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Digital Economy, Factor Allocation and Urban–Rural Income Disparity: Insights from Prefecture-Level Data in China

Ran Wu [1,2], Jichun Wang [3] and Xiaolei Wang [4,*]

[1] School of Administration, Northeastern University, Shenyang 110167, China; wuran@neuq.edu.cn
[2] School of Economics, Northeastern University at Qinhuangdao, Qinhuangdao 066004, China
[3] College of Economics and Management, Nanjing Agricultural University, Nanjing 210095, China; wangjichun@stu.njau.edu.cn
[4] Business School, Harbin Institute of Technology, Harbin 150006, China
* Correspondence: 20b910039@stu.hit.edu.cn; Tel.: +86-15146468228

Abstract

The rapid expansion of digitalization is reshaping factor mobility and income distribution between urban and rural areas, with important implications for inclusive and sustainable development. Using panel data for 277 prefecture-level cities in China from 2012 to 2022, this study examines how DE affects urban–rural income disparity from the perspectives of nonlinear effects, factor allocation, and spatial interdependence. Compared with existing studies based mainly on provincial data, this paper provides a more fine-grained analysis at the prefecture level and combines mediation, double-threshold, and spatial analysis within a unified framework. The results show that DE has a significant U-shaped effect on urban–rural income disparity, suggesting that digital development may initially narrow the gap but widen it after a certain stage. Urban–rural factor allocation acts as an important transmission channel, and its role exhibits a double-threshold characteristic. The effect of DE also varies across urban agglomeration types and stages of urbanization, with stronger impacts in more developed and urbanized regions. In addition, the direct effect of DE follows a U-shaped pattern, whereas its spatial spillover effect shows an inverted U-shape. These findings indicate that digitalization is not automatically equalizing and that its distributional consequences depend on factor allocation conditions, regional development stages, and spatial linkages. The study provides evidence for policies aimed at reducing urban–rural inequality and promoting more balanced and sustainable development.

Keywords: digital economy; urban–rural income disparity; factor allocation; nonlinear relationship; urban agglomerations; spillover effect

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1. Introduction

Urban–rural income disparity remains a persistent challenge worldwide, reflected in the enduring gaps between agricultural and industrial regions in advanced economies and the pronounced divides across Asia, Africa, and Latin America [1,2]. The digital economy (DE) has become an important driver of productivity and growth, yet its uneven diffusion through unequal access to infrastructure and disparities in digital skills risks widening the gap between urban and rural areas, particularly in regions where infrastructure is limited and human capital is weak [3–5]. Understanding how digitalization shapes this inequality is therefore essential for addressing the challenges of balanced development in the digital era and for identifying effective policies that support inclusive growth.

China provides a particularly important case for examining these dynamics. Household incomes have risen rapidly, yet the urban–rural divide has widened and now constitutes the main source of overall inequality [6], which is evident from the fact that in 2024 urban disposable income was about 2.5 times that of rural residents. The Third Plenary Session of the 20th CPC Central Committee in 2024 stressed the need to "improve institutional mechanisms for integrated urban–rural development." This highlights the urgency of identifying new drivers to reduce the income disparity. Yet the expansion of DE in China has been highly unbalanced. In 2023, penetration rates were 45.63% in the tertiary sector and 25.03% in the secondary sector, but only 10.78% in the primary sector (China Digital Economy Development Report). Such disparities reveal significant imbalances across industries and within the urban–rural context. Extending digital technologies to rural regions is essential for transforming rural industries and promoting inclusive prosperity [7].

Improving factor allocation and promoting two-way flows of production factors across urban and rural regions are considered effective strategies for narrowing income gaps and reducing structural divides [8]. In China, this has translated into efforts to create more unified markets for land and labor, lower barriers to mobility, improve allocation efficiency, and reduce distortions that exacerbate urban–rural disparities. The rapid process of digitalization is reshaping patterns of factor mobility and is highly relevant to understanding the income divide. However, the mechanisms underlying this process remain insufficiently understood. More specifically, its impact on the allocation of land, labor, and capital requires further investigation. A systematic analysis of these mechanisms can help clarify the transmission pathways and provide a sounder theoretical and empirical basis for policies to reduce regional disparities and promote inclusive development. This study is guided by one multifaceted question: how does the digital economy affect urban–rural income disparity, and through what mechanisms, contextual conditions, and spatial interactions does this effect unfold? More specifically, the study examines whether the digital economy has a direct effect on urban–rural income disparity, whether urban–rural factor allocation serves as an important mediating mechanism, whether this effect varies across different urban agglomerations and stages of urbanization, and whether the digital economy generates significant spatial spillover effects on urban–rural income disparity across regions. This study contributes in several respects. By using prefecture-level data, it provides a more fine-grained analysis of the nonlinear relationship between DE and urban–rural income disparity, making it possible to identify regional variation in greater detail. It also incorporates urban–rural factor allocation into the analytical framework and examines both its mediating role and its threshold effect. This allows us to assess whether the impact of DE on income disparity varies across different levels of factor allocation efficiency. In addition, the study extends the analysis to regional heterogeneity and spatial spillover effects, thereby offering a more comprehensive understanding of how DE shapes urban–rural inequality across different development contexts. In doing so, it moves beyond a purely local perspective and provides additional evidence on the differentiated and interconnected effects of digitalization.

The rest of the paper is structured as follows: Section 2 reviews the relevant literature. Section 3 sets out the theoretical framework and examines the underlying mechanisms. Section 4 describes the data and methodology. Section 5 reports the empirical results and discussion, followed by Section 6, which presents the spatial analysis. Finally, Section 7 concludes with the main findings, theoretical contributions, research limitations and policy implications.

2. Literature Review

2.1. The Impact of DE on Economic Growth and Income Distribution

DE is an important driver of economic growth, offering new approaches to production organization and resource allocation [9]. Its influence is most evident in two areas: industrial digitalization and digital industrialization. Industrial digitalization involves the upgrading of traditional industries facilitated by data use, computing, and communication technologies. This process enhances resource allocation, improves production efficiency, and raises total factor productivity, thereby fostering industrial and technological advancement [10,11]. Digital industrialization, by contrast, positions data collection, processing, and storage as a distinct category of production factors that are deeply embedded in socioeconomic systems [12]. Together, these developments contribute to economic growth by restructuring traditional production factors and integrating data-driven ones, leading to new forms of production organization and value creation [13]. As a result, DE is expected to exert a significant influence not only on growth but also on patterns of income distribution.

2.2. DE's Impact on Urban–Rural Income Disparity

The impact of DE on the urban–rural income gap remains contested. On one hand, it can help narrow disparities through supporting urbanization, promoting industrial upgrading, and improving resource allocation [14–17]. Digital finance, in particular, expands access to credit and creates additional opportunities for jobs and entrepreneurial activity in rural areas, thereby raising household incomes [18]. On the other hand, the growth of information services and digital finance tends to be concentrated in urban centers, disproportionately benefiting high-skilled workers. Rural communities face constraints due to underdeveloped infrastructure and limited digital capabilities, and these limitations often create barriers to participation that can deepen existing divides [19]. Unequal infrastructure investment further reinforces the digital divide [20,21]. For instance, with lower education levels and reduced access to information, the limited capacity of rural populations to take advantage of digitalization can contribute to a widening income disparity [22].

2.3. Linear and Nonlinear Relationships Between DE and Income Disparity

The relationship between DE and urban–rural income disparity remains debated in the existing literature. Some studies suggest a linear relationship, where digital development reduces inequality by promoting urbanization and industrial upgrading. According to this view, as digital infrastructure improves, income gaps between urban and rural areas narrow due to increased productivity and better access to economic opportunities, particularly in underserved rural regions [23].

However, a growing body of research emphasizes nonlinear dynamics. Several studies propose an inverted U-shaped relationship, where digitalization initially reduces inequality but starts widening the gap after a certain threshold of development, particularly in more advanced regions with higher education and openness [24,25]. Other studies suggest a U-shaped pattern, where DE first narrows the income gap, but after surpassing a critical point, it contributes to widening disparities as rural areas, lagging in access to digital technologies, fall further behind [26–28]. Additionally, some research indicates that while DE may exacerbate inequality in more developed regions, it can promote convergence in less developed areas, leading to a complex and regionally differentiated impact on income distribution [29].

2.4. Factor Allocation Efficiency's Role in DE-Income Disparity

Efficient allocation of production factors, with a focus on data-driven resources, serves as a crucial pathway through which DE fosters growth and supports structural transformation. The mobility of data enables faster information flows and more efficient resource use, while also lowering restrictions on the mobility of land, labor, and capital [30]. By optimizing factor allocation, DE generates substantial income and welfare gains and encourages the integration of land, finance, infrastructure, and public services [31,32]. These changes also help unlock what has been described as new demographic and land-based dividends, thereby advancing urban–rural integration. Yet, distortions in factor allocation remain pronounced, particularly among rural households, where mismatches in capital and labor persist. Estimates suggest that correcting these imbalances could raise agricultural total factor productivity by more than 20% [33]. Further improvements in urban–rural factor allocation are therefore essential for reducing income disparities while enhancing overall economic efficiency.

2.5. Literature Review and Research Gaps

Previous research has made significant contributions to understanding the relationship between DE and urban–rural income disparity. Studies have shown how digitalization facilitates factor mobility and improves resource allocation, key factors in reducing income inequalities across urban and rural areas. Notably, digital finance, industrial upgrading, and infrastructure improvements have been highlighted as critical drivers that can help narrow income gaps by providing greater economic opportunities, particularly in rural regions. These contributions have advanced our understanding of how DE can address disparities and foster more inclusive growth. However, existing studies largely rely on provincial-level data, limiting their ability to capture the regional variations in the effects of digitalization. This has resulted in inconclusive findings regarding whether digitalization ultimately narrows or widens the income disparity, as studies often overlook the spatial and developmental nuances of different regions.

To address these gaps, the present study takes a more granular approach by using prefecture-level data, which allows for a more detailed examination of regional disparities that are often masked in broader analyses. Specifically, our study focuses on the mediating role of urban–rural factor allocation, testing whether the flow of labor and capital between urban and rural areas explains the relationship between DE and income disparity. Moreover, by incorporating threshold effects in factor allocation, this study goes beyond existing work to provide deeper insights into the nonlinear dynamics of DE and income disparity. These innovations offer a more comprehensive understanding of how DE shapes income inequality across regions at different stages of development.

3. Theoretical Assumptions and Mechanism Analysis

3.1. The Impact of DE on Urban–Rural Income Disparity

In its early stage, DE promotes inclusivity and innovation, which help bridge traditional urban–rural divides. It supports the digital upgrading of rural industries and improves the efficiency of factor markets by lowering information costs and reducing barriers related to search costs and information asymmetry [34,35]. As DE matures, however, its distributional effects may change. Although factor allocation efficiency in rural areas improves, a significant urban–rural digital access divide still limits the broad sharing of digital dividends [36]. At the same time, rapid digital expansion places growing pressure on traditional industries [37]. Successful digital transformation requires advanced infrastructure, efficient organizational support, and skilled labor, all of which are more concentrated in urban areas. Because rural sectors often remain in the lower segments of the

DE value chain and lack strong competitive advantages, DE activities tend to agglomerate in cities, thereby widening urban–rural income disparities [38].

Hypothesis 1. *The relationship between DE and urban–rural income disparity exhibits a U-shaped pattern, where the gap initially narrows but later widens.*

3.2. The Mediating Role of Urban–Rural Factor Allocation in Income Disparity

The efficiency with which labor and capital are allocated plays a central role in shaping income levels [39]. Consequently, the rational distribution of these factors across urban and rural areas directly influences the trajectory of income disparity. The development of DE enhances the allocation of labor, capital, land, information, and data, thereby reducing misallocation and improving the overall distribution of economic benefits. As a result, factor allocation becomes a key channel by which DE influences income distribution. Specifically, DE lowers barriers to factor mobility and improves market-oriented allocation by facilitating information flows and labor matching across regions [40]. It also promotes rural industrial upgrading, raising productivity and value-added potential in agriculture and related sectors [41]. In addition, the expansion of digital finance eases rural capital constraints by broadening financing channels and improving the efficiency of capital use, thereby supporting income growth [42].

Hypothesis 2. *The allocation of production factors across regions mediates the relationship between DE and urban–rural income disparity.*

However, the impact of DE on urban–rural factor allocation is neither static nor uniform. In the early stages of development, the broad application of digital technologies helps reduce information asymmetry and transaction costs, increases the efficiency of factor markets, and promotes the rational flow of capital, labor, and technology. These processes contribute to a more balanced factor allocation structure [43]. As digital technology advances, however, digital infrastructure, innovation capacity, and data resources tend to concentrate in urban regions, deepening the divide in factor access and utilization. Rural regions, constrained by limited digital resources, weaker technological support, and inadequate capital supply, face increasing difficulties in absorbing and optimizing factor allocation. These disadvantages hinder industrial upgrading and undermine extended economic growth [44]. Thus, the influence of DE on factor allocation is likely to vary across stages of development as a result of resource concentration effects.

Hypothesis 3. *The impact of DE on urban–rural factor allocation follows a nonlinear pattern.*

3.3. The Threshold Characteristics of Urban–Rural Factor Allocation

At lower levels of factor allocation, the conditions necessary for DE to improve urban–rural income distribution remain weak, so its effect on income disparity is limited [45]. When factor allocation reaches a higher level, digital technologies can more effectively improve resource allocation efficiency and strengthen the role of DE in reshaping urban–rural income distribution [46]. At this stage, however, the income effect of DE may also become more differentiated, as the concentration of high-quality resources in urban areas can reinforce uneven distributional outcomes. Therefore, the impact of DE on urban–rural income disparity is likely to vary across different levels of urban–rural factor allocation.

Hypothesis 4. *The impact of DE on urban–rural income disparity varies with the improvement of urban–rural factor allocation.*

As illustrated in Figure 1, the analytical framework of this study links DE, factor allocation, urban–rural income disparity, and spatial interdependence through four related hypotheses.

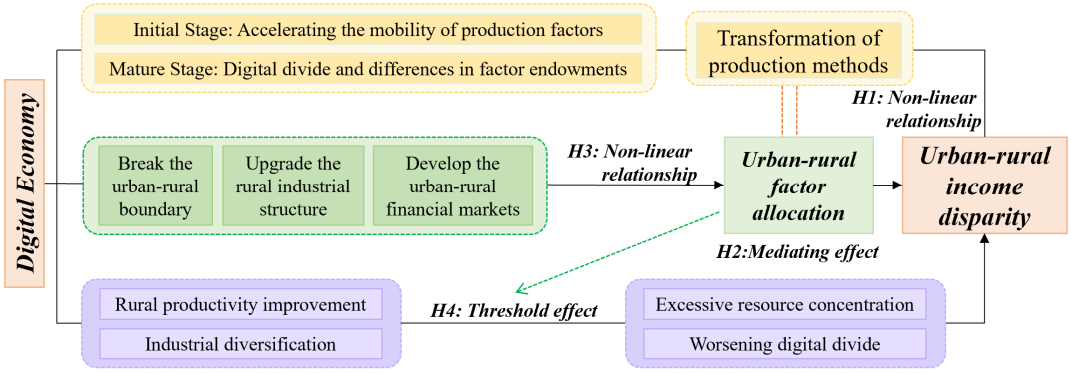


Figure 1. Theoretical framework.

4. Methodology and Data

4.1. Model Setting

4.1.1. Baseline Regression Model

A two-way fixed effects model is specified as follows:

$$Theil_{it} = \beta_0 + \beta_1 Dig_{it} + \beta_2 Dig2_{it} + \sum_{k=3}^{n} \beta_k Controls_{it} + \mu_i + \sigma_t + \varepsilon_{it}, \quad (1)$$

The dependent variable $Theil_{it}$ refers to the urban–rural income disparity of city i in year t. Dig_{it} represents DE development index, and its squared term $Dig2_{it}$ is included to capture potential nonlinear effects. $Controls_{it}$ refers to a set of control variables. μ_i and σ_t denote city and year fixed effects, respectively, while ε_{it} is the random error term.

4.1.2. Mediation Mechanism Test

To examine the mechanism through which DE affects urban–rural income disparity, this study tests the mediating role of factor allocation using the two-step method [47] and the causal steps approach [48]. Equations (2) and (3) are specified accordingly, where Factor denotes the level of urban–rural factor allocation in city i in year t.

$$Factor_{it} = \theta_0 + \theta_1 Dig_{it} + \theta_2 Dig2_{it} + \sum_{k=3}^{n} \theta_k Controls_{it} + \mu_i + \sigma_t + \varepsilon_{it}, \quad (2)$$

$$Theil_{it} = \beta_0' + \beta_1' Dig_{it} + \beta_2' Dig2_{it} + \beta_3' Factor_{it} + \sum_{k=4}^{n} \beta_k' Controls_{it} + \mu_i + \sigma_t + \varepsilon_{it}, \quad (3)$$

4.1.3. Threshold Effect Model

Given that the effect of DE may vary with the level of factor allocation, a panel threshold model is employed [49]. Equations (4) and (5) represent the single-threshold and double-threshold specifications, respectively, with Factor used as the threshold variable. I(·) is the indicator function, and γ, $\gamma 1$, and $\gamma 2$ denote the threshold values.

$$\begin{aligned} Theil_{it} = {} & \alpha_0 + \alpha_1 Dig_{it} \cdot I(Factor_{it} \le \gamma) + \alpha_2 Dig2_{it} \cdot I(Factor_{it} \le \gamma) \\ & + \alpha_3 Dig_{it} \cdot I(Factor_{it} > \gamma) + \alpha_4 Dig2_{it} \cdot I(Factor_{it} > \gamma) + \sum_{k=5}^{n} \alpha_k Controls_{it} + \mu_{it} + \sigma_{it} + \varepsilon_{it}, \end{aligned} \quad (4)$$

$$\begin{aligned} Theil_{it} = {} & \delta_0 + \delta_1 Dig_{it} \cdot I(Factor_{it} \le \gamma_1) + \delta_2 Dig2_{it} \cdot I(Factor_{it} \le \gamma_1) \\ & + \delta_3 Dig_{it} \cdot I(\gamma_1 < Factor_{it} \le \gamma_2) + \delta_4 Dig2_{it} \cdot I(\gamma_1 < Factor_{it} \le \gamma_2) \\ & + \delta_5 Dig_{it} \cdot I(Factor_{it} > \gamma_2) + \delta_6 Dig2_{it} \cdot I(Factor_{it} > \gamma_2) + \sum_{k=7}^{n} \delta_k Controls_{it} + \mu_{it} + \sigma_{it} + \varepsilon_{it} \end{aligned}, \quad (5)$$

4.1.4. Spatial Econometric Model

To account for spatial dependence and spillover effects, this study specifies a spatial econometric model, as shown in Equation (6). W denotes the spatial weight matrix, ρ and θ represent the spatial autoregressive and spatial correlation coefficients, and X includes the core explanatory and control variables. Two matrices are used: W1, a binary contiguity matrix, and W2, an inverse squared distance matrix defined in Equation (7).

$$Theil_{it} = \alpha + \rho \sum_{j=1}^{N} W_{ij} Theil_{it} + \beta X_{it} + \theta \sum_{j=1}^{N} W_{ij} X_{it} + \mu_i + \sigma_t + \varepsilon_{it}, \quad \varepsilon_{it} = \delta \sum_{j=1}^{N} W_{ij} \varepsilon_{it} + v_{it}, \quad (6)$$

$$W2_{ij} = \begin{cases} 1/d_{ij}^2, & i \neq j \\ 0, & i = j \end{cases}, \quad (7)$$

To verify the suitability of spatial econometric modeling, it is first necessary to test whether the main variables exhibit spatial autocorrelation. A widely used measure for this purpose is Moran's I, which is calculated as follows:

$$Moran's\ I = \frac{\sum_{i=1}^{n} \sum_{j \neq 1}^{n} W_{ij} (x_i - \overline{x}) (x_j - \overline{x})}{S^2 \sum_{i=1}^{n} \sum_{j \neq 1}^{n} W_{ij}}, \quad (8)$$

In this formula, n denotes the total number of cities, x_i represents the observed value for city i, $\overline{x}$ is the mean of all observations, and S^2 is the variance of the observations. Moran's I typically ranges from −1 to 1, with positive values indicating spatial positive autocorrelation.

4.2. Variables and Data

4.2.1. Dependent Variable

This study uses the urban–rural Theil index (Theil) as the core indicator to measure urban–rural income disparity. The Theil index captures not only relative income differences but also accounts for population heterogeneity between urban and rural groups, making it a more comprehensive and accurate measure of overall income distribution [50]. The formula is given as follows:

$$Theil_{it} = \sum_{j=1}^{2} \frac{y_{itj}}{Y_{it}} \ln\left(\frac{y_{itj}}{Y_{it}} / \frac{p_{itj}}{P_{it}} \right), \quad (9)$$

where y_{itj} denotes the per capita disposable income of group j in region i at time t, and p_{itj} represents the corresponding permanent resident population. Y_{it} and P_{it} refer to the total per capita disposable income and the total permanent population of region i in year t, respectively. The subscript j = 1,2 corresponds to the urban and rural groups. In essence, the index measures the weighted logarithmic deviation between income shares and population shares across urban and rural sectors, thereby reflecting disparities in overall income distribution.

4.2.2. Explanatory Variable

The core explanatory variables are the DE Development Index (Dig) and its square (Dig2). The construction of the index draws on three dimensions: digital infrastructure, the development of digital industries, and digital inclusive finance [51]. The specific indicators used are summarized in Table 1, all of which are positively oriented. Given the multidimensional nature of DE and the relatively strong correlation among the selected indicators, principal component analysis (PCA) is employed to reduce dimensionality, minimize information redundancy, and construct the composite index in a more objective manner. The detailed procedure is reported in Appendix A.

Table 1. Measurement of DE Development Indicators.

Criterion Level	Indicator Level	Indicator Description
Digital infrastructure	Broadband Internet infrastructure	(1) Number of broadband Internet users per 10,000 people
	Mobile Internet infrastructure	(2) Number of mobile phone users per 10,000 people
Digital industry development	Telecommunications scale	(3) Total volume of telecommunication services
	Software and IT industry scale	(4) Number of employees in information transmission, computer services, and software industry
Digital finance	Inclusive development	(5) China Digital Inclusive Finance Index

4.2.3. Mediating Variable and Threshold Variable

In developing countries, urban and rural areas are typically characterized by a dual structure, with cities dominated by industry and rural areas by agriculture. Under this setting, differences in urban–rural income distribution are closely related to how capital and labor are allocated between the two sectors [52]. Intuitively, the Factor indicator is designed to capture the degree of mismatch between the distribution of production factors across urban and rural areas. A higher value of this indicator implies a greater imbalance in factor allocation and, therefore, lower allocation efficiency. This study constructs the urban–rural factor allocation indicator (Factor) as follows:

$$Factor_{it} = \sum_{j=1}^{2} \frac{f_{itj}}{F_{it}} \ln\left(\frac{f_{itj}}{F_{it}} / \frac{l_{itj}}{L_{it}}\right), \tag{10}$$

In the formula, f_1 denotes the fixed asset investment in the agricultural sector, while f_2 refers to that in the non-agricultural sector. F_{it} and L_{it} represent the total fixed asset investment and total population of city i in year t, respectively. The shares of fixed asset investment in rural and urban areas are used as weights. Since urban–rural labor force data at the prefecture level are unavailable, population is used as a proxy for labor input, while fixed asset investment shares are used to approximate capital allocation. As a result, the Factor indicator provides an approximate rather than direct measure of urban–rural factor allocation.

4.2.4. Control Variables

To reduce omitted-variable bias, the model includes five control variables: urbanization rate (Urban), economic development (Pgdp), industrial structure rationalization (Inds), educational investment (Edu), and human capital (Stu). Urban is measured as the share of urban population in the total population, and Pgdp is proxied by per capita GDP. Inds is measured by a Theil-index-based indicator that compares the distribution of industrial

output with that of employment across sectors; lower values indicate a greater alignment between production and labor allocation and therefore a more rational industrial structure. Edu is measured as the share of education expenditure in local fiscal expenditure, and Stu is proxied by the share of full-time undergraduate and junior college students in the total population.

4.2.5. Data Sources and Descriptive Statistics

The data are drawn mainly from the China City Statistical Yearbook, the China Statistical Yearbook, the China E-commerce Yearbook, the CEIC China Economic Database, and the Peking University Digital Inclusive Finance Index. Based on data availability, the sample includes data on 277 prefecture-level cities from 2012 to 2022, forming an unbalanced panel. Table 2 reports the descriptive statistics. For the spatial analysis, Dig and Dig2 are mean-centered to reduce multicollinearity with their spatial lags. Because spatial models require balanced panels, missing observations are linearly interpolated. Given the limited number of missing values and the relatively smooth evolution of city-level indicators over time, this treatment is unlikely to affect the main results materially.

Table 2. Descriptive statistics.

Variables	Explanation	Obs	Mean	SD	Min	Max
Theil	Urban–rural income disparity	2188	0.069	0.036	0.003	0.230
Dig	DE development	2852	0.637	0.029	0.600	0.826
Dig2	The square of Dig	2852	0.407	0.039	0.360	0.683
Urban	Urbanization rate	2852	0.561	0.141	0.182	0.959
Pgdp	GDP per capita	2852	10.760	0.556	9.091	12.456
Inds	Industrial structure rationalization index	2818	0.286	0.197	0.000	0.863
Edu	Educational investment	2852	0.177	0.038	0.014	0.356
Stu	Human capital level	2852	0.020	0.026	0.000	0.195
Factor	Urban–rural factor allocation indicator	2641	0.456	0.216	0.007	1.350

5. Estimation Results

5.1. Baseline Regression Results

Table 3 reports the baseline regression results for the impact of DE on urban–rural income disparity. Column (1) includes only the core explanatory variable (Dig), which shows a positive and significant coefficient (0.148, $p < 0.01$), suggesting a widening effect on income disparity. In Column (2), after the inclusion of control variables, the coefficient of Dig remains positive but loses significance, indicating that part of the effect operates through other socioeconomic factors. Columns (3) and (4) add the quadratic term (Dig2) to capture nonlinear dynamics. The coefficient of Dig turns significantly negative, while Dig2 is significantly positive, confirming a U-shaped relationship, with the turning point located at approximately 0.664. These findings lend support to Hypothesis 1.

This U-shaped pattern is broadly consistent with the theoretical expectations of this study. In the early stage, DE helps narrow urban–rural income disparity by reducing information costs, improving resource matching, and facilitating the flow of labor and capital between urban and rural areas. It also supports the digital upgrading of rural industries and creates new income opportunities for rural households. However, as DE continues to expand, digital resources, infrastructure, and skilled labor tend to become more concentrated in urban areas and more developed regions. Under these conditions, rural areas may face increasing difficulties in fully absorbing digital dividends because of weaker factor endowments and lower industrial adaptability. As a result, the equalizing effect of DE weakens over time, and the urban–rural income disparity may widen again.

Table 3. Results of benchmark regression.

Variables	(1) Theil	(2) Theil	(3) Theil	(4) Theil
Dig	0.148 ***	0.081	−2.223 ***	−1.728 ***
	(0.052)	(0.049)	(0.610)	(0.522)
Dig2			1.700 ***	1.301 ***
			(0.433)	(0.373)
Urban		−0.069 ***		−0.062 ***
		(0.021)		(0.020)
Pgdp		−0.007 **		−0.006 **
		(0.003)		(0.003)
Inds		−0.010 ***		−0.010 ***
		(0.003)		(0.003)
Edu		0.065 ***		0.068 ***
		(0.020)		(0.019)
Stu		0.043		0.043
		(0.052)		(0.048)
Constant	−0.003	0.141 ***	0.816 ***	0.748 ***
	(0.033)	(0.052)	(0.214)	(0.188)
Year FE	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes
Observations	2188	2162	2188	2162
R-squared	0.660	0.701	0.675	0.709
Number of city	277	273	277	273

Note: Robust standard errors in parentheses: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Among the control variables, urbanization, economic development, and industrial structure rationalization are associated with lower urban–rural income disparity, whereas educational investment and human capital tend to show disparity-widening effects, likely reflecting the unequal spatial distribution of educational resources and skilled labor.

5.2. Robustness Test

5.2.1. Substitute the Dependent Variables

As a robustness check, the Gini coefficient is employed as a proxy indicator of income disparity. The Gini coefficient is calculated using Dagum's method [53], with the formula specified as follows:

$$Gini = \frac{p_u p_r |y_u - y_r|}{\mu}, \quad (11)$$

where p_u and p_r denote the population shares of urban and rural areas, respectively; y_u and y_r represent the per capita incomes of urban and rural residents; and μ is the national average income.

Column (1) of Table 4 reports the regression results, which confirm the robustness of the baseline findings. The estimates show that the nonlinear relationship between digitalization and urban–rural income disparity remains statistically significant.

5.2.2. Exclude Certain Samples

Since centrally administered municipalities vary significantly from other prefecture-level cities in terms of administrative hierarchy and economic development, they are excluded from the sample for re-estimation. The results, reported in Column (2) of Table 4, remain consistent with the baseline findings, indicating that the main conclusions are robust even after excluding these municipalities.

Table 4. Results of the robustness test.

Variables	(1) Gini	(2) Theil	(3) Theil	(4) Dig	2SLS (5) Dig2	(6) Theil
Dig	−2.755 ***	−1.683 ***	−2.986 ***			−2.142 ***
	(0.605)	(0.572)	(0.925)			(0.446)
Dig2	1.960 ***	1.259 ***	2.217 ***			1.577 ***
	(0.433)	(0.417)	(0.705)			(0.312)
L. Dig				−0.745 *	−2.104 ***	
				(0.433)	(0.612)	
L. Dig2				1.083 ***	2.299 ***	
				(0.314)	(0.449)	
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Constant	1.248 ***	0.733 ***	1.187 ***	0.749 ***	0.922 ***	0.856 ***
	(0.222)	(0.200)	(0.308)	(0.150)	(0.209)	(0.163)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2139	2118	2162	2089	2089	2089
R-squared	0.802	0.710	0.706			0.974
Number of city	250	269	273			277

Note: Robust standard errors in parentheses: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

5.2.3. Handle Outliers and Extreme Values

To mitigate potential bias from outliers and extreme observations, all variables are winsorized at the 5% level on both tails. The 5% threshold is adopted as a common and relatively conservative choice in empirical analysis to limit the effect of extreme observations without excessively distorting the sample. The regression results, presented in Column (3) of Table 4, show that the coefficients of Dig and Dig2 remain statistically significant at the 5% level, and their signs are consistent with those in the baseline model.

5.2.4. Mitigate Endogeneity via 2SLS Estimation

To address potential endogeneity concerns, this study employs the one-period lag of DE variable (L. Dig) and its squared term (L. Dig2) as instrumental variables and conducts a two-stage least squares (2SLS) regression. The results of the relevance tests confirm that the instruments are valid and have strong explanatory power. The first-stage regression, reported in Columns (4) and (5) of Table 4, shows a significant correlation between the instrumental variables and the endogenous regressors, supporting the validity of the estimation strategy. The second-stage regression results, presented in Column (6), indicate that the coefficients of Dig and Dig2 remain statistically significant at the 1% level, further reinforcing the robustness of the findings.

5.3. Mediation Effect Analysis

As reported in Table 5, Column (1) shows the regression results of DE and its squared term on the level of factor allocation. The findings reveal a nonlinear effect. When the value of Factor is lower, allocation efficiency is higher and the income gap narrows. When the value of Factor is higher, allocation efficiency is lower and the income gap widens. These results provide empirical support for Hypotheses 2 and 3.

The relationship between factor allocation and income disparity can be understood through both prior studies and logical reasoning. When factor allocation efficiency is low, institutional barriers and market segmentation restrict the efficient flow of resources across regions. This leads to the concentration of resources in cities, constrained rural development, and an expansion of the income disparity [54]. As allocation improves and crosses a critical threshold, however, institutional constraints are gradually relaxed,

resource use becomes more efficient, and rural productivity and incomes rise, which in turn contributes to narrowing the urban–rural income disparity [55].

Table 5. The mediating effect of factor allocation.

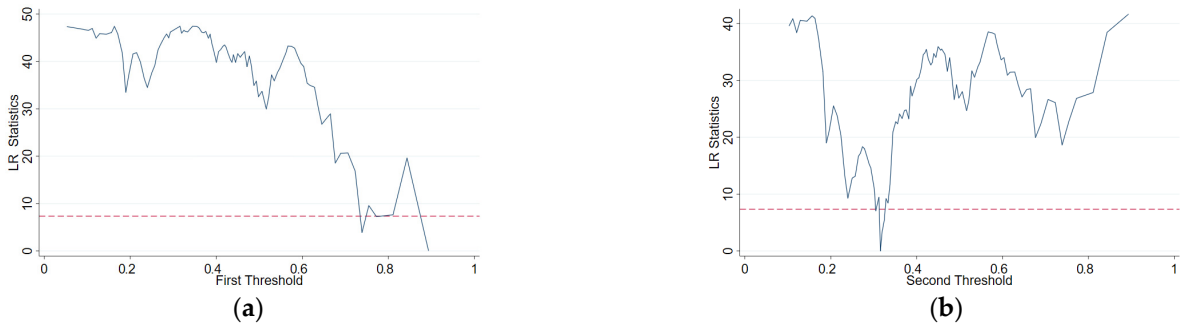
Variables	(1) Factor	(2) Theil	(3) Theil
Factor		0.022 ***	
		(0.006)	
Dig	−6.533 *	−1.667 ***	−1.728 ***
	(3.582)	(0.544)	(0.522)
Dig2	5.635 **	1.232 ***	1.301 ***
	(2.584)	(0.394)	(0.373)
Control Variables	Yes	Yes	Yes
Constant	3.945 ***	0.704 ***	0.748 ***
	(1.217)	(0.192)	(0.188)
Year FE	Yes	Yes	Yes
City FE	Yes	Yes	Yes
Observations	2622	1966	2162
R-squared	0.654	0.718	0.709
Number of city	256	231	273

Note: Robust standard errors in parentheses: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Further analysis is conducted using the traditional mediation effect model. Column (3) reports the baseline regression results mentioned earlier. Column (2) presents the estimates after including the mediating variable, and the coefficients of Dig and Dig2 remain significant at the 1% level, consistent with that in Column (3). This suggests that factor allocation partially mediates the positive U-shaped relationship. The positive and significant coefficient of Factor suggests that greater factor misallocation is associated with a wider income gap, whereas improvements in allocation efficiency help narrow the disparity. These findings highlight that the distributive effect of digitalization does not operate only through technological expansion itself, but also through the extent to which digital development improves the movement and matching of labor and capital between urban and rural areas. In this sense, factor allocation serves as a key institutional and structural channel linking digital transformation to income distribution.

5.4. Threshold Effect Analysis

A bootstrap procedure with 500 replications is used to test the number of thresholds. As reported in Table 6 and Figure 2, the results support a double-threshold effect of factor allocation in the relationship between DE and urban–rural income disparity.



(**a**) (**b**)

Figure 2. LR test for the threshold effect. (**a**) First threshold; (**b**) Second threshold.

Table 6. Results of the threshold effect significance test.

Variables	Threshold	F-Value	*p*-Value	1%	5%	10%
Theil	Single	37.39 ***	0.000	19.098	21.237	26.045
	Double	36.13 ***	0.000	13.279	15.311	21.477
	Triple	25.40	0.444	45.284	53.707	65.614

Note: Bootstrap = 500, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

As shown in Table 7, the model identifies two threshold values (γ_1 = 0.315 and γ_2 = 0.882), which divide the sample into three regimes of factor allocation imbalance. Lower values of factor indicate more coordinated allocation, whereas higher values indicate more severe imbalance. The findings suggest the following: within the two regimes where factor allocation is relatively efficient (Factor $\leq$ 0.315 and 0.315 < Factor $\leq$ 0.882), both DE variable (Dig) and its squared term (Dig2) display a statistically significant U-shaped relationship with income disparity. By contrast, when allocation efficiency is low (Factor > 0.882), this nonlinear relationship is no longer statistically well supported. These results demonstrate that as factor coordination improves, the influence of DE on the urban–rural income disparity becomes more stable and pronounced. This evidence confirms Hypothesis 4 and underscores that differences in factor allocation play a decisive role in shaping the marginal effect of DE on income disparity.

Table 7. Regression results of the panel threshold model.

Variables	Theil	Variables	Theil
Dig. I (Factor $\leq \gamma_1$)	−1.190 ***	γ_1	0.315
	(0.284)	γ_2	0.882
Dig. I (γ_1 < Factor $\leq \gamma_2$)	−1.069 ***	Control Variables	Yes
	(0.294)		
Dig. I (Factor > γ_2)	−0.936 **	Constant	0.542 ***
	(0.388)		(0.098)
Dig2. I (Factor $\leq \gamma_1$)	0.917 ***	Year FE	Yes
	(0.204)	City FE	Yes
Dig2. I (γ_1 < Factor $\leq \gamma_2$)	0.734 ***	Observations	1966
	(0.220)	R-squared	0.720
Dig2. I (Factor > γ_2)	0.549	Number of city	231
	(0.466)		

Note: Robust standard errors in parentheses: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

5.5. Heterogeneity Analysis

Based on economic development levels and national strategic priorities, China's 19 major national urban agglomerations can be divided into three categories. The first-tier agglomerations (Ua1) are relatively mature, fall under the "optimization and upgrading" category, and function as a key component of the national economy. The second-tier agglomerations (Ua2) are in the process of consolidation and require further growth, representing areas with considerable potential. The third-tier agglomerations (Ua3) are less developed, concentrated mainly in the northeast and central-western regions, and remain in need of cultivation and development. The detailed classification of urban agglomerations is presented in Table 8.

As reported in Table 9, the U-shaped relationship is confirmed mainly in the more developed urban agglomerations, namely Ua1 and Ua2, whereas the coefficients for Ua3 are not statistically significant. This pattern suggests that the distributional consequences of digitalization are conditioned by regional development foundations. In more mature urban agglomerations, digital infrastructure, market integration, industrial upgrading capacity,

and labor mobility are generally stronger, allowing the effects of digitalization on resource reallocation and income distribution to become more visible. By contrast, in less developed agglomerations, weaker infrastructure, thinner markets, and more limited absorptive capacity may constrain the transformation of digital inputs into sustained income effects, thereby weakening the estimated relationship.

Table 8. List and classification of urban agglomerations.

Type of Urban Agglomerations	The Included Urban Agglomerations
(1) Optimization and upgrading (denoted as Ua1)	(1) Beijing–Tianjin–Hebei; (2) Yangtze River Delta; (3) Pearl River Delta; (4) Chengdu–Chongqing; (5) Middle Yangtze River
(2) Growth and expansion (denoted as Ua2)	(1) Shandong Peninsula; (2) Guangdong–Fujian–Zhejiang coastal; (3) Central Plains; (4) Guanzhong Plain; (5) Beibu Gulf
(3) Cultivation and development (denoted as Ua3)	(1) Harbin–Changchun; (2) Central and Southern Liaoning; (3) Central Shanxi; (4) Central Guizhou; (5) Central Yunnan; (6) Hohhot–Baotou–Ordos–Yulin; (7) Lanzhou–Xining; (8) Ningxia Yellow River; (9) Northern Tianshan

Note: The cities included in the urban agglomerations are derived from relevant policy documents.

Table 9. Results of the heterogeneity test for urban agglomeration and urbanization level.

Variables	(1) Ua1	(2) Ua2	(3) Ua3	(4) Urban < 0.6	(5) Urban $\geq$ 0.6
Dig	−1.457 ***	−1.773 ***	−0.407	−3.029	−1.239 **
	(0.473)	(0.635)	(2.315)	(2.424)	(0.529)
Dig2	1.018 ***	1.304 ***	0.439	2.259	0.883 **
	(0.320)	(0.488)	(1.777)	(1.885)	(0.369)
Control Variables	Yes	Yes	Yes	Yes	Yes
Constant	0.644 ***	0.756 ***	0.323	1.162	0.618 ***
	(0.180)	(0.209)	(0.739)	(0.789)	(0.191)
Year FE	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes
Observations	820	606	228	1,296	866
R-squared	0.757	0.850	0.817	0.741	0.642
Number of city	91	72	40	192	151

Note: Robust standard errors in parentheses: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

As shown in Column (5), a similar logic applies to the urbanization-level results. In regions with higher urbanization (Urban $\geq$ 0.6) [56], digitalization is embedded in a more advanced economic structure and therefore exerts a clearer nonlinear effect on the urban–rural income gap. In less urbanized regions, however, digital development may still be too limited or fragmented to systematically reshape the urban–rural distribution of opportunities and returns.

6. Further Analysis of Spatial Effects

6.1. Spatial Correlation Test

Table 10 reports Moran's I statistics (calculated using W1) for DE development and urban–rural income disparity from 2012 to 2022. The results show that both variables display positive and statistically significant spatial autocorrelation. This indicates that regions with higher levels of digitalization or wider income disparities tend to be geographically clustered, suggesting a strong positive spatial association between the two phenomena.

Table 10. Global Moran's I statistics for DE and urban–rural income disparity.

Year	DE Development Index			Urban–Rural Theil Index		
	Moran's I	Z-Value	*p*-Value	Moran's I	Z-Value	*p*-Value
2012	0.395	9.073	0.000	0.354	8.112	0.000
2013	0.412	9.475	0.000	0.401	9.119	0.000
2014	0.400	9.210	0.000	0.454	10.295	0.000
2015	0.391	8.994	0.000	0.484	10.954	0.000
2016	0.388	8.926	0.000	0.482	10.909	0.000
2017	0.412	9.445	0.000	0.476	10.786	0.000
2018	0.399	9.123	0.000	0.483	10.947	0.000
2019	0.390	8.974	0.000	0.480	10.890	0.000
2020	0.375	8.602	0.000	0.478	10.836	0.000
2021	0.366	8.397	0.000	0.478	10.853	0.000
2022	0.353	8.093	0.000	0.477	10.826	0.000

6.2. Spatial Econometric Regression Results

A series of specification tests reported in Table 11 support the use of the two-way fixed-effects SDM as the benchmark spatial model.

Table 11. Spatial panel model selection.

Test Name	Statistic Value	*p*-Value
LM-lag	265.31	0.000
Robust LM-lag	3.922	0.048
LM-error	901.241	0.000
Robust LM-error	639.852	0.000
Wald Test for SAR	29.76	0.000
Wald Test for SEM	103.96	0.000
LR Test for SAR	32.30	0.000
LR Test for SEM	16.91	0.018
Hausman Test	53.585	0.000
Time LR Test	4432.21	0.000
Individual LR Test	81.68	0.000

The results in Table 12 confirm a U-shaped direct effect of DE on local urban–rural income disparity. By contrast, the coefficients on the spatially lagged terms display the opposite sign pattern, indicating an inverted U-shaped spillover effect from surrounding regions. This means that DE development within a city may initially reduce local disparity but later widen it, whereas DE development in neighboring regions may first intensify local disparity before eventually contributing to its reduction. Furthermore, the significantly positive spatial autoregressive coefficient (ρ) confirms the presence of spatial dependence and reinforces the importance of accounting for interregional linkages.

6.3. Spatial Spillover Effect

The decomposition results of the SDM are reported in Table 13. The direct effect of DE development (Dig) is significantly negative (−0.162), while the direct effect of its squared term (Dig2) is significantly positive (1.458), confirming a U-shaped relationship. For the indirect effects, the coefficient of Dig2 is significantly negative (−1.096), while the coefficient of Dig is positive (0.090) but not statistically significant. Taken together, the results point to an inverted U-shaped spatial spillover effect, indicating that DE development in neighboring regions initially worsens local income disparities but eventually contributes to their reduction.

Table 12. SDM regression results.

Variables	W1		W2	
	(1) Main	(2) Wx	(3) Main	(4) Wx
Dig	−0.168 ***	0.131 ***	−0.137 ***	0.132 **
	(0.039)	(0.050)	(0.040)	(0.059)
Dig2	1.551 ***	−1.362 ***	1.665 ***	−1.442 **
	(0.271)	(0.435)	(0.262)	(0.564)
Control variables	Yes	Yes	Yes	Yes
Rho	0.373 ***		0.691 ***	
	(0.024)		(0.040)	
Sigma2_e	0.000 ***		0.000 ***	
	(0.000)		(0.000)	
Year FE	Yes		Yes	
City FE	Yes		Yes	
Observations	2320		2320	
R-squared	0.205		0.389	
Number of city	232		232	

Note: Robust standard errors in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 13. Estimates of direct, indirect, and total effects.

Variables	W1			W2		
	(1) Direct	(2) Indirect	(3) Total	(4) Direct	(5) Indirect	(6) Total
Dig	−0.162 ***	0.090	−0.072	−0.135 ***	0.093	−0.043
	(0.038)	(0.057)	(0.057)	(0.040)	(0.134)	(0.132)
Dig2	1.458 ***	−1.096 **	0.362	1.631 ***	−0.769	0.862
	(0.241)	(0.444)	(0.478)	(0.237)	(1.352)	(1.383)
Urban	−0.057 ***	−0.019	−0.076 ***	−0.045 ***	0.075	0.030
	(0.007)	(0.015)	(0.016)	(0.007)	(0.058)	(0.058)
Pgdp	−0.015 ***	−0.013 ***	−0.028 ***	−0.009 ***	−0.036 ***	−0.045 ***
	(0.002)	(0.003)	(0.003)	(0.002)	(0.009)	(0.009)
Inds	−0.014 ***	−0.019 ***	−0.032 ***	−0.011 ***	−0.055 **	−0.067 ***
	(0.003)	(0.006)	(0.007)	(0.003)	(0.025)	(0.025)
Edu	0.058 ***	0.124 ***	0.183 ***	0.057 ***	0.297 ***	0.354 ***
	(0.012)	(0.026)	(0.030)	(0.012)	(0.097)	(0.099)
Stu	0.049	0.081	0.129	−0.001	0.836 **	0.835 *
	(0.031)	(0.093)	(0.107)	(0.031)	(0.423)	(0.432)
Observations		2,552			2,320	
R-squared		0.527			0.389	
Number of city		232			232	

Note: Robust standard errors in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

This pattern can be explained by the initial concentration of digital benefits. At this stage, gains from factor allocation are largely confined to urban areas, substantially outweighing those accruing to rural regions. Consequently, the spatial spillover effects tend to intensify urban–rural income disparities in neighboring areas. Over time, however, as institutional and infrastructural barriers to factor mobility are gradually reduced, DE promotes a shift from a parallel allocation model to one of greater urban–rural coordination. This transition facilitates the diffusion of emerging resources into rural areas, revitalizes traditional rural industries, and ultimately contributes to narrowing the urban–rural income gap [57].

7. Conclusions and Discussions

7.1. Main Findings

The main conclusions are as follows:

The relationship between DE and urban–rural income disparity follows a significant U-shaped nonlinear pattern. In the early stages, DE development helps narrow the income disparity, but as development deepens, the gap gradually widens. This conclusion is supported by multiple robustness checks, underscoring the reliability of the result.

The allocation of urban and rural factors mediates the impact of DE on income disparities, and this relationship exhibits a clear dual-threshold effect. When factor allocation efficiency is low, the effect of DE on the income disparity is relatively weak. As allocation efficiency improves and surpasses threshold levels, however, the influence becomes increasingly significant.

The effects of DE on urban–rural income disparity vary across urban agglomeration types and stages of urbanization. In regions with higher levels of urbanization and stronger economic development, the impact of digitalization on income disparity is more pronounced.

Spatial analysis reveals a significant positive spatial correlation between DE and income disparity. The direct effect of digitalization follows a U-shaped pattern, initially reducing the gap but later contributing to its widening. The spatial spillover effect exhibits an inverted U-shape. The development of DE in neighboring regions at first intensifies local disparities, but over time helps to narrow them.

7.2. Policy Implications

The following policy recommendations are proposed:

Strengthen rural digital infrastructure and skills development. To prevent digitalization from exacerbating the urban–rural income gap, it is crucial to enhance digital infrastructure in rural areas. This can be achieved through targeted investments in broadband expansion, ensuring universal access to high-speed internet in underserved regions. Additionally, digital literacy programs should be rolled out for rural workers, alongside incentives for private companies to build and maintain digital infrastructure. Telecommunication regulations should be adapted to support equitable access, with a focus on providing affordable and reliable internet services to rural populations.

Facilitate the flow of labor, capital, and technology. To improve economic opportunities in rural areas, policies should encourage the two-way flow of labor, capital, and technology between urban and rural regions. Specifically, tax incentives could be provided to businesses that invest in rural areas or establish digital factories. Capital grants or low-interest loans for rural startups should be introduced to foster local entrepreneurship. Furthermore, government-led initiatives like digital platforms for remote work can connect rural labor with urban industries, providing access to new income sources.

Tailored policies for regional development stages. Given the varying stages of digital development across regions, it is essential to design differentiated policies. For less developed regions, investment in foundational digital infrastructure should be prioritized, including subsidies for broadband, mobile internet, and basic ICT services. In more developed areas, policies should focus on fostering innovation and high-tech industries, with measures such as subsidies for research and development and support for tech incubators. These region-specific policies would leverage the unique strengths of urban agglomerations and promote equitable growth across urban and rural areas.

Promote cross-regional collaboration for digital integration. To maximize the benefits of digitalization, cross-regional collaboration must be enhanced. This includes removing barriers to the flow of digital knowledge, technology, and skilled labor between regions.

Specific measures could involve joint investment in digital clusters that bring together urban and rural players, focusing on sectors like agriculture technology or digital finance. Creating regional partnerships for shared technological resources, such as cloud computing services, can help narrow the digital divide and promote inclusive economic growth.

7.3. Discussion

This study offers several contributions to the understanding of digitalization and income distribution. Earlier studies relying on provincial data have yielded mixed evidence on whether DE narrows or widens the urban–rural income gap. Using prefecture-level data, this study provides a more granular assessment of this nonlinear relationship. More importantly, it introduces urban–rural factor allocation efficiency as a mediating variable for the first time, thereby deepening the understanding of the mechanisms through which digitalization affects income disparity. Furthermore, recognizing that urban–rural inequality is often intertwined with differences across cities, this study conducts heterogeneity tests at the level of national urban agglomerations. It also explores spatial dependence and spillover effects, providing a more comprehensive view of how DE shapes regional inequality through direct and indirect spatial channels.

Although this study is based on Chinese data, its findings still have broader relevance for other economies undergoing digital transformation. China provides a valuable setting because it combines rapid DE development with pronounced urban–rural disparities, allowing this study to examine how digitalization affects income distribution under conditions of regional heterogeneity and uneven development. In this respect, the main findings of this study, including the nonlinear impact of DE on urban–rural income disparity, the mediating role of factor allocation, and the existence of spatial spillover effects, may also offer useful insights for other countries facing similar urban–rural divides and regional imbalances. For emerging economies, these findings highlight the importance of improving access to digital infrastructure and strengthening the conditions for balanced factor allocation. For other countries with substantial regional inequality, the results also suggest that the effects of digitalization may vary across regions and development stages. Therefore, this study contributes to the broader discussion on inclusive growth in the digital era and offers policy implications for reducing territorial inequality through digital development. However, the applicability of these findings depends on differences in institutions, digital infrastructure, and governance across countries.

However, this study has certain limitations. Due to restrictions in the availability of factor allocation data, the sample period ends in 2022, which prevents the analysis from capturing more recent changes in DE development and urban–rural income disparity. In addition, high-quality data that accurately reflect the distribution of digital factors between urban and rural areas are still lacking, which limits the ability to represent factor allocation directly in the empirical analysis. In addition, although PCA helps reduce dimensionality and construct the digital economy index objectively, it is primarily variance-driven and may not fully capture the conceptual heterogeneity of different dimensions within the digital economy. As a result, some variables can only be measured through available proxy indicators, which may not fully capture the complexity of factor movements and digital resource distribution across regions. Moreover, because prefecture-level data are not equally complete for all cities and years, some missing observations had to be addressed through data processing methods, which may also affect the precision of the econometric estimates to some extent.

Future research could integrate micro-level survey data or other high-resolution data sources to provide a more precise depiction of digital factor distribution. Such efforts would improve the accuracy and reliability of analyses of factor allocation mechanisms.

Additionally, the study focuses on income disparity, leaving other important dimensions of inequality such as education, health, and access to services for future research.

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Appendix A

The DE index in this study is constructed using principal component analysis (PCA). PCA is employed to reduce dimensionality by extracting orthogonal components that capture most of the variance in the original variables. These indicators capture most of the information contained in the original variables while reducing redundancy, thereby simplifying the dataset and extracting its key features. Given n years of sample data and p indicators related to DE, the initial sample matrix can be expressed as

$$X = \begin{bmatrix} x_{11} & x_{12} & \dots & x_{1p} \\ x_{21} & x_{22} & \dots & x_{2p} \\ \vdots & \vdots & \ddots & \vdots \\ x_{n1} & x_{n2} & \dots & x_{np} \end{bmatrix} = \left(x_{ij}\right)_{n \times p}, \tag{A1}$$

where x_{ij} represents the value of the j-th indicator in the i-th year (i = 1, 2, . . ., n; j = 1, 2, . . ., p). The matrix is standardized to obtain the matrix Z_{ij}.

First, calculate the correlation matrix $R = (r_{ij})_{n \times p}$. The correlation coefficient r_{ij} between the i-th and j-th indicators is given by the following formula:

$$r_{ij} = \frac{Cov(X_i, X_j)}{\sqrt{s_i^2 \cdot s_j^2}}, \tag{A2}$$

where $Cov(X_i,X_j)$ denotes the covariance between the i-th and j-th indicators. s_i^2 and s_j^2 represent their variances.

Second, calculate the eigenvalues and eigenvectors of R. According to the eigenvalue equation $|R - \lambda I| = 0$, the eigenvalues are obtained, where R represents the correlation matrix and I the identity matrix. Ordering the eigenvalues in descending magnitude yields $\lambda_1, \lambda_2, \dots, \lambda_n$, with corresponding eigenvectors derived accordingly.

Third, the cumulative contribution is calculated to identify how many principal components should be retained, as presented in Equation (A3).

$$Q_m = \frac{\sum_{i=1}^{m} \lambda_i}{\sum_{i=1}^{p} \lambda_i}, \tag{A3}$$

In practice, principal components are retained until the cumulative contribution rate Q_m exceeds 85%, so that most of the information contained in the original variables is preserved. Following this criterion, the first two principal components were retained in this study, as they jointly captured the dominant share of the total variance and provided a parsimonious representation of the multidimensional characteristics of the digital economy. This component-selection strategy helps balance information retention and index simplicity, while reducing redundancy across highly correlated indicators.

References

1. Lagakos, D. Does Internal Migration Offer Opportunities? *J. Econ. Perspect.* **2020**, *34*, 174–192. [CrossRef]
2. Sulemana, I.; Nketiah-Amponsah, E.; Codjoe, E.A.; Andoh, J.A.N. Urbanization and income inequality in Sub-Saharan Africa. *Sustain. Cities Soc.* **2019**, *48*, 101544. [CrossRef]
3. Braesemann, F.; Lehdonvirta, V.; Kässi, O. ICTs and the urban-rural divide: Can online labour platforms bridge the gap? *Inf. Commun. Soc.* **2022**, *25*, 34–54. [CrossRef]
4. Curtis, M.E.; Clingan, S.E.; Guo, H.; Zhu, Y.; Mooney, L.J.; Hser, Y.-I. Disparities in digital access among American rural and urban households and implications for telemedicine-based services. *J. Rural Health* **2022**, *38*, 512–518. [CrossRef]
5. Williams, L.D. Concepts of Digital Economy and Industry 4.0 in Intelligent and information systems. *KeAi Commun. Co.* **2021**, *2*, 122–129. [CrossRef]
6. Zhong, S.; Wang, M.; Zhu, Y.; Chen, Z.; Huang, X. Urban expansion and the urban–rural income gap: Empirical evidence from China. *Cities* **2022**, *129*, 103831. [CrossRef]
7. Kosasih, A.; Sulaiman, E. Digital transformation in rural settings: Unlocking opportunities for sustainable economic growth and community empowerment. *J. Sustain. Tour. Entrep.* **2024**, *5*, 129–143. [CrossRef]
8. Zhan, L.; Wang, S.; Xie, S.; Zhang, Q.; Qu, Y. Spatial path to achieve urban-rural integration development-analytical framework for coupling the linkage and coordination of urban-rural system functions. *Habitat. Int.* **2023**, *142*, 102953. [CrossRef]
9. Zhang, Q.; Wu, P.; Li, R.; Chen, A. Digital transformation and economic growth efficiency improvement in the digital media era: Digitalization of industry or Digital industrialization? *Int. Rev. Econ. Financ.* **2024**, *92*, 667–677. [CrossRef]
10. Matt, D.T.; Pedrini, G.; Bonfanti, A.; Orzes, G. Industrial digitalization. A systematic literature review and research agenda. *Eur. Manag. J.* **2023**, *41*, 47–78. [CrossRef]
11. 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]
12. Zhang, T.; Li, N. Measuring digital economy: From the perspective of digital industrialization and industry digitalization. *Procedia Comput. Sci.* **2023**, *215*, 1006–1012. [CrossRef]
13. Guo, X.; Xu, D.; Zhu, K. Measuring digitalization effects in China: A global value chain perspective. *China Econ. Rev.* **2023**, *81*, 102021. [CrossRef]
14. Liu, Y.; Tian, G.; Zhang, X. Digital economy and China's path to common prosperity. *Digit. Econ. Sustain. Dev.* **2024**, *2*, 8. [CrossRef]
15. Danda, R.R. Innovations in Agricultural Machinery: Assessing the Impact of Advanced Technologies on Farm Efficiency. *J. Artif. Intell. Big Data* **2022**, *2*, 64–83. [CrossRef]
16. Aker, J.C. Dial "A" for agriculture: A review of information and communication technologies for agricultural extension in developing countries. *Agric. Econ.* **2011**, *42*, 631–647. [CrossRef]
17. Gao, X.; Li, M.-S. The impact of the digital economy on the urban-rural income gap: Evidence from provincial panel data in China. *Appl. Econ. Lett.* **2024**, *31*, 2233–2236. [CrossRef]
18. Zhan, Y.; Gao, D.; Feng, M.; Yan, S. Digital finance, non-agricultural employment, and the income-increasing effect on rural households. *Int. Rev. Financ. Anal.* **2025**, *98*, 103897. [CrossRef]
19. Deng, X.; Guo, M.; Liu, Y. Digital economy development and the urban-rural income gap: Evidence from Chinese cities. *PLoS ONE* **2023**, *18*, e0280225. [CrossRef]
20. James, J. Confronting the scarcity of digital skills among the poor in developing countries. *Dev. Policy Rev.* **2021**, *39*, 324–339. [CrossRef]
21. Wang, D.; Zhou, T.; Wang, M. Information and communication technology (ICT), digital divide and urbanization: Evidence from Chinese cities. *Technol. Soc.* **2021**, *64*, 101516. [CrossRef]
22. Ferrari, A.; Bacco, M.; Gaber, K.; Jedlitschka, A.; Hess, S.; Kaipainen, J.; Koltsida, P.; Toli, E.; Brunori, G. Drivers, barriers and impacts of digitalisation in rural areas from the viewpoint of experts. *Inf. Softw. Technol.* **2022**, *145*, 106816. [CrossRef]
23. Hong, X.; Chen, Q.; Man, D.; Shi, C.; Wang, N. The impact of digitalization on the rich and the poor: Digital divide or digital inclusion? *Technol. Soc.* **2024**, *78*, 102634. [CrossRef]

24. Xiao, J. Digital economy, industrial structure upgrading and urban-rural income gap. *Acad. J. Bus. Manag.* **2023**, *5*, 65–70. [CrossRef]
25. Li, Y.; Li, F. Digital economy, the income gap, and regional crime rates in China. *Financ. Res. Lett.* **2025**, *75*, 106861. [CrossRef]
26. Peng, Z.; Dan, T. Digital dividend or digital divide? Digital economy and urban-rural income inequality in China. *Telecomm. Policy* **2023**, *47*, 102616. [CrossRef]
27. Jiang, Q.; Li, Y.; Si, H. Digital Economy Development and the Urban–Rural Income Gap: Intensifying or Reducing. *Land* **2022**, *11*, 1980. [CrossRef]
28. Tao, J.; Wang, Z.; Xu, Y.; Zhao, B.; Liu, J. Can the digital economy boost rural residents' income? Evidence from China based on the spatial Durbin model. *Econ. Anal. Policy* **2024**, *81*, 856–872. [CrossRef]
29. Peng, X.; Yan, S.; Yan, X. Studying whether the digital economy effectively promotes China's common prosperity based on the spatial Durbin model. *Humanit. Soc. Sci. Commun.* **2024**, *11*, 4132. [CrossRef]
30. Wang, Y.; Peng, Q.; Jin, C.; Ren, J.; Fu, Y.; Yue, X. Whether the digital economy will successfully encourage the integration of urban and rural development: A case study in China. *Chin. J. Popul. Resour. Environ.* **2023**, *21*, 13–25. [CrossRef]
31. Cheng, K.; Liu, S. Does urbanization promote the urban–rural equalization of basic public services? Evidence from prefectural cities in China. *Appl. Econ.* **2024**, *56*, 3445–3459. [CrossRef]
32. Lu, Y.; Zhuang, J.; Yang, C.; Li, L.; Kong, M. How the digital economy promotes urban–rural integration through optimizing factor allocation: Theoretical mechanisms and evidence from China. *Front. Sustain. Food Syst.* **2025**, *9*, 1494247. [CrossRef]
33. Hsieh, C.T.; Klenow, P.J. Misallocation and manufacturing TFP in China and India. *Q. J. Econ.* **2009**, *124*, 1403–1448. [CrossRef]
34. Zhang, Y.; Hainan, L.; Feng, F.; Wu, X. Digital economy, education, human capital and urban–rural income disparity. *Financ. Res. Lett.* **2025**, *71*, 106464. [CrossRef]
35. Ye, B.; Yuan, J.; Guan, Y. Internet Finance, Financing of Small and Micro Enterprises and the Macroeconomy. *Emerg. Mark. Financ. Trade* **2022**, *58*, 2851–2866. [CrossRef]
36. Fong, M.W.L. Digital Divide Between Urban and Rural Regions in China. *Electron. J. Inf. Syst. Dev. Ctries.* **2009**, *36*, 1–12. [CrossRef]
37. Javaid, M.; Haleem, A.; Singh, R.P.; Sinha, A.K. Digital economy to improve the culture of industry 4.0: A study on features, implementation and challenges. *Green. Technol. Sustain.* **2024**, *2*, 100083. [CrossRef]
38. Zhang, Z.; Sun, C.; Wang, J. How Can the Digital Economy Promote the Integration of Rural Industries—Taking China as an Example. *Agriculture* **2023**, *13*, 2023. [CrossRef]
39. Xu, B.; Sendra-García, J.; Gao, Y.; Chen, X. Driving total factor productivity: Capital and labor with tax allocation. *Technol. Forecast. Soc. Change* **2020**, *150*, 119782. [CrossRef]
40. Johnson, M.; Jain, R.; Brennan-Tonetta, P.; Swartz, E.; Silver, D.; Paolini, J.; Mamonov, S.; Hill, C. Impact of Big Data and Artificial Intelligence on Industry: Developing a Workforce Roadmap for a Data Driven Economy. *Glob. J. Flex. Syst. Manag.* **2021**, *22*, 197–217. [CrossRef]
41. Ma, L.; Wang, T. The Impact of Digital Economy on the High Quality Development of Agricultural Enterprises: Evidence From Listed Agricultural Enterprises in China. *Sage Open* **2024**, *14*, 21582440241257360. [CrossRef]
42. Lin, H.; Peng, P. Impacts of Digital Inclusive Finance, Human Capital and Digital Economy on Rural Development in Developing Countries. *Financ. Res. Lett.* **2025**, *73*, 106654. [CrossRef]
43. Hu, Y.; Yu, H.; Chen, Q. Digitalization Driving High-Quality Converged Development of Rural Primary, Secondary, and Tertiary Industries: Mechanisms, Effects, and Paths. *Sustainability* **2023**, *15*, 11708. [CrossRef]
44. Fang, C.; Chen, Z.; Liao, X.; Sun, B.; Meng, L. Urban-rural digitalization evolves from divide to inclusion: Empirical evidence from China. *npj Urban. Sustain.* **2024**, *4*, 187. [CrossRef]
45. Chen, C.; Restuccia, D.; Santaeulàlia-Llopis, R. The effects of land markets on resource allocation and agricultural productivity. *Rev. Econ. Dyn.* **2022**, *45*, 41–54. [CrossRef]
46. Jiang, W.; Li, J. Digital transformation and its effect on resource allocation efficiency and productivity in Chinese corporations. *Technol. Soc.* **2024**, *78*, 102638. [CrossRef]
47. Jiang, T. Mediating Effects and Moderating Effects in Causal Inference. *China Ind. Econ.* **2022**, *5*, 100–120.
48. Baron, R.M.; Kenny, D.A. The moderator–mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations. *J. Pers. Soc. Psychol.* **1986**, *51*, 1173. [CrossRef] [PubMed]
49. Hansen, B.E. Sample splitting and threshold estimation. *Econometrica* **2000**, *68*, 575–603. [CrossRef]
50. Shen, H.; Luo, T.; Gao, Z.; Zhang, X.; Zhang, W.; Chuang, Y.C. Digital financial inclusion and the urban–rural income gap in China: Empirical research based on the Theil index. *Econ. Res. Istraz.* **2023**, *36*, 2156575. [CrossRef]
51. Zhao, T.; Zhang, Z.; Liang, S. Digital Economy, Entrepreneurship, and High-Quality Economic Development: Empirical Evidence from Urban China. *J. Manag. World* **2020**, *36*, 65–76. [CrossRef]
52. Li, Y.; Wang, X.; Zhu, Q.; Zhao, H. Assessing the spatial and temporal differences in the impacts of factor allocation and urbanization on urban-rural income disparity in China, 2004–2010. *Habitat Int.* **2014**, *42*, 76–82. [CrossRef]

53. Dagum, C. Decomposition and interpretation of Gini and the generalized entropy inequality measures. *Statistica* **1997**, *57*, 295–308. [CrossRef]
54. Long, H.; Tu, S.; Ge, D.; Li, T.; Liu, Y. The allocation and management of critical resources in rural China under restructuring: Problems and prospects. *J. Rural. Stud.* **2016**, *47*, 392–412. [CrossRef]
55. Yang, D.T. Education and allocative efficiency: Household income growth during rural reforms in China. *J. Dev. Econ.* **2004**, *74*, 137–162. [CrossRef]
56. Guan, Z.; Pan, P.P. New quality productive forces and new-type urbanization: Analysis of coupling coordination and influencing factors in China. *Land Use Policy* **2025**, *158*, 107724. [CrossRef]
57. Zhou, M.; Guo, F.; Sun, Y.; Ren, J.; Zhang, X. Promotion or inhibition? Exploring the influence of the digital economy on urban-rural integration: A case study of yellow River basin. *Sustain. Futur.* **2024**, *8*, 100293. [CrossRef]

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