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Impact of artificial intelligence innovation on labor structure: a study based on staggered DID method

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Abstract. In recent years, breakthroughs in computing power and algorithms have driven profound evolution in Artificial Intelligence (AI) applications. Beyond replacing repetitive manual labor, AI has penetrated into complex cognitive labor fields once deemed hard to automate, reshaping industry work paradigms, blurring traditional occupational boundaries, and triggering an unprecedented structural transformation in the labor market. Against this backdrop, exploring AI's far-reaching impact on employment patterns and its mechanisms has become a core concern for academia and policymakers, with vital theoretical and practical value for guiding workers to adapt to change and formulating forward-looking talent strategies. This paper uses the Difference-in-Differences method for empirical research. The study finds that AI innovation exerts a significant positive impact on the labor structure, optimizing the proportion of high-skilled and low-skilled labor. This indicates AI is not a simple labor replacement but a powerful enabler, pushing the overall labor structure toward higher skills and added value. It also provides strong empirical support for the "skill-biased technological change" theory, revealing a significant complementary synergy between technological progress and high-skilled labor in the AI era.

Keywords: artificial intelligence, technological innovation, labor structure, employment substitution

1. Introduction

Since the mid-20th century, Artificial Intelligence (AI) has evolved from early explorations focused on symbolic logic to the comprehensive rise of deep learning, and now to a new era of general artificial intelligence driven by Large Language Models (LLMs). This accelerated iteration of technological innovation is profoundly reshaping the global labor structure. In terms of employment institutions, the automation effects of AI have triggered significant task reorganization, leading to a coexistence of partial replacement of traditional low-skilled positions and the creation of emerging technology jobs. In terms of occupational distribution, the technological impact has rapidly expanded from repetitive physical labor to complex digital cognition and creative fields. Meanwhile, the demand for skills has fundamentally reversed, with a surge in market demand for interdisciplinary technical literacy, data processing capabilities, and complex decision-making skills. This structural change alters the supply-demand relationship of labor and poses severe challenges for human capital investment and occupational transformation, becoming a core issue in current labor economics research.

The international academic community has conducted in-depth discussions on how AI innovation shapes labor structure. Acemoglu and Restrepo [1] proposed a task-based framework, indicating that AI fundamentally reconstructs occupational distribution by automating traditional tasks while creating new tasks that require higher skills. This technological transformation has differentiated impacts on different skill groups; Autor and Dorn [2] found that AI is more likely to take over routine cognitive tasks, leading to a noticeable polarization in the labor market. Goldin and Katz [3] introduced the theory of "the race between education and technology", emphasizing that human capital accumulation is key to adapting to technological transformation; while Goos et al. [4] further confirmed the universality of this adaptation mechanism across different economies. However, the specific changes in employment structure due to AI's influence remain inconclusive and warrant further exploration, which is the core issue of our research.

2. Literature review

The academic understanding of the issues surrounding artificial intelligence and labor employment has undergone significant evolution, shifting from early concerns about large-scale unemployment caused by "automation substitution" to a focus on "human-machine collaborative integration" under technological empowerment.

Acemoglu and Restrepo [1] proposed a theoretical framework based on task-based production functions, systematically explaining how AI influences employment scales across different industries by reshaping task allocation. This framework indicates that the impact of AI on employment mainly manifests in the automation substitution of existing occupations and the creation of new ones. Brynjolfsson and McAfee [5] further deepened this discussion in their work, suggesting that the contemporary AI-driven "second machine age" is profoundly reshaping the occupational distribution in the labor market. Furman and Seamans [6] expanded the discussion on AI's impact from a macroeconomic and industrial policy perspective, defining it as a typical General-Purpose Technology (GPT). They noted that the impact of AI on labor structure exhibits significant phased characteristics: in the short term, the substitution effect of AI as a production factor dominates, leading to destructive shocks to existing occupational structures, resulting in job losses and wage fluctuations; however, in the long term, its diffusion as a general-purpose technology will generate entirely new occupational fields and employment demands through complementary innovations. Barth et al. [7] deepened the discussion on inequality from the perspective of inter-firm occupational structure differences. They found that the differentiation in the labor market is not only reflected in individual skill endowment differences but also in the significant differentiation in demand for high-skilled, medium-skilled, and low-skilled positions across different firms. Regarding the impact of education level on employment and career choices, Haltiwanger et al. [8] provided important empirical evidence. They pointed out that technological changes are profoundly altering the career trajectories of workers with different educational backgrounds. Specifically, highly educated employees, with their deep knowledge reserves and skill flexibility, can more smoothly transition to emerging occupational fields related to AI. In terms of gender differences, Tiemann and Rohrbach-Schmidt [9] provided important perspectives for understanding gender employment structures under technological change. From the perspective of career choices, the long-standing underrepresentation of women in Science, Technology, Engineering, and Mathematics (STEM) fields poses greater risks of job substitution and skill matching challenges in the AI era, which is centered on algorithms and automation. Regarding age and work experience, Agrawal et al. explored the differentiated impact of AI as a predictive technology on workers with different experience backgrounds. The study found that experienced older employees face significant "experience depreciation" risks, as the professional knowledge and intuition they accumulated through long-term practice are no longer scarce in the face of powerful AI predictive algorithms, eroding their competitive advantage. In contrast, younger employees, although lacking traditional experience, can more easily learn and master AI tools, quickly adapting to technological changes and gaining more opportunities in emerging occupations. According to Goldin and Katz [3], the "race" between the education system and technological advancement determines the direction of occupational evolution in the labor market. In discussing pathways to address current job losses and employment risks, the core role of educational investment in occupational transformation is becoming increasingly prominent.

The existing literature has conducted in-depth discussions on the impact of artificial intelligence on labor structure, focusing mainly on dimensions such as the evolution of occupational structure, distribution of employment opportunities, and transformation of skill demands. These studies strongly demonstrate the reshaping effect of technological advancement on task demands, particularly the ongoing shift from programmable tasks to non-programmable tasks. However, current discussions are mostly based on macro data at the industry or regional level, tending to describe overall trends in occupational distribution and polarization phenomena. The innovation of this paper lies in shifting to a micro data perspective, aiming to analyze the specific internal mechanisms of changes in labor structure. This paper seeks to reveal the patterns of labor structure adjustment under the impact of artificial intelligence at the micro level, thereby more accurately identifying the adaptive differences among different groups in the context of technological change.

3. Research design

3.1. Econometric model

To quantify the causal impact of Artificial Intelligence (AI) on labor structure at the micro or enterprise level, this study employs a staggered Difference-in-Differences (DID) method as the core empirical strategy. The DID method, as the most widely used quasi-experimental econometric model in policy evaluation, operates on the core logic of constructing a comparative framework between a "treatment group" and a "control group". It effectively eliminates fixed characteristics (individual fixed effects) that do not change over time but vary between individuals, as well as common factors (time fixed effects) that dynamically change over time but affect all individuals, thereby more accurately identifying the net effects of policy interventions or technological shocks in non-random experimental data.

The basic DID estimation equation established in this study is as Equation (1):

$$Y_{it} = \alpha + \beta(Treat_i \times Post_t) + \gamma X_{it} + \mu_i + \lambda_t + \dot{o}_{it} \tag{1}$$

Where, Y_{it} represents the labor structure indicator of the i-th unit (industry, enterprise, or region) in year t. $Treat_i$ is a dummy variable for the treatment group, which takes the value of 1 if the observation object applied for and obtained a patent during the study period, and 0 otherwise. $Post_t$ is a time dummy variable, indicating the boundary before and after the shock, with the years after the shock taking the value of 1 and those before taking the value of 0. The interaction term $Treat_i \times Post_t$ is the core explanatory variable of this paper, and its coefficient β reflects the average causal effect of the AI shock on labor compensation. Additionally, X_{it} represents a series of time-varying control variables, μ_i is the individual fixed effect, λ_t is the time fixed effect, and $\dot{o}_{it}$ is the random disturbance term.

3.2. Data sources

The financial data in the sample (2011-2024) is selected from the China Securities Market & Accounting Research (CSMAR) database for A-share listed companies, and the patent acquisition data is sourced from

China National Research Data Service Platform (CNRDS). This paper has processed the data sample as follows: excluded samples of ST, *ST, and delisted companies; excluded samples of financial companies (financial enterprises differ from ordinary enterprises, primarily focusing on off-balance-sheet business; their accounting standards also differ from those of ordinary enterprises); and applied 1% Winsorization (trimming) to the continuous variables used in the regression.

3.3. Variable setting

3.3.1. Dependent variable

Labor force structure Lstruct is defined as the proportion of high-skilled labor. The classification of high and low-skilled labor is primarily based on educational attainment: employees with a college degree or higher are considered high-skilled labor, while those with a high school diploma or lower are categorized as low-skilled labor.

3.3.2. Explanatory variables

Whether the enterprise has obtained a Patent (Patent). In fact, this variable is derived from the interaction of a group dummy variable for enterprises ($Treat_i$ where treatment group enterprises take 1 and control group enterprises take 0) and an event shock time dummy variable ($Post_t$ where the year of digital acquisition completion and subsequent years take 1, otherwise take 0). In the empirical framework of the Difference-in-Differences (DID) method, this paper uses whether a patent is obtained (Patent) as the core explanatory variable to examine whether treatment group enterprises experience significant differences in employment structure changes after patent approval compared to control group enterprises, thereby exploring the causal effect of digital transformation on labor employment. Additionally, since different enterprises complete digital acquisitions at different times, $Patent_{it} = Treat_i \times Post_t$ is a variable that changes simultaneously with individual enterprises and time; therefore, this paper employs a Staggered DID model for estimation.

3.3.3. Covariates

Covariates: Based on existing literature and research objectives, this paper selects matching covariates including Enterprise Size (Size), measured by the natural logarithm of operating income; debt-to-asset ratio (Lev), measured by the ratio of total assets to total liabilities; Employee Salary (Salary), measured by the natural logarithm of payable employee compensation; Enterprise Age (Age), measured by the natural logarithm of the number of years since the enterprise was established plus 1; government support (Subside), measured by government subsidy expenses; Board size (Boardsize), measured by the number of board members; whether the roles of chairman and general manager are combined (Dual), constructed as a dummy variable where both roles being held takes 1, otherwise takes 0. In the full sample regression before matching, all covariates will also be introduced as control variables to control for the impact of observable enterprise characteristics on the estimation results as much as possible. The definitions of the variables involved in the empirical analysis and descriptive statistics are detailed in Table 1.

Table 1. Descriptive statistics

VarName	VarDescrip	Obs	Mean	SD	Min	Median	Max
rHig	Labor Force Structure	11,542	0.301	0.209	0.040	0.238	0.877
Treat	Has AI Patent Got	11,542	0.068	0.251	0.000	0.000	1.000
Size	Enterprise Size	11,542	21.730	1.385	18.298	21.557	25.806
Lev	Debt-to-Asset Ratio	11,542	0.422	0.207	0.023	0.413	4.995
Eage	Enterprise Age	11,542	2.968	0.319	1.386	2.996	4.220

Table 1. Continued

Subside	Government Subsidy	11,542	16.563	1.875	0.000	16.599	22.281
ROA	Return on Assets	11,542	0.036	0.096	-2.555	0.037	5.035
Duality	Two roles are combined	11,542	1.694	0.461	1.000	2.000	2.000

4. Empirical results analysis

4.1. Empirical test

Table 2 reports the regression results. Column (1) shows the DID regression results without control variables; Column (2) includes control variables; Column (3) presents the DID regression results after PSM matching. Overall, the regression results are robust. The estimated results after adding control variables and PSM matching indicate that the estimated coefficient of the core variable DID is significant at the 5% statistical level. The results suggest that companies obtaining artificial intelligence patents significantly optimize their labor force structure. Furthermore, the estimated results of the control variables show that larger companies promote the improvement of labor force structure through artificial intelligence innovation; companies with higher debt-to-asset ratios suppress the improvement of labor force structure through artificial intelligence innovation; and the more government funding companies receive, the more they promote the improvement of labor force structure through artificial intelligence innovation.

Table 2. Regression results

Variable	(1) labor force structure	(2) labor force structure	(3) labor force structure
	Without control variables	Add control variables	Add PSM
DID	0.022** (0.008)	0.023*** (0.009)	0.023** (0.009)
Size		0.009 (0.006)	0.009 (0.006)
Lev		-0.032 (0.022)	-0.035 (0.022)
Eage		-0.039 (0.047)	00.044 (0.046)
Subside		0.001 (0.001)	0.003 (0.002)
ROA		-0.019 (0.017)	-0.032 (0.024)
duality		-0.014** (0.006)	-0.014 (0.006)
Firm fixed effects	Yes	Yes	Yes
Time fixed effect	Yes	Yes	Yes
Adj R2	0.872	0.873	0.873
Observations	7,568	7,562	7,528

4.2. Placebo test

This paper controls for multiple differences in enterprise characteristics, aside from patent acquisition, that may affect the treatment and control groups in the baseline regression section. However, unobservable factors at the firm-year level may still influence the estimation results. For robustness, we conducted a placebo test by randomly assigning firms that acquired artificial intelligence patents, ultimately replacing the pseudo core explanatory variable DIDit with DIDit psuedo in Equation (1). Figure 1 illustrates the distribution of estimation results from 2,000 random sampling processes, where the mean of β_j psuedo is very close to zero. At the same time, it can be seen that the actual estimation result β = 0.022 (the horizontal axis coordinate corresponding to the vertical dashed line, column (2) of Table (2) is significantly greater than the β_j psuedo values, indicating that the actual estimation result in this paper is an obvious outlier among the sampling estimation results, suggesting that the estimation results are unlikely to be driven by unobservable factors at the firm-year level.

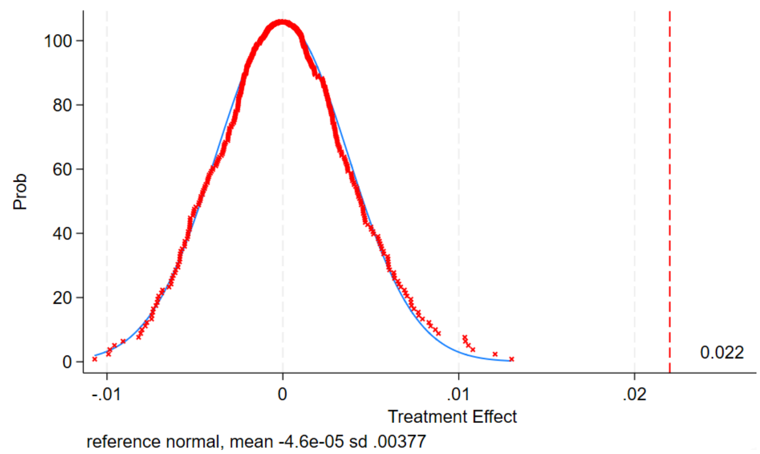

Figure 1. Placebo test: βj psuedo probability distribution

5. Conclusion

This paper explores the impact of artificial intelligence innovation on labor structure in depth. The study finds that the acquisition and application of artificial intelligence patents have a significant positive effect on the overall labor structure of enterprises. Regression analysis based on the Difference-in-Differences (DID) method indicates that, after controlling for covariates such as debt-to-asset ratio, enterprise size, and government subsidies, the employee structure of treatment group enterprises is superior to that of the control group.

In terms of theoretical contribution, this study enriches the theory of technological progress within the "task-based production function" framework, refining AI into specific innovative outputs (patents) and dynamically considering its asymmetric impact on labor structure, providing micro-empirical evidence for understanding the skill demands of labor in the context of a new technological revolution.

Based on the above conclusions, this paper proposes the following policy recommendations: First, increase targeted human capital investment and build a skill training system with multi-party participation from the government, enterprises, and society to help affected groups achieve career transitions; second, deepen education system reform by enhancing artificial intelligence literacy and interdisciplinary skills training in both basic and higher education to meet the talent demands of the digital age; third, improve the employment security system and explore new social security systems that adapt to the gig economy and remote work to mitigate the structural unemployment risks brought about by technological change.

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