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Mechanisms and spatial effects of digital rural development on the urban–rural income gap

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Abstract. Digital rural development has become one of the key initiatives for advancing rural revitalization and addressing unbalanced development. This study employs the Theil index to measure the urban–rural income gap and investigates the mechanisms and spatial effects of digital rural development using the entropy weighting method, spatial econometric models, and the instrumental variable approach. The results indicate that digital rural development contributes to narrowing the urban–rural income gap and exhibits significant spatial spillover effects. In addition, higher urbanization rates and greater human capital help reduce the income gap between urban and rural areas, whereas long-term fiscal support for agriculture does not produce a statistically significant effect. This study provides empirical evidence to support the acceleration of digital rural development and the promotion of integrated urban–rural development.

Keywords: spatial econometric model, digital rural development, urban–rural income gap, Theil index

1. Introduction

1.1. Research background and significance

In the course of rapid modernization, coordinated urban–rural development has become a central prerequisite for achieving common prosperity. The urban–rural income gap, as a key indicator of imbalance in urban–rural development, has long attracted widespread attention from both policymakers and scholars [1]. Although China has experienced sustained economic growth and remarkable improvements in living standards since the reform and opening-up, and the overall urban–rural income gap has shown a fluctuating yet narrowing trend, persistent regional disparities remain unresolved [2]. Differences in income levels and development opportunities between urban and rural areas continue to constrain economic development and the realization of common prosperity [3].

At the same time, the rapid advancement of digital technologies has opened new avenues for addressing urban–rural development imbalances. The *Opinions of the CPC Central Committee and the State Council on Further Deepening Rural Reform and Advancing All-Around Rural Revitalization (2025)* proposed the implementation of a special initiative to strengthen agriculture, benefit rural communities, and increase farmers' incomes through digital rural development. As an integral component of the Digital China strategy, digital rural development is reshaping rural production and daily life while transforming the allocation of factors between urban and rural areas through improvements in digital infrastructure, the digital transformation of agriculture, and the upgrading of rural public services [4]. In practice, digital rural development has not only accelerated the expansion of digital infrastructure, such as 5G networks and fiber-optic broadband, into rural areas but has also fostered new business models and industries, including rural e-commerce, smart agriculture, and online government services [5]. Against this backdrop, identifying the mechanisms through which digital rural development influences the urban–rural income gap, evaluating its policy effectiveness, and addressing the endogeneity and spatial dependence overlooked in previous studies are essential not only for enriching the literature on the digital economy and income distribution but also for optimizing digital rural development policies, facilitating the two-way flow of factors between urban and rural areas, and advancing common prosperity [6].

1.2. Literature review

1.2.1. The relationship between digital technology and the income gap

Existing research has produced extensive theoretical insights into the relationship between digital technology and income inequality, with most studies focusing on its dual effects on urban–rural income distribution. On the one hand, proponents of the "narrowing effect" argue that digital technology reduces information asymmetry [7], overcomes geographical constraints, and creates broader employment opportunities for economically disadvantaged regions and low-income groups, thereby alleviating income inequality. For example, the development of digital finance has provided convenient credit services for rural residents and small and micro enterprises that have traditionally been underserved by conventional financial institutions, easing financing constraints and promoting income growth [8]. Likewise, rural e-commerce platforms have expanded marketing channels for agricultural products, reduced transaction costs, and increased farmers' incomes. On the other hand, advocates of the "widening effect" contend that the adoption of digital technology is characterized by threshold effects. Individuals with higher levels of skills and income are better positioned to acquire and utilize digital technologies, enabling them to capture greater technological dividends. By contrast, low-skilled and low-income groups may become increasingly marginalized because of inadequate digital literacy and limited access to digital infrastructure, thereby intensifying the digital divide and widening income inequality [9]. Moreover, some studies have examined the impact of digital technology on the labor market, arguing that the diffusion of automation and intelligent technologies may replace low-skilled workers, suppress their wages, and consequently exacerbate income disparities [10].

Drawing on the existing literature, this study supports the "narrowing effect" perspective. Digital rural development contributes to reducing the urban–rural income gap by promoting rural industrial upgrading [11], optimizing the allocation of factors between urban and rural areas, and improving the provision of rural public services [12]. For instance, previous studies have shown that the expansion of rural e-commerce not only directly increases farmers' operating income but also stimulates the development of related industries, such as rural logistics and packaging, thereby creating substantial non-agricultural employment opportunities and raising wage income for rural residents [13]. Similarly, the adoption of smart agriculture enhances agricultural productivity and the value added of agricultural products, facilitates the large-scale and intensive development of agriculture, and provides strong support for sustained income growth among farmers [14].

1.2.2. Research methods on digital rural development and the urban–rural income gap

With regard to research methodology, existing studies have primarily relied on conventional econometric approaches, including Ordinary Least Squares (OLS) estimation and fixed-effects models [15]. Although some studies have attempted to address endogeneity by employing Instrumental Variable (IV) methods [16], two major limitations remain. First, previous research has largely overlooked spatial dependence among variables.

Both digital rural development and the urban–rural income gap exhibit pronounced spatial heterogeneity, and neighboring provinces may influence one another [17]. Conventional econometric models generally fail to account adequately for such spatial correlations, which may lead to biased estimation results. Second, approaches to addressing endogeneity remain relatively limited, and the validity of instrumental variables is often questionable. A bidirectional causal relationship may exist between digital rural development and the urban–rural income gap. On the one hand, digital rural development can contribute to narrowing the income gap; on the other hand, a reduced income gap may generate greater financial resources and stronger demand for digital rural development [18]. Existing studies frequently lack sufficient theoretical justification and empirical validation for their choice of instrumental variables, thereby undermining the credibility and robustness of their empirical findings.

2. Theoretical analysis and research hypotheses

2.1. Spatial heterogeneity theory

Given the substantial disparities across rural regions in terms of economic development and digital infrastructure, the impact of digital rural development on the urban–rural income gap exhibits pronounced spatial heterogeneity [19].

From the perspective of regional development, the effectiveness of digital rural development and its implications for income distribution differ considerably between economically developed and less-developed regions. Developed regions generally possess stronger economic foundations, earlier and more advanced digital infrastructure deployment, and higher levels of digital literacy among rural residents. Consequently, digital technologies have been more extensively integrated into agricultural production, rural e-commerce, and public service delivery in these areas [20]. Under such conditions, digital technologies facilitate the efficient allocation of production factors, accelerate industrial upgrading, and improve public services, thereby producing a stronger income-equalizing effect between urban and rural areas. In contrast, less-developed regions are constrained by weaker economic foundations, relatively underdeveloped digital infrastructure, and lower levels of digital literacy among rural residents. These limitations hinder the diffusion and application of digital technologies, reducing the effectiveness of digital rural development in narrowing the urban–rural income gap. In the short term, the persistence of the digital divide may even widen income disparities between urban and rural areas [21].

From the perspective of spatial interactions, the income distribution effects of digital rural development demonstrate significant spatial spillover effects [22]. Core provinces possess clear advantages in digital technology innovation, digital industrial development, and digital talent cultivation. The achievements of digital rural development in these provinces can spread to neighboring regions through technology diffusion, factor mobility, and policy imitation. For example, rural e-commerce platforms established in core provinces may expand into adjacent provinces, promoting the sales of agricultural products in neighboring areas. Likewise, digital technology enterprises from core provinces may invest in surrounding regions, relocate digital production capacity, and generate employment opportunities. Furthermore, successful digital rural development policies and practical experience in core provinces can serve as valuable references for neighboring regions, accelerating their own digital rural development. Through these spatial spillover effects, digital rural development in core provinces contributes to narrowing the urban–rural income gap in surrounding areas, thereby fostering coordinated regional development.

Accordingly, this study proposes the following hypothesis: H1: Digital rural development generates significant spatial spillover effects and exhibits substantial spatial dependence.

2.2. Mechanisms through which digital rural development affects the urban–rural income gap

As the product of the deep integration of digital technologies with rural development (Figure 1), digital rural development influences the urban–rural income gap through three primary channels: the factor allocation mechanism, the industrial upgrading mechanism, and the public service mechanism, thereby forming a multidimensional and multi-channel transmission framework [23].

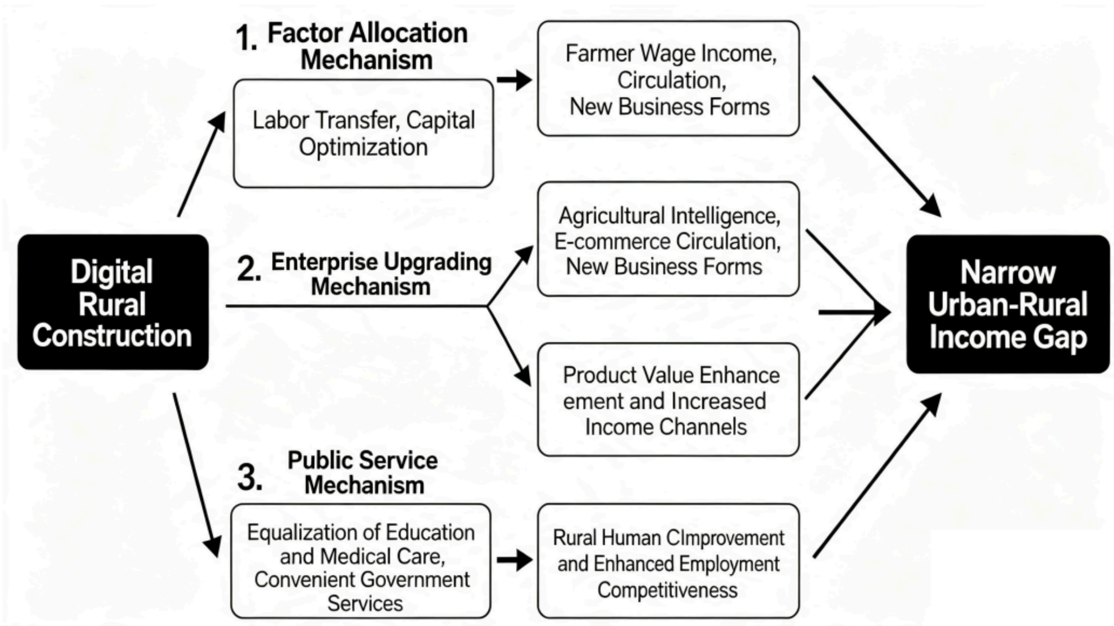

Figure 1. Transmission mechanisms through which digital rural development influences the urban–rural income gap

2.2.1. Factor allocation mechanism

Inefficient factor mobility has long been recognized as one of the principal causes of the persistent urban–rural income gap. The widespread application of digital technologies provides an effective means of removing barriers to factor mobility between urban and rural areas [24]. On the one hand, digital technologies reduce information asymmetry in the urban–rural labor market. Through internet-based platforms, rural workers can conveniently access urban employment opportunities and vocational training resources, thereby lowering both job search and migration costs and facilitating more efficient labor mobility from rural to urban areas. The orderly transfer of rural labor not only increases farmers' wage income but also promotes the large-scale operation of agricultural land, creating additional income-generating opportunities for those who remain in rural areas. On the other hand, the rapid development of digital finance has substantially alleviated credit constraints in rural areas [25]. Traditional financial institutions have generally provided limited financial support to rural communities because of insufficient collateral and underdeveloped credit systems. By leveraging big data and artificial intelligence technologies, digital finance can more accurately assess the creditworthiness of rural households and small and micro enterprises, develop innovative lending products and service models, and provide adequate financial support for rural industrial development and entrepreneurial activities. As a result, the allocation of rural capital is optimized, contributing to a reduction in the urban–rural income gap.

2.2.2. Industrial upgrading mechanism

Industrial disparities constitute one of the fundamental sources of the urban–rural income gap. Digital rural development promotes agricultural modernization and fosters new rural industries, thereby creating new avenues for increasing farmers' incomes [26]. In agricultural production, the application of digital technologies has facilitated the transition toward intelligent and precision agriculture. Technologies such as the Internet of Things (IoT) and sensor networks enable farmers to monitor soil moisture, crop growth, and pest infestations in real time, allowing for the precise application of fertilizers, pesticides, and irrigation water. These technologies improve agricultural productivity while enhancing the quality of agricultural products. Meanwhile, big data analytics enables farmers to assess market demand and price trends, optimize production decisions, and reduce market risks. In the circulation of agricultural products, the rapid expansion of rural e-commerce platforms has overcome geographical constraints associated with traditional marketing channels. Farmers can directly connect with urban consumers and large retail chains, reducing intermediary transactions, increasing the value added of agricultural products, and raising operating income. Furthermore, digital technologies have stimulated the emergence of new business models, including rural tourism, livestreaming e-commerce, and elderly care services in rural areas. These new industries have extended the agricultural value chain, diversified rural income sources, and promoted the integration of the primary, secondary, and tertiary industries, thereby narrowing both industrial disparities and income differences between urban and rural areas [27].

2.2.3. Public service mechanism

Disparities in public services between urban and rural areas are a key driver of the intergenerational transmission of income inequality. By promoting the integration of public services across urban and rural areas, digital rural development provides long-term support for narrowing the urban–rural income gap [29]. In the field of education, online education platforms enable high-quality urban educational resources to reach rural communities. Through online courses and remote tutoring, rural students can access educational opportunities comparable to those available to their urban counterparts, thereby alleviating shortages of educational resources and improving rural human capital. In healthcare, telemedicine technologies facilitate connectivity between leading urban hospitals and grassroots rural medical institutions. Rural residents can obtain high-quality medical services through remote diagnosis and online consultations, reducing healthcare costs while improving health outcomes. In public administration, digital government platforms allow rural residents to access a wide range of government services—including social security, medical insurance, and civil affairs—without leaving their communities. This substantially lowers transaction costs and enhances the accessibility of public services. By reducing disparities in public service provision between urban and rural areas, digital rural development enhances rural human capital over the long term, strengthens the employability and income-generating capacity of rural residents, and ultimately contributes to narrowing the urban–rural income gap at its source [28].

Accordingly, this study proposes the following hypothesis: H2: Digital rural development significantly reduces the urban–rural income gap.

3. Research design

3.1. Model specification

(1) Baseline Regression Model (Equation 1)

$$Tire_{it} = \alpha_0 + \alpha_1 Digital_{it} + \alpha_2 Controls_{it} + \mu_i + \lambda_t + \varepsilon_{it} \tag{1}$$

where $Tire_{it}$ denotes the Theil index of province i in year t; $Digital_{it}$ represents the composite digital rural development index; $Controls_{it}$ denotes the vector of control variables; μ_i and λ_t represent province and year fixed effects, respectively; and ε_{it} is the random error term.

(2) Endogeneity Correction Model (Equations 2 and 3)

First-stage regression (Equation 2):

$$Digital_{it} = \beta_0 + \beta_1 Digital_{it-1} + \beta_2 Controls_{it} + \mu_i + \lambda_t + \eta_{it} \tag{2}$$

Second-stage regression (Equation 3):

$$Tire_{it} = \gamma_0 + \gamma_1 \widehat{Digital}_{it} + \gamma_2 Controls_{it} + \mu_i + \lambda_t + \varepsilon_{it} \tag{3}$$

where $Digital_{it-1}$ is the one-period lag of the composite digital rural development index and serves as the instrumental variable; $\widehat{Digital}_{it}$ is the fitted value obtained from the first-stage regression; and η_{it} denotes the first-stage error term.

(3) Spatial Econometric Models

Spatial Lag Model (SLM) is as Equation 4:

$$Tire_{it} = \alpha_0 + \rho W Tire_{it} + \alpha_1 Digital_{it} + \alpha_2 Controls_{it} + \mu_i + \lambda_t + \varepsilon_{it} \tag{4}$$

Spatial Error Model (SEM) is as Equations 5 and 6:

$$Tire_{it} = \alpha_0 + \alpha_1 Digital_{it} + \alpha_2 Controls_{it} + \mu_i + \lambda_t + \varepsilon_{it} \tag{5}$$

$$\varepsilon_{it} = \lambda W \varepsilon_{it} + \nu_{it} \tag{6}$$

where W denotes the geographic contiguity spatial weight matrix, with a value of 1 assigned to adjacent provinces and 0 otherwise; ρ is the spatial autoregressive coefficient; λ is the spatial error coefficient; and ν_{it} is an independently and identically distributed disturbance term.

3.2. Variable definitions and data sources

This study employs the urban–rural income gap as the dependent variable, measured by the Theil index. The core explanatory variable is digital rural development, measured by a composite digital rural development index. To address potential endogeneity, the one-period lag of the composite digital rural development index is used as the instrumental variable. In addition, several control variables are introduced to account for other factors that may influence the urban–rural income gap, including the level of economic development, industrial structure, urbanization rate, fiscal support for agriculture, and human capital, thereby improving the explanatory power and robustness of the empirical model (Table 1).

Table 1. Variable definitions and data sources

Variable Type	Variable	Measurement	Data Source
Dependent variable	Urban–rural income gap (Theil)	Theil index	*China Rural Statistical Yearbook* (2014–2023)
Core explanatory variable	Digital rural development (Digital)	Composite digital rural development index	*China Digital Economy Development Report*; *China Rural Informatization Development Report*

Table 1. Continued

Instrumental variable	One-period lag of Digital rural development (Digitallag1)	One-period lag of the composite digital rural development index	Same as above, constructed using a one-period lag
Control variable	Economic development (PGDP)	Natural logarithm of GDP per capita	*China Statistical Yearbook* (2014–2023)
	Industrial Structure (IS)	Share of value added by the secondary and tertiary industries in GDP (%)	*China Statistical Yearbook* (2014–2023)
	Urbanization Rate (URB)	Urban resident population as a percentage of the permanent resident population (%)	*China Statistical Yearbook* (2014–2023)
	Fiscal Support for agriculture (FS)	Fiscal expenditure on agriculture as a percentage of total local general public budget expenditure (%)	*China Rural Statistical Yearbook* (2014–2023)
	Human Capital (HC)	Number of students enrolled in higher education as a percentage of the total population (%)	*China Education Statistical Yearbook* (2014–2023)

Note: The dataset consists of panel data for 31 provincial-level administrative regions in mainland China (excluding Hong Kong, Macao, and Taiwan) covering the period 2014–2023, yielding 310 observations in total. Missing values were imputed using linear interpolation, following established practices in the literature, while outliers were treated using Winsorization to reduce the influence of extreme values.

3.3. Calculation of the core indicators

3.3.1. Theil index

The Theil index is a widely used measure of income inequality. Owing to its decomposability, it can accurately capture the contribution of urban–rural disparities to overall income inequality [29]. This study adopts the Theil index for a dual urban–rural structure, as specified in Equation (7):

$$Tire_{it} = \sum_{k=1}^{2} \left(\frac{Y_{kit}}{Y_{it}} \right) \times ln\left(\frac{Y_{kit}/P_{kit}}{Y_{it}/P_{it}} \right) \tag{7}$$

where i denotes the province, t denotes the year, and k represents the area type, with k = 1 indicating urban areas and k = 2 indicating rural areas. Y_{kit} denotes the total per capita disposable income of residents in area k of province i in year t; Y_{it} is the total per capita disposable income of both urban and rural residents in province i during year t; P_{kit} denotes the permanent resident population in area k of province i in year t; and P_{it} represents the total permanent resident population of province i.

The Theil index ranges from 0 to 1, with larger values indicating a wider urban–rural income gap. A value of 0 signifies complete equality in income distribution between urban and rural residents. The principal advantage of the Theil index lies in its decomposability: it separates overall income inequality into within-group and between-group components, thereby isolating the inequality arising specifically from the urban–rural dual structure. Unlike the conventional urban–rural income ratio, the Theil index explicitly incorporates population weights, making it a more appropriate measure of the urban–rural income gap.

3.3.2. Entropy weighting method

The composite digital rural development index is constructed using nationwide data on digital rural development indicators. Following the framework proposed by Wang Fengli [30], an evaluation system comprising 12 indicators across four primary dimensions—digital infrastructure, digital industrial development, digital governance effectiveness, and digital service capacity—is established (Table 2). The entropy weighting method is then employed to determine indicator weights and comprehensively assess the level of digital rural development in China [31]. The sample consists of balanced panel data for 31 provincial-level administrative regions in mainland China (excluding Hong Kong, Macao, and Taiwan) from 2014 to 2023, yielding 310 observations. Consistent with previous studies, missing observations are imputed using linear interpolation.

Table 2. Composite digital rural development index

Primary Dimension	Secondary Indicator	Indicator	Attribute
Digital infrastructure	x11	Rural broadband coverage (%)	Positive
	x12	Number of 4G-or-above base stations per 10,000 rural residents	Positive
	x13	Proportion of administrative villages with postal service access (%)	Positive
Digital industrial development	x21	Rural e-commerce transaction volume (RMB 100 million)	Positive
	x22	Level of agricultural mechanization (10,000 kW)	Positive
	x23	Share of agriculture, forestry, animal husbandry, and fishery service output (%)	Positive
Digital governance effectiveness	x31	Consumer Price Index (CPI) for communication services	Negative
	x32	Volume of meteorological scientific data-sharing services (records)	Positive
	x33	Local fiscal expenditure on resource exploration, electricity, information, and related affairs (RMB 100 million)	Positive
Digital service capacity	x41	Rural Digital Financial Inclusion Index	Positive
	x42	Number of rural health technicians per 10,000 residents	Positive
	x43	Number of rural college and university graduates (10,000 persons)	Positive

The entropy weighting method is implemented through the following steps.

Step 1. Calculate the proportion of the j-th indicator in year t (Equation 8):

$$P_{ijt} = \frac{Z_{ijt}+\varepsilon}{\sum_{i=1}^{31}(Z_{ijt}+\varepsilon)} \tag{8}$$

where $\varepsilon = 10^{-8}$ is introduced to avoid undefined logarithmic values when $Z_{ijt} = 0$.

Step 2. Calculate the entropy value of the j-th indicator (Equation 9):

$$e_j = -\frac{1}{ln(31)} \sum_{t=1}^{10} \sum_{i=1}^{31} P_{ijt} \times ln(P_{ijt}) \tag{9}$$

The entropy value e_j ranges from 0 to 1. A smaller entropy value indicates lower information entropy, greater discriminating power of the indicator, and therefore a larger weight.

Step 3. Calculate the coefficient of variation (Equation 10):

$$g_j = 1 - e_j \tag{10}$$

Step 4. Calculate the indicator weight (Equation 11):

$$w_j = \frac{g_j}{\sum_{j=1}^{12} g_j} \tag{11}$$

where $\sum_{j=1}^{12}, \ w_j = 1$ and w_j denotes the weight assigned to the j-th secondary indicator.

Step 5. Calculate the composite digital rural development index (Equations 12–13):

$$Digital_{it} = \sum_{j=1}^{12} w_j \times Z_{ijt} \tag{12}$$

$$Digital_{it}^{*} = 100 \times Digital_{it} \tag{13}$$

where $Digital_{it}$ denotes the original composite digital rural development index for province i in year t, and $Digital_{it}^{*}$ is the standardized composite index used in the empirical analysis. A higher value indicates a higher level of digital rural development in the corresponding province and year.

4. Empirical results

4.1. Descriptive statistics and correlation analysis

4.1.1. Descriptive statistics

Using SPSS 25.0, the Theil index and the composite digital rural development index were calculated. Data for the control variables—including economic development, industrial structure, urbanization rate, fiscal support for agriculture, and human capital—were obtained from the corresponding national statistical yearbooks (Table 3).

Table 3. Descriptive statistics of the variables

Variable	Observations	Mean	Standard Deviation	Minimum	Maximum
Theil index (Theil)	310	0.0788	0.0363	0.0159	0.2183
Digital rural development index (Digital)	310	33.6204	8.7993	10.40	59.34
Economic development (PGDP)	310	10.5632	0.6891	8.9215	12.3456
Industrial Structure (IS)	310	91.2567	4.3210	78.9123	98.7654
Urbanization rate (URB)	310	0.6157	0.1194	0.2615	0.8947
Fiscal Support for agriculture (FS)	310	8.7654	2.1345	4.3210	15.6789
Human Capital (HC)	310	1.2345	0.4567	0.3210	2.9876

4.1.2. Correlation analysis

Correlation analysis provides a preliminary assessment of the relationships among the variables. As shown in Table 4, the composite digital rural development index is significantly and negatively correlated with the Theil index, providing initial support for Hypothesis H2. In addition, the urbanization rate and human capital are both significantly negatively correlated with the Theil index, whereas fiscal support for agriculture exhibits a significant positive correlation with the Theil index.

Table 4. Correlation matrix

Variable Name	Tire	Digital	PGDP	IS	URB	FS	HC
Tire	1.000	-0.238**	-0.187**	-0.056	-0.245**	0.312**	-0.121*
Digital	-0.238**	1.000	0.456**	0.198**	0.523**	-0.107*	0.389**
PGDP	-0.187**	0.456**	1.000	0.083	0.367**	-0.092	0.275**
IS	-0.056	0.198**	0.083	1.000	0.154**	-0.031	0.076
URB	-0.245**	0.523**	0.367**	0.154**	1.000	-0.148**	0.291**
FS	0.312**	-0.107*	-0.092	-0.031	-0.148**	1.000	-0.068
HC	-0.121*	0.389**	0.275**	0.076	0.291**	-0.068	1.000

Note: *, **, *** indicate significance at the 10%, 5%, and 1% levels, respectively; the same applies to the table below.

4.2. Baseline regression results

The baseline regression is estimated using the Ordinary Least Squares (OLS) method with both province and year fixed effects included. As reported in Table 5, the coefficient of the composite digital rural development index is significantly negative at the 1% significance level, indicating that a one-unit increase in the digital rural development index is associated with a 0.0028-unit reduction in the urban–rural income gap, as measured by the Theil index. This finding confirms that digital rural development contributes to narrowing the urban–rural income gap, thereby providing preliminary empirical support for Hypothesis H2. Among the control variables, both the urbanization rate and human capital exhibit significant income-equalizing effects. By contrast, fiscal support for agriculture is positively associated with the urban–rural income gap. This result may reflect inefficiencies in the allocation or utilization of agricultural fiscal expenditures, limiting their effectiveness in reducing income disparities.

Table 5. Baseline regression results

Variable	Coefficient	Standard Error	*t*-Statistic	*p*-Value
Constant	0.2156***	0.0312	6.91	0
Digital	-0.0028***	0.0004	-7	0
PGDP	0.0032**	0.0015	2.13	0.034
IS	-0.0005**	0.0002	-2.5	0.013
URB	-0.1876***	0.0245	-7.66	0
FS	0.0042***	0.0011	3.82	0
HC	-0.0015**	0.0006	-2.5	0.013
Province fixed effects	Yes	-	-	-
Year fixed effects	Yes	-	-	-
R^2	0.781	-	-	-
F-statistic	156.32***	-	-	0
Observations	310	-	-	-

4.3. Endogeneity analysis

Given the potential bidirectional causal relationship between digital rural development and the urban–rural income gap, this study employs the one-period lag of the composite digital rural development index as an instrumental variable and estimates the model using the Two-Stage Least Squares (2SLS) method.

4.3.1. First-stage regression

In the first-stage regression, the one-period lag of the composite digital rural development index is used as the instrumental variable to explain the current level of digital rural development. As reported in Table 6, the coefficient of the instrumental variable is positive and statistically significant at the 1% level. The first-stage F-statistic is 189.65, which is substantially greater than the conventional threshold of 10, indicating that the instrument is sufficiently strong and that the weak instrument problem is unlikely to arise. Furthermore, the Sargan test yields a statistic of 3.21, failing to reject the null hypothesis that the instrumental variable is exogenous, thereby confirming the validity and appropriateness of the selected instrument.

Table 6. First-stage regression results

Variable	Coefficient	Standard Error	*t*-Statistic	*p*-Value
Constant	12.3456***	2.1234	5.81	0.000
Digitallag1	0.6789***	0.0891	7.62	0.000
PGDP	0.8912**	0.3456	2.58	0.010
IS	0.0345***	0.0123	2.81	0.005
URB	5.6789***	1.2345	4.60	0.000
FS	-0.2345**	0.0987	-2.38	0.018
HC	0.1234**	0.0567	2.18	0.030
Province fixed effects	Yes	-	-	-
Year fixed effects	Yes	-	-	-
R^2	0.823	-	-	-
F-statistic	189.65***	-	-	0.000
Observations	279	-	-	-

4.3.2. Second-stage regression

In the second stage, the fitted values of the composite digital rural development index obtained from the first-stage regression are used to estimate their effect on the Theil index. After controlling for endogeneity, the absolute value of the coefficient on digital rural development increases from 0.0028 in the baseline regression to 0.0035, while remaining significantly negative at the 1% level (Table 7). This finding suggests that endogeneity causes the baseline regression to underestimate the income-equalizing effect of digital rural development. In addition, the Hausman test produces a statistic of 12.34, leading to the rejection of the null hypothesis that all explanatory variables are exogenous. This confirms the presence of endogeneity and indicates that the 2SLS estimates are more reliable than the baseline OLS estimates. Consequently, Hypothesis H2 receives further empirical support.

Table 7. Second-stage regression results

Variable	Coefficient	Standard Error	*t*-Statistic	*p*-Value
Constant	0.2567***	0.0345	7.44	0.000
$\widehat{Digital}$	-0.0035***	0.0006	-5.83	0.000
PGDP	0.0028*	0.0016	1.75	0.081
IS	-0.0006***	0.0002	-3.00	0.003
URB	-0.1765***	0.0267	-6.61	0.000

Table 7. Continued

FS	0.0045***	0.0012	3.75	0.000
HC	-0.0018**	0.0007	-2.57	0.011
Province fixed effects	Yes	-	-	-
Year fixed effects	Yes	-	-	-
R^2	0.765	-	-	-
Hausman test	12.34**	-	-	0.015
Observations	279	-	-	-

4.4. Spatial econometric results

Considering the possibility that digital rural development exhibits spatial dependence, this study constructs a geographic contiguity spatial weight matrix and conducts a series of spatial econometric analyses.

4.4.1. Spatial dependence tests

Spatial dependence is initially examined using Moran's I and Lagrange Multiplier (LM) tests. As reported in Table 8, Moran's I is significantly positive at the 1% significance level, indicating a significant positive spatial autocorrelation in digital rural development. In other words, provinces with relatively high levels of digital rural development tend to be geographically clustered with provinces exhibiting similarly high levels. This finding provides empirical support for Hypothesis H1. The LM tests indicate that both the spatial lag and spatial error effects are statistically significant. However, while the Robust LM Error test remains significant, the Robust LM Lag test is not statistically significant, suggesting that the Spatial Error Model (SEM) is more appropriate for the present study.

Table 8. Spatial dependence test results

Test	Statistic	*p*-Value	Conclusion
Moran's I test	2.89	0.004	Significant positive spatial autocorrelation
LM Lag test	8.76***	0.003	Spatial lag dependence exists
LM Error test	15.67***	0.000	Spatial error dependence exists
Robust LM Lag test	3.21	0.073	Spatial lag effect is not robust
Robust LM Error test	10.12***	0.001	Spatial error effect is robust

4.4.2. Estimation results of the SLM and SEM

Based on the spatial dependence tests, the Spatial Error Model (SEM) is selected as the preferred specification. For comparison purposes, the Spatial Lag Model (SLM) is also estimated. The results are reported in Table 9. Compared with the SLM, the SEM produces a higher log-likelihood (LogL) and lower Akaike Information Criterion (AIC) and Schwarz Criterion (SC) values, indicating a better overall model fit. The estimated spatial error coefficient is 0.3456 and is statistically significant at the 1% level, suggesting that spatially correlated unobservable factors are present across neighboring provinces. This result confirms the existence of significant spatial spillover effects in digital rural development, whereby regional characteristics and external influences from neighboring provinces jointly shape local development outcomes.

Table 9. Estimation results of the SLM and SEM

Variable	SLM		SEM	
Constant	Coefficient	*p*-Value	Coefficient	*p*-Value
Digital	0.1876***	0.000	0.2012***	0.000
PGDP	-0.0025***	0.000	-0.0027***	0.000
IS	0.0029*	0.087	0.0031*	0.062
URB	-0.0004**	0.045	-0.0005**	0.023
FS	-0.1654***	0.000	-0.1789***	0.000
HC	0.0038***	0.000	0.0041***	0.000
Spatial lag coefficient (ρ)	-0.0014**	0.021	-0.0016**	0.018
Spatial error coefficient (λ)	0.2345***	0.007	-	-
Province fixed effects	-	-	0.3456***	0.000
Year fixed effects	Yes	-	Yes	-
LogL	Yes	-	Yes	-
AIC	456.78	-	462.34	-
SC	-901.56	-	-912.68	-
Observations	-882.34	-	-895.46	-
Variable	310	-	310	-

4.5. Robustness checks

To examine the robustness of the empirical findings, two alternative specifications are employed. First, the sample period is shortened by excluding observations from 2014 and 2015, following the principle that earlier observations may be less representative of current conditions. Second, all municipalities directly under the central government are excluded from the sample to account for their distinctive policy environments, which could otherwise bias the estimation results. The robustness test results are presented in Table 10. Under both alternative specifications, the coefficient of the digital rural development index remains negative and statistically significant at the 1% level, with estimated coefficients ranging from −0.0029 to −0.0026. The relatively small variation in coefficient magnitude indicates that the baseline findings are highly robust.

Table 10. Robustness check results

Robustness Test	Coefficient of Digital	Standard Error	*p*-Value	Conclusion
Alternative sample period (2016–2023)	-0.0029***	0.0006	0.000	Robust
Excluding municipalities directly under the central government (27 provinces retained)	-0.0026***	0.0005	0.000	Robust

5. Conclusion and policy implication

5.1. Conclusion

Digital rural development contributes to narrowing the urban–rural income gap. This study demonstrates that digital rural development reduces the urban–rural income gap through the factor allocation mechanism, the industrial upgrading mechanism, and the public service mechanism.

Digital rural development exhibits significant spatial spillover effects. This study confirms the existence of spatial spillover effects in digital rural development through interregional factor mobility, technology diffusion, and policy imitation. Regions with higher levels of digital rural development are more likely to be adjacent to other regions with similarly high levels of digital rural development, whereas regions with lower levels of digital rural development tend to be clustered with other low-level regions.

The urbanization rate and human capital contribute to narrowing the urban–rural income gap, whereas long-term fiscal support for agriculture does not have a significant effect on reducing the urban–rural income gap.

5.2. Policy implication

Based on the findings of this study, the following policy recommendations are proposed to further improve digital rural development policies, promote integrated urban–rural development, and narrow the urban–rural income gap.

Improve rural digital infrastructure to strengthen the foundation for urban–rural digital integration. Digital infrastructure is the prerequisite and foundation of digital rural development and is also the key to narrowing the digital divide. Policymakers should pay close attention to the digital needs of vulnerable groups in rural areas by providing digital device training for older adults, persons with disabilities, and other disadvantaged populations, while developing age-friendly and accessible digital services to lower the barriers to digital technology adoption and ensure that rural residents can equally benefit from digital infrastructure. At the same time, a long-term mechanism for the construction, maintenance, and management of rural digital infrastructure should be established to ensure cybersecurity and the stable operation of digital networks.

Strengthen regional coordination mechanisms to enhance the spatial spillover effects of digital rural development. Fully exploiting the spatial spillover effects of digital rural development requires a sound regional coordination mechanism. Regional collaboration in the digital economy should be strengthened by facilitating the gradual transfer of digital industries from the eastern region to the central and western regions. Establishing digital industrial parks, data centers, and related projects in rural areas of central and western China would create more employment opportunities and increase rural incomes by enabling rural labor to secure employment closer to home.

Improve the efficiency of fiscal support for agriculture and enhance the precision of resource allocation. In view of the finding that fiscal support for agriculture may temporarily widen the urban–rural income gap, greater emphasis should be placed on improving the efficiency and allocation structure of agricultural fiscal expenditures. The investment mechanism for fiscal support should be optimized by adopting a model that combines government guidance, market-oriented operation, and broad social participation. This approach would attract private capital to participate in digital rural development, diversify funding sources, and alleviate fiscal pressure.

Promote the two-way flow of production factors to facilitate integrated urban–rural development. Restricted factor mobility is a fundamental cause of the persistent urban–rural income gap, while digital rural development provides an important opportunity to promote the two-way movement of production factors. Policymakers should leverage digital technologies to establish integrated platforms for the market-based exchange of labor, land, capital, technology, and other production factors, thereby facilitating the efficient transfer of rural resources to urban areas while simultaneously encouraging digital industries, advanced technologies, and skilled professionals from urban areas to expand into rural regions.

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