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Assessing the effect of rural industrial integration on rural innovation and entrepreneurship in China

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Introduction: Rural innovation and entrepreneurship is a key initiative to promote rural revitalization, enhance farmers' incomes, and promote the coordinated development of urban and rural areas. However, existing research lacks consideration of the relationship between rural industrial integration and rural innovation and entrepreneurship. This study empirically investigates the influence and internal mechanism of rural industrial integration on the development of rural innovation and entrepreneurship.
Methods: Panel data from 1,759 counties in 26 provinces in China, spanning from 2014 to 2021, is analyzed using a dual machine learning (DML) model.
Results: The findings indicate that the integration of rural industries plays a key role in promoting the growth of rural innovation and entrepreneurship. This conclusion remains valid even after conducting a series of rigorous tests to ensure its reliability. Analysis of the mechanism reveals that the integration of rural industries might stimulate innovation and entrepreneurship in the agricultural and industrial sectors by fostering economic concentration. The heterogeneity results suggest that the impact of rural industrial integration on empowering rural innovation and entrepreneurship development is stronger in areas with high facility agriculture and a high agricultural base, compared to areas with low facility agriculture and a low agricultural base.
Discussion: Overall, this study derives a comprehensive theoretical framework of "foundation-dependency", suggesting that sustainable rural development follows a sequential logic where consolidating the agricultural foundation is a prerequisite for unlocking the full potential of industrial integration. This paper proposes policy proposals to expedite the advancement of rural industrial integration, foster economic concentration, and execute customized solutions based on local circumstances, aiming to offer guidance for achieving rural regeneration.

KEYWORDS
dual machine learning, economic agglomeration, rural industrial integration, rural innovation and entrepreneurship, sustainable development

1 Introduction

In the contemporary global economic landscape, rural areas are undergoing a paradigm shift from being purely production-oriented to becoming diversified economic spaces. Concepts such as "multifunctional agriculture" and the "sixth industry" highlight a shared global trend: agriculture is merging with manufacturing, tourism, and digital services to foster innovation and resilience (Sahal, 1985). Within this context, innovation and entrepreneurship have been widely recognized as crucial drivers for revitalizing rural economies and promoting sustainable development (Liu and Wang, 2022; Zheng, 2015). However, a conceptual ambiguity often exists in current literature and practice between "rural industrial development" (quantitative growth) and "rural industrial integration" (qualitative structural transformation). Drawing upon the theory of industrial convergence, true integration involves the cross-sectoral penetration and reorganization of primary, secondary, and tertiary industries (NDRC Research Group, 2016; Xiao and Du, 2019). This process creates a "multiplier effect" by extending the agricultural value chain, thereby generating "new combinations" of production factors—technology, capital, and talent—and spawning entirely new business models (Fagerberg, 2003; Tu, 2022).

In China, this integration strategy has been elevated to a national priority to address the "new normal" of economic transition and modernize the agricultural sector (Liu and Hui, 2024). Despite these policy pushes, rural innovation and entrepreneurship still face significant bottlenecks, such as the lack of effective connecting mechanisms between smallholders and markets, and the scarcity of high-end elements like digital talent (Li, 2023). Crucially, while existing studies have extensively explored external drivers like the digital economy (Liu and Hui, 2024), digital financial inclusion (Lei et al., 2023), and infrastructure investment (Li et al., 2022), they largely overlook the internal mechanisms of how the industrial integration process itself—specifically through the channel of economic agglomeration—reshapes the rural entrepreneurial ecosystem (Sun, 2024). This represents a critical research gap: current literature often treats integration as a policy outcome rather than examining how its spatial clustering effects internally drive innovation dynamics.

This study aims to bridge this gap by conducting a rigorous empirical analysis using panel data from 1,759 counties across 26 provinces in China from 2014 to 2021. Employing a Dual Machine Learning (DML) model to address high-dimensional control variables and potential non-linearities, this paper investigates the impact of rural industrial integration on innovation and entrepreneurship.

Our empirical analysis yields several key findings. First, rural industrial integration plays a significant role in promoting rural innovation and entrepreneurship, with a notably stronger impact on innovation (technological and product upgrades) than on entrepreneurship (new venture creation). Second, mechanism analysis reveals that economic agglomeration acts as a critical transmission channel. Integration fosters the spatial clustering of industries, which generates positive externalities—such as resource sharing, labor matching, and knowledge spillovers—that nurture the innovation ecosystem. Third, heterogeneity analysis indicates that the efficacy of integration follows a "foundation-dependency" logic: the positive effects are significantly amplified in regions with high facility agriculture and a strong agricultural base, compared to resource-limited areas.

This study makes distinct contributions to both literature and practice by strengthening the dialogue with existing research. First, from a theoretical perspective, it clarifies the conceptual boundaries of rural industrial integration and verifies the "multiplier effect" of cross-sectoral synergy, moving beyond the mere conflation of general industrial growth with qualitative structural transformation. By identifying economic agglomeration as an internal transmission mechanism, this research addresses a critical gap regarding how spatial economic reconfiguration drives innovation clusters. Second, regarding methodology, this paper employs the Dual Machine Learning (DML) model to mitigate the "curse of dimensionality" and potential non-linearities common in traditional econometric approaches. This ensures more robust causal inference within the complex rural socioeconomic system. Finally, this study offers practical policy pathways by revealing the "foundation-dependency" of integration, suggesting a transition from general advocacy to differentiated interventions based on regional resource endowments.

2 Theoretical analysis and research hypotheses

2.1 Conceptual definitions

To ensure theoretical rigor, we first delineate the core concepts and acknowledge the existing academic debates surrounding them.

Rural Industrial Integration: drawing upon existing literature (Chen et al., 2024; Xiao and Du, 2019; Gou and Yang, 2020; NDRC Research Group, 2016), rural industrial integration is defined as a dynamic process rooted in agriculture, involving the cross-sectoral merging and collaboration among primary, secondary, and tertiary industries. By extending the agricultural value chain and leveraging the multifunctionality of agriculture through technological penetration and organizational innovation (Sahal, 1985; Xie et al., 2024), this process aims to foster new business forms, optimize resource allocation, and generate synergistic development effects (Knickel et al., 2009).

Rural Innovation and Entrepreneurship: rural innovation and entrepreneurship represent key drivers of rural revitalization (Liu and Hui, 2024; Lei et al., 2023; Sun, 2024). Rural Innovation: drawing on Schumpeterian theory and the OECD framework, this encompasses the generation and adoption of new ideas, technologies, and organizational forms within rural contexts. It specifically pertains to creating novel solutions to address rural challenges (Li et al., 2022). Rural Entrepreneurship: this involves identifying and pursuing opportunities to create new ventures in rural areas (Pato and Teixeira, 2016). Innovation often serves as the foundation for entrepreneurial activity, while entrepreneurship provides the vehicle for commercializing innovation.

Existing debates: while the prevailing literature posits a positive nexus between industrial integration and rural development, debates persist. Proponents argue that integration creates a "multiplier effect," fostering an ecosystem ripe for innovation (Knickel et al., 2009). However, critics caution that without proper mechanisms, integration might lead to "elite capture," potentially stifling small-scale grassroots entrepreneurship. This study examines the specific mechanism—economic agglomeration—through which integration empowers broad-based rural innovation.

2.2 Impact of rural industrial integration on innovation and entrepreneurship

From the perspective of Schumpeterian Innovation Theory, rural industrial integration functions as a fundamental engine for the "carrying out of new combinations" of production means (Fagerberg, 2003). This process is not merely a quantitative expansion but a qualitative structural transformation that fosters innovation through three specific interlinked pathways. First, through the mechanism of technological penetration, advanced industrial technologies—such as the Internet of Things (IoT), big data, and biotechnology—are introduced into the agricultural production process. This creates "new methods of production" that significantly enhance efficiency and precision (Tu, 2022). Second, through industrial chain extension, integration transforms raw agricultural outputs into high-value-added processed goods. This vertical integration results in the creation of "new products," enabling farmers to capture a larger share of the value chain. Third, through functional expansion, the integration of agriculture with tourism, culture, and wellness sectors opens up "new markets." This leads to the emergence of service-oriented business models, such as agro-tourism and experiential farming, which were previously non-existent in traditional agriculture (Lei and Wang, 2022). Collectively, this multi-dimensional transformation triggers a process of "creative destruction," compelling the rural economy to evolve from low-efficiency homogeneity to high-value diversity.

Complementing the innovation perspective, Resource Endowment Theory and Resource Dependence Theory explain the underlying drivers of rural entrepreneurship. Rural areas have historically suffered from a scarcity of critical production factors. Rural industrial integration actively enriches the local endowment by facilitating the inflow of external capital, attracting skilled labor, and enhancing technology transfer, thereby mitigating traditional resource constraints (Zeng et al., 2022). However, the mere availability of resources is insufficient to trigger entrepreneurship if environmental risks remain too high. According to Resource Dependence Theory (Pfeffer and Salancik, 2015), startups require stable exchanges with their environment to survive. Rural entrepreneurs often face high environmental uncertainty and market volatility. Industrial integration addresses this by establishing stable organizational linkages (e.g., contract farming, cooperative alliances) and internalizing transaction costs. By vertically integrating the supply chain, rural enterprises can reduce their dependence on external uncertainties and secure access to critical resources. This creation of a stable and predictable business environment significantly lowers the risk threshold for rural residents, thereby increasing their propensity to engage in entrepreneurial activities. Based on the theoretical analysis outlined above, we propose the following hypotheses:

Hypothesis 1: Rural industrial integration significantly promotes the development of rural innovation and entrepreneurship.

2.3 Rural industrial integration, economic agglomeration and innovation and entrepreneurship

Crucially, the impact of integration on innovation is not merely direct but is mediated by the spatial reorganization of economic activities, known as Economic Agglomeration. The merging of rural and industrial sectors fosters agglomeration through two primary modes: the extension of the agricultural industry chain, which clusters processing and manufacturing industries near raw material bases (Li and Xu, 2021), and the multifunctional expansion of agriculture, which clusters service-oriented businesses like leisure tourism in specific zones (Li and Du, 2023).

This spatial clustering generates powerful agglomeration economies that facilitate innovation and entrepreneurship through the specific mechanisms of sharing, matching, and learning (Duranton and Puga, 2004). Firstly, regarding the sharing mechanism, agglomeration allows rural small and medium-sized enterprises to share specialized infrastructure (e.g., cold chain logistics, waste treatment facilities) and public services. This sharing effect significantly reduces the high fixed costs of entry and operation that typically deter rural startups. Secondly, regarding the matching mechanism, a concentrated industrial cluster attracts a specialized pool of labor and talent (e.g., agricultural technicians, e-commerce operators). This thick labor market improves the matching efficiency between specialized skills and entrepreneurial ventures, effectively solving the talent shortage and skill mismatch often faced by isolated rural firms. Thirdly, regarding the learning mechanism, innovation in rural areas often relies on tacit knowledge that is difficult to codify. The spatial proximity fostered by agglomeration encourages face-to-face interactions and the exchange of technical know-how among firms (Shao et al., 2019). This "local buzz" reduces information acquisition costs and stimulates collaborative innovation. As noted by Porter (1998), such clusters improve productivity and drive firms to differentiate themselves to survive competitive pressures. Therefore, integration reshapes the fragmented rural economy into efficient, clustered ecosystems, which then act as a breeding ground for sustained innovation and new venture creation. Based on the theoretical analysis outlined above, we propose the following hypotheses:

Hypothesis 2: Economic agglomeration mediates the relationship between rural industrial integration and the growth of rural innovation and entrepreneurship.

3 Empirical research design

3.1 Model setup

To accurately evaluate the causal impact of rural industrial integration on rural innovation and entrepreneurship, selecting an appropriate econometric model is crucial. Traditional methods like Ordinary Least Squares (OLS) often assume linear relationships between control variables and the outcome (Chen et al., 2025; Yan and Dong, 2024). However, rural economic systems are complex, and the impact of integration may be influenced by high-dimensional, non-linear confounding factors. Relying solely on OLS may lead to omitted variable bias due to model misspecification or the inability to include sufficient controls (the "curse of dimensionality") (Athey et al., 2019; Yang et al., 2020). Similarly, while Difference-in-Differences (DID) is powerful, it relies strictly on the parallel trends assumption, which can be difficult to satisfy given the heterogeneity of resource endowments across China's 1,759 counties.

To overcome these limitations, this study adopts the Dual Machine Learning (DML) approach proposed by Chernozhukov et al. (2018). Compared to OLS and DID, DML offers distinct advantages in addressing endogeneity arising from selection on observables and model misspecification (Wang and She, 2020). First, it utilizes machine learning algorithms to flexibly learn the non-linear relationships between high-dimensional control variables and the core variables, effectively reducing omitted variable bias without assuming strict functional forms. Second, by employing a "double orthogonalization" procedure (residual-on-residual regression), DML isolates the variation in the treatment variable that is uncorrelated with the confounders, thereby providing a consistent estimate of the causal effect.

3.1.1 Model specification

Following the partial linear regression framework of the DML model, the relationship between rural industrial integration and rural innovation and entrepreneurship is specified as follows:

$$\mathrm{Y_{it}} = \theta \mathrm{D_{it}} + \mathrm{g(X_{it})} + \varepsilon_{\mathrm{it}} \tag{1}$$

$$D_{it} = m(X_{it}) + v_{it} \tag{2}$$

Y_{it} represents the outcome variable (Rural Innovation and Entrepreneurship, IEI) for county i in year t. D_{it} is the treatment variable (Rural Industrial Integration, DR). X_{it} is a vector of high-dimensional control variables (covariates), including financial development, infrastructure, and other socioeconomic factors detailed in Table 1. θ is the target causal parameter to be estimated. $g(X_{it})$ and $m(X_{it})$ are unknown nuisance functions that capture the complex, potentially non-linear relationships between the covariates and the outcome/treatment variables. $\varepsilon_{it}$and v_{it} are error terms with conditional mean zero.

3.1.2 Estimation logic and assumptions

The DML estimation proceeds in two stages to ensure robustness. In the first stage, machine learning algorithms are used to predict Y_{it} and D_{it} based on X_{it}, generating the residuals $\tilde{Y}_{it} = Y_{it} - \hat{g}(X_{it})$ and $\tilde{D}_{it} = D_{it} - \hat{m}(X_{it})$. In the second stage, the causal coefficient θ is estimated by regressing $\tilde{Y}_{it}$ on $\tilde{D}_{it}$.

To ensure the validity of this estimator, the model relies on two key assumptions:Unconfoundedness (Exogeneity of Controls): $E[\varepsilon_{it}|D_{it}, X_{it}] = 0$ and $E[v_{it}|X_{it}] = 0$. This implies that, conditional on the high-dimensional controls X_{it}, the treatment D_{it} is effectively randomly assigned. Common Support: the probability of being treated is strictly between 0 and 1 (overlap assumption), ensuring that comparable units exist across different values of X_{it}. By adhering to these assumptions and utilizing cross-fitting techniques, DML effectively mitigates overfitting and regularization bias, providing a more robust theoretical foundation for causal inference in this context compared to traditional linear models.

3.2 Explained variables

Level of entrepreneurship and innovation in rural areas (Overall index: IEI; Rural Innovation Index: II; Rural entrepreneurship index: EI). This paper uses the "China Rural Innovation and Entrepreneurship Index Report" from ZJU Carter-Enterprise to determine the actual level of rural innovation and entrepreneurship development. Specifically, it looks at the rural innovation and entrepreneurship index at the county level in China between 2014 and 2021. The index comprises seven secondary indicators that provide a comprehensive picture of the development history and current state of innovation and entrepreneurship in China's rural areas. These indicators include brand innovation, technological innovation, digital innovation, green innovation, and entrepreneurship in family farms, farmers' cooperatives, and related industries.

3.3 Explanatory variable

Integration of industry in rural areas (DR). Building an indicator system to track the evolution of rural industrial integration is challenging because of the dynamics and complexity of this integration, as well as the data availability constraints at the county level. In light of this, this paper, citing Xu (2023), chooses 100 demonstration counties for rural industrial integration that are chosen annually by the Ministry of Agriculture and Rural Development between 2019 and 2021. It then combines the selection period to create a policy dummy variable that serves as a gauge for rural industrial integration. The pilot counties were chosen primarily because of their exceptional performance in the integrated growth of the agriculture sector, which is characteristic and valuable for promotion. They are also capable of leading and propelling the all-encompassing rehabilitation of the countryside in comparable regions.

3.4 Mechanism variables

In order to promote economic agglomeration, this article will examine how rural industrial integration affects the growth of rural innovation and entrepreneurship. To quantify the degree of economic agglomeration among them, the economic agglomeration level (EAL) is defined as the ratio of the value contributed of the secondary

TABLE 1 Variable definitions and descriptive statistics.

Type	Variable	Symbol	Measurement/Definition	Average value	Standard deviation	Minimum value	Maximum value
Dependent	Rural Innovation and Entrepreneurship	IEI	Comprehensive index from ZJU Carter-Enterprise	16.6955	5.9640	0.2900	44.7600
	Rural Innovation (Sub-index)	II	Sub-index of IEI	20.4335	9.4954	0	68.2100
	Rural Entrepreneurship (Sub-index)	EI	Sub-index of IEI	12.2719	5.2045	0	46.4700
Independent	Rural Industrial Integration	DR	Dummy variable: 1 if listed as a pilot county, 0 otherwise	0.0255	0.1577	0	1.0000
Mechanism	Economic Agglomeration	EAL	(Value added of secondary + tertiary industries)/Administrative area	0.1191	0.2593	0	5.5851
Controls	Financial Development Level	FDL	Loan balance of financial institutions/Savings balance of residents	1.3634	1.6420	0	79.9964
	Industrial Development Level	IDL	Value added of secondary sector/Nominal GDP	0.3849	0.1521	0.0131	0.9048
	Infrastructure Level	ICL	Nominal GDP/Total fixed asset investment	1.1893	1.4880	0	109.0909
	Government Intervention	IGL	Local general budget revenue/Nominal GDP	0.0635	0.0406	0.0047	1.5278
	Educational Development	EDU	Students in general secondary schools/Total year-end population	0.0481	0.0199	0.0020	0.6660
	Enterprise Development	EDL	Log(Number of industrial enterprises above designated size)	3.8881	1.3497	0	7.8228
	Population Density	PDR	Total year-end population/Administrative area	0.0293	0.0297	0	0.3876
	Communication Infrastructure	CIL	Fixed-line telephone subscribers/Total year-end population	0.0943	0.0945	0.0001	2.4047
	Non-farm Employment	NAPL	Rural non-farm employees/Total rural employees	0.7996	2.2531	0.0117	77.5393
	Medical Care Level	ML	Log(Number of beds in hospitals and health centers)	7.3104	0.8493	3.1354	9.4454

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and tertiary sectors to the area of the administrative area (Shao et al., 2019).

3.5 Control variable

To mitigate the potential bias caused by omitted variables, this study controls for a set of socioeconomic factors that may influence rural innovation and entrepreneurship, drawing on existing literature (Hou et al., 2023; Cheng et al., 2024; Jia and Zhu, 2025). These variables cover multiple dimensions including financial development, industrial structure, infrastructure, government intervention, education, enterprise scale, population density, communication, non-farm employment, and medical care.

3.6 Data sources

This paper initiates an empirical investigation based on unbalanced panel data of 1,759 counties in 26 provinces of China from 2014 to 2021. Data regarding the rural industrial integration policy is manually collected from the lists of "National Rural Industrial Integration Demonstration Zones" published annually on the official websites of the Ministry of Agriculture and Rural Affairs (MARA) and the National Development and Reform Commission (NDRC). The measurement of rural innovation and entrepreneurship relies on the "China Rural Innovation and Entrepreneurship Index" from the China Academy for Rural Development—Qiyan China Agri-research Database (CCAD), Zhejiang University. Other county-level socioeconomic control variables are primarily extracted from the China County Statistical Yearbook, the China Statistical Yearbook, and the China Rural Statistical Yearbook. To ensure the representativeness and statistical comparability of the sample, a rigorous screening and matching process was applied. First, linear interpolation was applied to fill a small number of missing values to ensure data continuity. Second, the four municipalities (Beijing, Tianjin, Chongqing, and Shanghai) were excluded due to their distinct administrative structures. Third, regions with severe data limitations (Hong Kong, Macao, Taiwan, and Tibet) were removed. Finally, after matching the remaining counties with the index data, the final dataset comprises a balanced panel of 1,759 counties.

3.7 Descriptive statistics

Table 1 presents the descriptive statistics for the main variables. The results demonstrate that the average values of rural industrial integration and rural innovation and entrepreneurship are 0.0255 and 16.6955, respectively. The standard deviations indicate significant regional disparities in development levels across the sampled counties, suggesting that rural industrial integration in China is still in a developmental phase with substantial heterogeneity.

4 Results and discussion

4.1 Benchmark regression results

Building on the theoretical analysis, this paper employs a Dual Machine Learning (DML) model to empirically analyze the impact of rural industrial integration on rural innovation and entrepreneurship. This approach utilizes K-fold cross-validation (validating internal and external consistency) to improve data utilization, prevent overfitting, and strengthen parameter estimation. Following Chernozhukov et al. (2018), we set the cross-validation to fivefold (a 1:4 sample split ratio), which is considered optimal. Furthermore, the Random Forest algorithm is employed for the estimation of nuisance parameters. Table 2 displays the empirical regression results.

Column (1) of Table 2 demonstrates that rural industrial integration has a positive effect on rural innovation and entrepreneurship when the primary terms of control covariates, year fixed effects, and county fixed effects are included. This effect is significant at the 1% level with a positive coefficient, suggesting that rural industrial integration effectively promotes development in this domain. Specifically, a one-unit increase in rural industrial integration leads to a 1.5686-unit increase in the level of rural innovation and entrepreneurship. To improve accuracy, Column (2) adds quadratic terms of control variables. The coefficient remains significantly positive with minimal change in magnitude, further demonstrating the robustness of the results. This finding aligns with the research of Zhang and Wu (2023), who also observed positive economic outcomes from integration policies, and supports Hypothesis 1.

Columns (3) and (4) report the regression results for the sub-dimensions: rural entrepreneurship and rural innovation, respectively. The results show that rural industrial integration significantly promotes both dimensions at the 1% level. Notably, the coefficient for rural innovation (2.0587) is larger than that for rural entrepreneurship (0.7800). This disparity may stem from the nature of integration in China, where traditional agriculture is often combined with modern technologies like smart agriculture and deep processing. Technological innovation is frequently a prerequisite for development in these fields, potentially making integration a stronger driver for innovation than for pure entrepreneurial volume. Furthermore, evolving consumption habits in rural markets—favoring quality and branding—compel agribusinesses to innovate to maintain competitiveness, rather than merely expanding via labor inputs. While the government promotes entrepreneurship, persistent structural issues in rural areas (e.g., poor infrastructure, asymmetric information, capital constraints) may still dampen entrepreneurial growth compared to the rapid adoption of technological innovations supported by policy and capital.

4.2 Robustness check

(1) Removal of outlier effects

To mitigate the influence of outliers, we winsorized all continuous variables at the 1 and 5% levels. The regression results

TABLE 2 Benchmark regression results of rural industrial integration on rural innovation and entrepreneurship.

Variable	(1) IEI	(2) IEI	(3) EI	(4) II
DR	1.5686***	1.5600***	0.7800***	2.0587***
	(0.2003)	(0.2001)	(0.1883)	(0.3190)
control variable with one term in the hierarchy	Yes	Yes	Yes	Yes
quadratic term of the control variable	No	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
County fixed effects	Yes	Yes	Yes	Yes
observed value	14,072	14,072	14,072	14,072

*, ** and *** denote significant at the 10%, 5%, and 1% statistical levels, respectively, with robust standard errors in parentheses. The same applies below.

TABLE 3 Robustness test.

Variable	(1) Winsorization		(2) Sample split ratio		(3) Algorithm	
	1% Level	5% Level	Ratio 1:2	Ratio 1:6	Lasso	GBDT
DR	1.5123***	1.3755***	1.4942***	1.5620***	0.3961**	1.5576***
	(0.1988)	(0.2110)	(0.2012)	(0.1988)	(0.1634)	(0.2516)
Control variable with one term in the hierarchy	Yes	Yes	Yes	Yes	Yes	Yes
Quadratic term of the control variable	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
County fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observed value	14,072	14,072	14,072	14,072	14,072	14,072

The symbols *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

TABLE 4 Endogeneity test.

Variable	(1) IV: Bartik	(2) IV: Lagged
DR	3.8566***	1.8417***
	(0.6315)	(0.3228)
Control variable with one term in the hierarchy	Yes	Yes
Quadratic term of the control variable	Yes	Yes
Year fixed effects	Yes	Yes
County fixed effects	Yes	Yes
Observed value	14,072	14,072

Model (1) IV: Bartik uses the interaction term between the number of public library collections in 2008 and the pre-phase rural industrial integration as the instrumental variable. Model (2) IV: Lagged uses the one-period lagged value of rural industrial integration as the instrumental variable. The symbols *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

(see Table 3) demonstrate that the baseline findings are robust, with the coefficient for rural industrial integration remaining significantly positive at the 1% level.

(2) Changing the sample split ratio

While it has been suggested that a fivefold crossover strategy, or a sample split ratio of 1:4, is ideal, the sample split ratios in this paper's regression analyses were adjusted to 1:2 and 1:6 to prevent discrepancies in the results caused by sample split ratio settings. After resetting the sample split ratio, the results demonstrate (see Table 3) that the impact of rural industrial integration on the growth of innovation and entrepreneurship in rural areas is still significant. Additionally, the regression coefficients are positive and the size is not significantly different from the baseline regression, which is sufficient to demonstrate the validity of the initial conclusions.

(3) Replacement algorithm

This paper further explores the potential impact of the algorithms on the conclusions of the benchmark regression results by substituting the original random forest algorithm with the gradient boosting and lasso regression algorithms, so as to prevent the algorithm from affecting the reliability of the estimation results. The results (see Table 3) indicate that replacing the algorithm with Lasso regression and gradient boosting still yields positive and significant impact effects for rural industrial integration at the 5 and 1% significance levels, respectively, further validating the benchmark study's conclusions.

4.3 Endogeneity test

Despite controlling for high-dimensional variables, potential endogeneity issues may still persist. Following the methodology of Huang et al. (2019), this study employs the interaction term between the pre-phase of rural industrial integration and the 2008 public library book collection size as an instrumental variable. Additionally, with reference to the approach of Chernozhukov et al. (2018), the partial linear instrumental variable model of dual machine learning was constructed for the analysis. where Z_{it} represents DR_{it}'s instrumental variable.

$$Y_{it} = \alpha_1 DR_{it} + g(X_{it}) + U_{it} \tag{3}$$

$$Z_{it} = m(X_{it}) + v_{it} \tag{4}$$

On the one hand, the total collection of public libraries has a highly positive correlation with rural industrial integration, which is consistent with the endogeneity of the instrumental variable selection. On the other hand, the total collection of public libraries plays a significant role in rural industrial integration and serves as a valuable cultural soft power. However, the total number of public library collections in 2008 is exogenous due to its historical characteristics and has no direct correlation with the growth of rural innovation and entrepreneurship in 2014–2021. Additionally, this work regresses the lagged period of rural industrial integration as additional instrumental variable in order to avoid the causal association between rural innovation and entrepreneurship development and rural industrial integration. After taking endogeneity into account, the regression results (see Table 4) continue to be strong and demonstrate that rural industrial integration has a significant positive impact on the development of rural innovation and entrepreneurship.

5 Further analysis

5.1 Mechanism analysis

Based on the previous verification that rural industrial integration has a significant promoting effect on the development of rural innovation and entrepreneurship, this section further explores the mechanism of rural industrial integration's impact on rural innovation and entrepreneurship. Considering that there may be a reciprocal causal relationship between the mediating variable and the outcome variable, this paper draws on the mechanism testing approach of Jiang (2022) to examine whether economic agglomeration is a viable path for rural industrial integration to support the growth of rural innovation and entrepreneurship.

To empirically verify the transmission mechanism, this study measures economic agglomeration using the ratio of the value added of secondary and tertiary industries to the administrative area. The regression results (see Table 5) demonstrate that rural industrial integration has a significantly positive impact on economic agglomeration at the 1% level. Specifically, for every unit increase in rural industrial integration, economic agglomeration increases by 0.0073 units. This finding confirms that rural industrial integration acts as a catalyst for rural entrepreneurship and innovation by fostering economic agglomeration. These empirical findings provide strong evidence for the transmission mechanism proposed in our theoretical framework. Therefore, Hypothesis 2 is validated. This result is consistent with Marshall's theory of agglomeration externalities and corroborates findings by Xu et al. (2022) regarding the efficiency gains from industrial clustering.

TABLE 5 Mechanism analysis results.

Variable	(1)IEI	(2)EAL
DR	1.5600***	0.0073***
	(0.2001)	(0.0028)
Control variable with one term in the hierarchy	Yes	Yes
Quadratic term of the control variable	Yes	Yes
Year fixed effects	Yes	Yes
County fixed effects	Yes	Yes
observed value	14,072	14,072

The symbols *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

The underlying logic of this mechanism can be explained from two aspects. First, rural industrial integration entails not only merging agriculture with secondary and tertiary sectors but also integrating distinct linkages within agriculture, such as planting, processing, and marketing. This facilitates the construction of a full industrial chain, encouraging related businesses and services to concentrate geographically, thereby boosting industrial density. Second, the resulting economic agglomeration stimulates rural innovation and entrepreneurship by lowering transaction costs, concentrating resources, and fostering a competitive yet collaborative innovation ecosystem. Supported by national policies like the Rural Revitalization Strategy, this agglomeration effect enhances resource utilization efficiency and attracts talent and investment, ultimately providing rural entrepreneurs with expanded market opportunities and robust support for economic advancement.

Heterogeneity analysis

(1) Impact of facility-based agriculture

The Central Committee's 2024 Document No. 1 placed a strong emphasis on the necessity of "promoting the modernization and upgrading action of facility agriculture and strengthening the construction of agricultural infrastructure." Modern facility agriculture, while boosting farmers' income, also spurs the development of related industries, balance the economic cycles of the urban and rural areas, and hasten the integration of primary, secondary, and tertiary industries in rural areas. Thus, this paper creates an interaction term between rural industrial integration and the area occupied by facility agriculture as the research focus variable based on the mean value of the area occupied by facility agriculture in each county from 2014 to 2021. The median is used as the boundary to divide the sample into two groups: high and low facility agriculture samples. Also, in order to prevent extreme values from influencing the results, we take logarithms for facility agriculture (area occupied by facility agriculture: AG). Table 6's findings demonstrate that, in the high-facility agriculture sample, rural industrial integration positively impacts innovation and entrepreneurship; but, in the low-facility agriculture sample,

TABLE 6 Results of heterogeneity analysis.

Variable	(1) High-facility agriculture	(2) Low-facility agriculture	(3) High agricultural base	(4) Low agricultural base
Rural industrial integration* Facility-based agriculture	2.6836**	0.4713		
	(1.0590)	(2.6713)		
Rural industrial integration* Gross value of agricultural, forestry, animal husbandry and fishery production			0.8475***	−2.6521
			(13.1718)	(2.1273)
Control variable with one term in the hierarchy	Yes	Yes	Yes	Yes
Quadratic term of the control variable	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
County fixed effects	Yes	Yes	Yes	Yes
Observed value	7,040	7,032	7,040	7,032

The symbols *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

the positive correlation is not statistically significant. Facilities that are constructed for facility-based agriculture in China usually feature superior infrastructure and more sophisticated technologies, like smart greenhouses, automated irrigation systems, and precision farming methods. In addition to increasing agricultural productivity, these technologies draw in related service and processing sectors, which in turn encourages the integration of agriculture with secondary and tertiary industries. This accelerates the process of rural-to-urban industrial integration, which fosters innovation and entrepreneurship. The lack of sufficient water, energy, and transportation infrastructure impedes the growth of facility agriculture and the integration of rural enterprises in less developed facility agricultural areas, particularly in distant and impoverished areas.

(2) Impact of the agricultural base

In 2024, the Central Committee's Document No. 1 stressed the need "to promote Chinese-style modernization, we must persistently strengthen the foundation of agriculture and promote the comprehensive revitalization of the countryside." A strong agricultural base may boost rural economic growth, accelerate agricultural modernization and industrialization, and serve as a cornerstone for rural industrial integration. Agriculture is a crucial industry for rural industrial integration. The average gross value of agricultural, forestry, animal husbandry, and fishery output in each county from 2014 to 2021 is used to divide the sample into high and low agricultural base samples, with the median serving as the border. The interaction term between rural industrial integration and the gross value of agricultural, forestry, animal husbandry, and fishery output is then constructed as the study's main variable. At the same time, in order to prevent the influence of extreme values on the results, we take the logarithm of the agricultural base (gross value of agriculture, forestry and fisheries: GA). Table 6's findings demonstrate that, in the high agricultural basis sample, rural industrial integration positively facilitates innovation and entrepreneurship; in contrast, the low agricultural base sample experiences a non-significant, negative facilitating effect. A higher degree of agricultural modernity, including cutting-edge machinery and technology as well as effective agricultural management techniques, is frequently present in counties with a strong agricultural foundation. The added value of agricultural products and the vertical integration of rural industries are promoted by these factors, which also help to improve the quality and production efficiency of agricultural products and foster a diverse range of rural industry development. Related processing, storage, logistics, and other supporting industrial chains are more comprehensive. The scale and efficiency of agricultural production, as well as the integration of agriculture with the secondary and tertiary sectors, are restricted in counties with a low agricultural base due to issues like resource scarcity and inadequate infrastructure. Additionally, the low level of marketization of agricultural products limits the potential for rural innovation and entrepreneurship by making it harder to draw in outside capital and service resources.

6 Conclusions and policy recommendations

6.1 Conclusions

Based on the rigorous empirical analysis of panel data from 1,759 counties in China using the Double Machine Learning (DML) approach, this study derives three pivotal conclusions that advance the theoretical understanding of rural revitalization:

First, Rural industrial integration functions as a potent endogenous engine, rather than a mere policy artifact, for rural modernization. Our findings elucidate that integration significantly propels both rural innovation and entrepreneurship. However, a structural asymmetry is observed: the impact on innovation (technological and product upgrades) is markedly stronger than on entrepreneurship (new venture creation). This suggests that while integration successfully triggers the Schumpeterian "recombination of factors," translating these technical innovations into viable business entities remains a complex challenge that requires a more mature market environment.

Second, Economic agglomeration constitutes the core transmission mechanism, offering a novel theoretical insight. The novel takeaway of this study is that rural industrial integration is fundamentally a process of spatial economic reconfiguration. It does not merely mix industries but actively fosters economic agglomeration. This spatial clustering generates positive externalities—specifically through resource sharing, labor matching, and tacit knowledge spillovers—which are the true drivers of the rural innovation ecosystem. This finding bridges the gap between industrial economics and spatial geography, shifting the paradigm from treating integration as a "sectoral mix" to understanding it as a creator of "innovation clusters."

Third, the efficacy of integration is contingent upon resource endowments, leading to an integrated conceptual logic of "foundation-dependency." The heterogeneity analysis reveals that the positive effects are significantly amplified in regions with robust facility agriculture and strong agricultural bases. This implies that industrial integration operates as a "multiplier" of existing strengths rather than a substitute for foundational weaknesses. The overarching inference is that sustainable rural development follows a sequential logic: consolidating the agricultural foundation is a prerequisite for unlocking the full potential of industrial integration. Consequently, integration strategies must be stage-specific, avoiding premature implementation in regions lacking the necessary industrial bedrock.

6.2 Policy recommendations

Our research provides robust evidence that advancing rural industrial integration is a critical strategy for fostering innovation and entrepreneurship. Based on the empirical findings—specifically the mediating role of economic agglomeration and the "foundation-dependency" effect—we propose the following policy recommendations.

First, deepen the quality of rural industrial integration through technological and organizational upgrading. Given the positive impact of integration, policies should shift focus from mere quantitative expansion to enhancing the depth of cross-sectoral collaboration. Authorities should actively promote the "smart agriculture" model by integrating advanced technologies (e.g., IoT, AI) into production and processing, which aligns with our finding that integration strongly drives technological innovation. Furthermore, it is crucial to encourage diversified models—such as combining agriculture with tourism and wellness—while strengthening interest-sharing mechanisms between farmers and enterprises to build robust, symbiotic industrial ecosystems. Continued investment in digital and logistical infrastructure is also essential to support these complex value chains.

Second, strategically foster rural economic agglomeration to create innovation clusters. Recognizing agglomeration as a key transmission mechanism, policies should move beyond supporting isolated entities and aim to cultivate localized industrial clusters. This can be achieved by establishing specialized rural industrial parks or innovation bases tailored to local strengths (e.g., a food processing cluster or a regional tourism hub). To facilitate this, governments should provide targeted incentives such as shared facilities and land use support. Additionally, reducing barriers to the flow of capital and talent, and establishing knowledge networks among research institutions, universities, and rural enterprises, will foster the "local buzz" and knowledge spillovers necessary for a thriving innovation ecosystem.

Third, implement differentiated policies tailored to regional resource endowments. Our heterogeneity analysis confirms that a "one-size-fits-all" approach is ineffective. For regions with high facility agriculture and a strong agricultural base, strategies should focus on "elevation"—promoting precision agriculture, deep processing, and brand building to maximize value addition. Conversely, for resource-constrained regions (low facility agriculture or weak base), the priority should be "consolidation"—investing in fundamental infrastructure (water, power, transport) and basic technology adoption. For these areas, policy should focus on improving production efficiency and exploring niche markets rather than prematurely pushing for complex integration models.

Fourth, specifically address the structural barriers to rural entrepreneurship. Since our results indicate that integration's impact on new venture creation is weaker than on innovation, targeted measures are needed to convert technical advances into business realities. Policymakers should improve access to finance by developing products tailored to rural startups, such as supply chain finance. Simultaneously, entrepreneurial training programs should be strengthened, focusing on management, e-commerce, and financial literacy. Finally, optimizing the rural business environment by streamlining administrative procedures and reducing information asymmetry will lower the risks for potential entrepreneurs, helping to bridge the gap between innovation capacity and entrepreneurial activity.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding authors.

Author contributions

QL: Data curation, Validation, Methodology, Software, Investigation, Resources, Writing – original draft, Conceptualization, Formal analysis, Project administration. QH: Validation, Software, Writing – review & editing. HH: Resources, Writing – review & editing. XY: Funding acquisition, Writing – review & editing, Supervision. LC: Writing – review & editing, Visualization, Conceptualization, Project administration.

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Conflict of interest

The author(s) declared that this work was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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