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Digital Economy, Employment Structure and Labor Share

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Abstract: The COVID-19 pandemic significantly disrupted employment, making it challenging to increase the labor share. However, the recent expansion of the digital economy has revitalized economic growth and markedly improved productivity. This raises a critical question: can the growth of the digital economy not only boost labor productivity but also increase labor share and reduce income inequality? This paper explores the impact of digital economic development on labor share, examining the underlying mechanisms at play. Our findings suggest that the digital economy has the potential to reshape employment structures, leading to an increase in the labor share. However, the extent of this impact varies across different industries. Furthermore, from an industrial chain perspective, the digital economy has created technology spillover effects that benefit upstream and downstream sectors. In light of these findings, it is crucial to continue fostering the growth of the digital economy to address potential negative impacts on the labor share in the future.

Keywords: digital economy; employment structure; labor share; industrial chain

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1. Introduction

Since the 1970s, many countries have witnessed a decline in labor share [1], a trend that has been particularly impactful in China. With a relatively low proportion of property income and a greater reliance on labor income, the decrease in labor share has posed significant challenges. Labor share has long been a critical focus in economic research, as it is a fundamental aspect of national income distribution. Increasing labor share is essential for narrowing income disparities and advancing common prosperity. Labor shares influence residents' living standards, income inequality, and social stability, shaping the future of economic development by determining whether growth is driven by investment or consumption. Since 2019, the COVID-19 pandemic has further strained global economic development, applying significant downward pressure on the worldwide economy. This is likely due to the economic disruptions caused by lockdowns [2]. Additionally, uncertainties and risks from trade frictions have exacerbated these challenges, leaving China with a challenging employment situation.

With the advancement of information-related technologies, the digital economy has emerged as a new socio-economic organization, succeeding the agricultural and industrial economies. This digital economy, rich in content, harnesses communication technologies such as cloud computing, big data, artificial intelligence, the Internet of Things, blockchain, and mobile Internet to boost productivity and transform lifestyles through technological innovation and industrial integration. As a result, it has profoundly influenced economic development, inspiring us with its potential to revolutionize how we work and live. According to the "China Digital Economy Development Report (2023)" by the China Academy of Information and Communications Technology (CAICT), China's digital economy has increased. Its added value rose from 2.6 trillion yuan in 2005 to 50.2 trillion yuan by 2022. For 11 consecutive years, nominal growth in the digital economy has outpaced nominal GDP growth, with its share of GDP increasing from 14.2% in 2005 to 41.5% in 2022. This

underscores the digital economy's growing significance in the national economy. Given this vigorous development, the digital economy is set to drive structural changes in the broader economy, leading to shifts in labor relations and impacting the labor market.

Extensive research has examined the impact of various digital technologies, such as ICT [3], automation [4], and robotics [5], on employment. At the macro level, changes in employment influence the labor share, with increases in employment generally boosting the labor share and decreases causing it to fall. This relationship is further reflected in wage levels, structural changes, and labor market characteristics. In addition, some literature has explored the skill structure [6,7], income structure [8], and the effect of industry structure [9] on the labor share, which provides a research basis for the topic of this paper.

Therefore, exploring the effects and mechanisms through which these changes impact labor income shares is crucial. Unlike much of the existing research, this paper considers the overall impact of the digital economy, which encompasses a broad range of technologies and services. The focus is on how the digital economy affects employment structures and labor shares. Figure 1 shows the research step design diagram. Firstly, the paper begins by proposing research hypotheses based on a review of the existing literature, exploring how the digital economy influences the labor share and the role of changes in employment structure. It then utilizes provincial and firm-level panel data to test these hypotheses using fixed and mediated effects models. Finally, the paper discusses its limitations, presents conclusions, and offers policy recommendations for the future. The potential contributions of this paper include providing a comprehensive analysis of how employment structures mediate the impact of the digital economy on labor income shares. Additionally, it expands the study of the digital economy's influence on industries by examining its effects on labor income shares from the perspective of the industrial chain.

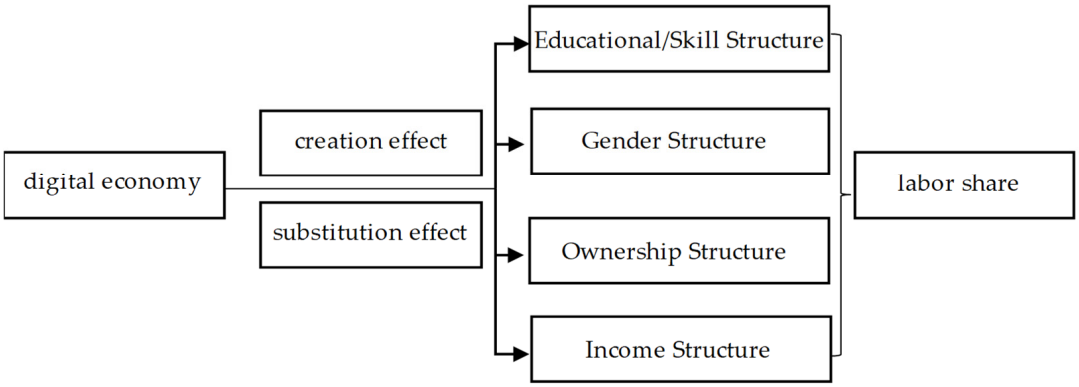


Figure 1. Research step design diagram.

The remainder of this paper is organized as follows: Section 2 presents the theoretical analysis and research hypotheses. Section 3 describes the data and outlines the econometric modeling approach. Section 4 discusses the study's findings, and Section 5 concludes the paper.

2. Theoretical Analysis and Research Hypotheses

Throughout history, every technological revolution has reshaped the labor process, and today's digital technology-driven societal changes are no exception. In the workplace, two distinct types of AI application illustrate this transformation. The first involves using AI-based analyses and algorithms to replace or augment managerial functions, such as recruiting, monitoring, supervising, and training workers, and scheduling work hours and breaks—commonly called "algorithmic management". The second type focuses on automating tasks performed by workers, mainly routine and repetitive ones that machines can efficiently handle [10]. From the first perspective, the digital economy contributes to more efficient labor allocation, reducing the risk of unemployment. It enhances the efficiency of matching labor supply and demand [11], significantly reducing search time,

improving matching accuracy, and lowering the risk of structural unemployment. This shift inevitably reshapes the labor market, leading to new forms of employment that help alleviate employment pressures [12]. The digital economy broadens employment opportunities and introduces new employment models. In this context, traditional limitations of time and space no longer confine workers, who can participate in work anytime and anywhere with Internet access. As Freeman [13] noted, "the labor market will expand in cyberspace", signaling a shift toward non-standardized forms of labor, such as crowdsourcing, gig work, and the sharing economy. The digital economy creates more job opportunities and generates new work tasks, which have driven significant employment growth in the United States [14]. This shift positively impacts entrepreneurs by opening up new avenues for innovation and business development [15]. However, from the second perspective, some studies suggest that the digital economy also has a substitution effect on employment. For example, research using data from the China Household Tracking Survey (CFPS) found that a one standard deviation increase in robot use leads to a 1 percent decrease in labor force participation and a 7.5 percent decline in employment in China [5]. When digital technology has a comparative advantage over labor, it tends to replace human workers, particularly in tasks that can be completed by following explicit rules [16]. This substitution can lead to wage declines and increase the probability of unemployment.

Therefore, when assessing the impact of the digital economy on labor income share, it is crucial to consider the balance between its creation and substitution effects. Suppose the creation effect outweighs the substitution effect. In that case, the expansion of employment and the increase in wage levels driven by the digital economy will lead to a rise in the labor income share. Conversely, the labor income share may decline if the substitution effect dominates. Based on the analysis above, and given the uncertainty surrounding the relative strength of these two effects, we propose the following competing research hypotheses:

H1a: *The job creation effect of the digital economy outweighs the substitution effect, leading to an increase in the labor income share.*

H1b: *The employment substitution effect of the digital economy surpasses the creation effect, reducing the labor income share.*

The development of the digital economy not only impacts the quantity of employment but also brings about changes in employment structure [17,18]. These changes can be summarized as follows:

Technological advancements in the digital realm have significantly altered the structure of employment skills and education. These advancements produce promotional and substitutive effects on workers with varying skill levels and educational backgrounds. According to Autor et al. [16], well-educated workers often have a comparative advantage in non-routine tasks compared to routine tasks. As firms focus on long-term development goals, there is a growing emphasis on enhancing innovative capabilities, which drives an increasing demand for high-skilled labor [19]. This trend contributes to a polarization in the employment structure. Additionally, low-skilled workers in the service sector are more likely to be assigned computer-assisted roles than university graduates in the same industry [20], with these routine tasks being more vulnerable to automation. Research suggests that 47% of occupations may face significant automation impact within the next twenty years [21]. When the promotional effect of digital economy development on high-skilled workers outweighs the substitutive implications for low-skilled workers, it upgrades the employment skill structure, thereby increasing the labor income share. Conversely, if the substitution effect on low-skilled workers dominates and hampers upgrading the employment skill structure, it suppresses the increase in the labor income share. Based on this analysis, we propose the following competitive hypothesis:

H2a: *The development of the digital economy increases the labor income share by promoting the upgrading of the employment skill (education) structure.*

H2b: *The development of the digital economy suppresses the labor income share by inhibiting the upgrading of the employment skill (education) structure*.

The digital economy has transformed the ownership structure of employment. The rise of new platforms has made employment patterns more flexible, allowing certain forms of work to transcend traditional time and space limitations. This shift has expanded the scope of informal employment. Lan et al. [22] developed a three-sector individual employment model, demonstrating that increased urban private-sector employment can account for the rise in the labor share. The "platformization" of work has further increased the proportion of the private sector in the economy, stimulating economic vitality and broadening the economic pie. According to data from the National Development and Reform Commission of China in 2022, the private economy now represents over 80% of urban employment. The growth in this employment sector is particularly beneficial for increasing the share of high labor income. Based on this, we propose the following hypothesis:

H3: *The development of the digital economy will increase the labor income share by expanding the proportion of employment in the private and individual economies*.

The development of the digital economy can impact the gender structure of employment. Women often face challenges different from those of men in the labor market, including disparities in education and job opportunities. However, the rise of digital technology has increased employment opportunities and attracted women to roles in technology-related fields [23], leading to a higher proportion of women in the workforce. Grigoli et al. [24] argue that the digital economy boosts women's labor participation rates while decreasing men's. Although artificial intelligence creates more employment opportunities overall, its impact on female employment, mainly through automation, can be more pronounced [25]. As women are often involved in repetitive and standardized tasks, the digital economy may intensify the substitution effect on female labor, potentially increasing employment pressure and negatively affecting the labor income share. Based on this analysis, we propose the following hypothesis:

H4: *The development of the digital economy may decrease the proportion of female employment, which could subsequently lead to an increase in the labor income share*.

The evolution of the digital economy has significantly reshaped the structure of employment income. Automation driven by digital technologies has transformed the employment landscape and altered income distribution patterns. Some studies suggest that this transformation may exacerbate income disparity. On the one hand, the digital economy tends to create a polarization effect in employment, increasing income polarization and widening the income gap among workers. This is partly due to the expansion of low-skilled jobs, which intensifies competition and exerts downward pressure on wages, further enlarging the wage gap between high- and low-skilled workers. High-skilled and highly educated employees tend to dominate income distribution [26]. However, other research indicates a more complex relationship between the digital economy and income disparity. Specifically, the digital economy can narrow the urban–rural income gap before reaching a certain inflection point [27,28].

Furthermore, advancements in Information Technology (IT) allow grassroots employees to collect and process information more efficiently, thereby increasing the value of their skills and potentially enhancing their labor remuneration [29]. Additionally, research indicates an inverse relationship between labor income share and income inequality, as measured by the Gini coefficient [30]. Based on this, we propose the following competitive hypothesis:

H5a: *The development of the digital economy will narrow income disparities, increasing the labor income share*.

H5b: *The development of the digital economy will widen income disparities, leading to a decrease in the labor income share.*

Furthermore, input–output linkages can propagate shocks directly and indirectly across production networks [31]. For example, suppose a specific industry faces a negative shock that increases the price of its goods. In that case, it will adversely affect all industries that use this good as an intermediate input. This impact then propagates further across the production network. Acemoglu et al. [32] similarly demonstrated that shocks transmitted through input–output relationships can have significant economic consequences. Network effects are a prominent feature of the digital economy. As digital technologies deepen industry integration, they enhance industrial linkages within production networks, amplifying technological shocks' impact. Based on this, we propose the following hypothesis:

H6: *The digital economy may influence labor income share through the effects of upstream and downstream industries, which are mediated through input–output relationships.*

3. Data Description and Econometric Models

3.1. Data

Based on the research hypotheses, and considering data availability, this study uses provincial-level data from the "China Statistical Yearbook" (https://www.stats.gov.cn/sj/ndsj/, accessed on 5 January 2024) and "China Labor Statistical Yearbook" (https://cnki.ctbu.edu.cn/CSYDMirror/trade/Yearbook/Single/N2018070151?z=Z001, accessed on 5 January 2024) from 2011 to 2017. Due to the unavailability of public data on labor income share beyond 2017, the data collection period concludes in that year. The analysis focuses on 28 provinces, excluding those with significant missing data, to ensure data integrity, resulting in a balanced panel dataset. Data on listed companies were sourced from the China Stock Market and Accounting Research (CSMAR) database, focusing on manufacturing enterprises from 2011 to 2022. No adjustments were made for employment data before 2011 due to substantial missing information. Additionally, specific ST companies were excluded, and a 1% winsorization was applied to continuous variables to handle outliers. The final panel dataset consisted of 629 samples over 12 years. As shown in Table 1, the mean labor income share at the provincial level was 49%, notably higher than the 11% observed at the enterprise level. The overall standard deviations of other variables are relatively minor, meeting the requirements for regression analysis.

Table 1. Descriptive statistics.

Variables	Obs.	Mean	Std. Dev.	Min.	Max.
Ls1	196	0.491	0.046	0.379	0.602
De1	196	0.236	0.117	0.08	0.685
Ind	196	0.473	0.091	0.327	0.827
Rd	196	0.206	0.138	0.072	0.625
Pgdp	196	10.695	0.429	9.691	11.832
Gov	196	0.244	0.082	0.121	0.456
Ls2	7548	0.113	0.061	0.0050	0.568
De2	7548	0.007	0.020	0	0.445
Size	7548	22.484	1.233	19.528	27.621
Lev	7548	0.423	0.187	0.007	1.056
BM	7548	1.097	1.066	0.047	13.291
Indep	7548	0.371	0.0553	0.182	0.800
TobinQ	7548	1.930	1.267	0.681	21.296

In China's national income accounting system, national income is composed of four major components: compensation of employees (C), depreciation of fixed assets (D), operating surplus (O), and net production taxes (T). There are two main methods for calculating the labor income share using macroeconomic data: (1) the GDP-based method: This method

calculates the labor income share by dividing the compensation of employees by GDP. The formula is LS = C/(C + D + O + T); (2) the Factor-based method: This approach calculates the labor income share by subtracting production taxes from GDP [33] and then computing the labor income share. The formula is LS = C/(C + D + O). There is academic debate regarding these methods, particularly concerning net production taxes, which are not classified as either capital or labor income. An increase in taxes may lead to underestimating the labor income share. Therefore, both methods are employed at the provincial level to calculate the labor income share. The GDP-based method (Ls1) is used as the baseline for regression analysis, while the Factor-based method (Ls3) is utilized for robustness checks.

Scholars commonly measure the labor income share at the enterprise level using the ratio of total employee compensation to enterprise value added. This ratio reflects the relationship between labor input and output within the enterprise, and indicates the share of labor income in the distribution of the enterprise's income. This study adopts the approach of Wang et al. [34], measuring the labor income share by the proportion of total labor compensation to total operating income. Two methods are used for this measurement: (1) the Cash Flow Statement method. This method measures the proportion of "payments to employees and payments for employees" in the cash flow statement relative to total operating income. This item represents actual payments made by the company to employees, including wages, bonuses, allowances, subsidies, and costs for various employee benefits (e.g., pension insurance, unemployment insurance, supplementary pension insurance, housing provident fund, housing subsidies for employees in difficulty, and retirement expenses paid to retirees). It excludes wages paid to construction personnel. (2) The Accrued Compensation method. This method measures the proportion of "accrued employee compensation payable" in the notes to the financial statements relative to total operating income. This reflects all monetary and non-monetary compensation employees receive during and after employment. Both methods are used for baseline regression and robustness checks (Ls2, Ls4).

Given the broad scope of the digital economy, there currently needs to be a unified standard for measurement. Scholars use various surrogate indicators to gauge digital economic development [35,36]. Due to the complexity of accurately measuring digital economic progress, relying on a single predictor while reflecting the scale of development needs more objectivity and comprehensiveness. Multiple indicators can only indirectly capture certain aspects of digital economic growth and may only partially represent its breadth. To address this limitation, we constructed a composite index to provide a more comprehensive and objective reflection of China's digital economy's overall trend. This composite index is designed to align with the actual development of China's digital economy and includes indicators covering diffusion level, infrastructure, development scale, and business applications. We used the entropy weight method to integrate these dimensions into a digital economy index. Table 2 provides details on the specific indicators used.

Digital transformation involves significant changes to an entity's physical attributes by applying information, computing, communication, and connectivity technologies [37]. Consequently, digital technologies play a pivotal role in driving the digital transformation of enterprises, which is a crucial economic activity within the digital economy. At the enterprise level, the degree of digital transformation is measured using data from the CSMAR database. This is done by analyzing keyword frequencies related to digital economy technologies in the financial reports of listed companies. These keywords are categorized into five dimensions: artificial intelligence, blockchain technology, cloud computing, big data, and digital technology applications. The entropy weight method is then used to create a Digital Transformation Index, reflecting the extent of digital transformation. Table 3 provides details on the specific keywords and their frequencies.

Table 2. Construction of digital economy development index.

Level 1 Indicators	Level 2 Indicators
Penetration of the digital economy	Internet penetration Internet broadband access users
Digital economy infrastructure	IP v4 address weight Number of domain names per 10,000 people The length of the long-distance fiber optic cable line Mobile phone exchange capacity
The scale of the development of the digital economy	Mobile phone penetration
Business applications in the digital economy	Software business revenue Telecommunications traffic per capita The total volume of express delivery business

Table 3. The degree of digital transformation of companies.

Classification of Indicators	Keywords
Artificial intelligence technology	Artificial Intelligence, Business Intelligence, Image Understanding, Investment Decision Assistance System, Intelligent Data Analysis, Intelligent Robotics, Machine Learning, Deep Learning, Semantic Search, Biometrics, Face Recognition, Speech Recognition, Identity Verification, Autonomous Driving, Natural Language Processing
Blockchain technology	Digital Currency, Smart Contract, Distributed Computing, Decentralization, Bitcoin, Consortium Chain, Differential Privacy Technology, Consensus Mechanism
Cloud computing	In-Memory Computing, Cloud Computing, Stream Computing, Graph Computing, Internet of Things, Multi-Party Secure Computing, Brain-Inspired Computing, Green Computing, Cognitive Computing, Converged Architecture, 100 Million Concurrency, Exabyte-Level Storage, Cyber-Physical Systems
Big data technology	Big Data, Data Mining, Text Mining, Data Visualization, Heterogeneous Data, Credit Investigation, Augmented Reality, Mixed Reality, Virtual Reality
Digital technology applications	Mobile Internet, Industrial Internet, Mobile Internet, Internet Healthcare, E-Commerce, Mobile Payment, Third-Party Payment, NFC Payment, B2B, B2C, C2B, C2C, O2O, Networking, Smart Wearable, Smart Agriculture, Smart Transportation, Smart Medical, Smart Customer Service, Smart Home, Smart Investment Advisory, Smart Cultural Tourism, Smart Environmental Protection, Smart Grid, Smart Energy, Smart Marketing, Digital Marketing, Unmanned Retail, Internet Finance, Digital Finance, Fintech, Quantitative Finance, Open Banking

At the provincial level, the employment structure is measured using the following variables: Educational Structure of Employment (Edu1): this is represented by the proportion of urban residents with a college education or higher among the employed population. Ownership Structure of Employment (Priv): this variable indicates the proportion of individuals employed in the private sector relative to the total workforce. Gender Structure of Employment (Female): this is denoted by the proportion of urban female employees in the workforce. At the corporate level, employment structure is characterized by Educational Structure of Employment (Edu2): this is calculated as the proportion of employees with undergraduate education or higher (including bachelor's, master's, and doctoral degrees) within the workforce. Skills Structure of Employment (Skill): this variable categorizes employees based on their roles into high-skilled positions (such as technical, comprehensive management, and financial roles) and low-skilled positions (including production, customer service, and administrative roles). Income Structure of Employment (Gap): this is the logarithm of the ratio of management positions' average wage to ordinary employees' average salary.

Other factors besides the digital economy can impact the labor share, and we considered the following control variables to eliminate potential confounding effects: provincial-level control variables including industrial structure (Ind) and labor income shares can fluctuate due to shifts in industrial structure. Research indicates that changes in industrial structure, including upgrading and transformation, significantly impact labor income shares [38]. Technological progress (Rd) and technological advances can affect labor income shares. This study measured technological progress as the proportion of local government spending on scientific and technological research relative to total local government expenditure. Economic development scale (Pgdp): economic development is assessed using the logarithm of GDP per capita, which provides an indicator of the overall economic development of the region; government intervention (Gov): measured by the proportion of local government expenditure to GDP, reflecting the influence of government actions on labor–capital dynamics.

Control variables for listed companies include asset size (Size), measured by the logarithm of total assets, with larger enterprises likely to wield greater absolute power in labor–capital relations and thus have higher bargaining power; capital structure (Lev), specifically the ratio of total liabilities to total assets; Tobin's Q value (TobinQ), measured by the ratio of market value to total assets; the proportion of independent directors (Indep), represented by the ratio of independent directors to total directors; the book-to-market ratio (BM) is expressed as book value divided by total market value.

3.2. Model

This study employs panel data for empirical analysis, leveraging its unique advantages. Panel data combine features of both time-series and cross-sectional data, allowing for a more comprehensive analysis of various issues. Its dual temporal and individual dimensions provide a larger sample size and greater information volume, which enhance estimation precision. Additionally, panel data help address estimation biases arising from omitted variables. The model formulation is as follows:

$$Ls_{it} = \alpha_1 + \beta_1 DE_{it} + \beta_2 Z_{it} + u_i + \varphi_t + \epsilon_{it} \quad (1)$$

Within this framework, Ls_{it} denotes the labor income share of individual i (province or company) in year t, DE_{it} represents the digital economy index for individual i in year t, Z_{it} signifies a series of control variables, u_i accounts for individual effects, φ_t denotes time effects, and ε_{it} denotes the random disturbance term.

Building upon Model (1), a two-step approach was employed to validate the proposed mechanisms outlined earlier to assess the mediating effects. When the mediating variable theoretically has a causal relationship with the dependent variable, the existence of mediating effects can be verified by constructing the following model:

$$ET_{it} = \alpha_2 + \beta_3 DE_{it} + \beta_4 Z_{it} + u_i + \varphi_t + \epsilon_{it} \quad (2)$$

Here, ET_{it} represents the mediating variable of this study: employment structure; the meanings of the remaining variables are consistent with those in Equation (1).

4. Results

4.1. Baseline Regression

Following the model specifications outlined earlier, we address the core issues of this paper, with a particular emphasis on the coefficient β_1 associated with the development of the digital economy (DE). A positive β_1 indicates that the advancement of the digital economy leads to an increase in labor income share, whereas a negative β_1 suggests a reduction. The model also accounts for individual and time effects to control for unobservable factors that could influence the regression results.

As illustrated in Column (1) of Table 4, the effect of digital economic development on the overall labor income share at the macro level was examined. The findings reveal that,

during the sample period, the positive impact of digital economic development outweighed any potential substitution effects. This result supports Hypothesis H1a, demonstrating that digital economic growth significantly enhances the labor income share. In Table 5, Column (1) presents the regression analysis of the digital economy's effect on the labor income share of listed companies. The results confirm that digital economic development significantly increases the labor income share within these enterprises, further validating Hypothesis H1a.

Table 4. Baseline regression and mechanism analysis at the provincial level.

	(1)	(2)	(3)	(4)
Variables	**Ls1**	**Edu1**	**Priv**	**Female**
DE1	0.132 ***	0.191 ***	0.349 ***	−0.167 **
	(0.043)	(0.060)	(0.132)	(0.065)
Ind	−0.039	0.080	−0.649 **	−0.019
	(0.063)	(0.092)	(0.281)	(0.054)
Rd	−0.048 **	−0.023	0.050	−0.002
	(0.020)	(0.036)	(0.067)	(0.018)
Pgdp	−0.052 *	−0.088 **	0.058	−0.006
	(0.029)	(0.037)	(0.095)	(0.019)
Gov	0.083	−0.052	0.450 **	−0.055
	(0.074)	(0.096)	(0.222)	(0.058)
Constant	1.024 ***	1.055 **	−0.257	0.482 **
	(0.323)	(0.432)	(1.118)	(0.225)
Individual fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
R^2	0.932	0.980	0.838	0.867

Note: *, ** and *** indicate that the regression results pass the significance test at the 10%, 5%, and 1% confidence levels, respectively; values in parentheses are robust standard errors.

Table 5. Firm-level benchmark regression and mechanism analysis.

	(1)	(2)	(3)	(4)
Variables	**Ls2**	**Edu2**	**Skill**	**Gap**
DE2	0.086 **	0.415 ***	0.624 ***	−4.977 ***
	(0.036)	(0.070)	(0.105)	(1.700)
Size	−0.019 ***	0.006 **	−0.009 **	1.253 ***
	(0.002)	(0.003)	(0.004)	(0.102)
Lev	0.003	−0.035 ***	0.002	−0.837 ***
	(0.005)	(0.008)	(0.012)	(0.316)
TobinQ	−0.000	0.003 ***	−0.002	0.075 **
	(0.001)	(0.001)	(0.001)	(0.036)
Indep	−0.019 *	0.028	−0.032	1.457 *
	(0.010)	(0.018)	(0.022)	(0.753)
BM	0.004 ***	−0.000	0.000	−0.456 ***
	(0.001)	(0.001)	(0.002)	(0.061)
Constant	0.543 ***	0.090	0.530 ***	−22.478 ***
	(0.036)	(0.056)	(0.084)	(2.266)
Individual fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
R-squared	0.800	0.880	0.855	0.712

Note: *, ** and *** indicate that the regression results pass the significance test at the 10%, 5%, and 1% confidence levels, respectively; values in parentheses are robust standard errors.

Moreover, the analysis of control variables indicates a negative impact of firm size on labor share. This can be attributed to the fact that larger firms with greater profitability tend to dominate the labor market, and thus exert more bargaining power. The nascent digital economic development stage is one potential explanation for the increased labor

income share. Although digital technology has been available for some time, its widespread application and integration with other industries require significant time. As the digital sector grows and attracts a larger workforce, it drives changes in employment structures. Additionally, technological transformation only partially affects medium- and low-skilled workers rather than completely displacing them.

4.2. Analysis of Mechanisms of Action

We conducted a mechanism analysis following Jiang's [39] recommendations based on the theoretical framework and model specifications outlined earlier. This two-step approach, utilizing Models (1) and (2), explores how the digital economy influences employment structure. The results are detailed in Tables 4 and 5. Columns (2) to (4) of Table 4 analyze the mechanism at the provincial level. The findings show that the digital economy significantly increases the proportion of highly educated employees, boosting the labor share. Adopting digital technology raises skill requirements, benefiting those with more robust learning capabilities. Highly educated individuals typically have greater bargaining power, which leads to a higher overall labor share, supporting Hypothesis H2a.

The digital economy also enhances the labor income share by shifting employment from state-owned to private-sector positions. This shift is attributed to the digital economy's job opportunities and workforce growth expansion, thereby supporting Hypothesis H3. Furthermore, the digital economy reduces the proportion of female employees, contributing to a higher labor income share, confirming Hypothesis H4.

Table 5 examines these mechanisms at the enterprise level. Column (2) highlights the role of educational structure in employment. The increase in highly educated employees leads to a more sophisticated employment structure, enabling the handling of more complex tasks and producing higher value-added output. This also enhances employee bargaining power, further raising the labor share and validating Hypothesis H2a. Column (3) shows that digitization improves the labor income share by advancing the employment skills structure. The growing proportion of high-skilled employees, driven by digitization, requires workers who can quickly adapt to new technologies. This improves operational efficiency and demands specialized talents, thus supporting Hypothesis H2a. Column (4) demonstrates that digitization helps narrow the wage gap between ordinary employees and executives, increasing the labor income share and validating Hypothesis H5a.

4.3. Robustness Checks

Measurement error is a common cause of endogeneity, leading to biased estimates when variables are inaccurately measured. To address this, robustness checks were performed by substituting the dependent variable to minimize measurement errors. Columns (1) and (3) of Table 6 show that the regression results remain consistent with the baseline findings, reinforcing the reliability of the study's core conclusion that digital economic development increases the labor income share. Additionally, digital economic development may exhibit delayed effects. To explore this, we included a one-period lag of digital economic growth in our regression analysis. The results, shown in Columns (2) and (4) of Table 6, indicate that the impact of each variable remains unchanged compared to the baseline regression, confirming the persistence of the effect over time.

We used instrumental variables to eliminate any correlation between the explanatory variables and error terms to address potential endogeneity. Specifically, we employed the first-order lag of digital economic development as an instrument. The results from the two-stage least squares (2SLS) regression are presented in Table 7. The instrumental variables passed tests for relevance and weak instruments, and the results are consistent with the baseline findings. This further validates the robustness of this study's core conclusions.

Table 6. Replacing the explanatory variable with the lagging explanatory variable.

	(1)	(2)		(3)	(4)
Variables	**Ls3**	**Ls1**		**Ls4**	**Ls2**
De1 (L.De1)	0.141 ***	0.146 **	De2 (L.De2)	0.103 ***	0.080 *
	(0.045)	(0.063)		(0.039)	(0.043)
Ind	−0.120 *	−0.012	Size	−0.019 ***	−0.021 ***
	(0.067)	(0.074)		(0.002)	(0.002)
Rd	−0.052 **	−0.033	Lev	0.007	0.005
	(0.021)	(0.022)		(0.005)	(0.005)
Pgdp	−0.078 **	−0.044	TobinQ	−0.000	−0.000
	(0.032)	(0.035)		(0.001)	(0.001)
Gov	0.020	0.121*	BM	0.004 ***	0.004 ***
	(0.073)	(0.071)		(0.001)	(0.001)
			Indep	−0.014	−0.012
				(0.010)	(0.010)
Constant	1.436 ***	0.920 **	Constant	0.534 ***	0.575 ***
	(0.355)	(0.380)		(0.038)	(0.041)
Individual	Yes	Yes		Yes	Yes
Year	Yes	Yes		Yes	Yes

Note: *, ** and *** indicate that the regression results pass the significance test at the 10%, 5%, and 1% confidence levels, respectively; values in parentheses are robust standard errors.

Table 7. Instrumental variable method.

	(1)		(2)
Variables	**Ls1**		**Ls2**
De1	0.170 *	De2	0.131 **
	(0.077)		(0.072)
Control variables	Yes		Yes
Individual fixed effects	Yes		Yes
Year fixed effects	Yes		Yes
Kleibergen–Paap rk LM statistic	26.490		48.271
	(0.000)		(0.000)
Kleibergen–Paap rk Wald F statistic	108.182		80.228
	(16.38)		(16.38)

Note: * and ** indicate that the regression results pass the significance test at the 10%, and 5% confidence levels, respectively; values in parentheses are robust standard errors.

4.4. Heterogeneity Analysis

The impact of digital technology varies across industries due to differences in productive nature, input requirements, and substitution elasticities. Following Lu et al. [40], this paper classified manufacturing enterprises into three categories—labor-intensive, capital-intensive, and technology-intensive—based on the Guidelines on Industry Classification of Listed Companies (2012 Revision) by the China Securities Regulatory Commission. Columns (1) to (3) of Table 8 present the regression results for these industry types. The findings reveal that the digital economy's effects on employment creation and substitution are not significant for labor-intensive and capital-intensive enterprises. However, there is a significant positive effect for technology-intensive enterprises, indicating that digitization complements high-skilled labor.

The nature of property rights also affects how the digital economy influences the share of labor income. In China, where the economic system is predominantly based on public ownership with various forms of ownership coexisting, there are notable differences in social responsibilities and operational mechanisms between state-owned and non-state-owned enterprises. These differences are evident in management philosophies and distribution systems, which can impact income distribution effectiveness. The regression results show that the effect of digital economic development on state-owned

enterprises is insignificant. This may be attributed to state-owned enterprises' relatively stable labor–capital contract structure. In contrast, non-state-owned enterprises operating in a more competitive environment are more likely to increase employee labor income. Table 9 presents specific results.

Table 8. Industry heterogeneity analysis.

	(1)	(2)	(3)
Variables	**Ls2**	**Ls2**	**Ls2**
DE2	−0.016	−0.055	0.136 ***
	(0.081)	(0.066)	(0.048)
Control variables	Yes		Yes
Individual fixed effects	Yes		Yes
Year fixed effects	Yes		Yes
Constant	0.630 ***	0.212 ***	0.611 ***
	(0.072)	(0.043)	(0.060)
R-squared	0.808	0.812	0.792

Note: *** indicate that the regression results pass the significance test at the 1% confidence levels; values in parentheses are robust standard errors.

Table 9. Analysis of property rights heterogeneity.

	(1)	(2)
Variables	**Ls2**	**Ls2**
DE2	−0.050	0.103 ***
	(0.089)	(0.037)
Control variables	Yes	Yes
Individual fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Constant	0.371 ***	0.544 ***
	(0.039)	(0.046)
R-squared	0.850	0.785

Note: *** indicate that the regression results pass the significance test at the 1% confidence levels; values in parentheses are robust standard errors.

4.5. Expansion Analysis Based on the Industry Chain Perspective

According to Hypothesis H6, the development level of the digital economy in an industry not only directly affects the labor income share of enterprises within that industry but can also indirectly influence the labor income share of enterprises in upstream and downstream sectors within its supply chain. To explore the industry chain effects of digital economic development on labor income share, we drew on the approach used by Acemoglu et al. [32] and used the 2012 China input–output table data to construct industry linkage weights. Since our data covered 2011 to 2020, we relied on the 2012 input–output table to establish these industry linkage weights. This approach assumes that the input–output relationships between industries are fixed and do not change over time, allowing us to analyze the effects of industry chain transmission on the digital economy. The model is constructed as follows:

$$Ls_{it} = \alpha_3 + \beta_5 DE_{it} + \beta_{up} up_{it} / \beta_{down} down_{it} + \beta_6 Z_{it} + u_i + \varphi_t + \epsilon_{it} \quad (3)$$

In the analysis, "*up*" represents the interaction term between the linkage coefficient of industry *i* with its downstream industries and the development of the digital economy, while "*down*" represents the interaction term between the linkage coefficient of industry *i* with its upstream industries and the development of the digital economy. All other variables are consistent with those in the baseline regression. Table 10 presents the results from the Model (3) regression. Columns (1) and (2) show the impact on the labor

income share without accounting for the digital economy development level of the current industry. These regression coefficients capture the technology spillover effects of the digital economy's development within the current industry, and the impact of non-technological spillovers, such as those through intermediate goods markets. Columns (3) and (4) examine the effects on labor income share while controlling for the digital economy development level of the current industry. The estimated coefficients primarily reflect non-technological spillover effects, such as those through intermediate goods markets. The regression results in Table 10 indicate that digitization positively affects the labor income share in upstream and downstream industries, demonstrating technological spillovers. In contrast, non-technological spillover effects through intermediate goods markets are found to be insignificant.

Table 10. Analysis of the industrial chain.

	(1)	(2)	(3)	(4)
Variables	**Ls1**	**Ls1**	**Ls1**	**Ls1**
up	0.061 ***		0.043	
	(0.021)		(0.040)	
down		0.067 **		0.140
		(0.028)		(0.415)
DE2			0.032	−0.094
			(0.068)	(0.533)
Control variables	Yes	Yes	Yes	Yes
Individual fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Constant	0.543 ***	0.543 ***	0.544 ***	0.543 ***
	(0.036)	(0.036)	(0.036)	(0.036)
R-squared	0.800	0.800	0.800	0.800

Note: ** and *** indicate that the regression results pass the significance test at the 5%, and 1% confidence levels, respectively; values in parentheses are robust standard errors.

5. Conclusions

Our research focused on the broader macroeconomic effects of COVID-19 on employment in China, though it did not explore its specific impacts on the labor force. Previous studies have extensively examined how lockdowns have affected the workforce [2]. The digital economy tends to thrive in regions with robust financial sectors, underscoring the importance of finance for economic growth [41]. Consequently, varying research contexts can lead to divergent findings, such as the literature indicating that the income gap widens irrespective of gender [42]. Additionally, the existing literature addresses models of digital economy development, including Germany's Industry 4.0 [43] and the United States' digital innovation initiatives [44]. The way digital technology is employed is crucial. For example, Acemoglu et al. [45] emphasized that, if automation is the sole focus of new AI technologies, the resulting productivity gains may not be distributed to workers. However, if AI creates new tasks and enhances human capabilities, the benefits will likely be shared with the labor force. Conversely, if AI is used predominantly for monitoring and controlling workers, it could shift the balance of power between workers and managers, potentially reducing the share of productivity gains received by the labor force. Similarly, Autor [46] suggested that, if used effectively, AI has the potential to reinstate the middle-skilled, middle-class segment of the US labor market, which has been eroded by automation and globalization. This literature indicates that the digital economy's effects on labor vary and should be considered in a broader context. The discussion presented in this paper aimed to contribute to existing research and draw greater attention to this field.

Our theoretical analysis revealed that the development of the digital economy produces both job creation and substitution effects, which impact the labor income share by altering employment structures. We constructed an index system using provincial- and enterprise-level data to gauge digital economic development and measure the labor income

share. Through a two-way fixed effects econometric model, we examined how the digital economy affects the labor income share and its underlying mechanisms. The findings are as follows: (1) The digital economy exhibits a more substantial job-creation effect than its substitution effect. Although digital technologies may affect some job positions, they boost the labor income share by generating new occupations and enhancing roles within digitalized sectors. (2) The digital economy impacts the labor income share by reshaping employment structures. It increases the proportion of highly educated and skilled workers, expands private and individual enterprises, reduces female employment proportions, and narrows income disparities, thus promoting a higher labor income share. (3) The effects of digital economic development on the labor income share vary across industries. Technology-intensive industries experience more significant increases in the labor income share compared to others. Additionally, non-state-owned enterprises are more likely to enhance the labor income share than state-owned enterprises. (4) From an industry chain perspective, our study identifies a technological spillover effect of the digital economy on the labor income share in upstream and downstream industries. Overall, technological advancements primarily drive this effect, while the impact from intermediate goods markets is minimal.

From the theoretical perspective, this paper found that the digital economy can promote the increase of the labor share, and this positive effect stems from the fact that the employment creation effect exceeds the substitution effect; then, through the in-depth analysis of employment changes, we found that the digital economy affects the employment structure of different dimensions, and this structural change is beneficial to the increase in the labor share. From a practical perspective, this paper argued that we should achieve the development of the digital economy and the rise of the labor share through the following measures: Firstly, seize opportunities presented by digital advancements and mitigate external adverse impacts to expand employment opportunities. Secondly, support the development of high-end digital skills, promote comprehensive digital skills training, and enhance workforce quality. Thirdly, social security and income distribution mechanisms should be strengthened to boost the labor income share.

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