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Research Article

Exploring the Dual Impact of AI on Employment and Wages in Chinese Manufacturing

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Abstract

Purpose- This study investigates AI's impact on employment and wage dynamics within the manufacturing sector.

Design/Methodology- Utilizing data from 3,522 manufacturing firms between 2007 and 2021, we analyze the effects of AI adoption on labor markets.

Findings- AI adoption correlates with reduced employment numbers yet enhances wage rates, with some employees seeing wage increases as high as 83.86%. Heterogeneity analysis reveals variability in these impacts, dependent on contextual factors. The deployment of artificial intelligence in manufacturing sectors leads to an upgraded wage structure, emphasizing the importance of advancing individual professional skills to capitalize on these wage improvements. Additionally, compared to larger firms in the eastern region, small and medium-sized enterprises in the central and western regions stand to gain more substantially from the integration of artificial intelligence technology.

Practical Implications- Policymakers need targeted interventions to address job losses while leveraging wage growth benefits, emphasizing reskilling and inclusive AI integration strategies. The study provides empirical evidence on AI's dual effect on employment and wages, offering nuanced insights into sector-specific AI consequences.

Introduction

The expanding use of Artificial Intelligence (AI) across diverse domains has drawn significant attention concerning its influence on the employment market. Numerous studies delve into AI's effects on workforce demand and work conditions and its multifaceted impact on the digital economy across various sectors (Meng, 2021). The rise of AI represents a technological revolution, presenting opportunities and challenges in employment dynamics worthy of exploration. This is the motivation behind our study. In this study, we provide an all-encompassing and systematic perspective by analyzing pertinent research, thus enhancing our understanding of the interaction between AI and the employment market.

Considered central to the Fourth Industrial Revolution, AI is a critical technological driver of nations' socio-economic development. China's focus on the digital economy has led to increased high-tech employment and decreased labor-intensive and medium-technology industries (Meng, 2021). These policies are highlighted in the "Fourteenth Five-Year Plan and Long-Term Goals for 2035" (Republic of China National Development and Reform Commission, 2021, p. 48). AI is quickly evolving and merging with traditional sectors in the digital economy, emerging as a powerful growth engine. Nevertheless, it also has systemic implications for the employment market. The complex relationship between AI and employment, especially in China's unique economic landscape, represents a research gap that this study aims to fill.

AI exhibits robust permeability as a general-purpose technology, seamlessly integrating into various economic activities, including production, distribution, exchange, and consumption. Unlike previous technological advancements, AI extends into non-traditional work tasks, resulting in a marked increase in labor income (Xiao et al., 2022) and enabling unprecedented levels of automation to replace human effort (Wang et al., 2022).

A new era characterized by AI and industrial transformation has emerged due to recent advances in science and technology. The Chinese government has enacted a series of relevant policies to guide the growth and innovation of high-tech industries (Hui & Yang, 2022), address the aging population's impact on economic development (Ma & Shen, 2021), and work towards industrial digitization and intelligent transformation (Wang et al., 2022). Understanding the influence of these policies on AI development in China is a significant aspect of our research.

AI was included as a critical task in the State Council's "Guiding Opinions on Actively Promoting the 'Internet Plus' Action", issued in July 2015, which catalyzed AI's advancement in China to a new stage. In 2017, the "Development Plan for the New Generation of Artificial Intelligence" was released, presenting a three-step strategy for advancing AI to the level of national strategy. In 2019, the "Government Work Report" promoted AI to "Intelligent Plus," and the "Principles of Responsible Development of the New Generation of AI" represent the first articulation of AI governance principles. In addition, the "Fourteenth Five-Year Plan" identified the new generation of artificial intelligence as one of seven critical frontier science and technology areas.

Given AI's swift growth in China, its vast employment base, and workforce imbalances, it is crucial to understand AI's employment impact. This represents the main objective of our study. As a global manufacturing powerhouse, China's manufacturing sector is crucial to its national economic development, ensuring overall employment equilibrium through stable manufacturing employment. Our research will contribute to a more holistic and higher-quality understanding of AI's impact on employment in China's manufacturing sector.

China is experiencing a critical transition from high-speed to high-quality economic development. As demographic dividends diminish and the population ages, the impetus for upgrading and transforming the manufacturing sector has steadily increased. The study also aims to explore the challenges and opportunities for adapting to industrial digitization and intelligent transformation in China, given its sizeable working-age labor force and educational disparities.

For low- to medium-skilled workers struggling with technological progress, the employment imbalance is shifting from quantity to quality concerns (Ding et al., 2018). This denotes that AI's rapid promotion and application are likely to exert a more profound impact on employment for low- to medium-skilled labor in China than in developed countries.

The transition to intelligent manufacturing has sparked public concern regarding the employment market. Are there any implications for employment positions within manufacturing enterprises because of AI's rapid development? How will it affect the compensation levels of employees in the manufacturing sector? This study aims to quantify AI's impact on employment and wages within China's manufacturing sector and provide policy recommendations. We can avert the unfounded panic about robots replacing humans amidst the irrevocable technological revolution and industrial transformation by understanding how AI affects manufacturing employment. This study analyzes the impact of AI applications on employment in manufacturing enterprises, focusing on publicly listed A- share companies linked to AI.

Literature Review

The Impact of Artificial Intelligence on Employment Scale

There are three primary perspectives on AI's impact on employment.

Positive View: Proponents believe that AI's job creation effect surpasses its substitution impact, leading to higher employment levels. Artificial intelligence will create new jobs, industries, and models, increasing the demand for the corresponding labor force. Technology-related jobs include artificial intelligence trainers and intelligence-assisted (IA) positions, which contribute to the need for labor adaptable to new technologies (Korinek & Stiglitz, 2021). As a complementary tool for improving labor productivity, artificial intelligence directly increases labour's marginal productivity and the demand for labor. In the United States, OpenAI predicts that 15% of tasks can be completed faster, and with the right software and tools, this proportion will increase to 47%–56% (Eloundou et al., 2023). In the future, artificial intelligence can assist labor on a larger scale, resulting in higher production efficiency. In their European Union manufacturing data study, Gregory et al. (2016) found that automation technology increases labor demand more than job substitution. Trajtenberg (2018) states that artificial intelligence improves productivity by requiring more labor participation in production.

Furthermore, Bessen (2019) suggested that computers and artificial intelligence have reduced manufacturing jobs and increased employment in other industries. Acemoglu and Restrepo (2019) believed that in the long term, with improved social productivity, artificial intelligence will create many new positions, resulting in a more significant job creation effect than job substitution, promoting overall social development. He Qin and Qiu Yue (2020) found that artificial intelligence significantly positively affects employment scale through product innovation. A study by Peng Yingying and Wang Xinyu (2020) examined the employment of 270 manufacturing companies in Guangdong Province. It concluded that artificial intelligence increases employment through the creation effect when certain positions are replaced. Huang Zeqing and Chen Xiangguang (2022) argued that in the current stage of the use of artificial intelligence, there are hidden aspects like algorithm updates, data screening, and non-programmable work decomposition that require the participation of the labor force and create some jobs that are not obvious.

Negative View: Critics argue that AI will decrease employment as its substitution impact surpasses its creation effect. In recent years, robots that represent artificial intelligence have started to replace labor for routine tasks in production workshops. By the end of 2022, with the emergence of generative artificial intelligence represented by ChatGPT, it had begun to replace work previously defined as non-routine tasks, such as copywriting, data analysis, and image generation. Due to AI advancements, enterprises have restructured their production processes, reducing labor demands. Under the background of "intelligent manufacturing," advanced intelligent technologies have changed the production process and given rise to small-batch and customized, flexible production methods, reducing the labor demand per unit of production, especially for low-skilled positions in traditional manufacturing industries (Wang Linhui et al., 2020). Frey and Osborne (2017) analyzed data from over 700 occupations using a probabilistic classification model. They found that approximately 47% of occupations, including logistics services and office clerks, would be replaced in the short term. Acemoglu and Restrepo (2017), in their empirical study on the impact of industrial robots on manufacturing employment, found that the substitution effect of new technology on the labor market outweighs the creation effect. Acemoglu and Restrepo (2020) conducted a study indicating that seven workers are displaced for each additional robot employed, and there is little evidence to suggest that employment growth in other sectors can offset these losses. Rolf (2021) even stated that traditional job positions will gradually disappear with the rapid development of machines and automation. Using data samples from listed companies from 2003 to 2014, Bai Jun et al. (2018) analyzed the relationship between technological innovation and employment growth. They concluded that enterprise innovation has a substitution effect on employment growth. According to Yan Xueling et al. (2020), artificial intelligence significantly affects employment positions in the manufacturing industry, especially for low-skilled workers. Drawing from the innovation diffusion theory, He Qin et al. (2020) developed a mechanism model for the impact of artificial intelligence on employment based on panel data from 115 manufacturing companies. They found that adopting AI technology harms the number of employees in the manufacturing industry. Using data collected from microenterprises and laborers, Cui Yan (2022) hypothesized that new technologies like artificial intelligence would lead to job tasks becoming routinely automated through intelligent systems.

Uncertain View: Some scholars contend that AI's immediate impact on employment remains uncertain, emphasizing the need for additional research. Liu Taoxiong et al. (2021) argued that a smooth adjustment of industrial structure would determine whether artificial intelligence will significantly affect overall employment in China. Acemoglu et al. (2020), through empirical analysis of online job vacancy data, found that artificial intelligence is replacing some human jobs. However, it is still being determined how much it will impact the overall labor market. Based on LASSO regression and random forest methods, Xie Lu et al. (2019) suggested that new technology has intertemporal effects. Matuzeviciute et al. (2017) argued that technological progress has both "substitution effects" and "compensation effects" on employment positions, and the overall effect is uncertain. According to Brynjolfsson et al. (2018), the role of artificial intelligence in the labor market will vary according to the stages of its development. As a result, it is not possible to judge the impact of artificial intelligence on employment in the short term. Xue Zaixing's (2018) investigation identified both pros and cons of AI for college students' employment. However, since it depends on several social, political, and cultural factors and technological advancement, it is currently necessary to determine the net effect. According to Wang Jun et al. (2017), even though technological advancements may cause technological unemployment or structural unemployment in the short term, the creation effect may outweigh the destruction effect in the long run. Based on Cai Xiao and Huang Xumei's (2019) findings, AI technology impacts employment differently depending on the dynamic changes in substitution and creation effects.

The Impact of Artificial Intelligence on Wage Income

Three primary perspectives are prevalent in current research concerning the impact of artificial intelligence on wage income.

In the first instance, some scholars contend that, as low-skilled labor is displaced from the market, high-skilled workers will benefit from the complementary effects of artificial intelligence. This will result in an increase in income due to artificial intelligence. Using artificial intelligence, Yang Xiaofeng (2018) demonstrates that it enhances human capital in manufacturing, optimizes the distribution structure, and raises average wages. Peng Yingying and Wang Xinyu (2020) observed a significant rise in employee income with the shift to automation. From their micro-level analysis, Cheng Hong et al. (2020) determined that artificial intelligence positively influences employee income.

The opposing view posits that the substitutive effect of artificial intelligence on labor leads to firms curbing their labor investment, resulting in reduced worker income. Through a two-stage overlapping generation model, Benzell et al. (2015) deduced that high-productivity artificial intelligence reduces labor inputs and wages. By analyzing data from 31 Chinese provinces from 2009 to 2017, Meng Yuanyuan and Chen Jin (2019) asserted that economic growth diminishes the positive effect of artificial intelligence on wage scales and labor quality.

The third stance argues that artificial intelligence's overall influence on wage income is inconclusive. As per Cai Yuezhou and Chen Nan (2019), advancements in artificial intelligence mainly cause a structural shift, redistributing income from low-skilled to high-skilled workers while keeping the overall amount relatively unchanged.

Mechanism Analysis and Research Hypotheses

The diverse academic opinions on artificial intelligence's employment impacts derive from an overly focused approach to particular effects. Skeptics may overrate the substitution speed of artificial intelligence, while optimists might exaggerate the employment potential of emerging technologies. This research posits that artificial intelligence in China is still nascent. Predominantly, it is deployed at the forefront of production and manufacturing, targeting labor substitution to curtail production costs. However, the extensive application of artificial intelligence can bolster labor productivity, thus reducing production factor costs. As companies invest more in artificial intelligence, labor substitutions might increase, but the count of employees substituted by artificial intelligence might dwindle as the AI adoption rate surges. Empirical findings from Acemoglu and Restrepo (2017, 2020) and Frey and Osborne (2017) underscore the risk of job displacement due to AI, supporting the prediction that AI adoption may reduce employment numbers in manufacturing sectors. Thus, this study presents Hypothesis 1. H1: The adoption of AI technology by manufacturing enterprises will harm the number of employees.

The development of AI technology affects not only the number of employees but also how wages are distributed. The allocation of capital by an organization determines employee wages. Due to the substitutive effect of artificial intelligence on labor, the preference for capital in enterprises shifts from human to AI technology. Nevertheless, at this stage, the application of artificial intelligence in enterprises is still in the stage of "human-machine collaboration." The demand for labor in enterprises is gradually shifting from quantity to quality.

Consequently, there is intense talent competition within the industry, and companies may choose to train current employees or recruit highly skilled individuals to fill high-demand positions. There will be an increase in employee wages due to factors such as improved productivity, improved skill levels, and a more competitive environment for talent. As the adoption rate of artificial intelligence increases, employee wage income will also increase. Studies by Yang Xiaofeng (2018), Peng Yingying and Wang Xinyu (2020), and He Qin et al. (2020) indicate that AI can enhance wage outcomes through improved productivity and the creation of higher-value roles, validating the potential for AI to increase employee wage income in the manufacturing industry. Therefore, this study proposes Hypothesis 2.

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H2: The adoption of AI technology by manufacturing enterprises will positively impact employee wage income.

Methodology

Data Source

Data for this research was sourced from the Oriental Fortune Choice website (http://www.eastmoney.com) and the Guotai'an database (http://www.gtarsc.com). This analysis uses panel data from A-share-listed manufacturing companies involved in artificial intelligence from 2007–2021. This study excluded ST, *ST companies, and samples with missing variables, resulting in a sample of 3522 listed firms. This study's shortcoming is that, while this dataset offers a robust foundation for analyzing trends in publicly listed manufacturing companies. Moreover, listed firms are subject to regulatory and shareholder scrutiny, which could influence the degree to which AI impacts their operational and wage decisions. Future research could address these limitations by incorporating a broader spectrum of firms, including small to medium-sized enterprises (SMEs) and startups, to provide a more comprehensive view of AI's impact across different business environments.

Model Specification

To examine the impact of artificial intelligence on the number of employees and wage income in the manufacturing industry, we designed the following panel data model:

$$\ln Empnum_{i,t} / \ln Wage_{i,t} = \alpha_0 + \alpha_1 \ln AI_{i,t} + \sum Control + \varepsilon_{i,t} \quad (1)$$

$$\ln Empnum_{i,t} / \ln Wage_{i,t} = \beta_0 + \beta_1 \ln AI_{i,t} + \sum Control + \delta Code_i + \theta Year_i + \varepsilon_{i,t} \quad (2)$$

Among them, "i" represents distinct firms, "t" represents different years, and ln(AIi, t) is the natural logarithm of the AI adoption level, reflecting the intensity of AI utilization within each firm. Σ Control represents a series of control variables, which include Capital Preference, Asset Size, Capital Deepening, Operational Capability, Product Innovation. The choice of each control variable reflects several dimensions of company behavior and market factors, grounded in their anticipated significance to the study's objectives and corroborated by research demonstrating their impact on employment and wage dynamics. To reduce heteroscedasticity and ensure the reliability of the results, all variables undergo a logarithmic transformation in the subsequent empirical process. $\varepsilon_{i,t}$ represents the residual term.

Equation (1) represents a fixed regression model with the company's number of employees and wage income as the dependent variables. It introduces equation (2), incorporating individual and time-fixed effects to address the issue of omitted variables caused by unmeasured factors. Here, "Code" and "Year" represent the company's and the year's individual effects. These equations are structured to robustly estimate the impacts of AI, controlling for a comprehensive set of factors that influence labor dynamics in the manufacturing sector. By applying a logarithmic transformation to all variables, we mitigate issues of heteroscedasticity and non-linearity, ensuring more reliable and interpretable results from our regression analysis. This methodological approach, guided by the work of Yan Xueling et al. (2020), is designed to provide a nuanced understanding of how technological advancements like AI are reshaping employment patterns and compensation structures in contemporary manufacturing environments.

Variable Description

Dependent Variables: This study analyzes the impact on manufacturing companies from the perspective of changes in the number of employees and wage income. The number of employees (Empnum) is characterized by the total number of employees in the company annually. Wage income (Wage) is the average wage at the end of the year, calculated as the disclosed total staff compensation and payroll expenses in the cash flow statement divided by the total number of employees of the listed company.

Explanatory Variable: The explanatory variable in this study is the adoption level of artificial intelligence (AI). In the manufacturing process, the adoption level of artificial intelligence is closely related to the number of employees, employment structure, and labor income of the company. He Qin et al. (2020) used the per capita value of the company's machine equipment to assess the adoption level of artificial intelligence. This value is derived by dividing the machine book value, as disclosed in the company's fixed asset statement, by the total number of employees.

Control Variables: The control variables are chosen based on their relevance to the company characteristics rather than specific regions or time periods, ensuring consistency across the sample. Based on existing literature, the empirical model selected the following indicators to control for a variety of essential characteristics of the company: Capital preference (precp), characterized by the ratio of research and development investment to staff compensation. The investment in artificial intelligence will inevitably result in a substitution effect on labor, impacting the company's capital allocation. As artificial intelligence increases productivity, companies tend to invest more in research and development, leading to an imbalance between labor and capital inputs, which affects wages and the number of employees. The total assets of the listed company used to calculate asset size (ass). The asset size of a listed company directly affects the number of employees and income.

Table 1 - Variables and Descriptions

Variable Type	Symbol	Variable Name	Measurement Indicator
Dependent Variables	Empnum	Number of Employees	Total number of employees in the company on an annual basis
	Wage	Wage Level	Average wage at the end of the year
Explanatory Variable	AI	Adoption Level of Artificial Intelligence	Machine book value divided by the total number of employees
Control Variables	precp	Capital Preference	Ratio of research and development investment to staff compensation
	ass	Asset Size	Total assets of the listed company
	fixcp	Capital Deepening	Investment in fixed assets
	ato	Operational Capability	Total asset turnover ratio of the company
	innovate	Product Innovation	Ratio of intangible assets' book value to total assets

Note: Data for this research was sourced from the Oriental Fortune Choice website (http://www.eastmoney.com/choice/) and the Guotai'an database (http://www.gtarsc.com).

Fixed asset investment, which the company's capital deepening (fixcp) represents. Capital deepening reflects the rate of capital accumulation, and a higher degree of capital deepening often indicates higher labor productivity, which will affect employment and wages.

Operational capacity (ato), calculated as the ratio of a company's total assets to its total assets. This indicator reflects the efficiency of the company's use of assets, and companies with more substantial operational capabilities tend to allocate funds to labor more reasonably.

The return on the company's net assets, which measures profitability (prof). Companies with more robust profitability also have a more substantial capacity to absorb funds and labor.

The book value of intangible assets to the company's total assets serves as a proxy for product innovation (innovate). Rapid technological advancements accelerate product innovation, and companies must invest in technological research and development to keep up with technological advances, indirectly reducing labor investment. Please refer to Table 1 for a detailed explanation of each variable.

Findings

The section begins by examining the descriptive statistics which consist of three sub periods; pre-crisis, during crisis and post-crisis.

Descriptive Statistics and Correlation Analysis

Descriptive statistics and correlation analysis are conducted as the initial step in the empirical analysis.

Descriptive Statistics

Firstly, descriptive statistics provide an overview of the variables under consideration. The results are presented in Table 2. The sample consists of 17,548 observations, and there are two dependent variables: lnEmpnum (natural logarithm of employee count) and lnWage (natural logarithm of wage income). The mean values of these variables are 7.779 and 11.567, respectively. To ensure the robustness of the regression analysis, both lnEmpnum and lnWage were tested for normality. The skewness and kurtosis statistics show that these variables are approximately normally distributed based on log-transformed realizations and are suitable for linear regression modeling. Similarly, the control variables lnprecp, Lnass, lnfixcp, lnato, lnprof, and lninnovate have a near-normal distribution, as evidenced by their proximity to mean values and standard deviations, which improves the robustness of our analysis.

The primary explanatory variable is lnAI. Featuring a mean value of 12.923 (SD = 1.058) ranging from 10 to 16, this variable quantifies AI technology adoption by representing the logarithmic ratio of machine book value to total employee count.

In addition to the primary explanatory variable, lnAI, our analysis incorporates several control variables. These include lnprecp, with an average of -4.294, indicating the firm's capital preference in technological innovation versus human capital expenditure.; Lnass, reflecting the total assets of the firms with a mean value of 22. 197; lnfixcp, denoting the firm's investment in fixed assets, averaging at 20.235; lnato, indicating the degree of automation within firms with a mean of -0.634; lnprof, illustrating profitability with a mean value of -2.653; and finally, lninnovate, expressing the firms' innovation capabilities, featuring an average of -3.537. The extreme values recorded in variables such as lnprecp (-9.3 to -2.2) and lnato (-2.2 to 0.84) signify outliers or firm-specific extremes that are essential for evaluating the influence of differing degrees of capital preference and operational efficiency on the dependent variables. Despite being flagged for their possible impact on regression estimations, these outliers are kept for thorough analysis.

Table 2 - Descriptive Statistics

VarName	Obs	Mean	SD	Min	Max
lnEmpnum	17548	7.779	1.216	5.4	11
lnWage	17548	11.567	0.515	10	13
lnAI	17548	12.923	1.058	10	16
lnprecp	17548	-4.294	1.343	-9.3	-2.2
Lnass	17548	22.197	1.309	20	26
lnfixcp	17548	20.235	1.683	16	25
lnato	17548	-0.634	0.564	-2.2	0.84
lnprof	17548	-2.653	0.858	-5.5	1. 1
lninnovate	17548	-3.537	1.060	-7.6	-1.3

Baseline Regression

The baseline regression results of the impact of AI adoption on employment in the manufacturing sector are presented in Table 3. 'CODE' represents company-specific fixed effects, controlling for invariant characteristics across firms, such as corporate culture and management strategies. 'YEAR' fixed effects account for annual changes that affect all firms, such as economic cycles or policy shifts, ensuring that our findings reflect true effects of AI rather than temporal fluctuations. 'INDUSTRY' fixed effects are used to adjust for sector-specific variables that might influence employment and wages, providing a clear analysis isolated from industry-related impacts. Together, these fixed effects help to accurately isolate the impact of artificial intelligence on employment and wage outcomes by controlling for company, time, and industry-specific influences.

The variables used in this analysis are the same as those described in the "Descriptive Statistics" section. The coefficient of -0.827*** for lnAI on employment (lnEmpnum) suggests a substantial negative impact, where an increase in AI adoption is associated with a decline in the number of employees. This reflects the automation of routine and repetitive jobs which AI can perform more efficiently than human workers. For instance, with a 1% increase in AI adoption (measured in natural log terms), we expect to see approximately a 0.827% decrease in the number of employees, holding other factors constant. This highlights a significant shift in labor requirements, reducing the demand for jobs that are susceptible to automation. The first four columns examine the effect of AI adoption on employee count, and the results consistently show a significant negative coefficient for the core explanatory variable, lnAI, regardless of controlling for individual and time effects. This confirms the validity of hypothesis H1, indicating that AI adoption suppresses the number of employees in manufacturing enterprises.

In recent years, China has increasingly emphasised AI and actively encourages and guides companies to adopt AI technologies. However, the overall application of AI in the country is still relatively early. Currently, AI is primarily used in simple and repetitive tasks. Manufacturing businesses are labor-intensive, and AI significantly impacts them because it can effectively replace many frontline positions with higher productivity. Thus, at this stage, AI adoption negatively influences the employee count in the manufacturing sector.

The last four columns of the table examine the effect of AI adoption on employee wage levels. The results indicate a significant positive impact of AI adoption on employee wages, supporting hypothesis H2. Based on the coefficients for AI adoption in the regression model, the percentage increases in wages are approximately 23.86% for a coefficient of 0.214, and 83.86% for a coefficient of 0.609.This suggests that traditional manufacturing industries have a significant demand for a large number of frontline workers, and the introduction of AI technology has replaced simple and repetitive assembly line work, resulting in a sharp decline in the number of employees. However, due to the constraints of AI technology development, the adoption of AI also generates a greater demand for high-skilled labor, requiring more qualified professionals with expertise and knowledge of cutting-edge technologies to complement the application of AI. Companies attract more high-quality and highly educated talents by offering higher salaries.

Additionally, employees, in order to avoid being replaced, continuously strengthen their knowledge and skills. Improving employee quality also contributes to an increase in their income levels. Therefore, at this stage, AI adoption has a significant positive impact on employee wage levels.

Table 3 - Baseline Regression Results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	lnEmpnum	lnEmpnum	lnEmpnum	lnEmpnum	lnWage	lnWage	lnWage	lnWage
lnAI	-0.340***	-0.827***	-0.882***	-0.880***	0.214***	0.609***	0.505***	0.504***
	(0.024)	(0.011)	(0.013)	(0.013)	(0.015)	(0.014)	(0.017)	(0.016)
lnprecp		0.023***	0.001	0.001		0.076***	0.030***	0.030***
		(0.004)	(0.004)	(0.004)		(0.006)	(0.005)	(0.005)
Lnass		0.258***	0.157***	0.166***		0.558***	0.363***	0.351***
		(0.008)	(0.012)	(0.011)		(0.010)	(0.015)	(0.014)
lnfixcp		0.683***	0.715***	0.708***		-0.425***	-0.366***	-0.358***
		(0.010)	(0.011)	(0.011)		(0.012)	(0.013)	(0.013)
lnato		0.123***	0.106***	0.108***		0.291***	0.251***	0.252***
		(0.009)	(0.009)	(0.009)		(0.015)	(0.014)	(0.014)
lnprof		-0.027***	-0.018***	-0.018***		-0.027***	0.006*	-0.007**
		(0.003)	(0.003)	(0.003)		(0.004)	(0.004)	(0.004)
lninnovate		0.022***	0.017***	0.017***		0.016***	0.005	0.007
		(0.004)	(0.004)	(0.004)		(0.005)	(0.005)	(0.004)
cons	11.272***	-0.900***	1.116***	1.103***	8.165***	0.411**	4.262***	4.254***
	(0.291)	(0.106)	(0.208)	(0.235)	(0.179)	(0.169)	(0.287)	(0.284)
CODE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
YEAR	Yes	No	Yes	Yes	Yes	No	Yes	Yes
INDUSTRY	No	No	No	Yes	No	No	No	Yes
N	17548	17548	17548	17548	17548	17548	17548	17548

t-statistics in parentheses: *** p<0.01, ** p<0.05, * p<0.1

Robustness Test

Endogeneity Test

Endogeneity can arise from three main factors: (a) omitted variable bias, as the panel data used in this study involves complex variable types and may have undisclosed data, leading to potential omitted variables that can bias the regression results regarding employment. (b) bidirectional causality, as the adoption of artificial intelligence can affect both the level and quantity of employees, while the reduction in employee count and the increase in wage levels can also influence a firm's capital investment in artificial intelligence. (c) sample self-selection, as financially stronger companies are more likely to undergo intelligent transformation, resulting in higher AI adoption. This may introduce sample self-selection issues.

By using the lagged value of the explanatory variable as an instrumental variable, this study addresses the endogeneity concerns arising from omitted variable bias and bidirectional causality. In order to identify the endogeneity of the regression results, the Two-Stage Least Squares (2SLS) method is employed to control individual and time effects. The instrumental variable regression results are presented in columns (a)-(c) of Table 4. Observing the results below, it is evident that, after controlling for endogeneity, the core explanatory variable, artificial intelligence adoption, has a significantly negative impact on the dependent variable of employee quantity and a positive and significant impact on the dependent variable of wage. These results hold at a significance level of 1%, indicating the robustness of the empirical findings presented earlier.

The R-squared values listed in Table 4 indicate the proportion of variance explained by the models for each dependent variable, providing insight into the goodness of fit. For instance, an R-squared of 0.961 for the impact of lnAI on lnEmpnum suggests that the model explains 96.1% of the variability in employee numbers, highlighting the strong explanatory power of the model setup for this aspect of the study.

Table 4 - Endogeneity Test

VarName	(a)	(b)	(c)
	stage 1	stage 2	
	lnAI	lnEmpnum	lnWage
L.lnAI	0.800***		
	(98.781)		
lnAI		-0.869***	0.262***
		(-169.625)	(36.774)
Constant	1.767***	-0.981***	7.091***
	(20.826)	(-12.446)	(76.537)
No of Obs.	12,116	12,116	12,116
R-squared	0.926	0.961	0.485
Controls	YES	YES	YES
YEAR	YES	YES	YES

t-statistics in parentheses,* p<0.01, ** p<0.05, * p<0.1**

Controlling for Firm Fixed Effects

Private enterprises have played an increasingly important role in economic development since the beginning of economic reforms. Due to the rapid technological advancements occurring today, private enterprises, with their flexibility and autonomy, have a more remarkable ability to adjust the level of AI adoption and the size of their labor force to meet the needs of their business. Differences in firm characteristics may lead to deviations in empirical results. To further examine the robustness of the empirical findings, this study extracts a subsample of private enterprises and conducts a robustness test. Observing the regression results, it can be seen that the test results are consistent with the baseline regression results and that the study's main conclusions are still valid.

Table 5 - Robustness Test - Controlling for Private Enterprises

	(a)	(b)	(c)	(d)
VarName	**lnEmpnum**	**lnEmpnum**	**lnWage**	**lnWage**
lnAI	-0.913***	-0.877***	0.330***	0.497***
	(-292.962)	(-209.677)	(60.805)	(76.156)
Constant	-0.292***	1.314***	5.847***	4.587***
	(-5.970)	(15.883)	(68.626)	(35.504)
Controls	YES	YES	YES	YES
No of Obs.	12,390	12,390	12,390	12,390
R-squared	0.961	0.938	0.419	0.743
CODE	NO	YES	NO	YES
YEAR	NO	YES	NO	YES

t-statistics in parentheses,* p<0.01, ** p<0.05, * p<0.1**

Heterogeneity Analysis

Regional Heterogeneity

AI technology levels and adoption likely vary across regions in China due to regional disparities in economic development, industrial structure, and production technology. The eastern region, benefiting from its geographical advantage and favorable policies of reform and opening-up, generally exhibits higher levels of development and technological advancement in the manufacturing industry than the central and western regions. The disparity arises from the eastern region's industries, which are more capital- and technology-intensive, facilitating AI adoption. This leads to a reduction in employee numbers while simultaneously increasing the demand for high-skilled workers and their wages. To further examine the impact of AI adoption on the number of employees and wage income in the manufacturing industry, this study uses the classification method Shao and Deng (2016) adopted to divide enterprises into eastern and central/western regions. It conducts regression analysis for each group to assess the impact of AI adoption. The regression results are presented in Table 6.

As shown in Table 6, most AI-related manufacturing enterprises are located in the country's eastern region. The impact of AI adoption on the number of employees shows a significant negative effect in both regions, with a more substantial negative effect in the eastern region. The eastern region's stronger influence can be attributed to economic development and the existence of industries that use more complex production processes. Artificial intelligence adoption significantly impacts the wage income of employees in the manufacturing industry in the eastern region rather than in the central/western region, indicating apparent regional heterogeneity. This phenomenon may be because the eastern region is more economically developed and consists primarily of technology-intensive and capital-intensive manufacturing enterprises. Due to the fierce competition among these enterprises in the technology field, they are required to invest more to attract high-tech talent and gain a competitive edge. This leads to a significant increase in employee wage income. In contrast, in the relatively slower-developing central/western regions, enterprises may need to be more responsive to AI.

Table 6 - Regional Heterogeneity

	(a)	(b)	(c)	(d)
VarName	**eastern region**	**central and western regions**	**eastern region**	**central and western regions**
lnAI	-0.880***	-0.891***	0.508***	0.501***
	(-206.650)	(-131.181)	(81.297)	(45.561)
Constant	1.093***	1.221***	4.497***	3.793***
	(12.869)	(9.462)	(36.088)	(18.162)
Controls	YES	YES	YES	YES
No of Obs.	12,791	4,757	12,791	4,757
R-squared	0.930	0.943	0.748	0.743
CODE	YES	YES	YES	YES
YEAR	YES	YES	YES	YES
t-statistics in parentheses, *** p<0.01, ** p<0.05, * p<0.1				

To address potential omitted variable bias across regions, several control variables are included in the regression models. These controls account for factors such as industry type, firm size, and regional economic characteristics. By controlling for these variables, we enhance the robustness of the model and ensure that the observed effects of AI on employment and wages are isolated from other region-specific or firm-specific characteristics. The R-squared values in Table 6 indicate how well the models fit the data. For employee count, the R-squared values are 0.930 for the eastern region and 0.943 for the central and western regions, showing that the model explains over 93% of the variance in employment levels across regions. For wage levels, the R-squared values are 0.748 and 0.743 for the eastern and central/western regions, respectively, indicating that the model explains approximately 74-75% of the variance in wages. These high R-squared values suggest a strong model fit, particularly in capturing regional differences in employment and wage outcomes. The constant terms in the model are also significant, providing baseline levels of employment and wages across regions. The constants for employment (1.093 in the eastern region and 1.221 in the central/western region) suggest baseline employment levels that are higher in the central and western regions, while the wage constants (4.497 in the eastern region and 3.793 in the central/western regions) indicate a higher baseline wage level in the eastern region. These constants provide insight into regional baseline differences, with the eastern region showing higher wages, likely due to more advanced industry structures and economic conditions.

Enterprises Size Heterogeneity

There are considerable differences among enterprises regarding their resource endowment, financial capacity, and technological research and development capabilities, primarily influenced by their size. Consequently, there is potential for heterogeneity in AI adoption capacity and asset allocation among companies of varying scales. According to the classifications provided on the official website of the National Bureau of Statistics of China, this study examines whether the influence of AI adoption on employee numbers and wage income varies by company size. Specifically, a large enterprise is defined by an operating income equal to or exceeding 400 million yuan and a workforce of 1,000 or more employees. In order to qualify as a medium- sized enterprise, an enterprise must have an operating income between 20 million and 400 million yuan and a staff strength of between 300 and 1,000 employees. Enterprises that only meet these criteria are categorized into a lower bracket once they satisfy the requirements for that specific category. Following this classification, we conduct a regression analysis, accounting for individual and temporal effects. The results of this analysis are detailed in Table 7.

From Table 7, it can be observed that AI adoption significantly negatively affects the number of employees for both large enterprises and SMEs. However, the effect is more substantial for large enterprises. Control variables have been added to the model to reduce the influence of confounding factors. These factors include the type of industry, the age of the firm and market conditions, which can potentially affect employment and wage levels. By introducing these control variables, the net effect of AI applications on the number of employees and wages can be more accurately estimated, improving the robustness and explanatory power of the model results. This could be attributed to large companies have the financial resources and technical capability to rapidly adopt and integrate AI technologies on a large scale, which can lead to significant productivity gains. However, replacing large numbers of low-skilled jobs will primarily achieve these efficiency gains. For example, large firms can afford the high upfront costs of AI systems, such as purchasing advanced equipment, recruiting and training skilled workers, and the ongoing costs of iterating and upgrading technology, allowing them to more fully replace repetitive jobs. As a result, workers in large firms experience the displacement effects of AI to a greater extent than workers in small and medium-sized firms. Conversely, SMEs typically face more limited financial and resource constraints when implementing AI technologies. SMEs generally lack the capital to cover the high upfront costs of AI systems, in particular the cost of purchasing equipment and technology. Furthermore, SMEs do not have the same talent pool and technical support as larger companies, making it difficult for them to adopt AI technologies quickly and use them effectively. As a result, SMEs are replacing workers at a relatively lower rate and scale when adopting AI, and the negative impact of AI on their overall workforce is somewhat limited.As a result, the application of AI technology in large enterprises is faster, leading to a more pronounced substitution effect on the number of employees.

Additionally, it is found that AI adoption has a significant positive effect on wage income for employees in large enterprises, while no significant effect is observed for SMEs. This phenomenon may be because large enterprises have more financial flexibility in investing in artificial intelligence technology, allowing them to increase employee wages while investing in AI technology. In contrast to this, SMEs are already facing greater financial pressures to further increase employee salaries due to limited financial resources during the introduction of AI. Due to limited flexibility, small and SMEs usually cannot attract and retain high-quality technical talent by increasing wages.This results in SMEs finding it more difficult to compete with larger firms in terms of wage levels after the application of AI, which may make it difficult to retain key technicians or highly skilled employees. Such economic constraints can lead to a loss of high-quality labour when SMEs adopt AI, to the detriment of their technological development. The R-squared score indicates that the model accurately predicts employment and salary levels. The employment regression model has an R-squared value of around 0.90 for both large enterprises and SMEs, indicating that it explains roughly 90% of the variation in the number of employees. In contrast, the R-squared value of the wage level regression model is about 0.70 for both large and SMEs, indicating that the model explains about 70% of the variation in wage levels. The higher R-squared values reflect the strong explanatory power of the model in capturing the main changes in employment and wage levels, thus adding credibility to the results of the analysis.

Table 7- Enterprises Size Heterogeneity

	(a)	(b)	(c)	(d)
VarName	**large enterprises**	**SMEs**	**large enterprises**	**SMEs**
lnAI	-0.884***	-0.843***	0.535***	0.501***
	(-167.229)	(-150.340)	(64.200)	(62.827)
Constant	1.500***	0.966***	3.598***	5.032***
	(11.551)	(7.994)	(17.560)	(29.274)
Controls	YES	YES	YES	YES
No of Obs.	7,731	9,817	7,731	9,817
R-squared	0.909	0.905	0.702	0.738
CODE	YES	YES	YES	YES
YEAR	YES	YES	YES	YES

t-statistics in parentheses: *** p<0.01, ** p<0.05, * p<0.1

Enterprises Nature Heterogeneity

Analyzing the impact of AI adoption across different enterprises, particularly differentiating between public and private entities, offers a deeper understanding of how ownership structures might influence the outcomes of integrating AI technologies.

As seen in Table 8, both public and private enterprises show a significant negative relationship between AI adoption and the number of employees. However, public enterprises exhibit a slightly more substantial negative effect with a coefficient of -0.909, compared to -0.877 for private enterprises. This suggests that incorporating AI might lead to a more pronounced reduction in the workforce in public enterprises than in their private counterparts. This could be due to public enterprises generally have more standardized work processes and a higher degree of bureaucratization. In public enterprises, the decision-making process and job tasks are often subject to stricter procedures and regulations, leading to a higher degree of repetitiveness and structuring in many job contents. As a result, the standardized processes and bureaucratic hierarchies within public enterprises are more susceptible to being replaced by artificial intelligence technologies, such as process automation or the application of decision-making algorithms. Private companies, on the other hand, are generally more flexible, their work processes and tasks are less standardized, and the content of their work can be more easily adapted to market demand, so the labor substitution effect of AI is weaker. Therefore, the labor substitution effect is more pronounced when AI is adopted by public enterprises.

On the wage front, both public and private enterprises exhibit a positive correlation between AI adoption and wage income. The coefficient for public enterprises stands at 0.538, slightly higher than the 0.497 for private enterprises. This indicates that AI adoption contributes to an increase in wage income for employees in public enterprises at a marginally higher rate than in private enterprises. A possible explanation for this could be that public enterprises, with their often-larger financial backing and state support, can invest more in AI technology and human capital. As they integrate AI into their operations, they might also invest in upskilling their employees, leading to increased wage compensation. On the other hand, while still seeing a positive impact on wages due to AI adoption, private enterprises might have more variability in their capacity to upscale wages, especially among smaller private entities. Private enterprises, especially smaller ones, on the other hand, face greater market pressures and higher operating costs, and are more constrained in terms of wage increases after the introduction of AI. These enterprises pay more attention to cost control in a fiercely competitive market and cannot raise wages as leisurely as public enterprises to retain highly skilled talents. Therefore, although the adoption of artificial intelligence has a positive impact on the wages of private sector employees, its growth potential is more limited compared to public sector enterprises.

In summary, while public and private enterprises in China's manufacturing sector witness workforce reductions with AI adoption, public enterprises seem slightly more affected. This phenomenon reveals the heterogeneous characteristics of enterprises with different ownership types in the process of AI automation, reflecting that public enterprises are more susceptible to AI substitution in more standardized processes. However, both types of enterprises see a wage increase with AI adoption, with public enterprises showing a marginally stronger positive effect. This wage disparity highlights the potential of public enterprises, under policy support, to improve employee skill levels and wage levels, whereas private enterprises may have limited capacity for wage growth due to market factors. This heterogeneity in the impact, based on the nature of enterprise ownership, underscores the need for tailored policy recommendations and strategies for AI integration across different enterprise types.

In table 8, the control variables ensure that the observed changes in employment and wages are primarily attributed to the adoption of artificial intelligence, rather than errors caused by changes in market conditions, industry differences, or firm size. Table 8 shows that the R-squared of the employment model is 0.920 (for public enterprises) and 0.938 (for private firms), which indicates that the model explains about 90% of the change in employment in both public and private enterprises. This high rate of explanation suggests that our model is able to better capture the impact of AI adoption on employment. In the wage model, the R-squared values of 0.753 (public enterprises) and 0.743 (private enterprises) indicate that the model explains about 74-75% of the variation in wages. These R-squared values indicate that the model of this study has high adaptability and reliability in explaining the impact of artificial intelligence on employment and wages across different types of enterprises.

Table 8 - Enterprises Nature Heterogeneity

	(a)	**(b)**	**(c)**	**(d)**
VarName	**Public Enterprises**	**Private Enterprises**	**Public Enterprises**	**Private Enterprises**
lnAI	-0.909***	-0.877***	0.538***	0.497***
	(-126.830)	(-209.677)	(53.208)	(76.156)
Constant	1.294***	1.314***	3.716***	4.587***
	(8.357)	(15.883)	(17.005)	(35.504)
Controls	YES	YES	YES	YES
No of Obs.	4,890	12,390	4,890	12,390
R-squared	0.920	0.938	0.753	0.743
CODE	YES	YES	YES	YES
YEAR	YES	YES	YES	YES

t-statistics in parentheses, *** p<0.01, ** p<0.05, * p<0.1

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Conclusion

The incorporation of artificial intelligence (AI) in Chinese manufacturing enterprises manifests a notable substitutive effect on employment. In the short term, AI adoption may result in job displacement as automation replaces some tasks. However, in the long run, AI integration may create new job possibilities, such as those in AI maintenance, oversight, and human-AI collaboration roles that require specialized skills. While AI in China is still nascent, with a confined application spectrum, its profound amalgamation with manufacturing might precipitate a decline in employee numbers in the imminent future — nevertheless, the long-term ramifications of AI on employment mandate augmented scrutiny and study. For instance, as AI matures, potential new job avenues may emerge, such as positions in AI-driven innovation, human-machine interface design, or data analysis.

The deployment of AI technology in the manufacturing sector is poised to escalate employee wage structures. To allure adept labor consonant with the elevated proficiency prerequisites of AI, firms augment salaries. Concurrently, enhancing individual expertise in the workforce also bolsters wage brackets. For instance, as AI becomes integrated, a collaboration between human workers and AI systems could create hybrid roles that combine domain expertise with AI interaction, leading to higher value roles and, consequently, higher wages. The influence of AI on remuneration in the manufacturing domain reveals pronounced disparities. Specifically, while larger corporations in the eastern regions are more likely to benefit from AI due to advanced resources and infrastructure, SMEs in the central and western vicinities may face challenges in adopting AI technology due to limited resources and technical expertise. Such differences highlight the importance of stakeholder collaboration to ensure that the benefits of AI are distributed equitably across regions and enterprise sizes.

Moreover, the ethical implications of AI in potentially displacing jobs should also be critically examined, considering the broader societal implications. Ethical and responsible use of AI need legislative frameworks. Safeguards for vulnerable employees and reskilling initiatives to help those who have lost their jobs find new ones are both necessary.

In light of the determinations mentioned above, these policy advisories are proffered:

Grasp the substitutive impact of AI astutely. With AI's rapid advancements, the imminent automation of specific roles is anticipated, culminating in potential job redundancies. Industries should initiate bespoke training modules for diverse roles to expedite the realization of a symbiotic "human-AI collaboration" paradigm. Concurrently, government and industry could collaborate to develop modular training programs inspired by successful models, such as Germany's dual training system, which combines in-company training with classroom education. This approach could provide workers with practical AI-related skills. Government agencies might also establish partnerships with key industries to co-fund reskilling programs, and focus on frontline industrial workers most vulnerable to AI's disruptions.

Capitalize on the human capital augmentation opportunities ushered in by AI. AI adoption is expected to boost wages, particularly for workers who possess advanced skills to operate and collaborate with AI technologies. As industries integrate AI, roles requiring hybrid skills that blend domain expertise with AI competencies are likely to grow. This trend is leading to wage increases as employers compete for qualified talent, creating an incentive for continuous skill development among the workforce. AI adoption is driving demand for professionals who can work alongside AI, particularly in roles requiring data literacy, problem-solving, and technical skills. In tandem, state entities should promote initiatives that fund or subsidize technical education programs, consistently channeling avant-garde talents to industries.

Comprehend the application breadth and magnitude of AI judiciously. Given that AI's repercussions on employment oscillate based on regional and enterprise dimensions, the state should craft and enforce germane policies resonating with local exigencies as industries assimilate AI. For regions such as the central and western areas, it is important to build the basic infrastructure for AI and offer SMEs financial incentives to use AI technology. These regions can build AI innovation hubs through public-private partnerships. This can serve as a catalyst for regional AI integration and a training ground for SME employees. In the eastern region, where high-skilled labor is more prevalent, policies should focus on upskilling initiatives that enhance the AI capabilities of the existing workforce. This could include subsidized training programs in advanced AI applications and support to transform industries into technology-intensive enterprises.

Additionally, state bodies should also provide guidance and support for SMEs as they begin to adopt AI. Tailored support such as simplified access to AI technologies, subsidies for AI training programs, and specialist consultancy services for AI adoption, will help SMEs overcome initial hurdles and integrate quickly into the new industrial landscape.

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