Digital Transformation of Enterprises and Share of Labor Income: evidence from China

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Abstract. Promoting the digital transformation of enterprises and increasing the proportion of labor remuneration in the initial distribution are necessary guarantees for constructing a modern economic system and realizing the essential requirements of socialism. Based on the data of A-share listed firms, the essay explores the impact of digital transformation on labor income share. It is shown that the digital transformation of enterprises significantly increases the share of labor income, which is still valid after dealing with endogenous problems and a series of robustness tests. The research also finds that the digital transformation of enterprises increases the proportion of high-skilled talents, and then increases the wage rate and labor productivity. Its positive effect on the wage rate exceeds the positive impact on labor productivity. Additionally, the essay points out that the impact on labor income share is more significant in non-state-owned firms, large-scale firms, firms located in the eastern and western regions, and firms belonging to high-tech industries. Finally, from the perspective of the specific content of the digital transformation of enterprises, the promotion effect of the application of digital technique on labour income share is the most evident. The findings help assess the impact of digital transformation on the share of labor income and provide policy implications for the two-way empowerment of the digital economy and common prosperity.

Keywords: Digital transformation of enterprises; Share of labor income; Wage rate; Labor productivity.

1. Introduction

The digital economy is gradually becoming the forerunner of the world's scientific and technological revolution and industrial transformation, which is an important engine for China's high-quality economic development. China's "14th Five-Year Plan and the Outline of Vision 2035" points out that it is necessary to "promote the deep integration of digital technology and the real economy," and "accelerate the digital industrialization and industrial digital transformation." Digital transformation is a strong driving force in improving production efficiency (Zhao et al., 2021) and also plays a positive role in the scale and structure of employment (Meng, 2021).

Shared prosperity is the essential requirement of socialism, and the share of labor income measures the proportion of labor income in national income. The percentage of labor income should be relatively stable in the macro-economy (Kaldol,1957). However, China's labor income share shows a downward trend in fluctuation (Bai & Qian, 2009; Bai & Qian, 2010; Zhao & Zhang, 2013). It has led to the slow growth of residents' consumption (Zou & Yu, 2011) and threatened China's social stability and stable economic operation. The relevant research on the determinants of labor income share has been relatively affluent. From a macro perspective, the transformation of industrial structure, international trade and the relaxation of short-selling restrictions are clearly tired to the labour income share (Bai & Qian, 2009; Zhao et al., 2012; Zhu et al., 2022). At the micro level, exports, labor bargaining power and corporate bond financing have also a clear correlation with labor income share (Jason et al., 2012; Bai & Yang, 2019; Jiang & Jia, 2021). In recent years, China's artificial intelligence industry has developed rapidly under the joint promotion and guidance of policy, capital, and market demand, profoundly impacting many areas of China's economy and society. Based on the practical background of China's practice, scholars pay attention to whether artificial intelligence can increase labor income share. Still, they have not yet formed a unified conclusion. Jin et al.(2020) believe that the application of artificial intelligence significantly increases the percentage of labor income of enterprises. However, Lu & Zhu (2021) believe that artificial intelligence has a significant inhibitory
effect on the share of labor income, and regional heterogeneity exists in this effect. Chao & Zhou (2021) find that artificial intelligence would reduce the share of labor income, especially in the primary industry. Currently, no research in china explores the impact of enterprise digital transformation on the percentage of labor income. Although digital transformation and artificial intelligence have the same characteristics, artificial intelligence is a single dimension to measure enterprise digital transformation. It is not easy to fully represent the overall digital transformation of an enterprise by using only artificial intelligence indicators. The research concludes the impact of enterprise digital transformation on the share of labor income from the micro level, which has special practical and policy significance.

The paper uses a two-way fixed-effect model, to explore the impact of the digital transformation of enterprises on the share of labor income. The robustness tests are carried out to verify the identified causality further. On this basis, the study explores the underlying logic of the influence of digital transformation on labor income share from the perspective of the wage rate effect and labor productivity effect. Then, for the differences in property rights, enterprise scale, and regions, we also find the heterogeneous impact of firm digital transformation on labor income share. Finally, we analyze the impact of various sub-dimensions of the enterprise digital transformation on the share of labor income. The results show that the promotion of cloud computing technology, big data technique, and the application of digital technology in digital technology plays a significant role in promoting the share of labor level, and the application of digital technology is the most essential in promoting the share of labor income.

The marginal contribution of this paper is shown as follows. First, we analyze the micro-share of labor income from the new perspective of digital transformation of enterprises, which broadens the research area of the driving factors of the share of labor income and provides micro-empirical evidence for enterprises’digital transformation to promote the increase of the percentage of labor income significantly. Secondly, the results reveal the internal mechanism of increasing labor income share in enterprises’digital transformation from the wage rate effect and labor productivity effect. Digital transformation of enterprises would stimulate labor productivity and raise the wage rates of the employees. However, the positive effect of the wage rate is dominant, which eventually leads to the increase of the share of labor income. Thirdly, we discuss the heterogeneous impact of enterprise digital transformation on allocating labor income under the constraints of firm property right attribute, scale, region, and high-tech industry factors. We analyze that the promotion of cloud computing technology, big data technique, and the application of digital technology has significantly increased the share of labor level, and the promotion effect of the application of digital technology is the most obvious. Lastly, we provide effective micro-evidence for relevant policy formulation, such as promoting digital transformation and upgrading enterprises, fostering new economic development momentum, and realizing shared prosperity.

The paper is organised as follows. The second part analyzes the influence mechanism of enterprise digital transformation on labor income share from the perspective of wage rate and labor productivity; The third part concludes with sample selection, empirical model, and variable description; The fourth part shows the main empirical results and their analysis; The last part is conclusions and policy recommendations.

2. Theoretical Analysis and Research Assumptions

We decompose labor income share into wage rate and labor productivity and then explore the impact of firm digital transformation on wage rate and labor productivity.

Under the tide of the digital economy, the traditional demographic dividend has weakened, and the digital technology of enterprises has developed rapidly. However, the skill structure of the labor force affects the economic growth performance, and the increase in the proportion of skilled labor force is more conducive to the promotion of high technique in the economy (Wei & Hao, 2015). The transformation and upgrading of technology within the enterprise is a fundamental reason for the
increase in the relative demand for highly skilled talents (Autor et al., 1998). As China's economy gradually moves towards the "medium-to high-speed" new normal development, the skill structure and premium have taken on new features and trends. The average number of highly skilled labor and the average remuneration of highly skilled labor has increased significantly (Wang, 2019). As a highly skilled biased technology, digital technique will further adjust the skill structure and increase the labor skill premium.

As far as wage rates are concerned, the digital transformation of enterprises has an increasing effect on wage rates. The digital transformation of enterprises will birth new industries and models, create new jobs and expand the employment space of firms (Sabbagh et al., 2013). With the popularization of the digital economy and the improvement of the quality of the labor force, the demand for high-standard technology jobs and the supply of high-quality talents are promoted at the same time. Enterprises have a strong need for highly professional skills. However, training high-skilled personnel is expensive and generally has high remuneration expectations and strong bargaining power (Kofler et al., 2020). The remuneration package of the regular labor force is difficult to attract high-skilled talents to choose a job, and there is still a significant talent gap in the employment market. The imbalance between supply and demand has pushed up the average salary of enterprises (Hyrynsalmi et al., 2018), which is represented by an increase in the wage rates.

As far as labor productivity is concerned, the digital transformation of enterprises has a promoting effect on improving labor productivity. The digital transformation of firms improves the skill structure of firms, increases the proportion of high-skilled talents, effectively exerts the promotion effect of high-quality human capital on the production efficiency of enterprises (Diermeier et al., 2017), and forms a “new demographic dividend”. With the in-depth integration of technologies with the real economy, enterprises' production, operation, and service systems have been modernized and updated. Then, the optimization of resource allocation, internal control, and information exchange have been strengthened, thus promoting operational efficiency and automation within the organization.

Based on the above analysis, the digital transformation of enterprises may have a positive or negative impact on the share of labor income under different circumstances. The increase in wage rate positively affects the share of labor income, while the increase in labor productivity harms the share of labor income. Therefore, the specific impact of enterprise digital transformation on labor income share depends on the combined effect of the positive impact of wage rate and the negative effect of the labor income share. The digital change of enterprises positively impacts the share of labor income when the positive effect is more significant. On the contrary, the promotion of enterprises' digital transformation harms labor income allocation. The two approaches have different directions, so the net effect symbol needs to be explored through empirical analysis.

**Figure 1. The Path of Enterprise Digital Transformation Affecting Labor Income Share**
3. Research Design

3.1 Sample Selection

We select the Shanghai and Shenzhen A-share data from 2007 to 2021 as research samples from the CSMAR and the Wind databases. Among them, the index data of high-skilled talents are from the Wind database, and the rest are from the CSMAR database. We select the samples for this period from 2007 to 2021, because the CSMAR database only provides data from 2007 to 2021 for the core explanatory variables of enterprise digital transformation. The number of employees with different academic qualifications is required to represent the proportion of highly skilled personnel, which are only available in the Wind database from 2012 to 2021, so the data from 2012 to 2021 are selected.

The sample data are processed as follows to avoid outlier interference: First, remove ST and delisted samples during the period. Second, exclude the data of financial enterprises. Third, remove the observation samples of digital transformation of enterprises and the missing variable of the labor income share. Fourth, exclude the samples that the labor income share is less than 0 or greater than 1. Last, all continuous variables are subjected to a [1%, 99%] winsorization.

3.2 Empirical Model

This essay focuses on the impact of enterprise digital transformation on the share of labor income and sets the following benchmark model:

\[ LIS_{i,t} = \alpha_0 + \alpha_1 DT_{i,t} + \beta Controls_{i,t} + \gamma_t + \mu_i + \varepsilon_{i,t} \quad (1) \]

Among them, the explained variable is expressed as, representing the enterprise’s share of labor income inyear; The core explanatory variable represents the digital transformation of the enterprise in year; represents a set of control variables, including enterprise size, enterprise age, return on net assets, capital intensity and capital-output ratio. In addition, represents time-fixed effect, represents firm-fixed effect and represents a random disturbance term. Considering the possible heteroscedasticity and autocorrelation problems, we use robust standard error clustering at the firm level.

3.3 Variable Description and Descriptive Statistics

1). Interpreted variables. The explanatory variable in the paper is the share of labor income, which generally refers to the proportion of labor remuneration in GDP (Bai & Qian, 2009). At the micro-economic level, different scholars have different manifestations of the share of labor income. Using the study conducted by Wang & Huang (2017) for reference, the paper measures the labor income share by using the proportion of cash flow paid to and operating income paid for employees.

2). Explanatory variables. The explanatory variable in this paper is the digital transformation of enterprises. There are mainly qualitative and quantitative methods to measure the digital transformation of enterprises. In recent years, researchers have primarily focused on using the word frequency database to search and match the corresponding keywords in the financial reports disclosed by listed companies as proxy indicators of corporate digital transformation (Wu et al., 2021). The CSMAR database classifies the relevant indicators of enterprise digital transformation into five categories: artificial intelligence technology, blockchain technology, cloud computing technology, big data technique, and the application of digital technology. Each category contains several sub-indicators with a total of 79 keywords. In this essay, the sum of the frequency of five types of word frequency indicators in the CSMAR database is added to one. Then the logarithm of the sum is taken as a measure of the digital transformation of enterprises.

3). Control variables. To eliminate the interference of other factors on the share of labor income, we select a series of control variables (Jin et al., 2020; Ni & Liu, 2021; Ren & Liu, 2021). They include the size of the enterprise (, the natural logarithm of the total assets of the firm), the age of the enterprise (, difference between the year of the statistical cut-off date and the date of establishment
of the firm), the rate of return on equity (net profit/average total assets, average total assets = (total assets ending balance+total assets beginning balance) /2), capital intensity (, total assets/operating income) and capital-output ratio (, total operating income/net fixed assets). The descriptive statistical results are shown in Table 1.

| Variable | N   | Mean  | SD   | Min  | Max   |
|----------|-----|-------|------|------|-------|
| LIS      | 15863 | 2.3488 | 2.3180 | 0.0054 | 13.7179 |
| DT       | 15863 | 2.7273 | 1.3536 | 1    | 6.0434 |
| Size     | 15863 | 22.1980 | 1.3263 | 19.3312 | 26.0622 |
| Age      | 15259 | 9.4641 | 7.5544 | 0    | 26    |
| ROE      | 15863 | 0.0805 | 0.1387 | -0.6828 | 0.4209 |
| Cor      | 15863 | 0.4150 | 0.5516 | 0.0053 | 4.0426 |
| Klr      | 15862 | 2.3832 | 1.9308 | 0.3782 | 13.3568 |

4. Analysis of empirical results

4.1 Benchmark Regression

Table 2 presents the benchmark regression result of the share of labor income in the digital transformation of enterprises. From column (1) to column (5) of Table 2, the study is gradually added control variables on the original basis, and the relevant regression coefficient is still positive. Column(1) is significant at the level of 10%. Column (2) to column (4) is substantial at the level of 5%, and the final result of column (5) as the benchmark regression is significant at the level of 1%. The relevant regression coefficient increased from 0.0370 to 0.0591 with the inclusion of control variables. It indicates that firms' digital transformation has a positive and stable impact on the labor income share. From the point of view of column (5), the regression coefficient of enterprise digital transformation is 0.0591. It shows a higher significance when the time effect, individual effect, and all control variables are controlled simultaneously. The economic implication is that the share of labor income will increase by 0.0591% when the digital transformation of enterprises changes by 1%. The results indicate that enterprises’ digital transformation is beneficial to increasing the share of labor income.
Table 2. Benchmark Regression

|       | (1)      | (2)      | (3)      | (4)      | (5)      |
|-------|----------|----------|----------|----------|----------|
| LIS   | 0.0370*  | 0.0424** | 0.0438** | 0.0503** | 0.0591***|
|       | (1.7746) | (2.0966) | (2.1602) | (2.4600) | (2.9179) |
| Size  | -0.1973*** | -0.1566** | -0.1247* | -0.1460** | -0.2473***|
|       | (-2.8278) | (-2.2917) | (-1.8386) | (-2.1151) | (-3.4718) |
| Age   | -0.0997  | -0.0957  | -0.1071  | -0.0822  |          |
|       | (-0.8183) | (-0.7983) | (-0.8745) | (-0.7317) |          |
| ROE   | -1.0790*** | -0.7581*** | -0.5179*** |          |          |
|       | (-6.7422) | (-4.7812) | (-3.4564) |          |          |
| Cor   |          | 0.7741*** | 0.2729**  |          |          |
|       |          | (6.4846) | (2.1478)  |          |          |
| Klr   |          |          |          | 0.2923*** |          |
|       |          |          |          | (9.6921)  |          |
| _cons | 5.9284*** | 4.9597*** | 4.4409*** | 4.5103*** | 6.2757***|
|       | (4.0632) | (3.4740) | (3.1323) | (3.1010) | (4.2262) |
| Year-fixed Effect | Yes | Yes | Yes | Yes | Yes |
| Firm-fixed Effect | Yes | Yes | Yes | Yes | Yes |
| N     | 15863    | 15259    | 15259    | 15259    | 15258    |
| R²    | 0.0657   | 0.0690   | 0.0817   | 0.1109   | 0.1675   |

Note: The values of T in brackets, ***, **, * are significant at the level of 1%, 5% and 10%, respectively.

4.2 Robustness Test

This paper uses several methods to ensure the stability of the regression results.

1). Replace the explained variable. To avoid the possible measurement error in the measurement method of labor income share, this paper refers to the existing academic research and recalculates the labor income share. The concept of factor cost added value is used to estimate the share of labor income of an enterprise, which is expressed as the employee compensation payable/operating income-operating cost+employee compensation payable+depreciation of fixed assets (Bai et al., 2008). As can be seen from column (1) of Table 3, after changing the measurement method of labor income share, the estimation coefficient of enterprise digital transformation is 0.2889 and is significant at 1%.

2). Replace the control variable. To prevent the measurement of control variables from affecting the regression results, we replace the control variables of enterprise size and ROE to verify the robustness of the results. The size of an enterprise is expressed in terms of a logarithmic annual number of employees. ROE is still expressed as net profit/average balance of shareholders' equity, but the average proportion of shareholders' equity is changed to the closing balance of shareholders' equity. At the same time, consider replacing the ROE with the return on assets indicator, expressed as net profit/average total assets. From column (2), column (3), and column (4) in Table 3, it can be seen that the estimation coefficient of enterprise digital transformation is still positive and significant at the level of 10% after changing the representation method of enterprise scale, and is significant at the level of 1% after changing the measurement method of return on net assets of the control variable. After changing the control variable ROE indicator to return on investments, the enterprise's digital transformation estimation coefficient is still positive and significant at the level of 1%.
Table 3. Robustness Test: changing variables

|        | (1)                                      | (2)                                      | (3)                                      | (4)                                      |
|--------|------------------------------------------|------------------------------------------|------------------------------------------|------------------------------------------|
| DT     | Replace the Interpreted Variable LIS2    | Replace the Control Variable LIS         | Replace the Control Variable LIS         | Replace the Control Variable LIS         |
|        | 0.2889***️🏻 0.0397*                      | 0.0585***️🏻 0.0540***️🏻                   |                                         |                                          |
|        | (2.9317) 1.9579                         | (2.8958) 2.6821                         |                                         |                                          |
| Controls| Yes                                      | Yes                                      | Yes                                      | Yes                                      |
| Year-fixed Effect | Yes                                      | Yes                                      | Yes                                      | Yes                                      |
| Firm-fixed Effect | Yes                                      | Yes                                      | Yes                                      | Yes                                      |
| N      | 15258                                    | 15077                                    | 15253                                    | 14998                                    |
| R²     | 0.2338                                   | 0.1593                                   | 0.1675                                   | 0.1680                                   |

Note: The values of T in brackets, ***️🏻, **️🏻, *️🏻 are significant at the level of 1%, 5% and 10%, respectively.

3). Lag one or two phases. Considering the delay of the impact of enterprise digitalization transformation on the share of labor income, we use one or two periods of delay of enterprise digitalization transformation as explanatory variables for benchmark regression. Columns (1) and (2) in Table 4 indicate that when the core explanatory variable lags one stage, the regression result is significant at at the level of 1%. When the core explanatory variable lags two phases, the regression coefficient is positive, and the regression result is significant at the level of 10%.

4). Delete the particular year. When faced with the impact of major financial events, the digital transformation process of enterprises will be hindered, and the share of labor income will be adversely affected. This paper considers removing economic risk factors, deleting the sample data of China's stock market crash (2015), and then performing benchmark regression again.

5). Replace the interval length. The interval selected by the sample data specifically influences the benchmark regression results. In 2010, China completed the construction of infrastructure for enterprise digital transformation. Considering China's enterprises' digital transformation infrastructure needs to be improved before 2010, the data from 2010 to 2021 are taken as regression samples. The regression coefficient is 0.0415, and the result is significant at the level of 5%, as obtained in column (4) of Table 4. Considering that the production and operation of Chinese enterprises are greatly affected by the epidemic factors in 2020 and 2021, the data from 2007 to 2019 are taken as regression samples. The regression coefficient is 0.0697, and the result is significant at the level of 1% in column (5).
Table 4. Robustness Test: Lag One or Two Phases, Delete Special Year and Replace Interval Length

|                  | (1) Lag One Phase LIS | (2) Lag Two Phases LIS | (3) Delete Special Year LIS | (4) Replace Interval Length LIS | (5) Replace Interval Length LIS |
|------------------|-----------------------|------------------------|----------------------------|-------------------------------|-------------------------------|
| IDT              | 0.0604***             |                        |                            |                               |                               |
|                  | (2.8029)              |                        |                            |                               |                               |
| l2DT             | 0.0367*               |                        |                            |                               |                               |
|                  | (1.7006)              |                        |                            |                               |                               |
| DT               |                       | 0.0619***              | (2.8497)                   |                               |                               |
| DT               |                       |                        |                            | 0.0415**                     | (2.2608)                      |
|                  |                       |                        |                            |                               | 0.0697***                    |
|                  |                       |                        |                            |                               | (3.3968)                      |
| Controls         | Yes                   | Yes                    | Yes                        | Yes                           | Yes                           |
| Year-fixed Effect| Yes                   | Yes                    | Yes                        | Yes                           | Yes                           |
| Firm-fixed Effect| Yes                   | Yes                    | Yes                        | Yes                           | Yes                           |
| N                | 11406                 | 9257                   | 13957                      | 14679                         | 12654                         |
| R²               | 0.1840                | 0.1916                 | 0.1680                     | 0.1718                        | 0.1474                        |

Note: The values of T in brackets, *, **, *** are significant at the level of 1%, 5% and 10%, respectively.

6). Endogenous treatment. The endogenous problem of this study mainly stems from the causal relationship between the digital transformation of firms and the share of labor income, i.e., the digital transformation of firms can increase the percentage of labor income and whether the increase of labor income can also promote the digital transformation of firms is uncertain.

The paper uses the instrumental variable method to solve the potential endogenous problem. First, we take the key explanatory variable, the lag of the first phase and the second phase of the enterprise digital transformation, as the instrumental variables, respectively. As can be seen from the first stage regression results of columns (1) and (3) in Table 5, the regression estimation coefficients of the tool variables are 0.3507 and 0.1111, respectively, which are significantly positive at the level of 1%. In the first stage, the F statistics are 1366.88 and 92.62, far greater than the critical value (10) of the rule of thumb, thus rejecting the original assumption that "tool variables are weak tool variables." In columns (2) and (4) of Table 5, the second stage regression coefficient is greater than the benchmark regression result coefficient. Its economic significance indicates that for every 1% increase in firm digital transformation, the share of labor income will decrease by approximately 0.3507% and 0.1723%, which is because the instrumental variable method can correct the coefficient deviation caused by missing variables and overcome causal problems in the regression, thus solving the problem that the regression coefficient is underestimated. To find a more convincing tool variable, referring to Fisman & Svensson (2007), we use the average value of the digital transformation of other enterprises in the same industry as the tool variable of the firm's digital transformation. This tool variable is related to the firm's digital transformation but has nothing to do with the enterprise's labor income share. Column (6) of Table 3 indicates that the estimation coefficient of enterprise digital transformation is more remarkable than the benchmark regression without any sign and significance level change. The value of F in the first stage is 246.63, which indicates that the benchmark regression result has strong robustness.
Table 5. Endogenous Treatment

|                  | (1)   | (2)   | (3)   | (4)   | (5)   | (6)   |
|------------------|-------|-------|-------|-------|-------|-------|
| DT Stage I       |       | One Phase Lag Digital Transformation of Enterprises | Two Phases Lag Digital Transformation of Enterprises | The Average Value of Enterprise Digital Transformation of One Enterprise and Other Enterprises in the Same Industry |       |
| DT Stage II      | 0.3507*** |       |       |       |       |       |
|                  | (0.0095) |       |       |       |       |       |
| L2DT             | 0.1111*** |       |       |       | 0.3420*** |       |
|                  | (0.0115) |       |       |       | (0.0218) |       |
| Mean_DT          |       |       |       |       |       | 0.1723*** |
|                  |       |       |       |       |       | (4.1000) |
| DT               | 0.1723*** | 0.3109* |       |       | 0.6036*** |       |
|                  | (4.1000) | (1.9404) |       |       | (6.2660) |       |
| Controls         | Yes   | Yes   | Yes   | Yes   | Yes   | Controls |
| Year-fixed Effect| Yes   | Yes   | Yes   | Yes   | Yes   | Yes   |
| Firm-fixed Effect| Yes   | Yes   | Yes   | Yes   | Yes   | Yes   |
| N                | 10943 | 10943 | 7666  | 7666  | 14484 | 14484 |
| R²               | 0.1774 | 0.1612 | 0.1612 |       | 0.0399 |       |
| One-stage f value| 1366.88 | 92.62 | 246.63 |       |       |       |

Note: The values of T in brackets, *** for 1%, ** for 5% and * for 10%, respectively.

4.3 Mechanism Analysis

Starting from the manifestation of labor income share, we decompose the impact of digital transformation on labor income share, resulting in wage rate effect and labor productivity effect. Using Bai et al. (2008) and Fang (2011) for reference, we use the factor cost method to estimate the value-added. The wage rate is the proportion of the salary payable to the employees and the number of employees employed by the enterprise, and the labor productivity is the ratio of the value-added to the number of employees employed by the enterprise, in which the value-added is the sum of the operating profit, the total amount of wages payable and the depreciation of fixed assets. In this paper, the high-skilled talents index draws lessons from Wind database classification and classifies the employees with high school and below high school education level as low-skilled talents and the employees with high school or above education level as high-skilled talents (Liu & Zhao, 2020). The proportion of high-skilled talents in an enterprise is measured by the ratio of high-skilled talents to all employees.

Table 6 shows the influence mechanism of enterprise digital transformation on labor income share. Column (1) in table 6 shows that the estimation coefficient of high-skilled talents is 0.2575, which is significant at the level of 1%, indicating that the digital transformation of enterprises is indeed helpful in promoting the increase of the proportion of high-skilled talents in enterprises, thus improving the wage rate and labor productivity of enterprises. As seen in columns (2) and (3), the estimated wage rate and labor productivity coefficients are 0.2749 and 0.2733, respectively. The digital transformation of enterprises has significantly improved the wage rate and labor productivity by 1%, and the impact on the wage rate is more significant than the impact on labor productivity. The digital
transformation of enterprises requires matching high-skilled talents to improve the digital competitiveness of enterprises. The training cost and salary expectations of high-skilled talents are higher than those of ordinary employees. In order to increase the attraction of talents, the enterprise optimizes the salary standard, which increases the average salary of the enterprise. Therefore, the wage rate effect is more evident in the labor income share’s decomposition effect.

### Table 6. Mechanism Analysis

|            | (1) Proportion of highly skilled personnel | (2) Wage Rate      | (3) Labor Productivity |
|------------|------------------------------------------|--------------------|------------------------|
| DT         | 0.2575***                                | 0.2749***          | 0.2733***              |
|            | (11.8773)                                | (20.4307)          | (20.4814)              |
| Controls   | Yes                                      | Yes                | Yes                    |
| Year-fixed Effect | Yes                                      | Yes                | Yes                    |
| Firm-fixed Effect | Yes                                      | Yes                | Yes                    |
| N          | 5613                                     | 15076              | 14753                  |
| R²         | 5613                                     | 15076              | 14753                  |

Note: The values of T in brackets, ***, **, * are significant at the level of 1%, 5% and 10%, respectively.

### 4.4 Heterogeneity Analysis

1). Property right attribute. As state-owned enterprises have the capital and political support, they have an advantage in resource acquisition, capital support, and market reputation. They have insufficient endogenous power for innovative reforms such as the digital transformation of enterprises, and the correlation between attracting high-tech talents and the salary level is weak. However, private enterprises strongly desire digital transformation, while talent bargaining power and talent guarantee system are weak. They are more inclined to attract high-tech talents by improving their remuneration packages and competitiveness, thus increasing the share of labor income. As can be seen from columns (1) and (2) of Table 7, the estimated coefficient of the labor income share of the state-owned enterprises’ digital transformation is positive, but the promotion effect is not apparent. In contrast, the estimated coefficient of the non-state-owned enterprises is positive and significant at 1%. The difference between enterprises with different property rights is noticeable.

2). Scale attribute. The leading enterprises have perfect digital facilities, a strong desire for transformation, and a solid ability to pay salaries, and tend to adopt higher salaries to attract top high-tech talents. However, small and medium-sized enterprises have insufficient funds, low market share, and small main business volume. They mainly adopt the traditional business model and have a relatively low demand for digital transformation, with minor pay differences. Column(3) and column(4) of Table 7 show that the estimation coefficient of digital transformation of small-scale enterprises is negative, and there is no significant effect, while the digital transformation of large-scale enterprises significantly improves the share of labor income, which indicates that the differences among enterprises with different scales are pronounced.
Table 7. Heterogeneity Analysis: Ownership Nature, Enterprise Scale

|                  | (1) State-owned Enterprise LIS | (2) Non-state-owned Enterprises LIS | (3) Small-scale Enterprises LIS | (4) Large-scale Enterprises LIS |
|------------------|-------------------------------|-----------------------------------|--------------------------------|-------------------------------|
| DT               | 0.0485                        | 0.2811***                        | -0.0103                        | 0.0789***                     |
|                  | (1.2504)                      | (3.6266)                         | (-0.4886)                      | (2.7337)                      |
| Controls         | Yes                           | Yes                              | Yes                            | Yes                           |
| Year-fixed Effect| Yes                           | Yes                              | Yes                            | Yes                           |
| Firm-fixed Effect| Yes                           | Yes                              | Yes                            | Yes                           |
| N                | 5202                          | 699                              | 7335                           | 7923                          |
| R²               | 0.1897                        | 0.3561                           | 0.2096                         | 0.1809                        |

Note: The values of T in brackets, ***, **, * are significant at the level of 1%, 5% and 10%, respectively.

3). Regional differences. Compared with the central and western regions, the eastern region has a developed economy, excellent infrastructure, a high degree of marketization, and a strong sense of reform and innovation, enjoying a significant first mover advantage in digital transformation. The digital transformation of enterprises has further promoted the digital talents concentration in the eastern region and increased the labor income share. The western region is relatively short of an economy but rich in resources and sparsely populated. In recent years, the national policy has strongly supported the data center cluster in the western region, activated the western economy, attracted talents from developed regions to obtain employment, and boosted the share of labor income in the western region. In contrast, the central region's economic, resources, and policy advantages are difficult to highlight, and most are labor-intensive enterprises. From column (1), column (2), and column (3) of Table 8, it can be seen that the estimation coefficients of digital transformation of enterprises in the eastern and western regions are significant at the level of 5% and 1%, respectively. At the same time, there is no significant correlation in the central region. Therefore, the impact of digital transformation on the share of labor income varies significantly from region to region.

4). High and new technology. High-tech enterprises have strong innovation ability and solid preferential policies and occupy the advantages of talent recruitment and tax relief. The enterprise's digital transformation further enhances the enterprise value, helps the research and development of core technologies, and provides employment for high-tech talents, thus boosting the share of labor income. In table 8, columns (4) and (5) show that for high-tech enterprises, the share of labor income increased by 0.0572 percentage points for every 1% increase in the digital transformation of enterprises, which is significant at the level of 5%, instead of insignificant adverse effects for high-tech enterprises. Therefore, the impact of high-tech enterprises on enterprises' digital transformation and labor income share is significantly different from others.

Table 8. Heterogeneity Analysis: Regional Differences, High-tech

|                  | (1) Eastern area LIS | (2) Midland LIS | (3) Western area LIS | (4) High-tech LIS | (5) Non-high-tech LIS |
|------------------|---------------------|----------------|----------------------|------------------|----------------------|
| DT               | 0.0495**           | -0.0102        | 0.2162***           | 0.0572**         | -0.0181              |
|                  | (2.1331)           | (-0.2290)      | (3.1480)            | (2.2204)         | (-0.4458)            |
| Controls         | Yes                 | Yes            | Yes                  | Yes              | Yes                  |
| Year-fixed Effect| Yes                 | Yes            | Yes                  | Yes              | Yes                  |
| Firm-fixed Effect| Yes                 | Yes            | Yes                  | Yes              | Yes                  |
| N                | 11369               | 2402           | 1484                 | 5250             | 4177                 |
| R²               | 0.1571              | 0.2243         | 0.2697               | 0.1779           | 0.1368               |

Note: The values of T in brackets, ***, **, * are significant at the level of 1%, 5% and 10%, respectively.

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4.5 Further Analysis

The benchmark regression shows that the overall digitalization transformation of enterprises can promote the increase of labor income share, while the promotion effect of specific digital technique is still unclear. In this paper, five indicators of digital technology are considered: artificial intelligence technology, blockchain technology, cloud computing technology, big data technique, and the application of digital technique. Columns (1) to (5) in Table 9 show that the application of cloud computing, big data, and digital technology is significant at 1%, and the estimation coefficient of the application of digital technique is the largest. Therefore, the promotion of cloud computing technology, big data technique, and the application of digital technology within digital technology has a significant effect on the share of labor level, and the promotion effect of the application of digital technology is the most evident.

Table 9. Heterogeneity of Digital Technology

|                | (1) | (2) | (3) | (4) | (5) |
|----------------|-----|-----|-----|-----|-----|
| LIS            | LIS | LIS | LIS | LIS | LIS |
| DigitalTechApplication | 0.0324 | (1.2321) | 0.0158 | (0.7223) | 0.0769*** | (2.8673) |
| BlockChainTechnology | 0.1332*** | (4.5792) | 0.1340*** | (4.4773) |
| CloudComputingTech | 0.1705 | 14998 | 14998 | Yes | Yes |
| BigDataTechnology | 0.1669 | 14998 | 14998 | Yes | Yes |
| AITechnology | 0.1666 | 14998 | 14998 | Yes | Yes |
| Controls | Yes | Yes | Yes | Yes | Yes |
| Year-fixed Effect | Yes | Yes | Yes | Yes | Yes |
| Firm-fixed Effect | Yes | Yes | Yes | Yes | Yes |
| N | 14998 | 14998 | 14998 | 14998 | 14998 |
| R² | 0.1669 | 0.1666 | 0.1681 | 0.1713 | 0.1705 |

Note: The values of T in brackets, ***, **, * are significant at the level of 1%, 5% and 10%, respectively.

5. Conclusions and policy recommendations

Increasing the share of labor income and the proportion of labor elements in the initial distribution reflects the essential requirements of socialism, which is also related to the realization of the strategic goal of achieving shared prosperity. The digital transformation of enterprises can drive the demand for high-skilled talents, raise the average wage, and increase the share of labor income. Based on the data of non-financial listed companies from 2007 to 2021, this paper explores the impact of digital transformation on labor income share and draws the following conclusions:

Digital transformation of enterprises can significantly increase the share of labor income. After considering a series of robustness tests, such as missing control variables, endogeneity treatment by using an instrumental variable method, and changing variables’ representation, the conclusion still holds. Second, the mechanism analysis finds that it is beneficial to improving the quality and efficiency of enterprises, breaking through the data barriers, and thus improving labor productivity. At the same time, the enterprise’s digital transformation attracts high-tech talents, pulls the average wage, and ultimately increases the wage rate. Regarding the decomposition of labor income share, labor income share not only increases the wage rate but also promotes labor productivity improvement. However, the positive effect of the former is more prominent, which leads to an
increase in labor income share. Third, heterogeneity analysis finds that the promotion effect of digital transformation on the labor income share of non-state-owned enterprises and large-scale enterprises is more evident than others. Affected by regional differences and actual characteristics, the digital transformation of enterprises in the eastern and western regions of China has a more significant role in promoting the share of labor income than in the central area. For the firms belonging to the high-tech industry, the digital transformation of the enterprises will improve the allocation of labor income better than others. Within digital technology, cloud computing technology, big data technique, and the application of digital technology have both significant promotion effects, and the application of digital technique has the most apparent promotion effect.

Based on the above conclusions, this paper has the following policy implications:

First, the digital transformation of enterprises provide a path to increase the proportion of labor elements in the initial distribution. Therefore, the government and enterprises need further promote the digital transformation of enterprises. The government should strengthen the top-level design, promote system reform and innovation, open up barriers to the digital transformation of enterprises, and then give full play to the value of data element.

Second, the impact mechanism of the digital transformation of enterprises on the share of labor income is mainly through the positive effect of a wage rate increase. The digital transformation of companies stimulates innovation and increases the demand for high-skilled talents, thus increasing the wage rate of enterprises. Therefore, firms need to attach importance to the core role of skills, improve investment in research, and provide technical and personnel support for transforming enterprise organizational form and business model.

Third, the need to promote digital transformation varies from enterprise to enterprise and from place to place. The paper finds that non-state-owned enterprises are better than state-owned firms, and leading enterprises are better than small and medium-sized enterprises. In China, firms in the eastern and western regions are better than those in the central area in terms of the effect of increasing the share of labor income in the digitalized transformation firms. Policy-makers should accelerate the reform of state-owned firms, improve the market-oriented operation mechanism, and give full play to the leading enterprises' driving effect within the industry. What is more, optimize the business environment of small- and medium-sized enterprises, implement supporting policies such as tax relief in the central region, and improve the housing and employment subsidies for highly skilled talents.

The digital transformation of companies has a more prominent effect on promoting the share of labor income of enterprises in the high-tech industry. So, the government should prioritize supporting the digital transformation and upgrading of enterprises in the high-tech sector, creating leading model firms, and driving other firms to transform.

Last, there are differences in the promotion effect of digital technique on the share of labor income. The promotion of cloud computing technology, big data technique, and the application of digital technology have significant promotion effects on the percentage of labor income, and the promotion effect of the application of digital technology is the most obvious. Therefore, enterprises should closely follow the trend of the information age and scientifically and reasonably popularize the application of cloud computing technology, big data technique, and digital technology. They are expected to promote the digitalization of corporate decision-making, service systems, and product research and development and realize cost reduction, quality improvement, and efficiency enhancement of decision-making, services, and products.

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