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From Fragmentation to Coupling: Leveraging Entrepreneurial Vitality to Synchronize Digital Inclusive Finance with Rural Revitalization

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Abstract

The entrepreneurial ecosystem theory posits that regional development emerges from synergistic interactions among entrepreneurs, institutions, and markets. This study positions entrepreneurial vitality as the core catalyst synchronizing digital inclusive finance (DIF) with rural revitalization—two systems often advancing in isolation, leading to unbalanced rural development. Using a coupling coordination degree model and provincial panel data from China (2011–2020), we demonstrate that entrepreneurial vitality significantly strengthens DIF–rural revitalization coupling coordination, following a nonlinear threshold pattern. Coordination gains accelerate only after vitality passes empirically identified critical levels, explaining persistent regional disparities in coupling coordination. Furthermore, the vitality–coordination link is moderated by technological infrastructure, organizational electronic commerce (e-commerce) engagement, and regional economic development, as outlined by the Technology–Organization–Environment framework. Framing DIF as an e-commerce-related ICT input, this paper advances the entrepreneurial ecosystem, e-commerce, and ICT-for-development (ICT4D) literature by revealing the threshold-driven nature of resource coordination in rural contexts. The findings offer a contextualized framework for catalyzing balanced and inclusive rural development in emerging economies.

Keywords: entrepreneurial ecosystem theory; entrepreneurial vitality; digital inclusive finance; rural revitalization; coupling coordination; electronic commerce

1. Introduction

Rural communities in developing economies often suffer from fragmented markets and weak financial linkages that constrain their growth. These communities are frequently characterized by an agricultural sector composed of many small, dispersed farms with limited access to banking services and credit [1]. Such fragmentation not only reduces productivity but also raises barriers to entry—thereby increasing the risks and transaction costs faced by potential and existing entrepreneurs (e.g., smallholders and agri-startups) who require external capital. Consequently, rural regions tend to lag behind urban areas in income and enterprise dynamism, reinforcing spatial inequality and limiting inclusive growth. Recognizing these challenges, policymakers worldwide have launched rural revitalization initiatives to better integrate rural economies into national growth [2]. This global trend is strongly exemplified by China, where the government has designated rural revitalization as a national strategic priority, establishing comprehensive policies that make it a compelling setting for our investigation.



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Digital inclusive finance (DIF)—the use of mobile phones, internet services, and online platforms to deliver affordable banking, credit, and payment services—has emerged as a promising instrument for advancing rural revitalization by mitigating traditional financial exclusion and enhancing the accessibility of financial services for rural entrepreneurs [3–5]. In this study, we explicitly frame DIF as an electronic commerce-related (e-commerce-related) information and communication technologies (ICT) input that operates through payment, digital credit, and transaction-data channels, and emphasize that its mere presence does not guarantee systemic gains unless local systems can absorb and operationalize these digital channels. For example, in China, the provincial median DIF index increased nearly tenfold between 2011 and 2020 [6], while foundational rural digital infrastructure, such as Internet coverage (see Figure 1), improved only modestly. This asynchrony suggests that the two systems often advance in isolation; the challenge, therefore, lies not only in technology deployment or rural-development efforts alone, but in achieving effective coordination between DIF and rural revitalization—a gap that cannot be explained by either system in isolation [7].

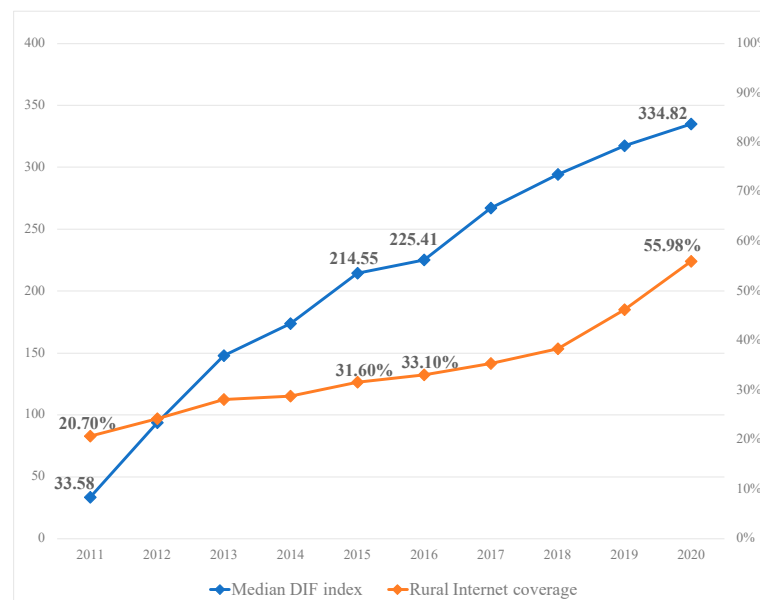


Figure 1. Asynchronous development of DIF and rural Internet coverage in China (2011–2020). Source: rural Internet coverage data is concluded from the Statistical Report on the Development Status of China’s Internet released by the Cyberspace Administration of China (<https://www.cac.gov.cn/index.htm>) (accessed on 8 May 2025).

Entrepreneurial ecosystem theory posits that the density, connectivity, and dynamism of local actors, supportive institutions, and a conducive culture fundamentally determine a region’s capacity to both generate and scale new ventures and to mobilize and embed new resources into productive activities [8,9]. This ecosystem, in turn, cultivates key micro-foundations—notably entrepreneurial orientation and absorptive capacity—that enable local actors to recognize and operationalize synergies between ICT inputs such as DIF and rural development [10]. Therefore, we argue that the synchronization between DIF and rural revitalization is contingent upon the region’s underlying entrepreneurial ecosystem. In this study, we capture the functional output of this ecosystem through the entrepreneurial vitality concept—a region’s latent capacity to initiate and sustain entrepreneurial action—which we posit as a pivotal catalyst for coordinating DIF with rural revitalization.

Importantly, in resource-constrained rural settings, behaviors captured by bricolage and effectuation—for example, repurposing equipment, pooling community funds, launching small micro-pilots, and forming local partnerships—help entrepreneurs iteratively

adapt DIF-based services to local needs and scale promising practices [11,12]. Because these adaptive, distributed actions depend on recurrent interactions, local learning and sufficient actor density to produce spillovers, we posit that the catalyzing effect of entrepreneurial vitality on the integration of DIF and rural revitalization is nonlinear: limited below a critical mass, but accelerating once network effects and learning accumulate.

Finally, we propose that the strength and position of this catalyzing effect are moderated by key contextual conditions in the Technology–Organization–Environment (TOE) framework—specifically digital infrastructure, enterprise e-commerce engagement, and regional economic development—which shape the capacity of ecosystems and enterprises to absorb, adapt, and scale DIF-enabled opportunities.

Based on the above motivations, this paper operationalizes the synchronization between DIF and rural revitalization using the notion of coupling coordination—a systems lens that captures the degree to which these two subsystems co-evolve and mutually reinforce one another. Our research is conducted within the context of China, because it presents a uniquely informative context for examining this coupling coordination and our inquiry, for three reasons. First, it exhibits pronounced and internally diverse “digital divides,” with advanced urban digital ecosystems coexisting alongside vast rural areas where digital adoption is evolving [13]. This spatial heterogeneity within a single governance framework enables a powerful comparative analysis of how contextual factors moderate core relationships. Second, China has been at the forefront of integrated digital finance and rural e-commerce deployment (e.g., Alipay, WeChat Pay, and Taobao Villages), creating a rich empirical landscape to observe the real-time interaction between coupling coordination and entrepreneurial action development. Finally, the simultaneous presence of strong, top-down policy initiatives (notably the national “Digital China” and “Rural Revitalization” programmes) provides a clear policy backdrop to critically assess the bottom-up, emergent role of entrepreneurial vitality, offering insights relevant to other developing economies pursuing similar coordinated strategies. Together, these features make China a powerful “laboratory” for this study. Empirically, our key research questions are as follows:

- (1) What is the status and characteristic of coupling coordination between DIF and rural revitalization in China?
- (2) Can entrepreneurial vitality promote coupling coordination between DIF and rural revitalization, and does this impact exhibit nonlinear (threshold) dynamics?
- (3) Which contextual conditions (technology, organization, and environment)—operationalized as digital infrastructure level, enterprise e-commerce engagement level, and economic development level—moderate the vitality–coupling relationship?

To address these questions, our empirical analysis uses three longitudinal datasets covering 30 Chinese provinces from 2011 to 2020: the Peking University Digital Inclusive Finance Index (PKU-DFIIC), a China Regional Innovation and Entrepreneurship Index (IRIEC), and a newly constructed Rural Revitalization Index. We quantify coupling coordination with a coupling coordination degree model and test baseline, threshold, and moderation hypotheses using panel and threshold regression techniques.

This study contributes to the literature at the intersection of entrepreneurship, e-commerce, and ICT4D in three ways. First, it introduces and empirically validates entrepreneurial vitality as a critical catalyst for coordinating DIF and rural development, moving beyond prior work that predominantly treats DIF as a unidirectional enabler of rural revitalization. Second, by uncovering threshold dynamics, it advances a contingent understanding of when entrepreneurial ecosystems drive systemic change, highlighting the importance of achieving critical mass. Third, by situating the analysis within the TOE framework, operationalizing specific moderators, and framing DIF as an e-commerce-related ICT input, we identify how contextual technological, organizational, and environmental

conditions shape the impact of entrepreneurial vitality on coupling coordination, thereby speaking directly to e-commerce and ICT4D debates about when digital financial inputs produce tangible developmental outcomes. Practically, this paper also offers empirically grounded insights for platform and policy design in other developing economies to promote balanced regional development.

2. Theoretical Background and Hypotheses

2.1. *The Coupling Coordination Between DIF and Rural Revitalization*

DIF and rural revitalization constitute two interdependent subsystems whose developmental impacts depend on the degree of their functional integration. Coordination theory [14] suggests that aligning otherwise fragmented subsystems (finance, institutions, technology) yields synergistic outcomes. From this perspective, effective rural development requires not only advances in each subsystem, but the establishment of linkages and feedback that allow financial innovation to be absorbed into local production and service systems.

Specifically, DIF—conceptualized as an e-commerce-related ICT input (payment platforms, digital credit mechanisms, and transaction-data flows)—provides financial fuel for rural revitalization. Grounded in financial development theory [15], DIF addresses rural credit constraints by leveraging digital channels to lower service costs, expand geographic reach, and introduce alternative information signals for underwriting. This enables targeted capital infusion into rural economies, allowing farmers and nascent entrepreneurs to invest in productivity-enhancing technologies and working capital needs, thereby raising productive capacity and household incomes [16]. In addition, DIF-generated transaction records and digital footprints can mitigate information asymmetries that traditionally hamper rural lending.

At the same time, evolving rural economic conditions shape demand-side incentives for DIF innovation. As rural areas diversify and incomes rise, the heterogeneity and sophistication of local financial needs increase, creating opportunities for tailored DIF products (e.g., embedded credit for e-commerce sellers, parametric insurance aligned to local risk profiles). These demand signals can encourage financial providers and platforms to adapt products and delivery models to rural contexts [1,17]. Yet such complementarities do not arise automatically. They depend on institutional alignment (governance, regulation, data standards) and local technological and organizational capacity. Institutional fragmentation raises transaction costs for DIF providers [18], while “last-mile” gaps in connectivity and human capital hinder adoption [19,20]. Thus, measuring coupling coordination—the extent to which DIF and rural development are functionally integrated—provides a diagnostic of where systemic gaps persist and where targeted interventions may be necessary. China’s experience is uniquely instructive due to the scale and speed of its DIF expansion, coupled with stark regional disparities in rural development, creating a powerful natural experiment to examine how the coupling coordination evolves in time and space.

2.2. *The Impact of Entrepreneurial Vitality on DIF–Rural Coupling Coordination*

We argue that synchronizing DIF and rural revitalization is contingent upon the region’s entrepreneurial ecosystem, and that entrepreneurial vitality should be conceptualized as a preconditional catalyst—a region-level absorption and mobilization capacity that determines whether digital financial inputs are translated into sustained, place-based outcomes. Entrepreneurial ecosystem theory identifies policy, finance, human capital, markets, and support services—and the relational networks connecting them—as domains whose functioning shapes the capacity to generate, scale, and embed new ventures [8,21].

From this vantage, entrepreneurial vitality strengthens the coupling coordination between DIF and rural revitalization through four proximate pathways.

First, market formation. Entrepreneurial vitality stimulates the creation of new, often digitally enabled markets in rural areas by actively shaping demand and innovating business models that integrate production, processing, distribution, and sales [22]. Examples include e-commerce ventures for specialty agricultural products, agri-tech services, and rural tourism bundles [23]. These ventures produce concrete, localized demand for finance—working capital, embedded payments, and supply-chain finance—which in turn provide observable signals for DIF providers to design and deploy products. The transactional footprints of such ventures also improve the informational basis for risk assessment, tightening the match between supply and demand and fostering closer coupling.

Second, resource orchestration. Entrepreneurial actors coordinate dispersed assets—human skills, local capital, social networks, and technologies—so that DIF-provided funds are combined with complementary inputs to form scalable projects [24]. Through networks and intermediaries, entrepreneurs mobilize external investment, aggregate savings, and run training programs that raise digital capabilities among producers, thereby reducing the risk of misapplied finance [25]. This orchestration typically unfolds via bricolage—the recombination of existing resources—and effectuation—small, affordable, iterative experiments using DIF-enabled mechanisms [11,12]. These adaptive processes improve absorptive fit and help convert financial innovations into operational practices that support rural development.

Third, localized information production. A vibrant entrepreneurial ecosystem generates rich micro-level data on supply chains, sales, and consumer behavior that is otherwise scarce in rural contexts. These data streams reduce information asymmetries and enable DIF providers to refine credit scoring, design tailored insurance, and de-risk small-value lending [26]. As a result, improved information flows enhance the accessibility and effectiveness of digital financial services, which supports further entrepreneurial activity by lowering financing frictions.

Fourth, institutional entrepreneurship. Certain actors—cooperative leaders, platform pioneers, local officials, or intermediary organizations—actively create or legitimize institutional arrangements [27,28]. These institutional entrepreneurs can pioneer data-sharing protocols, convene multi-stakeholder governance arrangements, or advocate for sandbox regulatory arrangements that permit DIF experimentation. By reducing transaction costs and establishing trust and standards, institutional entrepreneurship creates the rules of the game that facilitate larger-scale collaboration between DIF providers and rural actors.

Taken together, these pathways imply a cumulative and interactional process: isolated pilots and localized bricolage produce limited local gains, whereas systemic coupling coordination emerges when market formation, resource orchestration, information production, and institutional adjustments coalesce. Two features are particularly important. First, actor density and repeated interaction are crucial: orchestration and reliable information flows require a minimum mass of entrepreneurs, transactions, and intermediaries to generate robust signals and to justify product customization by DIF providers. Second, positive feedback and network externalities amplify returns after a critical mass is reached—more ventures generate more data, attracting more tailored finance and lowering costs for subsequent entrants. Hence, the marginal effect of entrepreneurial vitality on coupling coordination is likely to be modest at low activity levels but accelerates once critical thresholds of activity and connectivity are surpassed. This conceptual logic leads us to hypothesize, first, an enhancing relationship (H1) and, second, a theoretical refinement (H2):

H1. *Higher entrepreneurial vitality positively enhances the coupling coordination between DIF and rural revitalization.*

H2. *The effect of entrepreneurial vitality on the coupling coordination exhibits a nonlinear (threshold) pattern such that its marginal impact increases after surpassing critical thresholds.*

2.3. Moderating Effects on the Vitality–Coupling Relationship: A TOE Framework

The effect of entrepreneurial vitality on DIF–rural coupling is contingent on contextual conditions: although H2 articulates when vitality’s influence intensifies (i.e., beyond a critical mass), it does not specify under which external configurations this influence is amplified or attenuated. In other words, the moderating factors that alter the strength of the relationship between entrepreneurial vitality and DIF–rural coupling need to be identified. Prior research has frequently examined technological, organizational, and environmental factors in isolation, yielding a fragmented picture of these boundary conditions. To address this gap, we adopt the TOE framework [29], which is well-suited here for three complementary reasons. First, it offers an integrative, multidimensional lens to theorize how technological readiness, organizational capabilities, and broader environmental endowments jointly shape the vitality–coupling link, that is, how these external conditions set the stage for entrepreneurial vitality to be more or less effectively translated into systemic coordination. Second, TOE is a well-established meta-framework in technology adoption and ICT4D studies, aligning directly with our interest in integrating DIF into rural socio-economic systems. Third, the framework is operationally convenient: each TOE dimension maps onto measurable regional capacities theoretically relevant to rural China (digital infrastructure; enterprise e-commerce engagement; regional economic development), allowing us to formulate concrete, testable moderation hypotheses.

Technological context: digital infrastructure. This dimension comprises connectivity and computational capacity (broadband, mobile networks, and back-end infrastructure) that establishes the technical foundation for both DIF services and digitally enabled entrepreneurial ventures. It does not constitute entrepreneurial action, but fundamentally shapes the terrain on which such action unfolds. Superior infrastructure lowers the intrinsic costs of digital transactions and data exchange associated with using digital financial tools and scaling ventures [30]. Consequently, in such settings, the marginal impact of entrepreneurial vitality on coupling coordination is heightened because the technical barriers to implementing and scaling innovative, finance-integrated ventures are reduced. The infrastructure thus moderates the relationship by lowering the threshold at which entrepreneurial vitality translates into enhanced coupling coordination.

Organizational context: enterprise e-commerce engagement. The extent to which established local enterprises engage in e-commerce reflects a region’s organizational maturity within the digital economy. This engagement generates a flow of transactional data and embeds digital channels into local commerce, creating a context rich in market signals. This context exists largely independently of the new entrepreneurial vitality we measure. However, it provides a fertile environment for that vitality to take root and produce effects. From a resource-based perspective [31], digital competency is a valuable organizational capability that amplifies the practical impact of entrepreneurial experimentation by enabling faster commercialization, better demand forecasting, and improved creditworthiness signals. When entrepreneurial actors in regions with high levels of enterprise e-commerce engagement launch new ventures or experiment with novel business models, they operate within an organizational landscape that is already digitally attuned. This existing digital maturity amplifies the practical effect of their actions on DIF–rural coupling, as the necessary linkages between commerce and finance are more readily established. Moreover, digital clusters

(e.g., China's "Taobao Villages") create spatial spillovers: when one village's e-commerce hub prospers, neighboring rural areas gain access to new markets and investment. Therefore, enterprise e-commerce engagement serves as an organizational-level moderator that enhances the efficiency with which vitality is converted to coupling coordination.

Environmental context: regional economic development. This dimension represents macro-level institutional and market readiness. Regions with higher economic development typically possess more sophisticated market institutions, clearer regulatory frameworks, and better public services, all of which reduce uncertainty and external transaction costs [18]. In such environments, the potential value created by entrepreneurial ventures faces fewer external impediments to realization, and DIF providers perceive lower risk in tailoring services to local needs. As a result, a unit increase in entrepreneurial vitality is expected to yield a larger gain in coupling coordination in more developed regions, as the environmental "friction" is lower. Regional economic development thus acts as an environmental moderator that magnifies the positive association between entrepreneurial vitality and coupling coordination. Accordingly, this paper derives the moderation hypotheses:

H3a. *The level of digital infrastructure (technological context) positively moderates the effect of entrepreneurial vitality on DIF–rural coupling coordination.*

H3b. *The intensity of enterprise e-commerce engagement (organizational context) positively moderates the effect of entrepreneurial vitality on DIF–rural coupling coordination.*

H3c. *Regional economic development (environmental context) positively moderates the effect of entrepreneurial vitality on DIF–rural coupling coordination.*

The theoretical model is summarized in Figure 2, which depicts entrepreneurial vitality as the primary catalytic antecedent affecting coupling coordination, with TOE dimensions shaping the strength and threshold of this relationship.

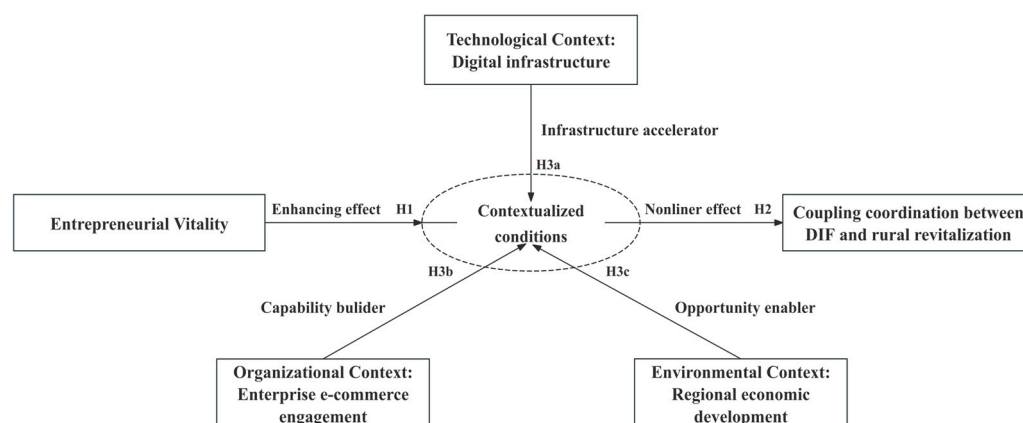


Figure 2. Theoretical model.

3. Methodology

3.1. Coupling Coordination Measurement

3.1.1. Coupling Coordination Degree Model

To assess the synergy between DIF and rural revitalization, we employ a coupling coordination degree model, adapted from physics to analyze interdependent systems [32]. The model is specified by Formulas (1)–(3), taking DIF and rural revitalization as two subsystems:

$$C = \sqrt{\frac{DF \times VR}{(DF + VR)^2}} \quad (1)$$

$$T = \eta_1 DF \times \eta_2 VR \quad (2)$$

$$OH = \sqrt{C \times T} \quad (3)$$

where C represents the coupling degree, reflecting interaction strength. DF and VR indicate the development levels of DIF and rural revitalization, respectively. T is a comprehensive coordination index capturing the combined contribution of the two subsystems to the coordination process, defined using contribution coefficients η_1 and η_2 . In this paper, we set $\eta_1 = \eta_2 = 0.5$, assigning equal weight to DIF and rural revitalization. Finally, OH denotes the overall coupling coordination degree of the two subsystems, and is classified into ten coordination levels [33], ranging from extreme imbalance to high-quality coordination (see Table 1).

Table 1. Evaluation criteria for coupling coordination degree.

Coupling Coordination Degree	Section OH
Extreme imbalance	[0, 0.1)
Serious imbalance	[0.1, 0.2)
Moderate imbalance	[0.2, 0.3)
Mild imbalance	[0.3, 0.4)
Verge of imbalance	[0.4, 0.5)
Reluctant coordination	[0.5, 0.6)
Primary coordination	[0.6, 0.7)
Moderate coordination	[0.7, 0.8)
Good coordination	[0.8, 0.9)
High-quality coordination	[0.9, 1]

3.1.2. Indicator Selection and Data Sources

The DIF level is measured using the PKU-DFIIC, a widely recognized composite index covering coverage breadth, usage depth, and digitalization degree [34]. For rural revitalization, this paper constructs a comprehensive index system based on China's national policy framework—Chinese National Rural Revitalization Strategic Plan (2018–2022)—and prior research [35], encompassing five dimensions: industrial prosperity, ecological habitability, affluence of living, rural civilization, and governance effectiveness, operationalized through 18 specific indicators (see Table 2).

To objectively determine indicator weights, we apply the entropy weight method, which minimizes subjective bias by calculating weights based on data variability [36]. The calculation steps are as follows.

Step 1. Standardize initial data.

For positive indicators, this paper positions the standardization process as Formula (4), while for negative indicators, the process follows Formula (5):

$$X'_{ij} = \left[\frac{X_{ij} - \min X_j}{\max X_j - \min X_j} \right] + 0.01 \quad (4)$$

$$X'_{ij} = \left[\frac{\max X_j - X_{ij}}{\max X_j - \min X_j} \right] + 0.01 \quad (5)$$

where i represents province; j represents indicator; X_{ij} and X'_{ij} represent the raw data before processing and the data after standardization, respectively.

Table 2. Evaluation index system of DIF and rural revitalization.

System Layer	Dimension Layer	Index Layer	Indicator Attributes	Weight
DIF		Cover breadth	+	0.3618
		Usage depth	+	0.3574
		Digitalization degree	+	0.2807
Rural revitalization	Industry prosperity	Comprehensive grain production capacity (ten tons/hectare)	+	0.2958
		Contribution rate of agricultural science and technology progress (%)	+	0.0644
		Agricultural labor productivity (ten thousand yuan/person)	+	0.0315
		The retail sales of rural products accounted for the total social sales (%)	+	0.0250
	Ecological habitability	Rural green coverage rate (%)	+	0.0350
		Average number of domestic waste transfer stations	+	0.0505
		Number of public toilets per 10,000 rural residents	+	0.0830
	Affluence of living	Rural gas penetration rate (%)	+	0.0483
		Number of licensed (assistant) doctors per thousand rural residents	+	0.0474
		Per capita housing area of rural residents (m ² /person)	+	0.0622
		The Engel coefficient of rural residents (%)	–	0.0139
		Per capita road area of rural residents (m ² /person)	+	0.0231
		Income ratio between urban and rural residents	–	0.0163
		Number of township cultural stations	+	0.0592
	Rural civilization	Average years of education for rural population	+	0.0117
		Rural expenditure on education, culture, and entertainment accounted for in the total expenditure (%)	+	0.0196
	Governance effectiveness	Proportion of heads of village committees concurrently serving as Party secretaries (%)	+	0.0628
		Number of villages and towns with construction management institutions	+	0.0503

Notes: “+” indicates a positive indicator, whereas “–” indicates a negative indicator. Source: weights are sourced from author’s calculation based on Stata 18.

Step 2. Calculate the proportion P_{ij} of each indicator X_{ij} using Formula (6):

$$P_{ij} = \frac{X_{ij}}{\sum_{i=1}^n X_{ij}}, i = 1, 2, \dots, n; j = 1, 2, \dots, m \quad (6)$$

where n represents the number of provinces and m represents the number of indicators.

Step 3. Calculate the entropy E_j of the j indicator according to Formula (7):

$$E_j = -\frac{1}{\ln n} \sum_{i=1}^n P_{ij} \ln P_{ij} \quad (7)$$

Step 4. Calculate the comprehensive weight W_j of each indicator applying to Formula (8):

$$W_j = \frac{1 - E_j}{\sum_{j=1}^m (1 - E_j)} \quad (8)$$

where $1 - E_j$ is the difference coefficient of the j indicator, and the larger the coefficient, the more important the indicator X_j is in the evaluation index system.

Step 5. Calculate the overall score of each province with Formula (9):

$$S_i = \sum_{j=1}^m W_j X_{ij} \quad (9)$$

Data for this study were drawn from multiple authoritative sources. PKU-DFIIC data were obtained from the Institute of Digital Finance, Peking University (publicly available for 2011–2020). The index captures multiple financial domains (payments, banking, credit, insurance, investment), is normalized to a 0–100 scale for cross-region comparability, and has been validated in recent studies [34,37].

The rural revitalization index was built from authoritative national yearbooks (*China Statistical Yearbook*; *China Rural Statistical Yearbook*; *China Statistical Yearbook of Urban and Rural Construction*; *China Health Statistics Yearbook*; *China Culture and Tourism Yearbook*; *China Civil Affairs Yearbook*). Indicator construction followed three steps: (1) direct extraction of core metrics (e.g., rural green coverage and gas penetration); (2) calculation of derived measures (e.g., urban–rural income ratio and Engel coefficient) as specified in Table 2; and (3) imputation of sporadic missing values (excluding Tibet) by linear interpolation. Sensitivity checks indicate interpolation did not introduce systematic bias (mean absolute error < 0.05).

The analytical sample comprises 30 mainland provinces; Tibet is excluded due to insufficient and sporadic data coverage in the official sources used to construct our Rural Revitalization Index. Excluding Tibet preserves temporal consistency and cross-sectional comparability and follows common practice in province-level analyses under similar data constraints [38–40]. The 2011–2020 timeframe was selected because the PKU-DFIIC series is available and because it captures the formative phase of China’s DIF–rural integration: an initial infrastructure build-out (roughly 2011–2015) followed by active integration and policy experimentation (2016–2020), including the 13th Five-Year Plan and Digital Village pilots. National reports also indicate the DIF architecture stabilized around 2020 [41], making this period a coherent basis for analyzing coupling dynamics.

3.2. Empirical Model Setting

3.2.1. Baseline Regression Model

To test the enhancing effect of entrepreneurial vitality on coupling coordination, we construct a baseline regression model with fixed effects to minimize endogenous problems, as seen in Formula (10):

$$OH_{it} = \alpha_0 + \alpha_1 EV_{i,t-1} + \alpha_2 CTL_{it} + \delta_i + \theta_t + \varepsilon_{it} \quad (10)$$

where i and t represent province and year, respectively; $EV_{i,t-1}$ indicates entrepreneurial vitality; CTL_{it} represents the set of control variables, including industrial structure, educational development level, opening-up level, government intervention level, and traditional

finance development level; α_0 is the constant term; α_1 and α_2 are the coefficients; δ_i and θ_t are province and year fixed effects, respectively; and ε_{it} is the random disturbance item. This paper adopts balanced short-panel data; robustness checks have conducted (Section 4.3) to address endogeneity concerns.

3.2.2. Threshold Regression Model

To examine whether the influence of entrepreneurial vitality on coupling coordination is nonlinear, we adopt Hansen's [42] panel threshold approach. The single-threshold specification is as follows:

$$OH_{it} = \tau_0 + \tau_1 EV_{i,t-1} I(EV_{i,t-1} \leq \gamma) + \tau_2 EV_{i,t-1} I(EV_{i,t-1} > \gamma) + \tau_3 CTL_{it} + \varepsilon_{it} \quad (11)$$

and the double-threshold extension is as follows:

$$OH_{it} = \tau_0 + \tau_1 EV_{i,t-1} I(EV_{i,t-1} \leq \gamma_1) + \tau_2 EV_{i,t-1} I(\gamma_1 < EV_{i,t-1} \leq \gamma_2) + \tau_3 EV_{i,t-1} I(EV_{i,t-1} > \gamma_2) + \tau_4 CTL_{it} + \varepsilon_{it} \quad (12)$$

Among them, $EV_{i,t-1}$ is both the threshold variable and the independent variable; τ_0 represents the constant term; other τ symbols refer to the coefficients; γ symbols represent the unknown true threshold ($\gamma_1 < \gamma_2$); $I(\cdot)$ is an indicative function that equals 1 when $EV_{i,t-1}$ is less than γ , and 0 otherwise; other symbols have the same meanings as the baseline model. Other multiple threshold models can be extended based on the single threshold model as well, but are omitted in this study.

3.2.3. Moderating Effect Model

To test contextual moderators, we augment the baseline model by adding alternative moderators and their interactions with entrepreneurial vitality:

$$OH_{it} = \beta_0 + \beta_1 EV_{i,t-1} + \beta_2 Mod_{lit} + \beta_3 (Mod_{lit} \times EV_{i,t-1}) + \beta_4 CTL_{it} + \delta_i + \theta_t + \varepsilon_{it} \quad (13)$$

where Mod_{lit} ($l = 1, 2, 3$) denotes the three moderators: digital infrastructure (*Infra*), enterprise e-commerce participation (*Parti*), and regional economic development (*Develop*). $Mod_{lit} \times OH_{it}$ represents the interaction term between moderating variables and coupling coordination degree, indicating the moderating effect; β_0 represent the constant term, while the remaining β symbols represent the coefficients of the variables. The meanings of other variables are consistent with previous definitions. In the testing process, if β_3 is significant, then it can be judged that the moderating effect exists.

3.2.4. Variable Selection

The dependent variable is *OH*, reflecting the coupling coordination degree between DIF and rural revitalization.

The independent variable, entrepreneurial vitality (*EV*), is operationalized as a composite construct capturing both behavioral agency and outcome performance in regional entrepreneurial ecosystems. Rooted in entrepreneurial ecosystem theory [8,9], *EV* integrates two synergistic dimensions: (1) knowledge creation capacity, reflecting a region's ability to generate and commercialize novel ideas, measured by indicators such as patent grants; (2) market entry dynamism, quantifying the intensity of entrepreneurial actors' engagement in financial markets, proxied by indicators such as new enterprise registrations. To operationalize this construct, this study employs the IRIEC, a multidimensional metric spanning the period 1990–2020. The IRIEC synthesizes five objective dimensions from the National Industrial and Commercial Enterprise Registration Database: newly established enterprises (*New*), foreign direct investment attraction (*FDI*), venture capital attraction (*VC*), patent authorizations (*Patent*), and trademark registrations (*TM*). Each dimension

is normalized (0–100); the composite score is log-transformed to reduce volatility. In all empirical specifications of this study, *EV* is entered as a one-period lag ($EV_{i,t-1}$) to impose temporal ordering, mitigate simultaneity and look-ahead bias, and reflect the delayed impact of entrepreneurial vitality on the coupling coordination outcomes. The IRIEC data were sourced directly from the official repository of Peking University's Enterprise Big Data Research Center.

Three moderating variables are considered in this paper: (1) digital infrastructure level (*Infra*) is represented by the proportion of regional fixed investment in information transmission, software, and information technology services to regional GDP; (2) enterprise e-commerce engagement intensity (*Parti*), measured by the proportion of enterprises engaged in e-commerce transactions relative to the total number of enterprises in the region; (3) economic development level (*Develop*), represented by the logarithm of regional per capita GDP.

Five control variables are selected based on previous research. *Str* represents industrial structure, characterized by the ratio between the added value of the tertiary industry and the added value of the secondary industry. *Edu* means the level of educational development, measured by the ratio of regional financial education expenditure to total financial expenditure. *Ope* is the level of regional opening-up to foreign markets, measured by the ratio of the total import and export trade (RMB) to the regional GDP. *Gov* indicates the level of government intervention, measured as the ratio of local financial general budget expenditure to regional GDP. Additionally, *Tra* represents the development level of traditional finance, measured by the logarithm of the ratio of deposit and loan balances of regional financial institutions to the regional GDP. The data source of the moderating variables and control variables is the *China Statistical Yearbook*; PKU-DFIIC and other indicators are as described in Section 3.1.2.

Descriptive statistics for all variables are shown in Table 3.

Table 3. Descriptive statistics of variables.

Variables	Obs	Mean	S.D	Min	Max
<i>OH</i>	300	0.578	0.113	0.271	0.807
<i>EV</i>	300	4.365	0.221	3.135	4.605
<i>Infra</i>	300	0.888	0.634	0.043	4.062
<i>Parti</i>	300	7.772	3.791	1.501	22.800
<i>Develop</i>	300	10.791	0.439	9.682	12.001
<i>Str</i>	300	1.324	0.729	0.527	5.244
<i>Edu</i>	300	0.164	0.026	0.099	0.222
<i>Ope</i>	300	0.274	0.290	0.008	1.464
<i>Gov</i>	300	0.264	0.114	0.120	0.758
<i>Tra</i>	300	1.154	0.284	0.529	2.017

Notes: italic type denotes variable names, same as below. Source: author's calculation based on Stata 18.

4. Results and Analysis

4.1. Coupling Coordination Results and Spatiotemporal Evolution

The results of the coupling coordination degree are displayed in Appendix A Table A1.

4.1.1. Time-Order Characteristic

Figure 3 summarizes the 2011–2020 evolution of the coupling coordination degree between DIF and rural revitalization. Overall, coupling coordination increased steadily over

the decade, but the pace of improvement slowed after 2015, and the national mean remained at the “primary coordination” level by 2020 (national average = 0.689). This pattern of diminishing marginal gains suggests that the initial diffusion of DIF and rural development is insufficient to drive the system toward higher-quality coordination. It indicates that overcoming the coordination plateau may require a catalytic element beyond the direct expansion of DIF or rural revitalization, pointing to the potential role of endogenous, dynamic factors like entrepreneurial vitality in reinvigorating synergistic growth.

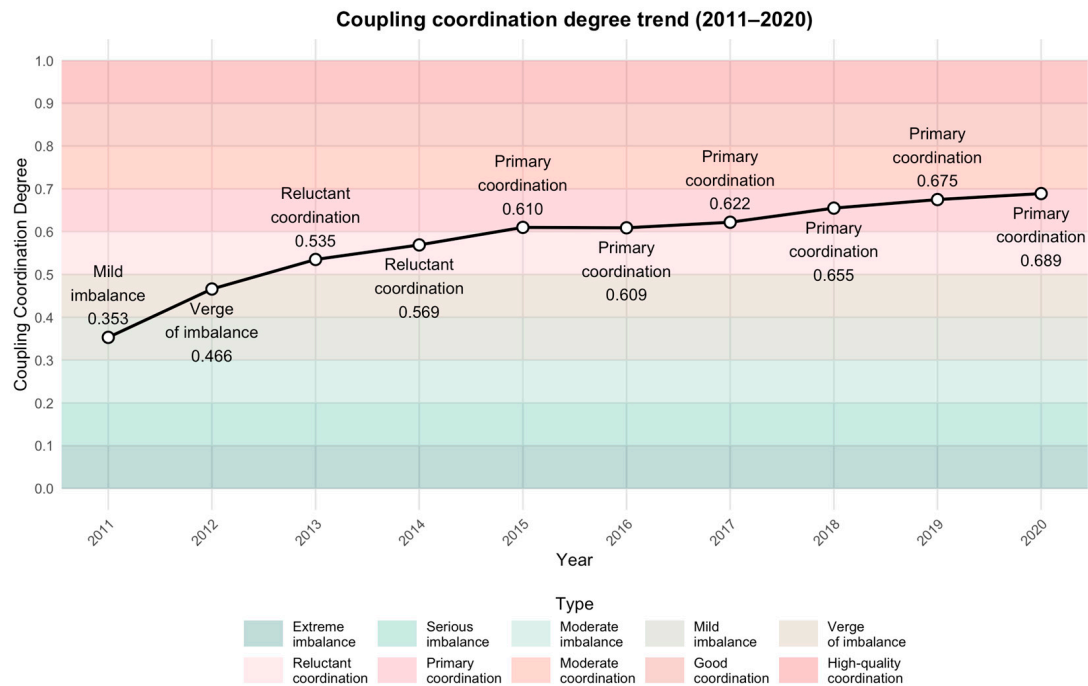


Figure 3. The time-order performance of coupling coordination development. Source: author’s calculation.

4.1.2. Regional Heterogeneity

Recognizing China’s vast geography and the substantial interprovincial development disparities [38], we have adopted the National Bureau of Statistics’ regional framework to group provinces into three broad regions (Eastern, Central, and Western) to verify whether there is regional heterogeneity in the coupling coordination development (see Appendix A Table A1 for the full mapping). This approach reflects regional socio-economic realities in a thoughtful and balanced way while helping to streamline our analysis with greater clarity and purpose. As shown in Figure 4, spatially, coupling coordination exhibits pronounced regional differentiation. Between 2011 and 2020, the distribution shifted rightward—many provinces moved from imbalance or “verge of imbalance” toward primary or better coordination—but a persistent pattern of “strong in the east, moderate in the central belt, weak in the west” remains. Notably, Sichuan reached the “good coordination” category by 2020, whereas 16 provinces still fell below the national average. While this geographical gradient is consistent with broader regional inequalities in China, its persistence in the context of DIF–rural coordination raises a critical question: why do some regions succeed in synchronizing DIF with rural development while others lag? This observed heterogeneity motivates our subsequent investigation into whether entrepreneurial vitality, which itself is known to vary regionally, can serve as a key to explaining and potentially overcoming this coordination divide.

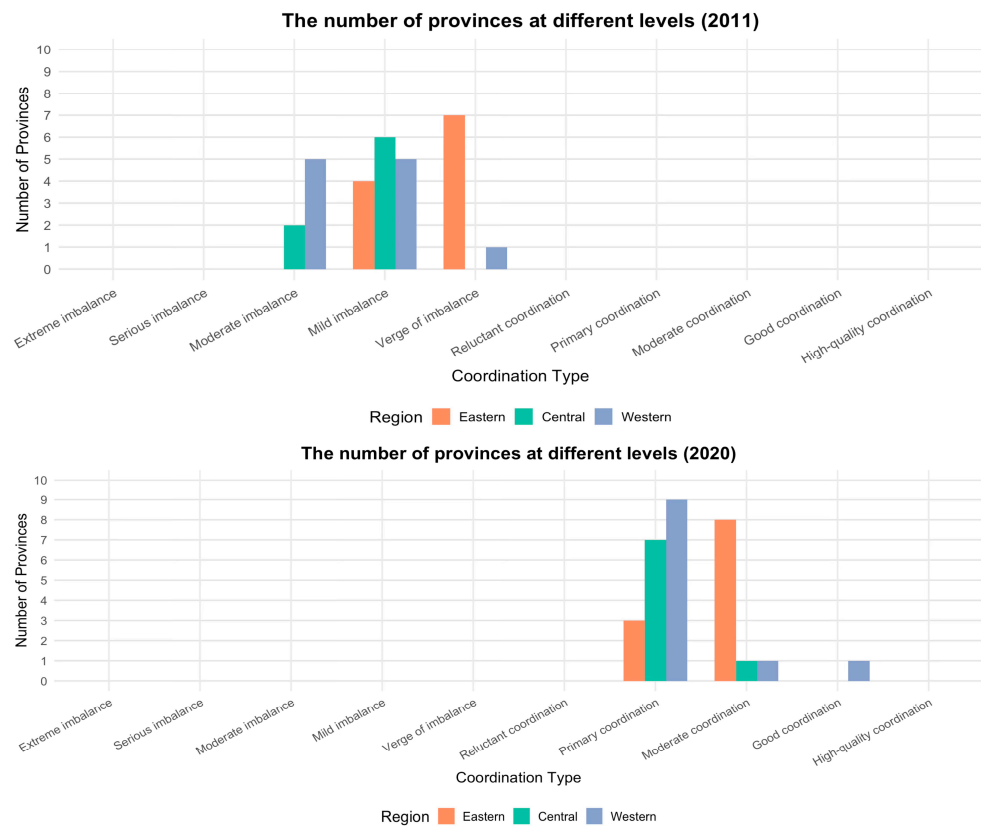


Figure 4. Spatial distribution of coupling coordination degree in 2011 and 2020.

4.2. Regression Results

4.2.1. Baseline Result

Since this paper uses panel data, the disturbance terms for the same individual may be correlated over time, so it is necessary to control for both individual and time effects. We employ the Hausman test to determine whether to use a fixed effects model or a random effects model for parameter estimation. The test assumes that if the individual effects are correlated with the independent variables, the fixed effects model is preferred; if uncorrelated, the random effects model is more suitable. The Hausman test results yield a p -value < 0.000 , indicating that using the fixed effects model for parameter estimation in the baseline regression is more effective. The regression results are shown in Table 4.

Models 1 and 2 present the baseline estimates from the mixed OLS regressions, while Models 3 and 4 report the results from the fixed-effects specifications. Across all four specifications, the coefficients of *EV* are positive and statistically significant, lending robust support to Hypothesis H1.

Regarding the control variables, regions characterized by a more advanced industrial structure and more developed traditional financial sectors exhibit significantly higher coupling coordination degrees. Taken together, these findings underscore the primary importance of entrepreneurial vitality, alongside structural and traditional financial factors, in fostering synergistic development between DIF and rural revitalization.

4.2.2. Threshold Result

In this study, we employ a bootstrap procedure with 300 replications to test for the presence and statistical significance of threshold effects. The results reported in Table 5 indicate that both the single- and double-threshold models are statistically significant at 5% level, whereas the triple-threshold specification fails to reach significance. These findings justify the adoption of a double-threshold framework.

Table 4. Results of the baseline regression.

Variables	Dependent Variable: <i>OH</i>			
	Model 1	Model 2	Model 3	Model 4
<i>EV</i>	0.288 *** (0.020)	0.354 *** (0.028)	0.526 *** (0.027)	0.261 *** (0.031)
<i>Str</i>		0.016 * (0.008)		0.098 *** (0.026)
<i>Edu</i>		−0.091 (0.199)		0.579 * (0.320)
<i>Ope</i>		−0.104 *** (0.022)		−0.064 (0.051)
<i>Gov</i>		0.089 (0.084)		−0.340 (0.176)
<i>Tra</i>		0.141 *** (0.028)		0.340 *** (0.051)
CONS	−0.670 ** (0.085)	−1.117 *** (0.138)	−1.698 *** (0.116)	−1.061 *** (0.149)
Year and Province	NO	NO	YES	YES
N	300	300	300	300
Adjust R ²	0.420	0.603	0.544	0.726

Source: author's calculation based on Stata 18; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; standard errors in parentheses; same as below.

Table 5. Test of the threshold effect.

Threshold Variable	Model	F Statistic	p-Value	Critical Value		
				10%	5%	1%
<i>EV</i>	Single threshold	25.230	0.017	18.724	21.146	29.222
	Double threshold	25.890	0.007	17.319	20.432	25.211
	Triple threshold	12.180	0.363	17.679	19.931	27.642
	Estimated value			95% confidence interval		
	Single threshold value	4.347		[4.339, 4.348]		
	Double threshold value	4.503		[4.494, 4.505]		

Source: author's calculation based on Stata 18.

The double-threshold regression was then processed, and the results are presented in Table 6. The coefficient on *EV* exhibits a positively increasing step-function pattern, confirming a non-linear relationship with entrepreneurial vitality and the coupling coordination degree. Specifically, when *EV* falls below the first threshold (4.347), its marginal effect on the coupling coordination degree is 0.237. As *EV* moves into the intermediate regime ($4.347 \leq EV < 4.503$), this effect increases to 0.249, and once *EV* exceeds the second threshold (4.503), its impact further rises to 0.262. Thus, the greater the entrepreneurial vitality level, the stronger its incremental contribution to enhancing the synergy between DIF and rural revitalization. Collectively, these results provide support for Hypothesis H2.

The identification of dual-threshold effects reveals that entrepreneurial vitality exerts a nonlinear, stage-dependent influence on the coupling coordination degree, contingent on regional development trajectories. To unravel the spatiotemporal heterogeneity of these thresholds across China, Figure 5 presents a matrix heatmap classifying provinces into three *EV* tiers (Low: $EV \leq 4.347$; Mid: $4.347 < EV \leq 4.503$; and High: $EV > 4.503$) and maps their distribution in 2011 and 2020.

The heatmap elucidates two interconnected patterns central to disentangling regional disparities. First, it captures a widespread upward mobility, evidenced by 86% of provinces surpassing the first vitality threshold ($EV > 4.347$) by 2020; this temporal dynamic is associated with accelerated coordination gains, particularly in the eastern region, where

a trajectory of cumulative advantage has propelled the majority of provinces beyond the high threshold ($EV > 4.503$) and consolidated their lead.

Table 6. Results of the double-threshold regression.

Variables	Coefficient	S.D	T-Value	p-Value
<i>Str</i>	0.032	0.026	1.26	0.210
<i>Edu</i>	0.702	0.296	2.38	0.018
<i>Ope</i>	−0.131	0.049	−2.68	0.008
<i>Gov</i>	−0.232	0.164	−1.42	0.158
<i>Tra</i>	0.309	0.047	6.54	0.000
$EV \leq 4.347$	0.237	0.030	7.98	0.000
$4.347 < EV \leq 4.503$	0.249	0.029	8.51	0.000
$EV > 4.503$	0.262	0.029	8.89	0.000
CONS	−0.915	0.142	−6.46	0.000
N		300		
Adjust R ²		0.767		

Source: author's calculation based on Stata 18.

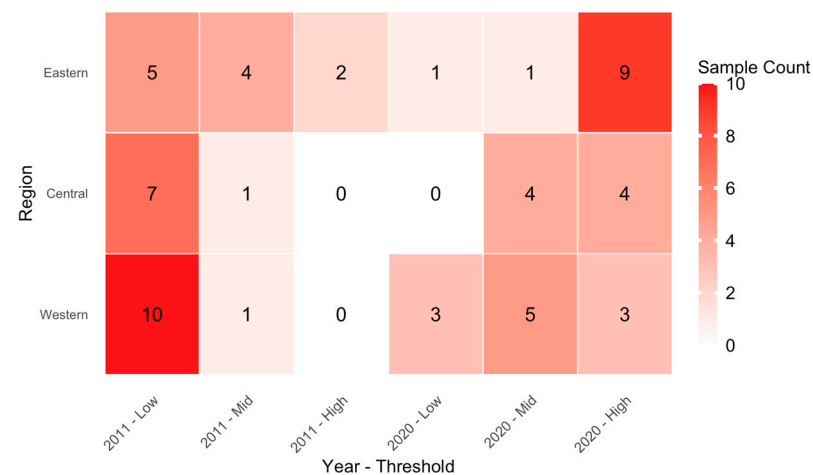


Figure 5. Heatmap of the distribution of threshold regression samples.

The threshold narrative also aligns with the Sichuan case. By 2020, Sichuan sits in the high entrepreneurial vitality tier and exhibits an unusually high coupling coordination score for a western province. This pattern is consistent with targeted provincial initiatives to stimulate entrepreneurship [43], such as provincial start-up grants, returnee founder programs, and municipal innovation zones, which likely increased local venture density and market activity, thereby facilitating the synchronization of DIF and rural revitalization. This case demonstrates that when a central or western province successfully crosses the critical vitality threshold—often through targeted interventions—it can disrupt the inertia of fragmented development and initiate a virtuous cycle of coordination, akin to those observed in eastern hubs.

4.2.3. Moderating Effect Result

The results of the moderation effect are presented in Table 7. Models 1, 2, and 3 present the moderating effects of digital infrastructure (*Infra*), the enterprise e-commerce engagement intensity (*Parti*), and regional economic development (*Develop*), respectively. In each specification, the interaction term between the moderator and entrepreneurial vitality ($Mod \times EV$) is positive and statistically significant. Collectively, these empirical findings substantiate Hypotheses H3a, H3b, and H3c.

Table 7. Results of the moderating effect models.

Variables	Dependent Variable: <i>OH</i>		
	Moderating Variable: <i>Infra</i>	Moderating Variable: <i>Parti</i>	Moderating Variable: <i>Develop</i>
	Model 1	Model 2	Model 3
<i>EV</i>	0.274 *** (0.034)	0.201 *** (0.032)	0.101 (0.337)
<i>Mod</i>	−0.198 ** (0.086)	−0.096 *** (0.026)	−0.089 * (0.129)
<i>Mod</i> × <i>EV</i>	0.045 ** (0.021)	0.023 *** (0.006)	0.014 * (0.030)
<i>Str</i>	0.075 ** (0.027)	0.030 (0.028)	0.105 *** (0.026)
<i>Edu</i>	0.552 * (0.317)	0.496 (0.309)	0.468 (0.312)
<i>Ope</i>	−0.084 (0.051)	−0.031 (0.050)	−0.044 (0.051)
<i>Gov</i>	−0.350 ** (0.175)	−0.141 (0.174)	−0.419 ** (0.176)
<i>Tra</i>	0.347 *** (0.053)	0.330 *** (0.050)	0.343 *** (0.050)
CONS	−1.079 *** (0.162)	−0.785 *** (0.154)	−0.056 (1.454)
Year and Province	YES	YES	YES
N	300	300	300
Adjust R ²	0.731	0.748	0.735

Source: author's calculation based on Stata 18. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

The positive and significant interaction terms indicate that the effect of entrepreneurial vitality on DIF–rural coupling is conditional on contextual readiness. In particular, better digital infrastructure lowers fixed and transaction costs for digital finance and entrepreneurship, enabling DIF to be absorbed and scaled more rapidly; stronger enterprise e-commerce engagement enhances enterprises' absorptive capacity and generates transaction data that improve financial product–market matching; and higher regional economic development enlarges demand and institutional capacity, reducing uncertainty and encouraging tailored financial innovation. Together, these moderating patterns corroborate the TOE-based framework: entrepreneurial vitality matters most where technological, organizational, and environmental preconditions permit entrepreneurial action to be translated into systemic coordination.

4.3. Robustness Test

4.3.1. Endogenous Treatment

Two complementary approaches are adopted to address endogeneity, and the corresponding results are presented in Table 8.

First, we estimate a System GMM, treating the independent variable (*EV*) and the lagged dependent variable (*L.OH*) as endogenous to capture dynamic effects (Model 1). The independent variable is positive and significant (*EV* coefficient = 0.149, $p < 0.05$), and the lagged dependent exhibits strong persistence (*L.OH* coefficient = 0.525, $p < 0.000$). Diagnostic tests indicate Arellano–Bond (1) in differences ($p = 0.005$) but no Arellano–Bond (2) ($p = 0.179$). Although the Hansen test yields a p -value of 0.015, the difference-in-Hansen test ($p = 0.969$) supports instrument exogeneity and mitigates concerns about weak instruments.

Second, to control for omitted variable bias, we implement a two-stage least squares (2SLS) strategy using two instrument variables (IVs) for *EV*. The first IV, *Brand*, is con-

structed as the product of provincial time-honored brands (cross-sectional data from China's Ministry of Commerce) and lagged national R&D expenditure (time-series data from the *China Statistical Yearbook*). The IV's relevance is justified by its historical exogeneity and strong correlation with regional innovation and entrepreneurial activity [44]. First-stage diagnostics (Model 2) confirm that *Brand* is a relevant IV with moderate-to-strong strength (Kleibergen–Paap rk Wald $F = 13.052 > 10$, $p < 0.000$). An Anderson–Rubin test robust to weak instruments further reject the null of no effect ($F(1,293) = 4.18$, $p < 0.05$), confirming that the second-stage effect is detectable even under weak-IV procedures. Second-stage estimates (Model 3) reveal a persistently positive and significant coefficient for *EV* (coefficient = 0.161, $p < 0.1$) after addressing endogeneity.

Table 8. Endogenous treatment results.

Variables	System GMM	Use Instrumental Variable			
		Stage I	Stage II	Stage I	Stage II
	Model 1	Model 2	Model 3	Model 4	Model 5
<i>L.OH</i>	0.525 *** (0.039)				
<i>EV</i>	0.149 ** (0.045)		0.161 * (0.083)		1.416 *** (0.010)
<i>Brand</i>		0.034 *** (0.004)			
<i>Taobao</i>				0.019 ** (0.006)	
Control Variables	Control	Control	Control	Control	Control
Year and Province	YES	YES	YES	YES	YES
N	270	300	300	300	300
Adjust R ²	—	0.725	0.399	0.679	0.523

Source: author's calculation based on Stata 18. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

We use Taobao Villages to measure regional e-commerce agglomeration and as a second IV for *EV*. A Taobao Village is an administrative rural village that meets Alibaba Research Institute's criteria (annual e-commerce turnover $\geq$ RMB 10 million and ≥ 100 active shops, or active shops $\geq 10\%$ of households) [45]. We measure the IV as *Taobao*, defined as the lagged value of $\ln(n + 1)$, where n is the number of Taobao Villages in a region; Taobao Village counts are drawn from Ali Research (<http://www.aliresearch.com/cn/index> (accessed on 27 December 2025)). The lagged logarithm reduces the likelihood that the IV reflects contemporaneous shocks to the outcome while capturing long-run differences in local e-commerce infrastructure that plausibly drive entrepreneurship [46]. First-stage diagnostics (Model 4) indicate that *Taobao* is a relevant IV with moderate-to-strong strength: Kleibergen–Paap rk Wald $F = 14.51 > 10$, $p < 0.000$. Weak-instrument-robust inference further supports identification: the Anderson–Rubin test strongly rejects the null of no effect ($F(1,293) = 157.25$, $p < 0.000$). The corresponding second-stage 2SLS (Model 5) estimate for *EV* is positive and highly significant (coefficient = 1.416, $p < 0.000$). Taken together, the System GMM and IV–2SLS estimates provide evidence consistent with a causal interpretation of the positive effect of entrepreneurial vitality on the DIF–rural coupling.

4.3.2. Other Robustness Test

Four additional robustness tests are conducted, results are reported in Table 9. First, given the unique administrative status and exceptionally high urbanization levels of China's four municipalities (Beijing, Shanghai, Tianjin, and Chongqing), these regions are excluded to mitigate potential confounding effects arising from their distinct socioeconomic charac-

teristics. Re-estimation (Model 1) yields an *EV* coefficient of 0.201 ($p < 0.000$), close to the baseline 0.261, indicating that results are not driven by municipality-specific characteristics.

Table 9. Robustness test results.

Variables	Exclude Municipalities	Replace Dependent Variable	Replace Independent Variable			Add Control Variables
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
<i>EV</i>	0.201 *** (0.032)	0.616 *** (0.067)				0.174 *** (0.029)
<i>Scientific_EV</i>			0.289 *** (0.032)		0.199 *** (0.051)	
<i>Commercial_EV</i>				0.266 *** (0.032)	0.113 ** (0.050)	
Control Variables	Control	Control	Control	Control	Control	Control
Year and Province	YES	YES	YES	YES	YES	YES
N	260	300	300	300	300	300
Adjust R ²	0.753	0.696	0.735	0.725	0.739	0.807

Source: author's calculation based on Stata 18. *** $p < 0.01$, ** $p < 0.05$.

Second, we log-transform the dependent variable (*lnOH*) to address potential nonlinearity/heteroscedasticity (see Model 2). The relationship remains significant (*EV* coefficient = 0.616, $p < 0.000$), confirming that the baseline functional form does not drive the findings.

Third, to resolve the potential conflation of distinct entrepreneurial pathways within the composite *EV* index, we decompose *EV* into science-driven (innovation-oriented) dimension—represented by *Patent* and *VC*; and market-driven (commercial-oriented) dimension—represented by *New*, *FDI*, and *TM*. Following the IRIEC weights [47], we form the science component as $Scientific_EV = 0.25 \times VC + 0.25 \times Patent$, and the commercial component as $Commercial_EV = 0.20 \times New + 0.15 \times FDI + 0.15 \times TM$. Each raw score is converted to the log scale, and the one-period lag is used to re-estimate the baseline fixed-effects specification, consistent with the treatment of the original *EV*. When entered separately (Model 3 and 4), both sub-indices are positive and highly significant ($Scientific_EV = 0.289$, $Commercial_EV = 0.266$; both $p < 0.000$). In the joint specification (Model 5), both sub-indices remain positive, but science-driven entrepreneurship exhibits a larger and more robust effect ($Scientific_EV = 0.199$, $p < 0.000$; $Commercial_EV = 0.113$, $p < 0.05$). These decomposition results suggest that the DIF–rural coupling operates more strongly through innovation-oriented (technology) entrepreneurship than through expansions in market entry. This pattern accords with entrepreneurial ecosystem theories [48,49]: innovation-driven ventures generate knowledge spillovers, higher-quality investment opportunities, and richer transaction data that more readily mobilize and be absorbed by digital financial inputs than mere expansions in enterprise counts or trademarks.

Moreover, to mitigate potential omitted-variable bias we introduce three additional province-level controls that prior literature identifies as salient for regional development and financial integration. First, to account for institutional capacity and policy implementation quality, local governance quality is proxied by the natural logarithm of the frequency of governance-related keywords in provincial government work reports. Text-based measures of policy emphasis and administrative capacity have been widely used as parsimonious proxies for subnational governance and strategic priorities [50]; conceptually, stronger governance reduces transaction costs and misalignment between public and private actors, thereby facilitating the absorption and institutional coordination necessary for DIF–rural coupling [18]. Drawing on previous literature [51], the specific keywords encompass

community services, public security, integrated law enforcement, urbanization, floating population, and land-expropriated farmers, among others; full keyword list are reported in Appendix A Table A2. Python software (version 3.9) was employed to systematically extract keyword frequencies from the reports. Second, to capture the social foundations of market and financial interaction, social capital is proxied by the logged number of registered social organizations. Social capital and associational density lower collective action costs, improve information flows, and support trust-based intermediation—factors that have been shown to enhance the local effectiveness of financial and entrepreneurial interventions [52,53]. Data are drawn from the National Bureau of Statistics. Third, because land institutions condition both entrepreneurial entry and access to finance in rural China [54], land-tenure dynamics are captured by the land-transfer rate (the share of household-contracted cultivated land that is transferred), which measures the extent to which land use is tradable and reallocated. Secure and fluid land-use arrangements influence farmers' investment incentives and their ability to access credit [55], thereby affecting both entrepreneurial opportunities and the willingness of financial providers to extend tailored credit. Transfer-rate series were compiled from the *China Rural Management Statistical Annual Report* and the *China Rural Policy and Reform Statistical Annual Report*. When these three controls are added to the baseline specification (Model 6), the coefficient on *EV* remains positive and statistically significant (coefficient = 0.174, $p < 0.000$), indicating that our main result is robust to accounting for variation in governance capacity, social capital, and land-tenure institutions.

5. Discussion

This study situates DIF within a systems perspective and examines how regional entrepreneurial vitality conditions the functional coupling between DIF and rural revitalization. The results engage three strands of literature—entrepreneurial ecosystems, ICT4D/digital finance, and e-commerce—and produce several interpretive insights that refine and extend existing accounts.

First, our empirical confirmation that entrepreneurial vitality materially strengthens DIF–rural coupling advances the entrepreneurial ecosystem literature by demonstrating a clear antecedent role for ecosystem capacity in determining technology-to-development translation. While prior work often treats entrepreneurship as an outcome of regional development or as an explanation for enterprise-level heterogeneity [8,9], our findings recast entrepreneurial vitality as a catalytic conditioning variable: it enables digital channels (payments, embedded credit, transaction data) to be operationalized in ways that align finance with place-based commercial opportunities. This perspective complements studies emphasizing demand-side co-creation of ICT value [56] and situates entrepreneurship squarely within the mechanisms that convert ICT inputs into sustained economic processes.

Second, the identification of nonlinear (threshold) dynamics refines standard linear assumptions in ICT4D and digital finance assessments. The empirical threshold—showing that marginal gains in coupling accelerate only after vitality surpasses critical levels—resonates with Schumpeterian and diffusion logics while adding precision for rural contexts, where actor density and data availability are constrained [57]. This threshold helps explain why isolated pilot projects or limited entrepreneurial efforts, despite showing promising local results, often lead to only modest broader impacts. It highlights that until there is a critical mass of participants, ongoing transactions, and meaningful institutional experimentation, the benefits of network effects and shared learning remain underdeveloped—and the motivation for DIF providers to tailor their offerings stays low. By making this accumulation process empirically observable, the study contributes to an emerging literature that interrogates the conditions under which ICT interventions scale beyond pilot stages.

Third, the TOE-based moderation findings elaborate how technological, organizational, and environmental configurations shape the vitality–coupling link. The stronger conditional effects associated with digital infrastructure and enterprise e-commerce engagement underscore the salience of platform- and data-related mechanisms for e-commerce-oriented readers. In particular, e-commerce engagement appears to operate as a proximate conduit: enterprises' participation in online marketplaces generates regular transactional traces and demand signals that materially reduce information frictions for digital lenders and platform finance offerings. This observation provides an empirical bridge between platform studies in e-commerce—where transaction data and embedded services are central—and ICT4D studies emphasizing infrastructural prerequisites for impact.

Moreover, the spatial and temporal contours of our findings merit emphasis. The asymmetric expansion of DIF and baseline digital infrastructure in the Chinese panel contextualizes the threshold effects: rapid platform and service innovation can precede the infrastructural and organizational substrates required for broad-based coupling. At the same time, the rapid advancement of platform and service innovation invites a critical examination of longer-term socio-economic implications [58–60]: the very platform ecosystems that enable swift DIF diffusion may also engender distributional and governance risks that weaken coupling gains. The data-driven, network-centric model of major platforms [61], if left unchecked, can create new forms of dependency for rural economies. Centralization of transaction data and market access may lead to asymmetric power relationships, where value extraction by platform intermediaries outweighs value creation for local producers. Furthermore, the imperative for standardized data flows, although crucial for reducing financial information asymmetry, could also intensify surveillance and data privacy concerns or marginalize smallholders who cannot produce data in the required format. Consequently, policy design should therefore pair capacity-building and infrastructure investment with institutional protections, ensuring that the benefits of digital integration are equitably distributed and that local entrepreneurial ecosystems retain sufficient agency. These safeguards both protect rural actors and help ensure that platform-enabled coordination yields broadly shared, sustainable development outcomes. Additionally, heterogeneity across provinces—whereby more advanced regions exhibit earlier threshold-crossing—reinforces that coupling coordination is not uniformly time-invariant but shaped by region-specific trajectories of technological and organizational development. This insight complements comparative ICT4D studies that document divergent pathways of digital impact across locales.

Finally, beyond the specific background of the Chinese context, our findings offer transferable insights for diverse developing economies. Our study highlights a universal sequence: grassroots entrepreneurial energy is essential for translating DIF into sustained coordination, but contextual thresholds limit its efficacy. For instance, in countries like India or Nigeria [2], where digital infrastructure and platform ecosystems may be nascent or uneven, our findings underscore the risk of fragmented, small-scale pilot interventions that fail to generate system-level effects. The key is not merely deploying technology but fostering a critical mass of local entrepreneurial activity to unlock network effects. Similarly, in contexts with more fragmented governance or weaker state capacity, such as Colombia and Bangladesh [62,63], the integrated policy framework observed in China may be absent. Nevertheless, our study suggests that policymakers and platforms should prioritize minimizing contradictory signals and fostering institutional experiments (e.g., local data co-operatives, sandbox regulations) to lower transaction costs for entrepreneurs and financial providers alike. Thus, while the Chinese path, with its scale and state coordination, is distinctive, the underlying imperative to strategically align entrepreneurial ecosystem development with digital and rural policy is of broad relevance.

6. Conclusions

This paper reframes the relationship between DIF and rural revitalization as a framework of coupling coordination and demonstrates that entrepreneurial vitality serves as a decisive catalytic antecedent for such coupling. Using provincial panel data from China (2011–2020), we show that higher entrepreneurial vitality is associated with stronger DIF–rural integration and that this association is characterized by nonlinear threshold dynamics: coordination gains accelerate once entrepreneurial activity, data flows, and institutional interactions attain critical mass. Moreover, technological readiness (digital infrastructure) and organizational engagement (enterprise e-commerce activity), together with the broader economic context, materially condition the magnitude and threshold at which vitality translates into system-level coupling.

In sum, the analysis provides an integrated, empirically grounded depiction of how local entrepreneurial capacities, technological channels, and organizational practices interrelate to produce—or fail to produce—sustained coupling between digital finance and rural development. This reframing emphasizes that the emergence of coordinated digital-financial systems in rural contexts depends on accumulated actor density, repeated transactions and stabilizing institutional arrangements that together enable digital channels to be meaningfully embedded in local economic life.

7. Implications

7.1. Theoretical Implications

This study advances theory in three specific ways by integrating entrepreneurial ecosystem perspectives with ICT4D, platform/e-commerce studies, and technology-adoption frameworks.

First, this paper innovatively puts DIF and rural revitalization in an integrated frame, studying their mutual and, more specifically, reciprocal relationship. This extends ICT4D insights by showing that while DIF can play a positive role in rural revitalization, the relationship is characterized by coupling coordination, whose synchronization is fundamentally dependent on entrepreneurial vitality. Rather than treating entrepreneurship solely as a downstream outcome or as enterprise-level heterogeneity, we conceptualize entrepreneurial vitality as a region-level, conditioning capacity that precedes and shapes the capacity of technological inputs to produce systemic change. This shifts entrepreneurial ecosystem theorizing toward an antecedent-role logic: scholars should treat ecosystem vitality not only as a dependent variable but as a causal selector that determines whether and when ICT-enabled interventions can be operationalized into sustained regional coordination.

Second, this paper extends the TOE and ICT4D studies by introducing threshold boundary conditions. The findings operationalize the TOE frame conditionally: technological, organizational and environmental factors do not merely shift average treatment effects but systematically alter the thresholds at which entrepreneurial vitality yields systemic coupling. This adds precision to TOE-based theorizing in ICT4D by turning boundary conditions into threshold parameters, encouraging scholars to explicitly model nonlinearity when theorizing development impact in technology.

Finally, this paper bridges e-commerce/platform theory and digital finance scholarship by advancing a data-affordance framing. We conceptually connect platform and e-commerce studies (transaction data, embedded services) with digital finance theory by proposing that transaction data affordances serve as a proximal mechanism facilitating product adaptation and underwriting. This framing articulates how marketplace participation can generate information goods that reconfigure financial intermediation logics, thereby extending platform theory into the domain of rural finance and offering a cross-

disciplinary agenda for future theory development on platforms as infrastructures for localized financial innovation.

7.2. Practical Contributions

Our findings offer actionable guidance for policymakers, development practitioners, and platform operators in China and other developing economies seeking to foster synergistic rural development.

First, build transaction-oriented digital infrastructure (reach + reliability + use-case alignment). Strong, reliable connectivity lowers the accumulation threshold at which entrepreneurial vitality produces system-level coupling by enabling dependable payment, credit and transaction-data channels. Operationally, this means prioritizing connectivity investments that target high-transaction nodes (marketplaces, logistics hubs, cooperatives and township service points) and ensuring network uptime and latency profiles suitable for real-time payments and data synchronization. Infrastructure rollout should be guided by analytics of local transaction patterns so that upgrades directly support areas where embedded finance is most operationally viable. However, realizing the full value of this infrastructure requires parallel investments in digital literacy programs to address competency deficits among rural users, ensuring safe and effective use of digital payment and credit tools.

Second, activate density through localized entrepreneurial hubs that integrate e-commerce and fintech linkages. Threshold effects require sufficient actor density and recurrent transactions; strategically designed hubs accelerate market formation and generate the repeatable data streams that attract DIF productization. In practice, counties or municipalities should host low-cost incubation facilities combining seller enablement (e-commerce onboarding, basic logistics and order fulfillment), shared computing and connectivity, training for digital operations, and a dedicated fintech liaison function that coordinates platform pilots and data interoperability. These training components should accommodate low digital literacy, incorporating local languages and intuitive interfaces, to effectively bridge the competency gap and prevent excluding less digitally savvy entrepreneurs. Hubs should also be configured explicitly to produce measurable transaction volumes and standardized records that reduce onboarding friction for digital lenders.

Third, institutionalize platform–intermediary data arrangements and sandboxed experimentation. Transactional data and standardized sharing protocols are the proximate mechanisms that reduce information asymmetry and permit tailored digital finance products. Operational steps include creating interoperable, privacy-aware data-sharing frameworks (minimal data standards, API specifications, and robust consent procedures that are comprehensible to rural users) and establishing local regulatory sandboxes that allow platforms, cooperatives, and financial institutions to trial data-driven underwriting and embedded-finance models under controlled governance rules. A critical environmental factor limiting implementation is the lack of trusted data governance; therefore, sandboxes should mandate and pilot transparent data-usage policies and establish accessible grievance redressal mechanisms to build the essential trust among rural communities, mitigating privacy concerns that could stifle participation. The overarching goal of such governance innovation is to ensure that data value accrues to its generators and that communities maintain meaningful control over their digital footprints, preventing data extraction that benefits distant intermediaries at the expense of local development. Such arrangements both protect users and provide the legal and technical scaffolding needed to operationalize transaction data as a credible input for credit and risk models.

Finally, mobilize blended risk-sharing finance and staged pilot-to-scale pathways. Early market formation is risky and often underfunded; blended instruments and staged

expansion help traverse initial thresholds without locking in unsustainable subsidies. Practically, this entails deploying hybrid instruments (guarantees, first-loss reserves, catalytic grants) to de-risk initial platform–entrepreneur experiments, and adopting a standardized pilot–monitor–scale protocol with clear, empirically grounded triggers—transaction frequency, active sellers, data completeness, and default metrics—that govern when resources are scaled. Key environmental limitations include the high perceived risk of early-stage rural digital ventures and the lack of traditional collateral. The proposed blended finance instruments must therefore be designed to also cover the initial costs of digital skills training and cybersecurity measures, addressing the foundational barriers that increase perceived risk for both lenders and borrowers. This staged approach aligns financing with observed market signals and ensures that DIF offerings are expanded only when local ecosystems demonstrate the density and data quality needed for sustainable underwriting.

8. Limitations and Future Research

This study is subject to several limitations that also point to avenues for future research. First, this paper was conducted within the Chinese context, where strong central policy support may limit the external validity of our findings for countries with more decentralized governance or weaker institutions. Second, our analysis relies on a relatively short panel constrained by available DIF data, limiting inference on longer-term dynamics. Simultaneously, we acknowledge that the COVID-19 period accelerated digital adoption that may have altered coupling dynamics. Third, the research design prioritizes establishing foundational causal and threshold relationships before unpacking the specific mechanisms through which entrepreneurial vitality enhances coordination. Additionally, while we propose four proximate pathways (market formation, resource orchestration, localized information production, and institutional entrepreneurship) through which entrepreneurial vitality may strengthen DIF–rural coupling, these pathway constructs are processual and operate primarily at enterprise, platform, or village levels. Our province–year panel lacks direct, consistently measured indicators for these microprocesses, so formal mediation tests are beyond the scope of the current analysis.

Future research could extend this work in several directions. Cross-national comparative studies could test the applicability of the coupling coordination framework in countries with differing governance models, such as India or those in Sub-Saharan Africa, and whether the identified thresholds hold in contexts with weaker digital infrastructure or entrepreneurial density. Future work should also revisit the post-2020 period when harmonized provincial or platform-level data become available (for example, platform activity metrics and number of rural microloans). Such data would enable complementary approaches, such as high-frequency panel/event-study designs or difference-in-differences analyses, to assess whether and how the pandemic reshaped the threshold dynamics identified in this study. Further, mediation analyses could formally test using micro-level or higher-frequency data. Promising, quantifiable mediators may include: e-commerce transaction volumes per capita, counts of fintech–cooperative partnerships, number of rural incubators, and coverage of digital credit scoring. Methodologically, robust causal mediation with micro-level panel data or structural equation models can be complemented by qualitative methods, such as comparative case studies, to capture governance and institutional dynamics.

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Appendix A

Table A1. Coupling coordination degree in China from 2011 to 2020.

Region	Province	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
Eastern	Beijing	0.487	0.581	0.648	0.677	0.712	0.714	0.718	0.716	0.761	0.773
	Tianjin	0.431	0.519	0.577	0.606	0.649	0.655	0.664	0.688	0.697	0.692
	Hebei	0.334	0.445	0.518	0.540	0.580	0.582	0.605	0.647	0.671	0.680
	Liaoning	0.359	0.458	0.524	0.562	0.603	0.598	0.597	0.626	0.637	0.648
	Shanghai	0.476	0.566	0.628	0.652	0.684	0.676	0.679	0.704	0.720	0.725
	Jiangsu	0.414	0.516	0.579	0.610	0.654	0.654	0.669	0.705	0.722	0.729
	Zhejiang	0.442	0.532	0.599	0.624	0.669	0.667	0.694	0.744	0.761	0.791
	Fujian	0.403	0.497	0.565	0.593	0.636	0.631	0.651	0.697	0.722	0.731
	Shandong	0.386	0.504	0.577	0.613	0.658	0.657	0.667	0.694	0.708	0.739
	Guangdong	0.435	0.514	0.575	0.603	0.640	0.637	0.662	0.700	0.723	0.733
Central	Hainan	0.384	0.482	0.547	0.578	0.633	0.628	0.645	0.691	0.698	0.702
	Shanxi	0.361	0.470	0.539	0.565	0.587	0.591	0.599	0.626	0.644	0.652
	Jilin	0.286	0.421	0.481	0.530	0.556	0.550	0.561	0.581	0.600	0.618
	Heilongjiang	0.324	0.416	0.481	0.516	0.557	0.557	0.553	0.574	0.637	0.602
	Anhui	0.314	0.437	0.504	0.547	0.579	0.584	0.609	0.647	0.666	0.679
	Jiangxi	0.300	0.433	0.515	0.541	0.571	0.575	0.591	0.640	0.645	0.667
	Henan	0.334	0.448	0.524	0.559	0.598	0.603	0.625	0.662	0.685	0.697
	Hubei	0.349	0.466	0.578	0.582	0.624	0.627	0.635	0.676	0.696	0.707
Western	Hunan	0.321	0.447	0.520	0.556	0.608	0.603	0.616	0.643	0.663	0.676
	Inner Mongolia	0.306	0.425	0.495	0.534	0.579	0.567	0.563	0.595	0.613	0.635
	Guangxi	0.331	0.433	0.497	0.529	0.576	0.580	0.592	0.624	0.644	0.657
	Chongqing	0.338	0.543	0.626	0.658	0.702	0.704	0.712	0.745	0.769	0.781
	Sichuan	0.441	0.579	0.657	0.687	0.748	0.744	0.775	0.797	0.728	0.807
	Guizhou	0.271	0.410	0.473	0.533	0.580	0.588	0.607	0.652	0.682	0.694
	Yunnan	0.279	0.414	0.477	0.518	0.560	0.563	0.583	0.619	0.636	0.648
	Shaanxi	0.349	0.437	0.489	0.529	0.558	0.557	0.568	0.603	0.637	0.645
	Gansu	0.273	0.383	0.446	0.490	0.530	0.527	0.543	0.579	0.608	0.655
	Qinghai	0.275	0.361	0.442	0.478	0.535	0.528	0.539	0.591	0.610	0.631
	Ningxia	0.311	0.403	0.466	0.517	0.571	0.554	0.570	0.590	0.622	0.627
	Xinjiang	0.289	0.434	0.509	0.530	0.574	0.560	0.574	0.604	0.637	0.644

Source: author's calculation based on Stata 18.

Table A2. Keyword dictionary for constructing the local governance quality index.

Dimensions	Keywords
Community governance	community services, community development, public security, community volunteering, integrated law enforcement, community self-governance, residents' committees, grassroots self-governance, harmonious society, grassroots-level security, community functions, professional management, social governance, grid-based governance, social work, emergency management, hub-type social organizations, public security prevention and control, community service centers, community service networks, standardization of community governance, safe community, smart community, community burden reduction and efficiency improvement, alley stewardship programs, subdistrict administration
Urbanization of the agricultural population	urbanization, urban–rural integration, migrant workers, floating population, agricultural transfer population, citizenization, rural-to-urban labor migration, accompanying migrant children, household registration (hukou) system reform, land-expropriated farmers

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