

# **Large Language Models in the Firm and Labor Income Share**

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Keywords: Large Language Models, human capital structure, human-machine synergy, labor income share

## Abstract

In the context of the rapid development of global artificial intelligence technology and profound changes in the labor market, it is of great significance to study the income distribution problem from the perspective of the firm application of Large Language Models (LLMs). This paper adopts two-way fixed effects difference-in-differences (TWFE) model to explore the impact and mechanism of firm application of LLMs on labor income share. The results of the study find that the application of LLMs by firms significantly increases their labor income share. Mechanism analysis shows that the upgrading of human capital structure brought about by the application of LLMs and the "human-machine synergy" effect are the key paths to increase the labor income share. Heterogeneity analysis shows that this effect is more significant in firms with low financing constraints, technology-intensive industries, industries with high competition, firms with self-developed LLMs, and firms that apply LLMs to customer service. This study explores the influence of the application of LLMs in firms on three key aspects: the human capital structure, human-machine synergy, and labor income share. Furthermore, it seeks to offer crucial insights to facilitate economic transformation and upgrading, as well as to drive high-quality development.

**Keywords:** Large Language Models, human capital structure, human-machine synergy, labor income share

## I. Introduction

In the digital age, emerging technologies such as the Internet, cloud computing, big data, the Internet of Things, and artificial intelligence are advancing rapidly. The global market size of the artificial intelligence sector is projected to reach \$638.2 billion in 2024, which is expected to significantly influence the global economic structure and industrial ecosystem. Among these technologies, Large Language Models (LLMs) in the field of AI is particularly prominent, which, relying on its superior data processing capabilities and advanced deep learning algorithms, has become a leading force in promoting the digital transformation of various industries. LLMs has not only made remarkable achievements in the core areas of mathematical reasoning, natural language processing, image recognition, and speech recognition (Durante et al. 2024; Imani et al. 2023), but also demonstrated a wide range of application potentials in the professional fields of finance, healthcare, education, and law (Hou and Ji 2024; Luo et al., 2024; Blair-Stanek et al. 2023). As a result, the breakthroughs in LLMs will inevitably lead to revolutionary changes in the

production methods, operation modes, and workforce structures of firms. Against this backdrop, this study aims to conduct an in-depth analysis of the specific impact of the application of LLMs within firms on the labor income share. It also explores the theoretical logic behind this impact, thereby providing important insights into how technological changes affect the labor market.

The share of labor income in the initial distribution truly reflects the fairness of distribution and has an increasingly significant impact on optimizing the distribution structure and promoting balanced social development (Piketty et al. 2019). Improving the structure of income distribution is not only an urgent need to alleviate social inequality and promote social justice, but also a key way to realize inclusive economic growth. This paper explores the impact of firm application of LLMs on labor income share from the micro level. First, the application of LLMs will increase the demand for high-quality labor and bring about the upgrading of human capital structure. Given that high-quality labor typically commands higher compensation, when firms utilize LLMs to drive the upgrading of human capital, it further enhances the labor income share of firms. Second, the application of LLMs enhances employee productivity. This is because employees work alongside large models, boosting their efficiency. This means that employees create more income for the company. As a result, employees receive a larger share of the income distribution.

At the empirical level, this paper takes Chinese listed companies as the research sample for the following reasons. In recent years, China's LLMs are deeply empowering traditional industries, and the development of China's LLMs is becoming more mature. According to Nature, China's large language model, DeepSeek-R1, has achieved a level of reasoning task performance comparable to that of OpenAI's o1 level. It also has a significant cost advantage and even demonstrates a certain degree of explain ability (Gibney 2025). Furthermore, the widespread application and in-depth development of LLMs across various industry scenarios in China are noteworthy. Globally, the number of LLMs has reached 1,328, with 36% originating from China<sup>2</sup>. Given that China's LLMs are deeply empowering traditional firms, exploring the application of LLMs in Chinese firms and their economic consequences will facilitate a deeper understanding and assessment of the social impacts brought about by the use of LLMs. This

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<sup>2</sup> White Paper on the Global Digital Economy (2024), published by the China Academy of Communications

exploration also offers valuable theoretical and practical insights for firm decision-making. In this paper, using a sample of A-share listed firms in Shanghai and Shenzhen from 2019-2023, the PSM-DID model is used to systematically examine the impact and mechanism of firms' application of LLMs on their labor income shares. The empirical results find that firms applying the LLMs significantly increase their labor income share. Mechanism analysis shows that the upgrading of human capital structure and the "human-machine synergy" effect brought by the application of LLMs are the key paths to increase the labor income share. Heterogeneity analysis shows that this effect is more significant in firms with low financing constraints, technology-intensive industries, industries with high competition, firms with self-developed LLMs, and firms that apply LLMs to customer service.

The possible marginal contributions of this paper are as follows: First, the academic community has shown a high level of attention to the topic of firm artificial intelligence (AI) applications, studying the impact of AI technology on the development of micro firms (Vrontis et al. 2023; Talaei-Khoei et al. 2024; Li et al. 2024; Deng et al. 2023). Some literature explores the application of AI technology from the perspective of human-computer collaboration, discussing how it can better facilitate the combination of humans and machines, thereby enhancing corporate decision-making and predictive accuracy (Lu and Zhang 2024; Cao et al. 2024; Boyacı et al. 2023). Meanwhile, some scholars have conducted in-depth research on the relationship between AI and employee innovation ability and labor productivity (Chu et al. 2024; Bughin 2024). LLMs represent a significant technological breakthrough and an important milestone in the development of artificial intelligence in recent years. Represented by ChatGPT, these LLMs have grown rapidly and are increasingly being applied in firms (Talaei-Khoei et al. 2024; Eisfeldt and Schubert 2024; Vrontis et al. 2023; Eisfeldt et al. 2023). However, research in the area related to whether firms apply LLMs has yet to advance further. This study approaches from the perspective of firm application of LLMs, delving into their impact on the labor income share and the underlying mechanisms. It innovatively expands the research framework in the field of artificial intelligence.

Second, this study enriches and extends the research literature on the impact of firm application of artificial intelligence on the labor income share, providing systematic evidence for an accurate understanding of the digital empowerment

brought about by the application of LLMs in firms. Although some of the literature has already explored the impact of digital transformation, robotics application, and AI on labor income share through human capital structure adjustment, substitution effects, and complementary effects (Jiang et al. 2024; Miao et al. 2024; Li et al. 2024; Chen et al. 2023; Du et al. 2024; Chen et al. 2024; Qian et al. 2023). However, there is little literature on the impact of the use of LLMs on labor income share and its mechanism. This paper innovatively explores how the use of LLMs by firms can promote an increase in the labor income share through two pathways: labor force structure adjustment and human-computer synergy, thereby enriching the literature on firm labor income shares.

## **II. Theoretical analysis and research hypotheses**

On the one hand, the application of LLMs increases firms' demand for high-quality labor and promotes the upgrading of the human capital structure, which in turn boosts the labor income share. First, in today's wave of artificial intelligence, firms have widely introduced LLMs, a move that has profoundly reshaped firms' traditional business models (Eisfeldt and Schubert 2024). The reshaping of business models has changed the mix of factors of production on which firms rely, leading to a gradual increase in the investment in high-quality labor factors. Specifically, the application of LLMs technologies requires firms to have people with specialized skills in data analytics, machine learning, and artificial intelligence to support the development and operation of LLMs. These high-quality laborers are better able to understand and apply LLMs to create more value for companies. According to Acemoglu and Restrepo (2018), technological advances tend to have complementary effects on the labor market. In this process, LLMs, as a complementary technology, have a significant complementary effect on high-skilled labor, which increases firms' demand for this type of labor. Second, when the demand for high-quality labor increases, the number and share of firms' high-quality labor force increases, which means that firms will pay higher wages and thus have a higher share of labor income. The demand for high-quality labor shows a continuous increase after firms apply LLMs. When the supply of these talents fails to meet the demand, their bargaining power is enhanced, compelling firms to increase compensation and benefits to attract and retain them, thereby continuously driving up salary levels. According to Autor and Dorn (2013), skill-biased growth brought about by technological advances leads to changes in the share of labor income. As firms' demand for high-skilled labor

increases, the optimization of labor structure leads to higher wage rates, which directly and positively affects the labor income share. Li et al. (2024), through a study of Chinese A-share listed companies in Shanghai and Shenzhen, found that an increase in the proportion of high-skilled labor within firms during the digital transformation process is one of the key drivers of the increase in labor income share.

On the other hand, the application of LLMs in firms has facilitated the synergy between humans and LLMs to improve the efficiency of employees, thus enhancing the share of labor income. First of all, the use of LLMs in firms and the synergy between LLMs and human resources have significantly improved the efficiency of laborers and created more value for firms. Specifically, LLMs assist workers in completing repetitive tasks through automated processing, intelligent analysis and decision-making, and human-computer collaborative working modes. LLMs can optimize work processes, improve work efficiency, and enable more accurate and timely decisions and predictions. This allows workers to devote more time and energy to innovation and the resolution of complex problems. For example, in the manufacturing industry LLMs can process a large amount of image data to quickly identify potential product defects, while human workers can review and judge the results of machine detection and deal with some complex or ambiguous situations with their professional knowledge and experience. This human-machine synergy model gives full play to the strengths of both the LLMs and the human, improving the accuracy and efficiency of the inspection and greatly increasing the labor efficiency of the employees. Cao et al. (2024) point out that humans provide significant incremental value in the "human + machine" collaboration and significantly reduce the number of extreme errors. The synergy between humans and machines is also demonstrated, showing how humans can leverage their strengths to better adapt to the growing capabilities of AI. Durante et al. (2024) demonstrated that AGENT AI, constructed with large language models (LLMs) and visual language models (VLMs), is capable of better understanding user inputs in domains such as gaming, robotics, and healthcare. This results in the formation of complex and adaptive human-computer interaction systems, thereby promoting "human-computer synergy". This synergy between people and LLMs not only improves the labor efficiency of employees, but also creates more value for the firm. Secondly, when the employees create more value for the firm, the employees can take a higher share of the new value, and then increase the share of labor income.

Based on this, the following hypotheses are proposed in this paper:

H1: All else being equal, firms applying LLMs will significantly increase their labor income share

### **III. Research design**

#### **(i) Sample selection and data sources**

To explore the impact of LLMs on the labor income share of firms, this study uses the listed companies on the Shanghai and Shenzhen Stock Exchanges from 2019 to 2023 as the research sample. It employs Python to scrape keywords related to LLMs from the annual reports of these listed companies. Subsequently, through manual judgment, the sample is divided into a treatment group and a control group. Due to the specificity of the financial industry, this paper excludes the industry, and also excludes the firms labeled as ST, \* ST and the missing data samples that cannot be processed. In addition, this study employs Propensity Score Matching (PSM) to conduct one-to-one matching between the treatment and control groups. After matching, 2366 firm-year observations are obtained. Data for the explanatory variables and each control variable in the paper are taken from the CSMAR database and the RESSET database. To improve the effectiveness of the results, we winsorize the main continuous variables at 1 % and 99 % percentiles.

#### **(ii) Definition of variables**

##### **1. Labor Income Share (LS)**

Following the research of Alvarado et al. (2013) and Yang et al. (2023), this study measures the labor income share (LS) by the ratio of cash payments to employees in the current period to the total operating revenue of the firm.

##### **2. Firm Applying Large Language Models (LLM)**

###### **(1) Manual identification**

First, in line with the "Announcement on the Release of Registered Information for Generative Artificial Intelligence Services" issued by the Cyberspace Administration of China in conjunction with relevant departments, and drawing on previous literature related to LLMs (Hou and Ji, 2024; Luo et al., 2024; Durante et al., 2024), this study constructs a set of keywords<sup>3</sup> related to the application of LLMs in firms. Second, python is used to analyze the text of the annual reports to identify the relevant firms that mention the keywords of LLMs in the annual reports. Again, to ensure the accuracy of the results, this paper manually judges the firms that mentioned LLMs in the annual reports to confirm the earliest time of the firms applying LLMs. If

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<sup>3</sup> The specific keyword set is as follows: "big model", "GPT", "ERNIE", "BERT", "AIGC", "AGI", "General Artificial Intelligence", "General AI", "Generative", "Intelligent Agents", "Large Language Models", "LLM".

the firms did apply LLMs, they are the treatment group, otherwise they are the control group. Finally, the core explanatory variables are defined according to the practice of difference-in-differences model, and if the firms in the treatment group use LLMs in the current year, they take the value of 1 for the current year and the following years, and vice versa.

## (2) Cross-validation

This section further tests the accuracy of the results of the manual identification of LLMs by means of an econometric regression, where we argue that firms that use LLMs increase their demand for jobs related to LLMs, and in order to have tested this hypothesis, we use the following regression model:

$$LLMJOB_{i,t} = \alpha_0 + \alpha_1 LLM_{i,t} + \sum Controls_{i,t} + \gamma_i + \delta_t + \varepsilon_{i,t} \quad (1)$$

Where  $LLMJOB$  denotes whether firm  $i$  publishes the recruitment information of the LLMs-related jobs in year  $t$ , and it is 1 if it publishes, otherwise it is 0. The employee recruitment data in this article comes from the website 51job (<https://www.51job.com/>), hereinafter referred to as 51job. As a company listed on NASDAQ, 51job specializes in internet recruitment services and holds significant domestic influence in this field, making it an important platform for internet recruitment in China. This study utilizes corporate internet recruitment data and employs Python for keyword recognition. Based on the set of keywords related to the application of LLMs in firms discussed earlier, it determines whether the positions recruited by companies are related to LLMs. Explanatory variables  $LLM$  denotes the dummy variables of the firm application LLMs.  $Controls$  indicates a series of control variables.  $\gamma_i$  denotes firm fixed effects.  $\delta_t$  denotes time fixed effects.  $\varepsilon_{i,t}$  denotes random interference term. The sample is the main regression sample, as explained below, and the regression results are shown in the Table 1.

The regression results in Table verify the reliability of the explanatory variables (LLM) in this paper. The results in column (1) of Table 1 indicate that the regression coefficient is significantly positive at the 5% level, suggesting that the application of LLMs in firms encourages the recruitment of tech personnel related to the R&D of LLMs. This indicates to some extent that our manually identified explanatory variables for firms applying LLMs are reliable because firms using LLMs do recruit employees related to LLMs as well.

Insert Table 1 here

## 3. Control variables

Based on previous research literature (Yang et al. 2023; Jiang et al. 2024), this paper controls the following variables in the model: firm size (Size), return on assets (ROA), leverage (Lev), growth rate of operating income (Growth), management shareholding ratio (Mshare), proportion of independent directors (Indep), top ten shareholders' shareholding (Top10), firm age (Firmage) and cashflow ratio (Cashflow), as well as the level of economic development at the regional level (GDP), and industrial structure (IndStr). The definitions of the specific variables can be found in Table 2.

Insert Table 2 here

### (iii) Modeling

Due to the small amount of data on firms applying the Big Model, in order to alleviate the self-selection problem, in the regression analysis, we first match the propensity scores of firms applying and not applying LLMs, and then use the matched samples to launch the regression analysis. The alternative control group for matching is firms that always did not apply the Big Model; the experimental group is firms that applied the Big Model during the sample period. In order to reflect the overall situation of firms applying the Big Model, we use all control variables as covariates and perform 1-to-1 near-neighbor matching in the full sample. Specific regression models are constructed in the matched sample using difference-in-differences model as follows.

$$LS_{i,t} = \alpha_0 + \alpha_1 LLM_{i,t} + \sum Controls_{i,t} + \gamma_i + \delta_t + \varepsilon_{i,t} \quad (2)$$

where  $LS$  denotes the labor income share of firm  $i$  in year  $t$ . Drawing on Alvarado et al. (2013), Yang et al. (2023), this paper uses the firm's current cash payments to employees divided by total operating revenue to measure the labor income share (LS). The explanatory variable  $LLM$  denotes a dummy variable for firms applying LLMs.  $Controls$  denote A series of control variables.  $\gamma_i$  denotes firm fixed effects.  $\delta_t$  denotes time fixed effects.  $\varepsilon_{i,t}$  denotes a random interference term. In the specific empirical analysis, in order to exclude the influence of heteroskedasticity and serial correlation on the regression results, this paper adjusts the standard errors of the regression coefficients for clustering at the firm level. The estimated coefficient focused on in this paper is  $\alpha_1$ , which captures the actual impact of firm application of LLMs on firm labor income share. According to the theoretical analysis, if  $\alpha_1$  is significantly greater than 0, it means that firms' application of LLMs enhances firms' labor income share, i.e., Hypothesis 1 is valid.

## IV. Results

### (i) Descriptive Statistics

Table 3 shows the results of the descriptive statistics of the main variables. The mean and median of LS are, respectively, 0.232 and 0.183, which means that 20% of the operating revenues of the listed companies in China are used to pay wages. The maximum value of LS is 0.710 and the minimum value is 0.0140, which indicates that there is a big difference between different listed companies. The mean value of LLM is 0.207, which indicates that most of the firms have not yet used LLMs, indicating that there are large differences between different firms.

Insert Table 3 here

### (ii) Baseline results

#### 1. Propensity score matching

This paper utilizes A-share listed companies from 2019-2023, which are divided into a treatment group and a control group according to whether or not they use LLMs, and matches the propensity scores of the two groups of data. Specifically, this study uses the Logit model to estimate the propensity score, uses the "one-to-one matching method" to determine the weights, and imposes the "common support" condition, which ultimately results in 2366 firm-year observations.

#### 2. Main regression results

In order to test the causal relationship between firms' application of LLMs and labor income share, this paper conducts regressions on the sample data based on the econometric model (2). Table 4 presents the results of the main regressions. The results in column (1), which control for firm-level characteristics as well as firm and year fixed effects, find that the *LLM* coefficient is 0.009, which is significantly positive at the 5% level, suggesting that firms' application of LLMs enhances labor income share. Further controlling for area-level characteristics in column (2), the regression coefficient of *LLM* is found to be, both in value and significance, insignificantly unchanged and still significantly positive at the 5% level, suggesting that LLMs application enhances firms' labor income share. In particular, column (2) is used as an example to illustrate the economic significance of firms applying LLMs. It is found that the estimated coefficient of the *LLM* is 0.009, and given that the mean value of firms' pre-policy labor income share is 0.217, this implies that, on average, the application of LLMs is able to increase firms' labor income share by 4.1% ( $0.009/0.217$ ), and that this increase is economically significant. Overall, these

results indicate that the application of LLMs by firms can significantly increase the labor income share, thus supporting the research hypotheses previously proposed.

Insert Table 4 here

### 3. Balance test

The sample used for the main regression in this paper is obtained based on 1:1 propensity score matching, so to ensure the reliability of the results, it is important to make sure that there is no significant difference between the treatment group and the control group in terms of observable variables after propensity score matching. Table 5 shows that after matching, the absolute value of the standard deviation of the variables of firm size (*Size*), return to assets (*ROA*), leverage (*Lev*), growth rate of operating income (*Growth*), management shareholding ratio (*Mshare*), proportion of independent directors (*Indep*), top ten shareholders' shareholding (*Top10*), firm age (*Firmage*) and cashflow ratio (*Cashflow*), the level of economic development(*GDP*), and Industrial structure (*IndStr*) have decreased significantly. It indicates that there is no significant difference between the observable variables of the treatment and control groups after matching, and one-to-one matching is effective.

Insert Table 5 here

### (iii) Robustness tests

#### 1. parallel trend test

we assess the validity of the parallel trends assumption underlying our difference-in-differences estimation. This assumption requires that the average change in labor income share exhibits similar pretreatment trends for both treatment and control companies. Accordingly, this study examines the dynamic effect of the firm's application of the grand model on labor income share using the event study method. Specifically, this paper constructs the following intertemporal dynamic model:

$$LS_{i,t} = \alpha + \beta_1 \text{Before\_4}_{i,t} + \beta_2 \text{Before\_3}_{i,t} + \dots + \beta_6 \text{After\_2+}_{i,t} + \sum \text{Controls}_{i,t} + \gamma_i + \delta_t + \varepsilon_{i,t} \quad (3)$$

We replace *LLM* with five dummy variables indicating the number of years before or after the application of LLMs. *Before\_i* is a dummy variable that indicates the *i*th year before the application of LLMs (*i*=1, 2, 3, and 4), whereas *After\_j* is a dummy variable that indicates the *j*th year after the application of LLMs (*j*=1). *After\_2+* is an indicator variable that equals 1 for the period starting two years after the application of LLMs in a firm. We drop *Before\_1* to use 1 year prior to the application of LLMs as the benchmark. If the parallel trends assumption is satisfied, we should not observe

any significant differences in the regression coefficients of Before\_i. Table 6 presents the results. We also plot the trend in coefficients for these dummy variables in Fig. 1. Consistent with our expectation, the coefficients of Before\_4 – Before\_2 do not differ significantly from one another, whereas the coefficients of After\_1 and After\_2+ have an overall significant increasing trend. This suggests that the observed increase in labor income share among our treatment groups occurs after LLMs are applied. In sum, these results indicate that our analysis satisfies the parallel trends assumption.

Insert Table 6 here

Insert Fig.1 here

## 2. Difference-in-differences sensitivity test

Recent studies have argued that even if the parallel trend hypothesis test is passed, it is not enough to prove that the parallel trend hypothesis is valid, due to the low validity of the parallel trend hypothesis test (Freyaldenhoven et al., 2019; Roth,2022). In order to solve this problem, Roth (2022) came out with an alternative solution, In order to solve this problem, Rambachan and Roth (2023) came out with an alternative solution, which is to test whether the treatment effect still holds by violating the parallel trend hypothesis to some extent. First, some limitations need to be imposed on the extent to which the parallel trend assumption is violated:

$$\Delta(\bar{M}) = \left\{ \beta: \forall t \geq 0, |\beta_{t+1} - \beta_t| \leq \bar{M} \times \max_{s < 0} |\beta_{s+1} - \beta_s| \right\} (4)$$

where  $\Delta(M)$  restricts the maximum violation of the post-treatment parallel trend assumption to no more than M times the maximum violation of the pre-treatment parallel trend assumption. The assumption is justified by the fact that the confounding factors that violate the parallel trends assumption have a similar impact on the outcomes both prior to and following the treatment (Rambachan and Roth, 2023). In this paper, sensitivity tests can be performed by setting the value of M. For example,  $M = 0.5$  implies that the degree of violation of the parallel trend assumption after treatment is no more than half of the maximum degree of violation of the parallel trend assumption before treatment.

Rambachan and Roth (2023) in their study further proposed a methodology to determine the confidence intervals for the treatment effects and conducted statistical tests accordingly. This study adopted the methodology of Rambachan and Roth (2023) to test the sensitivity of parallel trends and the results of the sensitivity test of the treatment effect for the year of policy implementation are presented in Fig. 2 . It is

found that the estimate of the treatment effect is still significantly different from zero when setting the value of  $M$  at 0.5. This indicates that, even if the parallel trends assumption does not fully hold after the policy implementation, as long as the degree of violation does not exceed the maximum violation before the policy was implemented, the treatment effect remains significantly positive. The robustness of the treatment effect estimates is further confirmed by the results of the sensitivity tests.

Insert Fig.2 here

### 3. Regression using different samples

#### (1) Full sample regression

Since PSM loses a large number of control group samples, these lost samples may affect the reliability of the regression results. Therefore, to ensure the robustness of the regression results, this paper uses the full sample before PSM matching for the regression, and the regression results are shown in column (1) of Table 7. The coefficients of firm applying LLMs ( $LLM$ ) are significantly positive at the 1% level, indicating that the conclusions are robust.

#### (2) PSM-IPW-DID

Following the approach of Guadalupe et al. (2012) and Brucal et al. (2019), this paper uses an inverse probability weighted matching (IPW) method to match the samples of firms in the treatment and control groups. Since other matching methods only retain samples that are comparable to the treatment group, this results in a large sample loss and the estimable sample will be very small. According to Guadalupe et al (2012), IPW matching is based on propensity scores and assigns different weights to each sample, which circumvents the sample loss problem and retains a larger sample. Specifically, in this paper, the propensity score  $\Pr(LLM_{i,t} = 1)$  is estimated with the Probit model and the weights assigned to each sample are calculated. Among them, the weight of the treatment group samples is  $1/\Pr(LLM_{i,t} = 1)$ , and the weight of the control group samples is  $1/[1 - \Pr(LLM_{i,t} = 1)]$ . After completing the matching, this paper uses model (2) for re-estimation based on the matched samples. The results are shown in column (2) of Table 7. The coefficients of firms applying LLMs ( $LLM$ ) are significantly positive at the 1% level, indicating that the main results remain robust.

#### (3) PSM in different proportions

The main regression of this study confirms that, using propensity score matching

under a 1:1 nearest neighbor matching scenario, the application of LLMs significantly increases the labor income share of firms. To ensure the robustness of the results, this paper uses different proportions of nearest neighbor matching to ensure the robustness of the results. As shown in column (3) of Table 7, the coefficient of firms applying LLMs (*LLM*) is significantly positive at the 1% level when 1:2 nearest neighbor matching is used; As shown in column (4) of Table 7, the coefficient of firms applying LLMs (*LLM*) is significantly positive at the 1% level when 1:3 near-neighbor matching is used; As shown in column (5) of Table 7, the coefficient of firms applying LLMs (*LLM*) is significantly positive at the 5% level when 1:4 near-neighbor matching is used. Combining the regression results from all different samples consistently indicates that the baseline results remain robust.

Insert Table 7 here

#### 4. Changing the measurement of the labor income share of firms

This study further employs other methods to measure and re-validate the labor income share of the firm. Specifically, considering the possible impact of accrual-based accounting on employee compensation, this study defines the total compensation paid by a firm to its employees as "cash paid by the firm to its employees in the current period + (employee compensation payable at the end of the period - employee compensation payable at the beginning of the period)". Further, this study measures the labor income share of the firm by calculating the ratio of total compensation to total operating revenues, which is denoted as *LS2*. Table 8 Column (1) demonstrates the results of the test, where the coefficient of *LLM* is significantly positive at the 1% level of significance, which further validates the robustness and reliability of the underlying findings of this study.

#### 5. Replacement fixed effects and clustering methods

Considering that different provinces may have experienced different policy changes during the sample period, and potential and unobservable macro factors may also have differential impacts on labor income shares across provinces. To rule out the impact of the above factors on the main results, the province-by-year interaction fixed effects are further controlled for in the main regression, and the regression results are shown in column (2) of Table 8. The coefficients of the firms applying LLMs (*LLM*) remain positive at the 10% significance level, proving the robustness of the core findings. Further, considering that some variables may be correlated in higher dimensions, the paper adjusts the clustering dimension from firm level to industry

level, and the results of the re-regression are shown in Column (3) of Table 8 of , the coefficient of the firms applying LLMs (*LLM*) is still positive at the 10% level of significance, which demonstrates that the conclusions are robust.

Insert Table 8 here

#### 6. Difference-in-differences heterogeneity treatment effect

According to the research by Chaisemartin and D'Haultfoeuille (2020), Goodman-Bacon (2021), and Borusyak et al. (2021), in the estimation process of the two-way fixed effects difference-in-differences (TWFE) model, the two-way fixed effects estimator is equal to the weighted average of all possible two-period difference-in-differences estimators in the sample. This may lead to instability due to heterogeneous treatment effects, such as issues caused by negative weights.

Because each firm applies LLMs at a different point in time, there are four types of contrasts in the research design of this paper: firms that use LLMs (the treatment group) versus firms that have never used LLMs (the never-treated group), firms that use LLMs (the earlier-treated group) versus firms that have not yet used LLMs (the later-treated group), firms that use LLMs (the treated group) versus firms that have always used LLMs (the sample period is all treated group), and using LLMs firms (later treated group) versus having used LLMs firms (earlier treated group). Of these four groups of contrasts, the first two are considered valid contrasts in that they explore the effect of using LLMs on firms' labor income shares. However, the latter two groups of contrasts may not have consistent treatment effects. If these two groups are overweighted in the average estimator, they may distort the results of the two-way fixed effects model and introduce errors (Liu, Chong et al., 2022). Therefore, the Goodman-Bacon decomposition was used in this study to assess whether the latter two contrast groups were overweighted. Based on the test results in the Table 9, we can see that the weight of the latter two groups of contrasts is relatively low in this paper, which indicates that the impact of firms' adoption of the large model on labor income shares does not come mainly from these two groups of contrasts.

As shown in Table 9 and Fig. 3, the main source of the difference-in-differences estimation results in this study is the estimates using untreated samples as the control group, which accounts for 71.4% of the weight. The second group accounts for 18.8% of the weight. The combined weight of these two groups is as high as 90.2%. Although the estimated coefficient of the third group is negative, the combined weight of the two groups that may introduce bias only accounts for 9.8%, which has a limited

impact on the overall estimation results and does not lead us to overestimate the impact of LLMs on the labor income share of firms. Summarizing the above analysis, the TWFEEDD estimation results used in this paper are reliable. Although the Baondecomp decomposition verifies that it is highly unlikely that this paper is affected by heterogeneous treatment effects, this paper still refers to the following methods to mitigate the potential heterogeneous treatment effect problem of TWFEEDD.

Insert Fig.3 here

Insert Table 9 here

First, Stacked DID Method (Stacked DID). This study follows on Cengiz et al. (2019) and Xuanyu Jiang (2024) to re-estimate the impact of firms' application of LLMs on labor income shares using the Stacked DID method. Specifically, the operation involves finding a "pure" control group that has not been affected by the policy for the treatment group affected by the policy around each policy change time point, merging these data sets, and then conducting stacking and regression analysis on these data sets with different treatment time points. According to the results of the regression analysis in column (1) of Table 10, the regression coefficients of the firm applying LLMs (*LLM*) are significantly positive, indicating that the estimation results of this study are highly robust.

Second, the S-A statistic. To address the interference of the heterogeneity treatment effect problem on the main results of this paper, the S-A statistic proposed by Sun and Abraham (2021) is further used for the dynamic effects test. Since the S-A statistic is a statistic that is adjusted to be free from the heterogeneity problem of treatment effects, the use of this statistic can effectively mitigate the estimation bias caused by the heterogeneity of treatment effects and improve the reliability of the main results. The specific results are shown in column (2) of Table 10. After using the S-A statistic for estimation to exclude the problem of heterogeneity of treatment effects, the regression coefficients of the firm applying LLMs (*LLM*) are still significantly positive, and the research conclusions of this paper still hold.

Third, Imputation Estimation (IE). Borusyak et al. (2022) provide an interpolation-based counterfactual approach to solve the estimation bias problem of TWFEEDD, which can obtain more accurate estimates by estimating the group fixed effects, time fixed effects, and treatment group-control group fixed effects. According to the regression analysis results in column (3) of Table 10, the regression coefficients

of the firm applying LLMs (*LLM*) are still significantly positive and the findings of this paper are still robust.

Insert Table 10 here

## 7. Placebo Test

### (1) Randomly Generated Treatment Groups

Based on the sample distribution of the variable of firm application of large models, the treatment group was randomly generated, and 1000 regressions were repeatedly conducted. A placebo test was performed by plotting the kernel density of the regression coefficient estimates. We plotted the kernel density to reflect the test results. As shown in Fig. 4, the coefficients in the 1000 replicated samples mostly fall around 0 and approximately follow a normal distribution, and thus are not statistically or economically significant, indicating that the main regression is not disturbed by other random factors and policies. This in turn indicates that the estimation results of the original model are robust and unlikely to be influenced by random factors.

Insert Fig.4 here

### (2) Virtual Space-Time Placebo Test

We set the sample period to 2017-2021 and advance the use of LLMs by two years to construct a false implementation time, which, if the results are not significant, indicates that the original model results are not affected by random factors. As shown in column (1) of Table 11, the *LLM* regression coefficients are no longer significant after advancing the use of LLMs by two years, which proves that the original model regression results are not affected by stochastic factors, and therefore the results of the original model are robust.

Insert Table 11 here

## 8. Instrumental Variables Approach

Prior research may be affected by potential endogeneity issues. On the one hand, firms may have increased their labor income share by applying LLMs; on the other hand, firms that already have a higher labor income share may be more inclined to adopt new technologies and actively apply LLMs, which may lead to bidirectional causality problems. In addition, bias in model setting or omission of key variables may also lead to endogeneity problems, e.g., other factors that simultaneously affect firms' application of LLMs and labor income share may be ignored. To mitigate the endogeneity problem, this paper not only controls for firm characteristics and

region-level control variables in the baseline model, but also controls for joint "province-year" fixed effects in the robustness test section to better absorb the effects of time-varying region-level unobservables to mitigate the omission problem. The problem of omitted variables is mitigated. Next, the instrumental variables approach is further applied to mitigate the possible negative impact of endogeneity on the findings.

This study selects the logarithm of the distance from the company's office to the nearest National Supercomputing Center (IV1) and the application rate of large models in the same industry and year, excluding the company itself (IV2), as instrumental variables. Theoretically, firstly, firms will need a lot of computility support for training LLMs, and National Supercomputing Centers can provide computility services for firms. Therefore, the closer to the National Supercomputing Center, the easier it is for firms to get computility support, which promotes the application of LLMs, satisfying the relevance condition; at the same time, the distance between the National Supercomputing Center and the firm does not directly affect the firm's income distribution decision, and the instrumental variable can only act on the share of labor income through the promotion of the application of LLMs, which satisfies the condition of exogeneity. Secondly, the application rate of LLMs in the same industry and year, excluding the company itself (IV2), affects the company's application of large models, satisfying the relevance condition. Meanwhile, the application rate of LLMs in the same industry and year, excluding the company itself, does not directly influence the company's income distribution decisions, satisfying the exogeneity condition. Columns (1) and (2) of Table 12 report the estimation results based on the two-stage least squares method with instrumental variables (IV-2SLS). In the first-stage regression, the coefficient of IV1 is significantly negative, and the coefficient of IV2 is significantly positive. This indicates that the distance from a company to the nearest National Supercomputing Center (IV1) and the application rate of LLMs in the same industry and year, excluding the company itself (IV2), are both strongly correlated with the company's application of LLMs, satisfying the relevance condition for instrumental variables. In addition Kleibergen-Paap rk LM statistic of 45.882 rejects the original hypothesis of insufficient identification of instrumental variables at 1% level; Cragg-Donald Wald F statistic is greater than the critical value of Stock-Yogo weak instrumental variable identification test at 10% significance level, rejecting the original hypothesis of weak instrumental variables; at

the same time, since this paper selects two instrumental variables for identification, so this paper carries out the instrumental variable over-identification test, Hansen J statistic p-value is greater than 0.05 accepts the original hypothesis that all instrumental variables are exogenous, indicating that the two instrumental variables selected in this paper are valid, the above test basically confirms the reasonableness of the instrumental variables selected in this paper. Table 12 In the second stage regression in column (2), the coefficient of *LLM* is significantly positive at the 1% level, indicating that the main conclusions of this paper still hold.

Insert Table 12 here

## **V. Further Analysis**

### **(i) Mechanism Test**

In the previous section, we demonstrated the positive impact of firms' adoption of LLMs on increasing the labor income share. In this section, we delve into the mechanisms behind this phenomenon. Based on previous theoretical analyses, we propose two main mechanisms: First, the adoption of LLMs by firms may increase the demand for high-quality labor, optimize the structure of human capital, and thereby increase the labor income share of firms. Second, the collaborative work between firm employees and LLMs can enhance work efficiency, make decision-making and predictions more accurate and timely, which helps employees create more value and may enable them to obtain a higher share of the added value, thereby increasing the labor income share. Based on the above logic, this section focuses on examining the following two questions to reveal the potential pathways and mechanisms of impact: first, whether firms' adoption of LLMs optimizes the structure of human capital by increasing high-quality labor; and second, whether employees' collaborative work with LLMs creates more value for the firm.

#### **1. Firms Apply LLMs to Optimize Human Capital Structure**

Based on our previous theoretical research, we find that advances in firms' adoption of LLMs may lead to the replacement of certain routine and repetitive low-skill jobs by automated technologies. This technological substitution effect helps firms to optimize and upgrade their human capital structure by reducing their reliance on low-quality labor. In addition, advances in big model technology may also increase firms' demand for high-quality labor. In order to verify whether the application of LLMs by firms can optimize human capital structure and further lead to the improvement of labor income share, we need to test whether the core logic chain of

"firm application of quality → human capital structure adjustment → improvement of labor income share" is valid. In this paper, we differentiate the level of human capital according to the education level of employees. Specifically, this study constructs a human capital structure indicator (*Highedu*). Workers with a bachelor's degree or above are classified as high-quality labor, while those with an associate degree or below are classified as low-quality labor. The human capital structure of a company is defined as the ratio of the number of high-quality workers to the number of low-quality workers employed. And reconstruct model (5) as follows:

$$Highedu_{i,t} = \beta_0 + \beta_1 LLM_{i,t} + \sum Controls_{i,t} + \gamma_i + \delta_t + \varepsilon_{i,t} (5)$$

Where *Highedu*<sub>*i,t*</sub> denotes the percentage of highly educated employees in firm *i* in year *t*, which is equal to the ratio of employees with a bachelor's degree or above to those with an associate degree or below. The definitions of the remaining variables are the same as in the main regression. This paper focuses on the significance of the coefficient  $\beta_1$  in model (5), according to the previous research hypothesis if the coefficient  $\beta_1$  is significantly positive, it implies that firms applying LLMs will contribute to the upgrading of the structure of human capital, which will in turn increase the share of labor income. In column (1) of Table 13, *LLM* is significantly positive for *Highedu* at 10% significance level, which indicates that the use of the Big Model can positively affect the labor income share of firms through the upgrading of their human capital structure. The above findings prove that firms can promote the optimization and upgrading of human capital structure through the application of LLMs, which in turn increases the share of labor income of firms. This finding supports the core logic chain of "firm application of quality → human capital structure adjustment → improvement of labor income share".

Insert Table 13 here

## 2. Human Collaboration With LLMs

Based on previous research findings, humans working in tandem with LLMs can bring greater value gains to the firm (Cao, 2024). When human-machine synergy creates more value for a company, employees can claim a larger share of the added value, thereby increasing the labor income share. In order to verify whether human-machine synergy can create more value and further lead to the increase of labor income share, we need to test whether the logic chain of "firm applies LLMs → human-machine synergy creates more value → improvement of labor income share" is valid. In this paper, we construct the following model to verify that human-machine

synergy can create more value for firms:

$$LnRevenue_{i,t} = \mu_0 + \mu_1 LnStaff_{i,t} + \mu_2 Size + \sum Controls_{i,t} + \gamma_i + \delta_t + \varepsilon_{i,t} (6)$$

$$LnRevenue_{i,t} = \theta_0 + \theta_1 LLM_{i,t} \times LnStaff_{i,t} + \theta_2 LnStaff_{i,t} + \theta_3 LLM_{i,t} + \sum Controls_{i,t} + \gamma_i + \delta_t + \varepsilon_{i,t} (7)$$

where the explanatory variable is  $LnRevenue_{i,t}$  denoting the logarithmic operating income of firm  $i$  in year  $t$ . The explanatory variable is the interaction term between  $LnStaff_{i,t}$  and  $LLM_{i,t}$ .  $LnStaff_{i,t}$  denotes the total number of employees of firm  $i$  in year  $t$  after taking the logarithm. While the interaction term of  $LnStaff_{i,t}$  with  $LLM_{i,t}$  means person and LLMs collaboration, the definitions of the remaining variables are the same as in the main regression. This paper focuses on the significance of the coefficient  $\theta_1$  of  $LLM_{i,t} \times LnStaff_{i,t}$  in model (7). According to the previous research hypothesis if the coefficient  $\theta_1$  is significantly positive, it means that human-machine synergy will create more value for the firm. The results in column (2) of Table 13 show that the coefficient of  $LnStaff$  is significantly positive at 1% level, indicating that employees can create value for the firm. The results in column (3) of Table 13 show that the coefficient of  $LLM_{i,t} \times LnStaff_{i,t}$  is significantly positive at 1% level, which indicates that the collaboration between people and LLMs can enhance the business revenue of the firm and create more value for the firm. The above results fully indicate that by applying LLMs, firms enable their employees to create more value, which in turn increases the share of labor income of the firm. This supports the logical mechanism of "firm applies LLMs  $\rightarrow$  human-machine synergy creates more value  $\rightarrow$  improvement of labor income share".

## (ii) Heterogeneity Analysis

### 1. Heterogeneity Analysis Based on Financing Constraints

The financing constraint index is a measure of the degree of restrictions and difficulties that firms face in the financing process. In this paper, we find that firms with lower financing constraints show more significant recruitment advantages than firms with higher financing constraints. Specifically, these firms can offer more generous compensation and benefits to these high-quality talents, attract and absorb more individuals with high skills and high-education backgrounds, and thereby further consolidate their attractiveness and competitiveness in the talent market. Further, firms with lower financing constraints have sufficient financial support to invest in and utilize advanced LLMs, enabling employees to utilize big models to improve productivity, innovation efficiency and create more value for the firm. Based

on the above analysis, this study concludes that the positive effect of the application of LLMs on labor income share is more significant in firms with lower financing constraints. To test this assumption, we use the SA index to measure the financing constraints faced by firms, which takes negative values and the larger the value, the lower the financing constraints. We group the SA index by its median into high and low financing constraint groups and conduct group regressions. The regression results are shown in columns (1) and (2) of Table 14. As shown in columns (1) and (2) of Table 14, it can be observed that in the low financing constraint group, the coefficient of LLM is significantly positive at the 1% level, and it is stronger than that in the high financing constraint group in terms of both magnitude and significance. The Permutation test results also indicate a significant difference in coefficients between the groups. This suggests that the application of LLMs has a stronger effect on increasing the labor income share of firms with lower financing constraints, consistent with expectations. This also provides further side evidence for the mechanism that the application of LLMs enhances the labor income share of firms by promoting the upgrading of human capital structure and "human-machine synergy".

Insert Table 14 here

## 2. Heterogeneity Analysis Based on Industry Type

In this paper, we argue that in technology-intensive industries where firms are more dependent on capital and technology, the employees of these firms are themselves highly receptive to new technologies. As a result, after these firms use LLMs, the employees are able to quickly realize the synergy with LLMs, which in turn improves efficiency and creates value. This synergy not only increases the overall value, but also enables employees to obtain a larger proportion of the newly created value, thus potentially increasing the share of labor income in total income. Based on the above analysis, this study concludes that the positive impact of the application of LLMs on the share of labor income is more significant in industries with low labor intensity. To verify this assumption, this paper uses the method of classification by factors of production to group regress all industries into industries with technology-intensive as well as industries with labor-intensive. As shown in columns (1) and (2) of Table 15, it can be observed that in the group with technology-intensive, the coefficient of LLM is significantly positive at the 1% level, and it is stronger than that in the group with labor-intensity in terms of both magnitude and significance. The Permutation test results also indicate a significant difference in coefficients between

the groups. This indicates that the application of the large model promotes the labor income share of technology-intensive industries more strongly, as expected. This also provides side evidence for the mechanism that the application of LLMs creates more value through "human-machine synergy", which in turn increases the labor income share of firms.

Insert Table 15 here

### 3. Heterogeneity Analysis Based on the Degree of Competition in the Industry

First, in highly competitive industries, firms need new technologies such as LLMs more than monopolies in order to maintain their market position, which means that there is more room for LLMs to play a role. Therefore, when firms in competitive industries apply new technologies such as LLMs, they need more high-skilled and highly educated talents, which leads to the upgrading of human capital structure, and then promotes the increase of labor income share. Secondly, in industries with intense competition, the emergence of LLMs has motivated firms to apply them more actively. This is aimed at leveraging the synergistic effect between employees and LLMs, thereby enhancing labor productivity. According to the previous discussion firms applying LLMs can promote human capital upgrading, play the synergistic effect of people and LLMs, improve labor productivity, and thus promote the labor income share. Therefore, this study concludes that the positive impact of the application of LLMs on labor income share is more significant in competitive industries. To verify this assumption, this paper uses the operating income share of the top four companies in the industry to measure the degree of competition in the industry, and divides the entire sample into industries with high degree of competition and industries with low degree of competition for group regression. As shown in columns (1) and (2) of Table 16, it can be observed that in industries with high competition, the coefficient of *LLM* is significantly positive at the 1% level, and it is stronger than that in industries with low competition in terms of both magnitude and significance. The Permutation test results also indicate a significant difference in coefficients between the groups. The results reveal that the promotion effect of LLMs applications on labor income shares is more significant in highly competitive industries, as expected. This further provides indirect evidence of the mechanism by which LLMs applications promote the optimization and upgrading of human capital structure and achieve "human-machine synergy", thus enhancing the share of labor income of firms.

Insert Table 16 here

#### 4. Heterogeneity Analysis Based on LLMs of Firm Applications

This paper further analyzes in Chinese the heterogeneity of LLMs applications firms. Firstly, companies can either develop LLMs independently or in collaboration with major AI firms. When firms apply self-developed LLMs, they usually need to recruit more high-quality labor to accelerate the development and application of LLMs due to the lack of external cooperation. When companies apply LLMs developed in collaboration with major AI firms, the demand for high-quality labor is relatively low. This is because companies often do not need to retrain the LLMs from scratch but only need to make minor adjustments to the already developed LLMs. In addition, firms big models can make full use of the data accumulated by the firm and its industry, enabling the trained big models to more fully reflect the idiosyncrasies of the firm itself, thus enabling better synergy with employees. Therefore, for firms, self-developed LLMs are more likely to promote the upgrading of their human capital structure, bring into play the in-depth synergy between LLMs and the workforce, and thus more effectively increase the labor income share of firms .

Therefore, if the previous theoretical analysis holds, firms applying self-developed LLMs have a stronger effect on labor income shares relative to firms applying LLMs in cooperation with other firms. Based on this, we categorize the explanatory variables into *C (LLM\_Self)* and LLMs in cooperation with others (*LLM\_Co*) according to whether LLMs applied by firms are self-developed or not. Specifically, when firms disclose the use of self-developed LLMs in their annual reports, *LLM\_Self* takes the value of 1 for the current year and the following years, and vice versa takes the value of 0. Similarly, when firms disclose the application of LLMs in cooperation with others in their annual reports *LLM\_Co* takes the value of 1 for the current year and the following years, and vice versa takes the value of 0. We introduce the two dummy variables as new explanatory variables into model (2) and conduct the regression again. The results, as shown in column (1) of Table 17, indicate that the coefficient for *LLM\_Self* is 0.013 and significant at the 5% level, while the coefficient for *LLM\_Co* is 0.004 and not significant. This suggests that when companies apply LLMs developed independently, it significantly increases the labor income share of the firm.

Secondly, the application areas of LLMs include customer service field and other fields. In the field of customer service, there are typically a large number of routine and repetitive tasks. By collaborating with LLMs, employees can handle these routine

and repetitive tasks more efficiently. On the one hand, this significantly increases employees' productivity. On the other hand, it enables employees to devote their energy and time to more complex and strategically significant work. Therefore, the LLMs in the field of customer service on the one hand can more effectively play the synergistic effect of LLMs and employees, on the other hand can more effectively realize the human capital upgrade. According to the theoretical analysis of this paper , the application of LLMs in the customer service domain has a stronger effect on the labor income share compared to firms that apply LLMs to other aspects of the value chain.

Based on this, we categorize the explanatory variables into those applied to customer service (*LLM\_Cus*) and those applied to other fields (*LLM\_Non-Cus*) according to whether firms apply LLMs in customer service. Specifically, when firms disclose the use of LLMs in customer service in their annual reports, *LLM\_Cus* takes the value of 1 for the current year and subsequent years, and vice versa for 0. Similarly, when firms disclose the use of LLMs in other areas in their annual reports, *LLM\_Non-Cus* takes the value of 1 for the current year and subsequent years, and vice versa for 0. We introduce the two dummy variables as new explanatory variables into model (2) and conduct the regression again. The results, as shown in column (2) of Table 17, indicate that the coefficient for *LLM\_Cus* is 0.010 and significant at the 10% level, while the coefficient for *LLM\_Non-Cus* is 0.006 and not significant. This suggests that when companies apply LLMs in the field of customer service, it significantly increases the labor income share of the firm.

Insert Table 17 here

## VI. Conclusion

Improving the remuneration of workers is one of the key measures to promote shared prosperity. However, the popularity of AI technology has had an increasingly significant impact effect on the labor market. LLMs, as a milestone event in the history of AI development, is of great research significance. With the popularization of LLMs, it may trigger changes in the share of labor income as well as an increase in the inequality of income distribution, which have attracted extensive attention from all walks of life. In order to comprehensively assess the impact of corporate adoption of LLMs on labor income share, this paper develops an in-depth analysis. Taking A-share listed companies in 2019-2023 as the research sample, this paper empirically examines the impact of corporate adoption of LLMs on labor income share and its

mechanism. The empirical results find that firms applying big models significantly increase their labor income share, and this conclusion still holds after a series of endogeneity tests and robustness tests. The mechanism analysis shows that the upgrading of human capital structure and the "human-machine synergy" effect brought by the application of LLMs are the key paths to increase the labor income share. Heterogeneity analysis shows that this effect is more significant in firms with low financing constraints, in technology-intensive industries, in highly competitive industries, in firms that develop their own LLMs, and in firms that apply LLMs to customer service.

The research in this paper provides empirical evidence for understanding the impact of LLMs applications on the labor income share at the firm level in China, which has important policy implications for better stabilizing and enhancing workers' compensation and advancing common prosperity. First, firms should pay more attention to the deployment and application of LLMs and promote human-machine collaborative work patterns to create more value for the firm. The research in this paper shows that employees working with large models can improve the efficiency of employees, so that employees can detach themselves from the tedious work and have more time to devote to more valuable work, thus creating more value for the firm. Therefore, companies need to enhance their capital investment in the field of LLMs applications. By increasing capital, companies can promote synergies between employees and LLMs, which in turn improves efficiency and innovation. At the same time, companies should also focus on the application of LLMs in specific business scenarios to achieve more accurate market positioning and product optimization. This will enable firms to adapt more effectively to the trend of digital transformation and maintain their leading position in the highly competitive market environment. Secondly, the government should improve the labor skills training system, enhance on-the-job education and vocational skills training, and assist workers in re-employment. This study reveals that the application of LLMs by firms has led to a rise in the proportion of high-quality labor in the composition of their workforce, which in turn promotes the optimization and upgrading of the human capital structure. This phenomenon inevitably leads to a relative decline in the competitiveness of low-quality labor in the labor market. Therefore, the government should increase its investment in the labor skills training system, and help low-quality laborers improve their skills and enhance their competitiveness in the labor market by providing

diversified vocational skills training courses. At the same time, the government should encourage firms to carry out on-the-job education internally to provide employees with opportunities for continuous learning and growth in order to adapt to the changes in the work environment brought about by the application of LLMs. Finally, the government needs to introduce appropriate policies to support the independent research and development of domestically produced LLMs and give full play to the income distribution effect of LLMs applications. This study finds that LLMs independently developed by firms have more prominent effects in influencing the labor income share compared with the LLMs developed in cooperation. This suggests that the government should introduce policies to incentivize firms to independently research and develop domestically produced LLMs. By providing tax incentives, R&D subsidies and other measures, it can reduce the cost and risk of firms' independent R&D. Meanwhile, it can strengthen the protection of intellectual property rights and guarantee that firms' innovations are reasonably rewarded. This will help to promote the continuous innovation and development of LLMs and further enhance China's position in global scientific and technological competition.

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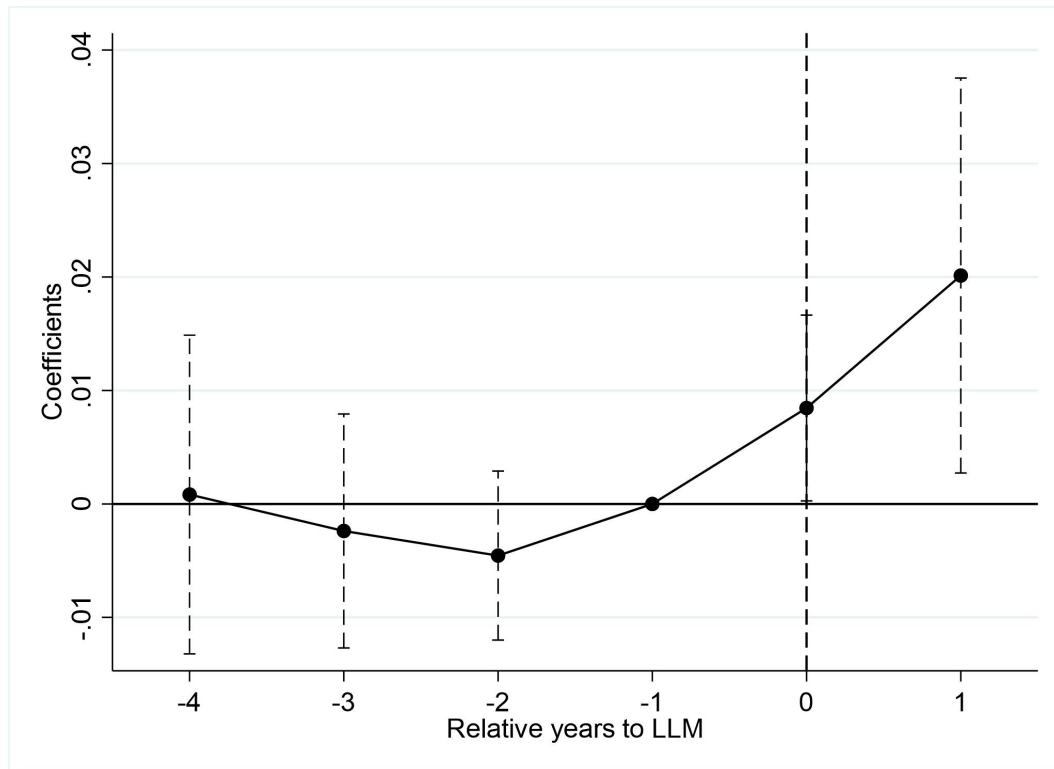
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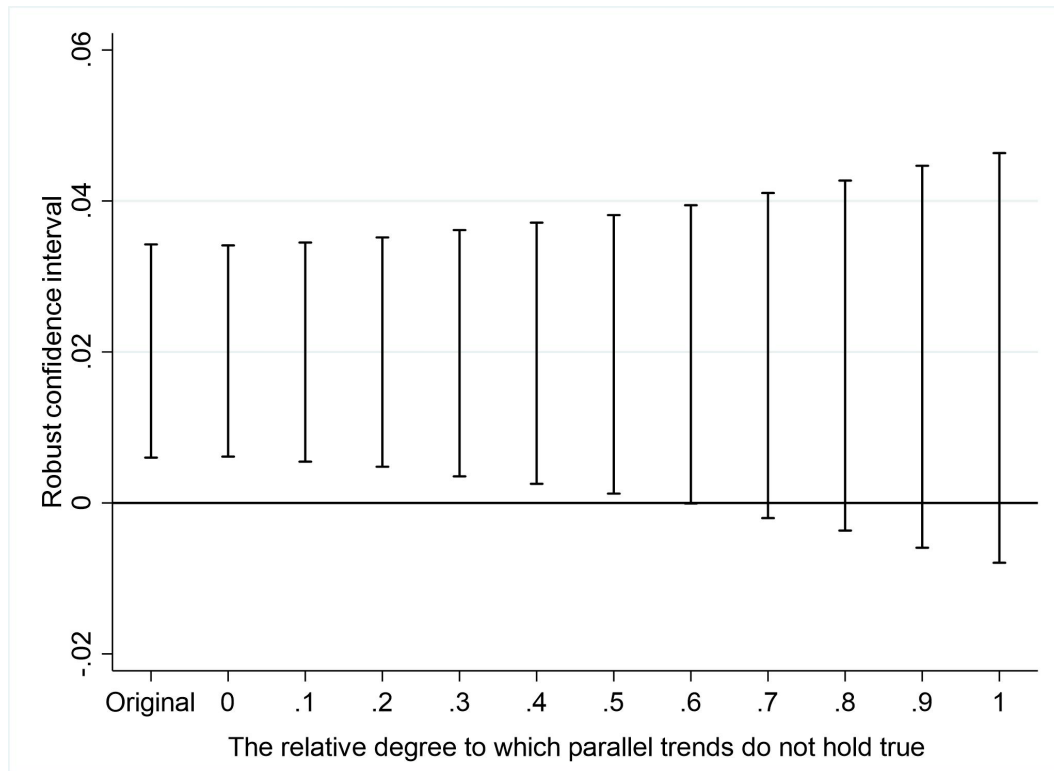
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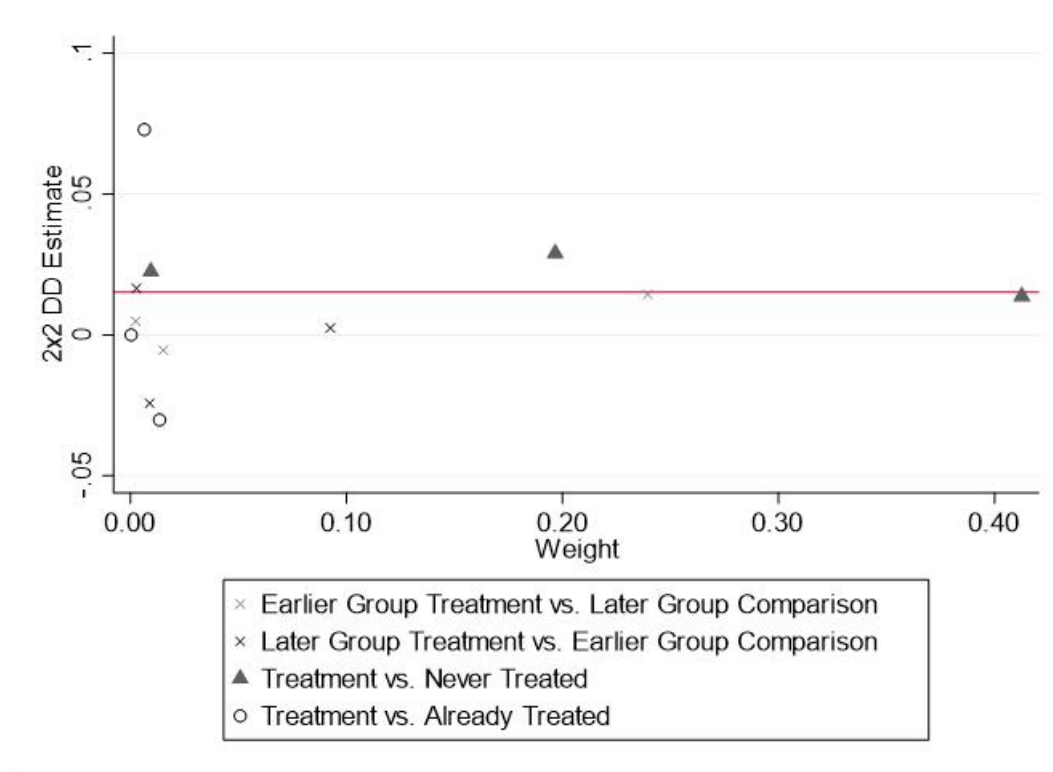


**Fig.1 Parallel trend tests of the effect of LLMs on labor income share.**

Figure 1 plots the impact of the firm applying LLMs (LLM) on labor income share (LS). The dashed lines represent 95% confidence intervals, adjusted for firm-level clustering.

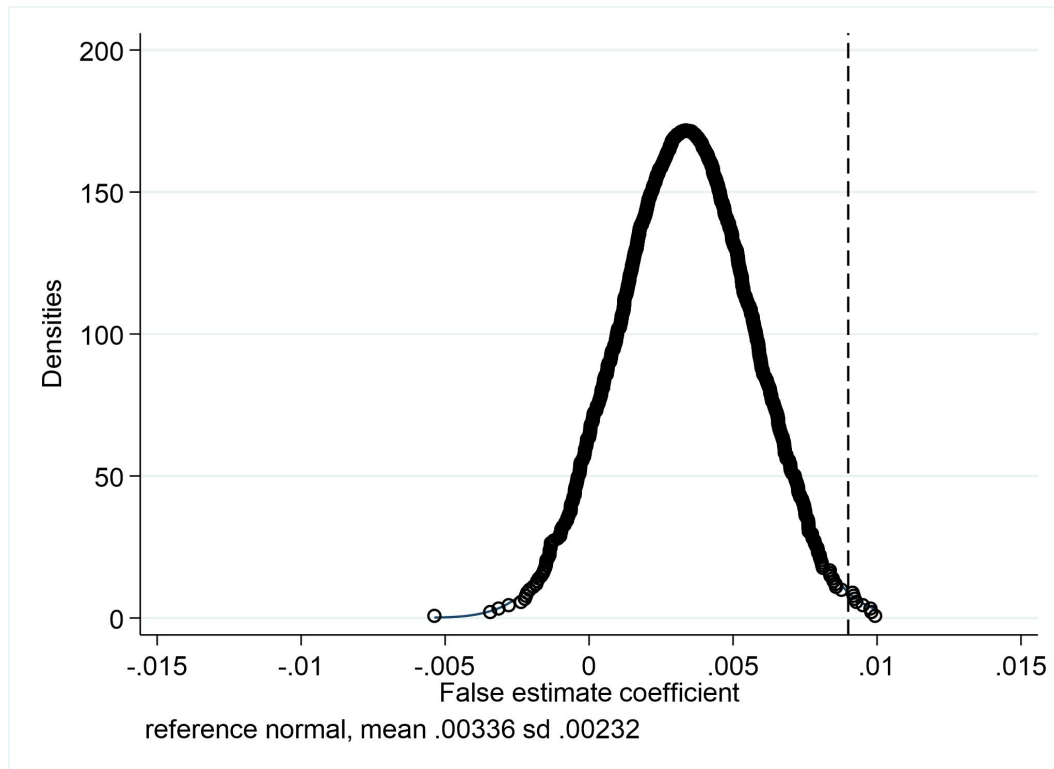


**Fig.2 Parallel trend sensitivity test.**



**Fig. 3 Bacon decomposition**

**Fig. 3** presents the scatter plots of the four groups resulting from the Bacon decomposition.



**Fig. 4 Placebo test kernel density plot**

Fig. 4 presents the distribution of coefficients based on placebo tests after randomly assigning independent variables 1000 times.

## Table1 Cross-validation

Table 1 reports regression results on the relationship between the firm applying LLMs (LLM) and the recruitment information of the LLMs-related jobs (LLMJOB). The definitions of these variables are provided in Table 2. T statistics computed with robust standard errors clustered by firm are reported in parentheses. All continuous variables are winsorized at the first and 99th percentiles. \*\*\*, \*\*, and \* indicate significance at the 1%, 5%, and 10% levels, respectively (two-tailed).

	(1) LLMJOB
LLM	0.047** (2.15)
Size	-0.031 (-1.09)
ROA	0.112 (0.99)
Lev	-0.020 (-0.22)
Growth	0.027 (1.36)
Mshare	-0.071 (-0.67)
Indep	-0.123 (-0.58)
Top10	0.000 (0.10)
FirmAge	-0.356 (-1.18)
Cashflow	-0.143 (-1.41)
GDP	0.117 (1.37)
IndStr	-0.234 (-0.49)
_cons	0.684 (0.59)
Observations	2366
R2_within	0.008
Year FE	Yes
Firm FE	Yes

Table2 Description of main variables

Variable	Definition and measurement	Source
<b>Dependent variable</b>		
<i>LS</i>	Cash paid for employees during the period divided by total operating income	CSMAR
<b>Independent variable</b>		
<i>LLM</i>	Dummy variable set to a value of 1 when a firm uses a large model for the current year and subsequent years and 0 otherwise.	Annual Reports
<b>Control variables</b>		
<i>Size</i>	The logarithm of total company assets	CSMAR
<i>ROA</i>	Net profit of the company divided by total assets	CSMAR
<i>Lev</i>	Total company liabilities divided by total assets	CSMAR
<i>Growth</i>	Revenue growth rate	CSMAR
<i>Mshare</i>	Management shareholding divided by total share capital	CSMAR
<i>Indep</i>	Independent directors divided by number of directors	CSMAR
<i>Top10</i>	Shareholding ratio of top ten shareholders of the company	CSMAR
<i>FirmAge</i>	The difference between the current year and the year of establishment of the firm is taken as a natural logarithm.	CSMAR
<i>Cashflow</i>	Net cash flows from operating activities divided by total assets	CSMAR
<i>GDP</i>	The logarithm of GDP of the province where the company's office is located	CSMAR
<i>IndStr</i>	Share of secondary industry in GDP of the province where the company's office is located	CSMAR
<b>Other variables</b>		
<i>LLMJOB</i>	Dummy variable set to a value of 1 when a firm publishes the recruitment information of the LLMs-related jobs and 0 otherwise.	51JOB
<i>LS2</i>	The ratio of total compensation to total operating revenues.	CSMAR
<i>IV1</i>	The logarithm of the distance from a company to the nearest National Supercomputing Center.	CSMAR
<i>IV2</i>	The application rate of LLMs in the same industry and year, excluding the company itself.	Annual Reports
<i>Higgedu</i>	The ratio of the number of employees with a bachelor's degree or above to those with an associate degree or below.	RESSET
<i>LnStaff</i>	The logarithmic total number of employees.	RESSET
<i>LnRevenue</i>	The logarithmic operating income.	CSMAR
<i>LLM_Self</i>	Dummy variable set to a value of 1 for self-development LLMs and 0 otherwise.	Annual Reports

<i>LLM_Co</i>	Dummy variable set to a value of 1 for in cooperation with major AI firm and 0 otherwise.	Annual Reports
<i>LLM_Cus</i>	Dummy variable set to a value of 1 when a firm applied LLMs to customer service and 0 otherwise.	Annual Reports
<i>LLM_Non-Cus</i>	Dummy variable set to a value of 1 when a firm applied LLMs to other fields and 0 otherwise.	Annual Reports

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### Table3 Descriptive Statistics

Table 3 presents descriptive statistics for all of the variables. N = number of observations. SD = standard deviation;

P50 = 50th percentile; Continuous variables are winsorized at the first and 99th percentiles of their distributions.

Variable	N	Mean	SD	Min	p50	Max.
LS	2366	0.232	0.173	0.014	0.183	0.710
LLM	2366	0.207	0.405	0.000	0.000	1.000
Size	2366	22.370	1.341	19.85	22.14	26.400
ROA	2366	0.0300	0.079	-0.269	0.036	0.236
Lev	2366	0.384	0.187	0.053	0.366	0.915
Growth	2366	0.0920	0.292	-0.606	0.068	1.766
Mshare	2366	0.120	0.158	0.000	0.029	0.659
Indep	2366	0.385	0.055	0.300	0.375	0.571
Top10	2366	53.770	16.110	22.94	53.820	90.550
FirmAge	2366	3.008	0.303	2.197	3.045	3.664
Cashflow	2366	0.045	0.068	-0.154	0.043	0.253
GDP	2366	11.010	0.574	8.577	10.890	11.820
IndStr	2366	0.339	0.108	0.149	0.395	0.485

#### Table4 Main regression results

Table 4 reports regression results on the relationship between the firm applying LLMs (LLM) and labor income shares (LS). The definitions of these variables are provided in Table 2. T statistics computed with robust standard errors clustered by firm are reported in parentheses. All continuous variables are winsorized at the first and 99th percentiles. \*\*\*, \*\*, and \* indicate significance at the 1%, 5%, and 10% levels, respectively (two-tailed).

	(1)	(2)
	LS	LS
LLM	0.009** (2.04)	0.009** (2.09)
Size	-0.027 *** (-3.64)	-0.027 *** (-3.66)
ROA	-0.248 *** (-8.33)	-0.251 *** (-8.40)
Lev	0.010 (0.45)	0.010 (0.45)
Growth	-0.046 *** (-8.58)	-0.046 *** (-8.54)
Mshare	-0.020 (-0.72)	-0.020 (-0.69)
Indep	0.012 (0.25)	0.014 (0.29)
Top10	0.000 (0.10)	0.000 (0.08)
FirmAge	0.078 (1.33)	0.076 (1.30)
Cashflow	-0.143 *** (-5.37)	-0.141 *** (-5.24)
GDP		0.009 (0.42)
IndStr		-0.226** (-2.04)
Observations	2366	2366
R2_within	0.277	0.279
Year FE	Yes	Yes
Firm FE	Yes	Yes

Table5 Balance test

Table 5 presents test statistics for covariate distributions for the treatment and control groups. All variables are defined in Table 2. All continuous variables are winsorized at the first and 99th percentiles.

Variable	Unmatched	Mean		%bias	%reduct bias	t-test	
	Matched	Treated	Control			t	p> t
Size	U	22.345	22.252	7.1		3.00	0.003
	M	22.345	22.39	-3.4	51.8	-1.05	0.295
ROA	U	0.02897	0.03749	-10.9		-4.83	0.000
	M	0.02897	0.02669	2.9	73.2	0.87	0.383
Lev	U	0.37663	0.40901	-16.5		-6.73	0.000
	M	0.37663	0.37636	0.1	99.2	0.04	0.965
Growth	U	0.0929	0.11409	-6.8		-2.68	0.007
	M	0.0929	0.09391	-0.3	95.3	-0.10	0.923
Mshare	U	0.11938	0.10922	6.2		2.52	0.012
	M	0.11938	0.11556	2.3	62.4	0.75	0.454
Indep	U	0.38506	0.37888	11.6		4.90	0.000
	M	0.38506	0.38718	-4.0	65.8	-1.23	0.220
Top10	U	53.608	59.156	-34.7		-15.28	0.000
	M	53.608	54.306	-4.4	87.4	-1.34	0.180
FirmAge	U	3.0055	3.0584	-17.6		-7.58	0.000
	M	3.0055	3.0064	-0.3	98.3	-0.09	0.925
Cashflow	U	0.04504	0.05202	-10.2		-4.34	0.000
	M	0.04504	0.04368	2.0	80.6	0.61	0.544
GDP	U	11	10.947	8.3		3.32	0.001
	M	11	10.991	1.4	83.0	0.49	0.622
IndStr	U	0.33556	0.37715	-43.1		-21.02	0.000
	M	0.33556	0.33346	2.2	94.9	0.61	0.544

### Table6 Parallel Trend Test

Table 6 reports results for the parallel trend test. The definitions of these variables are provided in Table 2. T statistics computed with robust standard errors clustered by firm are reported in parentheses. All continuous variables are winsorized at the first and 99th percentiles. \*\*\*, \*\*, and \* indicate significance at the 1%, 5%, and 10% levels, respectively (two-tailed).

	(1)
	LS
Before_4	0.001 (0.12)
Before_3	-0.002 (-0.45)
Before_2	-0.005 (-1.20)
After_1	0.008** (2.03)
After_2+	0.020** (2.27)
Size	-0.028*** (-3.76)
ROA	-0.249*** (-8.43)
Lev	0.011 (0.48)
Growth	-0.046*** (-8.62)
Mshare	-0.019 (-0.68)
Indep	0.012 (0.25)
Top10	0.000 (0.29)
FirmAge	0.081 (1.37)
Cashflow	-0.143*** (-5.34)
GDP	0.010 (0.47)
IndStr	-0.242** (-2.22)
_cons	0.581** (1.99)
Observations	2366
R2_within	0.282
Year FE	Yes

Firm FE

Yes

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Table7 Regression using different samples

Table 7 presents the result of regression using different samples. Columns (1) present the results of using the full sample before PSM for the regression. Columns (2) present the results of using the sample after IPW matching for the regression. Columns (3) to (5) present the regression results using 1-to-2, 1-to-3, and 1-to-4 PSM samples, respectively. The definitions of these variables are provided in Table 2. T statistics computed with robust standard errors clustered by firm are reported in parentheses. All continuous variables are winsorized at the first and 99th percentiles. \*\*\*, \*\*, and \* indicate significance at the 1%, 5%, and 10% levels, respectively (two-tailed).

	full sample	IPW	1:2	1:3	1:4
	(1)	(2)	(3)	(4)	(5)
	LS	LS	LS	LS	LS
LLM	0.015 *** (4.97)	0.011 *** (3.85)	0.010 *** (2.67)	0.010 *** (2.73)	0.008 ** (2.38)
Size	-0.031 *** (-10.00)	-0.028 *** (-5.35)	-0.024 *** (-3.95)	-0.028 *** (-4.65)	-0.027 *** (-4.76)
ROA	-0.255 *** (-19.80)	-0.279 *** (-12.66)	-0.245 *** (-10.08)	-0.262 *** (-10.38)	-0.261 *** (-10.72)
Lev	-0.015 * (-1.66)	0.006 (0.41)	0.005 (0.25)	-0.001 (-0.04)	-0.003 (-0.15)
Growth	-0.039 *** (-23.05)	-0.036 *** (-9.59)	-0.047 *** (-10.05)	-0.047 *** (-10.89)	-0.049 *** (-11.65)
Mshare	-0.026 *** (-4.58)	-0.029 ** (-2.27)	-0.027 (-1.23)	-0.028 (-1.21)	-0.036 (-1.59)
Indep	0.000 (0.01)	-0.005 (-0.18)	0.026 (0.72)	0.003 (0.09)	0.012 (0.37)
Top10	-0.000 (-0.12)	0.000 (0.63)	0.000 (0.01)	0.000 (0.09)	-0.000 (-0.15)
FirmAge	0.110 *** (5.26)	0.131 *** (3.49)	0.054 (1.04)	0.091 * (1.74)	0.085 (1.64)
Cashflow	-0.104 *** (-11.88)	-0.127 *** (-7.86)	-0.142 *** (-6.52)	-0.139 *** (-6.39)	-0.137 *** (-6.77)
GDP	-0.003 (-0.48)	-0.010 (-0.91)	0.010 (0.63)	-0.009 (-0.45)	-0.012 (-0.77)
IndStr	-0.067 * (-1.79)	-0.142 ** (-2.15)	-0.218 ** (-2.25)	-0.195 ** (-2.17)	-0.180 ** (-2.15)
N	21608	21608	3650	4865	5973
R2_within	0.286	0.293	0.281	0.290	0.291
Year FE	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes

Table8 Other Robustness Tests

Table 8 presents the result of other robustness tests. Columns (1) present the result using alternative measures of LS. This study defines the total compensation paid by a firm to its employees as "cash paid by the firm to its employees in the current period + (employee compensation payable at the end of the period - employee compensation payable at the beginning of the period)". The LS2 is measured as the ratio of total compensation to total operating revenues. Column (2) presents the result using province and year fixed effects. Column (3) presents the result using the robust standard errors clustered by industry. The definitions of these variables are provided in Table 2. T statistics computed with robust standard errors clustered by firm are reported in parentheses for columns (1) and (2). All continuous variables are winsorized at the first and 99th percentiles. \*\*\*, \*\*, and \* indicate significance at the 1%, 5%, and 10% levels, respectively (two-tailed).

	(1) LS2	(2) LS	(3) LS
LLM	0.020 *** (2.70)	0.008* (1.82)	0.009* (1.76)
Size	-0.026 ** (-2.55)	-0.026 *** (-3.39)	-0.027** (-2.10)
ROA	-0.363 *** (-7.05)	-0.257*** (-8.47)	-0.251*** (-4.75)
Lev	-0.002 (-0.05)	0.015 (0.67)	0.010 (0.51)
Growth	-0.026*** (-3.22)	-0.045*** (-8.56)	-0.046*** (-4.28)
Mshare	-0.057 (-1.30)	-0.012 (-0.41)	-0.020 (-0.64)
Indep	0.050 (0.75)	0.033 (0.71)	0.014 (0.29)
Top10	0.000 (0.76)	-0.000 (-0.04)	0.000 (0.08)
FirmAge	0.274** (2.02)	0.058 (0.96)	0.076 (1.13)
Cashflow	-0.132 *** (-3.24)	-0.136*** (-4.87)	-0.141** (-2.58)
GDP	0.026 (0.73)		0.009 (0.38)
IndStr	-0.501 ** (-2.44)		-0.226 (-1.34)
_cons	-0.136 (-0.24)	0.646*** (2.88)	0.597** (2.17)
Observations	2366	2348	2366
R2_within	0.137	0.278	0.279
Year FE	Yes	No	Yes
Pro*Year FE	No	Yes	No
Firm FE	Yes	Yes	Yes

### Table9 Bacon decomposition results

Table 9 presents the weights corresponding to the four groups resulting from the Bacon decomposition, along with their estimated coefficients.

Control Group Type	weights	estimated value
Treatment vs. Never treated	0.714	0.005
Earlier Group Treatment vs Later Group Comparison	0.188	0.008
Treatment vs. Already Treated	0.017	0.005
Later Group Treatment vs. Earlier Group Comparison	0.081	-0.002
DID-weighted estimation results		0.005

## Table10 Heterogeneous treatment effects

Table 10 presents the result of heterogeneous treatment effects tests. Columns (1) present the result using Stacked DID (Cengiz et al. 2019). Column (2) presents the result using S-A statistic (Sun and Abraham, 2021). Column (3) presents the result using the Imputation Estimation (Borusyak et al. 2022). The definitions of these variables are provided in Table 2. T statistics computed with robust standard errors clustered by firm are reported in parentheses. All continuous variables are winsorized at the first and 99th percentiles. \*\*\*, \*\*, and \* indicate significance at the 1%, 5%, and 10% levels, respectively (two-tailed).

	Stacked DID	SA DID	DID_Imputation
	(1)	(2)	(3)
	LS	LS	LS
LLM	0.009*	0.013**	0.013***
	(1.70)	(1.98)	(3.15)
Controls	Yes	Yes	Yes
Observations	3730	2366	2350
R2_within	0.240	0.281	0.280
Year FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes

Table11 Virtual Space-Time placebo test

Table 11 presents the result of virtual space-time placebo test. Column (1) presents the results of the regression using explanatory variables that are two years earlier. The definitions of these variables are provided in Table 2. T statistics computed with robust standard errors clustered by firm are reported in parentheses. All continuous variables are winsorized at the first and 99th percentiles. \*\*\*, \*\*, and \* indicate significance at the 1%, 5%, and 10% levels, respectively (two-tailed).

	(1)
	LS
LLM	0.008 (0.26)
Size	-0.021*** (-3.16)
ROA	-0.162*** (-7.19)
Lev	-0.042* (-1.78)
Growth	-0.040*** (-6.20)
Mshare	0.019 (1.15)
Indep	-0.071* (-1.86)
Top10	-0.000 (-0.01)
FirmAge	-0.010 (-0.16)
Cashflow	-0.058** (-2.44)
GDP	-0.017 (-1.19)
IndStr	-0.035 (-0.44)
_cons	0.950*** (4.02)
Observations	2198
R2_within	0.225
Year FE	Yes
Firm FE	Yes

Table12 Instrumental Variables Approach

Table 12 present the result of Instrumental Variables Approach. Columns (1) and (2) present the results using the IV approach for the first and second stages. We use the logarithm of the distance from a company to the nearest National Supercomputing Center. (IV1) and the application rate of LLMs in the same industry and year, excluding the company itself (IV2) as the instrumental variable. The definitions of these variables are provided in Table 2. T statistics computed with robust standard errors clustered by firm are reported in parentheses. All continuous variables are winsorized at the first and 99th percentiles. \*\*\*, \*\*, and \* indicate significance at the 1%, 5%, and 10% levels, respectively (two-tailed).

	(1) first LLM	(2) second LS
LLM		0.072*** (3.94)
IV1	-0.023* (-1.65)	
IV2	0.783*** (7.47)	
Size	0.046** (2.03)	-0.030*** (-4.04)
ROA	-0.081 (-0.80)	-0.245*** (-8.13)
Lev	-0.082 (-0.96)	0.018 (0.75)
Growth	0.007 (0.28)	-0.047*** (-8.45)
Mshare	0.023 (0.25)	-0.020 (-0.67)
Indep	0.153 (0.87)	0.001 (0.01)
Top10	-0.004*** (-2.69)	0.000 (0.82)
FirmAge	-0.651** (-2.51)	0.114* (1.88)
Cashflow	0.204* (1.76)	-0.155*** (-5.29)
GDP	0.024 (0.23)	0.009 (0.43)
IndStr	0.822 (1.39)	-0.257** (-2.31)
Observations	2,366	2,366
R2_within	0.078	0.183
Year FE	YES	YES
Industry FE	YES	YES

Table13 Mechanism test

Table 13 presents mechanism tests. Columns (1) present the result of optimize human capital structure. This study defines the human capital structure indicator (*Highedu*) as the ratio of the number of employees with a bachelor's degree or above to those with an associate degree or below. Columns (2) and (3) present the result of human-machine synergy. This study defines the *Lnstaff* as the total number of employees of firm *i* in year *t* after taking the logarithm. This study defines the *LnRevenue* as the logarithmic operating income of firm *i* in year *t*. Further, we define the interaction term of *LnStaff* with *LLM* as person and LLMs collaboration. The definitions of these variables are provided in Table 2. T statistics computed with robust standard errors clustered by firm are reported in parentheses. All continuous variables are winsorized at the first and 99th percentiles. \*\*\*, \*\*, and \* indicate significance at the 1%, 5%, and 10% levels, respectively (two-tailed).

	(1) Highedu	(2) LnRevenue	(3) LnRevenue
LLM× LnStaff			0.028*** (3.49)
LnStaff		0.334*** (5.52)	0.329*** (5.41)
LLM	0.114* (1.82)		-0.207*** (-3.11)
Size	-0.020 (-0.17)	0.567*** (10.04)	0.557*** (9.98)
ROA	-0.186 (-0.35)	0.825*** (6.33)	0.813*** (6.29)
Lev	-0.355 (-1.03)	0.104 (0.86)	0.108 (0.89)
Growth	0.080 (1.32)	0.241*** (9.16)	0.246*** (9.35)
Mshare	0.291 (0.82)	0.085 (0.58)	0.050 (0.34)
Indep	1.051 (1.19)	0.108 (0.57)	0.084 (0.44)
Top10	0.017*** (3.31)	-0.000 (-0.12)	-0.001 (-0.30)
FirmAge	0.344 (0.31)	0.294 (0.97)	0.416 (1.38)
Cashflow	-0.161 (-0.55)	0.295** (2.04)	0.298** (2.09)
GDP	-0.621 (-1.34)	0.309 (1.08)	0.295 (1.00)
IndStr	-2.101 (-1.34)	0.030 (0.05)	-0.018 (-0.03)
_cons	7.911 (1.39)	1.963 (0.60)	2.055 (0.62)
Observations	2366	2366	2366
R2_within	0.016	0.600	0.602

Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes

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**Table14 Heterogeneity Analysis of Financing Constraints**

Table 14 presents the heterogeneity analysis based on financing constraints. We group the SA index by its median into low financing constraint and high financing constraint groups and conduct group regressions. The definitions of these variables are provided in Table 2. T statistics computed with robust standard errors clustered by firm are reported in parentheses. All continuous variables are winsorized at the first and 99th percentiles. \*\*\*, \*\*, and \* indicate significance at the 1%, 5%, and 10% levels, respectively (two-tailed).

	(1)	(2)
	Low financing constraints	High financing constraints
	LS	LS
LLM	0.016*** (2.68)	0.001 (0.18)
Size	-0.032** (-2.04)	-0.025*** (-2.81)
ROA	-0.283*** (-6.16)	-0.244*** (-5.89)
Lev	0.025 (0.68)	-0.010 (-0.34)
Growth	-0.047*** (-5.67)	-0.046*** (-6.51)
Mshare	-0.061* (-1.67)	0.030 (0.74)
Indep	0.053 (0.77)	0.031 (0.54)
Top10	-0.000 (-0.16)	0.000 (0.30)
FirmAge	0.048 (0.32)	0.198*** (2.82)
Cashflow	-0.123*** (-2.84)	-0.174*** (-4.71)
GDP	-0.006 (-0.26)	0.306 (1.60)
IndStr	-0.254** (-1.98)	-0.386 (-1.60)
_cons	0.926* (1.68)	-3.011 (-1.43)
Permutation test	0.015*	
Observations	1183	1183
R2_within	0.290	0.327
Year FE	Yes	Yes
Industry FE	Yes	Yes

Table15 Heterogeneity Analysis of Labor Intensity

Table 15 presents the heterogeneity analysis based on industry type. We use the method of classification by factors of production to group regress all industries into industries with technology-intensive as well as industries with labor-intensive. The definitions of these variables are provided in Table 2. T statistics computed with robust standard errors clustered by firm are reported in parentheses. All continuous variables are winsorized at the first and 99th percentiles. \*\*\*, \*\*, and \* indicate significance at the 1%, 5%, and 10% levels, respectively (two-tailed).

	technology-intensive	labor-intensive
	(1)	(2)
	LS	LS
LLM	0.017 *** (3.47)	-0.005 (-0.75)
Size	-0.044 *** (-5.80)	-0.001 (-0.06)
ROA	-0.329 *** (-8.24)	-0.126 *** (-3.25)
Lev	-0.011 (-0.42)	-0.006 (-0.15)
Growth	-0.046 *** (-6.93)	-0.043 *** (-5.10)
Mshare	-0.011 (-0.32)	-0.040 (-0.95)
Indep	-0.010 (-0.22)	0.114 (1.31)
Top10	0.000 (0.47)	-0.000 (-0.23)
FirmAge	0.095 (1.44)	0.074 (0.66)
Cashflow	-0.159 *** (-4.85)	-0.115 *** (-3.17)
GDP	0.031 (1.20)	-0.035 (-0.42)
IndStr	-0.358 ** (-2.31)	0.102 (0.77)
_cons	0.754 ** (2.26)	0.293 (0.31)
Permutation test	0.022*	
Observations	1676	690
R2_within	0.349	0.205
Year FE	Yes	Yes
Industry FE	Yes	Yes

**Table16 Heterogeneity Based on Degree of Industry Competition**

Table 16 presents the heterogeneity analysis based on the degree of competition in the industry. We use the operating income share of the top four companies in the industry to measure the degree of competition in the industry, and divides the entire sample into industries with high degree of competition and industries with low degree of competition for group regression. The definitions of these variables are provided in Table 2. T statistics computed with robust standard errors clustered by firm are reported in parentheses. All continuous variables are winsorized at the first and 99th percentiles. \*\*\*, \*\*, and \* indicate significance at the 1%, 5%, and 10% levels, respectively (two-tailed).

	(1)	(2)
	High degree of competition in the industry LS	Low degree of competition in the industry LS
LLM	0.014 *** (2.66)	-0.016 (-1.62)
Size	-0.036 *** (-3.09)	-0.003 (-0.26)
ROA	-0.304 *** (-6.38)	-0.109 *** (-3.35)
Lev	-0.003 (-0.08)	-0.009 (-0.29)
Growth	-0.059 *** (-6.56)	-0.034 *** (-4.42)
Mshare	0.001 (0.02)	-0.114 ** (-2.53)
Indep	-0.068 (-1.10)	0.073 (1.04)
Top10	-0.000 (-0.09)	0.001 (0.89)
FirmAge	0.055 (0.67)	0.100 (1.18)
Cashflow	-0.161 *** (-3.99)	-0.110 *** (-3.14)
GDP	0.062 (1.07)	-0.034 (-1.36)
IndStr	-0.222 (-0.92)	0.008 (0.08)
_cons	0.317 (0.49)	0.325 (0.88)
Permutation test	0.031 ***	
Observations	1317	1049
R2_within	0.381	0.166
Year FE	Yes	Yes
Industry FE	Yes	Yes

Table17 Heterogeneity of firms' large model characteristics

Table 17 presents the heterogeneity analysis based on *LLM*. We define *LLM\_Self* as 1 for self-development LLMs and 0 otherwise, and *LLM\_Co* as 1 for in cooperation with major AI firm and 0 otherwise. Column (1) presents results by incorporating these two dummy variables into Model (1). We define *LLM\_Cus* as 1 when a firm applied LLMs to customer service and 0 otherwise, and *LLM\_Non-Cus* as 1 when a firm applied LLMs to other fields and 0 otherwise. Column (2) presents results by incorporating these two dummy variables into Model (1). The definitions of these variables are provided in Table 2. T statistics computed with robust standard errors clustered by firm are reported in parentheses. All continuous variables are winsorized at the first and 99th percentiles. \*\*\*, \*\*, and \* indicate significance at the 1%, 5%, and 10% levels, respectively (two-tailed).

	(1)	(2)
	LS	LS
LLM_Self	0.013** (2.39)	
LLM_Co	0.004 (0.96)	
LLM_Cus		0.010* (1.85)
LLM_Non-Cus		0.006 (1.29)
Size	-0.027*** (-3.68)	-0.027*** (-3.66)
ROA	-0.250*** (-8.40)	-0.251*** (-8.39)
Lev	0.010 (0.44)	0.010 (0.43)
Growth	-0.046*** (-8.57)	-0.046*** (-8.55)
Mshare	-0.019 (-0.67)	-0.019 (-0.69)
Indep	0.013 (0.29)	0.013 (0.29)
Top10	0.000 (0.15)	0.000 (0.09)
FirmAge	0.068 (1.17)	0.076 (1.28)
Cashflow	-0.142*** (-5.26)	-0.141*** (-5.23)
GDP	0.008 (0.36)	0.009 (0.41)
IndStr	-0.228** (-2.07)	-0.225** (-2.04)
_cons	0.633** (2.15)	0.599** (2.04)
Observations	2366	2366
R2_within	0.281	0.279

Year FE	Yes	Yes
Industry FE	Yes	Yes

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