

The Impact of Artificial Intelligence on China's Labor Market

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Abstract: This research explores the effects of artificial intelligence (AI) on the labor market across various regions of China, using provincial-level data from 2006 to 2022. To address issues of reverse causality and ensure analytical accuracy, a fixed-effects distributed lag model is employed. The study investigates three key dimensions: total employment, wages, and employment across different skill levels. COVID-19 indicators are included to account for policy changes and economic fluctuations. The results reveal a relationship between the rising adoption of AI and employment opportunities for low- to medium-skilled workers; however, high-skill occupations appear less affected. Evidence also suggests that the integration of AI technologies influences wages, consistent with the assumptions of skill-biased technological change (SBTC). These findings provide empirical confirmation of the disruptive impact of AI on the Chinese labor market, offering insight into how technological advancement affects employment in emerging economies. The study offers guidance for policymakers and corporate leaders addressing labor challenges in an AI-driven economy.

Keywords: AI, Employment Structure, Total Employment, Wage

1. Introduction

Artificial intelligence (AI) is described as the ability of machines to replicate human intellectual capabilities so that they can perform sophisticated tasks with greater efficiency and precision than human workers (Ertel, 2018). Its core capabilities, such as pattern recognition, decision-making, and process automation, have led to its widespread adoption across various sectors (Flasiński, 2016). Although AI concepts were conceived in the 20th century, the pace of advancement of digital technology in the 21st century has significantly accelerated its development and application (Liu et al., 2018). AI is now revolutionizing industries by enhancing efficiency and streamlining processes. In healthcare, for instance, robotic surgeries are enhancing precision and shortening patient recovery times (Wang et al., 2019). In marketing, consumer insights powered by AI support the development of personalized advertising strategies (Gkikas & Theodoridis, 2022). Similarly, in industry, AI improves logistics, quality, and operational efficiency, and hence it is a key driver of industrial modernization (Akerkar, 2019).

The growing application of artificial intelligence in economic frameworks has sparked a lot of controversy about its effects on the job market. On the bright side, artificial intelligence boosts productivity through augmenting human decision-making and assisting companies in maintaining their competitive edge (Makridakis, 2017). AI-powered predictive models assist workers in making informed, data-driven choices, thus improving efficiency across various sectors (Agrawal et al., 2019). On the other hand, there have been fears about the possibility of job displacement due to AI's growing automation of routine and repetitive processes. Industries like manufacturing and customer services have already faced heightened AI integration, decreasing the need for human workers in certain positions (Webb, 2019). Aside from job displacement, AI also alters wage structures as it reconfigures labor demand. As low-skilled jobs are substituted with automation, salaries for these roles may decrease, and demand for high-skilled workers in AI-intensive industries rises, boosting income inequality (Georgieff, 2024).

These labor market changes are particularly applicable in China, a nation transitioning from a labor-intensive to a technology-driven economic system (Shi, 2019). China, with a workforce of more than 750 million individuals, offers a distinctive environment for examining AI's effects on jobs since it has a dense mixture of low-skilled and high-skilled labor. Unlike more mature

economies—where AI mainly enhances productivity in existing high-tech sectors—China's economic structure causes AI to both displace low-skilled jobs and generate new opportunities in technology-driven industries. Grasping this dual impact is essential for analyzing AI's broader effects on employment structures.

Although the discussion around artificial intelligence and labor markets has been largely centered on advanced economies, especially those of Europe and North America, the effects of AI on employment in emerging economies have not been researched much. With China's speedy technological progress and specificities of its labor market, a study of developments in its AI-influenced labor market may assist in filling this research gap and also offer results relevant for other emerging countries with similar developments in progress.

2. Literature Review

2.1. Theories

The interaction between technological progress and labor dynamics has been a topic of debate among researchers. Early economists like Marx argued that machines replace labor to enhance productivity but also lead to job losses (Wang, 2020). Marshall highlighted the benefits of mechanization in improving efficiency and enabling improved specialization of functions (Marshall, 2013). Schumpeter introduced the term "creative destruction," showing how new technology can break existing job patterns while opening paths to new roles and industries (Barbieri et al., 2019). Samuelson noted the interaction between technological innovation and wage changes, suggesting that if productivity rises due to technological advancements, then so do wages (Samuelson & Nordhaus, 2010). Recent research by Acemoglu examined the influence of technological advancement on the skills of the labor force based on the Skill-Biased Technological Change (SBTC) theory. The research shows that technological advancement is expected to favor some kinds of workers more than others, hence increasing wage gaps across various skill levels (Acemoglu, 2002). Further, the Routine-Biased Technological Change (RBTC) theory builds on this model by showing how automation primarily replaces routine tasks of jobs, resulting in job polarization (Lago & Biagi, 2018).

2.2. Empirical Evidence

Job Loss: AI-driven automation has led to job displacement across economies. In Europe, Chiacchio et al. (2018) found that every additional robot per 1,000 workers reduces employment by 0.16%-0.20%. In the U.S., Acemoglu & Restrepo (2020) reported that industrial robots decrease employment-to-population ratios by 0.2% and wages by 0.42%. In China, Zhou et al. (2020) estimate that AI may cut up to 278 million jobs by 2049, hitting low-income and less-educated workers the hardest.

Job Creation: AI also generates employment. Balsmeier & Woerter (2019) found that AI-related job postings in the U.S. increased significantly between 2010 and 2019. In Germany, Dauth et al. (2017) reported that while industrial robots reduce manufacturing jobs, they create jobs in non-manufacturing sectors. In China, Gu et al. (2022) found that AI expansion positively affects employment in the service sector, as AI-driven efficiency gains stimulate demand and create new job categories.

Impact on Wages: The effect of artificial intelligence on wages is not uniform for everyone. Berger and Frey (2016) assert that sectors with a high dependence on technology tend to experience an increase in wages since firms require employees with special complementary skills. Conversely, Frey and Osborne (2017) identified lower-paid jobs as the most susceptible to automation. Likewise in a different context, the study conducted by Borland and Coelli (2017) in Australia showed that technological advancement has remained a major driver of widening wage disparities between skilled and less-skilled labor. Similarly, Jiang et al. (2024) found a similar pattern in China, where AI mainly helps skilled workers, leaving less-skilled workers behind and widening the wage gap.

Impact on Employment Structure: AI is also altering the nature of available jobs, with various skill groups being impacted differently. Autor et al. (2006) explained how America went through "job polarization," i.e., middle-class jobs began to vanish, and high- and low-wage jobs grew. Likewise, Acemoglu et al. (2022) concluded that the new job opportunities being generated by AI require more sophisticated skills. In China, the changes have been most notable in Eastern provinces. Xie et al. (2021) discovered that AI has contributed to more rapid job displacement for low-skilled occupations than increased employment for high-skilled occupations, significantly reshaping the local labor market.

3. Research Methodology

3.1. Conceptual framework

AI adoption directly affects employment levels, wage levels, and employment structure. As the adoption of AI technology increases, employment levels in the labor market may be affected, wage structures may evolve, and the distribution of employment across different skill levels may shift. Control variables may influence the relationship between AI adoption and employment as well as employment structure. For instance, a growing GDP typically leads to higher employment levels as economic expansion creates more job opportunities. Conversely, a shrinking GDP may result in job losses. Urban areas generally offer higher wages compared to rural areas due to the higher cost of living and greater demand for skilled labor. R&D investment can drive job creation in high-tech sectors by fostering innovation but may also lead to job losses in routine tasks due to automation. Social security spending influences employment by affecting labor participation—higher benefits may reduce work incentives, while economic stability from social support can boost consumer demand and job opportunities.

3.2. Data

This study examines the effects of AI on China's employment, wage dynamics, and labor market structure. The study is based on provincial panel data from 2006 to 2022 and includes 22 provinces, 4 municipalities, and 5 autonomous regions. The core independent variable is AI adoption, measured by the number of AI-related patents per province per year. AI patent data was collected based on the *Key Digital Technology Patent Classification System (2023)* issued by the China National Intellectual Property Administration. Using the technical branches under AI as keywords, patents were retrieved from the Wanfang database. The dataset was filtered to include only domestic, authorized invention patents from 2006 to 2022, given their higher technical standards. All data for the dependent and control variables were obtained from the National Bureau of Statistics of China, the China Labor Statistics Yearbook, and the China Statistical Yearbook.

3.3. Methodology

The econometric analysis employs a Fixed Effects Model (FEM) to account for unobserved heterogeneity across provinces. The appropriateness of the fixed effects specification is confirmed by the Hausman test, which is shown in Table 1.

Table 1. Hausman test

Test	Chi-squared	p-value	Preferred Model
Emp	265.23	0	Fixed Effects
Wage	238.48	0	Fixed Effects
EmpL	210.16	0	Fixed Effects
EmpM	208.06	0	Fixed Effects
EmpH	15.48	0.0168	Fixed Effects

The model specifications are as follows:

1. $Emp_{i,t} = \alpha_i + \beta_1 AI_{i,t} + \beta_2 pgdp_{i,t} + \beta_3 urban_{i,t} + \beta_4 r\&d_{i,t} + \beta_5 sec_{i,t} + \beta_6 year_t + \beta_7 Covid_t + \mu_i + \varepsilon_{i,t}$
2. $Wage_{i,t} = \alpha_i + \beta_1 AI_{i,t} + \beta_2 pgdp_{i,t} + \beta_3 urban_{i,t} + \beta_4 r\&d_{i,t} + \beta_5 sec_{i,t} + \beta_6 year_t + \beta_7 Covid_t + \mu_i + \varepsilon_{i,t}$
3. $EmpH_{i,t} = \alpha_i + \beta_1 AI_{i,t} + \beta_2 pgdp_{i,t} + \beta_3 urban_{i,t} + \beta_4 r\&d_{i,t} + \beta_5 sec_{i,t} + \beta_6 year_t + \beta_7 Covid_t + \mu_i + \varepsilon_{i,t}$
4. $EmpM_{i,t} = \alpha_i + \beta_1 AI_{i,t} + \beta_2 pgdp_{i,t} + \beta_3 urban_{i,t} + \beta_4 r\&d_{i,t} + \beta_5 sec_{i,t} + \beta_6 year_t + \beta_7 Covid_t + \mu_i + \varepsilon_{i,t}$
5. $EmpL_{i,t} = \alpha_i + \beta_1 AI_{i,t} + \beta_2 pgdp_{i,t} + \beta_3 urban_{i,t} + \beta_4 r\&d_{i,t} + \beta_5 sec_{i,t} + \beta_6 year_t + \beta_7 Covid_t + \mu_i + \varepsilon_{i,t}$

AI is the main independent variable of interest, measured by the number of AI-related patents. The dependent variables include total employment quantity (Emp), real average wage (Wage), and both the employment quantity and the proportion of employment across different skill levels, specifically high-skill employment (EmpH), medium-skill employment (EmpM), and low-skill employment (EmpL). The control variables include real per capita GDP (pgdp), representing regional economic development; urbanization rate (urban), reflecting demographic changes; real R&D investment (rd), indicating the level of technological progress; and real social security spending (sec), serving as a proxy for labor protection policies. The year dummy variable (year) captures time fixed effects from 2007 to 2022, with 2006 as the reference year, while the COVID-19 dummy (Covid) accounts for the impact of the pandemic during 2020, 2021, and 2022. All variables will be log-transformed to reduce skewness and allow for elasticity-based interpretation. To address potential endogeneity caused by reverse causality, a fixed effects model combined with a distributed lag model (DLM) will be employed.

4. Results and Discussion

4.1. Descriptive Statistics

Table 2. Descriptive Statistics

	(1)	(2)	(3)	(4)
	mean	sd	min	max
log_Emp	16.32532	.9691948	12.76269	18.08284
log_Wage	10.82927	.5510398	9.639496	12.24678
log_emp_L1	15.90466	.9775236	12.74656	17.72454
log_emp_M1	14.84786	1.152408	8.627481	17.13867
log_emp_H1	13.35826	2.313199	-9.21034	16.03354
log_emp_L2	-.4206589	.2526479	-1.634756	-.0105555
log_emp_M2	-1.477458	.4312967	-4.625373	-.8312605
log_emp_H2	-2.861486	.9604375	-9.21034	-.7569393
log_AI	-.3776465	5.967928	-9.21034	9.092233
log_pgdp	9.825194	1.125848	5.658469	12.43479
log_rd	22.93335	2.652001	-9.21034	26.47732
log_sec	24.34249	1.013835	20.0097	26.11405
log_urban	-.6145595	.2693215	-1.554476	-.1098148
Observations	527			

Table 2 presents the descriptive statistics for the key variables in the panel dataset, comprising 527 observations. Each variable is listed in a separate row, with the corresponding columns showing the mean, standard deviation (sd), minimum (min), and maximum (max) values.

Table 3. Fixed Effects Regression

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	model1	model2	model3	model4	model5	model6	model7	model8
VARIABLES	log Emp	log Wage	log emp L1	log emp M1	log emp H1	log emp L2	log emp M2	log emp H2
log_AI	-0.028*** (0.007)	0.016*** (0.003)	-0.035*** (0.007)	-0.029*** (0.005)	-0.062 (0.050)	-0.006*** (0.001)	-0.000 (0.005)	0.010 (0.013)
log_pgdp	-0.256*** (0.034)	0.004 (0.008)	-0.266*** (0.037)	-0.173*** (0.037)	-0.013 (0.228)	-0.010 (0.008)	0.082*** (0.025)	0.122* (0.066)
log_rd	0.007** (0.003)	-0.010*** (0.003)	0.009** (0.004)	0.042*** (0.004)	0.546*** (0.018)	0.002 (0.001)	0.035*** (0.004)	0.148*** (0.008)
log_sec	0.645*** (0.066)	0.354*** (0.041)	0.555*** (0.082)	0.632*** (0.076)	0.578*** (0.090)	-0.090*** (0.021)	-0.014 (0.027)	0.115** (0.052)
log_urban	-0.922*** (0.265)	1.156*** (0.277)	-0.940*** (0.339)	0.360 (0.342)	2.498 (2.280)	-0.017 (0.114)	1.282*** (0.227)	2.415*** (0.570)
Constant	2.388 (1.460)	3.119*** (1.113)	4.203** (1.867)	0.427 (1.789)	-11.577*** (2.356)	1.815*** (0.526)	-1.961** (0.757)	-8.747*** (1.294)
Observations	527	527	527	527	527	527	527	527
R-squared	0.400	0.943	0.301	0.621	0.549	0.610	0.700	0.769
Number of	31	31	31	31	31	31	31	31

PR *** p<0.01, ** p<0.05, * p<0.1

4.2. Fixed-Effects Models

The fixed-effect model results suggest that AI expansion is linked to a decline in total employment in China. In Table 3, column (1), the significant negative coefficient (-0.028) suggests that AI adoption reduces employment, with a 1% increase in AI adoption leading to a 0.028% decline in aggregate employment, holding other factors constant. While automation can enhance productivity, the findings suggest that net displacement effects currently dominate, especially when AI-related job creation does not fully compensate for the jobs lost to automation.

In Table 3, column (2), the coefficient on AI adoption is 0.016, indicating that a 1% increase in AI adoption is associated with a 0.016% increase in average wages, holding other factors constant. This aligns with the concept of skill-biased technological change (SBTC), where AI-driven innovation disproportionately benefits employees with relevant expertise, leading to higher average wages. However, this trend may widen income inequality, particularly if workers lack the necessary education and training to transition into AI-enhanced roles.

Low-Skill Employment (L1 and L2): Both the absolute number (L1) and proportion (L2) of low-skilled workers decline with AI expansion. In Table 3, column (3), the coefficient on L1 (-0.035) is statistically significant, indicating that a 1% increase in AI adoption leads to a 0.035% reduction in low-skilled employment. In column (6), the coefficient on L2 (-0.006) suggests a 0.006% decrease in the share of low-skilled employment in total employment, holding other factors constant. The larger magnitude of L1 highlights a substantial absolute decline, reinforcing the idea that simple, repetitive tasks are particularly vulnerable to automation.

Medium-Skill Employment (M1 and M2): The regression results indicate that AI adoption significantly reduces the absolute number of middle-skilled jobs but has no significant effect on their share of total employment. In Table 3, column (4), the coefficient for M1 (-0.029) suggests that a 1% increase in AI adoption leads to a 0.029% decline in middle-skilled employment, highlighting the displacement effect of automation on routine-intensive jobs. However, in column (7), the coefficient for M2 (-0.000) is statistically insignificant, indicating that AI does not significantly alter the proportion of middle-skilled employment relative to total employment. This suggests that while AI-driven automation displaces middle-skilled workers in absolute terms, its

impact on overall labor market composition remains limited, possibly due to simultaneous adjustments in other skill groups.

High-Skill Employment (H1 and H2): In Table 3, columns (5) and (8), the coefficients for both the absolute number (H1) and proportion (H2) of high-skilled workers are statistically insignificant. H1 is negative but not significant, while H2 is weakly positive but also not significant. This suggests that AI development has not yet led to a significant increase in high-skilled employment. One possible explanation is that high-skill job growth depends on the availability of specialized talent and deeper AI adoption by firms—factors that vary across regions and industries. In the long run, as AI adoption deepens and companies invest more in innovation, the number of high-skilled positions may gradually increase.

4.3. Fixed-Effects Models with COVID-19 Dummy Variable

Table 4. Regression with COVID Dummy

VARIABLES	(1) model1 log_Emp	(2) model2 log_Wage	(3) model3 log_emp L1	(4) model4 log_emp M1	(5) model5 log_emp H1	(6) model6 log_emp L2	(7) model7 log_emp M2	(8) model8 log_emp H2
log_AI	-0.029*** (0.006)	0.015*** (0.002)	-0.035*** (0.006)	-0.029*** (0.006)	-0.062 (0.050)	-0.006*** (0.001)	-0.000 (0.005)	0.011 (0.013)
log_pgdp	-0.228*** (0.031)	0.018** (0.008)	-0.238*** (0.035)	-0.159*** (0.033)	0.004 (0.220)	-0.010 (0.008)	0.069** (0.026)	0.120* (0.065)
log_rd	0.008** (0.003)	-0.010*** (0.002)	0.010** (0.004)	0.042*** (0.004)	0.546*** (0.017)	0.002 (0.001)	0.034*** (0.005)	0.148*** (0.008)
log_sec	0.608*** (0.067)	0.335*** (0.035)	0.518*** (0.084)	0.613*** (0.074)	0.555*** (0.082)	-0.090*** (0.021)	0.004 (0.025)	0.117** (0.051)
log_urban	-1.298*** (0.352)	0.963*** (0.259)	-1.313*** (0.431)	0.166 (0.431)	2.262 (2.399)	-0.016 (0.114)	1.464*** (0.219)	2.438*** (0.598)
Covid	0.309*** (0.074)	0.159*** (0.021)	0.308*** (0.074)	0.160** (0.075)	0.194* (0.102)	-0.001 (0.013)	-0.150*** (0.015)	-0.020 (0.037)
Constant	2.718* (1.593)	3.289*** (0.981)	4.531** (2.021)	0.597 (1.836)	-11.370*** (2.322)	1.814*** (0.529)	-2.121*** (0.708)	-8.768*** (1.284)
Observations	527	527	527	527	527	527	527	527
R-squared	0.452	0.952	0.353	0.630	0.550	0.610	0.726	0.769
Number of provinceid	31	31	31	31	31	31	31	31

*** p<0.01, ** p<0.05, * p<0.1

In Table 4, in the COVID-inclusive models, AI’s effect on total employment (log_Emp) remains broadly consistent with the non-COVID results. This suggests that AI-driven employment declines persist regardless of the pandemic’s influence. However, the COVID dummy variable in column (1) shows a significantly positive coefficient of 0.309, indicating that overall employment experienced a temporary boost during the pandemic. This could be attributed to government policies aimed at job stabilization, financial support measures, and a surge in temporary employment in sectors such as logistics and delivery, which expanded due to increased online demand.

In Table 4, the effect of AI on wages remains positive, reinforcing the idea that skill-biased technological change benefits workers with AI-relevant expertise. This consistency suggests that the pandemic did not fundamentally alter the wage-enhancing effects of AI.

Regarding employment structure, the impact of AI on low-skilled jobs remains significant. In Table 4, column (3), the AI coefficient for the absolute number of low-skilled workers (L1) is approximately -0.035 , while the AI coefficient for the proportion of low-skilled employment (L2) is -0.006 in column (6), which is very similar to the non-COVID model. However, the COVID dummy variable (0.308) in column (3) for L1 suggests that pandemic-driven government support and the rapid expansion of online industries partially mitigated AI’s negative effects on low-skilled employment.

The results for medium-skilled employment reveal a more complex pattern. In both models, the AI coefficients in M1 and M2 are very similar to those in the non-COVID model, with M1 being negative and significant, while M2 is negative but not significant. However, the COVID dummy variable exhibits mixed effects across different regression specifications, with a positive impact on M1 (0.160) in Table 4, column (4), and a negative impact on M2 (−0.150) in column (7). These results suggest that while medium-skilled employment was somewhat protected or even expanded in absolute terms, its relative share in the workforce declined. This could be due to government interventions stabilizing medium-skilled jobs or a shift in employment composition favoring other skill levels. The findings highlight how the pandemic not only impacted employment levels but also contributed to changes in labor market structure.

For high-skilled employment, in Table 4, columns (5) and (8), the findings indicate that AI’s impact remains statistically insignificant, both with and without COVID-19 controls, suggesting that high-skilled jobs were relatively unaffected by pandemic-induced disruptions. The ability of high-skilled workers to engage in remote work and adapt to digital transformations may have contributed to their employment stability, making significant shifts in high-skilled employment levels difficult to detect during the pandemic.

4.4. Fixed-Effects Distributed Lag Models

Table 5. FE-DLM

VARIABLES	(1) model1 log_Emp	(2) model2 log_Wage	(3) model3 log_emp_L1	(4) model4 log_emp_M1	(5) model5 log_emp_H1	(6) model6 log_emp_L2	(7) model7 log_emp_M2	(8) model8 log_emp_H2
log_AI	-0.018*** (0.006)	0.004** (0.002)	-0.020*** (0.006)	-0.015** (0.006)	-0.010 (0.011)	-0.001 (0.001)	0.002 (0.002)	0.017*** (0.004)
log_pgdp	-0.175*** (0.039)	-0.030 (0.018)	-0.183*** (0.040)	-0.122*** (0.038)	-0.221*** (0.038)	-0.008 (0.008)	0.040*** (0.010)	0.046** (0.022)
log_pgdp = L,	-0.037** (0.017)	-0.006 (0.006)	-0.031* (0.018)	-0.052** (0.020)	-0.195*** (0.041)	0.006** (0.003)	-0.004 (0.007)	-0.004 (0.016)
log_pgdp = L,	0.011 (0.019)	-0.019*** (0.005)	0.013 (0.021)	0.028** (0.013)		0.002 (0.005)	0.021*** (0.007)	-0.042* (0.021)
log_pgdp = L,	-0.089*** (0.025)	0.001 (0.007)	-0.100*** (0.024)	-0.085*** (0.023)		0.013 (0.014)		0.043** (0.017)
log_pgdp = L,		0.002 (0.016)				-0.031* (0.015)		
log_pgdp = L,		-0.021** (0.008)						
log_rd	-0.028 (0.088)	0.029 (0.030)	-0.062 (0.100)	-0.047 (0.071)	0.770*** (0.054)	-0.019 (0.034)	-0.013 (0.043)	0.000 (0.071)
log_rd = L,	-0.020*** (0.007)	-0.006 (0.013)	-0.028*** (0.007)	0.065*** (0.004)	0.772*** (0.038)	-0.022 (0.020)	0.099*** (0.003)	0.241*** (0.010)
log_rd = L,	0.003 (0.010)	0.085*** (0.025)	0.012 (0.011)			0.007*** (0.002)	-0.010*** (0.002)	-0.030*** (0.007)
log_sec	0.351*** (0.097)	0.555*** (0.043)	0.168 (0.122)	0.330*** (0.087)	0.015 (0.141)	-0.162*** (0.044)	-0.022 (0.045)	0.312*** (0.100)
log_urban	0.676** (0.306)	0.513* (0.274)	0.921*** (0.321)	1.593*** (0.301)	-1.672** (0.754)	0.251** (0.113)	1.001*** (0.230)	1.110*** (0.343)
log_rd = L,	0.019** (0.009)		0.030*** (0.009)			0.011*** (0.002)	-0.036*** (0.003)	-0.045*** (0.008)
Constant	11.611*** (1.654)	-4.151*** (1.490)	16.457*** (1.847)	9.652*** (1.719)	-19.166*** (4.318)	4.384*** (0.683)	-1.799 (1.326)	-13.975*** (1.997)
Observations	434	372	434	434	496	403	434	434
R-squared	0.332	0.959	0.281	0.543	0.921	0.466	0.734	0.874
Number of provinceid	31	31	31	31	31	31	31	31

*** p<0.01, ** p<0.05, * p<0.1

The primary endogeneity concern in this study arises from reverse causality. In economic analysis, when the dependent variable influences the explanatory variables, regression estimates may become biased, affecting the identification of causal relationships. In the context of this study, there is probably a bidirectional relationship between GDP and employment, where economic growth may not only drive employment expansion but also be influenced by changes in the labor market. Similarly, R&D investment and skilled employment are interdependent — technological

advancements tend to increase the demand for skilled labor, while the availability of a highly skilled workforce may further incentivize firms to invest in R&D. These dynamic feedback mechanisms make it more challenging to identify the causal impact of AI adoption on employment and wage structures. To deal with this problem, the research employs a fixed effects (FE) model to control for unobserved variations across provinces. The FE model enables province-specific factors that are likely to be relatively time-invariant—such as industrial structures, policy environments, and economic fundamentals—to be controlled. Thus, the regression estimates primarily capture intra-province dynamic adjustments rather than inter-province disparities. However, although FE deals with heterogeneity across regions, it does not fully remove reverse causality issues, especially since variables like GDP and R&D spending themselves could be influenced by changes in the labor market. To deal with reverse causality issues more effectively, the study extends the FE approach by using a distributed lag model. This implies the inclusion of lagged values for R&D investment and per capita GDP, making it less likely that these variables are influenced by the dependent variable, i.e., employment patterns.

A key aspect of ensuring the efficacy of this method is identifying the optimal number of lags to consider. The present study applies the Sequential Testing Method (GS), as suggested by Han, Phillips, and Sul (2017), in order to ascertain the most suitable lag structure. The GS approach begins with a large model and then eliminates insignificant lagged variables until a lag with a considerable statistical effect is found [32]. A primary benefit of this approach is that it utilizes the maximum amount possible of the available dataset, hence enhancing the precision and credibility of the selected lag lengths.

In Table 5, results from the regression analysis indicate that the overarching patterns identified in the Fixed Effects–Distributed Lag Model (FE-DLM) closely resemble those detected within the conventional Fixed Effects (FE) methodology. In the context of the comprehensive employment model, artificial intelligence appears to have a detrimental impact on employment, particularly for workers possessing low to medium skill levels. Notably, the AI variable in column (8) attains significance within the FE-DLM framework when considering the H2 model, which focuses explicitly on the proportion of high-skilled employment. This is contrary to the traditional FE estimates, where AI was not significant for high-skilled occupations (H1 and H2). This difference can indirectly confirm the hypothesis that the addition of lagged per capita GDP (pGDP) and R&D variables reduces the endogeneity bias seen in the original FE approach, thus reflecting AI's true effect more clearly. In the straightforward FE specification, both R&D and pGDP variables may suffer from endogeneity issues, resulting in imprecision and obscuring the genuine effect of AI. By introducing lagged measures of R&D and pGDP in the FE-DLM specification, biases of this type are avoided, and a clearer picture of the effect of AI on labor outcomes is obtained.

This would be feasible because R&D and pGDP significantly affect employment in the short term and can overshadow AI's effect in the standard FE model—especially for high-skilled employment shares (H2). In contrast, the FE-DLM method uses lagged variables to spread these short-term effects so that AI's effect becomes more visible in H2. A second reason is that H2 measures the relative proportion of high-skilled employment in relation to overall employment, while H1 measures the absolute quantity of high-skilled jobs. Even if AI does not significantly increase overall levels of high-skilled employment, it can reduce lower-skilled jobs, increasing the relative share of high-skilled employment. This channel can explain why AI becomes significant in the H2 specification. These findings imply that AI uptake influences not only quantities of labor, but its structure and the Skill-Biased Technological Change (SBTC) hypothesis. It would follow from SBTC that AI is involved in increasing skill-based cleavages, reinforcing relatively high-skilled job dominance in contrast to providing a large volume of new high-skilled employment.

From the results shown in Table 5, in the short term, pGDP negatively affects overall employment and certain low- and medium-skilled jobs, suggesting that economic growth may be accompanied by industrial upgrading and automation, thereby reducing demand for traditional jobs. Additionally, the impact of pGDP on wage growth is not notable and, in some cases, even negative,

possibly due to the decline in low-skilled jobs dragging down average wages. However, in certain skill groups (such as H2 high-skilled employment), pGDP exhibits a positive effect in the short term (at the current and second lag), indicating that economic growth may lead to a quicker increase in demand for high-skilled positions. In the short term, R&D investment tends to replace traditional jobs, while significantly boosting high-skilled employment, reflecting the skill-biased nature of technological progress. In the long run, the impact of R&D on overall employment and certain low-skilled jobs gradually turns positive, suggesting that technological advancements may eventually create new job opportunities. Moreover, the positive impact of R&D on wage levels mainly emerges in the longer lag periods. However, in some skill groups, negative effects reappear at later stages, indicating that as technology continues to advance, structural adjustments and job redistribution remain ongoing challenges.

The empirical findings in Table 5 highlight significant yet distinct influences of social security expenditure (\log_sec) and urbanization (\log_urban) on labor market outcomes. Social security expenditure exhibits positive and statistically significant associations with overall employment in column (1) and wage levels in column (2), suggesting that enhanced social welfare provisions effectively promote employment stability and wage growth. Moreover, increased social security spending significantly raises medium-skilled employment in column (4) and high-educated employment in column (8), while negatively affecting low-educated employment in column (6). These results imply that expanded social welfare programs encourage employers to favor workers with higher skill or educational qualifications, leading to a structural upgrading of the labor force.

Urbanization also demonstrates robust positive impacts on overall employment and wage growth, as indicated by significant coefficients in column (1) and column (2). Additionally, urbanization strongly promotes low-skilled employment quantity in column (3), medium-skilled employment quantity in column (4), and the proportion of low- to high-skill employment groups in columns (6), (7), and (8). Notably, however, the coefficient for urbanization in relation to high-skilled employment quantity in column (5) is significantly negative. This counterintuitive result may arise from urbanization-driven structural shifts, such as industrial upgrading or automation, which often eliminate certain traditional high-skilled jobs while increasing demand for medium- and low-skilled positions. Alternatively, rapid urban expansion might intensify competition among high-skilled workers, creating labor market congestion or mismatch issues that temporarily suppress employment opportunities at higher skill levels.

5. Conclusion

This study finds that AI adoption in China leads to a net decline in employment, mainly affecting low- and medium-skilled workers, while slightly increasing average wages. The results support the Skill-Biased Technological Change (SBTC) hypothesis and indicate that AI reshapes labor markets not only by widening wage gaps but also by changing employment composition. Notably, the absence of significant growth in high-skilled job numbers suggests that the impact of AI depends heavily on regional innovation capacity and institutional readiness, emphasizing the influence of the broader socio-economic context in shaping outcomes. However, several limitations should be considered when interpreting these findings. The use of provincial-level aggregate data may obscure important differences at the firm or industry level, limiting the granularity of the analysis. In addition, due to data constraints, the proxy used for AI adoption may not fully reflect the depth, intensity, or quality of AI integration across regions. In light of these findings, some policy responses are necessary. Governments should strengthen vocational training and reskilling programs to support displaced workers and expand investments in tertiary education, particularly in AI-related disciplines, to address growing skill gaps. At the same time, enhancing social security systems through targeted financial assistance and retraining can help mitigate short-term job displacement effects. To ensure inclusive growth, policymakers should also promote more balanced regional development of AI by allocating resources and incentives to less-developed provinces, thereby reducing regional disparities and maximizing the economic benefits of AI adoption.

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