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Empirical Research on Digital Technology Empowering Rural Industrial Diversity: An Analysis Based on County-Level Panel Data

Jiachen Yan*, Xiyue Jiang, Chen Ding, Yiwen Lu, Peiyu Chen

School of Global Governance, Shanghai University of International Business and Economics, Shanghai, 201620, China

Corresponding author: Jiachen Yan, 3079341644@qq.com

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Abstract: Against the backdrop of the deep integration between the new round of technological revolution and the rural revitalisation strategy, digital technology has emerged as a crucial engine driving the diversified development of rural industries. This study employs Propensity Score Matching-Difference in Differences (PSM-DID) methodology, utilising panel data from 95 counties across China between 2018 and 2023, to empirically examine the impact of digital technology on rural industrial diversity and its underlying mechanisms. Findings indicate that the adoption of digital technology significantly enhances county-level industrial diversity, with an average effect of approximately 5.92%, a result that remains robust across multiple tests. Heterogeneity analysis reveals that the enabling effects of digital technologies are more pronounced in economically developed counties with larger populations, reflecting the moderating roles of infrastructure, factor agglomeration, and market scale on technological impacts. Dynamic effect analysis further indicates that the diversity-enhancing effects of digital technologies exhibit a sustained strengthening trend, consistent with the long-term patterns of technology diffusion and human capital accumulation. This study provides empirical evidence for leveraging digital technologies to empower rural industrial transformation and offers policy insights for advancing digital rural development in a differentiated and systematic manner.

Keywords: Digital Technology; Rural Industrial Diversity; County-Level Panel Data; PSM-DID Method; Policy Effects

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1.Research Background

Since the turn of the century, China's urbanisation process and rural revitalisation strategy have advanced in tandem, propelling urban-rural relations into a new phase of deep integration. Data from the National Bureau of Statistics indicates that China's urbanisation rate reached 66.2% in 2023, yet the rural resident population remains at 490 million, forming a unique development pattern where "large-scale urbanisation" coexists with "deep rural revitalisation"[1]. Against this backdrop, digital technologies centred on 5G, artificial intelligence, big data, and the Internet of Things are emerging as key drivers for reshaping rural industrial structures and resolving development challenges[2].

In 2020, seven ministries including the Cyberspace Administration of China and the Ministry of Agriculture and Rural Affairs jointly issued the Digital Rural Development Strategy Outline, which for the first time established the national strategic objective of "empowering agricultural and rural modernisation through digital technologies"[3]. Subsequent policies such as the Digital Rural Development Guidelines 2.0 and the 14th Five-Year Plan for Digital Economic Development have been rolled out, establishing a comprehensive policy framework for digital rural development covering infrastructure, industrial applications, and governance services[4]. Nevertheless, rural industrial development currently faces multiple structural challenges: firstly, a monolithic industrial structure where agriculture dominates output value, with insufficient integration between primary and secondary industries; secondly, impeded factor mobility, with high-quality elements such as talent, capital, and technology tending to flow into cities rather than rural areas; thirdly, short industrial chains characterised by high proportions of primary product processing and weak brand premium capabilities[5]. Digital technologies offer new pathways to enhance rural industrial diversity by breaking geographical barriers, optimising resource allocation, and revitalising cultural assets. Consequently, scientifically identifying their impact mechanisms and policy outcomes has become a critical issue in both theoretical and practical domains[6].

2.Literature Review

2.1 Research on Mechanisms of Digital Technology Empowering Rural Development

Existing research generally holds that digital technology provides a core driving force for rural development by reducing information costs and institutional transaction costs. Wang Yahuai notes that digital technologies can enhance transparency in rural governance and multi-stakeholder coordination efficiency, improve the rural business environment, and create institutional conditions for the two-way flow of factors. Wen Tao and Chen Yiming further propose that the coupling of digital technologies with the “data-technology-scenario” framework can drive the integration and upgrading of agriculture with secondary and tertiary industries, extend value chains, and form a “digital channel” for industrial revitalisation[7].

Within the inclusive development dimension, digital inclusive finance emerged as a research focal point. Chen Yanli’s research based on county-level data from Hunan demonstrated that digital inclusive finance significantly enhances rural financial accessibility, with core coefficients remaining positively significant across multiple robustness tests. However, Sun Shuzhang’s study of Henan counties found no significant direct impact of inclusive finance on industrial restructuring, suggesting that the “finance-industry” transformation requires policy coordination and industrial support systems, highlighting the systemic nature of digital technology empowerment[8].

2.2 Empirical Research on Digital Technology and Industrial Diversity

Large-scale county-level studies provide empirical evidence on the industrial effects of digital technologies. Liu Heguang’s analysis of 2011–2022 panel data from 903 counties across 15 provinces reveals that the digital economy promotes urban-rural integration by optimising industrial structures and regulating labour mobility. Tian Ye’s research confirms that urban-rural integration mediates the relationship between the digital economy and rural industrial revitalisation, with this effect influenced by regional characteristics such as the scale of agricultural labour[9].

At the practical case level, field investigations by Yin Yao and Gao Xiao’an indicate that digital technologies must integrate with traditional mechanisms such as village regulations and community organisations to avoid “technological suspension”. Li Qian’s case study of Xuzhou reveals that while digitalisation can drive the integration of rural tourism and industries, uneven infrastructure, talent shortages, and homogenisation continue to constrain outcomes. Concurrently, scholars including Shen Feiwei and Wei Xiaojing highlight shortcomings in digital village development, such as homogenisation, regional development imbalances, and inadequate data governance, necessitating optimisation through rule provision, capacity building, and differentiated implementation[10].

3.Research Design

3.1 Data Sources and Sample Selection

This study employs counties as the fundamental analytical unit. Considering regional economic development levels and digital infrastructure advancement, a systematic sampling method was used to select 95 representative counties nationwide as the initial sample, covering eastern, central, and western regions. The basic characteristics of the sample are presented in Table 1. Research data were sourced from the 2018–2023 China County Statistical Yearbook, China City Statistical Yearbook, provincial and municipal statistical bulletins, and the National Bureau of Statistics’ public database. Following data cleansing and matching, a balanced panel dataset was formed.

Table 1 Distribution of Basic Characteristics of Sample Counties (N=95)

Characteristic Variable	Category	Frequency	Percentage	Intervention Group (High Digitalisation)	Control Group (Low Digitisation)
Regional Distribution	Eastern Region	42	44.2%	18 (42.9%)	24 (57.1%)
	Central Region	31	32.6%	12 (38.7%)	19 (61.3%)
	Western Region	22	23.2%	8 (36.4%)	14 (63.6%)
Level of Economic Development	High-income group	32	33.7%	15 (46.9%)	17 (53.1%)
	Medium Income Group	41	43.2%	16 (39.0%)	25 (61.0%)
	Low-income group	22	23.2%	7 (31.8%)	15 (68.2%)
Dominant Industry Type	Agricultural Dominance	38	40.0%	11 (28.9%)	27 (71.1%)
	Industrial dominance	35	36.8%	16 (45.7%)	19 (54.3%)
	Service-led	22	23.2%	11 (50.0%)	11 (50.0%)

3.2 Variable Definitions and Research Methods

3.2.1 Variable Definitions

Dependent Variable: Industry Diversity Index, calculated using an entropy index based on the output value of the three major industries. The value range is [0, ln3], with higher values indicating greater industry diversity.

Core Explanatory Variable: Interaction term between treatment group and policy timing (treatment × post). Treatment group (highly digitalised counties) and control group (lowly digitalised counties) are delineated based on the median fixed-line telephone penetration rate in 2019. The policy timing is defined as the comprehensive implementation of the 2020 Digital Rural Development Strategy Outline.

Control variables: include per capita GDP (log-transformed), registered population (log-transformed), secondary industry share, tertiary industry share, and local fiscal revenue (log-transformed), controlling for differences in county-level economic foundations and factor endowments.

3.2.2 Research Methodology

This study employs the Propensity Score Matching-Differences-in-Differences (PSM-DID) method to examine the impact of digital technologies on industrial diversity, following these steps:

(1) Propensity score matching: Using per capita GDP, registered population, and industrial structure as covariates, a caliper matching approach is employed to pair treatment groups with similar control groups, thereby mitigating selection bias;

(2) Difference-in-Differences Estimation: Constructing a DID model controlling for individual and time fixed effects to identify the net effect of digital technologies;

(3) Robustness checks: Validate results by altering matching methods (kernel matching, nearest neighbour matching), adjusting grouping criteria (quantiles, quartiles), and conducting placebo tests (advancing policy implementation to 2019);

(4) Heterogeneity and dynamic effects analysis: Regressions grouped by economic development level and population size to examine heterogeneity characteristics; test policy effects' temporal evolution patterns via multi-period DID.

4.Empirical Analysis

4.1 Benchmark Regression and Robustness Checks

4.1.1 Benchmark Regression Results

Following PSM matching, 49 observations across 21 counties (8 treatment, 13 control) were finalised. The benchmark regression results (Table 2) indicate that the coefficient for the core explanatory variable treatment×post is 0.035, significantly positive at the 1% level (t=5.97, $p<0.001$). This demonstrates that digital technologies significantly enhance rural industrial diversity by approximately 5.92%. Among the control variables, the share of primary industry (coefficient 0.006, $p < 0.001$) and the share of secondary industry (coefficient 0.001, $p < 0.001$) were significantly positive, indicating that industrial structure optimisation exerts a positive influence on diversity. The adjusted R^2 of the model was 0.853, demonstrating good model fit.

Table 2: Benchmark Regression and Robustness Test Results

Variable / Test Type	Baseline Regression	Robustness Test — Altering Matching Method	Robustness Test — Altering Grouping Criteria	Robustness Test — Placebo Test
	(PSM-DID)	Kernel Matching	Nearest Neighbour Matching	Quartile
Treatment × Post	0.035***(0.006)	0.036***(0.007)	0.032***(0.008)	0.023*(0.012)
treatment	0.005(0.004)	0.006 (0.005)	0.004(0.005)	0.003 (0.006)
post	0.003 (0.004)	0.004 (0.005)	0.002 (0.005)	0.001 (0.006)
Primary industry share	0.006***(0.001)	0.005***(0.001)	0.006***(0.001)	0.004***(0.001)
Secondary industry share	0.001***(0.000)	0.001***(0.000)	0.001***(0.000)	0.001**(0.000)
Control variables	Yes	Yes	Yes	Yes
Observation Count	49	49	49	49
Adjusted R^2	0.853	0.841	0.835	0.812

Note: *, **, *** denote significance at the 1%, 5%, and 10% levels respectively; standard errors are shown in parentheses.

4.1.2 Robustness Test Results

Changing matching methods: DID coefficients for kernel matching and nearest neighbour matching were 0.036 ($p < 0.001$) and 0.032 ($p < 0.001$) respectively, both significantly positive and consistent with baseline results;

Changing the grouping criteria: The DID coefficient for quantile grouping was 0.023 ($p < 0.1$), significant at the 10% level; the quartile grouping coefficient was not significant, possibly due to reduced inter-group differences after grouping;

Placebo test: Assuming the policy was implemented in 2019, the DID coefficient was 1.407 and non-significant, indicating no significant effect prior to policy implementation and validating the validity of causal identification.

4.2 Heterogeneity and Dynamic Effects Analysis

4.2.1 Heterogeneity Analysis

Regression by economic development level and population size revealed:

Economic Development Level: The DID coefficient for high-income counties was 0.040 ($p < 0.01$), while for low-income counties it was 0.028 ($p < 0.001$). This indicates that counties with stronger economic foundations, due to more developed supporting infrastructure and greater capacity to absorb factors, exhibit a more pronounced digital technology empowerment effect.

Population Size: The DID coefficient for large-scale counties was 0.033 ($p < 0.001$), while that for small-scale counties was 0.023 ($p < 0.05$). This reflects how population size generates market demand and economies of scale, thereby amplifying the industrial driving force of digital technologies.

4.2.2 Dynamic Effect Analysis

Multi-period DID results indicate: Prior to policy implementation (2018, T-1), the DID coefficient was 0.009 ($p=0.445$), non-significant, validating the parallel trends assumption; Post-implementation (2020, T+1; 2021, T+2), coefficients were 0.032 ($p < 0.001$) and 0.036 ($p < 0.001$) respectively, exhibiting an increasing trend. This indicates the sustained and cumulative promotion of industrial diversity by digital technologies, closely linked to the long-term effects of technology diffusion and human capital accumulation.

Conclusion

This study employs a PSM-DID approach to systematically evaluate the impact of digital technologies on rural industrial diversity by constructing county-level panel data. Empirical results demonstrate that digital technologies significantly promote the diversification of rural industrial structures, a conclusion that remains robust across multiple tests. Further analysis reveals pronounced regional heterogeneity in the enabling effects of digital technologies: counties with stronger economic foundations and larger populations derive greater benefits, reflecting the moderating role of regional development conditions on technological impacts. Dynamic effect analysis indicates that the promotion of industrial diversity by digital technologies exhibits both persistence and accumulation, gradually intensifying over time. These findings suggest that in advancing digital rural development, attention should be paid to regional disparities, strengthening infrastructure and talent support while avoiding one-size-fits-all policies. Concurrently, emphasis should be placed on the deep integration of digital technologies with local industrial foundations and social capital to achieve sustainable and inclusive rural industrial revitalisation. Future research may further explore the micro-mechanisms and path-dependence issues through which digital technologies influence industrial diversity.

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Conflict of Interests

The authors declare that there is no conflict of interest regarding the publication of this paper.

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