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How does digital financial inclusion respond to the urban-rural income gap in counties: effect and mechanism test

RESEARCH ARTICLE

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Abstract

Given that counties encompass approximately 90% of the agricultural population, enhancing agricultural income levels and bridging the urban-rural income (URI) gap constitute fundamental prerequisites for achieving common prosperity. Utilizing panel data from 817 Chinese counties (2014–2019), this study empirically investigates how digital financial inclusion (DFI) influences the URI gap at the county level. The results demonstrate that DFI not only contributes to reducing URI gap through agricultural incomes growth, but also generates significant spatial spillover effect. on neighboring regions. Mechanism analysis reveals that county-level entrepreneurial activity serves as a critical mediating mechanism through which DFI alleviates income disparities. Furthermore, rural development policies — particularly the E-commerce Pilot Program in Agricultural Areas — significantly amplify DFI's equalizing effects. These findings provide actionable insights for optimizing DFI deployment to advance equitable development and common prosperity within China's county-level socioeconomic framework.

Keywords: agricultural income, digital financial inclusion, entrepreneurial activity, URI gap in counties
JEL codes: D31, O14, Q18

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1. Introduction

Developing countries frequently confront dual challenges of urban-rural income disparities and financial exclusion. As the world's largest developing economy, China's experience in addressing these issues through digital financial innovation provides critical insights for other nations undergoing analogous socioeconomic transitions. Narrowing the urban-rural income gap in developing economies fundamentally depends on elevating income levels in agricultural regions. China, as the the most populous developing country, has achieved significant progress in enhancing agricultural incomes and reducing urban-rural disparities (Kanbur *et al*., 2021), with the urban/rural income ratio declining from a 3.14 in 2007 to 2.5 in 2021 (Luo *et al*., 2020). Nevertheless, this ratio remains substantially higher than the global average (Meng *et al*., 2023; Piketty *et al*., 2019).

Existing literature predominantly examines China's urban-rural income (URI) gap at the provincial level or micro-individual scales in China (Li, 2014; Ravallion and Chen, 2022; Shi and Chuliang, 2010; Sicular *et al*., 2007). However, research on county-level income inequality remains limited (Chen *et al*., 2024; Lin and Brueckner, 2023; Zhang *et al*., 2022).The lack of county level analysis may obscure critical imbalances in urban-rural industrial development, hindering sustainable agricultural development. This study argues that focusing on URI gap at the county level — a smaller yet administratively pivotal scale — is imperative for two key reasons:

First, China's entrenched urban-rural dual structure persists despite reforms (Wei *et al*., 2021). Counties accommodate approximately 90% of the nation's agricultural population, making inter-county URI disparities a central determinant of national inequality. Although China's urban-rural income ratio decreased from 2.99 to 2.56 between 2010 and 2020, 52.5% of counties still exhibited ratios between 2 and 3 by 2020. Addressing county-level disparities is therefore essential for equitable rural development.

Second, Construal-Level Theory (CLT) posits that individuals employ more abstract representations for distant phenomena but focus on concrete details of proximal contexts (Trope and Liberman, 2010). Moreover, income disparity indicators exhibit less variation over larger geographic areas, thereby rendering the detection of subtle changes more challenging(Graham and Felton, 2006). The perception of the relative income gap is largely influenced by the observable and comparable objects within one's own environment (Easterlin, 2001). Consequently, it is crucial to bridge the urban-rural divide by enhancing agricultural incomes, which is an effective strategy for improving the well-being of individuals in rural communities engaged in agricultural activities.

To mitigate URI gaps, policymakers must diversify farmers' income sources through industrial support and market access, facilitated by financial interventions (Yang *et al*., 2022). While digital financial inclusion (DFI) promotes rural growth by lowering financial service costs and expanding credit access (Geng and He, 2021; Hu *et al*., 2023). However, the inclusive nature of digital finance does not make it a universal solution.

The role of DFI is contingent upon the advancement of internet infrastructure, the enhancement of regional economic development, and the expansion of digital literacy among users (Lee *et al*., 2023; Zhu, 2023). Studies have shown that the advent of DFI has the potential to place significant demands on the digital infrastructure, financial ecosystem, and cognitive capabilities of the clientele. Without a robust foundation, the growth of DFI could give rise to geographic disparities and a novel form of digital financial exclusion that might serve to further exacerbate the relative poverty gap between urban and agricultural areas (Goldfarb and Tucker, 2019; Kanga *et al*., 2022). As a result, the existing literature presents conflicting findings on the potential of digital financial inclusion (DFI) to reduce the URI gap.

In comparison to previous studies, our contributions can be summarized as follows: first, this study aims to examine the influence of DFI on the URI gap at the county level, rather than the provincial level. Additionally, it seeks to investigate the spatial spillover effects between the DFI and URI gap. Secondly, the study examines the impact of county-level entrepreneurial activity on the reduction of the URI gap through the promotion of DFI. Thirdly, this paper explores the impact of the e-commerce pilot policy in agricultural areas on the role of DFI in reducing the URI gap.

This provides a realistic foundation for the subsequent phase of enhancing the relevance of policy implementation. The structure of the paper is organized as follows: the second section includes a theoretical analysis, which presents the research hypotheses; the third section covers the research design, including model construction, indicator selection, and description; the fourth section discusses the baseline model and the analysis of spatial spillover effects; the fifth section concentrates on the mechanism test, with an emphasis on the mediating effect of entrepreneurial activity and the moderating effect of related policies; and the sixth section presents the discussion and main conclusions.

2. Theoretical background

2.1 Impact of DFI on narrowing the URI gap within counties

Traditional financial geography reveals that the spatial exclusivity of financial resource allocation (Leyshon and Thrift, 1995) and rural financial repression (Witcomb, 1974) jointly constitute the institutional roots of urban-rural income disparities. Particularly at the county level, agricultural residents face dual constraints: first, the disruption of the "innovation-credit" cycle impedes the upgrading of production factors (Schumpeter, 1934); second, the poverty trap model demonstrates that the lack of collateral triggers financial exclusion, restricting their participation in modern economic activities (Aghion and Bolton, 1997).To narrow the URI gap within the county, it is crucial that the agricultural income growth of rural residents outpaces that of urban residents (Guillaumont Jeanneney and Hua, 2001; Sicular *et al*., 2007). Compared with urban and suburban populations, those in agricultural areas face increased financial constraints and an underdeveloped financial market. The emergence of e-commerce and digital finance, the most frequently utilized digital economic resources by agricultural residents, will precipitate significant transformations in the trajectory of agricultural economic development (Couture *et al*., 2021; Guellec, 2021). Consequently, DFI has the potential to enhance the agricultural income of residents to a greater extent (Hu *et al*., 2023; Liu *et al*., 2023a).

DFI can offer more flexible and convenient financial support for agricultural residents lacking collateral by reducing financing and transaction costs, aiding in the expansion of their production scale (Li *et al*., 2024; Shen *et al*., 2023). Simultaneously, third-party payment platforms, like Alipay and WeChat have facilitated the sale of agricultural products by agricultural residents, thereby increasing their income from agricultural operations(Ding *et al*., 2018; Zhu, 2023). Empirical evidence demonstrates that a one-standard-deviation increase in county-level digital payment penetration is associated with a 23% improvement in agricultural operational loan accessibility *(Li et al*., 2024).

Moreover, DFI promotes employment and entrepreneurship among agricultural residents, thereby increasing their non-farm income(Fan *et al*., 2018; Zhang *et al*., 2024). Partially, DFI alleviates the mobility constraints faced by the entrepreneurial population. Additionally, DFI not only encourages agricultural entrepreneurship but also stimulates local employment, broadening non-agricultural employment opportunities for agricultural laborers who cannot leave their hometowns for various reasons.

Hypothesis 1: DFI contributes to a reduction in the URI gap within the county.

2.2 The spatial effects of DFI on the narrowing of the URI gap

The inherent digital characteristics of DFI eliminate the need for geospatial constraints on service coverage, leading to evident spatial spillover effects (Ash *et al*., 2018; Lee *et al*., 2023; Mastronardi and Cavallo, 2020). Spatial spillover effects are likely to be more pronounced at the county level than at the provincial or municipal levels attributed to counties being geographically closer and sharing more similar production conditions. Specifically, counties located at interprovincial borders, despite being part of different provinces and cities, engage in economic interactions more frequency than those within the same province (MacLeod and Goodwin, 1999).

Hypothesis 2: DFI has a more pronounced spatial spillover effect on the URI gap at the county level.

2.3 The role of DFI in reducing the URI gap within counties.

Emerging entrepreneurs confront an initial capital threshold imposed by liquidity constraints (Evans and Jovanovic, 1989). The conventional financial system exacerbates this challenge through credit rationing mechanisms that stem from information asymmetries (Stiglitz and Weiss, 1981) and are compounded by systemic collateral deficiencies (Banerjee and Newman, 1993). DIF, exemplified by platforms such as Ant Financial Services', employs multi-dimensional behavioral data analytics to assess creditworthiness, thereby circumventing traditional collateral requirements (Demirgüç-Kunt and Klapper, 2013). According to the 2020 County Entrepreneurship Report, jointly released by 58Town and Tsinghua University, more than half of county entrepreneurs return to their hometowns. The report further indicates that county entrepreneurship is predominantly characterized by home-based enterprises, with the majority of these businesses being small and micro-enterprises. Specially, 25.5% of county entrepreneurs opted for online lending to meet their modest capital needs, with 63.6% obtaining loans of less than RMB 50 000 online. Additionally, mobile payment is a popular choice among county entrepreneurs due to its convenience, efficiency, security, and reliability. Beyond meeting the financing needs of entrepreneurship, DFI can also stimulates labor inflow by offering employment opportunities and raising expected income (Liu *et al*., 2023b; Reljic *et al*., 2021), which supports the coordinated development of counties and reduces the income gap between urban and agricultural areas to a certain extent. Consequently, this paper posits the following hypothesis:

Hypothesis 3: DFI has the effect of reducing the URI gap by increasing entrepreneurial activity in the county.

Furthermore, a broad consensus among existing studies suggests that a series of urban-biased policies, implemented since the reform and opening-up, have been a significant contributor to China's substantial URI gap (Bezemer and Headey, 2008; Nie *et al*., 2023; Yang, 1999). China has introduced several key policies, including the "Village to Village" project, a pilot program for e-commerce in agricultural areas, network poverty alleviation initiatives, and the pilot project of digital villages. These policies have led to substantial improvements in rural connectivity, with the rate of fiber optic access to administrative villages reaching, and broadband access in impoverished villages and 4G coverage in administrative villages both exceed 99%. Furthermore, comparable network speeds have been achieved in both urban and agricultural areas, stimulating the development vitality of agricultural areas. The rural revitalization strategy, along with other policies, provides institutional support for the widespread distribution of the digital technology dividend through market and social mechanisms (Qian and Chen, 2023; Zeqi *et al*., 2019). Policy interventions have systematically restructured rural market architectures and stimulated value chain upgrading in agricultural sectors. Aligning with skill-biased technological change theory (Acemoglu, 2002), the proliferation of digital intermediation platforms demonstrates measurable labor market effects, particularly in generating wage premiums for non-agricultural occupations. Concurrently, the spatial expansion of digitized distribution networks has substantially mitigated information asymmetries in agricultural product markets, thereby enhancing producers' price-setting capabilities. Empirical evidence confirms that rural e-commerce growth operates as: (1) an infrastructure catalyst for logistics modernization; (2) a tertiary sector development multiplier through employment elasticity effects. Furthermore, this digital transition induces occupational specialization by decoupling commercial functions from primary production activities. This structural transformation ultimately contributes to sustainable rural development through productivity gains (Li and Qin, 2022). Consequently, this paper posits that:

> Hypothesis 4: The introduction and incremental implementation of the rural-focused pilot policy will promote the realization of the goal of DFI in enhancing financial inclusivity, thereby reducing the URI gap at the county level.

3. Research model and hypotheses

3.1 Variable

(1) URI gap. The existing literature on the income gap between urban and rural residents employs three main approaches: the income ratio between urban and rural residents, the Thiel index, and the Gini coefficient (De Maio, 2007; McCall and Percheski, 2010; Ravallion, 2014). Among these methods, the Gini coefficient is less appropriate for measuring the income gap between urban and rural residents separately (Amiel, 1999; Milanovic, 1997). Conversely, the Thiel index incorporates both the urban-rural population structure and income into a unified measurement of the URI gap(Silber, 2012). However, given the data limitations of this study, which are at the county level with a higher proportion of missing data on urban and rural populations, the Thiel index may not be the most appropriate for this analysis. To ensure sample availability, the paper employs the ratio of urban-rural disposable incomes as the primary indicator for measuring the URI gap. Data on disposable income per capita for urban and rural residents were sourced from the 2015–2020 China County Statistical Yearbook, selected prefecture-level city statistical yearbooks, and the Wind database.

(2) The DFI index. The DFI Index is developed by the Digital Finance Research Center at Peking University in collaboration with the Ant Group Research Institute. The index is composed of 33 specific indicators organized into three dimensions: breadth of digital financial coverage, depth of digital financial use, and degree of digitalization of inclusive finance. The dataset includes 31 provinces, 337 cities above the prefecture level, and approximately 2800 counties at the three aforementioned levels. Additionally, the group offers supplementary indices: the digital finance coverage breadth index, the digital finance use depth index, and the inclusive finance digitization degree index (Guo *et al*., 2016). To address endogeneity and ensure the robustness of the results, the DFI index is modeled as a logarithmic variable.

(3) Entrepreneurial activity. In the context of counties, a higher level of entrepreneurial activity is indicative of greater economic development vitality and a more conducive innovation atmosphere (Stel *et al*., 2005; Stoica *et al*., 2020; Urbano *et al*., 2019). Furthermore, a higher level of entrepreneurial activity is associated with greater importance placed on addressing county-level employment challenges and raising the income level of residents. In this study, the number of new enterprises registered in the county is used to gauge entrepreneurial activity, with the number of enterprises above the county level utilized as a standardizing reference(Cowden *et al*., 2024). This indicator of entrepreneurial activity is calculated by dividing the number of new enterprises by the number of enterprises above the county level.

(4) Control variables. To control for the impact of other factors on the URI gap within counties, this paper includes several control variables. Economic growth is a key determinant of income levels and disparities among regional residents (Saunders, 1992). We use per capita GDP as a measure of economic advancement within the county. The growth of the tertiary sector enhances employment opportunities and reduces income disparity between urban and rural regions (Kenessey, 1987). We use the tertiary sector's share to gauge the level of industrial sophistication within the county. Furthermore, access to traditional financial loans serves as an indicator of regional development. These factors have also been identified as significant influencers of income disparity between urban and rural residents. We use the county's annual loan balance as a percentage of GDP to gauge financial development. Moreover, fiscal spending significantly influences income disparity between urban and rural regions (Carrère and De Melo, 2012). We use the ratio of general budget expenditure to GDP as a proxy for government capacity. Additionally, regional human capital

accumulation and infrastructure improvements influence the URI gap (Gennaioli *et al*., 2012). We use the number of secondary school students per 10 000 people and fixed-line telephones per capita as indicators of human capital and infrastructure levels in counties.

3.2 Data

This study constructs a strongly balanced panel comprising 4902 county (district)-year observations for 817 counties (districts) in China from 2014 to 2019. The primary data infrastructure integrates government-published statistical compendiums including the China County Statistical Yearbook and prefecture-level municipal yearbooks, supplemented by market intelligence from the CSMAR database. Notably, the new enterprise registration metrics and Digital Financial Inclusion (DFI) index constitute independently sourced proprietary datasets. All variables demonstrate complete records with <2% missing observations, their distributional characteristics being systematically summarized in Table 1.

3.3 Model

We employ a two-way fixed effects model at the county and time level, with the baseline model specified as follows:

$$\ln \text{income}\_g_{irt} = \beta_0 + \beta_1 \ln \text{index}_{irt} + \beta_2 M + \beta_3 M + \lambda_t + \theta_r + \xi_{irt}$$

In this model, ln income$_g_{irt}$ represents the logarithm of the URI gap, while ln index denotes the logarithm of the DFI index. *M* serves as a mechanism variable, encompassing factors such as entrepreneurial activity and the status of a policy pilot. *X*, on the other hand, denotes control variables at the county level, including the presence of a policy pilot and other mechanism variables.

The model also incorporates time and county fixed effects, denoted by λ and θ, respectively. Finally, ξ represents the random error term.

4. Verification of hypotheses

4.1 Benchmark regression analysis

The results of the benchmark regression analysis are presented in Table 2. As noted, economic activities between counties are relatively proximate, suggesting the potential for forward or backward socio-economic

Table 1. Descriptive statistics

Variable	Observations	Mean	Min	Max	SD
URI	4902	2.41	0.91	6.15	0.61
DFI Index	4902	86.51	15.19	135.29	24.08
Coverage	4902	81.22	5.56	168.43	21.26
Usage	4902	98.47	6.54	190.85	33.74
Per_GDP	4902	39 739.72	5066.42	463 000	34 456.98
Budget Expense	4902	0.28	0.01	2.07	0.19
Entrepreneurial	4902	79.29	0.06	1380.75	98.72
Industry	4902	1.29	0.11	54.98	1.61
Loans	4902	1 270 000	36 737	28 200 000	1 920 000
Fixed-line Telephones	4902	41 224.03	413.00	979 000.00	50 133.56
Human Capital	4902	472.30	20.44	1353.11	154.05

correlations. Consequently, interactions between different counties in the same period are anticipated. This study begins by assessing between-groups heteroskedasticity, between-groups contemporaneous correlation, and within-groups autocorrelation on the panel data. The results of the test indicate that the sample counties do not exhibit intergroup heteroskedasticity. Nevertheless, there is a notable presence of intergroup contemporaneous correlation and intragroup autocorrelation. Accordingly, this study employs the feasible generalized least squares (FGLS) approach, which accounts for contemporaneous correlation in estimation, with results presented in models (5)–(8) of Table 2. For comparative purposes, models (1)–(4) in Table 2 present the results of ordinary panel regressions with a fixed-effects model that passes the Hausman test. Among the models, those numbered (1) and (5) regress the effect of the DFI index on the URI gap alone, with significantly negative results. Models (2) and (6) incorporate control variables and year fixed effects, with results remaining significantly negative. Additionally, the model's R^2 increases with the inclusion of control variables, underscoring their necessity. Isolating the impact of DFI on the URI gap, it is evident that DFI development contributes to reducing this gap.

To further examine the potential nonlinear relationship between DFI and URI gap within the county, this study incorporates the squared term of DFI in models (3) and (7). Furthermore, models (4) and (8) include control variables and time fixed effects. The findings show that the coefficient of DFI is significantly positive when the squared term is included, while the quadratic term is significantly negative. This suggests that the impact of DFI development on the URI gap within the county is characterized by an inverted "U" shape, which supports the conclusions of existing studies such as Jiang *et al*. (2022) and Zhang *et al*. (2019).

However, the impact of DFI appears to be contradictory in conjunction with the results from Model 6. This study suggests a potential explanation for this outcome: the accelerated expansion of Internet infrastructure in rural China between 2014 and 2019 may have led the influence of DFI on the URI gap to a point of inflection, signaling a monotonic decline. Accordingly, we further calculate the inflection point position of the logarithmic value of DFI to be 3 and obtain the nonlinear fitting graph of the two. The logarithmic values of DFI in the sample counties range from 2.7 to 4.95, placing the majority on the right side of the inflection point. Based on these findings, this study concludes that, while the impact of DFI on the URI gap is nonlinear, the current development trajectory of the sample counties suggests that DFI has started to reduce the URI gap within the county since 2014. Since 2013, the Chinese government has successively implemented the "Broadband China Strategy and Implementation Plan (2013–2020)" and the "National Internet Poverty Alleviation Program (2016–2020)". These programs have greatly improved the internet infrastructure in rural China. Relevant data shows that by 2020, the proportion of administrative villages with broadband access reached

Table 2. Results of the benchmark regression

	Ordinary Panel Regression Model				**FGLS**			
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
lnindex	−0.504***	−0.127***	1.863***	0.00550	−0.0563***	−0.0362***	0.155***	0.134**
	(−26.9923)	(−6.8711)	(8.8904)	(0.0295)	(−8.6210)	(−4.2232)	(3.1974)	(2.2447)
lnindex2			−0.295***	−0.0170			−0.0256***	−0.0225***
			(−11.3382)	(−0.7149)			(−4.2302)	(−2.8306)
Control variable	NO	YES	NO	YES	NO	YES	NO	YES
Year fixed effects	NO	YES	NO	YES	NO	YES	NO	YES
No. of observations	4902	4902	4902	4902	4902	4902	4902	4902
R^2	0.1285	0.4296	0.1506	0.4295				

Note: *t*-values in parentheses, *, ** and *** indicate significance at the 1, 5 and 10% level, respectively.

98% nationwide. The Construal-Level Theory also points out that the improvement of infrastructure makes it easier for farmers to perceive the direct impact of DFI (such as the convenience of mobile payments), which enhances the effectiveness of policy implementation (Trope and Liberman, 2010).

4.2 Spatial spillover analysis

As shown in Table 3, the Moran's I between the county's DFI and URI, weighted by geographic, exhibits a statistically significant positive correlation at the 1% level for the period from 2014 to 2019. This suggests a significant positive spatial correlation between the degree of DFI and URI in the county, along with evidence of spatial clustering in both (Kalogirou and Hatzichristos, 2007; Yamamoto, 2008).Furthermore, the Moran's I for the preceding years shows an increasing trend, indicating that the degree of spatial agglomeration between regions is increasing and that regional discrepancies are tending to expand. To determine the impact of DFI on the URI gap within counties, a spatial panel model will be utilized for the analysis.

The Spatial Durbin Model (SDM), as a general form of spatial econometric model, allows for the concurrent examination of both the spatially lagged term of the URI gap and the impact of spatially lagged explanatory variables on the URI gap (Anselin, 2010; Mur and Angulo, 2006). Thus, the SDM is formulated as follows:

$$\begin{aligned}\ln \text{income}\_g &= \rho\sum_{j=1}^{N} W_{ij} \ln \text{income}\_g + c \\ &\quad + \delta \ln \text{index}_{it} + \beta \ln x_{it} + \sum_{j=1}^{N} W_{ij} (\ln x_{jt} + \ln \text{index}_{jt})\theta + \mu_i + \lambda_t + \xi_{it}\end{aligned}$$

where θ and β are constant regression parameters to be estimated. The Likelihood Ratio (LR)test shows that the Prob>chi² values are 0.0002 and 0.000, respectively. Thus, we conclude that the SDM cannot degenerate into a spatial lag model or a spatial error model. The Hausman test indicates that the double fixed-effects SDM is the optimal choice.

The construction of the weight matrix plays a crucial role in determining the model's accuracy in characterizing spatial dependence relationships. In this study, three distinct spatial weight matrices are employed to capture multidimensional spatial interaction mechanisms: the 0–1 adjacency matrix, the geographical distance matrix, and the economic distance matrix. The 0–1 adjacency matrix, primarily emphasizing physical proximity (Takahisa and Asao, 2012), serves as a binary indicator to measure geographical contiguity between counties. This matrix assigns a value of 1 to adjacent county pairs and 0 to non-adjacent pairs. However, this approach has limitations in capturing potential associations between non-contiguous spatial units. The geographical distance matrix, constructed using either the threshold method or inverse distance weighting (Kelejian and

Table 3. Spatial autocorrelation between DFI and URI gap in counties, 2014–2019

Year	**DFI**		**URI gap**	
	Moran's *I*	***Z*-value**	**Moran's *I***	***Z*-value**
2014	0.432***	16.560	0.395***	15.126
2015	0.495***	18.963	0.421***	16.147
2016	0.538***	20.616	0.401***	15.377
2017	0.579***	22.176	0.404***	15.488
2018	0.592***	22.657	0.416***	15.940
2019	0.612***	23.422	0.421***	16.135

Note: t-values in parentheses, *, ** and *** indicate significance at the 1, 5 and 10% level, respectively.

Prucha, 2010), is particularly suitable for analyzing economic activities sensitive to transportation costs. In contrast, the economic distance matrix utilizes the reciprocal of economic indicator differentials as weights to capture non-geographical spatial associations (Case *et al*., 1993). This matrix is particularly effective in revealing the core-periphery structure of county economies (Krugman, 1991).The selection and implementation of these matrices enable a comprehensive examination of spatial interactions across different dimensions, providing a robust framework for spatial econometric analysis. Furthermore, the estimation results of the spatial lag model (SAR) with double fixed effects are presented in Table 4 for comparative purposes.

Table 4 reveals that the spatial autoregression coefficients are all significantly positive at the 1% level, suggesting that the county urban-rural per capita income gap exerts a positive spatial spillover effect on itself. Conversely, the coefficient of the spatial interaction term for DFI is negative, indicating that the expansion of DFI in neighboring counties exerts a detrimental influence on the local URI gap. This effect is notably pronounced when considering the economic distance and the adjacency weight matrix.

However, the spatial interaction coefficients do not fully capture the relationship between the two variables. Therefore, further calculation of the marginal effects of these variables is necessary. Table 4 shows that DFI has a profound impact on the URI gap within the county, both directly and indirectly, as well as cumulatively. The direct effect results reveal that the regression results of the three matrices are all significantly negative at the 1% level, suggesting that the level of DFI development within the county significantly reduces the URI gap in the county. Additionally, the indirect effect is significantly negative, indicating that the level of DFI development in neighboring counties contributes to the reduction of the local URI gap. This is consistent with Hypothesis 2.

Table 4. Spatial spillover effect regression result

	SAR			**SDM**		
	0–1	**(2) Economic matrix**	**(3) Distance matrix**	**(4) 0–1**	**(5) Economic matrix**	**(6) Distance matrix**
ρ	0.287***	0.151***	0.802***	0.276***	0.0949***	0.782***
	(18.04)	(5.06)	(31.77)	(16.81)	(3.04)	(29.09)
ln index	−0.0501***	−0.0550***	−0.0339***	−0.0462***	−0.0386***	−0.0337***
	(−11.50)	(−11.96)	(−8.10)	(−9.34)	(−7.16)	(−5.87)
ln index*W				−0.0143**	−0.0599***	−0.00365
				(−2.12)	(−5.31)	(−0.32)
Control variables	YES	YES	YES	YES	YES	YES
log likelihood	9765.9466	9629.2748	9983.114	9780.066	9656.3458	9999.8737
Direct effect	−0.0511***	−0.0550***	−0.0353***	−0.0481***	−0.0391***	−0.0351***
	(−11.20)	(−11.64)	(−7.90)	(−9.74)	(−7.11)	(−6.11)
Indirect effect	−0.0187***	−0.00957***	−0.137***	−0.0350***	−0.0699***	−0.138***
	(−9.26)	(−4.63)	(−5.60)	(−4.52)	(−5.88)	−3.29)
Total effect	−0.0698***	−0.0645***	−0.173***	−0.0831***	−0.109***	−0.173***
	(−11.16)	(−11.70)	(−6.33)	(−10.21)	(−10.24)	(−4.25)
N	4902	4902	4902	4902	4902	4902
R^2	0.020	0.012	0.013	0.002	0.003	0.009

Note: *t*-values in parentheses, *, ** and *** indicate significance at the 1, 5 and 10% level, respectively.

4.3 Robustness tests

4.3.1 Instrumental variables testing

Studies have shown that the impact of DFI on economic growth is endogenous. Thus, large sample sizes do not preclude the possibility of biased empirical results (Yu *et al*., 2022). To mitigate endogeneity, instrumental variables including geographic distance, neighboring region digital finance indices, Internet development levels, and historical Internet development can be utilized for DFI (Zhu, 2023).

When determining geographic proximity, we primarily consider the distance from each county to the provincial capital. This is due to the fact that the provincial capital is typically the economic hub of a province and often the epicenter of digital financial advancement. Thus, regions closer to the provincial capital are expected to have more advanced its levels of DFI.

Furthermore, the topographic relief of each county is identified as an instrumental variable (Feng *et al*., 2008).An inverse relationship exists between topographic relief and the costs associated with installing base stations and fiber optic broadband. With reduced topographic relief and flatter terrain, installation costs decrease, enabling more efficient information transmission. In contrast, areas with higher terrain, such as mountainous regions and counties with elevated topography, incur higher installation costs, which subsequently affects the pace of DFI development.

Since this study employs panel data and both distance and undulation are time-invariant variables, it is essential to apply a logarithmic transformation to the number of provincial mobile Internet users (MIU) during the observation period, for each county's respective province. This method captures the dynamic, time-varying aspects of the instrumental variables, thereby ensuring their synchronization with the bidirectional dynamics of time and county-specific factors (Guo *et al*., 2023; Nunn and Qian, 2014; Tao *et al*., 2022).

The impact of DFI on the URI gap at the county and district levels remains significantly negative, irrespective of the instrumental variable used, whether distance or slope. This provides further validation for the findings of the preceding analysis, indicating that the conclusions are relatively robust.

4.3.2 Replacement samples

To further verify the robustness of the findings, we performed supplementary regression analyses, altering the set of explanatory variables and the sample periods individually. The specific outcomes of these supplementary analyses are presented in Table 5. Models (1) and (2) replace the explanatory variables with the one-period lagged DFI, while models (3) and (4) segment the research intervals into 2014–2016 and 2015–2018, respectively. As shown in Table 5, all other results exhibit a significantly negative trend.

5. Mechanism testing

5.1 Mediating effects of entrepreneurial activity

The results of the mediating effect test for entrepreneurial activity in the county are presented in Table 6. Models (1) through (3) aim to test this transmission mechanism. Model (3) presents the regression outcomes with county entrepreneurial activity as a mediating variable. Table 6 illustrates that the Sobel test exhibits a Z-value of −5.869, which successfully passes the 1% significance level test. Furthermore, the coefficient for DFI decreases from 0.127 in the baseline model to 0.121. The Sobel test results suggest that the mediating effect explains 5.25% of the total effect, thereby confirming Hypothesis 3 and corroborating the findings of existing studies.

Table 5. Changing explanatory variables and study intervals

	Changing explanatory variables		**Study intervals**	
	(1)	**(2)**	**2014–2016**	**2015–2018**
ln index	-0.0564^{***}	-0.0470^{***}		
	(−22.1451)	(−8.6890)		
ln index			-0.0420^{***}	-0.0606^{***}
			(−6.0959)	(−7.4635)
Control variable	NO	YES	YES	YES
Year fixed effects	NO	YES	YES	YES
N	4085	4085	2451	3268
R^2	0.250	0.311	0.187	0.272

Note: *t*-values in parentheses, *, ** and *** indicate significance at the 1, 5 and 10% level, respectively.

Table 6. Mediation effect test of county entrepreneurial activity

	(1) URI	**(2) Entrepreneurial activity (EA)**	**(3) URI**	**(4) URI**
ln index	-0.1272^{***}	-0.3248^{***}	-0.1206^{***}	-0.1199^{***}
	(−6.87)	(−4.20)	(−6.52)	(−6.483)
Entrepreneurial activity			0.0205^{***}	0.0216^{***}
			(6.02)	(6.032)
EA×EP				−0.009813
				(−1.024)
Control variable	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES
N	4902	4902	4902	4902
R^2	0.4352	0.3150	0.4407	0.4420
Sobel *Z*-value			−5.869 (0.000)	−8.881 (0.000)

Note: *t*-values in parentheses, *, ** and *** indicate significance at the 1, 5 and 10% level, respectively.

Additionally, China identified three groups of counties, totaling 351, as pilot regions for the initiative to encourage migrant workers and other individuals to return to their hometowns and start businesses between 2016 and 2017. We can thus conclude that this policy contributes to an increase in entrepreneurial activity in counties. To further validate this conclusion, the paper examines the interaction term between entrepreneurial activity (EA) and entrepreneurial pilots (EP). The outcomes of this analysis, presented in model (4) of Table 6, confirm that the mediating effect's conclusion is robust.

5.2 Impact of pilot policy

To ascertain the moderating influence of the e-commerce-to-village pilot policy on the impact of DFI on the URI gap, we created an interaction term between the DFI index and the county's designation as an e-commerce-to-village pilot. The earlier a county's designation as a pilot, the greater the likelihood that the policy exerts a moderating effect. Accordingly, we include the duration of a county's pilot status in the model, creating interaction terms for the DFI index, the e-commerce pilot status, and the duration of the pilot status. The results are presented in Model (4) of Table 8. Models (1) and (3) exclude control variables, while Models (2) and (4) include control variables and use two-way fixed effects for cross-sectional and temporal dimensions.

Table 7 shows that the impact of the DFI index on the URI gap within the county remains significantly negative after the introduction of the moderating variable, namely the policy in question. Additionally, the designation of a county as a pilot region for e-commerce initiatives in agricultural areas has been shown to contribute to a reduction in the URI gap. However, concerning the interaction term, the interaction between the pilot counties of e-commerce in villages and DFI is not statistically significant when the number of years of piloting is not considered. Conversely, the coefficient of this interaction term is significantly positive when the number of years of piloting is controlled for. This seems to challenge the preceding hypothesis. However, when the coefficient of the Village E-commerce Pilots counties themselves (−0.298) is considered, the implementation of the Village E-commerce Pilots still reduces the URI gap.

6. Discussion and conclusions

6.1. Discussion

Initially, differences in regional development levels are examined by categorizing the sample counties based on their geographical location as eastern, central, and western regions. Second, the study compares the differences between impoverished and non-impoverished counties, utilizing the list of 832 nationally-designated poor counties as a reference during the poverty alleviation period. Third, the study assesses the varying impacts of DFI on the URI gap across different dimensions.

Table 8 shows that the implementation of DFI has the effect of reducing the URI gap within the eastern, central, and western counties. However, this impact is more pronounced in the central and western regions of the country. Additionally, the coefficient for impoverished counties is larger than for non-impoverished ones, indicating that the development of DFI is particularly advantageous for counties with lower income levels.

This study focuses on the dimensions of digital finance, examining not only the three dimensions of depth of use, breadth of coverage, and degree of digitization, but also exploring the heterogeneity within the depth of use, which includes payment, insurance, investment, and credit. Table 9 shows that both the depth of use and breadth of coverage of digital finance significantly reduce the URI gap within the county. However, the reverse impact of digitization may be due to the digital infrastructure gap between urban and agricultural areas. Regarding the sub-indicators of the depth of use of digital finance, the coefficients for payment,

Table 7. Moderating effects of village e-commerce pilots

	(1)	(2)	(3)	(4)
ln index	-0.0703^{***}	-0.0589^{***}	-0.0699^{***}	-0.0603^{***}
	(−25.5997)	(−8.5815)	(−25.5819)	(−8.5856)
E-commerce Pilots	0.0252	−0.0394	-0.298^{***}	-0.164^{**}
	(0.5175)	(−0.8998)	(−3.5473)	(−2.0016)
ln index × E-commerce Pilots	−0.00695	0.00699	0.0542^{***}	0.0306^{*}
	(−0.6460)	(0.7262)	(3.3455)	(1.9451)
ln index × Pilots × Years			0.00351^{***}	0.00139
			(4.0287)	(1.5780)
Control variable	NO	YES	NO	YES
Year fixed effects	NO	YES	NO	YES
N	4902	4902	4902	4902
R^2	0.300	0.362	0.309	0.363

Note: t-values in parentheses, *, ** and *** indicate significance at the 1, 5 and 10% level, respectively.

Table 8. Discussion of impact differences by region

	East	**Middle**	**West**	**Impoverished**	**Non–impoverished**
ln index	−0.0308***	−0.0625***	−0.0486***	−0.0458***	−0.0149***
	(−6.2725)	(−5.3756)	(−5.5437)	(−3.9327)	(−3.1589)
Control variable	YES	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES	YES
N	1272	2118	1512	1943	2869
Adj. R^2	0.4438	0.1108	0.3984	0.3134	0.1820

Note: *t*-values in parentheses, *, ** and *** indicate significance at the 1, 5 and 10% level, respectively.

Table 9. Impact of DFI sub-indicators

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
Depth	−0.0233***						
	(−4.9458)						
Coverage		−0.0401***					
		(−13.3537)					
Digitization			0.00726***				
			(3.0294)				
Payment				−0.0102***			
				(−5.6412)			
Insure					−0.00797***		
					(−4.9720)		
Invest						−0.00367	
						(−1.3691)	
Credit							−0.00570**
							(−2.0575)
N	4902	4902	4902	4902	4902	4902	4902
R^2	0.340	0.364	0.337	0.341	0.340	0.336	0.336
Adj. R^2	0.2054	0.2342	0.2025	0.2069	0.2055	0.2010	0.2015

Note: *t*-values in parentheses, *, ** and *** indicate significance at the 1, 5 and 10% level, respectively.

insurance, investment, and credit are all negative, suggesting that these aspects positively contribute to narrowing the URI gap.

This result can be attributed to the following factors: First, the development of third-party payment platforms, such as Alipay, can effectively reduce the transaction costs associated with sales and operations for rural residents (Ding *et al*., 2018), expand the scope of transactions, thereby increasing the income level of farmers (Jensen, 2007). Furthermore, digital credit addresses the need for small-scale financing among rural residents (Li, 2018; Liu *et al*., 2023a), while digital insurance mitigates the impact of production and market risks faced by farmers (Mottaleb *et al*., 2017). Nevertheless, the investment function of digital finance is not yet widely utilized among rural residents, limiting its current impact. As digital finance becomes more deeply integrated into rural communities, the income-enhancing potential of the investment function is likely to grow (Kling *et al*., 2022).

6.2 Conclusions

This study utilizes panel data from 2014 to 2019 at the county level to empirically examine the impact of DFI on the URI gap within counties and the underlying mechanisms. Specifically, the study investigates the mediating impact of county entrepreneurial activity in this process. The analysis employs panel double fixed-effects models, spatial econometric models, and mediating-effects models in a multidimensional and multilevel manner. The principal findings are:

Since 2014, DFI has significantly reduced the URI gap. There is a significant spatial spillover effect of the impact of the development of DFI on the URI gap within counties, which helps to improve the pattern of URI distribution among counties. Regarding the mechanism of action, DFI has reduced the URI gap by spurring entrepreneurial activity at the county level. Additionally, pilot programs promoting e-commerce in agricultural areas enhance the role of DFI in reducing the URI gap. The depth of DFI utilization has a more significant impact on narrowing the URI gap than the level of digitization.

Given that our data covers the critical period of China's targeted poverty alleviation campaign (2013–2020), the findings provide timely empirical evidence for developing countries implementing the UN Sustainable Development Goals (SDGs), particularly SDG 1 (No Poverty) and SDG 9 (Industry Innovation and Infrastructure). Our findings carry threefold implications for developing countries: first, the demonstrated spatial spillover effects suggest that neighboring counties can form synergistic clusters. This provides empirical support for developing countries to establish regional digital finance hubs instead of isolated county-level interventions. Second, the mediating role of entrepreneurship implies that digital finance policies should be coupled with entrepreneurial training programs — a cost-effective approach for resource-constrained developing nations. Third, the amplified effect under e-commerce pilots underscores the importance of policy sequencing: digital infrastructure development should precede large-scale financial inclusion initiatives.

6.3 Limitations

This paper is limited in several ways. First, due to the data and analytical requirements of this study, a balanced panel dataset of counties was utilized, which inevitably led to a reduction in the analytical sample size. Furthermore, the study does not encompass a complete national sample of counties. Secondly, the selected instrumental variables can only partially address the endogeneity issue. Further research is necessary to ascertain greater explanatory power and to identify more suitable methods to address the endogeneity issue. Third, while the implementation of the digital countryside pilot policy may significantly influence the impact of DFI, the brief duration of policy implementation to date precludes a comprehensive assessment of its policy effects.

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