The Influence of AI on Firm Employee Growth

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Abstract

In this paper, we examine the impact of a firm's AI adoption on its employment growth. Using an aggregation of AI scores among all of a firm's patents as a proxy, we find that AI adoption significantly negatively affects the firm's subsequent employee growth rate. The result is robust to various endogeneity and robustness tests. Moreover, this effect is more pronounced among firms in low-skilled industries, with lower operational complexity, and held by active investors. Overall, our findings suggest that AI adoption is adversely affecting employment growth.

Keywords: Artificial Intelligence, Labor, Employment, Innovation, Patent, Institutional Investor

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1. Introduction

The development and investment trends in Artificial Intelligence (AI) have seen dramatic shifts in recent years. AI, especially generative AI, has experienced a significant surge in both technological advancements and financial backing. According to the World Economic Forum (2024), while overall private AI investment declined in 2023, funding for generative AI skyrocketed to $25.2 billion, nearly nine times the amount from the previous year. This rapid growth in investment indicates a strong focus on AI technologies that can generate new content or insights, with applications spanning various sectors, from healthcare to entertainment and finance.

One of the most pressing concerns surrounding AI is whether it will replace human jobs, leading to widespread unemployment. According to the Wall Street Journal (October 2023), companies such as Salesforce, Microsoft, and Workday are integrating AI agents into their operations, including recruitment, sales, and IT management. While employees collaborate with AI to enhance efficiency, there are concerns about job displacement as AI takes on routine tasks. The Financial Times (October 2023) reported that labor unions, particularly the International Longshoremen's Association (ILA), are striking over automation fears, with the ILA opposing AI-driven changes at U.S. container ports that could eliminate jobs. The union argues for job security assurances, while employers cite automation as crucial for maintaining competitiveness. Additionally, the Financial Times (November 2023) discussed the transformation of workplace dynamics as AI becomes more integrated into daily tasks. Experts predict that generative AI will reshape work processes, requiring new leadership strategies to manage AI collaboration. Employees are likely to experience more interaction with AI, which may alter their roles, but concerns about job satisfaction and the rise of loneliness in hybrid work environments also emerge. These reports illustrate both the opportunities and challenges AI presents to employees across various industries.

In this paper, we examine the relationship between firm-level AI adoption, as measured by the AI Patent, and employee growth rate (EmployG). We construct the AI Patent using data from the United States Patent and Trademark Office - Artificial Intelligence and Patent Data (USPTO-AIPD), which utilizes machine learning to assign scores to each patent application based on various AI attributes, such as "Listening", “Speech”, “AI hardware”, "Deep learning" and so on (Giczy et al. 2020). Specifically, for each patent, we calculate an AI Patent by summing the individual AI aspect scores. For each firm, we aggregate the AI score of all patents granted in a given year and then take the logarithm of one plus this aggregated value.

Our empirical analysis reveals a significant negative relationship between AI Patent and employee growth rate after controlling for firm and year fixed effects. This result suggests that as AI technologies become more widespread and their adoption costs decrease, combined with rising labor costs and growing advocacy for labor rights, firms are increasingly inclined to adopt AI with adaptive learning capabilities as a substitute for traditional employees. AI technologies not only significantly enhance operational efficiency but also help address challenges in labor management, making them an attractive option for firms in their decision-making processes.

Next, we conduct an endogeneity test. First, we apply the entropy balancing method, which ensures proper covariate balance between the treatment group (firms with an AI Patent higher than the median for that year) and the control group. By assigning weights to observations, this method ensures that the means, variances, and skewness of the treated and control groups are balanced across all matching dimensions. The results remain consistently negative and significant.

Secondly, we incorporate state-level AI-related regulations, defining AI Regulation as a dummy variable that equals 1 if AI regulation legislation is in effect in the state, and 0 otherwise. The difference-in-differences results show a significant positive effect for firms affected by the regulation, consistent with the findings of Cuellar et al. (2024), which suggest that exposure to information about AI regulations reduces managers' intent to adopt AI technologies.

Moreover, the time trend analysis reveals that this effect has diminished over time, while the sub-sample analysis shows that the negative effect is significantly more pronounced in technology-related industries. Although the manufacturing and service industries are also affected, the financial industry is not significantly impacted. The cross-sectional analysis further shows that the main effect weakens for firms with higher organizational complexity and for those predominantly held by quasi-indexer investors. Conversely, the effect is more pronounced among firms held by transient investors.

Finally, we switch the independent variable to a treatment dummy variable and the average adjusted AI Patent. Additionally, we replace the dependent variable with a dummy variable indicating positive or negative employee growth rate, identifying whether the firm is expanding. We also change the firm fixed effects to industry fixed effects. All results remain consistent with the baseline negative significant findings.

The structure of this paper is as follows: Section 2 reviews the relevant literature and provides the background. Section 3 outlines the development of the hypotheses. Section 4 presents empirical analysis, including the baseline results, endogeneity tests, sub-sample analysis, time trend analysis, cross-sectional analysis, and several robustness checks. Finally, Section 5 discusses the conclusions.

2. Literature Review

Before AI became widely adopted as a transformative technological advancement, a significant body of research had already explored how various forms of innovation—such as robotics or patent—affect firm performance. Drawing from Romer (1990), Glaeser and Lang (2024) defines three key economic characteristics that distinguish innovation from other assets: novelty, nonrivalry, and partial excludability. Innovations are novel ideas or new ways of applying existing ones, and they offer the unique advantage of non-rivalry, meaning multiple parties can use them simultaneously without diminishing their utility. Additionally, partial excludability means that innovation owners cannot fully prevent others from benefiting, leading to knowledge spillovers that enhance economic growth. This theoretical framework underpins the importance of innovation for both firm and macroeconomic growth, as it allows for the scaling of production without the same limitations faced by rival goods like labor and capital. Furthermore, innovations like AI illustrate the broad, no rivalrous applications that continue to fuel growth across industries. Most studies use patent as a key proxy variable for firm innovation. Researchers have explored various dimensions, including the quantity and quality of patents, their technological impact, and their association with firm performance and growth (He and Tian 2013; Shu et al. 2022; Wu et al. 2020).

The academic research on AI can be categorized into three main areas: the impact of AI adoption on firm performance, the factors that determine firms' decisions to adopt AI, and how AI can assist humans.

In terms of the impacts of AI adoption to the firm performance, Babina et al. (2024) investigates that firms investing in AI exhibit superior growth in sales, employment, and market valuations, primarily driven by enhanced product innovation. Particularly, the study employs an instrumental variable approach using firms' exposure to the supply of AI graduates from universities, confirming the robustness of the results, which shows that the transformation relationship through people in high strengths of AI universities into the firm AI abilities. Similarly, Gofman and Zhao (2024) highlight a significant brain drain of AI professors from universities. The departure of these professors is associated with a decline in AI startup formation and fundraising by students from the affected universities. The impact is particularly pronounced for tenured professors, faculty from top universities, and those specializing in deep learning. They propose the explanation that the loss of professors reduces the AI knowledge available to potential startup founders, which is a critical determinant of successful startup creation and fundraising efforts.

Others focus on the firm's AI adoption and require job changes (Acemoglu et al. 2020). They show rapid growth in AI-related job postings between 2010 and 2018, driven primarily by establishments where workers perform tasks that align with AI's current capabilities. As these AI-exposed establishments adopt AI, they reduce hiring for non-AI positions while simultaneously altering the skill requirements for remaining job postings. Although this trend is evident at the establishment level, the aggregate effects of AI-driven labor substitute on employment and wage growth in more exposed occupations and industries are currently too small to be detected. Similarly, Yang (2022) shows a positive relationship between AI technology (proxied by the patent grants) and employment in Taiwan. Moreover, the adoption of AI technologies significantly reshapes workforce composition, reducing the proportion of Employs with educational qualifications at or below the college level. While Alonso et al. (2022) supposes that if AI (proxied by the robot) primarily substitutes unskilled labor, the terms of trade—and consequently GDP—may experience a permanent decline. Furthermore, Acemoglu (2020) highlights that AI impacts labor markets differently than previous technologies. It often complements high-skill tasks while displacing routine jobs, complicating workforce dynamics and cost structures.

Moreover, Other scholars (Babina et al. 2024) explore how firms' systematic risk evolves with the rise of AI in the 2010s. They find that firms investing more in AI experience increases in their systematic risk, as measured by equity market beta. The higher market beta of AI-investing firms cannot be attributed to factors such as financial or operating leverage, asynchronous trading, increased correlation with the tech sector, within-industry concentration, or correlated investor flows. The results suggest that AI investments provide firms with new growth options, making them more growth oriented. Another paper focused on the specific industry to discover the AI influence. Like one study proposed that AI adoption in health care is notably lower than in most other industries. Specifically, fewer than 3 percent of the hospitals in the data posted any jobs requiring AI skills between 2015 and 2018 (Goldfarb et al. 2020). As far as the AI responsibilities, Ahmed and Jia (2024) analysis reveals that firms with increasing demand for AI scientists—particularly in deep learning, which face an even tighter labor market—are more likely to embrace responsible AI principles. Additionally, corporate AI scientists' collaborations with academia and the publication records of their PhD-granting institutions on responsible AI further predict firms' adherence to such principles.

On the other hand, several papers analyze the motivation of firms' AI adoption. Alekseeva et al. (2021) finds that between 2010 and 2019, the U.S. economy experienced a significant rise in demand for AI skills across most industries and occupations. The demand is highest in IT occupations, followed by architecture and engineering, scientific, and management roles. Firms with larger market capitalizations, greater cash reserves, and higher R&D investments exhibit a stronger demand for AI skills. Additionally, they find a wage premium of 11% for positions requiring AI skills within the same firm and 5% within the same job title. Managerial roles command the highest wage premium for AI skills.

Moreover, other studies have explored how AI can assist humans across various domains. Cao et al. (2024) finds that AI analysts, trained to process corporate disclosures, industry trends, and macroeconomic indicators, have demonstrated superior performance in stock return predictions when compared to most human analysts. However, humans retain an edge in "Man vs. Machine" scenarios when institutional knowledge plays a critical role, such as in the evaluation of intangible assets and situations involving financial distress. In cases where the information is abundant but transparent, AI tends to outperform humans due to its ability to rapidly process large datasets.

Human capital, encompassing factors such as employee growth, wages, and skills development, is widely recognized as a critical form of capital expenditure for firms. Several studies discuss the dynamics of employee changes following firms' exposure to significant shocks or events. Serfling (2016) finds that firms reduce debt ratios following the adoption of such labour protection laws, with this result stronger for firms that experience larger increases in firing costs. Following the adoption of these laws, a firm's degree of operating leverage rises, earnings variability increases, and employment becomes more rigid. Barrot and Nanda (2020) examine the effects of Quickpay, a policy reform that introduced a permanent acceleration in payment schedules for small business contractors working with the U.S. government and reveals a significant positive impact of the reform on firm-level employment growth. Graham et al. (2023) argue that an employee's annual income decreases by 13% during the first full calendar year following their firm's bankruptcy. Over the subsequent six years, the total value of lost earnings amounts to 87% of the employee's pre-bankruptcy annual salary. Choi and Gipper (2024) analyze the outcomes of employees across different phases of fraudulent financial reporting—before, during, and after the fraud period. They find that employees at firms involved in fraud suffer significant economic consequences, including a 50% reduction in cumulative annual wages relative to a matched sample. Post-fraud, separation rates increase markedly. Interestingly, during the fraudulent period, these firms exhibited positive employment growth, characterized by overexpansion and the hiring of lower-paid Employs, a stark contrast to distressed firms, which typically contract. However, once the fraud is exposed, these firms undergo substantial layoffs, reversing the abnormal growth and driving the majority of wage losses. The adverse effects on wages are more pronounced in thin labor markets, and lower-wage Employs—despite being unlikely perpetrators of the fraud—experience more severe wage reductions compared to their higher-wage counterparts. In the emerging market (China), Li et al. (2020) find that the inducement effect of rising labor costs is more significant in non-state-owned enterprises, firms lacking political connections, and those with low labor productivity. Their findings align with the induced innovation hypothesis, which posits that wage increases stimulate invention and technological adoption. However, the results also reveal that government interventions, particularly through state ownership and political affiliations, substantially mitigate this inducement effect.

Moreover, the fundamental characteristics of a firm can significantly influence its employee hiring decisions. Ouimet and Zarutskie (2014) discover the relationship between the firm age, employee age and growth. They exhibit that young firms show a notable tendency to employ and recruit young workers disproportionately. On average, young employees at young firms earn higher wages compared to their counterparts at older firms. These young employees are more likely to join young firms characterized by significant innovation potential and higher growth trajectories, conditional on their survival. This trend can be attributed to the unique skills, risk tolerance, and dynamic adaptability of young workers, which align closely with the needs of young firms. Furthermore, evidence suggests a causal relationship between the supply of young workers and the creation of new firms in high-tech industries, as an increase in the availability of young labor is positively associated with entrepreneurial activity in these sectors.

3. Hypothesis Development

Employment growth, along with the quality of labor division, has become a central concern in the era of AI, drawing significant attention from governments, corporations, and individuals. The debate over the adoption of AI by companies is multifaceted, with crucial implications for labor markets.

On one hand, AI creates new industries and opportunities, especially in high-skill sectors such as data science, AI development, and system maintenance. According to the IMF (2024), AI and automation have the potential to generate new jobs and sectors, creating a so-called "reinstatement effect" where new tasks and roles emerge because of technological advancements. Firms that adopt AI are likely to see increased demand for skilled workers, particularly those with expertise in emerging AI technologies. Babina et al. (2024) employ a long-difference approach, conducting a cross-sectional regression where both the dependent and independent variables are measured as changes over the 2010–2018 period. Their results reveal that employment growth is positively associated with the concurrent change in the number of AI workers (as inferred from job posting data). The authors interpret this finding to suggest that, at least on net, AI adoption has not yet resulted in workforce displacement within firms.

On the other hand, the implementation of AI is often associated with job displacement, especially in low- and middle-wage occupations, as AI technologies automate human tasks (Autor 2015, Acemoglu and Restrepo 2018). Deloitte (2023) suggests that such "displacement effects" may reduce aggregate labor demand in sectors focused on automating existing tasks.

While AI presents transformative opportunities, its implications for employment remain uncertain. Therefore, we posit:

H1: Firms' adoption of AI technology, proxied by AI patent exposure, has a significant impact on their employment growth.

In terms of industry characteristics and labor demand, industries like service and manufacturing, which rely heavily on non-technical workers, are more vulnerable to labor displacement due to AI adoption. Companies in these sectors face stronger economic incentives to implement AI technologies to streamline operations and reduce reliance on low-skilled labor. Consequently, we posit:

H2: The impact of AI adoption on firms' employment growth is more pronounced for firms in industries that require low-skilled labor compared to those that need high-skilled labor.

Regarding the degree of complexity and AI Adoption, firms with lower complexity often have simpler operational structures, making it easier to integrate AI technologies and streamline processes. In such firms, the adoption of AI innovations is likely to result in more immediate workforce adjustments, including a reduction in employee growth rates, as tasks become automated, or processes become more efficient. This relationship underscores the role of organizational complexity as a moderating factor, where less complex firms may experience a more pronounced impact of AI adoption on employment dynamics. We state our hypothesis in its alternative form:

H3: The impact of AI adoption on firms' employment growth is more pronounced for firms with lower complexity compared to those with higher complexity

Active institutional investors often closely monitor firms' innovation activities, including their exposure to emerging technologies such as AI patents. These investors may encourage strategic adjustments, including workforce optimization, to ensure efficient allocation of resources and sustained value creation. Firms with higher levels of AI patent exposure may face greater scrutiny and pressure from active institutional investors to streamline operations, potentially leading to reduced employee growth rates. This dynamic reflects the dual role of institutional investors as both monitors and influencers in shaping firms' strategic decisions in response to technological advancements. We state our hypothesis in its alternative form:

H4: The impact of AI adoption on firms' employment growth is more pronounced for firms held by active institutional investors, as opposed to firms held by passive institutional investors.

4. Empirical Design

4.1 Sample construction

In measuring AI adoption, while numerous studies have assessed AI's impact through job posting data, this approach may not fully capture the specific AI-related skills that firms prioritize in their hiring processes. Moreover, job postings do not necessarily indicate whether the hired employees possess the requisite expertise to develop AI technologies or contribute meaningfully to a firm's AI-driven advancements. Recognizing these limitations, we propose the use of patent output as a more direct measure of a firm's AI capabilities.

Previous literature on patents has typically examined various types of patents without explicitly distinguishing those related to AI (He and Tian, 2013; Shu et al., 2022; Wu et al., 2020). This broad focus lacks the precision required to evaluate the specific technological advancements driven by AI. To address this gap, we utilize the *USPTO-AIPD* database (1970–2022), which provides a more nuanced approach to assessing firms' AI adoption. The USPTO employs machine learning algorithms to assign scores to patent applications based on various AI-related attributes, such as "Listening," "Speech," "AI hardware," and "Deep learning" (Giczy et al., 2020).

For each patent, we calculate the cumulative score across these AI-related dimensions to derive an overall AI patent score. We then aggregate the AI scores of all patents granted to a firm in a given year to measure the firm's annual AI patent activity. To integrate this patent data with firm-level fundamentals, we leverage the *KPSS* database (Kogan et al., 2017), which links patent IDs to firm IDs and has been widely used in previous research (Li et al., 2022; Shu et al., 2022).

Our dependent variable is the employee growth rate. Using the employee growth rate instead of the absolute number of employs offers several advantages. It eliminates the influence of firm size, captures dynamic changes in employment, standardizes relative variations across firms, mitigates cross-industry differences in labor intensity, and better reflects the temporal relationship between employment and other variables. This approach enhances comparability and is particularly suited for analyzing trends across firms and industries. Additionally, we include other fundamental firm control variables obtained from the *Compustat* database. The Institutional Ownership data form the *SEC 13F Holdings* data since 1980. We employ a lead-lag design, with 149,039 firm-year observations spanning from 1980 to 2022.

4.2 Model specification and summary statistics

To estimate the effect of adoption of AI on the firm's employee growth rate, we construct a lead-lag design regression model following prior studies:

$$\begin{aligned} EmployG_{it+1} = \beta_0 + \beta_1 AI\ Patent_{it} + \beta_2 SIZE_{it} + \beta_3 ROA_{it} + \beta_4 MTB_{it} + \beta_5 LEV_{it} \\ + \beta_6 CFO_{it} + +\beta_7 RD_{it} + \beta_8 CAPX_{it} + \beta_9 PPE_{it} \\ + \beta_{10} SALG_{it} + \beta_{11} IO_{it} + \beta_{12} PATENT_{it} \\ +Year\ FE + Firm\ FE + \varepsilon_{it,} \end{aligned} \tag{1}$$

where the dependent variable, *EmpolyG* is measured as the difference between the number of employs in year *t+1* and year *t*, scaled by the number of Employs in year *t*. We calculate the company's annual $AI\ Patent$, based on the *USPTO-AIPD*, as follows, for each patent, calculate its AI score by summing the various AI aspect scores (There are in total nine kinds of AI aspects, including "Knowledge processing", "Speech", "AI hardware", "Evolutionary computation", "Natural language processing", "Machine learning", "Computer vision", "Planning/control"). Then, for each firm, aggregate the AI score of all patents granted in the same year. Finally, take the logarithm of one plus this aggregated value.

In addition, we include the following variables to control factors affecting firms' Employee growth rate. Firstly, we control several firms' characters. *SIZE* is the natural logarithm of total assets. *ROA* is the income before extraordinary items scaled by total assets in the previous year. *MTB* is the sum of total debt and the market value of equity divided by total assets. *LEV* is the firm's market leverage calculated as the total debt of firm scaled by the sum of total book debt and the market value of common stock. *CFO* is defined as the operating cash flow divided by the total asset in the t-1. *RD* is R&D expenses scaled by total assets. *CAPEX* is defined as the ratio of capital expenditure to total assets. *PPE* is fixed assets scaled by total assets. *SALG* presents the ratio of change revenues to the lag year revenues. *IO* indicates the percentage of shares owned by institutions over the fiscal year scaled for being outstanding. Secondly, we control another aspect of patents. *PATENT* in logarithmic form, refers to the total number of patents filed by firms (the application number of patents), excluding published patents. We use ordinary least squares to estimate the coefficients and control for year and firm fixed effects. The reported t-values are based on standard errors clustered by the firm.

[Insert Appendix A about here]

Panel A of Table 1 exhibits descriptive statistics. All continuous variables are winsorized at the top and bottom percentile. The mean AI Patent is 0.25, indicating that 25% of the patents granted to the firms in the sample are related to artificial intelligence. The distribution of other variables closely aligns with prior studies (Barrot and Nanda 2020; Graham et al. 2023; He and Tian 2013; Shu et al. 2022).

[Insert Table 1 about here]

4.3 Baseline results

Table 2 presents the OLS regression results analyzing the relationship between AI Patent and a firm's Employee growth rate. A lead-lag design is utilized to mitigate concerns about reverse causality, acknowledging that the impact of AI adoption on employee-related decisions is not instantaneous, as managers require time to integrate AI utilization into firm operations and respond accordingly. The model includes both firm and year fixed effects. The inclusion of firm fixed effects is particularly relevant, given the concentration of AI adoption within specific types of firms, such as high-tech firms, where firms often leverage AI technologies to optimize operations and drive innovation, potentially influencing their hiring decisions. By controlling firm fixed effects, we account for firm-specific factors that could influence the relationship between AI Patent and EmployG. Similarly, year fixed effects control for time-specific shocks and trends that could affect all firms uniformly across years.

The coefficient on the AI Patent is -0.009, with a t-value of -4.19, indicating statistical significance at the 1% level. This result, derived from the model in column (3) of Table 2, incorporates control variables as well as firm and year fixed effects. In contrast, the PATENT variable, which serves as a proxy for traditional innovation, exhibits a significant positive effect, suggesting that conventional innovation typically increases the demand for Employs (Roy et al., 2018; Farre-Mensa et al., 2019). Firms engaging in traditional innovation often require substantial labor inputs, such as scientists and other skilled personnel, to support research and development activities. However, the AI capabilities of firms, while categorized as a specific form of technology or innovation, appear to have the opposite effect, potentially reducing the demand for labor compared to traditional innovation. AI distinguishes itself from traditional innovation and technology through its core mechanisms, versatility, impact on labor, and speed of evolution. Unlike traditional innovations, which are designed to perform specific tasks, AI emphasizes adaptive learning and decision-making, allowing it to enhance its performance without explicit reprogramming. This flexibility enables AI to be applied across diverse industries and functions, making it a more versatile tool compared to traditional technologies, which are often tailored to specific applications. Furthermore, while traditional technologies typically complement human labor by improving efficiency, AI has the potential to both replace routine and repetitive tasks and create new demands for highly skilled roles in its development and governance. Additionally, AI evolves at a significantly faster pace due to advancements in computing power and the availability of big data, whereas traditional technologies generally require longer development and adoption cycles. The finding suggests that AI adoption is associated with a negative impact on the employee growth rate of firms. Moreover, the economic significance of this relationship is substantial, highlighting the broader implications of AI adoption on workforce dynamics.

This negative association may reflect that, as AI technologies become increasingly widespread and their adoption costs decline, coupled with rising labor costs and growing advocacy for labor rights, firms are more inclined to adopt AI with adaptive learning capabilities as a substitute for traditional employees. AI technologies not only significantly enhance operational efficiency but also help mitigate challenges related to labor management, making them an attractive option in corporate decision-making.

From a policy perspective, this trend raises important considerations for its broader social and economic implications. On the one hand, policymakers need to address potential challenges arising from the widespread adoption of AI, such as privacy concerns, employment difficulties, and imbalances in the labor market, by exploring effective mitigation strategies. On the other hand, a key focus should be on developing policies that foster the integration of AI and human labor to maximize societal productivity. This may involve supporting skill enhancement programs, promoting the creation of innovative employment opportunities, and establishing transparent AI governance frameworks to ensure that technological advancements align with long-term societal development objectives.

RD presents a significant negative result with EmployG (-0.557, t value = -19.21). Increased R&D investment could suggest a focus on AI or other kinds of innovation, which might reduce the demand for additional labor.

Other control variables indicate that larger firms, those with higher market leverage, greater operating cash flow, and more tangible assets tend to exhibit lower employee growth rates. Several reasons could explain these relationships. First, larger firms often achieve economies of scale and operational efficiencies that reduce the need for labor expansion, as they can generate higher outputs with relatively fewer employees. Higher market leverage, reflecting a greater reliance on debt, may also discourage hiring, as firms focus on servicing their financial obligations rather than expanding their workforce. In addition, firms with higher operating cash flow may prioritize capital expenditures or debt repayments over hiring new employees, as they have sufficient liquidity to invest in other areas of their business. Finally, firms with more tangible assets, such as machinery and equipment, may rely on capital-intensive processes that require fewer employees for production, leading to slower employee growth. These findings underscore the complex dynamics between firm characteristics and labor demand, highlighting how financial and operational factors shape workforce strategies.

[Insert Table 2 about here]

4.4 Endogeneity

We propose two ways to mitigate the potential endogeneity of the main effect. Firstly, we adopt the Entropy Balancing way (Chapman et al. 2019; Chahine et al. 2020). This method ensures proper covariate balance between the treatment (AI Patent higher than the median value of all firms in the particular year) and control groups by assigning weights to observations such that the post-weighting means, variances, and skewness of the treat and control firms are equal across all matching dimensions. As reported in Panel A of Table 3, we use the firm fundamental control variables from the baseline regression as the matching dimensions (covariates). Panel A also shows that the differences in means of the covariates are minimal and statistically insignificant after applying entropy balancing matching, indicating that a proper balance was achieved.

We re-estimate Model (1) with the balanced sample shown in Panel B of Table 3. The regression results after entropy balancing continue to show a statistically significant negative relationship between AI Patent and EmployG in the subsequent year, with an AI Patent's coefficient of -0.013 at the 1% confidence level. These findings further confirm the robustness of our baseline results with the entropy balancing technique.

[Insert Table 3 about here]

Next, we employ a two-way fixed effects difference-in-differences (DID) approach. As AI technology becomes increasingly pervasive, its associated risks have garnered significant attention from policymakers. At the international level, the European Union has taken the lead by proposing the Artificial Intelligence Act on April 21, 2021. This Act categorizes and regulates high-risk AI applications, offering a model for other regions to follow.

In the United States, while the federal government has engaged in discussions on AI regulation—such as the National Artificial Intelligence Initiative Act, enacted on January 1, 2021, and the AI Risk Management Framework, released by NIST on January 26, 2023—a unified federal regulatory framework has yet to be established.

While individual states have taken the initiative to implement AI regulations tailored to local needs, addressing specific aspects of AI governance to balance public interests and technological advancement. On January 26, 2021, the Alabama (AL) Council on Advanced Technology and Artificial Intelligence was officially established in Alabama to provide comprehensive review and advisory support to the Governor, Legislature, and other stakeholders regarding the use and development of advanced technology and artificial intelligence within the state. Moreover, in 2021, under Bill 0709 in Illinois (IL), the Artificial Intelligence Video Interview Act was amended to include new provisions. These amendments mandate that employers relying solely on artificial intelligence to determine an applicant's eligibility for an in-person interview must collect and report specific demographic information to the Department of Commerce and Economic Opportunity. Furthermore, the Department is required to analyze the submitted data and report to the Governor and the General Assembly to assess whether the use of artificial intelligence reveals any racial bias. We summary and count in total 13 different states purposed the AI related regulations as presented in the Appendix B.

[Insert Appendix B about here]

Cuellar et al. (2024) conduct a randomized online survey experiment involving over 1,000 managers in the United States. Their findings reveal that exposure to information about AI regulation enhances managers' awareness of critical AI-related issues, including safety, privacy, bias, discrimination, and transparency. However, this heightened awareness comes with a tradeoff: it reduces managers' intent to adopt AI technologies. Furthermore, regulatory information increases managers' willingness to allocate resources toward developing AI strategies, particularly those addressing ethical considerations. However, this shift occurs at the expense of investments in AI adoption, such as employee training in AI or the procurement of AI software solutions.

Building on their latest findings, we posit that under the conditions imposed by published AI related regulations, firms may seek to reduce AI-related investments, thereby lowering their AI Patent. This reduction, in turn, could attenuate the negative relationship between the AI Patent and EmployG. We define AI Regulation as a dummy variable that equals 1 if AI Regulation legislation is in effect in the state, and 0 otherwise. Furthermore, we control not only for firm fixed effects but also for state*year fixed effects, which allows us to account for variations at the state level over time more effectively.

The regression model is presented as follows:

$$
\begin{aligned}
EmployG_{it+1} = \beta_0 + \beta_1 AI\ Regulation + \beta_2 SIZE_{it} + \beta_3 ROA_{it} + \beta_4 MTB_{it} + \beta_5 LEV_{it} \\
+ \beta_6 CFO_{it} + +\beta_7 RD_{it} + \beta_8 CAPX_{it} + \beta_9 PPE_{it} \\
+ \beta_{10} SALG_{it} + \beta_{11} IO_{it} + \beta_{12} PATENT_{it} \\
+Firm\ FE + State * Year\ FE + \varepsilon_{it,}
\end{aligned} \tag{2}
$$

The regression results presented in Table 4 reveal that the coefficient β_1 exhibits a significant positive effect (0.014, t-value = 2.12). This finding suggests that following the introduction of AI-related regulations, firms that are directly affected tend to reduce their AI-related investments. Consequently, their AI Patent declined, reflecting a decrease in AI-related activity. Moreover, the analysis indicates that the primary negative relationship between the AI Patent and the employee growth rate is attenuated under these circumstances. This suggests that as firms scale back their AI-related initiatives in response to regulatory changes, the previously observed adverse impact of AI on employment growth is weakened.

[Insert Table 4 about here]

4.5 Sub-sample Analysis

We categorize our sample into several industry groups and examine the main effects across different industries. First, we compare whether firms belong to technology-related industries. The technology industry includes sectors such as Computer Hardware (SIC 4 digit codes 3570–3577), Computer Software (SIC 4 digit codes 7371–7379), and Electronics (SIC 4 digit codes 3600–3674). From Panel A of Table 5, both categories show significant negative effects between the AI Patent and EmployG, with results significant at the 1% level. Specifically, the technology industry exhibits a much stronger negative relationship, with a coefficient of -0.011, as shown in column (1), compared to the non-technology industries, which show a coefficient of -0.007 in column (2). This result suggests that, while both sectors experience a negative impact of AI Patent on employment growth, the effect is more pronounced in the technology industry. This could be due to the rapid pace of technological innovation and industry disruption within the technological sectors, where firms not only experience fast cycles of technological advancement but are also more willing to adopt and apply new technologies in practice. As a result, these companies may face greater worker displacement due to the integration of cutting-edge AI technologies. In contrast, non-technology industries may have slower rates of technological adoption and innovation, resulting in a less significant negative effect on employment growth. Furthermore, these industries may be more cautious in applying new technologies, leading to a more gradual impact on employment.

Furthermore, we discover several other important industries, the manufacturing industry (SIC 2 digit between 20 and 39), the service industry (SIC 2 digit between 70 and 89) and the financial industry (SIC 4 digit codes between 6000 and 6999) respectively. The regression results are presented in panel B of Table 5, Columns (1), (2), and (3) display the results for mentioned industries previously. Both the manufacturing and service industries show a significant negative effect between AI Patent and EmployG, while the financial industry shows no significant relationship. This suggests that AI adoption has a more pronounced impact on employment growth in sectors where automation and technological advancements are directly applied to operations. In manufacturing, for example, the increasing implementation of Industry 5.0 technologies—such as advanced robotics and AI-driven production lines—has accelerated automation, leading to the displacement of workers. Similarly, in the service industry, the rise of AI applications like intelligent customer service systems, automated help desks, and unmanned service counters has increased the potential for job replacement, making roles traditionally performed by humans more vulnerable to automation.

In contrast, the financial industry shows no significant relationship, which can be attributed to several factors. While AI technologies are used in financial services for tasks such as data analysis and customer service, the industry also relies heavily on factors such as regulatory policies, corporate governance, and the accumulation of human expertise. Financial decisions often involve complex judgment calls, risk assessments, and client relationships that AI is less capable of fully replacing. Additionally, the sector is deeply intertwined with social networks, investor behavior, and nuanced market conditions, which require human experience and intuition. As a result, the impact of AI on employment in the financial industry may be more gradual and less disruptive compared to other sectors.

[Insert Table 5 about here]

4.6 Time trend analysis

To analyze the temporal dynamics of the primary variables, firms' AI Patent and its *EmployG*—we define the variable Trend as the difference between each fiscal year and the base year, 1980. The regression model is presented as follows:

$$
\begin{aligned}
EmployG_{it+1} = \beta_0 + \beta_1 AI\ Patent_{it} * Trend_i + \beta_2 SIZE_{it} + \beta_3 ROA_{it} + \beta_4 MTB_{it} + \beta_5 LEV_{it} \\
+ \beta_6 CFO_{it} + +\beta_7 RD_{it} + \beta_8 CAPX_{it} + \beta_9 PPE_{it} \\
+ \beta_{10} SALG_{it} + \beta_{11} IO_{it} + \beta_{12} PATENT_{it} \\
+ Year\ FE + Firm\ FE + \varepsilon_{it,}
\end{aligned}
\tag{3}
$$

The interaction term, capturing the time-varying effects of these variables, demonstrates a significantly positive coefficient (0.037, t-value = 2.83) as presented in Table 6. This result suggests that the substitution effect of AI on employment has become less pronounced in the years following the year 1980. This may be due to two factors: first, over time, the technological boundaries of AI have become narrower, meaning that AI's ability to fully replace human labor in certain tasks has diminished as the technology matures. Second, employees' education levels and skillsets have improved, enabling them to adapt to new roles and work alongside AI technologies, rather than being displaced by them. As workers acquire more specialized skills and technology reaches a point of integration, AI may serve more as a complement to human labor rather than a direct substitute, reducing its disruptive impact on employment.

[Insert Table 6 about here]

4.7 Cross-sectional analysis

First, we adopt different types of investors, specifically, we classify the institutional investor into three categories (as a percentage of shares outstanding) dedicated investors, quasi-indexer investors and transient investors. The regression model is presented as follows:

$$\begin{aligned} EmployG_{it+1} = {} & \beta_0 + \beta_1 AI\ Patent_{it} * IO\_horizon_{it} + \beta_2 SIZE_{it} + \beta_3 ROA_{it} + \beta_4 MTB_{it} + \beta_5 LEV_{it} \\ & + \beta_6 CFO_{it} + +\beta_7 RD_{it} + \beta_8 CAPX_{it} + \beta_9 PPE_{it} \\ & + \beta_{10} SALG_{it} + \beta_{11} IO_{it} + \beta_{12} PATENT_{it} \\ & + Year\ FE + Firm\ FE + \varepsilon_{it,} \end{aligned} \tag{4}$$

The regression results are presented in Panel A of Table 7. The interaction term with IO_horizon2, representing the effect of quasi-indexer investors, exhibits a positive but statistically insignificant impact on the firm's Employee growth rate (coefficient = 0.025, t-value = 0.19). In contrast, the interaction term with IO_horizon3, which proxies the effect of transient investors, reveals a negative and marginally significant effect on employee growth rate (coefficient = -0.018, t-value = -1.80). Quasi-indexer investors can be understood as passive investors, while transient investors represent active investors. This framework offers a distinct explanation for the interaction effects of these investor types and AI adoption on employee growth rates. Quasi-indexer investors, as passive stakeholders, tend to adopt a long-term holding strategy with limited intervention in a firm's operational decisions. As a result, they are less sensitive to the specifics of AI adoption and application within the firm. This passivity allows firms to focus on steady and sustainable growth when implementing AI technologies, without external pressure to make rapid or disruptive changes. Consequently, the impact of AI on Employee growth rates in firms with a higher proportion of quasi-indexed investors is less negative or even positive. In contrast, transient investors, as active stakeholders, pursue short-term gains and are highly sensitive to innovations that improve efficiency and profitability, such as AI technologies. Their active engagement often pressures firms to accelerate the deployment of AI, particularly in areas that enable cost reduction and labor substitution. This focus on immediate returns may lead to a more pronounced negative effect of AI adoption on employee growth rates, as the emphasis shifts towards automation rather than human capital development. This perspective highlights how the varying degrees of passivity or activity among investor types influence the relationship between AI adoption and employment outcomes.

Second, we examine the influence of complexity on the main effects. Loughran et al. (2024) highlight that complexity, as another firm-related construction, is both relevant and challenging to quantify due to its ambiguous definition and the lack of standardized measurement criteria. They propose one measurement approach as the natural logarithm of the net 10-K file size in bytes. The net file size reflects adjustments for the removal of binary-encoded ASCII (e.g., images), HTML, XBRL, and other non-textual elements. For our analysis, we adopt their Netfilesize data, spanning the years 1996 to 2021. The regression model is presented as follows:

$$EmployG_{it+1} = \beta_0 + \beta_1 AI\ Patent_{it} * Netfilesize_{it} + \beta_2 SIZE_{it} + \beta_3 ROA_{it} + \beta_4 MTB_{it} + \beta_5 LEV_{it} + \beta_6 CFO_{it} + +\beta_7 RD_{it} + \beta_8 CAPX_{it} + \beta_9 PPE_{it} + \beta_{10} SALG_{it} + \beta_{11} IO_{it} + \beta_{12} PATENT_{it} + Year\ FE + Firm\ FE + \varepsilon_{it,} \quad (5)$$

Our findings reveal that the interaction term between complexity and AI Patent has a significant positive effect on the Employee growth rate (0.006, t-value=2.13), as presented in Panel B of Table 7. This suggests that, as firms become more complex, the negative impact of AI Patent on EmployG is mitigated. This phenomenon can be attributed to several factors. First, more complex firms often have diversified operations and a broader range of activities, requiring nuanced human judgment and decision-making that AI cannot fully replicate. Second, complex firms tend to have more sophisticated organizational structures and processes, which may enable them to leverage AI as a complementary tool rather than a substitute for human labor. For example, AI can enhance efficiency in routine tasks, freeing Employs to focus on high-value, strategic functions that drive growth. Lastly, firms with higher complexity may face greater resistance to automation or require more tailored AI implementations, leading to a slower or more cautious integration of AI technologies. As a result, AI adoption in such firms tends to augment rather than reduce employment opportunities.

[Insert Table 7 about here]

4.8 Robustness Tests

First, we redefine the independent variable as a treatment effect, denoted as AI Treat. This dummy variable equals 1 if a firm’s AI Patent exceeds the median value of all firms in the corresponding year. The results presented in Panel A of Table 5 are consistent with the baseline findings. Furthermore, we replace the independent variable with the average AI Patent, adjusted by the total number of patents published by the firm in the same year. This adjustment aims to account for variations in patenting activity across firms and provide a normalized measure of AI intensity. Moreover, we redefine the dependent variable as a dummy variable, Expand_d, which is set to 1 if the employee growth rate is positive and 0 otherwise. This adjustment aims to better account for differences in hiring growth across firms of varying sizes, as the binary classification more directly reflects firms' responses to the impact of AI. Finally, we incorporate industry and year fixed effects into the model. The inclusion of industry fixed effects is particularly relevant, as firms' AI Patent tend to be disproportionately higher in specific sectors, such as computer science-related industries. More specifically, we define industries based on the first two digits of the SIC code. The results presented in Panel B of Table 5 are consistent with the baseline findings.

[Insert Table 8 about here]

5 Conclusion

In this paper, we examine the primary relationship between a firm's level of AI adoption, measured by its AI Patent based on their patents' exposure to AI, and the firm's employee growth rate in year *t+1*. Our findings reveal a significant negative effect, indicating that as AI technology advances, firms increasingly allocate resources to enhance their AI capabilities. Moreover, this effect is more pronounced among firms in low-skilled industries, with lower operational complexity, and held by active investors. Overall, our findings suggest that AI adoption is adversely affecting employment growth.

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Appendix A:

The table provides variable definitions.

Variable Name	*Definition*
EmployG	The difference between the current number of employees and the lagged number, divided by the lagged number, in the year t+1.
Expand_d	The dummy variable is assigned a value of 1 if the employee growth rate in year t+1 is greater than 0, and 0 otherwise.
Independent Variables	
AI Patent	For each patent, calculate its AI score by summing the various AI aspect scores. Then, for each firm, aggregate the AI scores of all patents granted in the same year. Finally, take the logarithm of one plus this aggregated value.
AI Treat	The dummy variable is set to 1 if the AI score exceeds the median value of all samples.
AI Patent Average	Calculated as the ratio of AI patent to the total number of published patents.
Control Variables	
SIZE	The natural logarithm of firm's total assets.
ROA	The operating income before depreciation and amortization divided by lagged total assets.
MTB	The sum of total debt and the market value of equity divided by total assets.
LEV	Total debt plus current liabilities divided by the sum of total debt and the market value of equity.
CFO	The cash flow generated from a company's core business operations.
RD	R&D expenses scaled by total assets.
CAPX	Cash payments for fixed assets net of cash proceeds from asset disposals, scaled by total assets.
PPE	Net property, plant, and equipment divided by total assets.
SALG	The difference between current sales and lagged sales, expressed as a proportion of lagged sales.
IO	Number of shares owned by institutions investors.
PATENT	The logarithm of one plus the total number of application patents by the firm.
Netfilesize	The natural log of the net 10-K file size in bytes. Net file size reflects the removal of binary-encoded ASCII (e.g., pictures), HTML, XBRL, and so forth. The process for creating the 10-K files is described at https://sraf.nd.edu/sec-edgar-data/cleaned-10x-files/10x-stage-one-parsingdocumentation/. From 1996-2021.
IO_horizon1	Ownership (as a percentage of shares outstanding) by dedicated investors.
IO_horizon2	Ownership (as a percentage of shares outstanding) by quasi-indexer investors.
IO_horizon3	Ownership (as a percentage of shares outstanding) by transient investors.

Appendix B:

This table provides the supplementary information of the AI related events used in the analysis.

STATE	Bill Number	YEAR
AL	SB78	2021
CO	SB21-169	2021
IL	HB0053	2021
MA	H.119	2021
NY	Int 1894-2020	2021
PA	HB2903	2021
TX	SB 475	2021
UT	SB 34	2021
VT	H.410	2021
VA	SB 1392	2021
WA	SB 5116	2021

Table 1: Summary Statistics

This table presents the summary statistics. Variables are defined in Appendix A. All continuous variables are winsorized at the 1st and 99th percentiles.

Variable	N	Mean	SD	p25	p50	p75
EmployG	149,039	0.07	0.31	-0.05	0.02	0.13
AI Patent	149,039	0.25	0.73	0.00	0.00	0.02
AI Dummy	149,039	0.22	0.41	0.00	0.00	0.00
SIZE	149,039	5.71	2.25	4.00	5.54	7.28
ROA	149,039	0.09	0.21	0.05	0.12	0.19
MTB	149,039	1.71	1.67	0.80	1.15	1.92
LEV	149,039	0.23	0.23	0.03	0.17	0.37
CFO	149,039	0.03	0.22	-0.01	0.07	0.13
RD	149,039	0.05	0.10	0.00	0.00	0.05
CAPX	149,039	0.06	0.06	0.02	0.04	0.08
PPE	149,039	0.30	0.24	0.10	0.23	0.44
SALG	149,039	0.18	0.55	-0.02	0.08	0.24
IO	149,039	0.40	0.30	0.12	0.35	0.65
PATENT	149,039	0.55	1.19	0.00	0.00	0.00

Table 2: Baseline Results

This table presents how AI Patent affects a firm's Employee growth rate in the coming year. The regression model is specified as follows,

$$\begin{aligned} EmployG_{it+1} = \beta_0 + \beta_1 AI\ Patent_{it} + \beta_2 SIZE_{it} + \beta_3 ROA_{it} + \beta_4 MTB_{it} + \beta_5 LEV_{it} \\ + \beta_6 CFO_{it} + +\beta_7 RD_{it} + \beta_8 CAPX_{it} + \beta_9 PPE_{it} \\ + \beta_{10} SALG_{it} + \beta_{11} IO_{it} + \beta_{12} PATENT_{it} \\ + Year\ FE + Firm\ FE + \varepsilon_{it,} \end{aligned} \tag{1}$$

All variables are defined in Appendix A. We use *OLS* to estimate coefficients and control for year and firm fixed effects. Reported t-values are based on standard errors clustered by firm. ***, ** and * represent significance levels at 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)
VARIABLES	*EmployG*	*EmployG*	*EmployG*
AI Patent	**-0.025*****	**-0.022*****	**-0.009*****
	(-10.45)	**(-8.54)**	**(-4.19)**
SIZE			-0.071***
			(-30.49)
ROA			0.082***
			(6.14)
MTB			0.032***
			(26.79)
LEV			-0.236***
			(-30.48)
CFO			-0.023**
			(-2.03)
RD			-0.557***
			(-19.21)
CAPX			0.017
			(0.65)
PPE			-0.149***
			(-9.52)
SALG			0.010***
			(3.69)
IO			0.008
			(1.07)
PATENT		-0.007***	0.006***
		(-4.05)	(4.20)
Constant	0.073***	0.076***	0.527***
	(119.56)	(82.22)	(37.52)
Firm, Year FEs	YES	YES	YES
Observations	149,039	149,039	149,039
R-squared	0.20	0.20	0.26

Table 3: Entropy Balancing Result

In this table, we apply the Entropy Balancing procedure to estimate the results. We use all control variables to construct a balanced sample across three dimensions: mean, variance, and skewness. Panel A presents the summary statistics of the balanced sample. We then re-estimate Model (1) using the matched sample generated by the entropy balancing procedure, with the results shown in Panel B.

$$\begin{aligned} EmployG_{it+1} = \beta_0 + \beta_1 AI\ Patent_{it} + \beta_2 SIZE_{it} + \beta_3 ROA_{it} + \beta_4 MTB_{it} + \beta_5 LEV_{it} \\ + \beta_6 CFO_{it} + +\beta_7 RD_{it} + \beta_8 CAPX_{it} + \beta_9 PPE_{it} \\ + \beta_{10} SALG_{it} + \beta_{11} IO_{it} + \beta_{12} PATENT_{it} \\ + Year\ FE + Firm\ FE + \varepsilon_{it,} \end{aligned} \tag{1}$$

All variables are defined in Appendix A. We use *OLS* to estimate coefficients and control for year and firm fixed effects. Reported t-values are based on standard errors clustered by firm. ***, ** and * represent significance levels at 1%, 5%, and 10%, respectively.

Panel A: Characteristics comparation after entropy balancing

	Treated (AI Treat=1)			*Control (AI Treat=0)*			
Covariates	*Mean*	*Variane*	*Skewnes*	*Mean*	*Variane*	*Skewnes*	*Std.Diff.*
SIZE	6.776	5.244	0.092	6.776	5.244	0.092	0.000
ROA	0.084	0.048	-2.052	0.084	0.048	-2.052	0.000
MTB	1.975	3.289	2.713	1.975	3.289	2.713	0.000
LEV	0.175	0.034	1.304	0.175	0.034	1.304	0.000
CFO	0.033	0.046	-2.580	0.033	0.046	-2.580	0.000
RD	0.088	0.013	2.437	0.088	0.013	2.437	0.000
CAPX	0.051	0.002	2.187	0.051	0.002	2.191	0.000
PPE	0.231	0.031	1.098	0.231	0.031	1.099	0.000
SALG	0.149	0.231	4.192	0.149	0.231	4.192	0.000
IO	0.527	0.077	-0.219	0.527	0.077	-0.219	0.000
PATENT	2.248	2.476	0.276	2.247	2.477	0.276	0.000

Panel B: Entropy Balancing

	(1)
VARIABLES	*EmployG*
AI Patent	**-0.013****
	(-2.44)
SIZE	-0.066***
	(-12.86)
ROA	-0.002
	(-0.06)
MTB	0.035***
	(14.75)
LEV	-0.215***
	(-9.15)
CFO	0.048*
	(1.83)

RD	-0.569***
	(-9.71)
CAPX	-0.091
	(-1.26)
PPE	-0.227***
	(-6.55)
SALG	0.005
	(0.40)
IO	-0.017
	(-0.63)
PATENT	0.003
	(0.66)
Constant	0.592***
	(16.11)
Firm, Year FEs	YES
Observations	149,039
R-squared	0.41

Table 4: Two-way-Fixed effect Difference in Difference (DID)

In Table 4, we report the results on the effect of AI Regulation legislation on corporate employee growth rate. We define AI Regulation as a dummy variable that equals 1 if AI Regulation legislation is in effect in the state, and 0 otherwise. All other variables are defined in Appendix A. We use OLS to estimate coefficients and control for firm fixed effects and state*year fixed effects. Reported t-values are based on standard errors clustered by the firm. ***, ** and * represent significance levels at 1%, 5%, and 10%, respectively.

	(1)
VARIABLES	*EmployG*
AI Regulation	**0.014****
	(2.12)
SIZE	-0.059***
	(-30.19)
ROA	0.066***
	(4.90)
MTB	0.034***
	(27.87)
LEV	-0.258***
	(-32.72)
CFO	-0.015
	(-1.33)
RD	-0.555***
	(-18.75)
CAPX	-0.040
	(-1.49)
PPE	-0.145***
	(-9.11)
SALG	0.008***
	(2.90)
IO	0.019***
	(2.61)
PATENT	0.001
	(0.62)
Constant	0.454***
	(38.19)
Firm Fe	YES
State*Year Fe	YES
Observations	136,810
R-squared	0.25

Table 5: Sub-sample Result

In this table, we analyze the impact of AI Patent on firm employee growth across different decades and industries. Panel A compares the technology industry with the non-technology industry. Column (1) presents the results for the technology industry, while column (2) focuses on the non-technology industry. Panel B highlights other key industries: column (1) corresponds to manufacturing, column (2) to the service industry, and column (3) to financial-related industries. All other variables are defined in Appendix A. We use OLS to estimate coefficients and control for year and firm fixed effects. Reported t-values are based on standard errors clustered by the firm. ***, ** and * represent significance levels at 1%, 5%, and 10%, respectively.

Panel A: Technology industry versus non-technology industry

	(1)	(2)
VARIABLES	*EmployG* (Technology)	*EmployG* (Non-technology)
AI Patent	-0.011***	-0.007***
	(-2.69)	(-2.60)
SIZE	-0.074***	-0.069***
	(-14.09)	(-26.84)
ROA	0.162***	0.059***
	(5.95)	(3.87)
MTB	0.035***	0.031***
	(14.55)	(22.29)
LEV	-0.238***	-0.240***
	(-11.55)	(-28.66)
CFO	-0.035	-0.020
	(-1.54)	(-1.55)
RD	-0.509***	-0.562***
	(-9.94)	(-16.11)
CAPX	-0.167**	0.044
	(-2.01)	(1.57)
PPE	-0.149***	-0.149***
	(-3.20)	(-8.95)
SALG	0.007	0.010***
	(0.93)	(3.62)
IO	0.023	0.004
	(1.19)	(0.53)
PATENT	0.006*	0.007***
	(1.96)	(3.66)
Constant	0.477***	0.531***
	(17.27)	(33.33)
Firm, Year Fes	YES	YES
Observations	21,870	127,169
R-squared	0.29	0.25

Panel B: Other important industries

VARIABLES	(1) *EmployG* (Manufacturing)	(2) *EmployG* (Service)	(3) *EmployG* (Financial)
AI Patent	**-0.008*** **	**-0.015*** **	**-0.007**
	(-2.82)	**(-3.11)**	**(-0.42)**
SIZE	-0.067***	-0.083***	-0.043***
	(-21.21)	(-14.69)	(-3.34)
ROA	0.039**	0.131***	0.076
	(2.30)	(4.13)	(1.04)
MTB	0.031***	0.037***	0.024***
	(21.12)	(14.46)	(3.78)
LEV	-0.230***	-0.258***	-0.225***
	(-21.66)	(-11.92)	(-4.00)
CFO	-0.013	-0.041	0.011
	(-0.87)	(-1.57)	(0.23)
RD	-0.548***	-0.620***	-0.733***
	(-16.35)	(-9.51)	(-3.26)
CAPX	0.037	-0.078	0.038
	(0.90)	(-0.96)	(0.25)
PPE	-0.224***	-0.214***	-0.160*
	(-10.37)	(-4.60)	(-1.74)
SALG	0.006*	0.007	0.013
	(1.79)	(1.03)	(1.02)
IO	0.017*	0.001	0.044
	(1.75)	(0.06)	(1.12)
PATENT	0.005***	0.014***	0.008
	(2.81)	(3.33)	(0.58)
Constant	0.495***	0.575***	0.326***
	(26.92)	(18.32)	(4.42)
Firm, Year Fes	YES	YES	YES
Observations	73,249	25,944	5,070
R-squared	0.24	0.30	0.25

Table 6: Time Trend Result

In this table, we examine how the effect of AI Patent on firm employee growth varies over time. We measure the time trend by *Trend*, which is calculated as current year minus 1980 (the initial year of the sample). All other variables are defined in Appendix A. We use OLS to estimate coefficients and control for firm fixed effect. Reported t-values are based on standard errors clustered by the firm. ***, ** and * represent significance levels at 1%, 5%, and 10%, respectively.

	(1)
VARIABLES	*EmployG*
AI Patent*Trend	**0.037*** **
	(2.83)
AI Patent	-0.021***
	(-4.29)
Trend	0.229***
	(10.54)
SIZE	-0.071***
	(-30.64)
ROA	0.082***
	(6.21)
MTB	0.034***
	(28.43)
LEV	-0.251***
	(-33.07)
CFO	-0.024**
	(-2.15)
RD	-0.570***
	(-19.63)
CAPX	-0.018
	(-0.68)
PPE	-0.131***
	(-8.45)
SALG	0.009***
	(3.29)
IO	-0.001
	(-0.10)
PATENT	0.007***
	(4.29)
Constant	0.483***
	(39.40)
Firm Fe	YES
Observations	149,039
R-squared	0.25

Table 7: Cross-sectional Result

This table reports results of several cross-sectional tests. In Panel A, we investigate different kinds of institutional investors' influence. *IO_horizon1*, *IO_horizon2*, *IO_horizon3* are ownership (as a percentage of shares outstanding) by dedicated, quasi-indexer, and transient investors, respectively. In Panel B, we examine how corporate complexity moderates the effect of AI Patent on firms' employee growth. The *Netfilesize* is the natural logarithm of the net 10-K file size in bytes, spanning the years 1996 to 2021. All other variables are defined in Appendix A. We use *OLS* to estimate coefficients and control for year and firm fixed effects. Reported t-values are based on standard errors clustered by firm. ***, ** and * represent significance levels at 1%, 5%, and 10%, respectively.

Panel A: Interaction with Ownership of Three types of Institutional Investors

	(1)
VARIABLES	*EmployG*
AI Patent*IO_horizon1	**-0.007**
	(-0.79)
AI Patent*IO_horizon2	**0.025*** **
	(4.19)
AI Patent*IO_horizon3	**-0.018***
	(-1.80)
AI Patent	-0.016***
	(-3.55)
IO_horizon1	-0.034
	(-1.04)
IO_horizon2	-0.063**
	(-2.12)
IO_horizon3	0.034
	(1.07)
Control Variables, Firm, Year FEs	YES
Observations	149,039
R-squared	0.26

Panel B: Interaction with Firm Complexity

	(1)
VARIABLES	*EmployG*
AI Patent*Netfilesize	**0.006****
	(2.13)
AI Patent	-0.088**
	(-2.44)
Netfilesize	-0.009**
	(-2.36)
Control Variables, Firm, Year FEs	YES
Observations	72,342
R-squared	0.29

Table 8: Robustness Tests

This table presents the results of several robust tests. In Panel A, we substitute the primary independent variable with an alternative measure, the AI treatment effect, to examine the relationship between the *AI Patent* and the firm's employee growth rate. Subsequently, as presented in Panel B, we replace the independent variable with the average AI Patent of the firm, computed as the mean *AI Score* across all patents. Panel C incorporates an alternative specification for industry and year fixed effects to evaluate the main regression model. In Panel D, we redefine the dependent variable as a binary indicator, *Expand_d*, which equals 1 if the firm's employee growth rate is positive and 0 otherwise. All variables are defined in Appendix A. Reported t-values are based on standard errors clustered by firm and year. ***, ** and * represent significance levels at 1%, 5%, and 10%, respectively.

Panel A: Alternative Independent Variable-Treatment effect

	(1)	(2)	(3)
VARIABLES	*EmployG*	*EmployG*	*EmployG*
AI Treat	**-0.029*****	**-0.022*****	**-0.011*****
	(-8.74)	**(-6.37)**	**(-3.37)**
SIZE			-0.071***
			(-30.80)
ROA			0.082***
			(6.18)
MTB			0.032***
			(26.78)
LEV			-0.235***
			(-30.44)
CFO			-0.022**
			(-2.02)
RD			-0.557***
			(-19.17)
CAPX			0.017
			(0.66)
PPE			-0.149***
			(-9.47)
SALG			0.010***
			(3.73)
IO			0.009
			(1.23)
PATENT		-0.009***	0.006***
		(-5.20)	(3.84)
Constant	0.073***	0.076***	0.529***
	(101.16)	(78.10)	(37.68)
Firm, Year FEs	YES	YES	YES
Observations	149,039	149,039	149,039
R-squared	0.20	0.20	0.26

Panel B: Alternative Independent Variable-Average adjusted

VARIABLES	(1) *EmployG*	(2) *EmployG*	(3) *EmployG*
AI Patent Average	**-0.025*****	**-0.022*****	**-0.013****
	(-10.45)	**(-8.54)**	**(-2.49)**
SIZE			-0.071***
			(-30.63)
ROA			0.082***
			(6.17)
MTB			0.032***
			(26.80)
LEV			-0.236***
			(-30.46)
CFO			-0.023**
			(-2.04)
RD			-0.558***
			(-19.22)
CAPX			0.018
			(0.68)
PPE			-0.149***
			(-9.48)
SALG			0.010***
			(3.73)
IO			0.008
			(1.12)
PATENT		-0.007***	0.005***
		(-4.05)	(3.12)
Constant	0.073***	0.076***	0.528***
	(119.56)	(82.22)	(37.53)
Firm, Year FEs	YES	YES	YES
Observations	149,039	149,039	149,039
R-squared	0.20	0.20	0.26

Panel C: Alternative Dependent variable

VARIABLES	(1) *Expand_d*	(2) *Expand_d*	(3) *Expand_d*
AI Patent	**-0.031*****	**-0.030*****	**-0.015*****
	(-6.90)	**(-6.41)**	**(-3.47)**
SIZE			-0.055***
			(-18.26)
ROA			0.239***
			(16.30)
MTB			0.036***
			(27.48)
LEV			-0.428***
			(-36.78)
CFO			-0.025**
			(-2.15)
RD			-0.551***
			(-16.56)
CAPX			0.013
			(0.37)
PPE			-0.089***
			(-4.44)
SALG			0.023***
			(8.44)
IO			0.008
			(0.69)
PATENT		-0.001	0.009***
		(-0.40)	(3.09)
Constant	0.587***	0.587***	0.955***
	(522.43)	(347.97)	(54.69)
Firm, Year FEs	YES	YES	YES
Observations	149,039	149,039	149,039
R-squared	0.21	0.21	0.24

Panel D: Alternative Fixed Effects

VARIABLES	(1) *EmployG*	(2) *EmployG*	(3) *EmployG*
AI Patent	**-0.010*****	**-0.009*****	**-0.007*****
	(-8.30)	**(-5.18)**	**(-4.47)**
SIZE			-0.005***
			(-8.00)
ROA			0.118***
			(10.61)
MTB			0.029***
			(28.61)
LEV			-0.124***
			(-26.12)
CFO			-0.071***
			(-6.81)
RD			-0.287***
			(-17.81)
CAPX			0.183***
			(8.04)
PPE			-0.082***
			(-11.31)
SALG			0.046***
			(18.49)
IO			0.013***
			(3.12)
PATENT		-0.001	0.001
		(-0.66)	(1.11)
Constant	0.069***	0.070***	0.083***
	(69.94)	(66.77)	(18.75)
SIC2, Year FEs	YES	YES	YES
Observations	149,039	149,039	149,039
R-squared	0.02	0.02	0.08