sustainability

MDPI

Article

Digital Economy and Urban–Rural Integration: Threshold Effects and Regional Heterogeneity in China

Haoyu Niu *, Jianluan Guo and Huijing Luo

Business School, Central University of Finance and Economics, Beijing 100081, China; guojianluan@cufe.edu.cn (J.G.); cqlhj20020213@163.com (H.L.)
* Correspondence: 2025110192@email.cufe.edu.cn

Abstract

Persistent urban–rural disparities remain a major challenge to inclusive and sustainable development in many developing economies. The digital economy is widely viewed as a potential mechanism for alleviating such inequalities, yet empirical evidence for its effectiveness across heterogeneous regional conditions remains limited. Using panel data from 30 Chinese provinces over the period 2013–2022, this study constructs composite indices of digital economy development and urban–rural integration based on the entropy weight method. Fixed-effects models, panel threshold regressions, and moderation analyses are employed to examine average and nonlinear effects, while instrumental variable approaches, including a Bartik-type instrument, are used to address potential endogeneity. The results indicate that the digital economy significantly promotes urban–rural integration, but the effect is highly conditional rather than uniform. Specifically, the positive impact becomes substantially stronger only after rationalization of industrial structure and education levels exceed critical threshold values. Government support and financial development further amplify this effect, and pronounced regional heterogeneity is observed, with stronger effects in eastern regions and clear late-mover advantages in western regions. These findings highlight the conditions under which digital transformation can effectively support inclusive urban–rural integration and offer policy-relevant insights for developing economies.

Keywords: digital economy; urban–rural integration; regional heterogeneity; threshold effects

1. Introduction

The persistent dualism between urban and rural sectors has long shaped the trajectory of economic and social development in many developing economies. According to the United Nations Sustainable Development Goals, particularly Sustainable Development Goal 10 (SDG 10), reducing inequalities within countries is a central objective, with the urban–rural divide constituting a core component of such inequality [1]. Beyond income inequality, such disparities are closely associated with unequal access to public services, education, employment opportunities, and social mobility, thereby constituting a core dimension of social sustainability. Achieving meaningful urban–rural integration is therefore widely regarded as a crucial pathway toward reducing structural inequality and promoting long-term, inclusive growth.

As digital technologies continue to expand, the digital economy increasingly functions as a potentially powerful mechanism for addressing urban–rural disparities. As data increasingly emerge as a key productive resource, digital development offers new opportunities to overcome long-standing geographical and informational constraints that hinder rural development [2]. By lowering information frictions, reducing transaction costs,

Check for updates

Academic Editor: Piotr Prus

Received: 1 February 2026
Revised: 28 February 2026
Accepted: 9 March 2026
Published: 11 March 2026

and optimizing the distribution of resources, digitalization may contribute to overcoming traditional spatial and institutional divides across urban and rural regions, thereby fostering greater inclusive development outcomes [3]. However, growing evidence suggests that the digital economy does not automatically generate equalizing effects. In regions lacking adequate industrial foundations, human capital, or institutional support, digital development may yield limited benefits or even reinforce existing inequalities, raising important questions about the conditions under which digital transformation can contribute to social sustainability.

A growing number of studies have investigated how digitalization influences economic development, with particular attention being paid to productivity growth, innovation, and regional disparities. Related studies have explored how digital technologies influence income distribution, employment structures, and access to public services. More recent research has increasingly examined how the digital economy shapes urban–rural relationships, with evidence suggesting that digital tools may facilitate factor mobility, improve rural market access, and enhance public service provision. Nevertheless, the connection of the digital economy to urban–rural integration remains contested. While some scholars argue that digital technologies can generate "digital dividends" that benefit rural areas [4], others caution that a persistent "digital divide," driven by inadequate infrastructure and limited digital skills, may instead exacerbate existing disparities [5]. Despite these advances, existing studies have largely emphasized average effects, providing limited evidence on how the digital economy generates differentiated outcomes under different structural and human capital conditions, particularly from a social sustainability perspective. Building on the existing literature on digitalization, inequality, and urban–rural development, this study moves beyond average-effect analyses by explicitly examining nonlinear and heterogeneous impacts across regions and institutional contexts.

In particular, two factors appear especially relevant in shaping the inclusiveness within digital transformation. First, the rationalization of industrial structures captures how efficiently resources are distributed across different sectors and regional economies, thereby shaping local capacities to absorb and utilize digital technologies. Second, education level captures the availability of human capital necessary to adopt, diffuse, and benefit from digital innovations. Regions with more advanced industrial structures and higher education levels may be better positioned to translate digital development into tangible improvements in urban–rural integration, while regions lacking these foundations may experience weaker or delayed effects. These considerations indicate a potentially nonlinear and conditional linkage between digital economy development and urban–rural integration rather than a uniform pattern.

As a large developing economy characterized by pronounced regional heterogeneity, China provides a representative setting in which to examine these issues. Despite rapid digital transformation at the national level, substantial disparities persist across regions in terms of industrial development, education, and institutional capacity, alongside persistent urban–rural disparities [6]. Coexisting regions at different development stages within a unified institutional framework provides a quasi-experimental setting to examine the heterogeneous and conditional effects of the digital economy on urban–rural integration [7]. Insights derived from this context may therefore offer broader implications for other developing economies seeking to leverage digitalization to promote inclusive and sustainable development.

Against this background, the present analysis investigates how the digital economy influences urban–rural integration, with particular attention paid to nonlinear effects and regional heterogeneity. This study was conducted using province-level panel data for China and incorporates multiple empirical strategies to ensure robustness.

https://doi.org/10.3390/su18062739

To contextualize the novelty of our approach, it is important to note that recent studies have increasingly employed provincial panel data within the 2013–2022 period to investigate the role of the digital economy in promoting urban–rural integration [8]. Among these studies, it has been shown that there is an inverted U-shaped nonlinear relationship, with diminishing marginal returns at higher levels of digital development, using quadratic specifications and threshold models [9]. In comparison with prior research, our study complements and extends this line of research in several key respects.

First, while the previous study demonstrated the existence of nonlinear effects, the analysis in this article focuses on the structural conditions under which such nonlinear dynamics operate. By incorporating industrial rationalization and education level as threshold variables, the study explicitly examines how regional absorptive capacity shapes the magnitude and sustainability of digital integration effects. This approach shifts attention from identifying curvature to identifying the boundary conditions that sustain digital dividends.

Second, whereas the previous research emphasized the internal composition of the digital economy, this study broadens the analytical framework to include external institutional and financial environments. Specifically, the study investigates the moderating roles of government support and financial development, highlighting how macro-contextual factors condition the effectiveness of digital expansion.

Third, regarding regional heterogeneity, the findings provide complementary evidence on western provinces. By considering structural conditions, this study shows that government support and digital development can generate meaningful integration effects even in relatively underdeveloped regions, suggesting a context-dependent dynamic rather than uniformly diminishing returns.

Taken together, these distinctions clarify the incremental contribution of this study within the recent 2013–2022 literature on digital development and urban–rural integration.

2. Theoretical Analysis and Research Hypotheses

2.1. Direct Effects of the Digital Economy on Urban–Rural Integration

Persistent urban–rural disparities are closely associated with the high transaction costs and severe information asymmetries arising from geographic fragmentation and institutional segmentation [10]. According to Transaction Cost Theory [11] and Information Asymmetry Theory [12], elevated coordination and information costs restrict market participation, impede efficient exchange, and distort factor allocation. These structural frictions constrain rural integration into broader economic systems and limit inclusive development.

As an emerging technological paradigm, the digital economy provides an institutional and technological solution to these structural constraints through multiple channels.

First, through the market integration effect, digital technologies reduce search, bargaining, and matching costs, thereby expanding market boundaries and improving price discovery mechanisms [13]. These mechanisms directly reflect the core assumption of Transaction Cost Theory: when transaction costs decline, exchange efficiency improves and market scope expands. By lowering spatial and informational barriers, digital platforms enable rural producers to connect with urban consumers, facilitating deeper urban–rural market integration.

Second, the digital economy enhances factor allocation efficiency not only through improved information flows but also through the mechanism of network externalities. According to Network Externalities Theory, the value of a digital network increases with the number of connected participants. As more firms, households, and institutions become digitally interconnected, information symmetry improves, coordination costs decline, and cross-sectoral collaboration becomes more efficient. The expansion of digital connectivity strengthens matching efficiency between capital and labor, reduces resource misallocation, and improves inter-regional factor mobility [14]. In this sense, network externalities facilitate the formation of integrated digital production networks, thereby improving the efficiency of factor allocation across urban and rural sectors.

Recent research on sustainable development provides complementary empirical evidence on the efficiency-enhancing role of technological innovation. Under the construction of low-carbon cities, green technology innovation has been shown to significantly improve ecological efficiency by enhancing resource utilization and optimizing the transformation of inputs into desirable economic and environmental outputs [15]. Furthermore, digital economy development has been found to promote green innovation, as expanded digital connectivity enhances knowledge sharing and improves the efficiency of information flows across markets [16]. Collectively, these studies support the broader argument that technological advancement improves efficiency and sustainable performance, thereby providing empirical backing for the efficiency-enhancing mechanisms that facilitate more efficient urban–rural factor allocation, which constitutes a central dimension of urban–rural integration in this study.

Third, digital development promotes employment transformation and income restructuring by expanding entrepreneurial participation and generating non-agricultural employment opportunities [17]. By improving labor mobility and diversifying income sources, digitalization contributes to narrowing the urban–rural income gap, which constitutes another central dimension of urban–rural integration.

In summary, Transaction Cost Theory explains how digitalization reduces market frictions and promotes market integration by lowering search, coordination, and bargaining costs, while Network Externalities Theory clarifies how expanding digital connectivity enhances information symmetry and improves the efficiency of factor allocation across urban and rural sectors. Together, these theoretical perspectives provide a coherent conceptual foundation for understanding how digital economy development may contribute to urban–rural integration.

Accordingly, this study proposes Hypothesis 1: The digital economy exerts a significant positive effect on urban–rural integration.

2.2. Threshold Regression Analysis

Although the digital economy possesses inclusive potential, its developmental impact may exhibit nonlinear characteristics [18]. The realization of digital dividends depends not only on digital expansion itself but also on the structural conditions under which digital networks operate.

According to Network Externalities Theory and Metcalfe's Law, network value increases disproportionately as user participation expands. When digital penetration remains below a critical mass, connectivity density is limited and coordination gains remain modest. However, once network scale surpasses a threshold, positive feedback mechanisms emerge, accelerating information diffusion, strengthening inter-sectoral linkages, and enhancing allocation efficiency [19]. In addition, technology diffusion theory emphasizes that the effects of technological adoption critically depend on users' absorptive capacity [20]. This theoretical logic predicts threshold-type nonlinear effects.

Such nonlinear dynamics are closely linked to the rationalization of industrial structure and education level. From the perspective of industrial structure rationalization, regions characterized by severe structural distortions may be unable to internalize network-based coordination gains [21]. In such contexts, digital capital may concentrate in already advantaged sectors without improving overall allocation efficiency, consistent with the "Solow Paradox" [22]. Only when industrial coordination reaches a sufficient level can network externalities translate into broad-based productivity improvements across sectors. Therefore, the rationalization of industrial structure determines whether digital connectivity can generate systemic urban–rural allocation gains.

Similarly, education level determines the absorptive capacity required for effective participation in expanding digital networks. Because digital technologies are inherently skill-biased [23], insufficient human capital may limit participation in digital platforms and constrain the realization of network scale effects. Once educational attainment surpasses a critical level, the labor force can more effectively utilize digital tools, enhancing productivity and enabling broader diffusion of digital dividends across urban and rural regions.

Accordingly, this study proposes Hypothesis 2: The impact of the digital economy on urban–rural integration exhibits threshold effects that depend on the degree of rationalization of industrial structure and the level of education.

2.3. Analysis of Moderating Mechanisms

2.3.1. The Moderating Role of Government Support

Urban–rural integration exhibits quasi-public-good characteristics, implying that market mechanisms alone may be insufficient to address coordination failures and underinvestment, particularly in rural areas with underdeveloped infrastructure [24]. From the perspective of New Institutional Economics, effective government involvement can improve the institutional environment, reduce uncertainty, and lower investment risks faced by private actors, thereby facilitating more efficient market outcomes [25]. Within the context of the digital economy, government support can help alleviate the high fixed costs associated with rural digital infrastructure and provide the basic physical conditions necessary for digital technologies to be widely adopted and effectively utilized [26].

Beyond infrastructure provision, government-led digital governance initiatives can enhance administrative efficiency and facilitate more balanced access to public services across urban and rural regions. By improving the accessibility of digital public services and strengthening local governance capacity, such initiatives can reinforce the ability of digital development to generate inclusive outcomes across regions [27]. In this sense, government support does not replace market mechanisms but rather complements them, amplifying the positive spillover effects of the digital economy on urban–rural integration.

Based on these arguments, this study proposes Hypothesis 3: Government support positively moderates the relationship between the digital economy and urban–rural integration.

2.3.2. The Moderating Role of Financial Development

Financial development constitutes a critical constraint on rural economic transformation and the effective participation of rural actors in digital economic activities [28]. According to Financial Exclusion Theory, traditional financial institutions tend to underserve rural clients due to high branch operating costs and pronounced information asymmetries, resulting in relatively limited access to formal credit and financial services [29]. In parallel, participation in the digital economy typically requires upfront capital inputs, such as investments in digital devices, internet access, and entrepreneurial startup funding.

A more developed financial system, particularly one characterized by the expansion of digital inclusive finance, can help overcome these constraints by leveraging the Long Tail Theory to cost-effectively reach rural populations that have traditionally been excluded from formal financial markets [30]. Improved financial access can alleviate credit constraints faced by rural households and enterprises, thereby facilitating investment in digital infrastructure and encouraging greater participation in digital economic activities. By easing financing frictions and supporting digital participation, financial development can facilitate stronger linkages between urban and rural factor markets, thereby reinforcing the role of the digital economy in advancing urban–rural integration [31].

Based on these arguments, this study proposes Hypothesis 4: Financial development positively moderates the relationship between the digital economy and urban–rural integration.

2.4. Regional Heterogeneity Analysis

China demonstrates substantial interregional differences in resource endowments, stages of economic development, and institutional environments, which may lead to heterogeneous development outcomes across regions [32]. The eastern region is generally characterized by more mature market mechanisms and relatively well-developed digital infrastructure, conditions that are conducive to the effective utilization of digital technologies and the realization of scale-related benefits associated with the digital economy. In contrast, the central, western, and northeastern regions often face constraints related to geographical conditions, economic foundations, and institutional capacity, which may limit the diffusion and effective application of digital technologies and result in differentiated marginal effects of digital development [33].

Given these regional differences, it is necessary to examine whether the impact of the digital economy on urban–rural integration differs systematically among areas rather than assuming uniform effects.

Based on the above analysis, this study proposes Hypothesis 5: The impact of the digital economy on urban–rural integration demonstrates significant regional heterogeneity. Figure 1 presents the analytical framework and hypothesized associations investigated within this research.

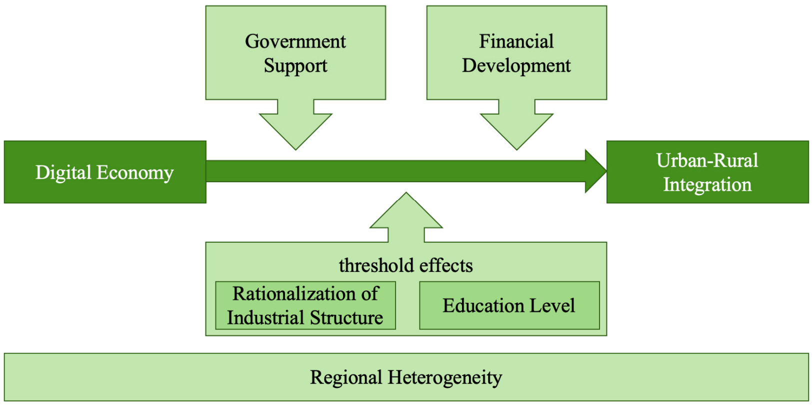

Figure 1. Conceptual framework of the study. The framework illustrates how the digital economy influences urban–rural integration (Hypothesis 1), the threshold effects associated with rationalization of industrial structure and education level (Hypothesis 2), the moderating roles of government support and financial development (Hypotheses 3 and 4), and the overarching context of regional heterogeneity (Hypothesis 5).

3. Materials and Methods

3.1. Data Sources

To ensure representativeness and data availability, this study includes 30 provinces, autonomous regions, and municipalities in China. Due to the unavailability of consistent data, Tibet, Hong Kong, Macao, and Taiwan are excluded. The study period spans 2013–2022, beginning in 2013 when large-scale digital infrastructure deployment and policy initiatives in China began to accelerate. The primary data are sourced from the official databases of the China Statistical Yearbook, China Rural Statistical Yearbook, China City Statistical Yearbook, and the statistical yearbooks of each province. All variables were manually collected and processed by the authors. All empirical analyses were conducted using Stata 17.

The final dataset forms a balanced panel comprising 30 provinces over ten years, yielding a total of 300 province-year observations. The number of observations is reported in each regression table. For a very small number of isolated missing values in certain variables, linear interpolation was applied to maintain panel consistency.

3.2. Variable Selection and Measurement

3.2.1. Dependent Variable: Urban–Rural Integration (Uri)

Urban–rural integration involves multiple interrelated dimensions, including economic, social, demographic, and ecological components, and evolves dynamically over time. Drawing on established research frameworks, this study develops a comprehensive evaluation system structured around four core dimensions—economic integration, social integration, demographic integration, and ecological integration—and eleven corresponding sub-indicators [34]. To minimize subjective bias in indicator weighting, the entropy weight (EWM) assigns relative importance to each variable and generates an aggregated index of urban–rural integration for each province [35]. To construct the composite indices of digital economy development and urban–rural integration, this study adopts the EWM, which is an objective weighting approach that determines indicator weights based on their informational entropy. Indicators with greater dispersion receive higher weights, reflecting their stronger discriminatory power across provinces. Compared with principal component analysis (PCA), which extracts latent components from the covariance structure of the data, the EWM preserves the original economic interpretation of each indicator and provides a transparent, data-driven weighting scheme. Given that our objective is to construct comprehensive development indices rather than to identify latent factors, the EWM is particularly suitable in this context.

The detailed indicator system is shown in Table 1. Figure 2 illustrates the spatial distribution of the urban–rural integration index across Chinese provinces in 2013 and 2022. The map shows substantial spatial heterogeneity, with relatively higher levels generally observed in eastern seaboard provinces and correspondingly lower levels across the central, western, and northeastern areas. Identical classification schemes and breakpoints are applied across both years to ensure temporal comparability.

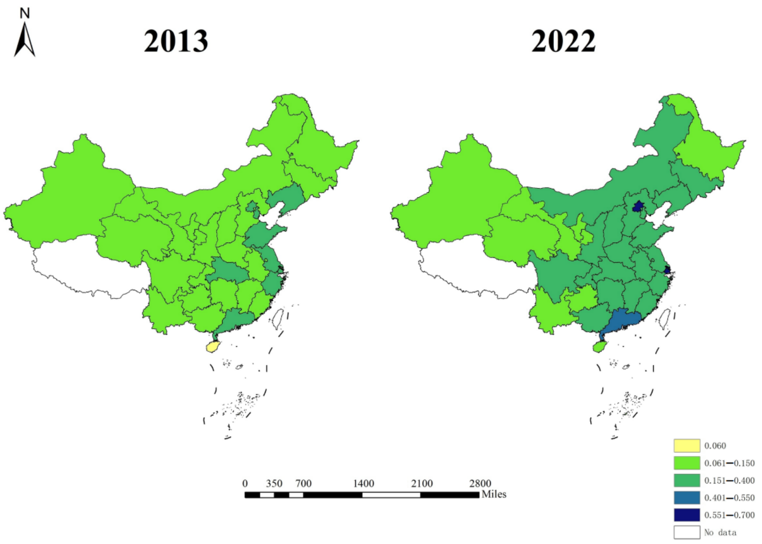

Figure 2. Spatial distribution of the urban–rural integration index across Chinese provinces in 2013 and 2022.

Table 1. Evaluation index system for urban–rural integration.

Dimensions	Indicators	Measurement Method
Economic Integration	Share of non-agricultural value added in GDP	Value added of secondary and tertiary industries/GDP
	Ratio of non-agricultural to agricultural value added	Value added of secondary and tertiary industries/ Value added of primary industry
	Industrial Synchronization Index	Value added of primary industry/Value added of secondary and tertiary industries
Social Integration	Urban–rural per capita disposable income ratio	Urban per capita disposable income/ Rural per capita disposable income
	Urban–rural per capita consumption expenditure ratio	Urban per capita consumption expenditure/Rural per capita consumption expenditure
	Urban-to-Rural Engel Coefficient Ratio	Urban Engel Coefficient/ Rural Engel Coefficient
Demographic Integration	Urban Population Share	Urban population/ Total population
	Ratio of non-agricultural to agricultural employment	Employment in secondary and tertiary industries/ Employment in primary industry
Ecological Integration	Green space area in built-up areas	Area of green space (unit: hectares)
	Green coverage area in built-up areas	Green coverage area (unit: hectares)
	Urban–rural difference in harmless domestic waste treatment capacity	Difference in treatment capacity (unit: tons/day)

3.2.2. Independent Variable: Digital Economy Development (Ded)

The digital economy reflects both digital industrialization and the digital transformation of traditional industries, thereby strengthening integration with the real economy. Based on data availability, continuity, and consistency, the present research develops an integrated digital economy development index with reference to widely adopted frameworks in the existing literature [36–38]. The index comprises four dimensions: digital infrastructure, digital industrialization, industrial digitalization, and the development environment, incorporating sixteen indicators. The level of digital economy development across 30 Chinese provinces is assessed using the entropy weight method (EWM). Detailed indicator definitions and measurement methods are reported in Table 2. Figure 3 illustrates the provincial pattern of digital economy development for the years 2013 as well as 2022. The pattern reveals a marked regional imbalance, characterized by stronger digital development in the eastern coastal areas and comparatively weaker performance in inland provinces. Consistent classification schemes are employed across both years to facilitate meaningful temporal comparison. To visualize the temporal evolution of the main indices, Figure 4 plots the overall trends of the digital economy development index and the urban–rural integration index from 2013 to 2022. As illustrated, both indices exhibit a continuous upward trajectory over the sample period.

Table 2. Evaluation index system for digital economy development.

Dimensions	Indicators (Unit)
Digital Infrastructure	Number of internet broadband access ports (10,000 ports) Length of optical fiber cables (10,000 km) Capacity of mobile telephone exchanges (10,000 subscribers) Telephone penetration rate (sets per 100 people) Number of registered internet domain names (10,000)
Digital Industrialization	Total business volume of postal services (CNY 100 million) Total business volume of telecommunications (CNY 100 million) Revenue from express delivery services (CNY 10,000) Revenue from software services (CNY 10,000) Revenue from software products (CNY 10,000) E-commerce sales (CNY 100 million)
Industrial Digitization	Employment in the information transmission, software and IT services sector (10,000 persons) Number of effective invention patents held by industrial enterprises above the designated size (pieces)
Development Environment	Transaction value in the technology market (CNY 100 million) R&D expenditure of industrial enterprises above the designated size (CNY 10,000) Full-time equivalent of R&D personnel in industrial enterprises above the designated size (person-years)

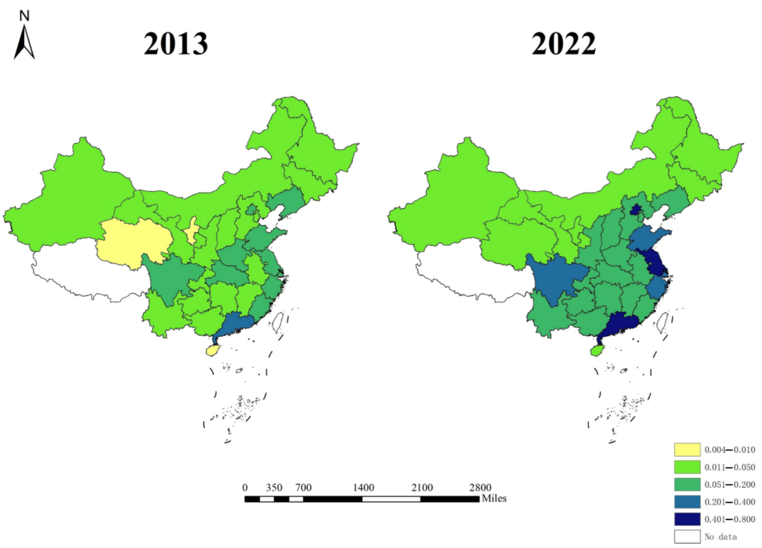

Figure 3. Spatial distribution of the digital economy development index across Chinese provinces in 2013 and 2022.

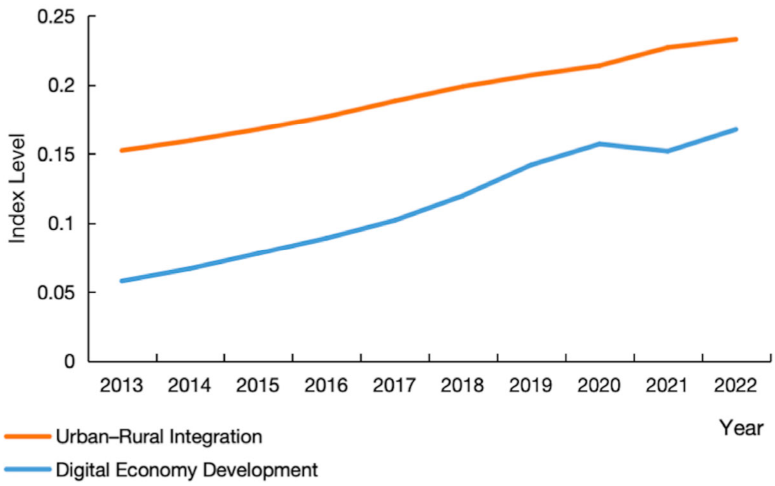

Figure 4. Temporal evolution of the digital economy development index and the urban–rural integration index in China, 2013–2022.

3.2.3. Control Variables

Following established empirical studies, several control variables are included to account for other factors that may influence urban–rural integration [39–42]. Economic development level (lngdp) is proxied by the logarithmic transformation of provincial GDP. Degree of openness (open) is measured by dividing the sum of imports and exports by GDP. Education level (edu) is measured by the number of higher-education students per capita. Rationalization of industrial structure (ris) is calculated as the inverse of the Theil index, capturing the efficiency of resource allocation across industries. Innovation capability (inn) is proxied by the number of patents per 10,000 people. Urbanization level (urr) calculated by dividing the urban population by the total population.

3.2.4. Threshold Variables

To examine potential nonlinear effects, rationalization of industrial structure (ris) and education level (edu) are selected as threshold variables. These variables capture structural and human capital conditions that may influence the capacity of regions to absorb and benefit from digital economy development.

3.2.5. Moderating Variables

Government support (gov) is measured by the ratio of local general public budget revenue to regional GDP, which reflects the fiscal capacity for macroeconomic regulation and the provision of public goods. Financial development (fin) is measured by the ratio of total deposits and loans to regional GDP, which reflects the degree of financial deepening. Table 3 presents the definitions and descriptive statistics of the variables used in the empirical analysis.

Table 3. Variable definitions and descriptive statistics.

Variable Name	Abbreviation	Variable Definition	Mean	Std. Dev.	Min	Max
Urban–rural integration	uri	Derived through the entropy weight method	0.193	0.114	0.060	0.696
Digital economy development	ded	Derived through the entropy weight method	0.113	0.127	0.004	0.767

Table 3. *Cont.*

Variable Name	Abbreviation	Variable Definition	Mean	Std. Dev.	Min	Max
Economic development level	lngdp	Natural logarithm of regional GDP	9.947	0.880	7.446	11.77
Degree of openness	open	Total import and export volume/GDP	0.259	0.257	0.008	1.257
Education level	edu	Number of higher-education students per capita	0.029	0.008	0.012	0.055
Rationalization of industrial structure	ris	Inverse of Theil Index	15.880	10.770	4.738	58.470
Innovation capability	inn	Number of patents per 10,000 people	5.572	5.701	0.456	28.010
Urbanization level	urr	Urban population/ Total population	0.607	0.115	0.378	0.896
Government support	gov	(Local general public budget revenue)/ Regional GDP	0.260	0.110	0.105	0.753
Financial development	fin	(Total deposits and loans)/ Regional GDP	3.534	1.087	1.912	7.609

3.3. *Econometric Model Strategy*

3.3.1. Baseline Regression Model

To investigate the impact of the digital economy on urban–rural integration, the baseline regression model is specified as follows:

$$uri_{i,t} = \beta_0 + \beta_1 ded_{i,t} + \sum\nolimits_k \beta_k X_{i,t} + \mu_i + \tau_t + \varepsilon_{i,t} \tag{1}$$

where i and t denote province and year, respectively; $uri_{i,t}$ represents the level of urban–rural integration in province i in year t; $ded_{i,t}$ denotes the level of digital economy development; $X_{i,t}$ is the vector of control variables; μ_i and τ_t represent province fixed effects and time fixed effects; $\varepsilon_{i,t}$ is the random error term; and β_0 is the constant term.

To ensure reliable statistical inference, standard errors are clustered at the provincial level to account for potential heteroskedasticity and serial correlation within provinces. In addition, we examine the presence of cross-sectional dependence using Pesaran's CD test. The test statistic is not statistically significant (CD = −0.782, p = 0.434), suggesting that cross-sectional dependence is not a serious concern in our sample. Therefore, the use of province-level cluster-robust standard errors is appropriate. Detailed results are reported in Appendix A Table A1.

3.3.2. Threshold Effect Model

To examine whether the effect of the digital economy on urban–rural integration follows a nonlinear relationship, this study employs the panel threshold model proposed by Hansen [43]. Rationalization of industrial structure (ris) and education level (edu) are selected as the threshold variables. The model is specified as follows:

$$uri_{i,t} = \alpha_0 + \alpha_1 X_{i,t} + \alpha_2 ded_{i,t} \cdot I(Z_{i,t} \leq \gamma) + \alpha_3 ded_{i,t} \cdot I\ (Z_{i,t} > \gamma) + \mu_i + \tau_t + \varepsilon_{i,t} \tag{2}$$

where $Z_{i,t}$ denotes the threshold variable; $X_{i,t}$ is the vector of control variables; γ represents the estimated threshold parameter; μ_i and τ_t represent province fixed effects and time fixed effects; $\varepsilon_{i,t}$ is the random error component; and α_0 is the constant term.

3.3.3. Moderation Effect Model

Government support and financial development may influence the effect of the digital economy on urban–rural integration. To examine these moderating effects, the following interaction model is constructed:

$$uri_{i,t} = \delta_0 + \delta_1 ded_{i,t} + \delta_2 M_{i,t} + \delta_3 (ded_{i,t} \times M_{i,t}) + \sum_k \delta_k X_{i,t} + \mu_i + \tau_t + \varepsilon_{i,t} \quad (3)$$

where $M_{i,t}$ denotes the moderating variable, which is government support or financial development. The coefficient δ_1 measures the direct effect of the digital economy, δ_2 measures the effect of the moderating variable, and δ_3 measures the magnitude and direction of the moderating effect. $X_{i,t}$ is the vector of control variables. μ_i and τ_t represent province and time fixed effects. $\varepsilon_{i,t}$ is the random error term, and δ_0 is the constant term.

4. Results

4.1. Baseline Regression Results

A fixed-effects model is employed to examine how digital economy development influences urban–rural integration. Columns (1) and (2) in Table 4 present the estimation results without and with control variables. Column (1) shows that the coefficient of digital economy development is 0.398 and is statistically significant at the 1% level, indicating a beneficial effect on urban–rural integration. After the inclusion of control variables, the coefficient increases to 0.449 and remains significant at the 1% level, as reported in Column (2). These results demonstrate that digital economy development promotes urban–rural integration across different model specifications. Overall, empirical evidence provides consistent support for Hypothesis 1.

Table 4. Baseline regression, robustness checks, and endogeneity tests.

Variables	Baseline Regression		Robustness Checks			Endogeneity Tests		Robustness Tests for Indicator Overlap			Alternative Measurement of Core Variables
	No Controls Variables	With Controls Variables	Alternative Core Variable	Excluding Direct Administration Municipalities	Lagged Regression	IV-2SLS	Bartik IV	Uri Without This Indicator	Model Without urr	Both As Robustness	Principal Component Analysis Method
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
ded	0.398 ***	0.449 ***	-	0.272 ***	-	0.601 ***	0.590 ***	0.468 ***	0.540 ***	0.572 ***	0.155 ***
	(2.85)	(4.32)		(7.31)		(3.97)	(3.20)	(4.29)	(3.79)	(3.73)	(3.82)
difi	-	-	0.001 ***	-	-	-	-	-	-	-	-
			(3.32)								
L.ded	-	-	-	-	0.421 ***	-	-	-	-	-	-
					(3.57)						
lngdp	-	0.072 *	0.031	0.003	0.083	0.014	0.015 *	0.075 *	0.006	−0.001	0.846 *
		(1.83)	(0.96)	(0.31)	(1.68)	(1.47)	(1.77)	(1.80)	(0.27)	(−0.03)	(1.72)
open	-	0.002	−0.086 **	0.036 ***	−0.016	0.100 ***	0.070	−0.002	−0.074	−0.087	−0.030
		(0.04)	(−1.77)	(2.33)	(−0.27)	(3.60)	(1.10)	(−0.03)	(−1.13)	(−1.26)	(−0.07)
edu	-	−0.783	−1.403	0.735 **	−0.983	0.065	0.092	−0.839	−2.078	−2.303	−14.302
		(−0.77)	(−1.24)	(2.41)	(−1.00)	(0.06)	(0.08)	(−0.79)	(−1.46)	(−1.52)	(−1.46)
ris	-	−0.001	−0.002	−0.001	0.002	0.004 *	0.004 *	−0.001	−0.001	−0.001	−0.003
		(−0.72)	(−1.05)	(−1.37)	(0.97)	(1.85)	(1.90)	(−0.69)	(−0.54)	(−0.48)	(−0.18)
inn	-	−0.005 ***	0.000	−0.001	−0.005 **	−0.007 ***	−0.006 **	−0.005 **	−0.006 **	−0.006 **	0.036 ***
		(−2.5)	(0.06)	(−0.68)	(−2.22)	(−2.61)	(−2.04)	(−2.49)	(−2.11)	(−2.08)	(2.85)
urr	-	−0.821 ***	−0.705 **	0.053	−0.837 *	0.177 **	0.183 **	−0.927 **	-	-	−7.969 ***
		(−2.02)	(−2.26)	(0.71)	(−1.90)	(2.08)	(1.97)	(−2.17)			(−2.93)
Constant	0.129 ***	−0.061	0.107	0.043	−0.170	−0.174 *	−0.181 **	−0.030	0.175	0.236	−4.214
	(10.18)	(−0.23)	(0.36)	(0.41)	(−0.44)	(−1.86)	(−2.41)	(−0.11)	(0.84)	(1.07)	(−1.04)
Observations	300	300	300	260	270	270	300	300	300	300	300
KP rk LM	-	-	-	-	-	-	8.951 (p = 0.0028)	-	-	-	-
KP rk Wald F	-	-	-	-	-	-	20.647	-	-	-	-
R-squared	0.714	0.817	0.797	0.955	0.784	0.896	0.895	0.798	0.767	0.735	0.918

Notes: t-statistics based on standard errors clustered at the provincial level are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. A dash (-) indicates that the corresponding variable is not included in the specification.

4.2. Robustness Checks and Endogeneity Tests

4.2.1. Alternative Core Variable

Column (3) of Table 4 reports the results obtained by replacing the core explanatory variable. The Peking University Digital Inclusive Finance Index (difi) is used as an alternative measure of digital development. The coefficient of difi is 0.001 and statistically significant at the 1% level, indicating that the positive effect on urban–rural integration remains stable under this alternative specification.

4.2.2. Excluding Direct Administration Municipalities

Column (4) presents the results after excluding the four municipalities under the central government, namely Beijing, Tianjin, Shanghai, and Chongqing, to mitigate potential bias arising from their distinct administrative and economic characteristics. After removing these observations, the estimated coefficient of digital economy development is 0.272 and remains statistically significant at the 1% level, suggesting that the estimated effect is not driven by these municipalities.

4.2.3. Lagged Regression

In light of the possible lagged effects of digital economy development and the limited possibility that current urban–rural integration could influence the digital economy development in the previous period, the one-period lag of digital economy development (L.ded) is therefore used to replace the core explanatory variable within the fixed-effects framework. Column (5) of Table 4 shows that the coefficient of L.ded is 0.421 and significant at the 1% level, demonstrating that the positive impact persists after mitigating concerns regarding reverse causality. As an additional robustness check, the one-period lag of digital economy development (L.ded) is employed as an instrumental variable. The lagged variable is theoretically strongly correlated with the current level of digital economy development and, as historical information, is plausibly uncorrelated with the contemporaneous error term, thereby satisfying the relevance and exogeneity conditions for a valid instrument.

Overall, all robustness tests lead to consistent results, thereby confirming the stability of the empirical findings and providing additional evidence in support of Hypothesis 1.

4.2.4. IV-2SLS

Column (6) of Table 4 presents the second-stage results of the instrumental variables estimation. The coefficient of digital economy development is 0.601 and remains statistically significant at the 1% level. The Durbin–Wu–Hausman test yields a p-value of 0.5076, indicating that the null hypothesis of exogeneity cannot be rejected and that no statistically significant endogeneity issue is detected. The IV-2SLS estimates align with the baseline results in terms of direction and economic implications and display a similar effect size.

4.2.5. Bartik IV

To further address potential endogeneity and to validate the robustness of the findings, we construct a Bartik (shift-share) instrumental variable following the framework of Goldsmith-Pinkham [44]. The instrument is defined as the product of each province's initial share of the digital economy in 2013 and the national digital economy growth rate calculated excluding that province. This construction exploits exogenous variation arising from initial structural differences and national growth dynamics. The initial shares are measured in the base year and are therefore predetermined with respect to subsequent changes in urban–rural integration, mitigating concerns about reverse causality.

In line with the shift-share framework, identification relies on plausibly exogenous cross-sectional variation in the initial shares. The 2013 provincial digital economy endowments were largely shaped by historical infrastructure conditions and institutional factors, making them unlikely to be driven by later shocks to urban–rural integration. Furthermore, the inclusion of province and year fixed effects absorbs time-invariant heterogeneity and common macroeconomic shocks. Conditional on province fixed effects and baseline urban–rural integration levels, the initial shares capture variation in early-stage digital infrastructure rather than persistent differences in overall development capacity. Accordingly, the identifying variation stems from differential exposure to national digital economy expansion through the shift component, rather than from pre-existing provincial development trajectories, consistent with the standard identification logic of shift-share instruments.

To further assess the plausibility of the exclusion restriction, we conduct a pre-trend validation exercise by regressing the early change in urban–rural integration during the pre-treatment period on the 2013 initial digital economy shares, controlling for baseline integration levels and other structural characteristics. The estimated coefficient on the initial shares is statistically insignificant at conventional levels ($p = 0.346$), indicating that provinces with higher initial digital economy endowments did not exhibit systematically different pre-existing integration trends. This finding reduces concerns that the initial shares proxy for differential underlying trajectories.

Standard diagnostic tests confirm instrument relevance. The Kleibergen–Paap rk LM statistic ($p = 0.003$) rejects the null of underidentification, and the Kleibergen–Paap rk Wald F-statistic (20.647) exceeds the Stock–Yogo critical value of 16.38 (10% maximal IV size), indicating no weak-instrument concern.

Column (7) of Table 4 reports the second-stage estimation results. The coefficient of ded is 0.590 and remains statistically significant at the 1% level, with a sign and magnitude consistent with the baseline estimates.

Finally, to address potential sensitivity to provinces with extreme initial shares (e.g., major metropolitan hubs), we verify that the baseline fixed-effects results remain robust after excluding direct-administration municipalities, as reported in Column (4) of Table 4.

4.2.6. Robustness Tests for Indicator Overlap

To further examine the robustness of the baseline results, we conduct additional specifications concerning the treatment of the urbanization rate (urr). Specifically, we consider three alternative specifications: (a) reconstructing the urban–rural integration (uri) index by excluding the urbanization rate from the demographic dimension, (b) re-estimating the regression without including urr as a control variable, and (c) implementing both adjustments simultaneously. The corresponding results are reported in Columns (8)–(10) of Table 4. As shown in these columns, the coefficient of digital economy development remains positive and statistically significant at the 1% level across all specifications. The estimated magnitude is comparable to that of the baseline results, indicating that the main findings are robust to alternative treatments of the urbanization rate.

4.2.7. Alternative Measurement of Core Variables

To ensure that our findings are not sensitive to the entropy-based weighting scheme, we reconstruct both the digital economy and urban–rural integration indices using principal component analysis (PCA). Specifically, we extract the first principal component from the same set of indicators and re-estimate the baseline fixed-effects model. As reported in Column (11) of Table 4, the coefficient on the PCA-based digital economy index remains positive and statistically significant at the 1% level ($\beta = 0.155$, $p < 0.01$). The magnitude and direction are comparable to those obtained using the EWM-based index. These findings indicate that our conclusions are robust to alternative index construction approaches.

Taken together, the findings suggest a consistently positive and statistically significant impact of digital economy development on urban–rural integration. These results offer strong empirical support for the core conclusions of the study and suggest that the estimates are not subject to substantial endogeneity bias.

Furthermore, a dynamic panel specification based on a two-step system GMM estimator is implemented to account for potential path dependence. The corresponding results are reported as an additional robustness check in Appendix A Table A2.

4.3. Threshold Effect Results

In order to assess the existence of threshold effects, it is first essential to identify the quantity of threshold points and the proper specification for the threshold regression model. A trimming parameter of 5%, following Hansen, is adopted to avoid extreme regime classifications and ensure reliable estimation within each regime. This trimming rule ensures that each regime contains a sufficient number of observations for stable estimation.

According to the results reported in Table 5, when the threshold variable is rationalization of industrial structure (ris), the p-value for the single-threshold test is 0.0000, which is significant at the 1% level. In contrast, the p-value for the double-threshold test is 0.7267, indicating that it does not pass the significance test. This suggests that ris exhibits a statistically significant single-threshold effect, rather than double or multiple thresholds.

Table 5. Threshold effect test results.

Threshold Variable	Threshold Model	F-Statistic	p-Value	Bootstrap Repetitions	Critical Value		
					10%	5%	1%
ris	Single Threshold	121.00	0.0000	300	27.6516	36.9751	57.0051
	Double Threshold	4.81	0.7267	300	144.5100	197.1728	435.6547
	Triple Threshold	2.83	0.8233	300	23.1635	126.1135	202.0193
edu	Single Threshold	60.93	0.0100	300	22.4807	27.1423	48.6982
	Double Threshold	16.92	0.1767	300	20.5208	25.1189	45.4277
	Triple Threshold	5.09	0.6233	300	20.8229	31.3531	45.1073

Similarly, the test results for education level (edu) show that the p-value for a single threshold is 0.0100, which is significant at the 1% level. As the number of thresholds increases, neither the double-threshold test nor the triple-threshold test reaches statistical significance.

Taken together, these findings indicate that both rationalization of industrial structure and education level are appropriately modeled using a single-threshold regression framework for subsequent parameter estimation and analysis.

As shown in Table 6, for the rationalization of industrial structure (ris), the estimated threshold value is 28.9041, with a 95% bootstrap confidence interval of [27.716, 30.844]. The bootstrap test rejects the null hypothesis of no threshold effect at the 1% level (F = 127.99). Among the 300 province–year observations, 269 fall below the threshold and 31 exceed it. When ris is below the threshold, the coefficient of ded is 0.393. Once this threshold is exceeded, the coefficient increases substantially to 0.764. This result suggests that the impact of the digital economy exhibits clear structural dependence. In regions where the industrial structure remains underdeveloped, the effect of the digital economy is comparatively limited. As the industrial structure becomes more rationalized and resource allocation efficiency improves, digital technologies become more deeply embedded in the overall economic system, which substantially enhances the incremental contribution of the digital economy.

Similarly, for education level (edu), the estimated threshold is 0.0366, with a 95% bootstrap confidence interval of [0.0365, 0.0369]. The single-threshold effect is statistically significant at the 1% level, with 259 and 41 observations in the respective regimes. The coefficient of the digital economy development (ded) increases from 0.406 to 0.600 below and above the threshold, and both estimates are significant at the 1% level. This result suggests that a higher education level enhances the adoption and diffusion of digital technologies.

Once a region's education level surpasses the threshold, the positive externalities generated by the digital economy for regional growth become further amplified.

Table 6. Threshold effect regression results.

Variables	Threshold Effect	
	Threshold Variable: ris	Threshold Variable: edu
ded (ris ≤ 28.9041)	0.393 *** (9.40)	-
ded (ris > 28.9041)	0.764 *** (15.20)	-
ded (edu ≤ 0.0366)	-	0.406 *** (9.02)
ded (edu > 0.0366)	-	0.600 *** (12.49)
lngdp	0.088 *** (6.48)	0.116 *** (8.25)
open	−0.044 ** (−2.23)	−0.038 * (−1.78)
edu	1.524 *** (3.31)	0.566 (1.14)
inn	−0.004 *** (−3.90)	−0.004 *** (−3.91)
urr	−0.189 ** (−4.27)	−0.406 *** (−4.92)
ris	−0.000 (−0.46)	0.000 (0.01)
Constant	−0.570 *** (−5.89)	−0.745 *** (−7.36)
Observations	300	300
Observations (Regime 1)	269	259
Observations (Regime 2)	31	41
R-squared	0.840	0.814
95% CI	[27.716, 30.844]	[0.0365, 0.0369]

Notes: For the coefficient estimates, *t*-statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. A dash (-) indicates that the corresponding variable is not included in the specification.

In order to further elucidate the economic significance of these estimated thresholds, we interpret them in light of structural transformation, factor allocation, and absorptive capacity perspectives.

Ris, measured as the inverse of the Theil index, captures inter-industry coordination and factor allocation efficiency. From the perspective of structural transformation and factor misallocation, the distributive effects of digital development depend on the degree of industrial coordination. When distortions remain substantial, digital technologies may reinforce advantages in already developed sectors rather than promote balanced growth. Prior studies indicate that digital transformation reduces the urban–rural income gap primarily through industrial structure upgrading and rationalization, and that the strength of this mechanism varies across development stages [45]. We therefore interpret the estimated threshold (ris = 28.9041) as marking a transition from a stage characterized by pronounced structural distortions to a stage of relatively coordinated industrial allocation. In our sample, this value broadly corresponds to provinces with more balanced secondary–tertiary structures, suggesting that it captures a meaningful development-stage transition.

Edu, measured as higher-education students per capita, reflects regional human capital accumulation and digital absorptive capacity. According to human capital and absorptive capacity theories, effective technology diffusion requires a minimum stock of skills. Existing research shows that the impact of digital development varies significantly with regional human capital levels and may exhibit threshold-type characteristics associated with educational attainment [5,46]. We therefore interpret the estimated threshold (edu = 0.0366) as a minimum human capital level necessary for digital technologies to generate broader inclusive effects. In our sample, this threshold corresponds to provinces where higher-education expansion has formed a basic skill base supportive of digital participation.

Overall, the results offer substantial empirical backing for Hypothesis 2.

4.4. Moderating Effect Results

This study further investigates the moderating mechanisms by incorporating government support and financial development as moderating variables. Table 7 reports the moderating effects of government support and financial development on the relationship between digital economy and urban–rural integration. In order to mitigate multicollinearity arising from interaction terms, all variables included in the interaction specifications are mean centered. After centering, the digital economy development (ded) variable is represented as c_ded, government support as c_gov, and financial development as c_fin.

Table 7. Moderating effect results.

Variables	Moderating Effect	
	Government Support	**Financial Development**
	(1)	**(2)**
c_ded	0.730 *** (9.53)	0.248 *** (5.75)
c_gov	0.307 *** (4.61)	-
c_ded × c_gov	2.854 *** (4.99)	-
c_fin	-	0.025 *** (5.11)
c_ded × c_fin	-	0.135 *** (9.43)
lngdp	0.077 *** (3.48)	0.099 *** (4.82)
open	0.026 (1.03)	0.018 (0.88)
edu	−0.998 * (−1.72)	1.054 * (1.90)
ris	−0.001 (−0.99)	−0.001 * (−1.96)
inn	−0.003 *** (−2.95)	−0.003 *** (−3.47)
urr	−0.873 *** (−9.22)	−0.439 *** (−4.92)
Constant	−0.010 (−0.05)	−0.539 *** (−2.96)
R-squared	0.836	0.880
Observations	300	300

Notes: *t*-statistics based on standard errors clustered at the provincial level are reported in parentheses. *** and * indicate statistical significance at the 1% and 10% levels, respectively. A dash (-) indicates that the corresponding variable is not included in the specification.

Column (1) presents the estimation results when government support is used as the moderator. The coefficient of the digital economy development (c_ded) is 0.730 and is statistically significant at the 1% level, indicating that the digital economy contributes meaningfully to urban–rural integration. The interaction term between the digital economy and government support (c_ded × c_gov) is 2.854 and also significant at the 1% level.

The results reveal that government support strengthens the effect of digital economy on urban–rural integration. The consistent signs of the main effect and the interaction term show that stronger government support enhances the capacity of the digital economy to promote integration. In regions where government support is more extensive, the marginal contribution of the digital economy to urban–rural integration becomes larger.

Column (2) examines the moderating effect of financial development. The coefficient of the interaction term (c_ded $\times$ c_fin) is 0.135 and is statistically significant at the 1% level. This result indicates that financial development enhances the effect of the digital economy on urban–rural integration. As an important mechanism for resource allocation, the financial system supplies essential capital to support digital infrastructure development and the implementation of digital applications. The positive and significant interaction term suggests that a more developed financial environment generates a "multiplier effect" which reinforces the contribution of digital economy to urban–rural integration.

Consequently, these results provide empirical support for Hypotheses 3 and 4.

We further estimated a triple-interaction specification (Digital Economy $\times$ Government Support $\times$ Financial Development). The three-way interaction term is statistically insignificant, suggesting no statistically significant compounded effect when both moderators are simultaneously considered. Detailed results are reported in Appendix A Table A3.

4.5. Heterogeneity Analysis

Given China's vast geographic diversity and pronounced regional variation in the development of digital economy, economic conditions, and resource endowments, the full observations are partitioned into the Northeast, Eastern, Central, and Western regions to conduct subgroup regressions and assess whether the effect of digital economy on urban–rural integration varies by region.

Based on the results reported in Table 8, the coefficients of the digital economy development variable (ded) are significantly positive in each of the four regions. This indicates that the digital economy consistently promotes urban–rural integration nationwide. However, the magnitude of this effect differs across regions, with the largest impact observed in the Eastern region, followed by the Western and Central regions, while the impact is relatively weaker in the Northeast.

The Northeast region shows a comparatively weaker effect, with a coefficient of 0.312 that is significant at the 5% level. Due to pressures from industrial restructuring and limitations associated with institutional factors, the penetration and effective application of digital technologies remain relatively low. Consequently, the contribution of the digital economy to urban–rural integration in this region continues to have substantial scope for improvement.

With a coefficient of 0.426 (significant at the 1% level), the Eastern region exhibits the strongest effect among all regions. This finding can be ascribed to its advanced digital infrastructure and more mature market mechanisms, which have enabled earlier and deeper integration of digital technologies into urban and rural industries and have generated notable scale effects.

For the Central region, the coefficient is 0.349 and remains significant at the 1% level, indicating a stable positive effect. As a core region linking eastern and western China, it is currently undergoing industrial transfer and structural upgrading. Although the impact of the digital economy in the Central region is slightly lower than that in the Eastern and Western regions, the effect remains highly robust. This finding reflects the sustained strengthening of digital momentum under the national strategy aimed at promoting the "Rise of Central China."

The Western region demonstrates strong "late-mover advantages," with a coefficient of 0.399 that is significant at the 1% level, suggesting heterogeneous digital economy effects across regions. This pattern is consistent with the notion that regions with relatively weaker initial economic and digital foundations may experience larger marginal gains from technological adoption.

Beyond initial infrastructure gaps, however, these "late-mover advantages" are reinforced by institutional and policy contexts. Since the launch of the Western Development Strategy in 2000, the central government has continuously implemented targeted fiscal transfers, infrastructure expansion programs, and industrial upgrading initiatives aimed at narrowing regional disparities. In recent years, digital transformation has been explicitly incorporated into these regional revitalization frameworks. National strategies such as "Digital China" and the "Eastern Data and Western Computing" initiative have positioned western provinces as key nodes in China's data center layout and computing capacity allocation. This policy alignment effectively lowers the fixed costs of digital infrastructure deployment and enhances complementary investments. Moreover, the western region is characterized by greater spatial dispersion, weaker traditional retail and financial networks, and higher transaction costs. Under such conditions, digital platforms—particularly rural e-commerce and digital financial inclusion—may generate disproportionately large marginal benefits by reducing spatial friction and improving market access. Compared with the eastern region, where industrial systems are relatively mature and digital penetration is already high, the marginal returns to further digitalization may be diminishing. In contrast, in the western region, digital technologies may contribute to stronger structural transformation and factor reallocation effects.

Table 8. Regional heterogeneity regression results.

Variables	**Heterogeneity Analysis**			
	Northeast	**Eastern**	**Central**	**Western**
	(1)	**(2)**	**(3)**	**(4)**
ded	0.312 **	0.426 ***	0.349 ***	0.399 ***
	(5.30)	(2.80)	(4.61)	(11.73)
lngdp	0.073 **	−0.014	−0.038 **	0.018
	(6.04)	(−0.08)	(−2.85)	(0.91)
open	0.001	0.098	−0.176	0.037 *
	(0.01)	(1.43)	(−1.73)	(2.02)
edu	0.814 *	−5.516 ***	0.900	0.651
	(3.32)	(−4.47)	(0.99)	(1.61)
ris	0.000	−0.003	0.003	0.001
	(0.93)	(−1.22)	(1.17)	(0.77)
inn	0.003	−0.003	0.001	−0.002
	(2.54)	(−1.12)	(1.17)	(−1.29)
urr	−0.384 ***	−1.346 ***	0.285	0.157 *
	(−5.53)	(−2.28)	(1.82)	(2.07)
Constant	−0.368	1.408	0.331 *	−0.172
	(−2.65)	(0.76)	(2.29)	(−1.08)
R-squared	0.994	0.856	0.984	0.965
Observations	30	100	60	110

Notes: *t*-statistics based on standard errors clustered at the provincial level are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. A dash (-) indicates that the corresponding variable is not included in the specification.

In this context, the digital economy functions not only as a technological improvement but also as an institutional accelerator that interacts with regional policy support. The interaction between relatively low initial digital saturation and sustained policy support amplifies the marginal impact of digital economy development on urban–rural integration. These combined effects provide a more comprehensive explanation for the stronger digital economy impacts observed in the western region, beyond a simple infrastructure-based interpretation.

Overall, the regional disparities in the digital economy's influence on urban–rural integration decrease sequentially from the Eastern region to the Western, Central, and Northeast regions. The empirical results indicate that while the digital economy promotes urban–rural integration across China as a general mechanism that is not fundamentally constrained by geographic location, the magnitude of its effect varies across regions. Therefore, Hypothesis 5 is supported.

5. Discussion

5.1. Main Findings and Interpretations

The empirical findings reveal a positive association between digital economy development and urban–rural integration in China, suggesting that digital development may play a role in alleviating elements of the long-standing urban–rural dual structure.

This result is largely in line with the "digital dividends" hypothesis, which posits that digital technologies can reduce information asymmetry and transaction costs, thereby facilitating more efficient flows of production factors between urban and rural regions. In this regard, the digital economy appears to function as an additional facilitating factor in integrated urban–rural development, complementing earlier processes of industrialization and urbanization.

The regional heterogeneity analysis reveals that the estimated effects of the digital economy on urban–rural integration differ across regions. Specifically, the eastern region exhibits a relatively stronger association, a pattern that may be related to its more advanced digital infrastructure and more mature market institutions. These conditions are likely to promote closer alignment between digital technologies and the real economy, allowing scale effects to materialize more fully.

Interestingly, the estimated effect in the western region is stronger than that observed in the central region. A possible explanation for this is that the inclusive features of digital technologies help relax constraints imposed by physical distance and inadequate traditional infrastructure. In regions where conventional infrastructure is relatively weak, the adoption of digital technologies may generate higher marginal benefits by improving access to markets and public services. Applications such as telemedicine, e-commerce, and digital public services may help compensate for longstanding infrastructure gaps and contribute to urban–rural integration. By contrast, the relatively weaker effect observed in the Northeast region may be related to rigid industrial structures and institutional constraints, which constrain the efficient diffusion and application of digital technologies. Overall, these findings suggest that digital development may generate differentiated integration effects across regions, depending on local conditions.

5.2. Thresholds and Mechanisms

An important insight from this study concerns the sustainability boundary conditions under which the digital economy is more likely to exert enabling effects on urban–rural integration. Panel threshold estimates suggest that the impact of digital development is not continuous across different stages of development. Rather, its contribution to socially sustainable urban–rural integration appears to depend in part on whether key structural conditions have reached identifiable threshold levels.

With respect to the rationalization of industrial structure, the estimated findings indicate that the positive association between the digital economy and urban–rural integration becomes markedly stronger once the rationalization of industrial structure exceeds the identified threshold, with the estimated coefficient increasing from 0.393 to 0.764. This pattern suggests that digital investment alone may have limited effects in regions where agriculture, manufacturing, and services are poorly coordinated. In areas characterized by rigid or inefficient industrial structures, the ability of digital infrastructure to facilitate resource reallocation and productivity improvements may remain constrained. Such findings are consistent with observations that some regions continue to experience a digital divide despite extensive network coverage, a phenomenon often discussed in relation to the Solow Paradox.

Similarly, the threshold associated with education level suggests that the accumulation of human capital is a critical condition for realizing the potential benefits of digital development. The estimated impact of the digital economy becomes markedly stronger once the education threshold is surpassed. This result implies that a minimum level of education and digital literacy may be necessary for residents to effectively adopt and utilize digital tools in production, employment, and daily activities. In this sense, education appears to serve as a foundational driver of inclusive digital development.

In addition, the moderation analysis highlights the complementary roles of government support and financial development. The positive moderating effect of government support suggests that, given the quasi-public-good characteristics of urban–rural integration, market mechanisms alone may lead to under-provision of relevant infrastructure and services. Government actions—such as investments in digital infrastructure and government support—can help create the basic conditions under which the digital economy can exert stronger integration effects. The positive moderating role of financial development further indicates that improved access to inclusive finance may alleviate credit constraints in rural areas, facilitate the adoption of digital technologies, and enable a broader range of rural households and enterprises to participate in digital economic activities.

5.3. Policy Implications

In light of the aforementioned results, the present research yields several policy implications for promoting urban–rural integration through digital development.

First, the results highlight the importance of adopting region-sensitive digital development strategies. In the eastern region, where digital infrastructure and market institutions are relatively mature, policy efforts may benefit from emphasizing the deeper integration of advanced digital technologies with industrial upgrading. In contrast, for the central, western, and northeastern regions, addressing gaps in digital infrastructure and improving basic connectivity remain important. In these regions, digital technologies may offer opportunities to relax constraints imposed by geographical distance and factor immobility, allowing regions to better leverage potential "late-mover advantages" and strengthen urban–rural linkages.

Second, the findings underscore the critical role of the "soft environment" in enabling regions to surpass key development thresholds. Rather than relying exclusively on hard indicators such as broadband penetration, greater attention to human capital accumulation appears essential. Increased investment in rural education and vocational training can help improve digital literacy and enhance the capacity of residents to effectively utilize digital technologies. At the same time, extending agricultural value chains and promoting the rationalization of industrial structure may broaden the use cases of digital technologies and enhance the effectiveness of digital development.

Third, the analysis points to the importance of coordination between government support and financial development. Government involvement can help create the basic institutional and infrastructural conditions necessary for digital transformation, while financial institutions play a complementary role by expanding access to inclusive finance. Advancing digital inclusive finance may help alleviate financing constraints faced by rural households and enterprises, facilitating broader participation in digital economic activities.

Together, these complementary efforts may help strengthen the contribution of the digital economy to urban–rural integration.

Finally, although this paper focuses on China, these findings offer broader insights for developing economies in the Global South that face persistent urban–rural dual structures. The identified threshold effects suggest that investments in digital infrastructure alone may be insufficient to foster inclusive urban–rural integration. Instead, digital strategies should be accompanied by improvements in the "soft environment," including rationalization of industrial structure and human capital development, to enhance local absorptive capacity. When digital infrastructure is aligned with these complementary conditions, the digital economy is more likely to contribute to reducing spatial inequalities and advancing Sustainable Development Goal 10 (Reduced Inequalities).

5.4. Limitations and Future Directions

Although the present research provides empirical evidence and meaningful perspectives on the relationship between the digital economy and urban–rural integration, several limitations should be acknowledged, which suggest avenues for future study.

First, the present research is conducted at the provincial level due to constraints related to the continuity and availability of digital economy statistics over the past decade. Although provincial panel data allow for a systematic examination of regional patterns, China's vast geographic size implies substantial heterogeneity within provinces. As a result, macro-level indicators may lack the necessary granularity to reveal localized disparities at the prefecture or county level. Future research employing more fine-grained city-level or county-level data could help identify spatial spillover effects and better capture the localized dynamics of urban–rural integration with higher spatial resolution.

Second, the generalizability of the findings should be contextualized within China's distinct institutional framework. The empirical results are derived from a setting characterized by a persistent urban–rural dual structure and a relatively strong role of government in promoting digital infrastructure development. Consequently, some of the mechanisms identified in this study—particularly the moderating role of government support—may operate differently in economies where market forces play a more dominant role. Future studies could conduct cross-country or cross-regional comparative analyses to examine whether the patterns observed in China's digitally driven urban–rural integration extend to emerging economies in Asia, Africa, or Latin America.

Third, this study focuses primarily on macro-level channels, such as government support and financial development, and does not directly observe behavioral responses at the household or individual level. The micro-foundations underlying how digital technologies influence rural livelihoods, such as how digital literacy affects non-farm employment decisions or how participation in e-commerce reshapes household income structures, remain insufficiently captured by macro-level regressions. Future research combining macro data with micro survey or administrative data would help clarify the micro-foundations of digital empowerment and provide a deeper understanding of how digital technologies contribute to narrowing the urban–rural divide.

6. Conclusions

The present research empirically demonstrates that the digital economy constitutes a meaningful, yet inherently conditional, driver of urban–rural integration in developing economies. Rather than functioning as an automatic equalizer, digital development enhances urban–rural integration through nonlinear and conditional effects, operating only when it is embedded within appropriate structural, human capital, and institutional contexts.

https://doi.org/10.3390/su18062739

The findings reveal that the effectiveness of the digital economy in reducing urban–rural disparities critically depends upon regional absorptive capacity. In particular, rationalized industrial structures and adequate education levels emerge as necessary preconditions for translating digital inputs into socially inclusive outcomes. Without these foundations, digital expansion alone may yield limited integration effects, suggesting that digital economy development must be aligned with broader development fundamentals to generate sustainable social benefits.

Importantly, this analysis reveals pronounced regional heterogeneity in the integration effects of the digital economy. While the eastern region capitalizes most effectively on digital development due to mature markets and advanced infrastructure, the western region exhibits clear late-mover advantages, suggesting that digital technologies can partially compensate for traditional geographic and infrastructural constraints. This finding implies that digital development does not follow a single spatial logic but instead interacts with region-specific development stages, producing differentiated integration outcomes.

Moreover, the results underscore the indispensable role of supportive institutional contexts and complementary arrangements. Government support and financial development significantly amplify the contribution of the digital economy to urban–rural integration, indicating that digital transformation should be understood as a co-evolutionary process involving technology, institutions, and factor markets rather than as a purely technological phenomenon.

Within the framework of sustainability, the present research directly contributes to the understanding of how digitalization can support the achievement of the United Nations Sustainable Development Goals, particularly SDG 10 (Reduced Inequalities). By demonstrating that digital development can promote urban–rural integration under appropriate structural and institutional conditions, the findings highlight the potential of digital strategies to reduce spatial and social inequalities within countries. However, they also caution that without complementary investments in education, industrial coordination, and inclusive financial systems, digital expansion alone may fall short of delivering equitable and sustainable outcomes.

By emphasizing the conditional and heterogeneous nature of digital economy effects, this study extends existing research beyond average-effect analyses and provides policy-relevant insights for developing economies seeking inclusive growth pathways. Although the empirical evidence is drawn from China, the conclusions offer broader implications for countries facing persistent urban–rural disparities amid rapid digital transformation.

Author Contributions: Conceptualization, J.G. and H.N.; methodology, H.N.; formal analysis, H.N.; investigation, H.N.; writing—original draft preparation, H.N.; writing—review and editing, J.G. and H.N.; supervision, H.L.; project administration, H.L. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: These data were derived from the following resources available in the public domain: National Bureau of Statistics of China (http://www.stats.gov.cn/, accessed on 1 December 2025).

Acknowledgments: Sincere thanks to the academic editors and anonymous reviewers for their kind suggestions and valuable comments.

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

Appendix A

Table A1. Pesaran Cross-Sectional Dependence (CD) Test.

Statistic	Value
CD statistic	−0.782
p-value	0.4344
Average absolute correlation	0.486

Notes: Pesaran (2004) CD test. The null hypothesis is cross-sectional independence.

Table A2. Dynamic panel estimation (Two-step System GMM).

Variables	Two-Step System GMM
L.uri	1.079 *** (52.25)
ded	−0.008 (−0.55)
lngdp	−0.000 (−0.87)
open	0.022 *** (4.66)
edu	−0.023 (−0.26)
ris	−0.000 * (−1.96)
inn	−0.000 (−1.40)
urr	−0.030 ** (−2.61)
Constant	0.019 ** (2.42)
Observations	270
Number of Instruments	24
AR (1) test (*p*-value)	0.192
AR (2) test (*p*-value)	0.435
Sargan test (*p*-value)	0.000
Hansen test (*p*-value)	0.699
Difference-in-Hansen test (*p*-value)	0.827

Notes: For the coefficient estimates, *t*-statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table A3. Results of the triple-interaction model.

Variables	Triple-Interaction Uri
c_ded	0.287 ** (2.66)
c_ded × c_gov × c_fin	0.794 (1.45)
lngdp	0.085 ** (2.73)
open	0.061 (1.42)
edu	1.276 * (1.84)
ris	−0.001 (−0.68)
inn	−0.003 (−1.54)
urr	−0.419 (−1.43)
Constant	−0.446 ** (−2.12)
R-squared	0.888
Observations	300

Notes: *t*-statistics based on standard errors clustered at the provincial level are reported in parentheses. ** and * indicate statistical significance at the 5% and 10% levels, respectively.

References

1. Sachs, J.D.; Schmidt-Traub, G.; Mazzucato, M.; Messner, D.; Nakicenovic, N.; Rockström, J. Six Transformations to Achieve the Sustainable Development Goals. *Nat. Sustain.* **2019**, *2*, 805–814. [CrossRef]
2. Goldfarb, A.; Tucker, C. Digital Economics. *J. Econ. Lit.* **2019**, *57*, 3–43. [CrossRef]
3. Deichmann, U.; Goyal, A.; Mishra, D. Will Digital Technologies Transform Agriculture in Developing Countries? *Agric. Econ.* **2016**, *47*, 21–33. [CrossRef]
4. Hjort, J.; Poulsen, J. The Arrival of Fast Internet and Employment in Africa. *Am. Econ. Rev.* **2019**, *109*, 1032–1079. [CrossRef]
5. Xia, H.; Yu, H.; Wang, S.; Yang, H. Digital Economy and the Urban–Rural Income Gap: Impact, Mechanisms, and Spatial Heterogeneity. *J. Innov. Knowl.* **2024**, *9*, 100505. [CrossRef]
6. Couture, V.; Faber, B.; Gu, Y.; Liu, L. Connecting the Countryside via E-Commerce: Evidence from China. *Am. Econ. Rev. Insights* **2021**, *3*, 35–50. [CrossRef]
7. Fan, J.; Tang, L.; Zhu, W.; Zou, B. The Alibaba Effect: Spatial Consumption Inequality and the Welfare Gains from E-Commerce. *J. Int. Econ.* **2018**, *138*, 103681. [CrossRef]
8. Man, J.; Liu, J.; Cui, B.; Sun, Y.; Sriboonchitta, S. Coupling and Coordination between Digital Economy and Urban–Rural Integration in China. *Sustainability* **2023**, *15*, 7299. [CrossRef]
9. Huo, Z.; Liu, H. Impact of China's Digital Economy on Integrated Urban–Rural Development. *Sustainability* **2024**, *16*, 5863. [CrossRef]
10. Bergquist, L.F.; Dinerstein, M. Competition and Entry in Agricultural Markets: Experimental Evidence from Kenya. *Am. Econ. Rev.* **2020**, *110*, 3705–3747. [CrossRef]
11. Coase, R.H. The Nature of the Firm. *Economica* **1937**, *4*, 386–405. [CrossRef]
12. Akerlof, G.A. The Market for "Lemons": Quality Uncertainty and the Market Mechanism. *Q. J. Econ.* **1970**, *84*, 488–500. [CrossRef]
13. Liu, P.; Tang, W.; Shao, Y.; Liu, L. The Impact of the Digital Economy on New Industrial-Agricultural and Urban–Rural Relations. *Front. Sustain. Food Syst.* **2025**, *9*, 1747418. [CrossRef]
14. Jones, C.I.; Tonetti, C. Nonrivalry and the Economics of Data. *Am. Econ. Rev.* **2020**, *110*, 2819–2858. [CrossRef]
15. Du, M.; Antunes, J.; Wanke, P.; Chen, Z. Ecological Efficiency Assessment under the Construction of Low-Carbon City: A Perspective of Green Technology Innovation. *J. Environ. Plan. Manag.* **2022**, *65*, 1727–1752. [CrossRef]
16. Luo, S.; Yimamu, N.; Li, Y.; Wu, H.; Irfan, M.; Hao, Y. Digitalization and Sustainable Development: How Could Digital Economy Development Improve Green Innovation in China? *Bus. Strat. Environ.* **2023**, *32*, 1847–1871. [CrossRef]
17. Leng, C.; Ma, W.; Tang, J.; Zhu, Z. ICT Adoption and Income Diversification among Rural Households in China. *Appl. Econ.* **2020**, *52*, 3614–3628. [CrossRef]
18. Farboodi, M.; Veldkamp, L. Long-Run Growth of Financial Data Technology. *Am. Econ. Rev.* **2020**, *110*, 2485–2523. [CrossRef]
19. Brynjolfsson, E.; Rock, D.; Syverson, C. The Productivity J-Curve: How Intangibles Complement General Purpose Technologies. *Am. Econ. J. Macroecon.* **2021**, *13*, 333–372. [CrossRef]
20. Duan, Y.; Liu, S.; Cheng, H.; Chin, T.; Luo, X. The Moderating Effect of Absorptive Capacity on Transnational Knowledge Spillover and the Innovation Quality of High-Tech Industries in Host Countries: Evidence from the Chinese Manufacturing Industry. *Int. J. Prod. Econ.* **2021**, *233*, 108019. [CrossRef]
21. Li, Z.; Wang, J. The Dynamic Impact of Digital Economy on Carbon Emission Reduction: Evidence City-Level Empirical Data in China. *J. Clean. Prod.* **2022**, *351*, 131570. [CrossRef]
22. Balland, P.-A.; Jara-Figueroa, C.; Petralia, S.; Steijn, M.; Hidalgo, C.A. Complex Economic Activities Concentrate in Large Cities. *Nat. Hum. Behav.* **2020**, *4*, 48–54. [CrossRef] [PubMed]
23. Lu, Z.; Gou, D.; Wu, Q.; Feng, H. Does the Rural Digital Economy Promote Shared Prosperity among Farmers? Evidence from China. *Front. Sustain. Food Syst.* **2025**, *9*, 1649753. [CrossRef]
24. Liu, Y.; Zang, Y.; Yang, Y. China's Rural Revitalization and Development: Theory, Technology and Management. *J. Geogr. Sci.* **2020**, *30*, 1923–1942. [CrossRef]
25. Rodrik, D.; Subramanian, A.; Trebbi, F. Institutions Rule: The Primacy of Institutions over Geography and Integration in Economic Development. *J. Econ. Growth* **2004**, *9*, 131–165. [CrossRef]
26. Briglauer, W.; Grajek, M. Effectiveness and Efficiency of State Aid for New Broadband Networks: Evidence from OECD Member States. *Econ. Innov. New Technol.* **2024**, *33*, 672–700. [CrossRef]
27. Zhu, B.; Zhong, R.; Wei, C. Measuring Digital Government Service Performance: Evidence from China. *China Econ. Rev.* **2024**, *83*, 102105. [CrossRef]
28. Bustos, P.; Caprettini, B.; Ponticelli, J. Agricultural Productivity and Structural Transformation. Evidence from Brazil. *Am. Econ. Rev.* **2016**, *106*, 1320–1365. [CrossRef]
29. Allen, F.; Demirguc-Kunt, A.; Klapper, L.; Martinez Peria, M.S. The Foundations of Financial Inclusion: Understanding Ownership and Use of Formal Accounts. *J. Financ. Intermed.* **2016**, *27*, 1–30. [CrossRef]

30. Zhang, X.; Wan, G.; Zhang, J.; He, Z. Digital Economy, Financial Inclusion and Inclusive Growth. *China Econ.* **2020**, *15*, 92–105. [CrossRef]
31. Burgess, R.; Pande, R. Do Rural Banks Matter? Evidence from the Indian Social Banking Experiment. *Am. Econ. Rev.* **2005**, *95*, 780–795. [CrossRef]
32. Wu, H.; Xue, Y.; Hao, Y.; Ren, S. How Does Internet Development Affect Energy-Saving and Emission Reduction? Evidence from China. *Energy Econ.* **2021**, *103*, 105577. [CrossRef]
33. Du, Z.-Y.; Wang, Q. Digital Infrastructure and Innovation: Digital Divide or Digital Dividend? *J. Innov. Knowl.* **2024**, *9*, 100542. [CrossRef]
34. Liu, H.; Wang, W. The Spatiotemporal Evolution and Driving Factors of Urban–Rural Integration over the Past Eight Years in China: Evidence from 31 Provinces. *PLoS ONE* **2025**, *20*, e0337317. [CrossRef]
35. Pan, W.; Xie, T.; Wang, Z.; Ma, L. Digital Economy: An Innovation Driver for Total Factor Productivity. *J. Bus. Res.* **2022**, *139*, 303–311. [CrossRef]
36. Yi, M.; Liu, Y.; Sheng, M.S.; Wen, L. Effects of Digital Economy on Carbon Emission Reduction: New Evidence from China. *Energy Policy* **2022**, *171*, 113271. [CrossRef]
37. Wang, S.; Li, J. Nonlinear Spatial Impacts of the Digital Economy on Urban Ecological Welfare Performance: Evidence from China. *Front. Ecol. Evol.* **2024**, *12*, 1361741. [CrossRef]
38. Ma, D.; Zhu, Q. Innovation in Emerging Economies: Research on the Digital Economy Driving High-Quality Green Development. *J. Bus. Res.* **2022**, *145*, 801–813. [CrossRef]
39. Liu, Y.; Yang, Y.; Li, H.; Zhong, K. Digital Economy Development, Industrial Structure Upgrading and Green Total Factor Productivity: Empirical Evidence from China's Cities. *Int. J. Environ. Res. Public Health* **2022**, *19*, 2414. [CrossRef]
40. Ding, C.; Liu, C.; Zheng, C.; Li, F. Digital Economy, Technological Innovation and High-Quality Economic Development: Based on Spatial Effect and Mediation Effect. *Sustainability* **2021**, *14*, 216. [CrossRef]
41. Wang, J.; Wang, B.; Dong, K.; Dong, X. How Does the Digital Economy Improve High-Quality Energy Development? The Case of China. *Technol. Forecast. Soc. Change* **2022**, *184*, 121960. [CrossRef]
42. Ren, S.; Hao, Y.; Xu, L.; Wu, H.; Ba, N. Digitalization and Energy: How Does Internet Development Affect China's Energy Consumption? *Energy Econ.* **2021**, *98*, 105220. [CrossRef]
43. Hansen, B.E. Threshold Effects in Non-Dynamic Panels: Estimation, Testing, and Inference. *J. Econom.* **1999**, *93*, 345–368. [CrossRef]
44. Goldsmith-Pinkham, P.; Sorkin, I.; Swift, H. Bartik Instruments: What, When, Why, and How. *Am. Econ. Rev.* **2020**, *110*, 2586–2624. [CrossRef]
45. Wen, C.; Xiao, Y.; Hu, B. Digital Financial Inclusion, Industrial Structure and Urban–Rural Income Disparity: Evidence from Zhejiang Province, China. *PLoS ONE* **2024**, *19*, e0303666. [CrossRef]
46. Liao, S.; Yang, C.; Zhang, Y. The Positive Impact of the Digital Economy on the Coordinated Development of the Rural Economy-Environment: Evidence from China. *Agriculture* **2026**, *16*, 322. [CrossRef]