

The Impact of Artificial Intelligence Policy on Employment: Evidence from China

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ABSTRACT

The impact of artificial intelligence (AI) policy on the labor market has attracted increasing attention. There is ongoing debate regarding the extent to which governments should intervene in the market with policy tools. This study addresses this issue by examining the effects of AI policies on the labor market. We constructed a panel dataset of listed companies on the A-shares market in China from 2009 to 2024, using the number of employees as a measure of enterprise employment. The difference-in-differences analysis indicates that AI policies significantly affect employment only for companies in AI-related industries. This finding suggests that AI policies positively influence the labor market for AI-related industries. Further analyses reveal that a lower proportion of R&D investment, a smaller number of highly educated employees, and higher average employee salaries strengthen the positive impact of AI policies on employment. This study offers significant theoretical contributions and practical implications for both academia and government regulators.

Keywords: Artificial intelligence, artificial intelligence regulation, government policy, labor market.

INTRODUCTION

Artificial intelligence (AI), as a major driving force behind a new wave of technological revolution and industrial transformation, is also a "super opportunity" for future technological innovation, permeating all aspects of industrial production and social life. From manufacturing and finance to education, AI continuously leads society towards greater intelligence (Miller 2019). On one hand, countries around the world are competing to seize the broad opportunities brought by the application of AI technology. On the other hand, governments worldwide are also making AI regulation a key national strategy. The race for AI regulation has become a new arena for competition among nations in the field of emerging technologies. By 2024, significant events regarding AI regulation have become commonplace globally. Various countries and regions are not only actively drafting and enacting laws and regulations to standardize AI technology but also issuing policy guidelines related to the positive development of AI technology. Studying AI regulation measures helps to clearly understand the steps and progress countries and regions are making to promote the reliable, beneficial, and trustworthy development of AI technology, identify different focuses of various governance models, and thereby facilitate in-depth comparisons, ultimately promoting the construction of a comprehensive, globally accepted AI regulation system. Moreover, it helps grasp the various types of risks generated by AI technology applications, assess the best ways to address these challenges, and thus gain a clearer understanding of future AI development trends.

In October 2022, the White House released the "Blueprint for an AI Bill of Rights," which proposed five fundamental principles: establishing safe and effective systems, avoiding algorithmic discrimination, using and designing systems fairly, protecting data privacy, and considering fairness and privacy protection as the core objectives of the bill. This can be seen as an important milestone in AI regulation. On March 9, 2023, the AI Commission's "AI Commission Report" further suggested building an AI regulatory governance framework based on five principles: efficiency, neutrality, proportionality, co-governance, and flexibility, to help the U.S. seize the window of opportunity for widespread application of AI technology. The European Union has always actively focused on AI regulation practices. Its purpose is not only to provide guidance and constraints to its member states but also to take the lead in establishing a comprehensive set of AI safety governance laws and regulations that cover the entire chain and process. On April 21, 2021, the EU released a proposal for the "Artificial Intelligence Act," exploring "hard law" support for AI regulation. On December 6, 2022, the EU Council adopted a common position on the "Artificial Intelligence Act," aiming to ensure that AI systems marketed and used within the EU are safe and comply with existing laws. On June 14, 2023, the EU's AI governance saw its latest progress, as the European Parliament voted to approve the "Artificial Intelligence Act," which includes provisions on banning real-time facial recognition and ensuring transparency for generative AI tools like ChatGPT.

Similarly, China has introduced a series of AI policy documents to regulate and guide the development and transformation of the new generation of AI technology. In July 2017, the State Council of China issued the national AI development strategy titled "Next Generation Artificial Intelligence Development Plan." This strategy outlines China's goal to become a global leader in the AI field by 2030. In 2020, the legislative work plan of the Standing Committee of the National People's Congress mentioned AI legislation for the first time, explicitly requiring "attention to the study of legal issues related to new technologies and fields such as AI, blockchain, and gene editing." On June 6, 2023, the State Council issued a notice on the 2023 legislative work plan, proposing to submit the AI law draft to the National People's Congress Standing Committee for review, under the strategies of

invigorating the country through science and education and promoting cultural confidence and strength. This indicates that national-level AI legislation in China has been put on the agenda, emphasizing parallel promotion and regulation to ensure orderly progress.

Employment, as a major livelihood issue in every country, is a topic of widespread concern. From Keynes' "technological unemployment" theory (Keynes 1930) to Schumpeter's "creative destruction" theory (Schumpeter 2013), and the "productivity paradox" theory (Brynjolfsson 1993), whether new technology leads to unemployment has been a long-standing topic of discussion and research among economists. As a modern technology, AI has sparked intense debate about whether it will replace human workers and cause mass unemployment. Historically, technological advancements have created more job opportunities than they have eliminated, leading to higher skill demands. Bessen (2015) explained the reasons and impacts of automation during the first industrial revolution, indicating that the automation of looms created numerous new jobs to meet the high demand for cheap fabrics. Automation did not eliminate weavers; instead, it transformed the role of weavers into that of spinners. In many cases, AI may not necessarily lead to unemployment but will change the pattern of skill demand in companies (Korinek and Stiglitz 2018). Workers may need to acquire completely new skills to adapt to new processes. Trajtenberg (2018) argues that since many occupations will indeed disappear with the emergence of AI as a new general-purpose technology, we should seek ways to mitigate the adverse effects of AI and enhance its positive impacts.

At the same time, the impact of AI on worker demand is asymmetrical, as workers with different skill levels and educational backgrounds perform different tasks (Aghion et al. 2017; Korinek and Stiglitz 2018). On the positive side, AI can inject new vitality into the real economy, bringing innovation and employment opportunities (Acemoglu and Restrepo 2020). In addition to the increase in traditional positions such as AI engineers and system operators (Aghion et al. 2017), the emergence of new professions such as data analysts and data annotation engineers also provides more job opportunities. On the downside, routine-intensive occupations and manual labor are more susceptible to automation (Frey and Osborne 2017). It is widely believed that the replacement of human workers by machines has reached unprecedented levels, leading to unemployment, reemployment, and the need for retraining to adapt to new roles. Policy, as a tool for governments to regulate the market, can to some extent affect the impact of AI on the labor market. At this point, exploring the impact of AI policies, rather than AI itself, on employment becomes particularly important.

So far, there is no direct empirical evidence to confirm the causal relationship between the implementation of AI policies and employment demand and structure, and empirical research on the complex relationship between the two is scarce. Therefore, this study uses the staggered difference-in-differences method, based on AI-related policies from various provinces and cities in China, along with employment and industry data, to investigate the impact of China's AI policies on the number of employees in enterprises. Empirical results indicate that the implementation of AI policies increases the number of employees in AI-related industries, while there is no significant impact on the entire industry or non-AI-related industries. Further investigation reveals that within AI-related industries, the lower the proportion of R&D investment, the fewer the number of highly educated employees, and the higher the average employee salary, the greater the impact of AI policies on the number of employees.

This study has several significant theoretical contributions and practical implications. First, the findings fill the gap in understanding the impact of AI policies on the labor market, providing both theoretical and empirical evidence. Second, by analyzing the effects of these policies in promoting employment, altering employment structures, and fostering balanced regional development, targeted policy recommendations can be proposed. This, in turn, provides empirical evidence for refining China's AI policy framework and facilitating a steady transformation of the labor force structure.

LITERATURE REVIEW

The Impact of Artificial Intelligence on the Labor market

The impact of AI on employment is contentious. Product innovation can create new job opportunities, but it may result in job polarization, while process innovation (often labor-saving) mostly disrupts employment (Dosi and Mohnen 2019; Staccioli and Virgillito 2021). Undoubtedly, the pace and scope of breakthroughs in AI technology can greatly alter the production methods of businesses. Meanwhile, there is widespread concern and increasing discussion about its potential to lead to mass unemployment and wage stagnation (Brynjolfsson and McAfee 2015). We can use the effect of robots on employment as an example. Chiacchio et al. (2018) reported negative impacts—every additional robot per thousand workers led to a decrease in employment rates by 0.16-0.20 percentage points in six EU countries. However, several studies found no impact of automation on total employment (Autor et al. 2015; Graetz and Michaels 2018). In data from Germany, Dauth et al. (2017) found no evidence of robots causing overall unemployment, but they had a significant negative impact on employment in the manufacturing sector.

AI is considered the most significant original technological transformation in recent years (Korinek and Stiglitz 2018). Its impact on skill demand can be predicted based on theories related to this transformation. The Skill-Biased Technological Change (SBTC) theory provides a general framework for analyzing the impact of technological change on skill demand patterns (Acemoglu 1998; Acemoglu 2002; Berman et al. 2005). In the initial SBTC view, the workforce is divided into two categories: high-skill and low-skill. We can analyze the two competing effects of AI on labor demand. In the displacement effect, AI performs tasks previously completed by low-skill workers, reducing the corresponding labor demand. In the creativity effect, AI creates new tasks better suited for high-skill labor and increases traditional low-skill jobs because lower production costs and improved labor productivity

lead to increased consumption and production scales. Thus, whether AI increases or decreases demand for any type of labor depends on the relative magnitude of these two effects.

Yang (2022) argues that Taiwanese electronics companies are better at developing intermediate components rather than branded final products, so the employment promotion effect may dominate the employment substitution effect. Empirical results show that AI technology positively impacts employment, increasing demand for high-skill labor in Taiwan's electronics industry, decreasing demand for medium-skill workers, while demand for low-skill workers remains relatively stable or increases. Aghion et al. (2017) indicates that AI-intensive companies may create more low-skill jobs compared to other companies. Due to profit growth at the company level, AI has not yet replaced low-skill jobs at a lower cost, which will be taken on by more low-skill workers. However, based on microenterprise data from China's manufacturing sector from 2011 to 2017, Xie et al. (2021) found that AI reduced the proportion of production workers by 2.468% and increased the proportion of technical workers by 1.56%. The impact on the proportion of the medium-skill group was not significant. Using panel data from 1,387 listed Chinese companies from 2007 to 2018, Xue et al. (2022) found that AI applications are positively correlated with overall employment and employment of non-academically trained workers without a college degree. With the advent of ChatGPT and the rapid development of large models, scholars believe that the impact of AI on employment has changed. Eloundou et al. (2023) argue that the higher the level of education and rich experience required for a good job, and the higher the wages of such jobs, the more they will be affected in the era of large models. Conversely, jobs that do not require the accumulation of human experience, post-learning, or "slow thinking" will be less affected in the era of large models.

Although many scholars have studied how the development of AI affects employment and employment structure from the enterprise level, few have explored its impact on employment from a policy perspective.

Artificial Intelligence Regulation

As early as the Industrial Revolution, significant technological innovations successfully transformed numerous manual tasks and processes that had reached the limits of human physical capability over decades. AI offers similar transformative potential, enhancing and potentially replacing human tasks and activities across a wide range of industrial, knowledge, and societal applications. The pace of change in the new era of AI technology is astonishing, with new breakthroughs in algorithmic machine learning and autonomous decision-making bringing continuous opportunities for innovation. The impact of AI could be enormous, potentially disrupting various industries including finance, healthcare, manufacturing, retail, supply chain, logistics, and utilities (Dwivedi et al. 2021). Consequently, AI regulation, which regulates and supports its development, has naturally attracted the attention of many scholars.

By comparing AI policies in the United States, the United Kingdom, and Uzbekistan, Abdumuratovich (2024) found that the US and UK emphasize leadership in AI innovation and ethics, while Uzbekistan focuses on integrating AI into its initial development strategy. These differing AI policy approaches reflect each country's unique socio-economic background, technological capability, and strategic priorities. Using text analysis and Hofstede's cultural dimensions as a basis for cross-national comparison, Robinson (2020) explored the influence of cultural values such as trust, transparency, and openness in Nordic AI policy documents and argued that extending the concept of "digital trust" to the AI field requires national policies that uphold cultural values and individual rights, ultimately reinforcing these values in society. Agrawal et al. (2019) highlighted two types of policy impacts in response to AI technological advancements: policies affecting the diffusion of AI and policies responding to the consequences of AI diffusion. The most relevant policy categories for diffusion include privacy, trade, and liability. The focus of policy design should be to achieve an optimal balance between encouraging diffusion and protecting societal values. As AI becomes widespread, it will impact employment, inequality, and competition. Addressing these consequences will fall under the purview of education policy, social safety nets, and antitrust enforcement.

However, several significant issues exist in the AI regulatory process. For instance, the ambiguity in definitions has made it challenging to reach a consensus in policy dialogues surrounding AI. AI researchers tend to emphasize definitions based on technical functionalities, while policymakers use definitions that compare AI systems to human thinking and behavior. This gap can lead to an overemphasis on future technologies in ethical and regulatory work, neglecting the urgent issues of currently deployed technologies (Krafft et al. 2020). Ulnicane et al. (2021) examined how governance frameworks in AI policy documents address public controversies surrounding AI. To resolve issues of governance characterized by oligopolistic control by a few large companies, which often neglect societal needs and concerns, AI policy documents assign a more active cooperative role to the state and society. In public controversies, the state is entrusted with promoting and advancing AI development while also acting as a guarantor of risk mitigation and a promoter of social participation. There are high expectations for public participation, seen as a way to enhance diversity, representativeness, and equality in the development and use of AI. Through a comprehensive comparative analysis using natural language processing methods, Hine and Floridi (2024) examined AI policies in China and the United States. They concluded that both countries are striving to become global leaders in the AI field. Despite their conflicting visions, there remains room for dialogue and collaborative development.

THEORETICAL BASIS AND RESEARCH HYPOTHESIS

Previous literature suggests that the development of artificial intelligence impacts overall employment in two ways: substitution and enhancement. On one hand, AI can augment workers' skills, thereby increasing their productivity and subsequently boosting

labor demand. On the other hand, AI can replace human workers in various jobs, including those requiring advanced and complex cognitive, analytical, or decision-making skills. These two effects are not simply conflicting but are complementary, making the impact of AI on employment relatively complex. The policy tools theory provides a systematic framework for analyzing the various means and instruments used by governments in the implementation of policies. (Schneider and Ingram 1990) proposed that policy tools can be classified based on their behavioral assumptions, including authoritative tools, incentive tools, symbolic tools, and learning tools. Based on this understanding, we believe that AI policy can serve as a tool to regulate and standardize the impact of artificial intelligence on employment, thereby addressing potential unemployment crises. That is, AI policies can serve as a stimulant for enterprises, supporting and amplifying the tasks completed by workers, leading to increased production efficiency and product extension effects, thus creating more job opportunities. The number of employees in enterprises to some extent reflects the overall employment situation in society, thus we propose the following hypothesis:

Hypothesis H1: *The implementation of AI policies will have a positive impact on the number of employees in enterprises.*

Not all industries will be affected by AI policies. For companies in AI-related industries, the implementation of AI policies may ensure their development, leading to business expansion and increased hiring. In contrast, for companies in industries not related to AI, the implementation of AI policies may not have a significant impact. This variation can be attributed to the differential relevance of AI technology to various industry operations. Industries such as finance or technology, where AI integration directly enhances efficiency and product innovation, are likely to be more affected by AI policies compared to sectors like traditional manufacturing or agriculture, where AI applications may not be as integral or immediately beneficial. Based on this, we further propose the following hypotheses:

Hypothesis H2a: *The implementation of AI policies will have a positive impact on the number of employees in AI-related enterprises.*

Hypothesis H2b: *The implementation of AI policies will have no impact on the number of employees in AI-unrelated enterprises.*

EMPIRICAL STUDY

Research Context

In China's institutional system, policies often play a crucial role in industrial development. China has been regulating specific AI applications (such as internet recommendation algorithms, deep synthesis technology, and generative AI) one by one, rather than formulating an all-encompassing AI regulation (like the EU's "Artificial Intelligence Act"). This enables China to create tailored rules for specific issues and steadily accumulate new policy tools and regulatory knowledge through each new regulation. Moreover, China has demonstrated the ability to rapidly amend regulations in response to the fast development of AI. For instance, the name of China's generative AI regulation, "*Interim Measures for the Management of Generative AI Services*," explicitly indicates that it is a "provisional" law, which will be continuously improved over time. This is due to China's political system allowing it to pass/amend laws faster than other countries, providing the capability to create iterative legislation. Additionally, China, with its large population base and labor market, is often considered the only country with all industrial categories listed in the United Nations International Standard Industrial Classification. Therefore, this study will use China's labor market as an entry point to examine the impact of AI policy formulation and implementation on employment.

Due to the high level of information disclosure of listed companies and their often larger scale, they are more representative of the entire industry. Therefore, this study will select a total of 5160¹ non-ST companies listed on the A-share market as research subjects to explore the impact of AI policies on firm employment. The term 'ST' or 'Special Treatment' is derived from the Chinese stock market context, indicating companies that pose financial risks or face other significant issues warranting increased scrutiny.

Dataset

This study focuses on the impact of Artificial Intelligence (AI)-related policy documents issued by Chinese governments at provincial levels. There are 34 such regions in total, including 23 provinces, five autonomous regions, four municipalities, and two special administrative regions. This study excludes Hong Kong, Macau, and Taiwan due to their unique political and administrative statuses. Using the keyword "artificial intelligence" in the title, we collected policy documents from the PKULaw database and official government websites. After eliminating obviously irrelevant policy documents, we pre-processed them and matched them with the date and place of issuance, resulting in 99 policy documents from 2009 to 2024. According to Figure 1, the peak of AI policy issuance in China is around 2019 and 2023. We believe that these two time points correspond to the resurgence of deep learning and the advent of generative AI (e.g., ChatGPT), respectively. The previous one is the focus of this study.

Employee-related data come from the Wind database. Other corporate-level data are sourced from the CSMAR financial database. Province-level data, such as per capita GDP and unemployment rate, are obtained from the National Bureau of Statistics of China.

¹ The number of 5,160 companies takes into account the sum of all currently listed and formerly listed companies, hence it may not correspond to the number of companies in a specific year.

The final dataset is yearly basis consisting of 47,980 firm-year observations for 5160 firms in 31 provinces from 2009 to 2024 (15 years).

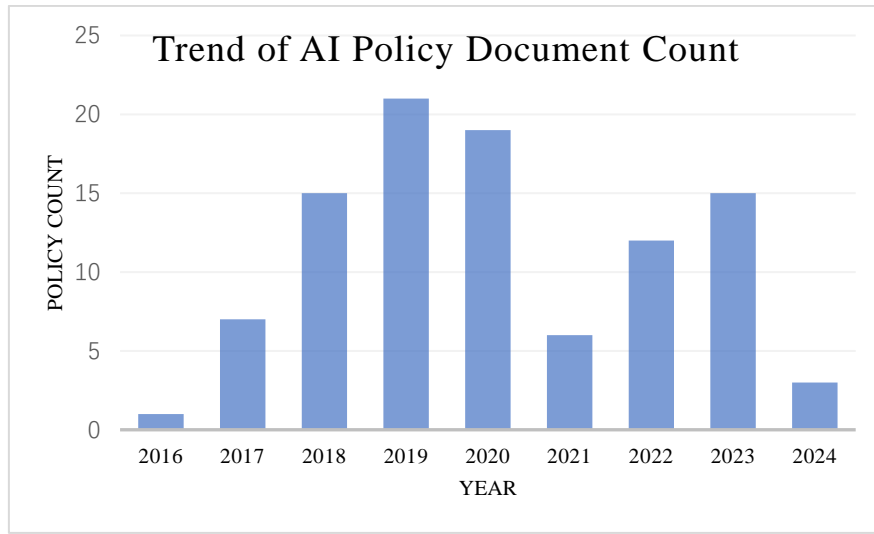


Figure 1: Trend of AI policy document count.

Econometric Models

Outcome Variables

In this study, we use the logarithm of the number of employees (*EmployeeCnt*), reflecting the employment situation (Yang 2022). This allows us to study the impact of AI policy on the labor market. Over time, from 2007 to 2022, the average number of employees has remained relatively stable, fluctuating between approximately 5,500 and 6,500.

Independent Variable

To study the impact of AI policy on the labor market, we define the independent variable as the issuance of AI policies (*AIPolicy*), which is a dummy variable taking the value of 1 if the local government has already issued AI-related policy documents.

Control Variables

This study selects the following control variables: (1) the logarithm of the total assets of the enterprise (*TotalAssets*), reflecting the size of the enterprise. a company's total assets can significantly impact its employment levels. The relationship is often mediated by the firm's capacity for investment and expansion, which can lead to increased hiring. (2) the logarithm of the intangible assets of the enterprise (*IntangibleAsset*), reflecting the level of innovation within the enterprise. It includes intellectual property, brand reputation, and R&D. Firms investing in intangible assets often experience growth in employment due to the innovative capabilities these assets bring. (3) the logarithm of the net profit of the enterprise (*NetProfit*), reflecting the profitability of the enterprise. It is a direct indicator of its financial health and ability to sustain and grow its workforce.

AI-Related/-Unrelated Industries

We define AI-related terms as follows: artificial intelligence, business intelligence, image understanding, investment decision support systems, intelligent data analysis, machine learning, deep learning, intelligent robots, semantic search, biometric technology, facial recognition, speech recognition, identity verification, autonomous driving, and natural language processing.

Based on the average and standard deviation of AI-related terms mentioned in the annual reports of various companies from 2007 to 2020, we define AI-related industries as those where the frequency of AI-related terms in the annual reports exceeds the mean plus one standard deviation. Through this calculation, we identified eight industries: (1) insurance, (2) internet and related services, (3) monetary financial services, (4) computer, communication and other electronic equipment manufacturing, (5) education, (6) software and information technology services, (7) culture and arts, and (8) postal services.

Difference-in-Differences Model

This study constructs a difference-in-differences (DID) model based on panel data to investigate the causal effect of AI policy on employment:

$$AmountCnt_{i,t} = \alpha_0 + \alpha_1 AIPolicy_{it} + \gamma X_{it} + \mu_t + v_i + \varepsilon_{it} \quad (1)$$

where $AmountCnt_{i,t}$ is number of employees for firm i in year t ; $AIPolicy_{it}$ is a binary variable indicating whether the province where company i is located enacted AI-related policies in year t ; X_{it} is the vector of control variables; μ_t represents the time fixed effects for the company, v_i represents the individual fixed effects for the company, and ε_{it} represents the random error term. The coefficient of main interest, α_1 , captures the effect of the AI policy on employment.

Table 1: Descriptive Statistics and Correlation Matrix

Variables	N	Mean	Std	Max	Min	<i>EmployeeCnt</i>	<i>AIPolicy</i>	<i>TotalAssets</i>	<i>IntangibleAsset</i>	<i>NetProfit</i>
<i>All Samples</i>										
<i>EmployeeCnt</i>	46,301	7.486842	1.672986	0	13.46383	1.0000				
<i>AIPolicy</i>	47,980	.3792414	.4852033	0	1	0.0180	1.0000			
<i>TotalAssets</i>	47,979	22.10682	1.58655	0	31.43093	0.6752	0.1066	1.0000		
<i>IntangibleAsset</i>	47,777	18.11911	2.93266	0	26.31364	0.4815	0.1016	0.4798	1.0000	
<i>NetProfit</i>	42,527	18.86131	1.68446	9.737177	26.62348	0.5539	0.1266	0.7951	0.3986	1.0000
<i>AI-related Industries</i>										
<i>EmployeeCnt</i>	7756	7.396656	1.873836	0	13.12851	1.0000				
<i>AIPolicy</i>	8122	.4826397	.4997293	0	1	0.0221	1.0000			
<i>TotalAssets</i>	8122	21.9857	2.004383	14.10822	31.43093	0.6990	0.0681	1.0000		
<i>IntangibleAsset</i>	8070	17.55958	2.835018	0	24.32195	0.4732	0.0854	0.4972	1.0000	
<i>NetProfit</i>	7123	18.83583	1.882083	11.66442	26.62348	0.6297	0.0768	0.8760	0.4331	1.0000
<i>AI-unrelated Industries</i>										
<i>EmployeeCnt</i>	38,545	7.504989	1.629005	0	13.46383	1.0000				
<i>AIPolicy</i>	39,858	.3581715	.4794689	0	1	0.0191	1.0000			
<i>TotalAssets</i>	39,857	22.1315	1.485895	0	28.64361	0.6704	0.1220	1.0000		
<i>IntangibleAsset</i>	39,707	18.23283	2.939149	0	26.31364	0.4852	0.1155	0.4814	1.0000	
<i>NetProfit</i>	35,404	18.86644	1.641809	9.737177	25.91784	0.5345	0.1394	0.7742	0.3935	1.0000

RESULTS

Descriptive Statistics

The descriptive statistics and correlation of variables are displayed in Table 1. We conducted statistical descriptions of the basic information for the entire sample, AI-related industry companies, and non-AI-related industry companies separately.

Main Model Results

The main model results are displayed in Table 2. The standard errors are clustered at the province level to ensure that the estimators are robust to cross-sectional heteroskedasticity and within-panel (serial) correlation.

As shown in column (1), the coefficients of $AIPolicy_{i,t}$ are not significant. For all industries, AI policies do not have a significant impact. H1 is not supported. As shown in column (2), the coefficient of $AIPolicy_{i,t}$ is positive and significant ($\beta=0.111$, $p<0.01$), indicating that the hypothesis H2a is supported. When the AI policy is implemented in the province where the enterprise is located, the number of employees of the enterprise will increase by 11.74% ($e^{0.111}-1$). As shown in column (3), the coefficient of $AIPolicy_{i,t}$ is insignificant ($\beta=0.0275$, $p>0.1$), indicating that the hypothesis H2b is supported.

These findings indicate that for companies within AI-related industries, the implementation of AI policies significantly increases their hiring numbers, thereby promoting social employment to some extent. This may be because government-issued AI policies usually include incentives such as financial support, tax reductions, and research and development subsidies. These supports can reduce operational costs for companies, increasing their investment in AI technology, thereby boosting the demand for AI talent. Moreover, government policies often enhance market confidence in the AI industry. The introduction of these policies signifies the government's emphasis and support for AI technology, encouraging companies to invest more resources in this field, expand their businesses, and subsequently increase hiring. Additionally, government policies often include support for AI talent development and education, such as funding AI-related disciplines in universities and providing training programs. This will increase the supply of AI talent in the market, and companies will take the opportunity to increase recruitment to attract emerging talent.

Table 2: Main model effect.

	(1)	(2)	(3)
	H1	H2a	H2b
	All Industry	AI Related Industry	AI Unrelated Industry
$DV=$	$EmployeeCnt_{i,t}$		
$AIPolicy_{i,t}$	0.0409	0.111***	0.0275
	(0.0348)	(0.0282)	(0.0366)
$TotalAssets_{i,t}$	0.480***	0.415***	0.503***
	(0.0205)	(0.0313)	(0.0240)
$IntangibleAsset_{i,t}$	0.118***	0.101***	0.121***
	(0.00655)	(0.0270)	(0.00960)
$NetProfit_{i,t}$	0.0908***	0.141***	0.0818***
	(0.0111)	(0.0191)	(0.0121)
<i>Constant</i>	-6.909***	-6.087***	-7.312***
	(0.319)	(0.668)	(0.364)
<i>Province FE</i>	YES	YES	YES
<i>Year FE</i>	YES	YES	YES
# of Obs.	42,267	7,058	35,209
# of Provinces	31	30	31
# of Firms	5,106	1,141	4,196
R^2	0.6177	0.6938	0.6052
<i>Adj. R²</i>	0.6172	0.6917	0.6047

Notes: Cluster-robust standard errors (at the province level) are shown in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Robustness Checks

Parallel Trend Test

The research method used in this study is the Difference-in-Differences (DID) method. The parallel trends assumption is a prerequisite for the applicability of DID. Therefore, this study tests the parallel trends of the model to observe whether the treatment and control group firms maintained the same trend before being affected by the AI policy. Referring to the approach of Beck et al. (2010), this study conducts a parallel trends test on the samples of the treatment and control groups (Beck et al. 2010).

We calculate the difference between the current year of each firm in the treatment group and the initial year when the AI-related policy was issued in the firm's province. This difference is then multiplied by the sample grouping variable treatment to form the interaction term $t \times \text{treatment}$. The interaction term before the issuance of the AI-related policy is denoted as pre_t , and the

interaction term after the issuance of the AI-related policy is denoted as $post_t$, with period 0 chosen as the base period. If the coefficients of pre_t are all insignificant, it indicates that the treatment and control group firms meet the parallel trends assumption before the issuance of the AI policy. The results of the parallel trends test are shown in Figure 2.

As shown in the regression results in Figure 2(b), for AI-related firms, the coefficients of pre_9 , pre_8 , pre_7 , pre_6 , pre_5 , pre_4 , pre_3 , pre_2 , and pre_1 are all insignificant, indicating that the number of employees in the treatment and control group firms was essentially the same in the years before the issuance of the AI-related policy. However, after the issuance of the AI-related policy in the firms' provinces, the subsequent coefficients of the interaction term are all significantly positive, indicating that the AI-related policy has a positive effect on the recruitment of AI-related firms. Conversely, firms across the entire industry and firms not related to the AI industry did not pass the parallel trends test, as shown in Figures 2(a) and 2(c).

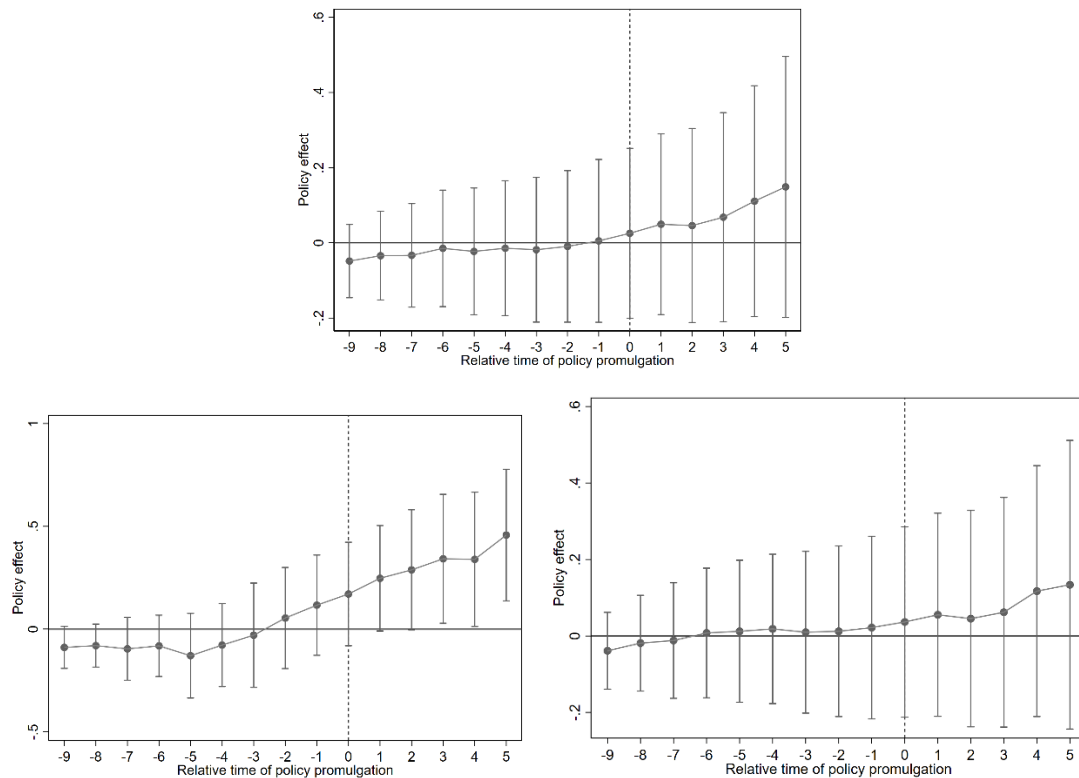


Figure 2: Parallel trend test: (a) All industries; (b) AI-related industries; (c) AI-unrelated industries.

Placebo Test

Due to different policy timings for different companies, we not only randomly select companies as the treatment group but also randomly select the time as the policy point. Finally, we generate interaction terms for regression. Repeating this process 500 times, we obtain 500 regression results. For Figure 3, the vertical dashed line represents the true model estimate of 0.111, and the horizontal dashed line represents the significance level of 0.1. Our true estimate of 0.111 is an outlier, and most of the estimated p-values are greater than 0.1, indicating that our estimate is unlikely to be obtained by chance and is therefore unlikely to be influenced by other policies or random factors.

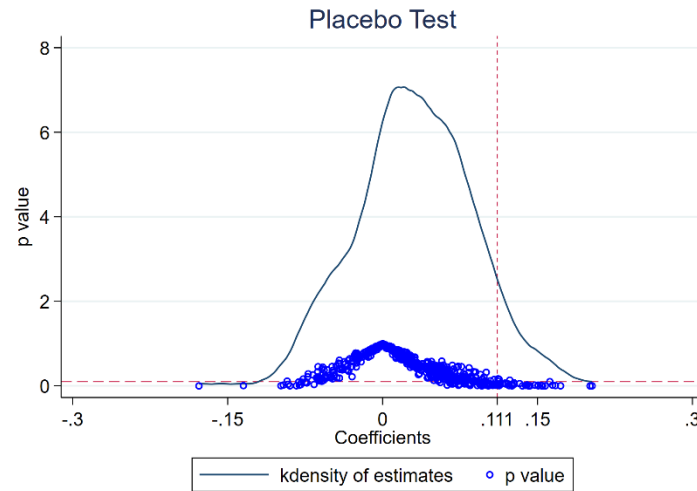


Figure 3: Placebo Test Diagram of AI-related Industries.

Propensity Score Matching

This study uses the number of employees in a company to study the impact of AI policies on the labor market. However, there may be differences between companies in provinces that have enacted AI policies and those that have not. Therefore, directly using the difference-in-differences method, with companies in provinces that have enacted AI policies as the treatment group and those in provinces that have not as the control group, might not satisfy the common trend assumption, potentially leading to biased estimates. To improve the accuracy of the estimates and eliminate differences between the treatment and control groups, this study employs the Propensity Score Matching (PSM) method to control for observable characteristic vectors between the treatment and control groups. The paper selects total company assets, intangible assets, and net profit as matching variables and uses 1:1 nearest neighbor matching to select control group samples. In traditional PSM matching, panel data is often treated as cross-sectional data, which may lead to repeated matching of the same sample. To ensure the scientific and rational nature of the matching, this study matches the treatment and control groups within the same year during the PSM process. Finally, this study examines the matching results. It is generally considered that the difference in matching variables between the treatment and control groups should not exceed 20% for the matching to be deemed effective. The differences in matching variables between the treatment and control groups in this study are relatively small.

As shown in column (1) of Table 3, the coefficient *AIPolicy* is positive and significant ($\beta = 0.101$, $p < 0.01$), indicating that for the data matched using PSM, the implementation of AI policies still has a significant promoting effect on the recruitment of companies in AI-related industries. This reflects the robustness of the results.

Alternative Model Specification

The strict assumptions of the two-way fixed effects model imply that it can only produce causally interpretable estimates in a parallel world where these assumptions hold true. Any failure of these assumptions can lead to biased estimates of causal effects. Following the approach of Liu et al. (2024), we use the FECT (Fixed Effects Counterfactual Estimators) approach to obtain more precise causal estimates for staggered set-up. Specifically, we use interaction fixed effects to predict counterfactuals, setting the factor number to 2. We apply this method to predict average treatment effects for the entire industry, AI-related industries, and non-AI-related industries.

As shown in Figure 4(b), for companies in AI-related industries, the average treatment effects of policies in each period are not significant before the base period. However, after the base period, the average treatment effects of policies in each period are significantly greater than zero. This indicates that policy implementation significantly promotes recruitment for companies in AI-related industries. In contrast, as shown in Figure 4(a) and figure 4(c), for the entire industry and non-AI-related industries, the average treatment effects of policies are not significantly different from zero, both before and after the base period. This suggests that the implementation of AI policies does not have a significant impact on recruitment for these industries.

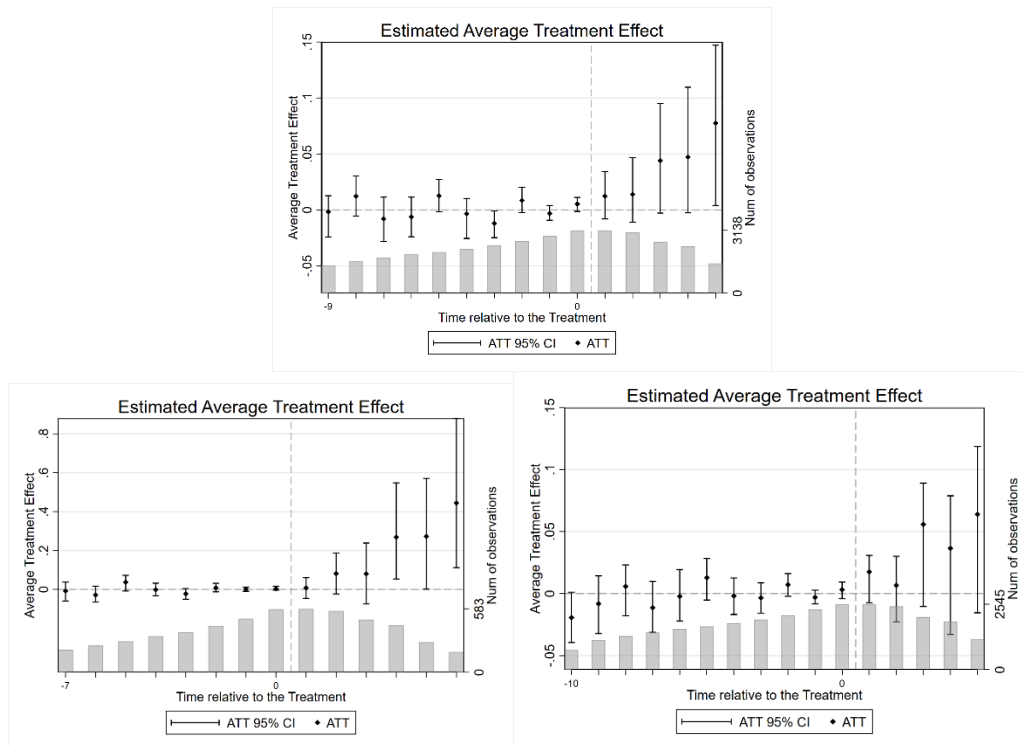


Figure 4: Event Study Plots using FECT for (a) All Samples; (b) AI-related Industries; (c) AI-unrelated Industries.

Alternative Measures of Outcome Variable

We changed the dependent variable by not taking the logarithm of the number of hires to verify the robustness of the results. As shown in column (2) of Table 3, for AI-related industries, the coefficient of *AIPolicy* remains significant and positive ($\beta = 1,803$, $p < 0.05$). This indicates that the implementation of AI policies continues to have a promoting effect on the number of employment, thereby confirming the robustness of the model.

Table 3: Results of robustness checks.

	(1)	(2)
	AI Related Industry	
	DID+PSM	DID+DV No Log
<i>DV=</i>	<i>EmployeeCnt_{i,t}</i>	
<i>AIPolicy_{i,t}</i>	0.101***	1,803**
	(0.0327)	(823.7)
<i>TotalAssets_{i,t}</i>	0.392***	10,584***
	(0.0360)	(3,420)
<i>IntangibleAsset_{i,t}</i>	0.132***	-1,797**
	(0.0215)	(873.4)
<i>NetProfit_{i,t}</i>	0.130***	3,059***
	(0.0183)	(963.8)
<i>Constant</i>	-5.887***	-250,590***
	(0.661)	(75,034)
<i>Province FE</i>	YES	YES
<i>Year FE</i>	YES	YES
<i># of Obs.</i>	5,833	7,058
<i># of Provinces</i>	29	30
<i># of Firms</i>	784	1,141
<i>R²</i>	0.7160	0.3989
<i>Adj. R²</i>	0.7136	0.3947

Notes: Cluster-robust standard errors (at the province level) are shown in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

DISCUSSION

Mechanism: Research and Development Spend Ratio

Research and development (RD) spend ratio (*RDSpendRatio*) is measured by the proportion of a company's R&D investment to its operating revenue, reflecting the company's innovation capability. The relevant data is sourced from the Corporate R&D Investment Report in the CSMAR database.

As shown in column (1) of Table 4, the coefficient *AIPolicy*•*RDSpendSumRatio* is negative and significant ($\beta = -0.006$, $p < 0.05$), indicating that the AI policy effects on employment is weaker for firms with higher ratios of R&D person. This may be because companies with low R&D investment might face significant pressure for technological transformation. The implementation of AI policies provides these companies with the urgently needed resources and support, enabling them to accelerate their technological transformation process. As a result, they become more proactive in recruitment to quickly fill AI-related positions, thereby enhancing their competitiveness.

Mechanism: Employee Education Level

The educational level of employees is measured by the number of employees with a graduate degree or higher (*PostGraduate*), reflecting the quantity and structure of highly educated talent within the company. Considering the magnitude of the coefficients, we processed the employee number data by dividing it by 1,000. The relevant data is sourced from the Wind database.

As shown in column (2) of Table 4, the coefficient *AIPolicy_{i,t}*•*PostGraduate* is negative and significant ($\beta = -0.0200$, $p < 0.001$), indicating that the AI policy effects on employment is weaker for firms as the number of highly educated employees in the company increases. A possible reason is that with the implementation of AI policies, the level of automation is increasing, leading to more positions focused on simple tasks like screwing bolts, while the demand for highly educated talent is decreasing.

Mechanism: Average Wage of Employees

Average wage of employees (*AvgWage*) is measured by the average salary of all employees in the company, which to some extent reflects the supply and demand situation of employees in the market. The relevant data is sourced from the annual reports of the listed companies.

As shown in column (3) of Table 4, the coefficient *AIPolicy_{i,t}*•*AverageWage* is positive and significant ($\beta = 0.0712$, $p < 0.01$), indicating that the AI policy effects on employment is stronger for firms with higher average wages. The implementation of AI policies has promoted the development of the AI industry, leading companies to recruit for AI-related positions. With the increase in market demand, the supply of talent cannot keep up in the short term, resulting in a corresponding rise in salaries.

Table 4: Mechanism.

	(1)	(2)	(3)
	AI-related Industries		
<i>DV</i> =	<i>EmployeeCnt_{i,t}</i>		
<i>AIPolicy_{i,t}</i>	0.106*** (0.0372)	0.109*** (0.0177)	-0.199*** (0.0431)
<i>RDSpendRatio_{i,t}</i>	-0.00488 (0.00485)		
<i>AIPolicy_{i,t}</i> • <i>RDSpendRatio_{i,t}</i>	-0.00584** (0.00253)		
<i>PostGraduate_{i,t}</i>		0.0411 (0.0243)	
<i>AIPolicy_{i,t}</i> • <i>PostGraduate_{i,t}</i>		-0.0200*** (0.00624)	
<i>AverageWage_{i,t}</i>			-0.0719*** (0.0111)
<i>AIPolicy_{i,t}</i> • <i>AverageWage_{i,t}</i>			0.0712*** (0.0117)
<i>TotalAssets_{i,t}</i>	0.705*** (0.0317)	0.369*** (0.0601)	0.476*** (0.0256)
<i>IntangibleAsset_{i,t}</i>	0.0516*** (0.0155)	0.111*** (0.0259)	0.0877*** (0.0231)
<i>NetProfit_{i,t}</i>	0.0784*** (0.0241)	0.147*** (0.0259)	0.144*** (0.0178)
<i>Constant</i>	-10.22*** (0.763)	-5.414*** (1.138)	-6.974*** (0.673)
<i>Province FE</i>	YES	YES	YES
<i>Year FE</i>	YES	YES	YES
<i># of Obs.</i>	5,730	5,106	6,669

# of Province	29	27	30
# of Firms	1,037	951	1,127
R ²	0.6389	0.7006	0.7125
Adj. R ²	0.6358	0.6979	0.7103

Notes: Cluster-robust standard errors (at the province level) are shown in parentheses. *p < 0.1; **p < 0.05; ***p < 0.01.

CONCLUSION AND LIMITATION

Over the past decade, artificial intelligence (AI) technology has advanced rapidly, significantly impacting enterprises, especially in labor demand. The implementation of AI policies has been instrumental in both fostering and regulating the development of AI, subsequently influencing enterprise hiring practices. We constructed a panel dataset of non-ST listed companies in the A-shares market from 2009 to 2024, utilizing the number of employees as the dependent variable, to investigate the effects of AI policy promulgation on employment. The empirical findings reveal that the promulgation of AI policies substantially increases the number of employees for companies within AI-related industries. This result is further supported by a series of robustness checks, underscoring the effectiveness of AI policies as a tool for promoting social employment. Additionally, our analysis indicates that within AI-related industries, the lower the proportion of R&D investment and the fewer highly educated employees, coupled with higher average employee salaries, the more pronounced the impact of AI policies on employment numbers. Employee-related data come from the Wind database. Other corporate-level data are sourced from the CSMAR financial database.

Our research has several limitations. First, we only focused on whether AI policies were enacted without further analyzing their content. Second, we only studied the impact of policy enactment on the number of employees, i.e., overall employment, without exploring the impact of policies on employment structure. We will address these issues in the future work.

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