Table 1.

Table 1. Descriptive Statistical Analysis.

Variable Type	Variable	Definition/Explanation	Mean	Std. Dev.	Min	Max
Dependent Variable Independent Var.	gap	Urban–rural income gap	−2.635	0.515	−4.068	−1.726
	dif	Digital inclusive finance	5.636	0.258	4.969	6.165
	taobao	Level of rural e-commerce development	116.3	319.4	1	2427
	agtfpgml	Agricultural green total factor productivity	0.615	0.258	0.183	1.102
Mediating Var.	loan	Agricultural supply loans	10,962	9834	297	65,566
	rep	Agricultural entrepreneurship activity	0.315	0.483	0.0247	2.846
	urban	Urbanization rate	61.09	12.62	26.23	89.33
Control Var.	gov	Government fiscal support level	0.287	0.163	0.0243	0.741
	edu	Human capital level	0.268	0.058	0.00919	0.436
	open	Degree of openness	0.234	0.0840	0.00757	1.216
	agr_gdp	Level of primary industry development	9.346	5.404	0.2171	25.16
	development	Level of economic development	12,570	8351	5768	49,335

Interaction: captures complementarities between DIF and RE. We interpret complementarity as a negative interaction in the log–log model, i.e., $\beta_3 < 0$ for $\ln DIF \times \ln RE$, which implies $\partial^2 \text{gap} / (\partial \ln DIF \partial \ln RE) < 0$ and thus stronger gap-reducing effects of each subsystem at higher levels of the other.

Mediators for the mechanism analysis include agricultural green total factor productivity (AGTFP), rural loan supply, and rural entrepreneurship (REP). AGTFP is constructed using the slack-based measure–global Malmquist–Luenberger (SBM–GML) index. Inputs comprise rural labor, land (sown area), agricultural machinery power, fertilizer, pesticide, agricultural plastic film, and effective irrigated area. The desirable output is gross agricultural output value (benchmarked to 2011), and the undesirable output is total agricultural carbon emissions. Loan supply is measured as provincial rural credit provision, while rural entrepreneurship is proxied by the share of rural employment in individual and private enterprises relative to the rural population.

Control variables include the urbanization rate (urban), government expenditure share (gov), human capital (edu), openness (open), primary-industry share (agr_gdp), and overall economic development (development). This full set is retained because these controls capture first-order structural determinants of the urban–rural income gap and help absorb confounding variation that may correlate with DIF and RE.

3.3. Econometric Specification

The baseline empirical analysis relies on a two-way fixed-effects panel model at the province–year level, capturing the direct and interactive effects of DIF and RE on the urban–rural income gap.

$$\text{gap}_{it} = \alpha + \beta_1 \text{dif}_{it} + \beta_2 \text{taobao}_{it} + \beta_3 (\text{dif}_{it} \times \text{taobao}_{it}) + \gamma' X_{it} + \mu_i + \tau_t + \varepsilon_{it} \quad (2)$$

Following the standard definition of technological complementarity, we regard the DIF–RE interaction as ‘synergy’ when $\beta_3 < 0$ in the log–log specification. Equivalently, the marginal effects satisfy $\partial \text{gap} / \partial \ln DIF = \beta_1 + \beta_3 \ln RE$ and $\partial \text{gap} / \partial \ln RE = \beta_2 + \beta_3 \ln DIF$, so that higher RE (DIF) makes the gap-reducing impact of DIF (RE) more pronounced. The model includes province fixed effects (μ) and year fixed effects (τ_t), along with a full

set of controls (X_{it}). Unless otherwise indicated, all continuous variables are expressed in natural logarithms, such that coefficients on logged regressors are interpreted as elasticities, while those on $\ln(1 + RE)$ represent semi-elasticities with respect to proportional changes in rural e-commerce.

Endogeneity is addressed using a two-stage least squares (2SLS) approach. Instrument relevance derives from the dependence of DIF on digital infrastructure: provinces with higher internet penetration in period $t - 1$ tend to exhibit higher DIF in period t . Internet penetration is not expected to directly affect the urban–rural income gap once current controls are included, and the use of lagged RE further alleviates simultaneity concerns. Accordingly, dif is instrumented with $\ln(\text{Internet penetration}) \times \text{lag}(RE)$, and both dif and the interaction term $dif \times RE$ are treated as endogenous regressors in the 2SLS framework. First-stage relevance and overidentification are assessed using the Kleibergen–Paap rk Wald F-statistic and the Hansen J test, respectively, with standard errors clustered at the province level. Diagnostics are reported for each endogenous regressor to ensure robustness.

Mechanism models for each mediator $M \in \{\text{AGTFP}, \text{loan}, \text{rep}\}$ are estimated using fixed effects in parallel to the baseline specification, allowing explicit evaluation of the productivity, credit, and entrepreneurship channels.

$$\begin{aligned} M_{it} &= \pi_0 + \pi_1 dif_{it} + \pi_2 taobao_{it} + \pi_3 (dif_{it} \times taobao_{it}) + \pi' X_{it} + \mu_i + \tau_t + \nu_{it}, \\ gap_{it} &= \delta_0 + \delta_1 dif_{it} + \delta_2 taobao_{it} + \delta_3 (dif_{it} \times taobao_{it}) + \delta_4 M_{it} + \delta' X_{it} + \mu_i + \tau_t + \eta_{it}. \end{aligned} \quad (3)$$

These equations enable tests of the productivity, finance, and entrepreneurship channels while preserving the FE structure.

We retain the level specification in logs because growth-rate outcomes (first differences of the log ratio) can be dominated by base effects and increase transitory noise, especially when macro-regions differ structurally. The log ratio with province and year fixed effects preserves the full panel variation while controlling for time-invariant geography-related factors and nationwide shocks.

3.4. Descriptive Patterns and Diagnostics

To document the sample properties, Table 1 reports descriptive statistics for all variables (mean, standard deviation, minimum, and maximum). Rural e-commerce (RE) exhibits substantial dispersion (mean = 116.3, SD = 319.4; min = 1; max = 2427), whereas DIF is comparatively concentrated (mean = 5.636, SD = 0.258). Key controls also vary widely—for example, the urbanization rate ranges from 26.23 to 89.33 (mean = 61.09, SD = 12.02). These distributional features indicate ample cross-sectional and temporal heterogeneity for identification in the two-way fixed-effects framework.

As part of the empirical analysis, a preliminary correlation test was conducted to examine whether statistically significant relationships exist among the variables. The results, reported in Table 2, indicate that the core explanatory variables and the dependent variable exhibit a clear negative correlation. In addition, the control variables also show consistent and statistically significant correlations with the dependent variable, further supporting their inclusion in the empirical specification.

Variance inflation factor (VIF) tests confirm the absence of excessive collinearity among the explanatory variables. These diagnostics indicate that the negative and significant interaction is not an artifact of multicollinearity, supporting its interpretation as genuine complementarity. Table 3 reports a mean VIF of 3.280, well below the conventional threshold of 10, supporting the simultaneous inclusion of DIF, RE, their interaction, and the full control set in the panel fixed-effects estimation.

Table 2. Correlation Test.

	Gap	Dif	Taobao	Urban	Gov	Development
gap	1					
dif	−0.489 ***	1				
taobao	−0.270 ***	0.374 ***	1			
urban	−0.898 ***	0.516 ***	0.252 ***	1		
gov	0.427 ***	−0.214 ***	−0.232 ***	−0.535 ***	1	
edu	0.427 ***	−0.214 ***	−0.232 ***	−0.535 ***	0.427 ***	
open	−0.665 ***	0.287 ***	0.334 ***	0.718 ***	−0.325 ***	
agr_gdp	0.559 ***	−0.299 ***	−0.302 ***	−0.629 ***	0.208 ***	
development	−0.752 ***	0.358 ***	0.197 ***	0.785 ***	−0.244 ***	1
	edu	open		Agr_gdp		development
edu	1					
open	0.116 *	1				
agr_gdp	−0.256 ***	−0.590 ***		1		
development	0.253 ***	0.846 ***		−0.653 ***		1

Note: ***, and * denote significance at the 1%, and 10% levels, respectively.

Table 3. Multicollinearity diagnostics (VIF test).

Variable	VIF	1/VIF
dif	1.820	0.551
taobao	1.590	0.628
urban	6.180	0.162
open	4.660	0.215
gov	1.870	0.536
edu	2.480	0.403
agr_gdp	2.050	0.488
development	5.630	0.178
Mean VIF	3.280	

In particular, the largest VIFs are observed for urbanization (6.180) and economic development (5.630), while the remaining variables range between ~1.6 and ~4.7 (see Table 3). At these magnitudes, multicollinearity primarily inflates standard errors rather than biasing the estimated coefficients, and the fixed-effects specification with province-clustered inference further safeguards against spurious precision.

Preliminary evidence suggests a moderate degree of interdependence between DIF and RE, with a positive correlation of $\rho = 0.374$ (Table 2). Multicollinearity is limited: the variance inflation factors (VIFs) for dif and taobao are 1.820 and 1.590, respectively, with a mean VIF of 3.280 (Table 3). These diagnostics confirm that the regressors are related but not collinear, supporting their joint inclusion in the model and validating the use of an interaction term without invoking an independence assumption.

Because AGTFP is constructed through the SBM-GML index, the indicator system incorporates inputs, desirable outputs, and undesirable outputs in a transparent and replicable structure, as detailed in Table 4.

The dispersion patterns in the descriptive statistics—particularly the wide variation in RE and openness relative to the more concentrated DIF distribution—provide sufficient heterogeneity for estimating the interaction effects presented in Section 4. Variance inflation factors are low, further supporting the validity of the empirical design. To address potential endogeneity in both dif and the interaction term $\text{dif} \times \text{taobao}$, the 2SLS specification treats them as jointly endogenous regressors. The instrument set comprises $\ln(\text{Internet penetration}) \times \text{lag}(\text{taobao})$ for dif and its product with taobao for the interaction, while the main effects of $\ln(\text{Internet penetration})$ and $\text{lag}(\text{taobao})$ are included as exogenous controls

to satisfy the exclusion restriction. First-stage regressions report the Kleibergen–Paap rk Wald F statistic to diagnose weak instruments, and second-stage estimates include the Hansen J test where overidentification applies. Throughout, standard errors are clustered at the province level.

Table 4. Agricultural Green Total Factor Productivity Index System.

Indicator	Variable	Variable Description
Input Factors	Labor input	Number of employees engaged in planting industry
	Land input	Total sown area of crops
	Agricultural machinery	Total power of agricultural machinery
	Fertilizer input	Amount of chemical fertilizer applied
	Pesticide input	Amount of pesticide used
	Agricultural film input	Amount of agricultural plastic film used
Expected Output	Irrigation input	Effective irrigated area of agriculture
	Agricultural GDP	Gross agricultural output value (base year: 2011 planting industry total output value)
Undesired Output	Agricultural carbon emissions	Total agricultural carbon emissions, calculated with reference to methods such as Li Boya

4. Results

This study employs a balanced panel of 31 provincial-level regions from 2014 to 2022. Unless otherwise specified, all regressions are estimated using two-way fixed effects—controlling for province and year—and heteroskedasticity-robust standard errors clustered at the province level. The dependent variable is the urban–rural income gap (gap). The core explanatory variables are the Digital Inclusive Finance Index (dif), Rural E-commerce development (taobao, abbreviated as RE), and their interaction term ($\text{dif} \times \text{taobao}$). Control variables include urban, gov, edu, open, agr_gdp, and development. To ensure interpretability on a percentage scale and to reduce distortions from cross-provincial heterogeneity, all continuous variables are expressed in logarithmic form. For transparency, Tables 2 and 3 report correlation and collinearity diagnostics: DIF and RE are positively correlated ($\rho = 0.374$) but exhibit low variance inflation factors, confirming that the regressors are empirically interrelated yet far from collinear. These results justify the simultaneous estimation of main effects and their interaction.

4.1. Baseline Estimates

Table 5 reports the baseline two-way fixed-effects regressions. The coefficient on dif is negative and statistically significant across specifications, with the preferred model yielding -1.3168 ($p < 0.01$). This indicates that digital inclusive finance contributes to narrowing the urban–rural income gap. The main effect of RE (taobao) is also negative. Most importantly, the interaction $\text{dif} \times \text{taobao}$ is negative and significant, demonstrating a synergistic effect: digital finance and rural e-commerce reinforce each other in reducing the gap. (Consistent with this, Table 3 documents moderate VIF levels—mean 3.280; maximum 6.180—that do not compromise inference.) In our log–log framework, this corresponds to $\beta_3 < 0$, i.e., a negative cross-partial, which is the precise criterion for complementarity (synergy) in narrowing the gap. The preferred specification incorporates the full set of controls with province and year fixed effects, sample size $N \approx 279$, with adjusted R^2 of 0.839, 0.844, 0.861 across columns (1)–(3), respectively. Consistent with this interpretation, the implied simple slopes indicate that the gap-reducing effect of DIF (RE) remains negative

at representative low and high levels of RE (DIF), with significance preserved under province-clustered inference.

Table 5. Baseline Regression.

	(1) Gap	(2) Gap	(3) Gap
dif	−1.3168 *** (0.33)		−0.7397 ** (0.27)
taobao		−0.0002 *** (0.00)	−0.0000 ** (0.00)
dif × taobao			−0.0090 *** (0.00)
urban	−0.0308 *** (0.00)	−0.0293 *** (0.00)	−0.0345 *** (0.00)
gov	−0.4103 *** (0.11)	−0.3697 *** (0.09)	−0.6719 *** (0.11)
edu	−17.8354 *** (1.78)	−25.5796 *** (2.18)	−22.3471 *** (2.00)
open	0.0830 (0.10)	−0.0614 (0.09)	0.1894 ** (0.08)
agr_gdp	−0.0096 *** (0.00)	−0.0102 *** (0.00)	−0.0191 *** (0.00)
development	−0.0000 (0.00)	−0.0000 *** (0.00)	−0.0000 * (0.00)
_cons	7.2973 *** (2.02)	0.1011 (0.13)	4.6797 ** (1.63)
Individual effects	Yes	Yes	Yes
Time effects	Yes	Yes	Yes
N	279	279	279
Adj. R ²	0.839	0.844	0.861

Note: ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

4.2. Robustness Checks

Three sets of robustness exercises further confirm the stability of the findings: (i) replacing the dependent variable with the urban/rural disposable income ratio, (ii) winsorizing continuous variables at $\pm 1\%$, and (iii) excluding directly administered municipalities (Beijing, Shanghai, Tianjin, Chongqing). Across all exercises, the signs and significance of the core parameters—including the interaction $\text{dif} \times \text{taobao}$ —are preserved. Table 6 summarizes the results, with the interaction coefficient consistently around -0.009 to -0.015 and statistically significant in all re-specifications. These findings strengthen the evidence for the gap-narrowing synergy between digital finance and rural e-commerce. Across all re-specifications, the interaction $\ln \text{DIF} \times \ln \text{RE}$ remains negative and statistically significant, indicating that the complementarity result is insensitive to alternative outcomes, tail adjustments, and sample exclusions.

Table 6. Robustness Test.

	(1) Gap	(2) Gap	(3) Gap	(4) Gap
dif	−0.7397 ** (0.27)	−1.5334 *** (0.23)	−0.7745 ** (0.26)	−0.7522 ** (0.24)
taobao	−0.0000 ** (0.00)	−0.0001 *** (0.00)	−0.0000 (0.00)	−0.0000 ** (0.00)
dif × taobao	−0.0090 *** (0.00)	−0.0153 *** (0.00)	−0.0090 *** (0.00)	−0.0104 *** (0.00)
urban	−0.0345 *** (0.00)	−0.0237 *** (0.00)	−0.0348 *** (0.00)	−0.0340 *** (0.00)
gov	−0.6719 *** (0.11)	−0.4841 *** (0.10)	−0.6341 *** (0.12)	−0.6399 *** (0.11)
edu	−22.3471 *** (2.00)	−13.6809 *** (2.96)	−21.1399 *** (2.37)	−18.6206 *** (2.16)
open	0.1894 ** (0.08)	0.4997 *** (0.06)	0.2127 * (0.09)	0.2318 ** (0.08)
agr_gdp	−0.0191 *** (0.00)	−0.0281 *** (0.00)	−0.0192 *** (0.00)	−0.0251 *** (0.00)
development	−0.0000 * (0.00)	0.0000 ** (0.00)	−0.0000 * (0.00)	−0.0000 * (0.00)
_cons	4.6797 ** (1.63)	13.2499 *** (1.33)	4.8574** (1.58)	4.6544 ** (1.44)
Individual effects	Yes	Yes	Yes	Yes
Time effects	Yes	Yes	Yes	Yes
N	279	279	279	243
Adj. R ²	0.861	0.534	0.861	0.865

Note: ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

4.3. Addressing Endogeneity: 2SLS

To address potential endogeneity, we implement a two-stage least squares (2SLS) approach, using $\ln(\text{Internet penetration}) \times \text{lagged RE}$ as the instrument for dif. The instrument exhibits strong relevance, with the first-stage Kleibergen–Paap rk Wald F-

statistic reaching 111.80, well above the conventional threshold of 10. Hansen’s J test (when overidentified) fails to reject the null, supporting instrument validity. The second-stage estimates confirm the robustness of the causal interpretation: the coefficient on $\text{dif} \times \text{taobao}$ remains negative and statistically significant, consistent with the fixed-effects results. Table 7 reports both the first- and second-stage outputs, demonstrating that the 2SLS framework preserves the complementarity effect, thereby reinforcing the evidence that digital inclusive finance and rural e-commerce interact synergistically in narrowing the urban–rural income gap.

Table 7. Endogeneity Tests (2SLS): First- and Second-Stage Estimates.

	First Stage (1)	Second Stage (2)
dif	19.6118 *** (2.422)	−0.3226 *** (0.111)
taobao	0.0882 *** (0.009)	−0.0000 (0.000)
$\text{int} \times \text{lag_taobao}$	−0.0191 *** (0.002)	
$\text{dif} \times \text{taobao}$		−0.0099 ** (0.004)
urban	−0.4915 *** (0.078)	−0.0342 *** (0.003)
gov	−20.3005 *** (2.572)	−0.6162 *** (0.128)
edu	361.7592 *** (104.091)	−24.4053 *** (3.344)
open	8.1637 ** (3.597)	−0.0689 (0.122)
agr_gdp	−0.5884 *** (0.105)	−0.0165 *** (0.004)
development	−0.0000 (0.000)	−0.0000 *** (0.000)
Constant	−69.2273 *** (12.774)	−1.2218 ** (0.478)
Observations	248	248
R-squared	0.809	0.868

Note: *** and ** indicate significance at the 1% and 5% levels, respectively.

Apart from endogeneity concerns, another challenge is the possibility of abrupt step changes in RE. This issue is addressed through three design safeguards. First, RE is entered as $\ln(1 + \text{RE})$ to compress right tails. Second, two-way fixed effects—province and year—are included to absorb time-invariant provincial heterogeneity and common policy shocks, complemented by the full set of controls. Third, targeted robustness and instrumental-variable checks are conducted: winsorization at $\pm 1\%$, exclusion of province-level municipalities, and 2SLS estimation that instruments dif and $\text{dif} \times \text{RE}$ using lagged digital-infrastructure exposure. These procedures limit the influence of sudden province-level RE spikes and support the stability of both main and interaction effects. Cross-checks are reported in Tables 6 and 7.

4.4. Mechanism Tests

Three theoretically grounded mechanisms are examined: green productivity, credit supply, and entrepreneurship. In each case, the interaction increases the mediators that compress the gap—productivity (AGTFP), rural credit, and entrepreneurship—while the mediator-augmented gap equations continue to yield a negative interaction, a pattern consistent with complementarity.

The green productivity channel, reported in Table 8, shows that dif significantly raises Agricultural Green Total Factor Productivity (AGTFP), and higher AGTFP is in turn associated with a smaller income gap (coefficient ≈ -0.196 , significant at the 5% level). When AGTFP is included in the gap equation, the interaction term $\text{dif} \times \text{taobao}$ remains negative, indicating that enhanced productivity partially mediates the synergy.

The credit channel, presented in Table 9, confirms that rural loan supply reduces the gap (coefficient ≈ -0.0636 , significant at the 1% level). Both dif and taobao independently increase rural loan provision, and their interaction further strengthens credit availability, which translates into greater income convergence.

Table 8. Mechanism Test (Agricultural Green Total Factor Productivity, AGTFP).

	(1) Agtfgm1	(2) Gap
dif	1.2823 *** (0.14)	−0.2616 (0.37)
taobao	0.0002 *** (0.00)	−0.0000 * (0.00)
dif × taobao	0.0040 *** (0.00)	−0.0063 *** (0.00)
agtfpgml		−0.1960 ** (0.06)
urban	0.0116 *** (0.00)	−0.0380 *** (0.00)
gov	−0.7497 *** (0.07)	0.1922 (0.29)
edu	0.1031 (1.70)	−15.5693 *** (3.01)
open	0.2867 *** (0.09)	0.3180 ** (0.10)
agr_gdp	0.0205 *** (0.00)	−0.0195 *** (0.00)
development	0.0000 * (0.00)	−0.0000 ** (0.00)
_cons	7.1067 *** (0.76)	1.9381 (2.22)
Individual effects	Yes	Yes
Time effects	Yes	Yes
N	270	270
Adj. R ²	0.382	0.873

Note: ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 9. Mechanism Test (Rural Credit Supply).

	(1) Loan	(2) Gap
dif	2.8682 *** (0.55)	−0.5574 (0.30)
taobao	0.0013 *** (0.00)	−0.0001 *** (0.00)
dif × taobao	0.0266 *** (0.00)	−0.0073 *** (0.00)
loan		−0.0636 *** (0.00)
urban	−0.0252 *** (0.00)	−0.0361 *** (0.00)
gov	−1.4043 *** (0.18)	−0.7612 *** (0.12)
edu	−17.3605 *** (3.56)	−23.4505 *** (1.89)
open	−0.6838 *** (0.12)	0.1459 (0.08)
agr_gdp	−0.0128 *** (0.00)	−0.0199 *** (0.00)
development	−0.0000 * (0.00)	−0.0000 ** (0.00)
_cons	−13.8822 *** (3.12)	3.7974 * (1.81)
Individual effects	Yes	Yes
Time effects	Yes	Yes
N	279	279
Adj. R ²	0.741	0.865

Note: ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

The entrepreneurship channel, shown in Table 10, demonstrates that higher rural entrepreneurial activity (REP) narrows the gap (≈ -0.1982 , significant at the 1% level). The interaction $\text{dif} \times \text{taobao}$ significantly raises REP, suggesting that the joint presence of digital finance and rural e-commerce stimulates entrepreneurship, which in turn reduces income disparities.

Table 10. Mechanism Test (Rural Entrepreneurship Activity).

	(1) Rep	(2) Gap
dif	0.4275 * (0.23)	0.0744 (0.31)
taobao	0.0002 ** (0.00)	−0.0001 *** (0.00)
dif × taobao	0.0112 *** (0.00)	−0.0077 *** (0.00)
rep		−0.1982 *** (0.02)
urban	−0.0059 *** (0.00)	−0.0415 *** (0.00)

Table 10. Cont.

	(1) Rep	(2) Gap
gov	−0.5692 *** (0.15)	0.2263 (0.25)
edu	−18.6923 *** (2.36)	−19.2948 *** (3.39)
open	0.4548 ** (0.18)	0.3519 *** (0.09)
agr_gdp	−0.0102 *** (0.00)	−0.0256 *** (0.00)
development	0.0000 *** (0.00)	−0.0000 (0.00)
_cons	−1.5312 (1.24)	0.2419 (1.88)
Individual effects	Yes	Yes
Time effects	Yes	Yes
N	270	270
Adj. R ²	0.760	0.879

Note: ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

4.5. Heterogeneity Analysis

Table 11 presents the results of the regional heterogeneity analysis. When the sample is split into Eastern, Central, and Western regions, the interaction term $dif \times taobao$ remains negative and statistically significant across all subsamples. The effect is most pronounced in the Western region, where the coefficient magnitude is largest. This pattern indicates that the marginal returns to the joint development of digital finance and rural e-commerce are greater in less developed areas, where conventional financial systems and market access are relatively weaker.

Table 11. Regional Heterogeneity Analysis.

Variables	Eastern Region (Gap)	Central Region (Gap)	Western Region (Gap)
dif	−1.9131 *** (0.56)	1.0294 *** (0.35)	−1.3616 *** (0.40)
taobao	−0.0000 * (0.00)	−0.0002 * (0.00)	−0.0143 *** (0.00)
$dif \times taobao$	−0.0030 * (0.00)	−0.0076 ** (0.00)	−0.0286 *** (0.01)
urban	−0.0180 * (0.01)	−0.0280 *** (0.00)	−0.0194 *** (0.00)
gov	−2.2398 *** (0.77)	1.6257 *** (0.47)	−0.2376 * (0.12)
edu	−16.9876 ** (7.61)	−43.4747 *** (4.38)	15.6847 *** (3.15)
open	0.3739 ** (0.17)	0.6293 * (0.33)	−0.5358 ** (0.22)
agr_gdp	0.0396 *** (0.01)	−0.0294 *** (0.00)	0.0146 * (0.01)
development	0.0000 (0.00)	0.0000 *** (0.00)	−0.0000 *** (0.00)
_cons	9.4085 *** (2.91)	−6.0736 *** (1.89)	6.4971 *** (2.35)

Note: ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

These patterns indicate that results are not driven by one macro-region and that the coupling effect is strongest where baseline frictions are greater, which aligns with the policy intuition behind regionally differentiated development.

Table 12 reports the results obtained by replacing the composite DIF index with its three subdimensions: coverage breadth (width), usage depth (depth), and digital service support (digit). Each subindex interacts negatively and significantly with RE, confirming the robustness of the complementarity effect. The strongest effects are observed for $depth \times RE$ and $digit \times RE$, indicating that the intensity of financial usage and the provision of digital support services within inclusive finance are especially synergistic with e-commerce development in reducing the urban–rural income gap.

Across the baseline regressions, robustness checks, instrumental-variable estimation, mechanism analysis, and heterogeneity tests, the findings consistently point to three conclusions. First, digital inclusive finance exerts a significant negative effect on the urban–rural income gap. Second, this effect is amplified by rural e-commerce, as reflected in the negative and significant coefficient on the interaction term $dif \times taobao$. Third, the complementarity operates through clearly identified mechanisms: it enhances agricultural green total

factor productivity, expands credit availability, and stimulates entrepreneurial activity. These effects are particularly pronounced in the less developed western regions and are strongest when the usage depth and digital-support components of digital inclusive finance are emphasized.

Table 12. Sub-Dimension Heterogeneity Analysis.

	(1) Gap	(2) Gap	(3) Gap	(4) Gap
taobao	−0.0000 ** (0.00)	−0.0001 *** (0.00)	−0.0000 ** (0.00)	−0.0001 *** (0.00)
dif	−0.7397 ** (0.27)			
dif × taobao	−0.0090 *** (0.00)			
width		−0.5985 *** (0.10)		
width × taobao		−0.0096 *** (0.00)		
depth			−0.8265 *** (0.09)	
depth × taobao			−0.0069 *** (0.00)	
digit				−0.1201 (0.37)
digit × taobao				−0.0094 *** (0.00)
urban	−0.0345 *** (0.00)	−0.0348 *** (0.00)	−0.0363 *** (0.00)	−0.0343 *** (0.00)
gov	−0.6719 *** (0.11)	−0.5535 *** (0.10)	−0.6498 *** (0.09)	−0.6289 *** (0.11)
edu	−22.3471 *** (2.00)	−24.4277 *** (1.86)	−18.8724 *** (2.23)	−23.8589 *** (1.57)
open	0.1894 ** (0.08)	−0.0341 (0.07)	0.3481 *** (0.09)	0.0637 (0.10)
agr_gdp	−0.0191 *** (0.00)	−0.0161 *** (0.00)	−0.0184 *** (0.00)	−0.0179 *** (0.00)
development	−0.0000 * (0.00)	−0.0000 *** (0.00)	−0.0000 ** (0.00)	−0.0000 ** (0.00)
_cons	4.6797 ** (1.63)	−2.6995 *** (0.59)	5.0625 *** (0.58)	1.2890 (2.29)
Individual effects	Yes	Yes	Yes	Yes
Time effects	Yes	Yes	Yes	Yes
N	279	279	279	279
Adj. R ²	0.861	0.861	0.880	0.859

Note: ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

5. Discussion

This study interprets the empirical findings through a systems perspective, framing Digital Inclusive Finance (DIF) and Rural E-commerce (RE) as interacting subsystems whose coupling reduces the urban–rural income gap. The results reveal three reinforcing channels—production efficiency, financial accessibility, and entrepreneurship—that together generate a coherent narrative of gap compression.

5.1. Subsystem Coupling and Mechanisms of Gap Compression

DIF and RE each enhance agricultural productivity, and their interaction yields further improvements. Higher Agricultural Green Total Factor Productivity (AGTFP) narrows the income gap, indicating that more efficient and sustainable agricultural practices contribute directly to reducing inequality.

The credit channel shows a similar complementarity. DIF lowers financing frictions through digital credit assessment, while RE expands viable projects by improving cash-flow visibility. Their interaction increases rural loan supply, which then translates into income gains.

Entrepreneurship provides the third mechanism. When DIF and RE interact, rural entrepreneurial activity rises and contributes significantly to narrowing disparities. By reducing entry barriers and opening markets, these subsystems foster job creation and non-farm business development.

Together, these channels form a feedback loop: DIF reduces transaction costs and financing thresholds, RE enlarges market access and information flows, and their coupling aligns incentives across production, finance, and entrepreneurship. The result is a mutually reinforcing system that compresses the rural–urban income gap.

5.2. Alignment with Core Estimates

The baseline models consistently show significant negative effects of DIF, RE, and their interaction on the income gap. These patterns remain robust under alternative specifications, data trimming, and instrumental-variable estimation, supported by strong instrument strength. Such consistency reduces concerns over endogeneity, reverse causality, and model sensitivity, reinforcing the reliability of the results.

5.3. Regional and Dimensional Heterogeneity

The collaboration effect is not uniform across space. It is strongest in the western region, where weaker financial systems and limited infrastructure create higher marginal returns to digital and e-commerce development. By contrast, more advanced eastern regions exhibit diminishing returns. This heterogeneity highlights that the gains from subsystem coupling are most pronounced in areas with greater baseline frictions.

Differences also emerge within DIF itself. Coverage and usage depth exert strong independent effects, while digital support services become most effective when interacting with RE. The findings suggest that broad access, deep usage, and service enablement together create the absorptive capacity needed for RE's market expansion to generate sustained rural income growth.

5.4. Boundary Conditions and Validity

Potential measurement limitations arise because DIF and RE are proxied through specific indices and platform footprints. Nonetheless, results remain stable under alternative outcomes and tail adjustments, and instrumental-variable estimation further addresses simultaneity concerns, with consistent results across stages and strong first-stage performance. Several alternative explanations also warrant consideration. First, time-varying shocks—such as interprovincial migration, county-level industrial policies, or commodity cycles—may co-move with DIF/RE and the income gap; province and year fixed effects, rich controls, and the IV strategy mitigate, though cannot fully eliminate, such confounding. Second, spatial spillovers and general-equilibrium adjustments could transmit effects across borders; while the fixed-effects design absorbs level differences, future work should apply spatial or network models. Third, measurement error is salient for the RE proxy: the Taobao Villages footprint primarily reflects platform-intensive e-commerce and may under-represent other channels or definitional changes over time. Accordingly, the RE coefficients are best interpreted as conservative lower-bound effects, and multi-platform triangulation is flagged as a priority. Finally, durability remains an open question because the sample ends in 2022; subsequent shifts in platforms and fintech ecosystems may attenuate or amplify the coupling effects.

The stronger effects observed in less developed regions emphasize that outcomes depend on initial infrastructure and institutional conditions. Policymakers should therefore expect heterogeneous returns, with the greatest benefits in underserved areas where digital and market linkages can most effectively bridge existing gaps.

5.5. A Systems Perspective

Rather than isolated coefficients, our findings describe a coupled system in which DIF and RE act as mutually enabling subsystems. DIF lowers search, payment, and screening costs, while RE enlarges addressable demand and information flows; the interaction increases the return to adopting each subsystem.

The validated channels—AGTFP, credit, and entrepreneurship—operate as a reinforcing loop. By compressing production risk and expanding formal finance and non-farm opportunities, they translate subsystem adoption into income-gap convergence and, in

turn, raise adoption incentives for DIF and RE. This feedback explains why the joint effect is stronger than the sum of parts, especially in regions with higher baseline frictions.

6. Conclusions and Policy Implications

6.1. Summary of Findings

This study investigates how Digital Inclusive Finance (DIF) and Rural E-commerce (RE), as two interacting subsystems of rural development, jointly influence the urban–rural income gap. Based on a balanced provincial panel of 31 Chinese provinces from 2014 to 2022 and a two-way fixed-effects design, three key findings emerge.

First, DIF and RE individually reduce the income gap, while their interaction generates a stronger gap-narrowing effect. The baseline estimates remain stable across robustness checks and instrumental-variable strategies, confirming the reliability of this collaborative effect.

Second, the synergy operates through three channels: (i) enhancing Agricultural Green Total Factor Productivity (AGTFP), (ii) expanding rural loan supply, and (iii) stimulating rural entrepreneurship. Together, these mechanisms form a reinforcing feedback loop linking productivity, finance, and entrepreneurial activity to income convergence.

Third, the effects are heterogeneous across regions and DIF subdimensions. The collaboration effect is stronger in Central and Western regions than in the East, reflecting higher marginal benefits in less developed areas. Within DIF, usage depth and digital support exhibit stronger complementarities with RE than coverage breadth, indicating that absorptive capacity and service enablement are critical for sustained gains.

Taken together, the findings support a systems perspective: DIF reduces financing and informational frictions, RE broadens markets and information flows, and their coupling aligns incentives across production, finance, and entrepreneurship, thereby closing the income gap.

6.2. Policy Implications

Policies should target the coupled system rather than isolated levers, i.e., invest in digital rails (broadband/5G, data interoperability), platform logistics, and e-commerce-linked credit so that feedback gains are realized. This includes expanding internet and 5G coverage in remote areas, designing user-friendly financial tools, and piloting e-commerce-linked credit products. Financial literacy programs and risk-hedging schemes such as “insurance + futures” can further enhance resilience.

Building a resilient rural e-commerce ecosystem requires lowering logistics costs, establishing county-level service centers, and integrating local agricultural products into digital platforms. Such measures diversify income channels and expand rural employment opportunities.

Aligning financial instruments with green productivity upgrading is also critical. Targeted credit, subsidies, and digital advisory services should incentivize low-carbon machinery, precision irrigation, and data-enabled farm management, linking finance explicitly to AGTFP improvements.

Rural credit allocation should be optimized through data integration. Using e-commerce transaction data for credit assessment, expanding medium- and long-term credit lines, and developing parametric insurance products can simultaneously improve risk control and income stability.

Finally, regional differentiation is necessary. Given the stronger coupling effects in Central and Western regions, public investment should prioritize digital infrastructure, logistics, and rural finance access points in these areas. In the East, where private capacity is greater, market-based incentives such as tax credits for platform-led training and cold-

chain construction should dominate. Entrepreneurship supports—such as makerspaces, incubators, platform-linked training, and subsidized credit—can further strengthen the employment and business income channel.

For rural entrepreneurs and cooperatives, priorities include SKU standardization, quality certification, logistics alliances, and verifiable record-keeping to strengthen eligibility for cash-flow-based credit and to leverage the complementarities of $DIF \times RE$. Investments in digital skills—such as inventory and fulfilment management or live commerce—together with the use of platform data in negotiating financing terms can further enhance outcomes. For financial institutions, e-commerce-linked underwriting that incorporates verified order and fulfilment data, pilot programs for inventory-backed working-capital lines with repayment schedules tied to platform payout cycles, and portfolio risk-transfer tools such as parametric insurance for logistics disruptions offer promising avenues, provided fair-lending and data-protection safeguards are maintained. At the cross-jurisdictional level, the coupling logic is portable where three conditions hold: broadband coverage in lagging regions, interoperable open-banking/payment rails, and trusted consent-based data sharing. Within frameworks such as GDPR and PSD2, rural SMEs may benefit from digital onboarding vouchers, incentive-compatible platform-lender data sharing, and policies to support logistics densification in low-density regions. These measures are context-contingent and should be piloted before large-scale implementation.

6.3. Limitations and Future Research

This study faces some limitations. First, reliance on provincial panels and composite indices provides broad insights but limits granularity. The RE proxy, in particular, is based on the count of Taobao Villages—a platform-specific footprint that may under-represent non-platform or multi-platform commerce and is subject to definitional updates over time. Such limitations raise the possibility of classical measurement error, which would attenuate interaction estimates toward zero and imply that the reported RE-related effects should be interpreted conservatively as capturing platform-intensive e-commerce. Accordingly, future research should integrate household-, firm-, and transaction-level data to more precisely uncover the underlying micro-level mechanisms.

Second, although extensive robustness checks and instrumental-variable methods mitigate endogeneity, further quasi-experimental designs—such as event studies, staggered policy difference-in-differences, or regression discontinuities—would enhance causal inference.

Third, the diffusion of benefits is mediated by both cultural and technological barriers, including digital literacy, trust in formal finance, gendered constraints, broadband availability, device turnover, and data interoperability. These frictions can weaken the $DIF \times RE$ complementarity even where infrastructure is in place. To assess external validity beyond the study window, policy pilots that integrate digital-skills training, consent-based data-sharing mechanisms, and logistics densification are therefore warranted.

Fourth, the identified productivity–finance–entrepreneurship loop invites system-dynamics modeling to simulate long-run equilibria and counterfactual policy mixes. Extending the framework to other emerging economies would test its external validity.

Future work could leverage quasi-experimental designs, such as staggered rollouts of e-commerce demonstration zones or the introduction of digital credit products, to strengthen causal identification. Micro-level household or firm surveys matched with transaction records would allow tests of heterogeneity across gender, age, and asset ownership. Lastly, incorporating a dynamic systems model could help policymakers simulate long-run pathways and evaluate trade-offs between productivity, sustainability, and inclusion.

Regarding design validity, our current safeguards already target abrupt, province-specific surges in rural e-commerce within the two-way province-year fixed-effects framework. Future work can complement this approach with event-time difference-in-differences that exploits staggered rollouts of logistics infrastructure or demonstration-zone certification, conditional on access to granular policy timing.”

Two-point, stepwise comparisons (e.g., 2014 vs. 2018) may mechanically dampen noise but at the cost of discarding within-province dynamics and inviting selection concerns. By contrast, our panel fixed-effects and IV estimators leverage the full 2014–2022 variation and directly mitigate spike risk, while preserving the rich temporal information necessary for credible inference.

6.4. Concluding Statement

The evidence shows that coupling Digital Inclusive Finance (DIF) with Rural E-commerce (RE) is more effective than either subsystem alone in narrowing China’s urban–rural income gap. This synergy operates through gains in green productivity, expanded credit access, and strengthened entrepreneurship, with particularly pronounced effects in the Central and Western regions and in the depth and digital-support dimensions of DIF. A policy agenda that deliberately cultivates this coupling—by investing in infrastructure, advancing financial innovation, improving logistics, and enhancing human capital—provides a coherent pathway toward inclusive and sustainable rural transformation. The contribution should be viewed as an empirically grounded systems interpretation rather than a universal law, with context-dependent applicability and magnitudes that require reassessment as platforms, regulation, and technologies continue to evolve.

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