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The Impact of Digital Rural Construction on Narrowing the Urban-Rural Income Gap

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Abstract

As a core strategy for advancing agricultural and rural modernization and breaking the urban-rural dual structure in the digital economy era, the implementation effects and impact mechanisms of digital rural construction have become key concerns in both academic research and policy making. Based on panel data from 41 prefecture-level cities in the Yangtze River Delta region covering 2014–2023, this study constructs a comprehensive evaluation index system for digital rural development using the entropy method, and empirically examines its influence on the urban-rural income gap with a two-way fixed-effects model. The results show that digital rural construction can significantly reduce the urban-rural income disparity. This effect is mainly transmitted through two intermediate channels: raising the comparative labor productivity of agriculture and improving the average educational attainment of rural residents. Further analysis indicates that digital inclusive finance and digital governance capacity play particularly prominent roles in narrowing the income gap. Meanwhile, the income convergence effect of digital rural construction is more pronounced in resource-based cities, low-income regions, and areas with a relatively high share of agriculture.

Keywords

Digital village; Urban-rural income gap; Theil index; Urban-rural dual structure.

1. Introduction

Digital rural construction stands as a pivotal strategy for advancing agricultural and rural modernization in the digital economy era, and also serves as a crucial support for breaking the urban-rural dual structure and moving toward common prosperity. The report to the 20th National Congress of the Communist Party of China clearly points out that the most arduous and demanding tasks in building a modern socialist country remain in rural areas, and it is essential to steadily promote the revitalization of rural industries, talent, culture, ecology, and organizations. The national 14th Five-Year Plan has also clearly integrated the development of digital villages with the goals of consolidating and expanding poverty alleviation achievements and effectively linking them with rural revitalization. Exploring how to systematically assess the policy effects of digital rural construction and verify its role in boosting rural residents' income and optimizing the urban-rural income distribution structure is not only a response to major national strategic arrangements, but also a critical theoretical and practical issue concerning inclusive growth and balanced socioeconomic development on the path of Chinese-style modernization.

Since the Digital Village Strategy was first included in the No.1 Central Document in 2018, relevant policies and planning documents have been continuously rolled out, aiming to reshape rural production, lifestyles, and governance models through digital transformation. The fundamental goal of such strategic deployment is to address the core of the "three rural issues"

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— continuously increasing farmers' income and narrowing the urban-rural development gap. Digital rural construction covers not only the hardware construction of information infrastructure, but also the software coordination of digital agricultural production, intelligent rural governance, and networked public services. With the penetration of digital technologies such as the Internet, mobile communication, and e-commerce, digital rural construction can help raise farmers' income by lowering information barriers, expanding market access, and promoting non-agricultural employment and entrepreneurship.

Nevertheless, the rapid advancement of digital technology may also deepen the digital divide, further widening the gap between regions with strong and weak digital foundations, especially between urban and rural areas. Therefore, a comprehensive assessment of digital rural construction should take into account not only its positive contribution to rural household income, but also its function in narrowing the urban-rural income gap and supporting coordinated regional development.

Currently, there is still disagreement in academia regarding whether the use of digital technology can narrow the urban-rural income gap. Sun Jingshui and Huang Qiuhong (2013) found through a questionnaire survey that the income gap between urban and rural residents in China is too wide [1], and some scholars have discovered through empirical analysis that the use of digital technology can actually lead to a further widening of the income gap between urban and rural residents [2]. If a prominent digital divide exists between urban and rural regions, even if the network infrastructure in rural areas is improved, urban residents often have clear advantages in digital literacy, skills training, and social capital, making it difficult for rural areas to quickly adopt new technologies and transform them into economic benefits [3]. Wei Junying et al. (2022) found that issues such as "vulnerable groups" and "digital divide" can affect the distribution of digital dividends, resulting in a situation where the more the digital economy develops, the greater the urban-rural gap becomes [4]. Daniel et al. (2006) found that the existence of a digital divide leads to expend the income gap between different income groups [5]. Even with the rapid development of the digital economy, different regions enjoy different benefits, with urban residents and more developed coastal areas being more likely to benefit [6]. Some scholars believe that digital construction has achieved significant results in increasing farmers' income, involving multiple dimensions, which can greatly promote the increase of farmers' income [2], and is conducive to empowering agricultural development, promoting farmers' income growth, and narrowing the urban-rural income gap [7]. Some scholars have used econometric methods to examine the threshold effect of the digital economy in narrowing the urban-rural income gap [8][9]. Cheng Mingwang and Zhang Jiaping (2019) found through research on data from all provinces in China from 2003 to 2016 that the popularization of the Internet caused the urban-rural income gap in China to show a trend of first increasing and then decreasing [10]. Scholars have not yet reached a unanimous agreement on how digital technologies correlate with the urban-rural income disparity, resulting in conflicting academic viewpoints. Overall, relevant research perspectives are diverse and conclusions vary, providing an important theoretical and empirical basis for clarifying the mechanism of action and grasping objective laws in the future.

This paper takes cities in the Yangtze River Delta region as the research object, constructs a more comprehensive and scientific measurement system for the development level of digital villages, identifies the specific effects of digital village construction on the income gap between urban and rural residents, and further explores its internal mechanism, regional heterogeneity, and potential impact channels. The possible marginal contribution of this paper lies in constructing a comprehensive index to evaluate digital village construction through the entropy method, comprehensively measuring its specific impact on the urban-rural income gap, making up for the deficiencies in variable measurement and research perspectives in existing literature, and enriching the cross-disciplinary research in the field of digital economy and

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income distribution. The research conclusions will provide empirical evidence for accurately evaluating the implementation effects of the "Digital Village Strategy", help policymakers to more comprehensively understand the multiplicity of its policy effects, and thus provide more targeted policy implications for optimizing the path of digital village construction in the future, maximizing the dual dividends of income increase and disparity reduction, and promoting inclusive digital development.

2. Theoretical Basis and Research Hypothesis

2.1. The impact of digital rural construction on the income gap between urban and rural residents

The potential convergence effect of digital rural construction on the urban-rural income gap is theoretically grounded in classical theories such as new economic growth and human capital, and has been supported by empirical research in the fields of digital economy and income distribution. The core logic lies in the fact that digital technology can overcome geographical barriers to some extent by improving rural infrastructure, promoting inclusive finance in rural areas, providing quality public services, and enhancing rural digital governance capabilities, thereby enabling growth momentum and development opportunities to penetrate rural areas more evenly.

According to the new economic growth theory, scholars represented by Romer and Lucas emphasize that knowledge, technology, and human capital are the core elements driving long-term endogenous economic growth [11]. Digital technology and its derivative applications essentially represent a revolutionary improvement in knowledge and information processing capabilities. The digital rural strategy, by investing in information infrastructure, promoting smart terminals, and fostering digital applications, essentially systematically introduces these core growth elements into rural areas, aiming to enhance the technological content and total factor productivity of the rural economy. This process helps to improve the overall level of rural income, laying a foundation for reducing the urban-rural income gap. A study by Chinese scholars Zhang Xun et al. (2019) found that the development of the digital economy has a positive impact on inclusive growth at the macro level in China. Furthermore, rural areas face high market transaction costs, which hinder the optimal allocation of resources and put farmers at a disadvantage in market competition [12]. According to Guo et al. (2020), digital inclusive finance helps improve the equity of income distribution by reducing barriers to financial access and cutting transaction costs. Given the inherent disparities in digital infrastructure between urban and rural regions, the core issue in narrowing the urban-rural income gap lies in converting digital access and utilization from a "divide" into a "dividend" [13]. Early research emphasized that the "first digital divide" exacerbates inequality [3]. However, when digital infrastructure penetration reaches a certain threshold, policy priorities shift to bridging the "second digital divide" and "third digital divide". Digital rural construction is a multidimensional and systematic intervention that not only addresses the "access" issue but also promotes "effective use" and "value creation" through training, demonstration, and ecological construction. Therefore, from a long-term and holistic perspective, proactively promoting digital rural construction can be seen as a public policy aimed at turning "gaps" into "bridges," with its design inherently guided by fairness. Tao Tao et al. (2022) conducted a quasi-natural experiment based on the national rural e-commerce demonstration program. Their findings confirmed that digital interventions of this kind can significantly boost farmers' earnings and deliver a measurable pro-poor impact [14]. Based on this, this paper proposes research hypothesis H1:

H1: The construction of digital villages helps narrow the income gap between urban and rural areas.

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2.2. Intermediary mechanism based on the improvement of agricultural comparative labor productivity

The low comparative labor productivity in agriculture is the structural root cause of the urban-rural income gap. Classical theories of development economics point out that the core of narrowing the urban-rural gap lies in achieving a modern leap in agricultural productivity. Digital rural construction, through technological penetration, organizational transformation, and market linkage, boosts the overall production efficiency of the agricultural sector, which can act as a core intermediate mechanism for bridging the urban-rural gap.

The Lewis dual-sector model clearly elucidates this macroeconomic mechanism: the traditional agricultural sector harbors a substantial number of surplus labor with zero marginal productivity, whose income level merely sustains their subsistence; the modern industrial sector, on the other hand, attracts labor migration with its higher productivity and wages [15]. The key to narrowing the urban-rural income gap lies in enhancing the labor productivity of the agricultural sector itself. Only when agricultural technological advancements and capital investments boost agricultural labor productivity, releasing labor while ensuring that agricultural output does not decline or even increases, can the entire economy leapfrog the "Lewis turning point" and enter a phase of balanced development between the industrial and agricultural sectors. Therefore, any strategy aimed at narrowing the urban-rural gap must confront the core task of enhancing agricultural labor productivity [16]. Digital technology has disrupted empirical agriculture by automating and modernizing agricultural production processes, significantly improving the utilization efficiency of factors such as land, water, fertilizer, and pesticides, as well as the management scale and output per unit of labor [17]. Zhong Wenjing et al.'s (2021) research points out that the digital transformation of agriculture is a key path to enhancing agricultural production efficiency, but its effects are contingent on certain conditions [18]. The construction of digital villages also enhances labor productivity by reshaping the agricultural industry chain. Under traditional smallholder farming, farmers are primarily engaged in production processes with low added value. New business forms such as rural e-commerce, live streaming sales, origin warehouses, and smart logistics, which have emerged in digital villages, have transformed farmers from mere producers to operators, service providers, and brand builders. Farmers gain value-added benefits in the circulation process by directly facing consumers through e-commerce platforms; participating in the agricultural product e-commerce supply chain also creates new non-agricultural employment opportunities. This transformation from "production-oriented" to "market-oriented" signifies a fundamental improvement in the market value created by unit agricultural labor (i.e., labor productivity) [19]. This improvement is not only reflected in monetary income but also in the complexity of labor value. Based on this, this paper proposes research hypothesis H2:

H2: Digital villages construction indirectly narrows the urban-rural income gap by enhancing the comparative labor productivity in agriculture.

2.3. Intermediary mechanism based on the improvement of rural human capital level

Human capital disparity is the underlying driver of long-term income inequality. According to human capital theory, education is the primary form of human capital investment, which enhances workers' knowledge, skills, and adaptability, thereby raising labor productivity and income capacity [16][20]. The urban-rural education gap directly translates into income differences. If digital rural construction can effectively improve the education level and quality of rural residents, it will become a fundamental and long-term channel for narrowing the urban-rural gap.

Digital technology can break through the physical constraints of scarce and unevenly distributed high-quality educational resources. In traditional education, rural areas have long

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been at a disadvantage. The construction of digital villages can, through improving infrastructure, network resources, and other means, deliver high-quality urban teachers and curriculum resources to rural schools at a lower cost [21]. This directly increases the opportunities for rural students to access high-quality education, helps promote educational equity from the outset, and enhances the average human capital stock of the future workforce in rural areas. Meanwhile, the ubiquitous digital environment itself is providing a pervasive informal education, where activities such as using digital devices, accessing online information, and participating in online communities subtly improve the information literacy, learning ability, and digital skills of rural residents. This constitutes an important component of basic human capital in the information age [3]. The construction of digital villages not only enhances the "stock" of education but also improves the "flow" and "monetization" efficiency of human capital. In addition, online recruitment platforms and gig economy platforms reduce job search costs and improve the matching efficiency between human capital and job opportunities. This means that education and skills acquired through digital channels can be converted into market income more quickly and accurately. Among them, online platforms promote the accumulation of human capital and increase wage income, and this effect also exists in rural areas [22]. Therefore, the construction of digital villages is expected to systematically improve the per capita education level and comprehensive human capital quality of rural residents by expanding the accessibility of high-quality educational resources, increasing the expected return on educational investment, and creating convenient conditions for lifelong learning. The improvement of human capital will enhance the competitiveness of rural labor and broaden their income sources, thus becoming a fundamental driving force for narrowing the urban-rural income gap in the long run. Based on this, this paper proposes research hypothesis H3:

H3: Digital villages construction indirectly narrows the urban-rural income gap by enhancing rural human capital level.

3. Research Design

3.1. Variable setting

3.1.1. Core explanatory variable

Drawing on the entropy method adopted by Zhu Honggen and Chen Hui (2022) to construct a comprehensive index (Dig) from four dimensions: digital infrastructure, digital inclusive finance, digital public services, and digital governance capacity [23], this index comprehensively reflects the overall level of digital rural construction in prefecture-level cities. Meanwhile, to refine the impact mechanism, the sub-indices of the above four dimensions are selected as the core explanatory variables for sub-dimensional regression, namely the digital infrastructure index (infr), digital inclusive finance index (fina), digital public service index (serv), and digital governance capacity index (gove). Drawing on the research of Jiang Zekun (2023), the overall digital rural construction index is measured using the entropy method [24], and the final score is denoted as $Dig_{i,t}$. The higher the index value, the higher the level of digital rural construction. Specific indicators are shown in Table 1.

Despite the fact that the entropy method is widely adopted as an objective weighting technique for indicator systems, it is prone to biased estimation of certain indicators due to factors inherent in the data. To test the robustness of the entropy method in weighting, this paper conducts a sensitivity analysis through Monte Carlo simulation. Firstly, assuming that there is a random measurement error of ±5% in the original observed values of each indicator, multiplicative perturbations that follow a uniform distribution U[0.95,1.05] are applied to the original values of each indicator to generate simulated datasets. Secondly, the entire process of the entropy method is repeated for each simulated dataset, and the weights of each indicator and the comprehensive score of the digital rural construction index are recalculated. The above

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Table 1. Index System for Digital Rural Construction

Primary Indicator	Secondary Indicator	Tertiary Indicator	Direction
Dig	infr	Proportion of administrative villages with broadband access	+
		Cable TV coverage rate	+
		Mobile phone coverage rate	+
	fina	Coverage breadth of inclusive finance	+
		Coverage depth of inclusive finance	+
		Digitalization degree of inclusive finance	+
	serv	Information technology service level	+
		Hardening rate of village roads	+
		Number of health technicians per thousand rural residents	+
	gove	Proportion of administrative villages with formulated village plans	+
		Proportion of administrative villages with completed village renovation	+

process is independently repeated 500 times, obtaining 500 sets of weights and 500 sets of comprehensive scores. The Spearman rank correlation coefficient between the comprehensive score of the city obtained from each simulation and the original score is calculated. The results are shown in Table 2. The average correlation coefficient of 500 simulations is as high as 0.9987 (with a standard deviation of 0.0001), and the correlation coefficients of all simulations are not lower than 0.9984.

Table 2. Spearman's rank correlation coefficient

Variable	Obs	Mean	Std. dev.	Min	Max
rho	500	0.9987385	0.000114	0.998385	0.9990375

The Spearman rank correlation coefficient is shown in Figure 3-1, indicating that even with random perturbations of ±5% applied to the original data, the ranking of the comprehensive development levels of various cities barely changes, demonstrating the high robustness of the evaluation results.

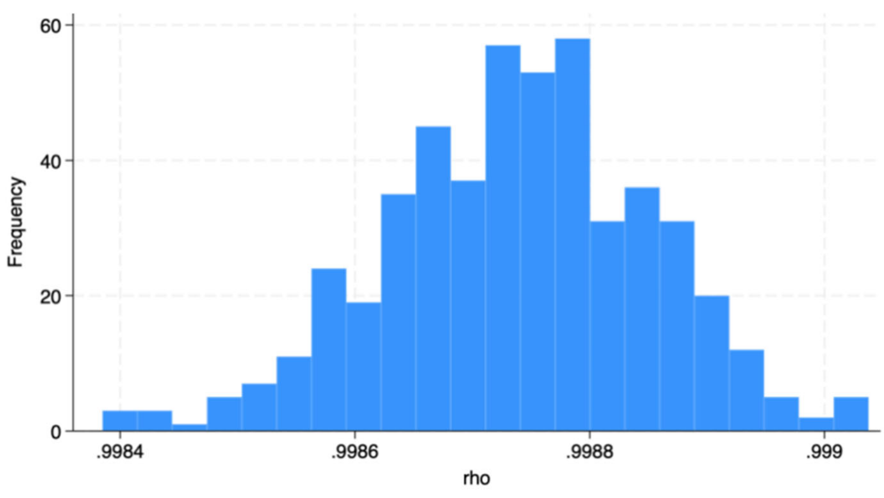

Figure 1. Distribution chart of Spearman's rank correlation coefficient

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3.1.2. Core explained variable

The research object of this paper is the income gap between urban and rural residents, which is measured using the Theil index. The Theil index is decomposable and can accurately reflect the contribution of income disparities between urban and rural areas and among different regions. Furthermore, it has low sensitivity to extreme values, making it more suitable for precise measurement of the income gap between urban and rural residents [25]. The calculation method is as follows:

$$Theil_{i,t} = \sum_{g=1}^{2}\sum_{i=1}^{n}\frac{y_{g,i,t}}{Y_{i,t}}\ln\frac{y_{g,i,t}/n_{g,i,t}}{Y_{i,t}/N_{i,t}} \quad (1)$$

In this context, $Theil_{i,t}$ denotes the Theil index, with a higher value representing a larger income gap. The subscript g takes a value of 1 or 2, referring to urban and rural regions respectively. $y_{g,i,t}$ and $n_{g,i,t}$ refer to total income and population of urban/rural residents, while $Y_{i,t}$ and $N_{i,t}$ represent the overall income and population of all residents..

3.1.3. Mediating variable

Based on the theoretical analysis in the previous text, two mediating variables are selected to reveal the transmission path of digital rural construction affecting the urban-rural income gap:

(1) Agricultural comparative labor productivity (prod): Agricultural comparative labor productivity is a core indicator for measuring agricultural production efficiency, reflecting the relative level of labor productivity in the agricultural sector compared to that of the entire society [26, 27].

(2) Rural human capital level (edu): The level of rural human capital is measured by the average years of education of rural residents. Referring to existing research [28], the years of education for rural residents with different educational levels are calculated.

3.1.4. Control variables

To avoid biases caused by omitted variables, drawing on existing research [28], the following control variables are selected, specifically including: per capita gross domestic product (Pgdp); population density (Density); government participation (Gov); per capita total agricultural machinery power (Mach); rural poverty incidence (Poverty); and urbanization rate (Urban). Descriptive statistics for the variables are presented in Table 3.

Table 3. Descriptive Statistics of Variables

Category	Variable	Obs	Mean	Sd	Min	Max
Explained Variable	Theil	410	0.049	0.024	0.014	0.116
Explanatory Variable	Dig	410	0.311	0.142	0.042	0.923
	infr	410	0.08	0.042	0.011	0.264
	fina	410	0.088	0.036	0.003	0.157
	serv	410	0.091	0.054	0.007	0.332
	gove	410	0.051	0.028	0	0.175
Mediating Variable	prod	410	0.372	0.175	0.085	1.01
	edu	410	2.403	0.656	1.275	5.557
Control Variable	Pgdp	410	8.696	4.283	1.53	20.628
	Density	410	0.245	0.114	0.068	0.646
	Gov	410	16.634	6.126	8.121	35.646
	Mach	410	1.481	0.457	0.681	3.826
	Poverty	410	76.258	6.456	43.402	87.228
	Urban	410	64.211	11.41	35.7	89.57

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3.2. Model Setting

This paper adopts a panel data model with double fixed effects, introducing individual and time dummy variables to control for individual heterogeneity and common time shocks, such as the introduction of national digital rural policies and macroeconomic fluctuations, respectively. This approach mitigates omitted variable bias and enhances the reliability of the estimation results. The model setup is as follows:

$$Theil_{i,t} = \alpha_0 + \alpha_1 Dig_{i,t} + \alpha_2 Control_{i,t} + \mu_i + \nu_t + \varepsilon_{i,t} \quad (2)$$

In the model, i represents each prefecture-level city in the Yangtze River Delta region, t represents the year, and $Control_{i,t}$ represents the values of a series of control variables. μ_i and ν_t represents individual and time fixed effects, and $\varepsilon_{i,t}$ represents random disturbance terms.

The Digital Rural Construction Index comprises four dimensions. To precisely identify the effects of each dimension on digital rural construction and provide a basis for differentiated policy formulation, this paper employs the model to explore the impact of digital rural construction on the urban-rural income gap across different dimensions. The econometric model is constructed as follows:

$$Theil_{i,t} = \beta_0 + \beta_1 Dig\_k_{i,t} + \beta_2 Control_{i,t} + \mu_i + \nu_t + \varepsilon_{i,t} \quad (3)$$

In the model, k takes values of 1, 2, 3, and 4, representing the four dimensions respectively.

4. Empirical Analysis

4.1. Benchmark regression analysis

This article uses robust standard error for estimation, gradually adding control variables and fixed effects to compare and analyze the robustness of the core explanatory variable coefficients. The regression results are shown in Table 4.

Model (1) excludes control variables and fixed effects. The estimated coefficient for the digital rural construction composite index is −0.0895, which is significantly negative at the 1% level. When control variables are incorporated into Model (2), the absolute value of the core explanatory variable's coefficient falls to 0.0316, remaining significantly negative at the 1% level. This implies that the inclusion of control variables may weaken the income gap-narrowing effect of digital rural development to a certain degree, yet the core impact remains statistically significant. After further introducing individual and time fixed effects in Model (3), the absolute value of the coefficient declines further to 0.0213, which is significantly negative at the 10% level. This demonstrates that the convergence effect of digital rural construction on the urban-rural income gap still holds after accounting for regional heterogeneity and common time shocks. These findings support the theoretical hypothesis that digital rural construction can reduce the urban-rural income gap by boosting rural development and raising the income of rural residents. In addition, most control variables are statistically significant, suggesting that the selection of control variables is appropriate and reliable.

ISSN: 2637-6067 DOI: 10.6918/IJOSSER.202606_9(6).0011

Table 4. Benchmark Regression Results

Variable	(1) Theil	(2) Theil	(3) Theil
Dig	-0.0895***	-0.0316***	-0.0213*
	(0.00427)	(0.00618)	(0.0111)
Pgdp		0.0000831	-0.000516***
		(0.000230)	(0.0000989)
Density		-0.00539	0.0150***
		(0.00762)	(0.000978)
Gov		0.000321***	0.000703***
		(0.0000961)	(0.0000660)
Mach		-0.00102	-0.00520**
		(0.000887)	(0.00214)
Poverty		-0.000512***	0.000309
		(0.000119)	(0.000216)
Urban		-0.00169***	-0.000928***
		(0.0000854)	(0.0000477)
_cons	0.0765***	0.203***	0.0881***
	(0.00267)	(0.0112)	(0.0201)
Individual fixed effect	NO	NO	YES
Time fixed effect	NO	NO	YES
Observations	410	410	410
R-squared	0.5204	0.8165	0.7563
F statistic			1198.8

Note: 1. The robust standard error is indicated in parentheses;

2. *p<0.1, **p<0.05, ***p<0.01.

4.2. Robustness test

In empirical research, the reliability of conclusions from benchmark regression and sub-dimensional regression is highly susceptible to issues such as model specification bias, variable measurement error, sample selection bias, and potential endogeneity. Relying solely on a single regression result to draw research conclusions may lead to biased estimation coefficients and distorted research findings. This paper draws on existing mainstream research paradigms and adopts various commonly used and mature robustness testing methods to verify the core conclusions from different dimensions. The specific testing methods and result analysis are as follows.

4.2.1. Replace the core explanatory variable

Measurement bias in core explanatory variables is one of the important reasons for endogeneity issues. To verify whether the core conclusions rely on a specific measurement method, this paper chooses principal component analysis as an alternative measurement method to reconstruct the digital rural construction index. The first column of Table 5 reports the robustness test results.

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Table 5. Robustness Test Results

Variable	(1) Theil	(2) Gini	(3) Theil	(4) Theil
Dig		-0.0478**	-0.0279**	-0.0324***
		(0.0169)	(0.0119)	(0.0125)
Principal Component Analysis	-0.00324*			
	(0.00162)			
Control variables	YES	YES	YES	YES
Fixed effects	YES	YES	NO	YES
Observations	410	410	400	410
F statistic	794.7	23627.5		196.2

Note: 1. The robust standard error is indicated in parentheses;
2. *p<0.1, **p<0.05, ***p<0.01.

The regression results in column (1) of Table 5 indicate that the regression coefficient of the Dig constructed using principal component analysis is -0.00324. This result is completely consistent with the sign of the regression coefficient of the core explanatory variable in the benchmark regression, both being negatively significant. This further demonstrates that the regression results of this study have good stability, and the core conclusions have not been reversed due to changes in the measurement method of the core explanatory variable.

4.2.2. Replace the core dependent variable

This study uses the Gini coefficient as an alternative to the Theil index. The Gini coefficient, ranging from 0 to 1, is a standard measure of income inequality where a higher value signals a wider gap. Following Xu (2003), the relevant calculation is adopted in this paper [29]. As shown in column 2 of Table 5, the coefficient of digital rural construction is -0.0478 and significant at the 5% level. This result is consistent with the baseline regression, confirming that digital rural construction significantly narrows the urban-rural income gap regardless of the measurement method, and the core conclusion is robust.

4.2.3. Eliminate some samples.

Extreme observations may distort empirical results. Shanghai, as a directly controlled municipality, has distinct advantages in the economy, urbanization and digital infrastructure, which may bias the estimation. To rule out such interference, this paper re-estimates the model by excluding the sample of Shanghai. Column 3 of Table 5 shows that the coefficient remains -0.0279 and significant at the 5% level, consistent with the baseline. This proves that the core conclusion is not affected by special samples..

4.2.4. Change the estimation method.

Model selection bias is also one of the important reasons for endogeneity issues. Different estimation methods may lead to differences in regression results due to varying assumptions. To verify whether the core conclusions rely on specific estimation methods, this paper chooses ordinary least squares (OLS) as an alternative estimation method to re-estimate the model. Table 5, column 4, reports the regression results obtained using OLS. The regression results indicate that after estimating with OLS, the regression coefficient for digital rural construction is -0.0324, which is significant at the 1% statistical level and consistent with the baseline regression results. This suggests that under different model choices, the narrowing effect of digital rural construction on the urban-rural income gap is significantly present.

4.2.5. Instrument variable test

The instrumental variable test is a commonly used method for analyzing endogeneity issues. In this study, there may be a mutual causality endogeneity issue between digital rural construction and the urban-rural income gap. And there may be some omitted variables that have not been included in the model, which simultaneously affect the level of digital rural construction and the urban-rural income gap, leading to biased regression coefficients.

Following standard empirical practices, this study adopts the instrumental variable (IV) method to address potential endogeneity. The one-period lagged digital rural construction index is chosen as the instrumental variable, considering data availability and rationality. This lagged index meets the correlation requirement because it well reflects the current trend of digital rural construction. Meanwhile, it satisfies the exogeneity condition since the past level of digital rural construction is pre-determined and unaffected by the current urban-rural income gap [12]. The regression results are reported in Table 6.

Table 6. The Result of the Instrumental Variable Method

	Benchmark Regression	Two-stage Least Squares	
		First Stage	Second Stage
Variable	Theil	Dig	Theil
Dig	-0.0895***		-0.0568**
	(0.00427)		(0.0277)
instrumental variable		0.517***	
		(0.0384)	
Anderson canon. corr. LM statistic		125.247***	
Cragg-Donald Wald F statistic		181.380	
		(16.38)	
Observations		369	369
R-squared			0.779

Note: 1. The robust standard error is indicated in parentheses;

2. *p<0.1, **p<0.05, ***p<0.01.

As shown in the first-stage results in Table 6, the coefficient of the instrumental variable is 0.517 and significant at the 1% level, confirming a strong positive correlation between the lagged digital rural construction index and its current value, which satisfies the correlation requirement. The Cragg-Donald Wald F statistic is 181.380, well above the critical value, indicating no weak instrument problem. The Anderson canonical correlation LM statistic is 125.247 and significant at the 1% level, suggesting no under-identification issue. These results jointly support the validity of the instrumental variable. In the second-stage regression, the coefficient of the digital rural construction index remains significantly negative, consistent with the baseline estimation. This demonstrates that the core conclusion is highly reliable and robust after addressing endogeneity.

4.2.6. Placebo test

To further eliminate the interference of other unobservable factors on the regression results and verify whether the core conclusions are caused by random factors, this paper conducts a placebo test based on a two-way fixed effects panel model by randomly permuting the core explanatory variables. The specific steps are as follows: First, while keeping the sample observations, dependent variables, and control variables unchanged, the cross-sectional dimension data of the core explanatory variables are randomly permuted to construct fake core explanatory variables. Second, the fake core explanatory variables are substituted into the benchmark regression model for regression estimation, and the fake estimated coefficients and corresponding P values are recorded. Third, the above random permutation and regression estimation process is repeated 500 times to obtain the fake estimated coefficients and corresponding fake P values. Distribution charts are then plotted and distribution characteristics are analyzed to assess the reliability of the core conclusions. The fake estimated coefficients and fake P values obtained through the placebo test in this paper are presented in Figure 2 and Figure 3, respectively.

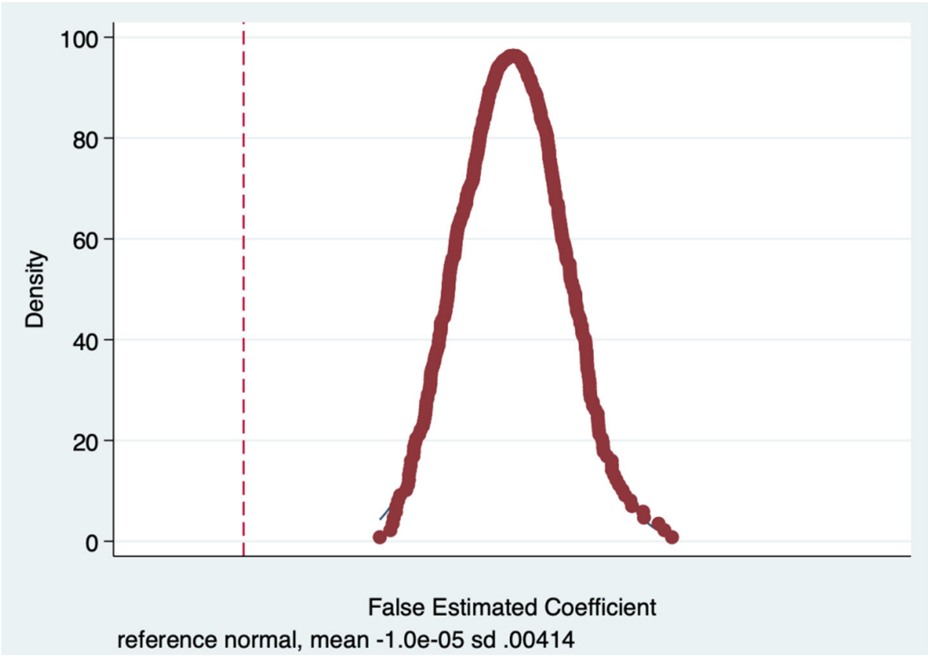

Figure 2. False Estimation Coefficient

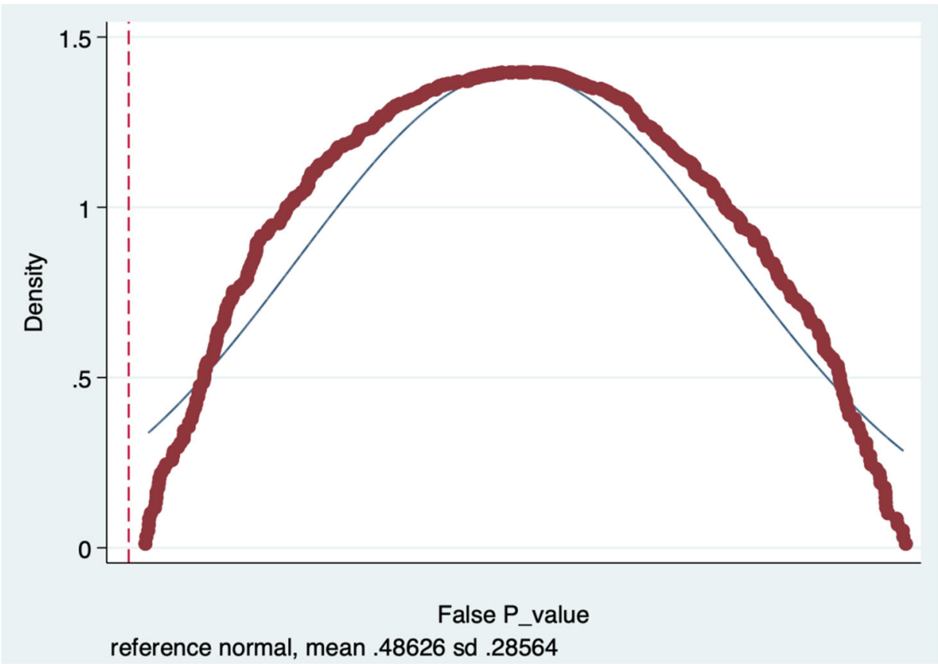

Figure 3. False P-value

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Figure 2 illustrates the kernel density distribution of the spurious estimated coefficients after 500 random permutations. Figure 3 displays the distribution of P values corresponding to the spurious estimated coefficients after 500 random permutations. Considering the above results, the true estimated coefficient of the core explanatory variable in the original regression significantly deviates from the concentrated distribution range of the spurious coefficients, and the spurious P values do not exhibit non-random clustering characteristics. This indicates that the original regression results are not caused by interference factors such as random factors, model specification errors, or omitted variables, and the empirical conclusions are robust.

4.3. Mechanism analysis

Based on the theoretical analysis above, the construction of digital villages may affect the income gap between urban and rural residents through two paths: enhancing agricultural comparative labor productivity and elevating the human capital level of rural residents. This section draws on the two-step mediation effect testing framework proposed by Jiang Ting [30] to construct a mediation effect model as follows:

$$Prod_{i,t} = \gamma_0 + \gamma_1 Dig_{i,t} + \gamma_2 Control_{i,t} + \mu_i + \nu_t + \varepsilon_{i,t} \quad (4)$$

$$Edu_{i,t} = \theta_0 + \theta_1 Dig_{i,t} + \theta Control_{i,t} + \mu_i + \nu_t + \varepsilon_{i,t} \quad (5)$$

Among them, $Prod_{i,t}$ and $Edu_{i,t}$ are mediating variables, representing agricultural comparative labor productivity and average years of education for rural residents, respectively. The regression results are shown in Table 7.

Table 7. The Regression Results of the Mediation Test

Variable	(1) Theil	(2) prod	(3) edu
Dig	-0.0213*	0.695***	1.196***
	(0.0111)	(0.180)	(0.288)
Control variables	YES	YES	YES
Fixed effects	YES	YES	YES
Observations	410	410	410
R-squared	0.756	0.081	0.958

Note: 1. The robust standard error is indicated in parentheses;

2. *p<0.1, **p<0.05, ***p<0.01.

First, the total effect is statistically significant. In the baseline regression, the coefficient of the digital rural construction index on the urban-rural income gap is significantly negative, which is consistent with earlier findings and robust to various checks.

Second, the core explanatory variable exerts significant effects on both mediators. The coefficient on agricultural comparative labor productivity is 0.695 and significant at the 1% level, suggesting that digital rural construction markedly improves agricultural production efficiency. By upgrading digital infrastructure and promoting digital inclusive finance, it supports agricultural mechanization and scaled-up operation, thus raising labor productivity. Meanwhile, the coefficient on rural residents' average years of schooling is 1.196 and significant at the 1% level, demonstrating that digital rural construction effectively enhances rural human capital. It expands access to online courses and live instruction, enabling rural residents to

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acquire high-quality educational resources and upgrade their skills. Improved digital public services also help optimize the allocation of educational resources in rural areas.

Following the two-step mediation framework proposed by Jiang (2022) [30], this paper further combines economic theory to interpret how mediators shape the dependent variable. Based on the empirical outcomes, we analyze the operating mechanisms through which agricultural comparative labor productivity and rural human capital influence the urban-rural income gap.

4.3.1. The impact mechanism of agricultural comparative labor productivity on the income gap between urban and rural residents

Agricultural comparative labor productivity reflects the production and factor allocation efficiency of the agricultural sector, which is closely linked to rural residents' earnings and fundamentally shapes the urban-rural income gap. Classical economic theory holds that the productivity gap between traditional agriculture and modern industry is the primary cause of urban-rural income disparity. Improving agricultural labor productivity helps narrow the gap by bringing agricultural efficiency in line with non-agricultural sectors through multiple channels.

First, higher agricultural productivity boosts operational income. Digital rural construction accelerates the integration of digital technologies into agricultural production. Precision farming and intelligent irrigation cut production costs and raise product value, while e-commerce platforms reduce circulation losses and maximize value realization for agricultural products.

Second, improved productivity optimizes rural labor allocation. Low agricultural efficiency leaves substantial surplus labor in rural areas, depressing income levels. As productivity rises, labor is transferred to non-agricultural sectors for higher wages [31]. This shift directly raises rural income and pushes up agricultural wages by reducing labor supply, forming a virtuous cycle that narrows the urban-rural income gap.

Third, higher agricultural productivity promotes industrial integration. Improved efficiency allows agriculture to link effectively with secondary and tertiary industries, extending the industrial chain and increasing value. Digital rural construction provides technical and factor support for industrial integration. Digital platforms integrate rural industrial resources, attract talent and investment, and optimize factor allocation. Industrial integration creates more jobs and entrepreneurial channels, supporting diversified income growth for farmers.

4.3.2. The impact mechanism of rural human capital level on the income gap between urban and rural residents

Human capital is the core driver of income growth, with education as its main source. Higher human capital boosts labor productivity and earnings, helping rural residents enhance productivity, employability, and entrepreneurship to narrow the urban-rural income gap. According to the empirical results, rising average schooling years reduce the income disparity through three channels.

First, better rural human capital strengthens the application of agricultural technology. Higher education improves rural residents' learning ability, allowing them to master precision planting, mechanized operations, and pest control more quickly [32][33]. Better-educated farmers are more capable of using modern agricultural machinery and digital extension services, which raises crop yields, reduces risks, and increases farming income, thus narrowing the urban-rural gap.

Second, improved human capital enhances non-agricultural employment competitiveness. Higher educational attainment equips rural labor with stronger vocational skills to meet urban industry demands, helping them access stable, high-wage jobs in manufacturing and services. This not only lifts wage income but also forms a virtuous cycle between human capital accumulation and income growth.

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Third, higher rural human capital stimulates rural entrepreneurship and innovation. Better-educated rural residents have stronger innovation awareness and resource integration capabilities, enabling them to seize opportunities from digital platforms and incubation bases. Rural entrepreneurship creates self-employment and local jobs, supporting diversified income growth and further reducing the income gap.

In summary, both agricultural comparative labor productivity and average years of schooling play significant mediating roles. Digital rural construction narrows the urban-rural income gap by boosting agricultural efficiency, optimizing labor allocation, promoting industrial integration, strengthening agricultural technology application, improving non-agricultural employment competitiveness, and encouraging entrepreneurship. The two mediators interact synergistically to accelerate income convergence.

5. Further Analysis

In the context of the deep integration of digital economy and rural revitalization, digital rural construction is an important lever to break the urban-rural binary structure and narrow the income gap. Due to the uneven regional development in China, there is significant regional heterogeneity in the contraction effect of digital rural construction. This article further examines its heterogeneity characteristics from multiple dimensions.

5.1. Analysis of the impact of different dimensions in digital rural construction

Digital villages construction comprises four dimensions. To precisely analyze the impact of digital village construction on the urban-rural income gap, this paper conducts regression analysis by dimension based on each secondary indicator of digital village construction. The regression results are presented in Table 8.

Table 8. Regression Results by Dimension

Variable	(1) Theil	(2) Theil	(3) Theil	(4) Theil
infr	-0.0688*			
	(0.0364)			
fina		-0.373**		
		(0.121)		
serv			-0.0135***	
			(0.00357)	
gove				-0.269***
				(0.0625)
Control variables	YES	YES	YES	YES
Fixed effects	YES	YES	YES	YES
Observations	410	410	410	410
R-squared	1294.8	416.5	1313.7	554.5

Note: 1. The robust standard error is indicated in parentheses;
2. *p<0.1, **p<0.05, ***p<0.01.

As shown in Table 8, the estimated coefficients of all four sub-indices are significantly negative, which supports the theoretical expectations. Balanced improvements in digital infrastructure help remove spatial barriers and facilitate two-way flows of information, capital, and talent between urban and rural areas. This enables rural residents to better access the digital market

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and reduces the income gap caused by the urban-rural digital divide. Digital inclusive finance expands financial coverage to underserved rural groups and provides more equitable access to financial services. Digital public services promote equal access to public resources; in particular, advances in distance education and telemedicine enhance rural human capital and health conditions, thereby strengthening the income-earning capacity of rural residents and narrowing the urban-rural income gap. In addition, digital governance raises administrative efficiency, accelerates the improvement of rural infrastructure and the development of new rural industries, and effectively boosts farmers' income while reducing urban-rural inequality.

5.2. Analysis of regional heterogeneity

5.2.1. Types of urban resources

Urban resource endowment is a key factor affecting regional economic growth and the urban-rural income gap. According to the *National Sustainable Development Plan for Resource-Based Cities* released by the State Council, this study classifies sample cities into resource-based and non-resource-based cities. The regression results are reported in columns 1 and 2 of Table 9.

Table 9. Regional Heterogeneity Analysis Table

Variable	(1) Theil	(2) Theil	(3) Theil	(4) Theil	(5) Theil	(6) Theil
Dig	-0.0539**	-0.0116	-0.0818**	-0.0338**	-0.0866***	-0.0718**
	(0.0166)	(0.0150)	(0.0333)	(0.0129)	(0.0158)	(0.0224)
Control variables	YES	YES	YES	YES	YES	YES
Fixed effects	YES	YES	YES	YES	YES	YES
Observations	120	290	230	180	170	240
R-squared	0.821	0.793	0.753	0.595	0.861	0.575

Note: 1. The robust standard error is indicated in parentheses;

2. *p<0.1, **p<0.05, ***p<0.01.

A As shown in Table 9, digital rural construction exerts heterogeneous effects on the urban-rural income gap across city types. In resource-based cities, the coefficient of the digital rural construction index is −0.0539 and significant at the 5% level, confirming a notable income-narrowing effect. By contrast, the coefficient in non-resource-based cities is −0.0116 and statistically insignificant, indicating a weak and non-significant impact. This heterogeneity stems from differences in industrial structure. Resource-based cities rely heavily on resource extraction and processing, with rural areas dominated by traditional agriculture, resulting in a striking urban-rural divide. Digital rural construction introduces digital technologies to foster rural specialized industries, raise rural incomes, and reduce industrial homogeneity. Non-resource-based cities feature a more diversified economy with developed service and high-tech sectors. Rural areas already have a solid industrial foundation. Although digital rural construction improves rural development to some degree, it cannot address all drivers of the income gap, leading to a relatively weak narrowing effect.

5.2.2. Income level of urban and rural residents

Resident income level reflects regional development and shapes the formation of the urban-rural income gap as well as the digital rural construction environment. This study divides the Yangtze Delta prefecture-level cities into high-income and low-income groups based on the median disposable income. As shown in columns 3 and 4 of Table 9, digital rural construction still presents a significantly negative impact on the income gap, but with obvious heterogeneity. The coefficient absolute value shows that the narrowing effect is stronger in low-income areas.

This heterogeneity reflects the law of diminishing marginal returns. Low-income rural residents have a lower income base and higher growth potential. Digital rural construction quickly expands their income channels by building network platforms, popularizing digital agricultural technology, and offering digital skills training, thus effectively narrowing the gap. By contrast, high-income regions face more complex inequality driven by unequal public services beyond pure income differences. Digital rural construction can only moderately raise rural income but hardly resolves such deep-rooted issues, resulting in a weaker convergence effect.

5.2.3. Industrial structure

Industrial structure is a key determinant of the urban-rural income gap, and the share of agriculture directly shapes rural economic development and income sources. This paper classifies cities in the Yangtze River Delta into high-agricultural-share and low-agricultural-share groups according to the average proportion of primary industry value-added. The regression results are reported in columns 5 and 6 of Table 9. Digital rural construction has a significantly negative impact on the income gap in both groups, with clear heterogeneity. The coefficient absolute value is larger in high-agricultural-share areas, indicating a stronger narrowing effect. This heterogeneity arises from structural differences. High-agricultural-share regions rely heavily on traditional farming with low efficiency and added value, leading to a pronounced urban-rural income gap. Digital construction effectively boosts agricultural efficiency and rural incomes. By contrast, low-agricultural-share regions have diversified economies and more mature non-agricultural industries in rural areas. Rural income sources are already diversified, weakening the focused effect of digital rural development. As a result, its income-narrowing impact is less pronounced than in high-agricultural-share regions.

6. Conclusion and Suggestions

Taking the panel data of cities in the Yangtze River Delta from 2014 to 2023 as the research sample, this paper systematically explores the influence and internal mechanism of digital rural construction on the urban-rural income gap. The empirical results reveal that digital rural development can effectively facilitate the balanced convergence of urban and rural income distribution. Furthermore, digital rural construction functions mainly through two pivotal mediating channels, namely the optimization of agricultural comparative labor productivity and the improvement of rural residents' average educational attainment. On the one hand, enhanced agricultural labor productivity raises rural residents' income by improving agricultural production efficiency and realizing rational allocation of rural labor factors. On the other hand, the elevation of rural human capital improves residents' labor market competitiveness and income-earning capacity. In addition, the income gap reduction effect of digital rural construction presents distinct structural heterogeneity. Among all dimensional indicators, digital inclusive finance and digital governance capacity exert the most prominent inhibitory effect on the urban-rural income disparity. In terms of regional differences, this optimization effect is more prominent in resource-based cities, low-income areas, and regions with a higher proportion of primary industry. On the basis of the above research findings, this paper puts forward targeted policy suggestions.

Firstly, strengthen the transformation orientation and release positive effects. Given that digital transformation has a significant positive effect on the labor income share of manufacturing enterprises, and this conclusion still holds true after robustness and endogeneity tests, promoting digital transformation in the manufacturing industry should be an important lever for optimizing income distribution in the future. The government should increase investment in digital infrastructure for the manufacturing industry, lower the technological and financial barriers for enterprise transformation, and encourage various manufacturing enterprises to actively carry out digital transformation. At the same time, guiding enterprises to establish a linkage mechanism between digital transformation benefits and labor income, ensuring that the production efficiency improvement and profit growth brought by transformation can be effectively transmitted to workers, strengthening the positive driving effect of digital transformation on labor income share, and consolidating the practical implementation foundation of research conclusions.

Secondly, based on heterogeneity characteristics, implement classified policies. The effect of digital transformation on the increase of labor income share has significant industry, property rights, development stage, and regional heterogeneity, and policy formulation should avoid a one size fits all approach. In the industry, we will focus on supporting the deepening digital transformation of high-end manufacturing industries, while increasing support for basic manufacturing industries to enhance their digital adaptability; In terms of property rights, guide state-owned enterprises to play a demonstrative role, while helping non-state-owned manufacturing enterprises alleviate transformation constraints; In terms of development stage, it is necessary to balance the basic transformation of early-stage transformed enterprises with the skill adaptation of deeply transformed enterprises; Regionally, tilt resources towards economically underdeveloped areas, improve their digital infrastructure and talent supply, and narrow the gap in regional transformation.

Thirdly, connect the core mechanisms and strengthen long-term empowerment. To ensure that digital transformation continues to increase the share of labor income in the manufacturing industry, efforts need to be made to streamline its core mechanisms. Given that digital transformation mainly plays a role in reducing the organic composition of capital and alleviating the substitution effect of capital on labor, enterprises should be guided to focus their digital investment on optimizing the allocation of production factors, reducing ineffective capital investment, and improving labor productivity. At the same time, it is necessary to reasonably guide the changes in the average profit margin of the industry, suppress its negative suppression of labor income share, strengthen the position of labor factors in value distribution through improving the factor allocation structure, and enable digital transformation to continuously empower the increase of labor income share through core mechanisms.

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