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The Evolution of Labor Income Share in the Wave of Digital Transformation: An Empirical Analysis Based on Chinese A-Share Listed Companies

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Abstract: With the booming development of the global digital economy, digital transformation has become a core driving force for China's economic restructuring and industrial upgrading. However, the impact of digital transformation on resource allocation efficiency and income distribution patterns, especially on the mechanism of its effect on labor income share, remains controversial. Against this backdrop, this study focuses on the impact of digital transformation on labor income share and its mechanism of action, aiming to provide a theoretical basis for relevant policy formulation. This study uses A-share listed companies in China from 2014 to 2023 as the initial research sample and employs econometric methods such as panel data analysis and threshold models to systematically study the impact of digital transformation on labor income share and its mechanism of action. The specific research contents include: (1) analyzing the direct impact of digital transformation on labor income share; (2) exploring the mediating effect of resource allocation optimization on digital transformation and labor income share; and (3) examining the heterogeneity characteristics of the impact of digital transformation on labor income share, including differences in industry, region, and enterprise size. The study found that digital transformation has a significant inverted U-shaped relationship with labor income share by optimizing resource allocation and improving labor productivity, but this impact is significantly heterogeneous across different industries, regions, and enterprise sizes. Therefore, policymakers should consider these factors and formulate differentiated policies to promote balanced development of digital transformation and ensure a reasonable increase in the share of labor income. At the same time, this study emphasizes the importance of enhancing workers' digital skills and optimizing the layout of digital infrastructure to meet the needs of digital transformation and drive high-quality economic development.

Keywords: Digital transformation, resource allocation, labor income share.

1. Introduction

With the booming development of the global digital economy, digital transformation has become a core driving force for high-quality economic development. In 2023, China's digital economy reached 53.9 trillion yuan, accounting for 42.8% of GDP, becoming a key force for economic growth. However, in the process of digital transformation, the imbalance in the development of the digital economy among regions has become increasingly prominent (necessity). The eastern region, especially the Yangtze River Delta region, with its strong economic foundation and abundant talent resources, has a much higher concentration of digital industry capital than the central and western regions. In contrast, the central and western regions face the dilemma of outflow of production factors and insufficient economic development momentum due to their relatively lagging digital transformation. Against this backdrop, the digital transformation of enterprises has become crucial for narrowing regional development gaps and improving resource allocation efficiency.

In recent years, the Chinese government has attached great importance to the development of the digital economy (national policy), issuing a series of policy documents to promote the deep integration of the digital economy and the real economy. In 2021, the State Council released the "14th Five-Year Plan for Digital Economy Development," explicitly proposing to accelerate the construction of digital infrastructure, promote the deep integration of digital technology with traditional industries, and increase the proportion of the digital economy in the national economy. In 2022, the National Development and Reform Commission and other departments jointly issued the "Guiding Opinions on Accelerating the Construction of a National Integrated Big Data Center Collaborative Innovation System," proposing to optimize the layout of data center construction and promote the efficient utilization of data resources. In 2023, the Ministry of Industry and Information Technology released the "Action Plan for the Innovative Development of the Industrial Internet (2021-2023)," aiming to improve the digitalization level of the manufacturing industry and promote industrial transformation and upgrading through the construction of the industrial internet. These policy documents provide clear policy support and guidance for enterprises' digital transformation.

2. Literature Review

In recent years, significant progress has been made in relevant theoretical research at home and abroad. Xiao Tusheng et al. (2022) found that the digital transformation of enterprises significantly improved the share of labor income by optimizing the human capital structure (positive correlation, which we consider to be a non-linear inverted U-shaped relationship), but this effect has regional heterogeneity, with the eastern region showing a significant effect due to the improved digital infrastructure [1]. Huang Kuiyou et al. (2023) found that the digital transformation of enterprises significantly improved the share of labor income based on the data of A-share listed companies, and the conclusion still holds after a series of robustness tests. Mechanism research found that the digital transformation of enterprises improved the share of labor income through two paths: alleviating financing constraints and strengthening internal control [2]. Zhao Chunming et al. (2023) found that the digital transformation of enterprises significantly improved the share of labor income (positive correlation) based on the data of A-share listed companies in Shanghai and Shenzhen, and the conclusion still holds after a series of robustness tests. The effect decomposition showed that this promoting effect was mainly reflected in the increase of average wages, but did not significantly improve labor productivity [3]. In addition, the "market-oriented allocation of data elements" strategy and the "eastern data, western computing" pattern proposed in the "14th Five-Year Plan for Digital Economy Development" provide a policy framework for alleviating the regional digital divide.

In the field of resource misallocation theory research, Hsieh and Klenow (2009) constructed a classic model that revealed the negative impact of factor market distortions on total factor productivity (TFP), pointing out that imperfections in factor markets lead to irrational resource allocation, resulting in a loss of production efficiency (a pioneer in the study of resource misallocation). They also found that digital technology can alleviate this resource misallocation phenomenon by reducing information asymmetry, thereby improving production efficiency. Petrin and Sivadasan (2013) further pointed out that digital transformation can not only reduce information asymmetry but also more effectively improve resource allocation by optimizing the efficiency of division of labor within enterprises and dynamically adjusting the marginal product ratio of capital and labor [4].

With the advancement of the national strategy of "building a unified national market," domestic scholars have begun to focus on the spatiotemporal evolution of regional resource misallocation and its profound impact on economic development. [5] Chen Yongwei et al. (2011) incorporated the analysis of resource misallocation and efficiency loss into the traditional growth accounting framework, proposing a method to quantify the impact of factor price distortions on TFP and output changes. They used this method to analyze the resource misallocation situation in China's manufacturing industry, finding that there is significant resource misallocation among various sub-sectors within China's manufacturing industry. This misallocation results in a gap of about 15% between actual output and potential output, and this distortion has not been significantly improved in recent years. Wang Songtao et al. (2016), based on a neoclassical production model of market segmentation, found that factor market segmentation exacerbates the degree of resource misallocation, especially when capital and labor are substitutes, and also reduces the share of labor income. Zhang Zhongwen (2015) constructed a growth accounting framework based on the industry production function of total output to measure the impact of industry resource misallocation on overall economic total factor productivity. This multi-sector model not only supplements the analysis of the role of intermediate inputs in the literature on resource misallocation, but also further explores the industry sources of resource allocation effects by introducing taxes or subsidies into industry capital and labor inputs to characterize factor price distortions at the industry level [6].

These research findings are highly consistent with the requirement of "optimizing the market-based allocation of factors of production" put forward in the "14th Five-Year Plan Outline," providing strong empirical support for solving the problem of unbalanced regional development, and also providing important theoretical basis for promoting high-quality economic development and building a unified national market [8].

Regarding the share of labor income, since the 1980s, the "Kaldor fact" of the stability of the share of labor income in Western countries has been overturned. [9] Many scholars have studied the factors affecting the change of the share of labor income from the perspectives of structural factors, biased technological progress, imperfect competition and globalization of goods and capital. [10] Autor et al. (2017) proposed the theory of "employment polarization", pointing out that the substitution effect of digitalization on medium-skilled jobs has exacerbated income inequality, and this has been verified in OECD countries. [11] Chinese scholars have carried out special research in conjunction with the goal of common prosperity [13]. Bai Chongen et al. (2010) used inter-provincial panel data of China from 1985 to 2003 to conduct regression analysis on the share of labor income from 1985 to 1995 and from 1996 to 2003. [12] The regression results showed that the industrial structure, the proportion of state-owned economy and the level of tax burden had a significant impact on the share of labor income in both periods, while the degree of economic openness and the level of financial development had a significant impact on the share of labor income from 1996 to 2003 [7]. In addition, the "14th Five-Year Plan for Employment Promotion" clearly proposes the "Digital Skills Enhancement Action," which aims to enhance workers' adaptability through vocational training system reform and provide policy tools for balancing efficiency and equity.

3. Theoretical Analysis and Research Hypotheses

3.1. A Theoretical Overview of Digital Transformation and Labor Income Share

This paper draws on the research of Xiao Tusheng (2022) and Zhao Chunming (2023) to construct a theoretical analysis framework for the impact of enterprise digital transformation on the share of labor income, providing a theoretical basis for the empirical research in the following paper.

Assuming a perfectly competitive factor market, representative firms produce based on capital, labor, and digital inputs. Specifically, their production function is a nested constant substitution elasticity function (CES):

$$Y_i(M,T) = [M^\delta + (S,T)^\delta]^{\frac{1}{\delta}},\ M(K,L) = [(A_iK)^\alpha + (B_iL)^\alpha]^{\frac{1}{\alpha}} \quad (1)$$

Here, M describes the traditional mode of production; A_i and B_i represent S_i capital-expanding, labor-expanding, and digital-expanding technologies, respectively; $\alpha \in (-\infty, 1)$ represents the elasticity of substitution parameters for capital and labor inputs; and, according to the definition of labor share, we can obtain:

$$LS_i = \frac{\omega L}{\gamma K + \omega L + \psi T} = \frac{\omega L}{Y} = \frac{\omega}{Y/L} \quad (2)$$

Here, the variables γ and ω represent the prices of capital, labor, and digital inputs, respectively ψ.

This study assumes that the firm's product price is 1, and that the firm's profit maximization is:

$$max(Y_i - \gamma K - \omega L - \psi T) \tag{3}$$

By combining the production function and the profit maximization condition, the rate of return on capital, wage rate, and price of digital input can be obtained:

$$\gamma = Y_i^{1-\delta}[(A_i K)^{\alpha} + (B_i L)^{\alpha}]^{\frac{\delta-\alpha}{\alpha}} A_i^{\alpha} K^{\alpha-1} \tag{4}$$

$$\omega = Y_i^{1-\delta}[(A_i K)^{\alpha} + (B_i L)^{\alpha}]^{\frac{\delta-\alpha}{\alpha}} B_i^{\alpha} L^{\alpha-1} \tag{5}$$

$$\psi = Y_i^{1-\delta} S_i^{\delta} T^{\delta-1} \tag{6}$$

Combining the above first-order conditions with the definitions of the production function and the labor income share, we can obtain:

$$LS_i = \{\frac{M^{\delta}+(S_i T)^{\delta}}{M^{\delta-\alpha}(B_i L)^{\alpha}}\}^{-1} = \{1 + (A_i/B_i)^{\alpha}(K/L)^{\alpha} + \frac{(S_i/B_i)^{\delta}(T/L)^{\delta}}{[1+(A_i/B_i)^{\alpha}(K/L)^{\alpha}]^{\delta-\alpha}}\}^{-1} \tag{7}$$

As shown in Equation (7), a company's labor income share depends on factor inputs (K, L, T), technological level (A, B, S), and substitution parameters. This paper uses the total frequency of digital keywords used by the company divided by the length of the MD&A paragraph in the annual report to measure the degree of digital transformation of micro-enterprises. Under the condition that other conditions remain unchanged, if digital transformation and labor are complementary, i.e. $\delta \in (-\infty, 0)$, digital expansion technology upgrades can promote the increase of labor income share, i.e., $\partial LS_i / \partial S_i > 0$... Conversely, if digital input and labor are substitutes, i.e. $\delta \in (0,1)$, the company's digital expansion technology upgrades will inhibit the increase of labor income share, i.e., $\partial LS_i / \partial S_i < 0$... As shown in Equation (7), a company's labor income share is affected by many factors such as factor inputs (K, L, T), technological level (A, B, S), and substitution parameters. In this paper, this study uses digital technology expansion S_i to measure the degree of digital transformation of enterprises. Under the condition that other conditions remain unchanged, if digital transformation and labor are complementary, then digital expansion technology upgrades will help promote the increase of labor income share. Conversely, if digital input and labor are substitutes, the company's promotion of digital expansion technology upgrades may inhibit the increase of labor income share.

In this context, businesses must carefully weigh the potential impact on labor income share when undertaking digital transformation. If digital transformation complements labor, businesses can increase labor income share by improving productivity and innovation, thereby incentivizing employees and increasing overall labor productivity. In this case, digital transformation not only brings technological progress but also promotes equitable income distribution, achieving a win-win situation for both businesses and employees. However, if digital transformation is a substitute for labor, businesses may reduce their reliance on human labor and rely more on technologies such as automation and artificial intelligence during the digitalization process. This could lead to a decline in labor income share, as machines and algorithms may replace some tasks previously performed manually. In this case, businesses need to consider how to enhance employee skills through training and education, enabling them to adapt to the new work environment and thus mitigating the negative impact of digital transformation on labor income share.

Furthermore, companies need to consider the impact of digital transformation on different industries and types of businesses. In some technology-intensive industries, digital transformation may proceed more rapidly, and changes in labor income share will be more pronounced; while in some labor-intensive industries, digital transformation may be slower, and changes in labor income share may not be as significant. Therefore, when formulating digital transformation strategies, companies need to comprehensively consider the characteristics of their industry and their own specific circumstances.

From a theoretical perspective, the share of labor income in a company's production process essentially depends on the magnitude of labor's contribution to the production process. Assume the company's production function is $Y = F(K, L, D)$, where Y is output, K is capital input, L is labor input, D and is the degree of digital transformation. According to the marginal productivity theory in economics, the wage level W can be expressed as the marginal product of labor, i.e., $W = \frac{\partial Y}{\partial L}$. The share of labor income can be expressed as the ratio of the product of wages and labor input to total output, i.e. $\frac{W \cdot L}{Y}$.

In the process of digital transformation, the impact of digitalization D on labor productivity is a key factor. If digital transformation and labor are complementary, then as the degree of digitalization increases, the marginal output of labor will increase, and consequently, the share of labor income will also rise. However, when the degree of digitalization reaches a certain level, a substitution relationship may emerge between digitalization and labor. At this point, the marginal output of labor will decrease due to further advancements in digitalization, and the share of labor income will also decline. Mathematically, we can assume that the function of the impact of digitalization on the marginal output of labor is $f(D) = aD - bD^2$ (where $a > 0$ and $b > 0$), which D is an increasing function when is small, but gradually decreases as D increases $f(D)$, eventually becoming a decreasing function. This indicates that in the early stages of digital transformation, the complementary effect between digitalization and labor is dominant, and the share of labor income will increase with the increase of digitalization; however, when the degree of digitalization reaches a certain level, the substitution effect begins to appear, and the share of labor income will decline with further increases in digitalization. Therefore, based on the above analysis, this paper proposes the following hypothesis regarding the relationship between labor income share and digitalization:

Hypothesis 1: At the micro level, digital transformation of enterprises is conducive to increasing the share of labor income, and this effect exhibits an inverted U-shaped relationship.

3.2. Research on the Mechanism of Mitigation of Corporate Financing Constraints

First, enterprise digital transformation has a significant "information effect." Information asymmetry is one of the key factors leading to corporate financing constraints. When external investors struggle to obtain accurate information about a company's true operating conditions, they cannot effectively distinguish between high-quality and low-quality companies, making it difficult to make accurate investment decisions, which puts companies in a financing predicament. Digital transformation, leveraging digital technologies, can efficiently and accurately process large amounts of business and financial data, and promptly "push" operating data and financial information to the external market through digital platforms, thereby significantly reducing the degree of information asymmetry between companies and external investors. As the level of information asymmetry decreases, companies can more easily obtain external investment, thus effectively alleviating financing constraints.

Secondly, there is a positive "exposure effect" when companies disclose information about their digital transformation. Digital transformation has become a hot topic in current social development. By undertaking digital transformation, companies not only align with national development strategies and gain more policy support, thus reducing financing costs, but also send a positive signal to the outside world that their competitiveness is continuously improving. This helps enhance external investors' confidence in the company's future performance and further improves its external financing capabilities. In summary, corporate digital transformation improves information transparency through the "information effect" and enhances external investor confidence through the positive "exposure effect." These two effects work together to effectively improve a company's ability to obtain external funding and significantly alleviate its financing constraints.

Wang et al. (2013) pointed out that financing constraints are one of the important reasons for the continuous and slow decline in the share of labor income over the years. In other words, easing financing constraints has a potentially positive effect on increasing the share of labor income.

The constraints of corporate financing on the share of labor income are mainly reflected in two key aspects: First, when companies encounter external financing difficulties, they often rely on internally accumulated funds to meet their funding needs, which directly reduces the company's distributable profits, leading to a decline in the share of labor income. Second, if companies cannot obtain sufficient operating funds from external sources, they usually tend to reduce labor costs, specifically by reducing the number of employees or lowering existing wage levels. The research findings of Jiang Xuanyu and Jia Jing (2021) show that companies effectively alleviate financing constraints by using bond financing, thereby increasing their share of labor income.

Hypothesis 2: Enterprise digital transformation alleviates the financing constraints of enterprises and increases the share of labor income through the "information effect" and "exposure effect".

4. Research Design

4.1. Sample Selection and Data Sources

This paper uses Chinese A-share listed companies from 2014 to 2023 as the initial research sample, and the sample is screened according to the following principles: (1) Information industry companies are excluded. Taking the 2012 CSRC industry classification as an example, it includes computer, communication and other electronic equipment manufacturing (C39) and information transmission, software and information technology services (I63, I64, I65); (2) Companies that went public during 2014-2023 are excluded; (3) ST, *ST and financially abnormal companies with a debt-to-asset ratio greater than 100% are excluded; (4) Samples with missing relevant variables are excluded; (5) Samples related to the financial industry are excluded. The equity nature data in this paper comes from the Guotai An CSMAR database and the CCER Xenophon database. The macro data comes from the statistical data of the "China Statistical Yearbook" over the years. The remaining data, unless otherwise specified, comes from the Guotai An CSMAR database.

4.2. Variable Definition

4.2.1. Labor Income Share (LS)

Referring to the research of Shi Xinzheng et al. (2019) and Xiao Tusheng et al. (2022), this paper uses the formula: (Cash paid by the enterprise to its employees in the current period + Employee compensation payable at the end of the period - Employee compensation payable at the beginning of the period) / Total operating revenue (LS).

4.2.2. Enterprise Digital Transformation

Enterprise digital transformation is a complex process, and accurately depicting it at the micro-enterprise level presents challenges. Currently, most research takes a macro-level approach, using regional or industry-specific digital economy indicators to represent the level of digitalization. Micro-level empirical studies typically measure it through information assets, the proportion of IT-enabled employees, and the application of information systems. However, these methods have limitations and cannot comprehensively reflect the true state of enterprise digitalization. For example, some studies use IT investment, telecommunications spending, or the proportion of digitally related intangible assets to measure IT density, but these indicators may be influenced by companies' showy investments, and investment levels do not equate to actual application levels. Other studies assess the degree of enterprise IT application through questionnaires, such as the proportion of IT personnel, but this method may only reflect simple network application behavior, which differs significantly from enterprise digitalization, and has limited sample size and representativeness. Still other studies focus on the construction of IT systems such as ERP systems, but this method is one-dimensional and fails to reflect the differences in the degree of enterprise digitalization. In recent years, with the application of textual big data in economics and finance, some studies have begun to use text analysis methods to characterize enterprise digital transformation. However, the key to text analysis methods lies in choosing an appropriate dictionary, which directly affects the accuracy of enterprise digitalization indicators.

4.2.3. Control Variables

Drawing on previous research (Shi et al., 2019; Xiao et al., 2022), this paper includes a series of control variables in the model, including firm-level factors such as company size, equity concentration (Top 10), return on total assets (ROA), capital structure (Lev), capital-output ratio (PPE), capital intensity (Capital), operating cash flow (CFO), company age (Age), and ownership structure (SOE), as well as regional-level factors such as economic development level (GDP), industrial structure (IndStr), and higher education status (Edu). Specific variable definitions are shown in Table 1.

4.3. Model Setting

Drawing on the research of Hu Yiming and Maimaitiyim

Zunong (2013), Shi Xinzheng et al. (2019), and Xiao Tusheng (2022), this paper constructs the following model (1) to examine the impact of enterprise digital transformation on the share of labor income:

$$Laborshare_{it} = \alpha_0 + \alpha_1 \times DigiLevel_{it} + \sum \alpha_x Controls_{it} + \varphi_i + \tau_t + \varepsilon_{it} \quad (8)$$

Among them, $Laborshare_{it}$: the firm's labor income share i over time t, i.e., the proportion of compensation paid to workers to the firm's total output. $DigiLevel_{it}$: the firm's i level of digital transformation $Controls_{it}$ over time, measured comprehensively through indicators such as digital investment and technology application. t: control variables, including firm size, industry competition level, firm age, etc. φ_i: individual fixed effects, controlling for unobservable factors at the firm level. τ_t: time fixed effects, controlling for the impact of time trends and the macroeconomic environment. ε_{it}: random error term, capturing the portion not explained by the model. $Lnwage_{it}$: the logarithm of $LnLabor_{it}$ the firm 's wage rate i over time , representing the average wage level paid to workers by the firm. t: the logarithm of the firm 's labor productivity i over time t, representing the output level per unit of labor input.

5. Conclusions and Policy Implications

In the booming global digital economy, digital transformation has become a core driving force for high-quality economic development. With the widespread application of digital technologies, enterprises have not only improved production efficiency but also optimized resource allocation and promoted industrial upgrading by introducing technologies such as big data, artificial intelligence, and the Internet of Things. However, the impact of digital transformation on resource allocation efficiency and income distribution patterns, especially its mechanism of action on labor income share, remains highly controversial. On the one hand, the complementary effect between digital transformation and labor force dominates in increasing labor income share. Digital transformation significantly improves labor productivity and the efficiency of worker skill utilization by optimizing labor allocation efficiency and achieving precise matching and dynamic adjustment of labor and work tasks. On the other hand, the technology substitution effect may lead to the substitution of labor factors by capital, thereby inhibiting the increase in labor income share.

This study systematically explores the direct, indirect, and differential effects of corporate digital transformation on labor income share by constructing a dynamic analysis framework and employing econometric methods such as panel data analysis and threshold models. The study finds that the impact of corporate digital transformation on labor income share exhibits significant non-linear characteristics, and this impact shows marked heterogeneity based on firm size, industry, and region. Specifically, a significant threshold effect exists at firm size at 21.6440, indicating that firm size has a significant moderating effect on the relationship between corporate digital transformation and labor income share. This finding reveals the crucial role of firm size in the digital transformation process and provides important evidence for understanding the differentiated performance of firms of different sizes in digital transformation.

For small businesses, capital structure and industry competition have a more significant negative impact on labor income share. Small businesses typically face funding and technological bottlenecks; a higher capital structure and intense industry competition may lead to greater challenges during digital transformation, thus negatively impacting labor income share. For large businesses, Tobin's Q and the proportion of R&D personnel have a more significant positive impact on labor income share. Large businesses typically possess stronger market value and innovation capabilities, and by increasing R&D investment and improving technological innovation, they can better enhance their labor income share. Furthermore, the complementary effect between digital transformation and labor force dominates in increasing labor income share, but the technology substitution effect may also lead to the substitution of labor by capital, thereby inhibiting the increase in labor income share. This finding suggests that businesses need to balance technological progress and labor allocation when promoting digital transformation to achieve both economic and social goals.

These findings not only provide a new perspective on understanding the impact of digital transformation on resource allocation and income distribution, but also offer theoretical support for further optimizing resource allocation, increasing the share of labor income, and promoting the healthy development of the digital economy. Against the backdrop of rapid global digital economic development, enterprise digital transformation is not only key to enhancing competitiveness but also an important pathway to achieving high-quality economic development. By optimizing resource allocation, increasing the share of labor income, and promoting the healthy development of the digital economy, social equity and sustainable economic development can be effectively promoted.

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