

The Impact of the Digital Economy on Urban-Rural Income Disparity: Perspectives from Industrial Structure Upgrading and Rationalization

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Abstract: Amidst accelerating digital transformation, the digital-driven economy emerges as a pivotal force for mitigating urban-rural income inequality and advancing shared prosperity through optimized resource distribution. Leveraging provincial-level panel data across China (2011–2022) and integrating industrial structure dynamics, this research employs fixed-effect and threshold regression models to dissect the mechanisms linking digitalization to income parity. Key findings reveal that digital economic growth exerts a statistically significant dampening effect on urban-rural income disparities. Notably, under tertiary industry dominance, this relationship demonstrates nonlinear dynamics with progressively diminishing marginal returns. Regional heterogeneity further underscores the need for tailored policy frameworks. Strategic recommendations emphasize interregional synergy cultivation, innovation-driven digital ecosystem development, industrial value-chain upgrading, and institutional safeguards for equitable prosperity.

Keywords: Digital economy, Urban-rural income disparity, Industrial structure upgrading, Industrial structure rationalization

1. Introduction

As a central catalyst for total factor productivity growth, the digital economy is fundamentally reconfiguring global production networks and resource distribution patterns. China prioritizes its development as a pillar of the modern economic system. By 2023, core digital economy industries contributed 10% of GDP, 5G user penetration exceeded 60%, and mobile IoT terminal users reached 80%, surpassing the "14th Five-Year Plan" targets ahead of schedule [1]. Narrowing urban-rural income disparities through digital integration has become a critical agenda. China actively promotes the fusion of digital technologies with agriculture and rural industries, fostering a comprehensive value chain to bridge the urban-rural divide. The Digital Rural Development Strategy Outline aims for the rural digital economy to account for 15% of agricultural added value by 2025, significantly reducing the "digital divide" [2].

The digital economy optimizes industrial structures, drives agricultural digitization, restructures urban-rural industries, enhances rural value-added, and facilitates factor mobility. By stimulating labor and capital flows, it reduces income disparities from both supply and demand perspectives. Utilizing empirical frameworks, the paper scrutinizes the synergistic linkages connecting digital innovation, structural economic shifts, and spatial income inequality.

2. Literature review

2.1. Digital economy and urban-rural income disparity

Scholarly consensus acknowledges the digital economy's capacity to mitigate urban-rural income inequality, albeit with heterogeneous spatial and temporal effects. Xu and Tao [3], employing a semi-parametric functional coefficient framework, revealed a nonlinear U-curve pattern in the digital economy's influence on income disparity. Contrastingly, Zhang et al. [4] demonstrated an inverse U-curve association between digital advancement and urban-rural consumption gaps, attributing this phenomenon to digital industrialization processes. Fan et al. [5] further emphasized the mediating role of persistent secondary digital divides in perpetuating inequality. Regional analyses by Wang and Xiao [6] identified asymmetric impacts: digitalization narrows income gaps in central-western regions, marginally exacerbates them in eastern coastal areas, and remains statistically inert in northeastern provinces.

Scholars have also explored underlying mechanisms. Gao and Li argued that industrial upgrading mediates the narrowing effect [7], while Ji cautioned that varying industrial integration levels can either mitigate or worsen disparities [8]. Zhao et al. emphasized that closing urban-rural digital development gaps directly reduces income inequality [9], whereas Ruan et al. warned that excessive digital inequality could reverse this effect [10].

2.2. Industrial structure and urban-rural income disparity

Most studies suggest that industrial upgrading reduces urban-rural income disparities. Zhao et al. found a significant negative correlation between industrial upgrading and income gaps [11]. Wu et al. demonstrated this effect using micro-level data [12], while Yang et al. argued that rising urban factor costs drive industrial relocation to rural areas, boosting employment and reducing disparities [13]. However, conflicting views exist. Zheng et al. found that industrial optimization in Inner Mongolia widened disparities by disproportionately benefiting urban residents [14]. Zhou and Li identified regional variations: an "N-shaped" curve in the east, a narrowing effect in central regions, and a widening trend in the west [15]. While industrial rationalization consistently narrows disparities, upgrading may sometimes expand them [16]. Some studies suggest a dual-threshold effect, where rationalization only significantly reduces gaps at advanced urbanization stages [17].

In summary, debates persist over the digital economy's role in income disparities. Existing research often emphasizes regional or urbanization perspectives but lacks a comprehensive integration of industrial upgrading and rationalization. Filling this research lacuna, the research systematically examines how digital transformation conditions rural-urban wealth disparities across industrial configuration's dual vectors: sectoral advancement and organizational efficiency.

3. Theoretical model and research hypotheses

The digital economy eliminates spatiotemporal barriers in education and training, providing rural residents with access to learning resources and enhancing human capital. According to human capital theory [18], this advancement fuels economic growth and may reduce income disparities. Simultaneously, platform economies (e.g., e-commerce and livestreaming) open new avenues for agricultural sales and rural tourism, strengthening market linkages and supply chains, consistent with the "trickle-down effect" [19]. Thus, Hypothesis 1 is proposed:

H1: The development of the digital economy narrows the urban-rural income gap.

According to the Petty-Clark theorem, the digital economy influences income distribution through technological penetration and factor reallocation. Initially, digital platforms drive labor migration to the tertiary sector, improving resource allocation. However, once the service sector surpasses a

certain threshold, technological premiums widen—knowledge-intensive services reap excess returns, while traditional sectors stagnate due to factor rigidity, creating structural imbalances in transformation dividends. This dynamic results in an inverted U-shaped relationship between the digital economy and income disparities. Thus, Hypothesis 2 follows:

H2: The impact of the digital economy on urban-rural income disparities exhibits nonlinear characteristics when dominant industries shift.

Resource-based theory highlights regional differences in technological resources, human capital, and infrastructure, leading to spatial variation in the digital economy's impact [20]. Tech-intensive regions harness digital technologies for industrial upgrading, fostering high-tech clusters and boosting incomes. In contrast, resource-dependent regions, limited by digital deficiencies, face slow industrial transitions and stagnant income growth. Thus, Hypothesis 3 is proposed:

H3: The narrowing effect of the digital economy on urban-rural income disparities exhibits regional heterogeneity.

4. Model setting and description of variables

4.1. Research design

4.1.1. Basic regression model

To analyze the relationship between the digital economy and income disparities, the baseline regression model as shown in Equation (1) is established.

$$\text{Theil}_{it} = \alpha_0 + \alpha_1 \ln \text{digeco}_{it} + \theta X_{it} + \mu_i + \omega_t + \varepsilon_{it} \quad (1)$$

In model (1), Theil_{it} represents the urban-rural income gap, digeco_{it} denotes the digital economy development level, X_{it} stands for a series of control variables, i indicates the province, t represents the year, α is the coefficient to be estimated, μ_i is the provincial fixed effect, ω_t is the time fixed effect, and ε_{it} represents the stochastic error term.

4.1.2. Threshold effect model

To further explore the impact mechanism of digital economy development on urban-rural income gap under the influence of industrial structure, this study constructs a Threshold Effect Model by taking the upgrading of industrial structure as the threshold variable, as shown in Equation (2).

$$\begin{aligned} \text{Theil}_{it} = & \alpha_0 + \alpha_1 \ln \text{digeco}_{it} \times I(\text{ISU}_{it} \leq \gamma_1) + \alpha_2 \ln \text{digeco}_{it} \times \\ & I(\gamma_1 < \text{ISU}_{it} \leq \gamma_2) + \alpha_3 \ln \text{digeco}_{it} \times I(\text{ISU}_{it} > \gamma_2) + \theta X_{it} + \mu_i + \omega_t + \varepsilon_{it} \end{aligned} \quad (2)$$

This study constructs another Threshold Effect Model by taking the rationalization of industrial structure as the threshold variable, as shown in Equation (3).

$$\begin{aligned} \text{Theil}_{it} = & \alpha_0 + \alpha_1 \ln \text{digeco}_{it} \times I(\text{SDEV}_{it} \leq \sigma_1) + \alpha_2 \ln \text{digeco}_{it} \times \\ & I(\sigma_1 < \text{SDEV}_{it} \leq \sigma_2) + \alpha_3 \ln \text{digeco}_{it} \times I(\text{SDEV}_{it} > \sigma_2) + \theta X_{it} + \mu_i + \omega_t + \varepsilon_{it} \end{aligned} \quad (3)$$

Where: $I(\cdot)$ is an indicator function taking values 1 or 0; γ and σ represent the threshold values to be estimated for the upgrading and rationalization of industrial structure, respectively.

4.2. Variable selection

This study operationalizes digital economic advancement through the Digital Economy Index (DEI) framework derived from authoritative national benchmarks [21]. The composite metric integrates

nine evaluative criteria spanning four foundational pillars. An entropy-weighted valuation technique determines hierarchical scoring coefficients across sub-indicators, subsequently synthesized into dimensional composite scores. Table 1 comprehensively details the measurement architecture, including standardized units, directional properties, and empirically derived weighting parameters.

Table 1: Construction of the digital economy indicator system

Primary indicators	Secondary indicators / Variable name / Weights	Tertiary indicators / Weights	Unit	Attribute
Digital economy	Level of digital infrastructure/LDI(20.2%)	Number of internet broadband subscribers(7.4%)	10,000 households	+
		Length of fiber optic cable lines(7.2%)	10,000 kilometers	+
		Year-end mobile phone subscribers(5.6%)	10,000 households	+
		Total volume of telecommunications services(14.1%)	100 million yuan	+
	Level of digital industry development/DIDL(35.4%)	Total software business volume(21.3%)	100 million yuan	+
		Digital inclusive finance index(3.0%)	None	+
	Added value from industrial digitalization/IDVA(7.2%)	Number of international internet users per 100 people(4.2%)	people	+
		Proportion of employees in information transmission, computer services, and software industry(10.7%)	%	+
	Level of digital economy innovation capacity/DEIC(37.2%)	Number of invention patent applications(26.5%)	applications	+

This study employs Theil's entropy measure as the benchmark metric for assessing interregional income disparity. While conventional approaches frequently utilize the Gini coefficient for inequality quantification [22], its methodological limitations in detecting polarization effects – particularly its heightened sensitivity to median-income fluctuations and reduced responsiveness to distributional shifts at socioeconomic extremes – render it suboptimal for analyzing rural-urban wealth divides. Theil's measure, conversely, demonstrates superior capacity to dissect asymmetrical income allocation patterns while providing intuitive economic interpretability: its scalar magnitude directly correlates with escalating spatial inequality. Aligning with prior validation by Fan et al., our analytical framework adopts this entropy-based metric, with computational specifications formalized in Equation (4).

$$\text{Theil}_t = \sum_{i=1}^2 \left(\frac{I_{it}}{I_t} \right) \ln \left(\frac{\frac{I_{it}}{P_{it}}}{\frac{I_t}{P_t}} \right) \quad (4)$$

Within the formula, Theil_t quantifies spatial income disparity through entropy-based measurement during period t ; I_{1t} and I_{2t} demarcate aggregate metropolitan and non-urban earnings respectively, derived from multiplying regional per capita disposable income by corresponding demographic figures; I_t constitutes combined urban-rural earnings; P_{1t} and P_{2t} reflect metropolitan versus rural composite population figures for the analyzed timeframe; P_t denotes total territorial residency.

For industrial structure upgrading (ISU), operationalized via tertiary-secondary output valuation ratio, following Gan et al.'s validated methodology [23]. For SDEV, which measures industrial

balance, existing studies typically use the structural deviation degree [24]. The formula is presented in Equation (5):

$$SDEV = \sum_{i=0}^3 \left| \frac{Y_i/L_i}{Y/L} - 1 \right| = \sum_{i=0}^3 \left| \frac{Y_i/Y}{L_i/L} - 1 \right| \quad (5)$$

Among these, Y and L represent output and employment, respectively, while i refers to each industrial sector. A larger SDEV value indicates a greater deviation between output and employment, meaning the industry's employment share exceeds its value-added share, suggesting lower labor productivity. When considering absolute values, a larger value reflects a greater imbalance between industrial and employment structures.

The analysis incorporates four control parameters to account for contextual influences: Fiscal expenditure intensity (govexp), quantified through provincial budgetary allocations; urbanization progression (ur), represented by the proportion of urban residents relative to total population; foreign investment penetration (fdi), calculated as foreign direct investment normalized against regional GDP; and transport infrastructure density (dtd), assessed through the combined railway and highway mileage relative to provincial land area. These metrics collectively capture fiscal, demographic, economic openness, and logistical development factors that potentially modulate the primary relationships under investigation.

4.3. Data source and descriptive statistics

This research analyzes longitudinal data spanning 2011-2022 from 30 provincial-level administrative units in mainland China (excluding Tibet and special administrative regions). The dataset integrates multi-source records from the National Bureau of Statistics, CSMAR platform, national and regional statistical compendiums, government publications, and official provincial data portals. Exploratory analysis reveals substantial heterogeneity in digital advancement metrics and subnational fiscal allocations across both temporal and spatial dimensions.

Table 2: Descriptive statistics of variables

Variable	Mean	Std Dev	Min	Max
Theil	0.086	0.041	0.017	0.223
Ln (100*digeco)	2.291	0.808	-0.465	4.286
SDEV	3.001	0.318	2.813	6.965
ISU	1.266	0.722	0.518	5.297
ur	0.600	0.122	0.350	0.940
Fdi*10	0.199	0.198	0.000	1.210
Ln (dtd+1)	0.652	0.277	0.088	1.195
Ln govexp	8.639	0.603	6.721	10.020

5. Analysis of empirical results

5.1. Benchmark regression analysis

Table 3 presents core econometric findings analyzing digitalization's influence on regional wealth divides. Sequential model specifications (Columns 1-5) demonstrate robustness through cumulative inclusion of covariates. The baseline specification (Column 1) reveals digital advancement metrics as the primary explanatory factor, with subsequent columns incorporating supplementary controls. Notably, digitalization displays a persistently significant negative coefficient, confirming its suppressive effect on spatial income disparity. Elasticity estimates indicate each percentage point

elevation in digital economic growth yields a 2.2% contraction in urban-rural inequality, thereby validating Hypothesis 1.

Supplementary covariates analysis reveals urbanization progression substantially attenuates regional income gaps. Transportation infrastructure expansion exhibits marginal downward pressure on wealth disparity, though lacking statistical robustness. Foreign capital influx initially shows insignificant correlation with inequality metrics, but manifests enhanced explanatory power when integrated with fiscal expenditure and logistical development parameters.

Table 3: Benchmark regression results (N=360)

Variable	Theil				
	(1)	(2)	(3)	(4)	(5)
Ln (100*digeco)	-0.038*** (0.006)	-0.024*** (0.006)	-0.023*** (0.006)	-0.023*** (0.006)	-0.022*** (0.006)
Constant	0.145*** (0.015)	0.281*** (0.039)	0.278*** (0.041)	0.286*** (0.042)	0.081 (0.107)
Control Variables	Yes				
Time, province fixed	Yes				
R ²	0.711	0.741	0.741	0.742	0.747

Note: Robust standard errors are in parentheses; ***, **, and * denote significance levels of 1%, 5%, and 10%, respectively, as in the table below.

5.2. Robustness test analysis

Three validation procedures were implemented to ensure analytical rigor. Initially, pandemic-induced anomalies were addressed by omitting 2020 observations, as COVID-19 containment measures introduced atypical economic distortions. Subsequent outlier mitigation involved truncating extreme values (1st/99th percentiles) across key metrics, preserving distributional integrity without altering core estimations. Conclusively, municipalities with administrative particularities (Beijing, Tianjin, Shanghai, Chongqing) were excluded to control for their divergent developmental trajectories in digitalization. All robustness checks yielded coefficient stability, confirming the model's resilience to temporal shocks, distributional extremes, and jurisdictional heterogeneity.

Table 4: Results of robustness test

Variable	Excluding Data	Winsorization	Excluding Direct Municipalities
	(1)	(2)	(3)
Ln (100*digeco)	-0.021*** (0.006)	-0.022*** (0.006)	-0.029*** (0.009)
Constant	0.096 (0.108)	0.093 (0.102)	-0.051 (0.125)
Control Variables	Yes		
Time, province fixed	Yes		
N	330	360	312
R ²	0.737	0.752	0.757

5.3. Threshold effect test

The analytical framework initiates with threshold-effect diagnostics. Table 5 delineates sectoral modulation effects, revealing structural optimization (SDEV) exhibits a statistically robust single-threshold signature ($p < 0.01$), whereas sectoral advancement (ISU) demonstrates no discernible transition point.

Subsequent econometric modeling (Table 6) uncovers nonlinear dynamics: Below the structural optimization threshold (≤ 2.970), digitalization exerts a -0.017 standardized impact on spatial wealth disparity. Beyond this critical juncture, the negative coefficient intensifies marginally (-0.021) while retaining statistical significance ($p < 0.05$), evidencing progressively diminishing marginal returns. This threshold-contingent behavior confirms digital transformation's capacity to alleviate regional inequality follows logistic rather than linear progression.

Table 5: Threshold effect test results

Threshold Variable	Model	Threshold	F-statistic value	P-value	BS count	Threshold value		
						1%	5%	10%
Rationalization	Single	2.970	18.86	0.043	300	26.419	17.794	15.520
Upgrading	Single	0.904	13.93	0.313	300	43.729	26.837	22.252

Table 6: Threshold regression results

Variable	Variable Symbol	Industrial Structure Rationalization
Rationalization ≤ 2.970	$\ln \text{digeco}_{it} \times I(\text{SDEV} \leq \sigma)$	-0.017*** (0.004)
Rationalization > 2.970	$\ln \text{digeco}_{it} \times I(\text{SDEV} > \sigma)$	-0.015*** (0.004)
Control Variables		Yes
Constant	constant	0.186*** (0.053)
Threshold	$\sigma(\gamma)$	2.970
N	observations	360
R ²	R ²	0.717

5.4. Heterogeneity analysis

Spatially heterogeneous effects emerge from China's multiregional analysis, structured per the National Bureau's geographical taxonomy (Eastern, Central, Western, Northeastern sectors). Fixed-effect specifications reveal digitalization's divergent spatial impacts: Eastern provinces exhibit significant inequality mitigation (-0.022 coefficient at 10% significance), where each percentage point of digital advancement yields a 2.2% spatial wealth disparity contraction. Conversely, Northeastern territories demonstrate paradoxical amplification effects (1% significance), with Central and Western zones showing statistically inert responses. Regional elasticity gradients highlight development-stage contingencies, with advanced Eastern digital ecosystems outperforming lagging Northeastern systems in equitable growth propagation.

Table 7: Heterogeneity analysis results

Variable	Theil			
	East	West	Central	Northeast
Ln (100*digeco)	-0.022* (0.012)	0.001 (0.011)	0.036 (0.033)	0.039*** (0.015)
Constant	0.274*** (0.077)	0.127 (0.237)	0.000 (0.000)	0.000 (0.000)
Control Variables				
Time, province fixed			Yes	
R ²	0.714	0.860	0.714	0.931
N	120	132	72	36

6. Conclusion and recommendation

6.1. Conclusion

Leveraging fixed-effects and nonlinear frameworks, this analysis uncovers digitalization's multifaceted role in modulating spatial wealth divides. Empirical evidence confirms digital advancement consistently attenuates regional income inequality, with baseline elasticity estimates indicating a 2.2% disparity contraction per percentage point of digital growth. Sectoral dynamics reveal moderated efficacy in service-oriented economies, where structural optimization thresholds ($SDEV > 2.970$) trigger diminishing marginal returns—wealth parity improvements decline from 1.7% to 1.5% post-threshold. Geographically, coastal zones exhibit significant inequality reduction, contrasting sharply with Northeastern territories where digital expansion paradoxically exacerbates disparities. Central and Western regions display neutral responsiveness, highlighting developmental-stage dependencies in digital equity outcomes.

6.2. Recommendation

To address urban-rural economic imbalances by leveraging the digital economy's income gap-reducing effects, this paper proposes three strategies:

First, accelerate digital economy growth by promoting corporate innovation, full supply chain digitalization, and collaborative ecosystems. Governments should develop long-term strategies integrating technology with real industries, ensuring cross-departmental coordination and balancing R&D, industrial upgrading, and security.

Next, optimize industrial structures by prioritizing sectors with strong digital integration potential, supporting them through tax incentives and R&D subsidies. Strengthening university-business-research partnerships can extend value chains into high-end segments, reducing income disparities. Additionally, digital empowerment in agriculture and manufacturing should be enhanced via a national rural land transfer platform, improved rural fintech systems, and better resource allocation.

Regionally, East China should emphasize smart services and manufacturing to enhance urban-rural resource flow. Northeast China requires job training, social security, and transition funds to modernize traditional industries. Central and Western China must expand affordable digital infrastructure and adopt smart agriculture, leveraging local resources to increase product value and incomes.

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