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Artificial Intelligence and Robots: Implications for Employment and Productivity at the Firm Level[*]

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Abstract

This paper examines the implications of Artificial Intelligence (AI) and robots on employment and productivity at the firm level, using data from the Survey of Business Activities provided by the Korean Statistical Office. While previous studies have explored the effects of AI and robots separately, this study investigates their effects within a unified framework by directly identifying firms that adopt these technologies. The analysis employs firm-level data combined with propensity score matching to control for firm characteristics, enabling a potential causal interpretation of the differential impacts of robots and AI. We find that the trends in adopting robots and AI differ significantly across industries. *The electricity, gas, steam, and air conditioning supply* sector and *the manufacturing* sector lead in robot adoption, while *the information and communication sector* dominates in AI adoption. Additionally, although the overall share of firms adopting robots is larger, AI adoption is more concentrated among relatively larger firms in terms of employment. Our main finding is that adopting both robots and AI increases either permanent or temporary employment; however, only firms that adopted AI experienced productivity gains in Korea. The productivity gains associated with AI adoption were accompanied by a decrease in the labor share for firms, suggesting a potential shift in value distribution favoring capital income. Furthermore, we find that the immediate impact of adopting both robots and AI together is an increase in temporary employment, but not permanent employment, highlighting lingering uncertainty in effectively integrating these two technologies. Moreover, there is no evidence that firms adopting both robots and AI achieve increases in labor productivity, underscoring a potential lack of synergy between these technologies at this stage.

Keywords
Artificial Intelligence, Robots, Employment, Productivity
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1. Introduction

The influence of Artificial Intelligence (AI) on the labor market differs in several ways from that of previous technological advancements such as software and robotics. Autor, Levy, and Murnane (2003) highlight that software development primarily displaces workers engaged in cognitive and manual tasks that adhere to explicit rules. Webb (2020) demonstrates that robots predominantly replace both routine and non-routine manual tasks. Additionally, he shows that software can substitute routine cognitive tasks. Similarly, Webb finds that AI can substitute both routine and non-routine manual tasks, but AI's distinct characteristic is its primary focus on non-routine cognitive tasks. Consequently, high-income and highly-educated workers are more exposed to AI.

One significant implication of adopting robots or AI relates to employment. Historically, there have been persistent concerns that technological advancements would displace workers permanently, leading to reduced employment levels. The Luddite movement of the early 19th century epitomizes such fears, as textile workers destroyed machines in protest against the automation of textile production. However, these concerns have not been realized, as evidenced by the rise in the employment-to-population ratio during the 20th century.[3] Bowen (1966) posits that the overall demand for goods and services plays a more crucial role in determining aggregate employment than technological change.

Despite these reassurances, the rapid adoption of robots has reignited fears, largely due to their anthropomorphic design, which suggests that robots could perform tasks identical to those done by humans, potentially leading to the complete displacement of human workers.[4] The declining trend in the employment-population ratio throughout the 21st century supports this view. Acemoglu and Restrepo (2020) provide robust evidence of the negative impact of robots on employment across U.S. commuting zones, asserting that the effects of robots are distinct from those of other forms of capital and technology. Their research stands out by examining the broader equilibrium effects of robots on local labor markets, indicating an overall reduction in employment levels. Additionally, Brynjolfsson and McAfee (2014) argue that AI, which emulates human cognitive tasks, tends to substitute rather than complement workers, further exacerbating concerns about job displacement.[5] Acemoglu and Restrepo

[3] According to the U.S. Bureau of Labor Statistics, the employment-population ratio in the U.S. reached its peak at 64.7% in 2000. However, it has been on a declining trend throughout the 21st century.
[4] Ford (2015), for example, argues that robots are encroaching upon the final frontier of machine automation, where they will vie for the remaining relatively routine, manual jobs that are still accessible to human workers.
[5] Brynjolfsson and McAfee (2014) distinguish the Second Machine Age that involves the automation of cognitive tasks, from the First Machine Age, or Industrial Revolution, which was characterized by complementarity between

(2020), utilizing a task-based framework that distinguishes between the displacement effect (automation taking over tasks previously performed by labor) and the productivity effect (increasing productivity and thereby boosting demand for labor in non-automated tasks), conclude that the net effect is negative.

However, regarding robots, there is substantial evidence suggesting that automation anxiety may be exaggerated. Autor (2015) argues that while robots do indeed substitute for labor, they also complement it, thereby increasing output in ways that lead to higher demand for labor. Autor and Salomons (2018), through the identification of three channels—(1) own-industry effects, (2) indirect upstream and downstream effects in linked sectors, and (3) final demand effects resulting from each industry's productivity growth contributing to aggregate incomes—conclude that robot adoption does not displace employment. They find that although the direct own-industry effect is negative, the positive indirect effects from the other two channels offset this initial impact, resulting in a net positive effect overall. Based on the German experience, Dauth et al. (2021) corroborate the findings of Autor and Salomons (2018), demonstrating that displacement effects in manufacturing are entirely offset by the creation of new jobs in the services sector. Additionally, Graetz and Michaels (2018), using panel data on robot adoption within industries across seventeen countries from 1993 to 2007, find that while robots reduce the employment share of low-skilled workers, they do not significantly decrease total employment. Even at the firm level, evidence suggests that the adoption of robots does not necessarily lead to decreased employment. Koch et al. (2021), using a rich panel dataset of Spanish manufacturing firms over a 27-year period (1990-2016), find that the impact of robot adoption on the exposed firms is net job creation at a rate of 10%. Similarly, Zhang et al. (2023), utilizing a unique firm-level dataset of online job postings in Dongguan, often referred to as "The World Factory" in China, reveal that robotization, specifically the "machine substitution" policy, encourages funded firms to expand their labor demand primarily due to increased productivity.

The impact of AI on employment remains a developing area of study. Acemoglu et al. (2022), based on online vacancy postings, find that while AI-exposed establishments reduce hiring for non-AI positions and alter the skill requirements for the remaining roles, the aggregate effects of AI-labor substitution on employment are currently too small to be detectable. Conversely, Babian et al. (2024) report that firms investing in AI experience higher overall employment. Similarly, Felten, Raj, and Seamans (2019a) find that occupations impacted by AI exhibit a small but positive change in wages, with no significant change in employment. In a related study, Felten, Raj, and Seamans (2019b) find that occupations affected by AI see employment growth, particularly in roles requiring complementary

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labor and machines.

skills and technologies. Furthermore, Georgieff and Hyee (2021) identify no clear relationship between AI exposure and overall employment growth; however, in occupations with high computer usage, greater AI exposure correlates with higher employment growth. Alderucci et al. (2020) also find that firms with AI-related innovations have 25% faster employment growth. Despite widespread concerns that AI could entirely replace human workers, there is currently no substantial evidence supporting this scenario.[6] Song et al. (2024), focusing on Korea's experience, find no significant impact of AI adoption on employment at the firm level.[7]

Another important area of the implication adopting robots or AI is its impact on productivity. The majority of research supports the notion that firms adopting robotic technologies exhibit increased productivity. Graetz and Michaels (2018), utilizing novel panel data on robot adoption within industries across seventeen countries from 1993 to 2007 and new instrumental variables based on robots' comparative advantage in specific tasks, find that increased robot use contributed approximately 0.36 percentage points to annual labor productivity growth. Similarly, Acemoglu and Restrepo (2020) confirm that robot adoption at the industry level is associated with greater value added and labor productivity in the U.S. Furthermore, Li et al. (2024) identify a positive causal effect of robot adoption on firm productivity based on firm-level data from China.

Studies are even more optimistic about the positive impact of AI on productivity. Babian et al. (2024) find that firms investing in AI experience higher growth in sales and market valuations, primarily driven by increased product innovation. There is an even more optimistic view regarding the recently developed generative AI, as its output in some areas is hardly distinguishable from that of humans. Indeed, ChatGPT became the fastest-spreading technology platform in history, amassing an estimated 100 million monthly users just two months after its launch. Praising its success, Hatzius et al. (2023), in a Goldman Sachs report, argue that generative AI could raise annual U.S. labor productivity growth by nearly 1.5 percentage points over a 10-year period following widespread adoption, potentially contributing to a 7% increase in global GDP. Chui et al. (2023), in a McKinsey report, suggest that generative AI, combined with other work automation technologies, could add between 0.5 and 3.4 percentage points annually to productivity growth through 2040. In experiments, both Peng et al. (2023)

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[6] Korinek and Suh (2024) propose a scenario in which the complexity of tasks that humans can perform is finite. If full automation is achieved under these conditions, wages could collapse, resulting in a situation where no tasks are left for humans to perform.

[7] Song et al. (2024) utilized the same dataset as ours. Their findings on AI's impact on employment, derived using the standard Difference-in-Differences (DID) method, are consistent with ours. However, we will show that by employing Propensity Score Matching (PSM) to achieve better matching between control and treatment groups, the impact of AI on employment becomes positive.

and Noy and Zhang (2023) find that workers exposed to generative AI exhibit higher productivity. Brynjolfsson et al. (2023) also find that in the actual workplace, access to generative AI assistance increases the productivity of agents by 14%. In contrast, Acemoglu (2024) offers a more moderate estimate, suggesting that while the macroeconomic effects are significant, they are modest—projecting no more than a 0.66% increase in total factor productivity (TFP) over a 10-year period.

Our study contributes to the literature in several key ways. First, we examine how the adoption of robots and AI influences both employment and productivity within a unified framework, using the same sample. Typically, robots excel in physical, repetitive tasks, often replacing human labor, whereas AI drives productivity in cognitive and decision-making processes, more frequently augmenting human work. This raises the question: Are there differences between robots and AI in their effects on employment and productivity? Second, rather than indirectly identifying robot or AI adoption through patents or job postings, we directly identify firms that adopt either robots or AI. This increases the precision of our analysis. Finally, instead of relying on regional or macro-level data, we employ firm-level data to investigate the immediate impact of robot or AI adoption at the firm level. This firm-level analysis allows us to match treated and control firms using propensity scores, thereby minimizing the potential non-equivalence of characteristics between the treatment and control groups and reducing bias introduced by covariates when estimating the treatment effect. Although some studies in the literature also use firm-level data, studies that incorporate matching between treated and control groups remain relatively rare.

This paper utilizes data from the Survey of Business Activities provided by the Korean Statistical Office to analyze the impact of artificial intelligence and robots on productivity and employment. Specifically, the Survey of Business Activities introduced a questionnaire on the adoption of digital technologies starting in 2017. This information is combined with various variables, including company-specific characteristics, to analyze the effects of robots and AI on employment and productivity.

We find that the trends in adopting robots and AI differ significantly across industries. While *the electricity, gas, steam, and air conditioning supply* sector and *the manufacturing* sector lead in robot adoption, *the information and communication* sector dominates in AI adoption. Additionally, while the share of firms adopting robots is larger overall, AI adoption is more concentrated among relatively larger firms in terms of employment. Furthermore, there appears to be a potential lack of synergy between robot and AI adoption, as evidenced by the relatively low correlation coefficient between the two, which remains around 0.2. We also observe that firms with larger sales, higher R&D intensity, and a lower share of manufacturing employment are more likely to adopt robots and /or AI.

The main finding of this paper is that the impacts of AI and robots on employment and productivity are quite different. While adopting both robots and AI increases either permanent or temporary employment, only firms that adopted AI experienced productivity gains in Korea. However, the increase in labor productivity associated with AI adoption led to a decrease in the labor share for firms, suggesting a potential shift in value distribution favoring capital income. Additionally, we find that the immediate impact of adopting both robots and AI is an increase in temporary employment, but not permanent employment, indicating lingering uncertainty in effectively integrating these two technologies. Furthermore, there is no evidence that firms adopting both robots and AI achieve increases in either employment or labor productivity, underscoring a potential lack of synergy between these technologies at this stage. Our findings, however, cannot be generalized to the entire economy without considering additional factors, such as the effects on other firms through input-output linkages.

The rest of the paper is organized as follows. The next section explains the data we used throughout the paper. Section 3 analyzes the characteristics of the firms that adopt robots or AI. In section 4, we investigate the impact of robot or AI adoption on both employment and productivity at the firm level. Section 5 concludes.

2. Data

The data used in this study are derived from the Survey of Business Activities, conducted annually by the Korean Statistical Office. This survey targets firms in all industries in Korea with at least 50 regular employees and a capital of at least 300 million Korean Won (approximately 220,000 US dollars), covering 13,824 corporations as of year 2022 across all industries.[8] While every firm is classified in an industry, if a firm is involved in multiple industrial activities, it is classified in the main industrial, and the sales from other sectors are included in the main industry. Industry classification follows Korean Standard Industrial Classification (KSIC) which closely resembles International Standard Industrial Classification (ISIC), revision 4. The survey is principally conducted through site visits, but some items have been substituted with administrative data from the National Tax Service and other sources.

The purpose of the survey is to comprehensively understand various business activities of

[8] In the retail and other service sectors, firms with less than 50 regular employees are included in the survey if their capital exceeds 1 billion Korean won.

enterprises, including management performance, diversification, affiliation, performance management systems, and changes in business strategies and industrial structures.[9] While the survey began collecting various firm-specific characteristics in 2005, it introduced a questionnaire on the adoption of digital technologies starting in 2017. This questionnaire was designed to verify how new digital technologies are diffused within the economy. Specifically, it inquires whether any of the following nine digital technologies are adopted: (1) AI, (2) robots, (3) Internet of Things, (4) cloud computing, (5) big data, (6) mobile technologies and services (including 5G), (7) blockchain, (8) 3D printing, and (9) augmented reality (AR)/virtual reality (VR).

A firm is classified as using AI or robots if it indicates in a survey that it utilizes these technologies in any of the following areas: product development, marketing strategies, production processes, organizational management, or sales objectives. This aspect highlights an advantage of this study: it mitigates the limitations of previous studies, which indirectly identified firms using related patents or job advertisements.[10] As noted by Song and Cho (2021), if a firm's use of AI is measured based on the possession of AI-related patents, there is a strong correlation with whether the company is developing AI technologies; however this does not necessarily indicate whether these technologies are being utilized in the production process. This study's direct approach provides a clearer assessment of technology usage within firms.[11]

Employees are categorized as either permanent or temporary workers. Permanent workers are those who have an employment contract with their employer for at least one year or who work as permanent staff without a fixed term of employment. In contrast, temporary workers have an employment contract for less than one year and include categories such as daily, part-time, and freelance workers. The classification of whether an employee is a manufacturing worker is applied only to permanent workers; thus, the share of manufacturing workers is calculated as the ratio of manufacturing workers to total permanent workers. Labor productivity is defined as value added per worker. When a company owns more than 50 percent of the total issued shares of another company, the former is designated as the parent company, and the latter as a subsidiary. If the former is from a foreign country, it is defined as foreign owned. Labor share is defined as the ratio of deflated labor costs to deflated value added. Capital intensity is measured as the sum of tangible and intangible assets divided by the total number of workers. Research and Development (R&D) expenses include all costs associated with

[9] The explanation on the survey is based on the Survey of Business Activities, 2022.
[10] For example, Alderucci et al. (2020) and Damiol et al. (2021) identify firms using AI by employing machine learning algorithms to analyze the text of U.S. patent grants. Similarly, Acemoglu et al. (2022) utilize establishment-level data on online job vacancies. Babina et al (2024) measure firm-level AI investments using employee resumes.
[11] Song and Cho (2021) used the same data as ours.

the company's research and development activities, such as labor costs, raw materials, depreciation of tangible assets, utilities, and supplies. R&D intensity is defined as R&D expenses divided by deflated sales. Export and import dummies are indicator variables that signify whether the firm engages in export or import activities.

Table 1 presents the summary statistics for the variables from 2016 to 2022, classified by different categories of firms: "Robots" indicates firms that adopt robots, "AI" indicates firms that adopt AI, "Both" refers to firms that adopt both technologies, "None" refers to firms that adopt neither, and "All" represents all firms in the sample.[12] The statistics suggest that firms adopting robots and/or AI are generally larger in terms of both employment and sales. Labor productivity is also higher among these firms. The labor share is similar across all classifications, except for firms that adopt both robots and AI, which exhibit a slightly lower labor share. Firms that adopt robots and/or AI are more likely to be publicly listed on the stock market. Additionally, capital intensity is higher for firms that adopt robots or both. R&D intensity is elevated for firms that adopt AI and the share of manufacturing workers is higher specifically among firms that adopt robots. Notably, only firms that adopt robots or both are more likely to be foreign-owned. These findings are based on a simple comparison across different categories without testing the statistical significance, and we will revisit these issues more rigorously in the next section.

In Figure 1, we present how the shares of firms adopting robots and AI changed across industries from 2017 to 2021. Figure 1.1 illustrates the changes in robot adoption, revealing that the proportion of firms implementing robots grew most rapidly in the *electricity, gas, steam, and air conditioning supply* sector (from 0.0% to 5.9%) and *the manufacturing* sector (from 0.1% to 2.6%). *The Information and communication* industry and *the accommodation and food service activities* sector also exhibit relatively high shares of robot-adopting firms. Interestingly, while *the education* sector had a quite high share of robot-adopting firms in 2017, this share has remained steady since then. Figure 1.2 shows trends in AI adoption, with rapid growth evident in four industries. From 2017 to 2021, the share of AI-adopting firms increased from 3.6% to 16.5% in *information and communication*, from 3.7% to 13.8% in *electricity, gas, steam, and air conditioning supply*, 1.9% to 11.9% in *education*, and from 1.3% to 7.7% in *financial and insurance activities*. Figure 1.3 depicts the shares of firms adopting both robots and AI. *The Information and communication* industry exhibits the highest share, increasing from 3.6% in 2017 to 16.5% in 2021. *Electricity, gas, steam, and air conditioning supply* also shows a significant growth,

[12] We excluded firms with outlier observations and those reporting inconsistent information regarding their adoption of robots or AI. Specifically, we removed entries from firms that initially reported adopting these technologies but later contradicted this information.

rising from 3.7% in 2017 to 13.8% in 2021. *Education* and *Financial and insurance activities* also exhibit notable shares of 11.9% and 7.7%, respectively, in 2021.

Figure 2 illustrates the shares of firms adopting robots, AI, or both, along with the corresponding employment shares, categorized by small, large, and all firms over time. Small firms are defined as those with fewer than 200 employees, while large firms include those with 200 or more employees. Figure 2.1 presents the share of firms adopting robots in Panel A and their employment shares of these firms in Panel B. In Panel A, both small (dotted line) and large firms (dashed line) show a steady increase in robot adoption over time. Among large firms, the share of robot-adopting firms rose from 1.2% in 2017 to 3.2% in 2021. For small firms, this figure increased from 0.1% in 2017 to about 1.2% in 2021. While large firms adopt robots at a relatively higher rate, the pace of growth is similar for both groups. In Panel B, the employment shares reveal a much larger gap between large and small firms. This suggests that robot adoption is more concentrated among relatively larger firms within the large-firm category. By 2021, 14.7% of employees in large firms worked at robot-adopting firms, compared to 1.4% of employees in small firms.

Figure 2.2 focuses on firm and employment shares of AI-adopting firms, with Panel A illustrating firm shares. The share of AI-adopting firms increased steadily from 2.4% to 6.7% among large firms and from 0.7% to 2.5% among small firms. Interestingly, while large firms' share of AI adoption is smaller than their share of robot adoption, small firms' share of AI adoption is greater than the corresponding share of robot adoption. Panel B shows the employment shares of AI firms, with employment shares in large firms increasing significantly from 8.9% in 2017 to 22.3% in 2021. This indicates that, compared to robot adoption, AI adoption is more concentrated among relatively larger firms. Figure 2.3 presents firm and employment shares for firms adopting both robots and AI. Panel A shows that firm shares remain relatively small, rising from 0.6% in 2017 to 1.5% in 2021 for large firms, with much lower figures for small firms. However, Panel B indicates that employment shares are more substantial, increasing from 3.9% to 12.1% among large firms. In contrast, employment shares for small firms remain extremely low.

Figure 3 illustrates the relationship between robot and AI adoption over time. The solid line represents the correlation coefficient between robot and AI adoption across firms. The dashed line indicates the correlation between firms adopting both robots and AI and those adopting only robots, while the dotted line represents the correlation between firms adopting both technologies and those adopting only AI. Notably, none of these three correlation coefficients show an upward trend over time, suggesting a potential lack of synergy between robot and AI adoption across industries. The correlation coefficient between robot and AI adoption remains relatively low, around 0.2.

Figure 4.1 shows the share of firms that adopted AI among those that had adopted robots, while Figure 4.2 presents the share of firms that adopted robots among those that had adopted AI, categorized by small firms, large firms, and total firms. In Figure 4.1, for large firms, the likelihood of adopting AI if they have already adopted robots is around 0.5. For small firms, this likelihood is significantly lower, around 0.2. Neither group shows an increasing trend in these figures over time. In Figure 4.2, for large firms, the likelihood of adopting robots given that they have adopted AI is considerably lower than in Figure 4.1, remaining between 0.2 and 0.25. For small firms, this likelihood is even lower, typically around 0.1. As with Figure 4.1, there is no evidence of these figures increasing over time. A comparison of Figures 4.1 and 4.2 reveals that firms are more likely to adopt robots if they have already adopted AI, rather than adopting AI if they have already adopted robots.

Figure 5 illustrates the changes in employment and labor productivity in relation to the adoption of robots (Figure 5.1), AI (Figure 5.2), and both technologies (Figure 5.3) at the industry level. In Panel A, the horizontal axis represents the change in the share of employment among firms that adopted robots from 2017 to 2021 within each industry, while the vertical axis shows the change in total employment for the same industry. In Panel B, the vertical axis indicates the change in labor productivity at the industry level. The size of each circle represents the employment size of the corresponding industry. The fitted lines are derived from weighted OLS regressions, with the initial level of employment serving as the weight. For Figure 5.1, the slope of the fitted lines is negative in both panels, suggesting no evidence that an increase in robot-adopting firms is associated with increases in either employment or labor productivity. Only the slope for labor productivity is statistically significant at the 1% level. Figure 5.2 illustrates changes in employment and labor productivity in relation to the adoption of AI. Here, the slope is positive in Panel A for employment but negative in Panel B for labor productivity. However, neither slope is statistically significant. Finally, Figure 5.3 presents changes in employment and labor productivity associated with the adoption of both robots and AI. The slope in Panel A is positive but statistically insignificant, while the slope in Panel B is negative and statistically significant at the 10% level. Overall, the industry-level data provide no strong evidence that robot or AI adoption is associated with increases in employment or labor productivity. However, these industry-level results lack a causal interpretation and may differ from firm-level analyses, which enable better matching between control and treated groups, allowing for a potential causal interpretation of the differential impacts of robots and AI. We will revisit this issue in Section 4.

3. Which Firms Adopt Robots and AI?

In this section, we explore the firm-specific characteristics that influence the adoption of robots and AI. Koch et al. (2021), utilizing a panel dataset of Spanish manufacturing firms from 1990 to 2016, find that larger firms (in terms of output), firms with a higher proportion of manufacturing and production workers, firms with greater capital intensity, and exporting firms are more likely to adopt robots. Conversely, firms with higher skill intensity, measured by the share of workers with a five-year university degree, are less likely to adopt robots.

Following their approach, we set up the equation as follows:

$$Robots_i = \beta \emptyset_{i0} + \beta F_{i0} + \beta G_{i0} + \mu_{s0} + \varepsilon_i \qquad (1)$$

where the dependent variable is an indicator variable for robot use for firm i during the sample period; $\emptyset_{i0}$ is a firm-specific size or productivity variable in the base year; F_{i0} is a vector of factor intensity variables in the base year; G_{i0} is a vector of globalization variables in the base year; μ_{s0} represents industry-base-year fixed effects; and ε_i is the error term. Koch et al. (2021) defined the base year as the first year that the firm appears in the sample. We defined the base year as year 2016 which is one year before the survey on AI and robot adoption started. We will similarly define AI_i as the dependent variable for the determination of AI adoption.

Firm size and productivity are measured by the logarithm of deflated sales and deflated value added per worker, respectively. The factor intensity variables include the firm's capital intensity (assets divided by the number of employees), R&D intensity (deflated R&D expenditure divided by deflated total sales), the share of manufacturing employment, and average wage (deflated total labor costs divided by the number of workers, in logarithmic form). For the globalization variables, we use indicator variables for whether the firm is an exporter or an importer and whether the firm is foreign-owned.

Table 2 presents the OLS regression results of equation (1). Specifically, Table 2.1 displays the results when the dependent variable is an indicator for robot use. The organization of Table 2.1 is as follows: Column (1) represents the baseline specification. Column (2) incorporates all factor intensity variables, while Column (3) adds all globalization variables. Column (4) includes both factor intensity and globalization variables. Columns (5) through (8) replicate Columns (1) through (4) but also include labor productivity as a regressor.

The results indicate that the coefficient for sales is positive and highly statistically significant, suggesting that larger firms are more likely to adopt robots. The average coefficient value across all estimates is approximately 0.007, implying that an increase by the standard deviation of the firm's base-year sales increases the probability of adopting robots by 3% (=0.007*1.49). While statistically significant only in columns (5) and (7), the coefficient for labor productivity is negative. The coefficient for capital intensity is also negative and highly statistically significant, indicating that firms with lower capital intensity (and thus greater reliance on labor) are more likely to adopt robots. Additionally, the coefficient for R&D intensity is consistently positive and generally statistically significant, implying that higher-skill firms are more inclined to adopt robots. Interestingly, the coefficient for the share of manufacturing workers is negative and highly statistically significant, suggesting that the primary motivation for adopting robots may not be to reduce the proportion of manufacturing workers.[13] Regarding globalization variables, the coefficients for exports, imports or foreign ownership are not statistically significant, indicating that these global variables are not associated with robot adoption.

Table 2.2 presents the results when the dependent variable is an indicator for AI use. The signs of the coefficients are generally similar to those in Table 2.1. However, the coefficient for R&D intensity is much more statistically significant, indicating that AI adoption is strongly associated with higher skill levels. Another noteworthy difference is that the coefficients for the global variables—foreign ownership, exports, and imports—are all negative, suggesting that AI adoption is primarily driven by domestic factors.[14] Additionally, while the coefficient for labor productivity is negative, the coefficient for average wage is positive and statistically

[13] This finding stands in clear contrast to that of Koch et al. (2021), which reports positive and highly statistically significant coefficients for the share of manufacturing workers. However, in Korea, labor unions are known to be highly militant, and one of the main motivations for adopting robots is to mitigate the pressure from hiring more workers. Brynjolfsson et al. (2023) support this view, finding that "robot hubs"—areas with significantly more robots than would be expected after accounting for industry and manufacturing employment—are associated with high levels of union membership.

[14] Only the coefficients for foreign ownership are statistically significant.

significant, indicating that one of the main motivations for adopting AI is to reduce labor costs. Table 2.3 shows the results when the dependent variable is an indicator for both robot and AI use. The findings are similar in that these firms are characterized by high sales and substantial R&D expenditure. Additionally, while the wage rate is generally high, labor productivity tends to be low.

Table 3 reports the probit estimation results of the same equation as in Table 2. The results for robot adoption are presented in Table 3.1, while those for AI adoption are shown in Table 3.2. The signs of the coefficients in Table 3.1 are very similar to those in Table 2.1, with the following notable differences. First, the estimated coefficients for imports are positive and consistently statistically significant, suggesting that robot adoption may be associated with import substitution. Second, the coefficient for labor productivity is generally no longer statistically significant. The signs of the estimated coefficients in Table 3.2 are even more consistent with those in Table 2.2, except that the estimated coefficients for foreign ownership are generally statistically insignificant. The results in Table 3.3, which pertain to firms adopting both robots and AI, differ somewhat from those in Table 2.3. Specifically, these firms exhibit lower capital intensity and a positive and statistically significant coefficient for import activity.

4. The Impact of Robot and AI Adoption on Employment and Productivity

In this section, we explore the impact of robot and AI adoption on employment and productivity. The standard two-way fixed effects (TWFE) that includes both firm and time fixed effects has been adopted to account for variation in timing:

$$Employment_{it} = \alpha_i + \alpha_t + \beta Robot_{it} + \epsilon_{it} \qquad (2)$$

where $Employment_{it}$ represents the log of employment for firm i, $Robot_{it}$ is an indicator variable that takes one if the firm i adopts robots at time t and zero otherwise, and α_i and

α_t are firm and time fixed effects, respectively. Goodman-Bacon (2021) illustrates that the estimated coefficient β is a weighted average of all possible 2x2 difference-in-differences (DID) estimators that compare the change in outcomes before and after treatment in treated versus control groups. However, de Chaisemartin, C., and D'Haultfœuille, X. (2020) highlight a limitation of this approach: the weights can be negative, leading to a scenario where the sign of β could be positive even though every individual DID estimator is negative.

To address the limitations of the standard Two-Way Fixed Effects (TWFE) method, we apply a two-group/two-period (2x2) estimator to analyze each pair of observations separately.[15] This method categorizes the data into two distinct periods: Period 1 and Period 2. Period 1 serves as the base year, representing the year before robot adoption, while Period 2 spans from the year of adoption up to four subsequent years. For instance, to assess the impact of robot adoption in 2017 on the firm in the same year, we designate 2016 as Period 1 and 2017 as Period 2, applying the 2x2 estimator to the data from these two years. Similarly, to analyze impacts in subsequent years such as 2018, we retain 2016 as Period 1 and treat 2018 as Period 2, conducting our analysis with data from these two years. An additional advantage of this approach is that it allows the impact of robot adoption to vary over time.[16] It is crucial to clearly define the counterfactual group for comparison with the treated group. We select the never-treated group as the counterfactual. For example, when estimating the impact of robot adoption in 2017, we compare firms that adopted robots in 2017 with firms that never adopted robots throughout the entire sample period.

This structured approach allows us to meticulously examine changes in employment from the year of adoption to four years post-adoption. We define a year dummy as an indicator variable for the periods of robot adoption: the dummy is set to 0 for Period 1 and to 1 for Period 2. Additionally, we introduce a robot dummy that takes a value of 1 if the firm adopts robots in the treatment year and 0 otherwise. This configuration enables us to estimate the impact of robot adoption for each year and to observe the temporal evolution of the effects of robot adoption. More specifically we estimate the following two-way fixed effects regressions for

[15] This approach is also taken by Song et al. (2024) to analyze the impact of AI on employment. They find that AI's impact on employment is negligible.
[16] Another problem with the standard TWFE approach is that it does not allow the impact to vary over time. See de Chaisemartin and D'Haultfoeuille (2022) for a survey of this literature to overcome this problem.

base year t:

$$Employment_{itp} = \alpha + \beta_1 Year_{tp} + \beta_2 Robot_{it} + \beta_3 Yeart_p * Robot_{it} + \gamma X_{itp} + \epsilon_{itp} \qquad (2)$$

where $Employment_{itp}$ is the number of employment for firm i in period p for the base year t, $Year_{tp}$ is a period dummy for the base year t, $Robot_{it}$ is a robot dummy that takes one if the firm i adopted robots in the treatment year and zero otherwise, X_{itp} denotes the characteristics of firm i in period p and ϵ_{itp} is the error term. For X_{itp}, we include an industry dummy and additional control variables as needed. We repeat this estimation for $t = 2016, 2017, 2018, 2019, 2020$. To assess the impact on productivity, we replace the dependent variable with $Productivity_{itp}$, which is measured by deflated value added per worker for firm i. For the investigation of AI's impact, we substitute the regressor, $Robot_{itp}$ with AI_{itp}, defined as an AI dummy that takes the value of 1 if the firm adopts AI in the treatment year and 0 if it does not, and the base year is year t. Note that the coefficient β_3 represents the treatment effect of adopting robots or AI.

Table 4 presents the impact of robot adoption on employment and labor productivity using the Difference-in-Differences (DID) approach. Table 4.1 reports the impact of robot adoption on permanent employment, while Table 4.2 focuses on temporary employment. In Table 4.1, the dependent variable is the log of permanent employment, with industry dummies included as additional explanatory variables.[17] The "treatment year" corresponds to the year in which the firm adopts robots, while "Period 1" serves as the base year, and "Period 2" as the measurement year. Consequently, T, T+1, T+2, T+3, and T+4 represent the time points at which effects are measured: the year of adoption, one year after, two years after, three years after, and four years after, respectively. All estimations include an intercept and industry dummies, although their coefficients are not reported. Robust standard errors are shown in parentheses.

For example, if the treatment, control, and measurement years are 2017, 2016, and 2018, respectively, the treatment effect measures the impact of robot adoption on employment

[17] Including other firm characteristics such as firm size and .. do not change the qualitative results.

in the second year after robot adoption in 2017, by comparing the differences in employment changes from 2016 to 2018. The last column tests the null hypothesis that trend coefficients are identical between the treatment and control groups prior to treatment, thereby assessing the parallel trend assumption. Note that the parallel trend test results for the same-year tests (T) are identical to those for T+1, T+2, T+3, and T+4 when the treatment year is the same, as the tests rely on the same prior periods. The test results indicate that the parallel trend assumption is strongly violated in all cases. Acknowledging this problem, the average treatment effect on the treated (ATT)—representing the impact of robot adoption on permanent employment for robot-adopting firms—remains statistically insignificant, as shown in the second column and estimated by the interaction term coefficient.[18]

In Table 4.2, we conduct the same analysis as in Table 4.1, but with the dependent variable as the log of temporary employment. In this table, in three out of five cases, the parallel trend assumption is not rejected at the 5% confidence level. However, the ATT is statistically insignificant in all but one instance—the same-year effect at T+4. Therefore, Table 4.2 confirms that robot adoption does not have a statistically significant effect on temporary employment. Overall, the standard DID approach suggests that robot adoption neither substitutes for nor increases labor, whether permanent or temporary.

In Table 4.3, we present the results of the impact of robot adoption on labor productivity by replacing the dependent variable in equation (2) with labor productivity. Table 4.3 is organized similarly to Tables 4.1 and 4.2. The parallel trend assumption is not rejected only in the instance where the treatment year is 2017. Furthermore, the ATT, as indicated by the coefficient of the interaction term, suggests that the impact of robot adoption on labor productivity is not statistically significant.[19] Assuming the validity of the ATT, this finding is unexpected, as prior studies generally conclude that robot adoption enhances firm-level productivity. We believe this outcome may be closely related to Korea's unique context, where the primary motivation for adopting robots may not be to replace labor or improve labor productivity. Given Korea's highly active labor unions, firms may introduce robots as a

[18] This finding is consistent with Song et al. (2024), although their study does not differentiate between permanent and temporary employment, focusing instead on total employment.

[19] The impact is statistically significant only when the treatment year is 2017 and the impact is measured in two years.

strategic response to alleviate union pressures by reducing the need to hire additional workers.

Table 5 reports the impact of AI adoption on employment and labor productivity using the Difference-in-Differences (DID) approach. In Tables 5.1 and 5.2, which present results for permanent and temporary employment, respectively, the parallel trend assumption is strongly violated. Acknowledging this issue, the ATT in the second column—estimated by the coefficient of the interaction term between year and AI dummies—represents the treatment effect on the treated across various combinations of treatment, control, and measurement years. The ATT estimates suggest that AI adoption does not have a statistically significant impact on either permanent or temporary employment. Table 5.3 displays the results for the effect of AI on labor productivity, where the parallel trend assumption is also strongly violated, and the ATT remains statistically insignificant. Overall, the standard DID approach appears inappropriate, and the ATT indicates no statistically significant impact of AI on employment or labor productivity.

Tables 6.1, 6.2 and 6.3 report the impact of both robot and AI adoption on temporary employment, permanent employment and labor productivity, respectively, relying on the same approach. Overall, the parallel trend assumption is largely violated, and acknowledging this issue, the ATT estimates are mostly statistically insignificant.

While the above approach allows for the impact of robot or AI adoption to vary over time, a key limitation of the standard Difference-in-Differences (DID) approach is that the non-equivalence of characteristics between the treatment and control firms introduces bias in estimating the treatment effect.[20] This limitation is underscored by the frequent violation of the parallel trend assumption, suggesting that simply comparing outcomes between treated and untreated firms can lead to incorrect conclusions. Ideally, we would observe the counterfactual scenario—specifically, how the same firm would have performed had it not adopted robots or AI—and then compare it with the firm's actual post-adoption performance. However, such a counterfactual scenario is not directly observable. A more feasible approach, therefore, involves comparing treated firms with similar but untreated firms. For this purpose, we utilize Propensity Score Matching (PSM), a quasi-experimental technique used to construct artificial control firms by matching each treated firm with non-treated firms that share similar pre-

[20] See Rosenbaum and Rubin (1983).

treatment characteristics.

Table 7 presents the impact of robot adoption on firm performance, utilizing PSM. This approach incorporates advanced matching techniques and additional covariates to ensure comparability between treated and control groups. Specifically, Table 7.1 focuses on the impact of robot adoption on employment. To assess the effects of robot adoption in 2017—the year a firm first employs robots—we restricted our analysis to data from 2016 and 2017, comparing treated firms with never-treated firms. Counterfactual matches were constructed using a logit regression model to estimate the likelihood of adopting robots in 2016, including only firms that either adopted robots in 2017 or never adopted them during the entire sample period.[21] Firms that adopted robots after 2017 were excluded from the analysis to eliminate potential anticipation effects, as the expectation of future robot adoption could influence their behavior in 2017.

Key regressors in the logit model included total employment (both permanent and temporary workers), labor productivity, a parent company dummy, and industry dummies. This methodological framework was instrumental in forming matches between firms in the treated and never treated firms, which exhibited similar probabilities of robot adoption based on their characteristics before treatment. This approach allows for a precise assessment of the impact of robot adoption on employment for 2017 (T) by comparing changes in employment between these matched firms. For subsequent analyses, such as the impact in 2018 (T+1), we retained the same matched firms and calculated the treatment effect based on employment differences from 2016 to 2018. This methodology is extended to further subsequent years, such as 2019 (T+2), allowing for a comprehensive analysis of the evolving impacts of robot adoption on employment. To assess the balance of covariates after propensity score matching, we report the average Standardized Mean Difference (SMD) both before and after matching. Note that, as in Table 7.2, if matching was not feasible, the results for the corresponding years are not reported.

To account for the possibility that the impact of robot adoption in 2018 may differ from that in 2017, we repeated the same procedure for firms adopting robots in 2018. This possibility arises from the rapid evolution of AI technology, such that the AI technology available in 2018

[21] To enhance the integrity of our analysis, we excluded firms with extremely low propensity scores from the construction of the counterfactual group, as their inclusion could potentially distort the results.

might differ from that in 2017. For this analysis, we retained data from 2017 and 2018 and constructed counterfactual firms using a logit regression model to estimate the likelihood of adopting robots in 2017, using the same set of regressors. We then estimated the impact of robot adoption in 2017 by comparing employment between the control and treatment firms. Similarly, we estimated the impacts on employment for subsequent years using the same methodology.

In Table 7.1, column (1) reports the Average Treatment Effects on the Treated (ATT) for robot adoption in 2017, analyzing the effects on permanent employment across the year T (the year of adoption), and the subsequent four years (T+1 to T+4). Column (2) details the ATT of robot adoption in 2018 on permanent employment, analyzing the effects in the year of adoption and the following three years (T, T+1 to T+3). Columns (3) through (5) present the ATT for robot adoptions in 2019, 2020, and 2021, respectively, with each column analyzing the effects in the year of adoption and the subsequent years within the available data range. In general, a comparison of SMDs before and after matching suggests that the matching was appropriately performed across the table.[22] Considering the estimates that are statistically significant, Table 7.1 reveals that firms that adopted robots in 2017 experienced an increase in permanent employment by the third year (T+3) post-adoption. Similarly, firms that adopted robots in 2018 saw an increase in permanent employment by the first year (T+1) following adoption.

Table 7.2 extends the analysis from Table 7.1 to temporary employment, showing that only firms that adopted robots in 2017 experienced a statistically significant increase in temporary employment within the same year. Table 7.3, which reports the ATT on labor productivity, reveals mixed results: firms that adopted robots in 2017 saw an increase in labor productivity the following year, whereas those that adopted in 2018 and 2021 experienced decreases in labor productivity in the next year and the adoption year, respectively. Finally, Table 7.4 examines the impact of robot adoption on labor share, indicating that only the firms adopting robots in 2021 experienced an increase in their labor share during the same year.

[22] This holds true for the remaining tables throughout the paper. Therefore, we will not explicitly discuss the validity of matching in subsequent sections.

Table 8 assesses the impact of AI adoption on firm performance using the methodology employed in Table 7. In Table 8.1, we report the effects of AI adoption on permanent employment. Firms that adopted AI in 2020 exhibited a statistically significant increase in permanent employment throughout 2020 and 2021. Similarly, firms that adopted AI in 2019 experienced an increase in permanent employment in 2021 (T+2). The results show that only firms that adopted AI after 2019 hired more permanent workers. Table 8.2 shows that firms adopting AI generally experienced increases in temporary employment as well. Specifically, firms that adopted AI in 2017 saw an increase in temporary employment by T+2; those in 2018 observed increases in the year of adoption (T) and the following year (T+1); and firms adopting in 2020 noted an increase in temporary employment by T+1. The results show that firms that adopted AI before 2019 hired more temporary workers. Moreover, Table 8.3 reveals that, while these firms experienced an increase either in permanent or temporary employment, there is a general increase in labor productivity associated with AI adoption. Table 8.3 shows that firms adopting AI in 2017 and 2019 saw increases in labor productivity by T+2. Firms adopting in 2018 saw productivity gains in the same year. However, there is no recorded increase in labor productivity for firms adopting AI in 2020 and 2021. The above results show that it takes about two-three years for the labor productivity to gain. Given the time it may take for productivity improvements to manifest, it remains possible that these firms could show productivity gains in future years not yet reported. Finally, Table 8.4 suggests that the increase in labor productivity associated with AI adoption led to a decrease in labor share for some firms. This indicates a potential shift in the distribution of value, favoring capital income within these firms following the adoption of AI technology.

Finally, Table 9 reports the results for firms adopting both robots and AI. Table 9.1, which presents the impact on permanent employment, yields mixed results: in two cases, the impact is negative and statistically significant, while in one case, it is positive and statistically significant. In Table 9.2, we observe that the immediate impact of adopting both technologies is an increase in temporary employment. This finding—that these firms increase temporary but not permanent employment—suggests lingering uncertainty in effectively combining these two technologies. Furthermore, Table 9.3 shows no evidence that adopting both robots and AI leads to improved labor productivity, as none of the cases are statistically significant, underscoring a potential lack of synergy between these technologies at this stage. For the impact on labor share, reported in Table 9.4, the results are mixed.

The impact is negative and statistically significant for firms that adopted both technologies in 2017, while it is positive and statistically significant for firms adopting them in the most recent year, 2021.

5. Conclusion

In this paper, we explore the impact of robot and AI adoption on employment and productivity at the firm level, utilizing data from the Survey of Business Activities conducted annually by the Korean Statistical Office. Our analysis integrates these impacts within a unified framework.

The standard two-way fixed effects Difference-in-Differences (DID) analysis yielded few statistically significant cases indicating impacts from robot or AI adoption. However, when we refined our approach by minimizing differences between firms that adopted robots or AI and those that did not—using propensity score matching—the results became more pronounced. Specifically, firms that adopted robots showed increases in employment but experienced decreases in productivity. In contrast, firms that adopted AI demonstrated gains in both employment and productivity.

It is crucial to recognize that our findings cannot be generalized to the entire economy without considering additional factors. As highlighted by Autor and Salomons (2018), there are at least two broader effects of robot or AI adoption that must be taken into account. Firstly, there are significant effects related to input-output linkages. While our study concentrates on the immediate impacts on firms that have adopted robots or AI, other firms interconnected through these linkages might also be affected. This includes increased demand for upstream firms and altered productivity for downstream firms. Secondly, increases in income resulting from robot or AI adoption can boost aggregate demand, thereby affecting even those firms not directly linked through input-output relationships. To comprehensively assess the impact on the overall economy, these expansive effects must be incorporated.

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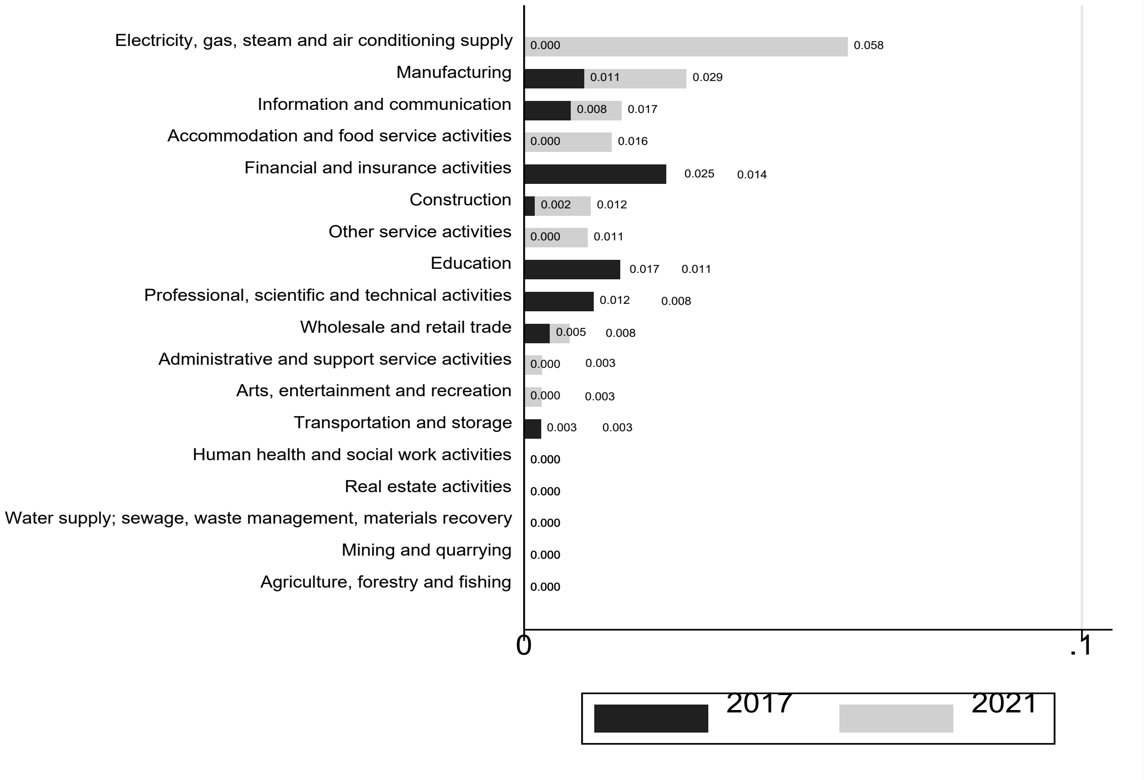
Figure 1: Shares of Firms Adopting Robots, AI, or Both by Industry

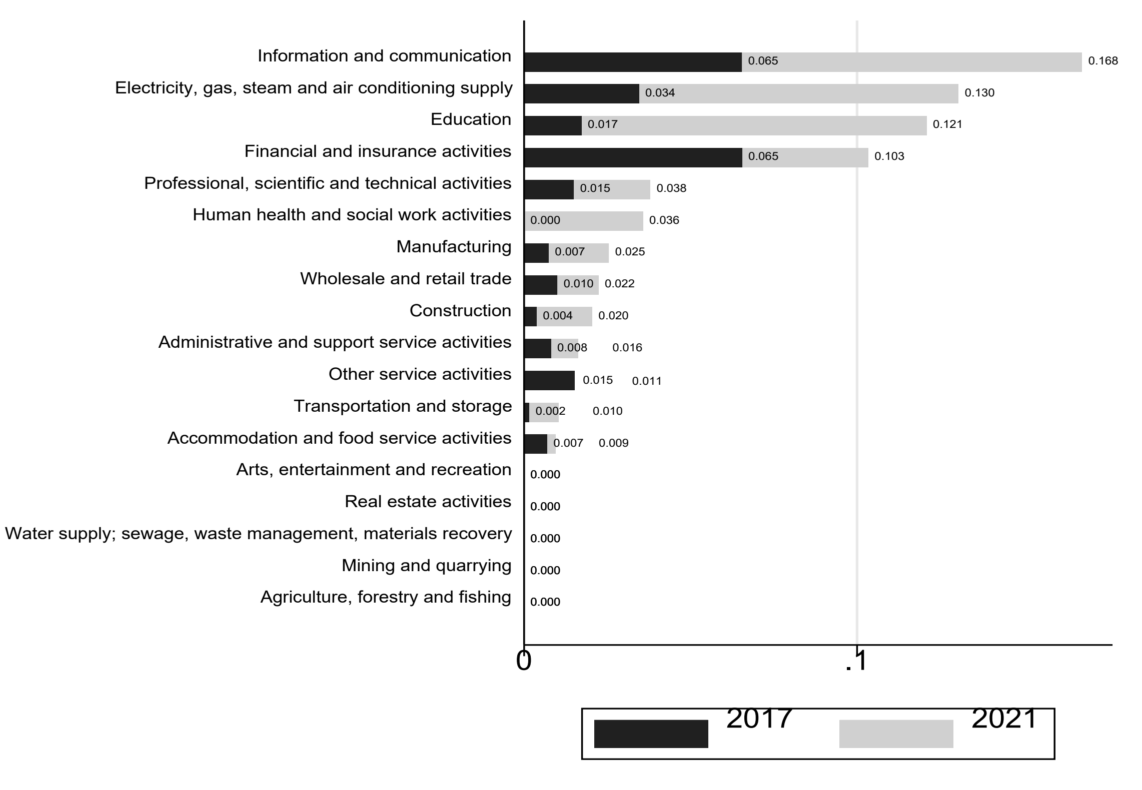
Figure 1.1: Robot-Adopting Firms



Notes: The Korean industry classification follows the 1-digit level of the Korean Standard Industrial Classification (KSIC). Industries without firms adopting robots are excluded. The share is calculated as the number of robot-adopting firms divided by the total number of firms within each industry.

Sources: Authors' calculations

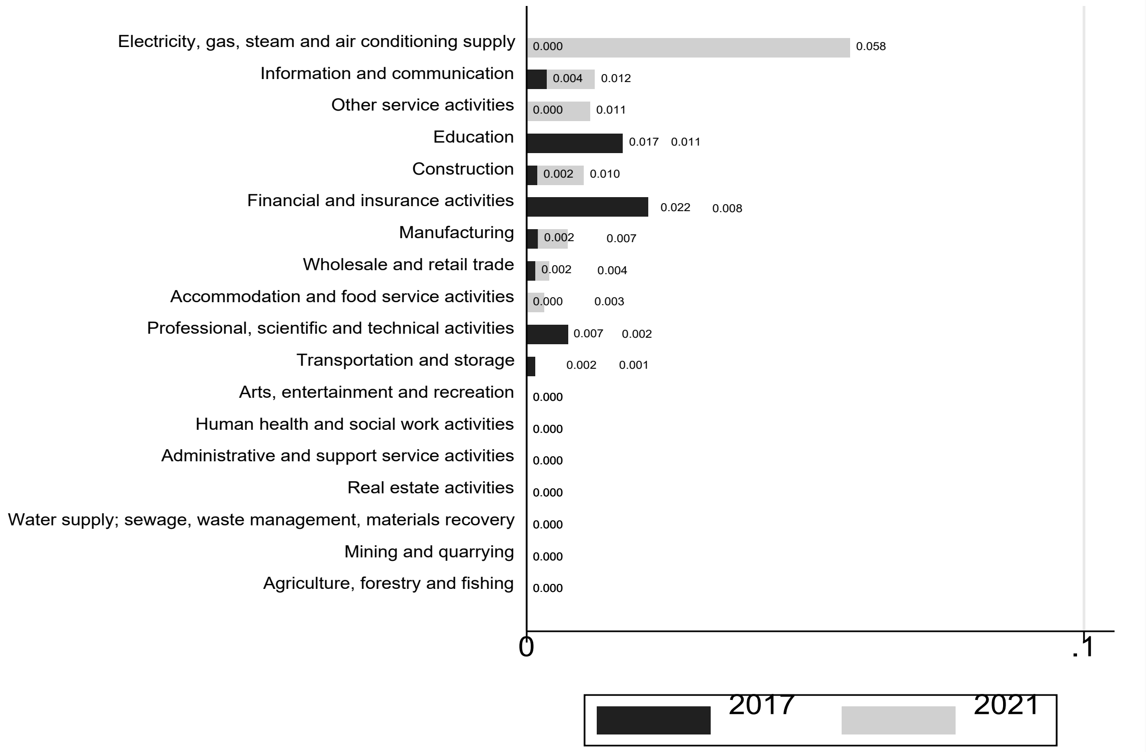
Figure 1.2: AI-Adopting Firms



Notes: The Korean industry classification follows the 1-digit level of the Korean Standard Industrial Classification (KSIC). Industries without firms adopting AI are excluded. The share is calculated as the number of AI-adopting firms divided by the total number of firms within each industry.

Sources: Authors' calculations

Figure 1.3: Firms Adopting Both Robots and AI



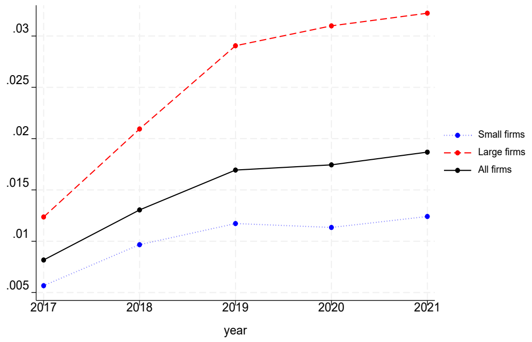
Notes: The Korean industry classification follows the 1-digit level of the Korean Standard Industrial Classification (KSIC). Industries without firms adopting both robots and AI are excluded. The share is calculated as the number of firms adopting both robots and AI divided by the total number of firms within each industry.

Sources: Authors' calculations

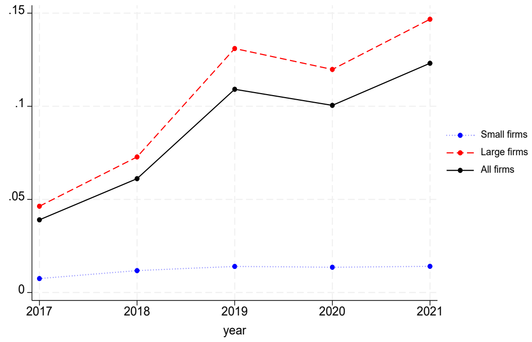
Figure 2: Evolution of Robot and AI Adoption in Korea

Figure 2.1: Robot Adoption

(a) Firm Shares



(b) Employment Shares

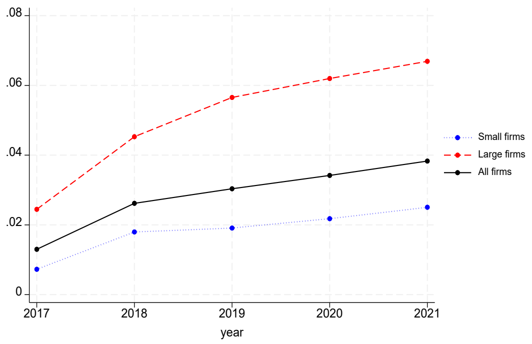


Notes: Panel (a) illustrates the shares of robot-adopting firms, categorized by small firms (dotted line), large firms (dashed line), and all firms (solid line). Small firms are defined as those with fewer than 200 employees, while large firms include those with 200 or more employees. Panel (b) presents the employment shares corresponding to these firms.

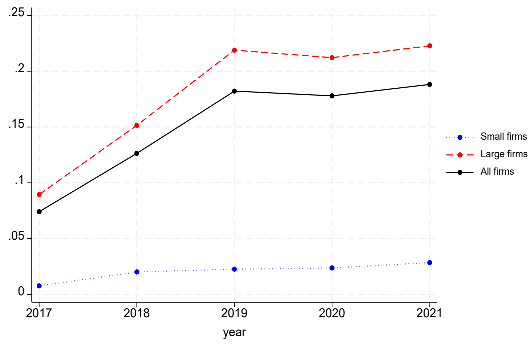
Sources: Authors' calculations

Figure 2.2: AI Adoption

(a) Firm Shares



(b) Employment Shares

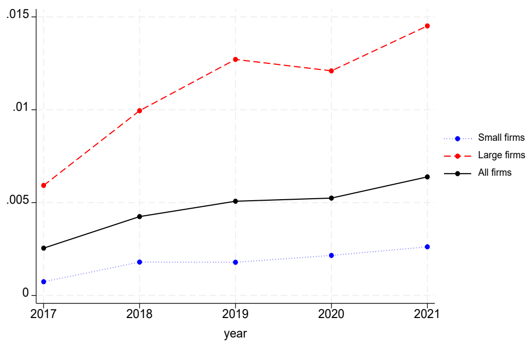


Notes: Panel (a) illustrates the shares of AI-adopting firms, categorized by small firms (dotted line), large firms (dashed line), and all firms (solid line). Small firms are defined as those with fewer than 200 employees, while large firms include those with 200 or more employees. Panel (b) presents the employment shares corresponding to these firms.

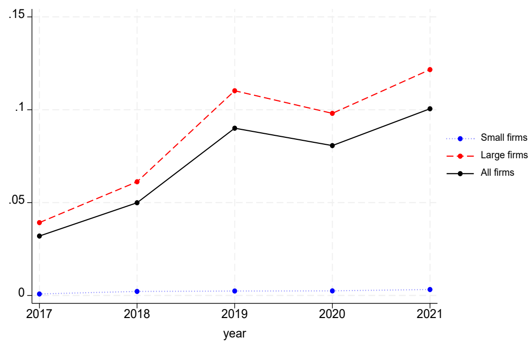
Sources: Authors' calculations

Figure 2.3: Both Robot and AI Adoption

(a) Firm Shares



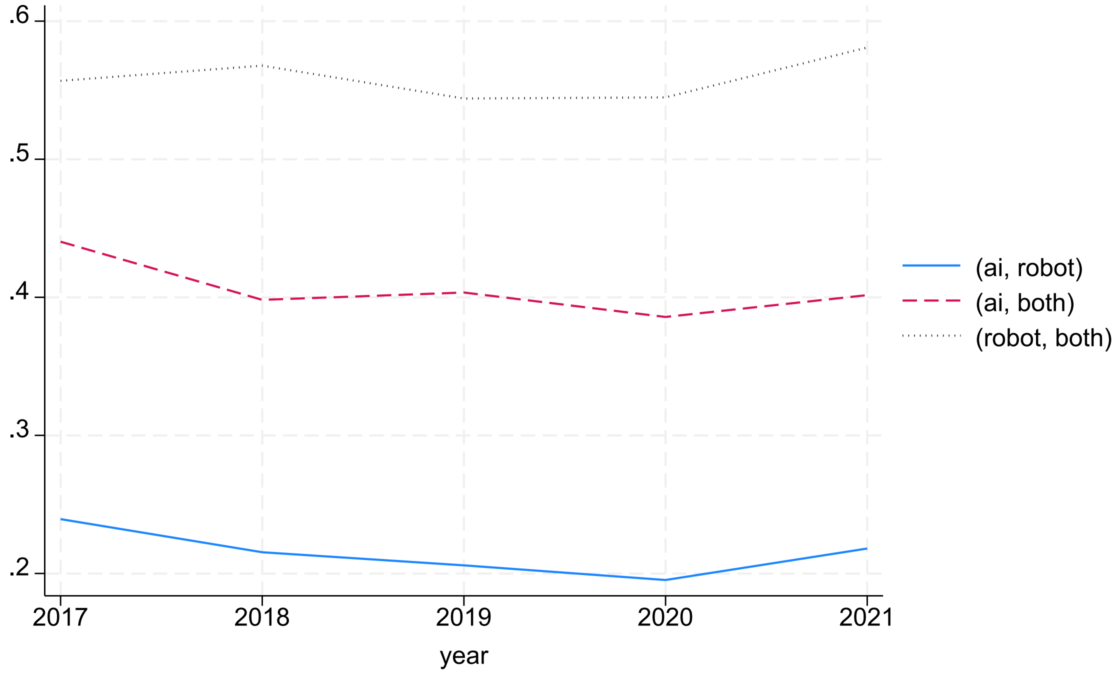
(b) Employment Shares



Notes: Panel (a) illustrates the shares of firms adopting both robots and AI, categorized by small firms (dotted line), large firms (dashed line), and all firms (solid line). Small firms are defined as those with fewer than 200 employees, while large firms include those with 200 or more employees. Panel (b) presents the employment shares corresponding to these firms.

Sources: Authors' calculations

Figure 3. Evolution of Correlation Coefficients among Robot-Adopting, AI-Adopting, and Both-Adopting Firms

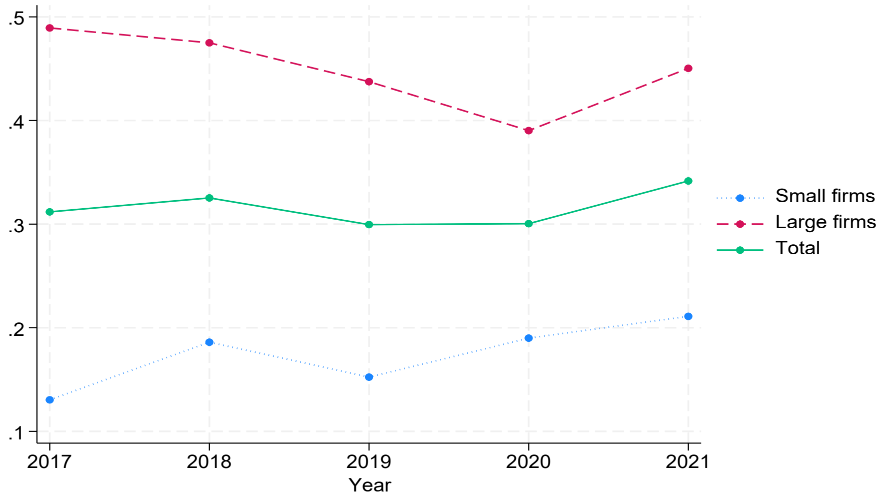


Notes: The solid line represents the correlation coefficient between robot and AI adoption across firms. The dashed line indicates the correlation between firms adopting both robots and AI and those adopting only robots, while the dotted line represents the correlation between firms adopting both technologies and those adopting only AI.

Sources: Authors' calculations

Figure 4: Proportion of Firms that Adopt Both Robots and AI

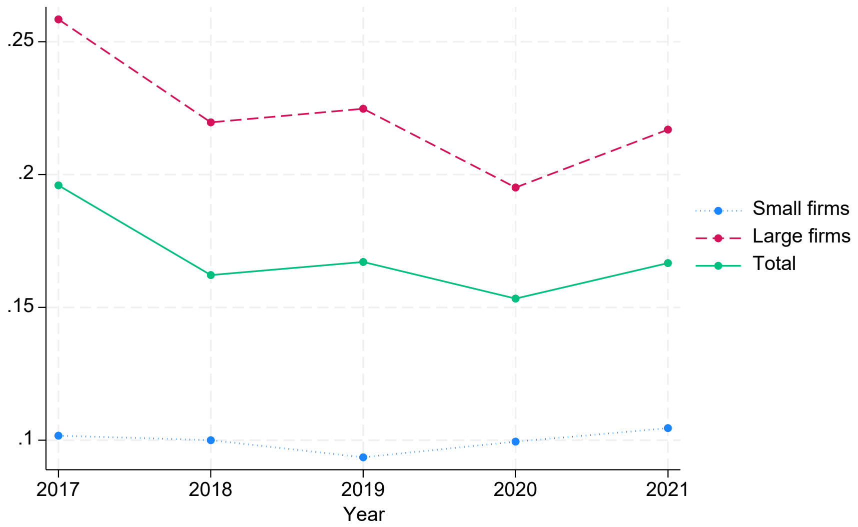
Figure 4.1: Robot-Adopting Firms



Notes: The shares of firms that adopted AI among those that had previously adopted robots are presented, with a breakdown for small firms (dotted line), large firms (dashed line), and all firms (solid line).

Sources: Authors' calculations

Figure 4.2: AI-Adopting Firms



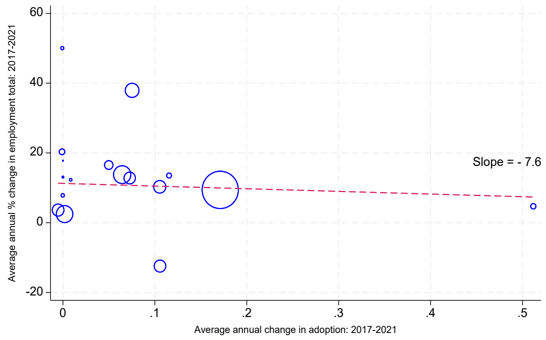
Notes: The shares of firms that adopted robots among those that had previously adopted AI are presented, with a breakdown for small firms (dotted line), large firms (dashed line), and all firms (solid line).

Sources: Authors' calculations

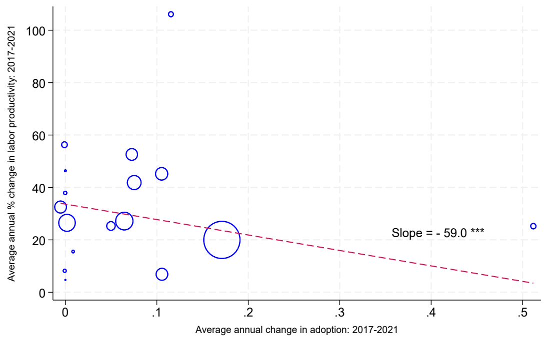
Figure 5: Changes in Employment and Labor Productivity Associated with the Adoption of Robots, AI, or Both at the Industry level

Figure 5.1: Robot Adoption

(a) Employment



(b) Labor Productivity

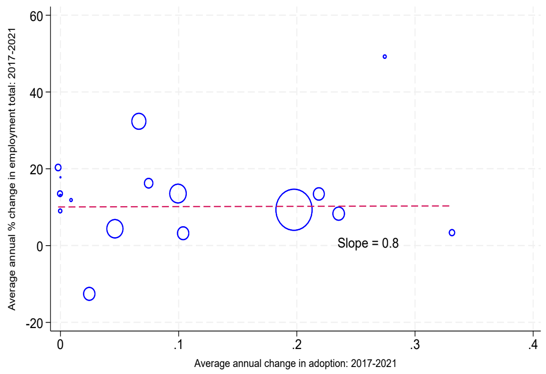


Notes: This figure presents changes in employment and labor productivity in relation to robot adoption at the industry level. In Panel A, the horizontal axis represents the change in the share of employment among firms that adopted robots within each industry from 2017 to 2021, while the vertical axis shows the change in total employment for the same industry. In Panel B, the vertical axis indicates the change in labor productivity at the industry level. The size of each circle represents the employment size of the corresponding industry. The fitted lines are derived from weighted OLS regressions, with the initial level of employment serving as the weight. *** denotes significance of the fitted line at the 1% level.

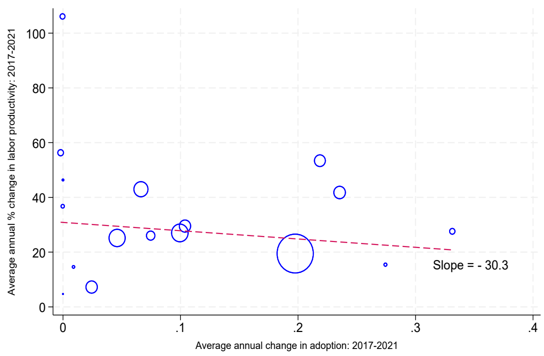
Sources: Authors' calculations.

Figure 5.2: AI Adoption

(a) Employment



(b) Labor Productivity

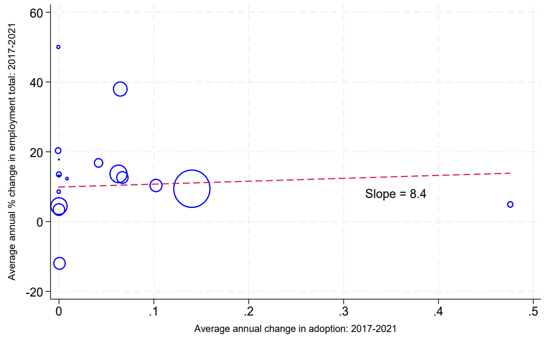


Notes: This figure presents changes in employment and labor productivity in relation to AI adoption at the industry level. In Panel A, the horizontal axis represents the change in the share of employment among firms that adopted AI within each industry from 2017 to 2021, while the vertical axis shows the change in total employment for the same industry. In Panel B, the vertical axis indicates the change in labor productivity at the industry level. The size of each circle represents the employment size of the corresponding industry. The fitted lines are derived from weighted OLS regressions, with the initial level of employment serving as the weight.

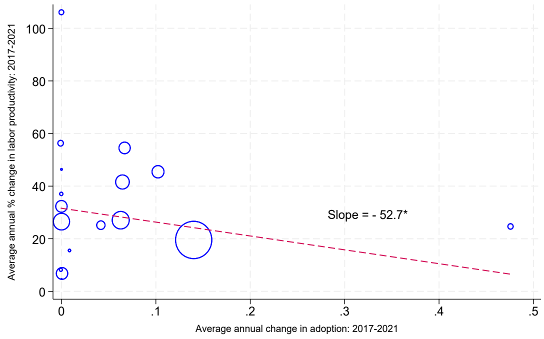
Sources: Authors' calculations.

Figure 5.3: Both Robot and AI Adoption

(a) Employment



(b) Labor Productivity



Notes: This figure presents changes in employment and labor productivity in relation to both robot and AI adoption at the industry level. In Panel A, the horizontal axis represents the change in the share of employment among firms that adopted both robots and AI within each industry from 2017 to 2021, while the vertical axis shows the change in total employment for the same industry. In Panel B, the vertical axis indicates the change in labor productivity at the industry level. The size of each circle represents the employment size of the corresponding industry. The fitted lines are derived from weighted OLS regressions, with the initial level of employment serving as the weight. * denotes significance of the fitted line at the 10% level.

Sources: Authors' calculations.

Table 1. Summary Statistics

	Robots	AI	Both	None	All
Permanent Employment	5.83	5.83	6.82	4.84	4.87
	(1.56)	(1.60)	(1.88)	(1.05)	(1.08)
Temporary Employment	3.54	3.42	4.51	2.63	2.67
	(2.06)	(2.02)	(2.12)	(1.81)	(1.82)
Total Employment	5.86	5.89	6.87	4.92	4.95
	(1.58)	(1.61)	(1.89)	(1.07)	(1.10)
Sales	7.28	7.13	8.60	5.95	5.98
	(2.08)	(2.28)	(2.47)	(1.45)	(1.49)
Labor Productivity	-0.05	-0.03	0.23	-0.26	-0.25
	(0.78)	(0.92)	(0.88)	(0.80)	(0.80)
Labor Share	0.72	0.73	0.66	0.77	0.77
	(0.60)	(0.63)	(0.54)	(0.59)	(0.59)
Parent Company	0.30	0.32	0.34	0.26	0.26
	(0.46)	(0.47)	(0.48)	(0.44)	(0.44)
Stock Listing	0.30	0.35	0.44	0.14	0.14
	(0.46)	(0.48)	(0.50)	(0.34)	(0.35)
Capital Intensity	0.12	-0.49	0.12	-0.51	-0.50
	(1.25)	(1.66)	(1.48)	(2.01)	(1.99)
R&D Intensity	-4.21	-4.01	-4.42	-4.43	-4.41
	(1.55)	(1.79)	(1.93)	(1.51)	(1.52)
Share of Manufacturing Workers	-0.67	-1.04	-1.00	-0.73	-0.73
	(0.89)	(1.18)	(1.17)	(0.89)	(0.90)
Exporter	0.87	0.73	0.87	0.80	0.80
	(0.33)	(0.44)	(0.34)	(0.40)	(0.40)
Importer	0.90	0.75	0.87	0.82	0.82
	(0.30)	(0.43)	(0.34)	(0.38)	(0.38)
Foreign owned	0.14	0.09	0.16	0.10	0.10
	(0.35)	(0.28)	(0.37)	(0.30)	(0.30)
Observations	945	1806	297	72221	74675

Notes: Permanent employment refers to individuals who have an employment contract with their employer for at least one year or who are employed as permanent staff without a fixed term. Temporary employment includes workers with contracts of less than one year and encompasses categories such as daily, part-time, and freelance workers. The classification of whether an employee is a manufacturing worker is applied only to permanent workers; thus, the share of manufacturing workers is calculated as the ratio of manufacturing workers to total permanent workers. Labor productivity is defined as value added per worker. Parent company refers to the case when there is a parent company that owns more than 50 percent of the total issued shares of the firm. If the parent company is from a foreign country, it is defined as foreign owned. Labor share is defined as the ratio of deflated labor costs to deflated value added. Capital intensity measures the sum of tangible and intangible assets divided by the total number of workers. Research and Development (R&D) intensity is defined by deflated R&D expenses that include all associated costs such as labor costs, raw materials, depreciation of tangible assets, utilities, and supplies, divided by deflated sales. Export and import dummies indicate whether the firm engages in export or import activities. Sales, labor productivity, capital intensity, R&D intensity, and the share of manufacturing workers are transformed using logarithms. Values in parentheses are standard deviations. "Robots" indicates firms that adopt robots, "AI" signifies firms that use artificial intelligence, "Both" refers to firms that utilize both technologies, "None" indicates firms that do not adopt any such technologies, and "All" encompasses all firms.

Sources: Authors’ calculations.

Table 2. Characteristics of Firms that Adopt Robots: OLS Estimation

Table 2.1 Robot Adoption

OLS	Robot adoption (0/1 indicator)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sales	0.004***	0.007***	0.004***	0.007***	0.005***	0.007***	0.005***	0.007***
	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Labor Productivity					-0.003**	-0.005	-0.002**	-0.005
					(0.001)	(0.003)	(0.001)	(0.005)
Capital Intensity	0.001	-0.005***		-0.005**	0.001***	-0.004***		-0.004***
	(0.000)	(0.001)		(0.001)	(0.001)	(0.001)		(0.001)
R&D Intensity	0.019***	0.021		0.021***	0.018***	0.021***		0.020***
	(0.004)	(0.006)		(0.007)	(0.004)	(0.006)		(0.007)
Share of Manufacturing employment		-0.010** (0.004)		-0.010** (0.004)		-0.010** (0.004)		-0.010** (0.005)
Average Wage		0.003		0.002		0.008		0.008
		(0.004)		(0.004)		(0.006)		(0.007)
Exporter			0.000	0.000			0.001	0.000
			(0.001)	(0.001)			(0.001)	(0.001)
Importer			0.001**	0.002			0.001	0.002
			(0.001)	(0.001)			(0.001)	(0.001)
Foreign Owned			-0.000	0.005			-0.000	0.005
			(0.001)	(0.004)			(0.002)	(0.004)

Observations	35826	14237	65852	13249	35826	14237	35626	14237
R-Squared	0.01	0.01	0.01	0.02	0.01	0.01	0.01	0.02

Notes: The dependent variable is an indicator for robot use by the firm during the sample period, 2017-2022. The independent variables are measured in the base year, 2016, which is one year prior to the commencement of the survey on AI and robot adoption. Definitions of the variables are detailed in the note to Table 1. Sales, labor productivity, capital intensity, R&D intensity, and the share of manufacturing workers are transformed using logarithms to normalize the data. We report the results of the OLS (Ordinary Least Squares) estimation. Column (1) represents the baseline specification. Column (2) incorporates all factor intensity variables, while Column (3) adds all globalization variables. Column (4) includes both factor intensity and globalization variables. Columns (5) through (8) replicate Columns (1) through (4) but also include labor productivity as a regressor. All estimations include an intercept and industry dummies, although their coefficients are not reported. Robust standard errors are indicated in parentheses, and asterisks $*$, $**$, $***$ denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Sources: Authors' calculations.

Table 2.2 AI Adoption

OLS	AI adoption (0/1 indicator)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sales	0.013***	0.013***	0.010***	0.015***	0.014***	0.015***	0.013***	0.015***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.002)
Labor Productivity					-0.005***	-0.017***	-0.007***	-0.018***
					(0.002)	(0.005)	(0.002)	(0.006)
Capital Intensity	-0.001	-0.001		-0.004***	-0.000	-0.001		-0.001
	(0.001)	(0.001)		(0.001)	(0.001)	(0.001)		(0.002)
R&D Intensity	0.221***	0.150***		0.163***	0.220***	0.146***		0.159***
	(0.031)	(0.036)		(0.040)	(0.031)	(0.036)		(0.040)
Share of Manufacturing employment		-0.015*** (0.004)		-0.015*** (0.005)		-0.016*** (0.004)		-0.016*** (0.005)
Average Wage		-0.007		-0.005		0.012		0.014**
		(0.005)		(0.006)		(0.008)		(0.009)
Exporter			-0.003	-0.004			-0.002	-0.004
			(0.002)	(0.003)			(0.002)	(0.003)
Importer			-0.004**	0.001			-0.005	0.000
			(0.002)	(0.003)			(0.002)	(0.003)
Foreign Owned			-0.009***	-0.008**			-0.010***	-0.007*
			(0.001)	(0.004)			(0.002)	(0.004)
Observations	35163	14178	64880	13195	35163	14178	34976	13195

R-Squared	0.03	0.03	0.02	0.04	0.02	0.04	0.02	0.04

Notes: The dependent variable is an indicator for AI use by the firm during the sample period, 2017-2022. The independent variables are measured in the base year, 2016, which is one year prior to the commencement of the survey on AI and robot adoption. Definitions of the variables are detailed in the note to Table 1. Sales, labor productivity, capital intensity, R&D intensity, and the share of manufacturing workers are transformed using logarithms to normalize the data. We report the results of the OLS (Ordinary Least Squares) estimation. Column (1) represents the baseline specification. Column (2) incorporates all factor intensity variables, while Column (3) adds all globalization variables. Column (4) includes both factor intensity and globalization variables. Columns (5) through (8) replicate Columns (1) through (4) but also include labor productivity as a regressor. All estimations include an intercept and industry dummies, although their coefficients are not reported. Robust standard errors are indicated in parentheses, and asterisks ∗, ∗∗, ∗∗∗ denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Sources: Authors' calculations.

Table 2.3. Both

OLS	Both adoption (0/1 indicator)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sales	0.003***	0.006***	0.003***	0.006***	0.004***	0.006***	0.004***	0.007***
	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)
Labor Productivity					-0.003***	-0.008*	-0.002*	-0.008*
					(0.001)	(0.004)	(0.001)	(0.004)
Capital Intensity	0.001**	-0.002***		-0.002***	0.002***	-0.001		-0.001
	(0.000)	(0.001)		(0.001)	(0.000)	(0.001)		(0.001)
R&D Intensity	0.010***	0.012***		0.014***	0.009***	0.011***		0.012***
	(0.002)	(0.004)		(0.004)	(0.002)	(0.004)		(0.004)
Share of Manufacturing employment		-0.005** (0.003)		-0.006** (0.003)		-0.006** (0.003)		-0.006** (0.003)
Average Wage		-0.001		0.001		0.009*		0.010*
		(0.002)		(0.003)		(0.006)		(0.006)
Exporter			-0.000	-0.001			-0.000	-0.001
			(0.000)	(0.001)			(0.000)	(0.001)
Importer			-0.000	-0.001			0.001	-0.001
			(0.000)	(0.001)			(0.000)	(0.001)
Foreign Owned			-0.001	0.000			-0.002	0.001
			(0.001)	(0.002)			(0.001)	(0.002)
Observations	36658	14683	67415	13671	36658	14683	36417	13671

R-Squared	0.01	0.02	0.01	0.03	0.01	0.02	0.01	0.03

Notes: The dependent variable is an indicator for robot and AI use by the firm during the sample period, 2017-2022. The independent variables are measured in the base year, 2016, which is one year prior to the commencement of the survey on AI and robot adoption. Definitions of the variables are detailed in the note to Table 1. Sales, labor productivity, capital intensity, R&D intensity, and the share of manufacturing workers are transformed using logarithms to normalize the data. We report the results of the OLS (Ordinary Least Squares) estimation. Column (1) represents the baseline specification. Column (2) incorporates all factor intensity variables, while Column (3) adds all globalization variables. Column (4) includes both factor intensity and globalization variables. Columns (5) through (8) replicate Columns (1) through (4) but also include labor productivity as a regressor. All estimations include an intercept and industry dummies, although their coefficients are not reported. Robust standard errors are indicated in parentheses, and asterisks $*$, $**$, $***$ denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Sources: Authors' calculations.

Table 3. Characteristics of Firms that Adopt Robots: Probit Estimation

Table 3.1 Robot Adoption

Probit	Robot adoption (0/1 indicator)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sales	0.24***	0.26***	0.21***	0.25***	0.25***	0.26***	0.26***	0.26***
	(0.02)	(0.03)	(0.01)	(0.03)	(0.02)	(0.03)	(0.02)	(0.03)
Labor Productivity					-0.11	0.02	-0.15**	0.00
					(0.08)	(0.15)	(0.07)	(0.15)
Capital Intensity	-0.05	-0.38***		-0.38***	0.03	-0.38***		-0.38***
	(0.04)	(0.07)		(0.07)	(0.04)	(0.08)		(0.08)
R&D Intensity	1.07***	0.81***		0.78***	1.03***	0.82***		0.78***
	(0.20)	(0.27)		(0.29)	(0.20)	(0.27)		(0.29)
Share of Manufacturing employment		-0.45** (0.20)		-0.46** (0.20)		-0.45** (0.20)		-0.46** (0.21)
Average Wage		0.23*		0.26		0.21		0.25
		(0.13)		(0.16)		(0.19)		(0.21)
Exporter			-0.02	0.07			0.03	0.07
			(0.07)	(0.14)			(0.10)	(0.14)
Importer			0.19**	0.49**			0.17	0.49***
			(0.08)	(0.19)			(0.12)	(0.19)
Foreign Owned			0.02	0.13			0.02	0.13
			(0.06)	(0.10)			(0.09)	(0.10)

Observations	35826	14237	65852	13249	35826	14237	35626	13249
Pseudo R-Squared	0.13	0.13	0.09	0.14	0.13	0.13	0.14	0.14

Notes: The dependent variable is an indicator for robot use by the firm during the sample period, 2017-2022. The independent variables are measured in the base year, 2016, which is one year prior to the commencement of the survey on AI and robot adoption. Definitions of the variables are detailed in the note to Table 1. Sales, labor productivity, capital intensity, R&D intensity, and the share of manufacturing workers are transformed using logarithms to normalize the data. We report the results of the probit estimation. Column (1) represents the baseline specification. Column (2) incorporates all factor intensity variables, while Column (3) adds all globalization variables. Column (4) includes both factor intensity and globalization variables. Columns (5) through (8) replicate Columns (1) through (4) but also include labor productivity as a regressor. All estimations include an intercept and industry dummies, although their coefficients are not reported. Robust standard errors are indicated in parentheses, and asterisks $*$, $**$, $***$ denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Sources: Authors' calculations.

Table 3.2 AI Adoption

Probit	AI adoption (0/1 indicator)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sales	0.26***	0.30***	0.21***	0.31***	0.27***	0.31***	0.26***	0.32***
	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)
Labor Productivity					-0.11***	-0.30**	-0.16***	-0.29**
					(0.04)	(0.12)	(0.04)	(0.12)
Capital Intensity	-0.07***	-0.13***		-0.15**	-0.05**	-0.08**		-0.10**
	(0.02)	(0.04)		(0.04)	(0.02)	(0.04)		(0.04)
R&D Intensity	2.64***	2.23***		2.28***	2.63***	2.18***		2.24***
	(0.26)	(0.33)		(0.36)	(0.26)	(0.33)		(0.36)
Share of Manufacturing employment		-0.63*** (0.17)		-0.60*** (0.17)		-0.65*** (0.17)		-0.62*** (0.17)
Average Wage		-0.20		-0.16		0.15		0.17
		(0.15)		(0.16)		(0.21)		(0.22)
Exporter			-0.09*	-0.15			-0.08	-0.15
			(0.05)	(0.11)			(0.07)	(0.11)
Importer			-0.08	0.18			0.04	0.17
			(0.05)	(0.14)			(0.07)	(0.13)
Foreign Owned			-0.25***	-0.11			-0.23***	-0.09
			(0.05)	(0.11)			(0.07)	(0.11)
Observations	35163	14178	64880	13195	35163	14178	34976	13195

Pseudo R-Squared	0.13	0.18	0.09	0.18	0.14	0.18	0.11	0.19

Notes: The dependent variable is an indicator for AI use by the firm during the sample period, 2017-2022. The independent variables are measured in the base year, 2016, which is one year prior to the commencement of the survey on AI and robot adoption. Definitions of the variables are detailed in the note to Table 1. Sales, labor productivity, capital intensity, R&D intensity, and the share of manufacturing workers are transformed using logarithms to normalize the data. We report the results of the probit estimation. Column (1) represents the baseline specification. Column (2) incorporates all factor intensity variables, while Column (3) adds all globalization variables. Column (4) includes both factor intensity and globalization variables. Columns (5) through (8) replicate Columns (1) through (4) but also include labor productivity as a regressor. All estimations include an intercept and industry dummies, although their coefficients are not reported. Robust standard errors are indicated in parentheses, and asterisks $*$, $**$, $***$ denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Sources: Authors' calculations.

Table 3.3 Both

Probit	Both adoption (0/1 indicator)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sales	0.35***	0.55***	0.31***	0.56***	0.37***	0.55***	0.39***	0.56***
	(0.03)	(0.07)	(0.02)	(0.08)	(0.03)	(0.02)	(0.01)	(0.02)
Labor Productivity					-0.28**	-0.09	-0.22**	-0.09
					(0.11)	(0.23)	(0.09)	(0.23)
Capital Intensity	0.01	-0.60***		-0.58***	0.08	-0.57***		-0.54***
	(0.06)	(0.14)		(0.14)	(0.07)	(0.16)		(0.16)
R&D Intensity	0.25	-4.27		-4.14	-0.25	-4.51		-4.39
	(1.05)	(5.26)		(5.34)	(1.32)	(5.15)		(5.24)
Share of Manufacturing employment		-0.86** (0.44)		-0.88* (0.45)		-0.86* (0.44)		-0.88* (0.46)
Average Wage		0.26		0.30		0.35		0.40
		(0.20)		(0.27)		(0.31)		(0.36)
Exporter			-0.11	-0.34			-0.22	-0.34
			(0.11)	(0.25)			(0.14)	(0.24)
Importer			0.05	0.53*			0.36*	0.52*
			(0.13)	(0.29)			(0.19)	(0.28)
Foreign Owned			-0.03	0.11			-0.12	0.12
			(0.09)	(0.16)			(0.13)	(0.17)
Observations	36658	14683	67415	13671	36658	14683	36417	13671

Pseudo R-Squared	0.27	0.41	0.21	0.41	0.27	0.41	0.28	0.42

Notes: The dependent variable is an indicator for robot and AI use by the firm during the sample period, 2017-2022. The independent variables are measured in the base year, 2016, which is one year prior to the commencement of the survey on AI and robot adoption. Definitions of the variables are detailed in the note to Table 1. Sales, labor productivity, capital intensity, R&D intensity, and the share of manufacturing workers are transformed using logarithms to normalize the data. We report the results of the probit estimation. Column (1) represents the baseline specification. Column (2) incorporates all factor intensity variables, while Column (3) adds all globalization variables. Column (4) includes both factor intensity and globalization variables. Columns (5) through (8) replicate Columns (1) through (4) but also include labor productivity as a regressor. All estimations include an intercept and industry dummies, although their coefficients are not reported. Robust standard errors are indicated in parentheses, and asterisks $*$, $**$, $***$ denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Sources: Authors' calculations.

Table 4. The Impact of Robot Adoption: DID Analyses

Table 4.1. The Impact of Robot Adoption on Permanent Employment

Dependent Variable: Permanent Employment						
	ATT	Treatment year	Control year	Measurement year	Observations	Parallel Trend Assumption Test
T						
	0.06 (0.06)	2017	2016	2017	22,588	0.000
	-0.01 (0.04)	2018	2017	2018	23,162	0.000
	-0.01 (0.10)	2019	2018	2019	24,555	0.000
	-0.01 (0.09)	2020	2019	2020	24,607	0.000
	0.03 (0.04)	2021	2020	2021	24,776	0.000
T+1						
	0.13 (0.08)	2017	2016	2018	23,886	0.000
	0.01 (0.07)	2018	2017	2019	23,249	0.000
	0.03 (0.06)	2019	2018	2020	24,524	0.000
	-0.08 (0.06)	2020	2019	2021	24,673	0.000
T+2						
	0.12 (0.10)	2017	2016	2019	23,972	0.000
	-0.01 (0.08)	2018	2017	2020	23,219	0.000
	0.07 (0.08)	2019	2018	2021	24,587	0.000
T+3						
	0.12 (0.13)	2017	2016	2020	23,941	0.000
	0.06 (0.11)	2018	2017	2021	23,283	0.000

T+4						
	0.10 (0.17)	2017	2016	2021	24,166	0.000

Notes: The dependent variable is the logarithm of permanent employment. The "treatment year" corresponds to the year in which the firm adopts robots, while "Period 1" serves as the control year, and "Period 2" as the measurement year. Consequently, T, T+1, T+2, T+3, and T+4 represent the years in which the effects are observed: the same year as the adoption, one year after, two years after, three years after, and four years after, respectively. All estimations include an intercept and industry dummies, although their coefficients are not reported. The last column tests the null hypothesis that trend coefficients are identical between groups, thus assessing the parallel trend assumption prior to treatment. Robust standard errors are shown in parentheses. Significance levels are denoted with asterisks: * for 10%, ** for 5%, and *** for 1%.

Sources: Authors' calculations.

Table 4.2. The Impact of Robot Adoption on Temporary Employment

Dependent Variable: Temporary Employment						
	ATT	Treatment year	Control year	Measurement year	Observations	Parallel trend Assumption test
T						
	-0.24 (0.53)	2017	2016	2017	6,060	0.089
	0.08 (0.23)	2018	2017	2018	6,122	0.003
	0.24 (0.55)	2019	2018	2019	6,460	0.218
	-0.67 (0.72)	2020	2019	2020	6,567	0.194
	0.34 (0.54)	2021	2020	2021	7,050	0.047
T+1						
	-0.57 (1.06)	2017	2016	2018	6,549	0.089
	0.40 (0.57)	2018	2017	2019	5,971	0.003
	0.47 (0.87)	2019	2018	2020	6,739	0.218
	0.25 (0.62)	2020	2019	2021	6,733	0.194
T+2						
	-1.68 (1.91)	2017	2016	2019	6,391	0.089
	-0.01 (0.98)	2018	2017	2020	6,243	0.003
	0.51 (0.87)	2019	2018	2021	6,902	0.218
T+3						
	-0.51 (0.52)	2017	2016	2020	6,667	0.089
	0.31 (0.83)	2018	2017	2021	6,409	0.003
T+4						

-0.83*** (0.11)	2017	2016	2021	6,830	0.089

Notes: The dependent variable is the logarithm of temporary employment. The "treatment year" corresponds to the year in which the firm adopts robots, while "Period 1" serves as the control year, and "Period 2" as the measurement year. Consequently, T, T+1, T+2, T+3, and T+4 represent the years in which the effects are observed: the same year as the adoption, one year after, two years after, three years after, and four years after, respectively. All estimations include an intercept and industry dummies, although their coefficients are not reported. The last column tests the null hypothesis that trend coefficients are identical between groups, thus assessing the parallel trend assumption prior to treatment. Robust standard errors are shown in parentheses. Significance levels are denoted with asterisks: * for 10%, ** for 5%, and *** for 1%.

Sources: Authors' calculations.

Table 4.3. The Impact of Robot Adoption on Labor Productivity

Dependent Variable: Labor Productivity						
	ATT	Treatment year	Control year	Measurement year	Observations	Parallel Trend Assumption Test
T						
	0.11 (0.17)	2017	2016	2017	15,640	0.335
	-0.04 (0.06)	2018	2017	2018	22,553	0.003
	-0.13 (0.10)	2019	2018	2019	24,555	0.000
	-0.06 (0.13)	2020	2019	2020	24,606	0.000
	-0.07 (0.08)	2021	2020	2021	24,775	0.000
T+1						
	0.44 (0.40)	2017	2016	2018	17,548	0.335
	-0.15 (0.11)	2018	2017	2019	22,640	0.003
	-0.06 (0.13)	2019	2018	2020	24,523	0.000
	-0.11 (0.13)	2020	2019	2021	24,673	0.000
T+2						
	0.34** (0.18)	2017	2016	2019	17,634	0.335
	-0.12 (0.12)	2018	2017	2020	22,609	0.003
	-0.03 (0.11)	2019	2018	2021	24,587	0.000
T+3						
	0.19 (0.36)	2017	2016	2020	17,602	0.335
	-0.19 (0.17)	2018	2017	2021	22,674	0.003
T+4						

0.33 (0.24)	2017	2016	2021	17,668	0.335

Notes: The dependent variable is the logarithm of labor productivity. The "treatment year" corresponds to the year in which the firm adopts robots, while "Period 1" serves as the control year, and "Period 2" as the measurement year. Consequently, T, T+1, T+2, T+3, and T+4 represent the years in which the effects are observed: the same year as the adoption, one year after, two years after, three years after, and four years after, respectively. All estimations include an intercept and industry dummies, although their coefficients are not reported. The last column tests the null hypothesis that trend coefficients are identical between groups, thus assessing the parallel trend assumption prior to treatment. Robust standard errors are shown in parentheses. Significance levels are denoted with asterisks: * for 10%, ** for 5%, and *** for 1%.

Sources: Authors' calculations.

Table 5. The Impact of AI Adoption: DID Analyses

Table 5.1. The Impact of AI Adoption on Permanent Employment

Dependent Variable: Permanent Employment						
	ATT	Treatment year	Control year	Measurement year	Observations	Parallel Trend Assumption Test
T						
	0.06 (0.04)	2017	2016	2017	22,129	0.000
	0.00 (0.02)	2018	2017	2018	22,664	0.000
	0.05 (0.03)	2019	2018	2019	23,960	0.000
	0.07 (0.06)	2020	2019	2020	24,020	0.000
	0.07 (0.05)	2021	2020	2021	24,212	0.000
T+1						
	0.07 (0.06)	2017	2016	2018	23,347	0.000
	0.01 (0.05)	2018	2017	2019	22,748	0.000
	0.07 (0.07)	2019	2018	2020	23,913	0.000
	0.08 (0.06)	2020	2019	2021	24,075	0.000
T+2						
	0.13 (0.10)	2017	2016	2019	23,430	0.000
	-0.02 (0.06)	2018	2017	2020	22,699	0.000
	0.08 (0.08)	2019	2018	2021	23,968	0.000
T+3						
	0.02 (0.17)	2017	2016	2020	23,384	0.000

	0.03 (0.07)	2018	2017	2021	22,755	0.000
T+4						
	0.02 (0.18)	2017	2016	2021	23,638	0.000

Notes: The dependent variable is the logarithm of permanent employment. The "treatment year" corresponds to the year in which the firm adopts AI, while "Period 1" serves as the control year, and "Period 2" as the measurement year. Consequently, T, T+1, T+2, T+3, and T+4 represent the years in which the effects are observed: the same year as the adoption, one year after, two years after, three years after, and four years after, respectively. All estimations include an intercept and industry dummies, although their coefficients are not reported. The last column tests the null hypothesis that trend coefficients are identical between groups, thus assessing the parallel trend assumption prior to treatment. Robust standard errors are shown in parentheses. Significance levels are denoted with asterisks: * for 10%, ** for 5%, and *** for 1%.

Sources: Authors' calculations.

Table 5.2. The Impact of AI Adoption on Temporary Employment

Dependent Variable: Temporary Employment						
	ATT	Treatment year	Control year	Measurement year	Observations	Parallel Trend Assumption Test
T						
	-0.17 (0.48)	2017	2016	2017	5,848	0.045
	0.52 (0.38)	2018	2017	2018	5,848	0.032
	0.16 (0.30)	2019	2018	2019	6,149	0.000
	0.33 (0.63)	2020	2019	2020	6,258	0.161
	0.18 (0.31)	2021	2020	2021	6,720	0.007
T+1						
	-0.51 (0.67)	2017	2016	2018	6,280	0.045
	0.57 (0.45)	2018	2017	2019	5,716	0.032
	0.09 (0.28)	2019	2018	2020	6,406	0.000
	0.33 (0.55)	2020	2019	2021	6,399	0.161
T+2						
	-0.17 (0.76)	2017	2016	2019	6,147	0.045
	0.50 (0.65)	2018	2017	2020	5,966	0.032
	-0.21 (0.42)	2019	2018	2021	6,534	0.000
T+3						
	-0.01 (0.78)	2017	2016	2020	6,396	0.045
	0.38 (0.80)	2018	2017	2021	6,098	0.032
T+4						

0.61 (0.98)	2017	2016	2021	6,520	0.045

Notes: The dependent variable is the logarithm of temporary employment. The "treatment year" corresponds to the year in which the firm adopts AI, while "Period 1" serves as the control year, and "Period 2" as the measurement year. Consequently, T, T+1, T+2, T+3, and T+4 represent the years in which the effects are observed: the same year as the adoption, one year after, two years after, three years after, and four years after, respectively. All estimations include an intercept and industry dummies, although their coefficients are not reported. The last column tests the null hypothesis that trend coefficients are identical between groups, thus assessing the parallel trend assumption prior to treatment. Robust standard errors are shown in parentheses. Significance levels are denoted with asterisks: * for 10%, ** for 5%, and *** for 1%.

Sources: Authors' calculations.

Table 5.3. The Impact of AI Adoption on Labor Productivity

Dependent Variable: Labor Productivity						
	ATT	Treatment year	Control year	Measurement year	Observations	Parallel Trend Assumption Test
T						
	-0.01 (0.16)	2017	2016	2017	15,296	0.012
	-0.02 (0.05)	2018	2017	2018	22,069	0.000
	0.02 (0.06)	2019	2018	2019	23,960	0.000
	0.02 (0.10)	2020	2019	2020	24,020	0.000
	-0.01 (0.06)	2021	2020	2021	24,212	0.000
T+1						
	0.14 (0.21)	2017	2016	2018	17,110	0.012
	-0.05 (0.07)	2018	2017	2019	22,153	0.000
	0.01 (0.11)	2019	2018	2020	23,913	0.000
	0.01 (0.10)	2020	2019	2021	24,075	0.000
T+2						
	0.07 (0.27)	2017	2016	2019	17,193	0.012
	0.01 (0.08)	2018	2017	2020	22,104	0.000
	0.13 (0.12)	2019	2018	2021	23,968	0.000
T+3						
	0.13 (0.29)	2017	2016	2020	17,147	0.012
	0.00 (0.10)	2018	2017	2021	22,160	0.000
T+4						

0.15 (0.35)	2017	2016	2021	17,203	0.012

Notes: The dependent variable is the logarithm of labor productivity. The "treatment year" corresponds to the year in which the firm adopts AI, while "Period 1" serves as the control year, and "Period 2" as the measurement year. Consequently, T, T+1, T+2, T+3, and T+4 represent the years in which the effects are observed: the same year as the adoption, one year after, two years after, three years after, and four years after, respectively. All estimations include an intercept and industry dummies, although their coefficients are not reported. The last column tests the null hypothesis that trend coefficients are identical between groups, thus assessing the parallel trend assumption prior to treatment. Significance levels are denoted with asterisks: * for 10%, ** for 5%, and *** for 1%.

Sources: Authors' calculations.

Table 6. The Impact of Robot & AI Adoption: DID Analyses

Table 6.1. The Impact of Robot & AI Adoption on Permanent Employment

Dependent Variable: Permanent Employment						
	ATT	Treatment year	Control year	Measurement year	Observations	Parallel Trend Assumption Test
T						
	0.103 (0.088)	2017	2016	2017	23,236	0.000
	-0.036 (0.066)	2018	2017	2018	23,808	0.000
	0.081 (0.061)	2019	2018	2019	25,220	0.000
	-0.033 (0.088)	2020	2019	2020	25,285	0.000
	0.076 (0.072)	2021	2020	2021	25,373	0.000
T+1						
	0.156 (0.125)	2017	2016	2018	24,550	0.000
	-0.019 (0.106)	2018	2017	2019	23,904	0.000
	-0.028 (0.106)	2019	2018	2020	25,190	0.000
	-0.020 (0.114)	2020	2019	2021	25,348	0.000
T+2						
	0.200 (0.192)	2017	2016	2019	24,645	0.000
	-0.075 (0.102)	2018	2017	2020	23,874	0.000
	0.021 (0.169)	2019	2018	2021	25,252	0.000
T+3						
	0.156 (0.227)	2017	2016	2020	24,615	0.000

	0.078 (0.182)	2018	2017	2021	23,936	0.000
T+4						
	0.149 (0.401)	2017	2016	2021	23,638	0.000

Notes: The dependent variable is the logarithm of permanent employment. The "treatment year" corresponds to the year in which the firm adopts both robots and AI, while "Period 1" serves as the control year, and "Period 2" as the measurement year. Consequently, T, T+1, T+2, T+3, and T+4 represent the years in which the effects are observed: the same year as the adoption, one year after, two years after, three years after, and four years after, respectively. All estimations include an intercept and industry dummies, although their coefficients are not reported. The last column tests the null hypothesis that trend coefficients are identical between groups, thus assessing the parallel trend assumption prior to treatment. Robust standard errors are shown in parentheses. Significance levels are denoted with asterisks: * for 10%, ** for 5%, and *** for 1%.

Sources: Authors' calculations.

Table 6.2. The Impact of Robot & AI Adoption on Temporary Employment

Dependent Variable: Temporary Employment						
	ATT	Treatment year	Control year	Measurement year	Observations	Parallel Trend Assumption Test
T						
	-0.386 (0.719)	2017	2016	2017	6,225	0.430
	0.138 (0.375)	2018	2017	2018	6,277	0.000
	0.667 (0.798)	2019	2018	2019	6,608	0.000
	0.001 (0.692)	2020	2019	2020	6,734	0.907
	0.288 (0.533)	2021	2020	2021	7,236	0.013
T+1						
	-0.925 (1.347)	2017	2016	2018	6,718	0.430
	0.488 (0.711)	2018	2017	2019	6,114	0.000
	0.311 (0.943)	2019	2018	2020	6,908	0.000
	0.156 (0.176)	2020	2019	2021	6,910	0.907
T+2						
	-1.680 (1.915)	2017	2016	2019	6,553	0.430
	0.453 (0.817)	2018	2017	2020	6,413	0.000
	0.628 (0.835)	2019	2018	2021	7,080	0.000
T+3						
	-0.682 (0.634)	2017	2016	2020	6,851	0.430
	-0.022 (0.539)	2018	2017	2021	6,583	0.000
T+4						

-0.859*** (0.099)	2017	2016	2021	7,023	0.430

Notes: The dependent variable is the logarithm of temporary employment. The "treatment year" corresponds to the year in which the firm adopts both robots and AI, while "Period 1" serves as the control year, and "Period 2" as the measurement year. Consequently, T, T+1, T+2, T+3, and T+4 represent the years in which the effects are observed: the same year as the adoption, one year after, two years after, three years after, and four years after, respectively. All estimations include an intercept and industry dummies, although their coefficients are not reported. The last column tests the null hypothesis that trend coefficients are identical between groups, thus assessing the parallel trend assumption prior to treatment. Robust standard errors are shown in parentheses. Significance levels are denoted with asterisks: * for 10%, ** for 5%, and *** for 1%.

Sources: Authors' calculations.

Table 6.3. The Impact of Robot & AI Adoption on Labor Productivity

Dependent Variable: Labor Productivity						
	ATT	Treatment year	Control year	Measurement year	Observations	Parallel Trend Assumption Test
T						
	0.216*** (0.071)	2017	2016	2017	16,102	0.527
	-0.017 (0.107)	2018	2017	2018	23,193	0.000
	-0.188 (0.117)	2019	2018	2019	25,220	0.000
	0.028 (0.103)	2020	2019	2020	25,284	0.000
	-0.057 (0.135)	2021	2020	2021	25,372	0.000
T+1						
	0.677*** (0.155)	2017	2016	2018	18,031	0.527
	-0.112 (0.138)	2018	2017	2019	23,289	0.000
	-0.303 (0.232)	2019	2018	2020	25,189	0.000
	-0.030 (0.144)	2020	2019	2021	25,348	0.000
T+2						
	0.388 (0.241)	2017	2016	2019	18,126	0.527
	-0.196 (0.177)	2018	2017	2020	23,258	0.000
	-0.244 (0.166)	2019	2018	2021	25,252	0.000
T+3						
	0.199 (0.535)	2017	2016	2020	18,095	0.527
	-0.172 (0.269)	2018	2017	2021	23,321	0.000
T+4						

0.388 (0.333)	2017	2016	2021	18,159	0.527

Notes: The dependent variable is the logarithm of labor productivity. The "treatment year" corresponds to the year in which the firm adopts both robots and AI, while "Period 1" serves as the control year, and "Period 2" as the measurement year. Consequently, T, T+1, T+2, T+3, and T+4 represent the years in which the effects are observed: the same year as the adoption, one year after, two years after, three years after, and four years after, respectively. All estimations include an intercept and industry dummies, although their coefficients are not reported. The last column tests the null hypothesis that trend coefficients are identical between groups, thus assessing the parallel trend assumption prior to treatment. Robust standard errors are shown in parentheses. Significance levels are denoted with asterisks: * for 10%, ** for 5%, and *** for 1%.

Sources: Authors' calculations.

Table 7. The Impact of Robot Adoption: Propensity Score Matching

Table 7.1. The Impact of Robot Adoption on Permanent Employment

Dependent Variable: Permanent Employment					
Robot	(1) Initial Year 2017	(2) Initial Year 2018	(3) Initial Year 2019	(4) Initial Year 2020	(5) Initial Year 2021
T	-0.04	0.01	0.04	-0.07	0.03
	(0.04)	(0.04)	(0.03)	(0.07)	(0.03)
Observations	5064	9889	11399	11371	11721
SMD Before	0.425	0.532	0.515	0.477	0.345
SMD After	0.042	0.107	0.147	0.119	0.109
T+1	-0.11	0.12*	-0.02	-0.05	
	(0.07)	(0.07)	(0.05)	(0.05)	
Observations	4857	9479	10577	10826	
SMD Before	0.419	0.526	0.501	0.469	
SMD After	0.210	0.176	0.106	0.126	
T+2	0.09	0.15	0.00		
	(0.21)	(0.11)	(0.13)		
Observations	4653	8843	10106		
SMD Before	0.419	0.517	0.495		
SMD After	0.336	0.160	0.110		
T+3	1.37*	0.13			
	(0.83)	(0.09)			
Observations	4349	8470			
SMD Before	0.416	0.513			
SMD After	0.111	0.084			
T+4	0.13				
	(0.34)				
Observations	4178				
SMD Before	0.415				
SMD After	0.164				

Notes: We report the impact of robot adoption on permanent employment for the year 2017 under Initial Year 2017, marking the year a firm first employed robots. A counterfactual group was constructed using a logit regression model to estimate the likelihood of adopting robots in 2016. This model incorporated key regressors, including total employment (both permanent and temporary workers), labor productivity, a parent company dummy, and industry dummies. We then analyzed changes in employment for these matched pairs by comparing employment differences from 2016 to 2017 (T). For subsequent analyses, such as the impact in 2018 (T+1), we retained the same matched groups and calculated the treatment effect based on differences in employment from 2016 to 2018, and so forth. To ensure the analysis accounted for variances in the impact of robot adoption from one year to the next, we repeated the procedure for firms adopting robots in 2018 under Initial Year 2018, and similarly for subsequent years. To assess the balance of covariates after propensity score matching, we report the average Standardized Mean Difference (SMD) both before and after matching. Significance levels are indicated by asterisks: * for 10%, ** for 5%, and *** for 1%.

Sources: Authors' calculations.

Table 7.2. The Impact of Robot Adoption on Temporary Employment

Dependent Variable: Temporary Employment				
Robot	(1) Initial Year 2018	(2) Initial Year 2019	(3) Initial Year 2020	(4) Initial Year 2021
T	0.01	0.10**	1.45	0.08
	(0.15)	(0.05)	(1.28)	(0.39)
Observations	1952	1764	1793	2064
SMD Before	0.785	0.700	0.430	0.610
SMD After	0.211	0.046	0.688	0.150
T+1	-0.47	-0.38	-0.05	
	(0.53)	(0.31)	(0.29)	
Observations	1472	1436	1667	
SMD Before	0.931	0.763	1.042	
SMD After	0.261	0.191	0.541	
T+2	0.28	0.20		
	(0.49)	(0.37)		
Observations	1233	1432		
SMD Before	1.058	0.667		
SMD After	0.159	0.243		
T+3	-0.083			
	(0.96)			
Observations	1217			
SMD Before	0.695			
SMD After	0.394			

Notes: We report the impact of robot adoption on temporary employment for the year 2018 under Initial Year 2018, marking the year a firm first employed robots. We do not report the results for Initial Year 2017 since the matching was not satisfactory for the firms that first employed robots in 2017. A counterfactual group was constructed using a logit regression model to estimate the likelihood of adopting robots in 2017. This model incorporated key regressors, including total employment (both permanent and temporary workers), labor productivity, a parent company dummy, and industry dummies. We then analyzed changes in employment for these matched pairs by comparing employment differences from 2017 to 2018 (T). For subsequent analyses, such as the impact in 2019 (T+1), we retained the same matched groups and calculated the treatment effect based on differences in employment from 2017 to 2019, and so forth. To ensure the analysis accounted for variances in the impact of robot adoption from one year to the next, we repeated the procedure for firms adopting robots in 2019 under Initial Year 2019, and similarly for subsequent years. To assess the balance of covariates after propensity score matching, we report the average Standardized Mean Difference (SMD) both before and after matching. Significance levels are indicated by asterisks: * for 10%, ** for 5%, and *** for 1%.

Sources: Authors' calculations.

Table 7.3. The Impact of Robot Adoption on Labor Productivity

Dependent Variable: Labor Productivity					
Robot	(1) Initial Year 2017	(2) Initial Year 2018	(3) Initial Year 2019	(4) Initial Year 2020	(5) Initial Year 2021
T	0.04	-0.12	-0.02	-0.06	-0.12*
	(0.12)	(0.09)	(0.09)	(0.13)	(0.07)
Observations	4471	9737	11267	11181	11565
SMD Before	0.465	0.569	0.512	0.473	0.034
SMD After	0.493	0.088	0.131	0.165	0.036
T+1	0.46**	-0.25**	-0.04	0.14	
	(0.22)	(0.11)	(0.12)	(0.09)	
Observations	4780	9331	10380	10653	
SMD Before	0.418	0.562	0.498	0.464	
SMD After	0.047	0.201	0.119	0.091	
T+2	-0.05	0.00	-0.09		
	(0.08)	(0.15)	(0.13)		
Observations	4591	8665	9929		
SMD Before	0.580	0.514	0.475		
SMD After	0.331	0.161	0.177		
T+3	-0.12	0.09			
	(0.29)	(0.11)			
Observations	4267	8324			
SMD Before	0.576	0.481			
SMD After	0.252	0.155			
T+4	-0.37				
	(0.67)				
Observations	4101				
SMD Before	0.417				
SMD After	0.423				

Notes: We report the impact of robot adoption on labor productivity for the year 2017 under Initial Year 2017, marking the year a firm first employed robots. A counterfactual group was constructed using a logit regression model to estimate the likelihood of adopting robots in 2016. This model incorporated key regressors, including total employment (both permanent and temporary workers), labor productivity, a parent company dummy, and industry dummies. We then analyzed changes in employment for these matched pairs by comparing employment differences from 2016 to 2017 (T). For subsequent analyses, such as the impact in 2018 (T+1), we retained the same matched groups and calculated the treatment effect based on differences in employment from 2016 to 2018, and so forth. To ensure the analysis accounted for variances in the impact of robot adoption from one year to the next, we repeated the procedure for firms adopting robots in 2018 under Initial Year 2018, and similarly for subsequent years. To assess the balance of covariates after propensity score matching, we report the average Standardized Mean Difference (SMD) both before and after matching. Significance levels are indicated by asterisks: * for 10%, ** for 5%, and *** for 1%.

Sources: Authors' calculations.

Table 7.4. The Impact of Robot Adoption on Labor Share

Dependent Variable: Labor Share				
Robot	(1) Initial Year 2018	(2) Initial Year 2019	(3) Initial Year 2020	(4) Initial Year 2021
T	-0.12	0.00	0.01	0.18*
	(0.15)	(0.06)	(0.40)	(0.11)
Observations	9889	11399	11369	11721
SMD Before	0.532	0.515	0.477	0.345
SMD After	0.107	0.147	0.208	0.109
T+1	-0.28	-0.01	-0.13	
	(0.42)	(0.17)	(0.12)	
Observations	9479	10574	10826	
SMD Before	0.526	0.501	0.469	
SMD After	0.176	0.071	0.126	
T+2	0.08	-0.79		
	(0.06)	(0.59)		
Observations	8842	10106		
SMD Before	0.517	0.495		
SMD After	0.203	0.110		
T+3	0.09			
	(0.14)			
Observations	8470			
SMD Before	0.513			
SMD After	0.084			

Notes: We report the impact of robot adoption on labor share for the year 2018 under Initial Year 2018, marking the year a firm first employed robots. We do not report the results for Initial Year 2017 since the matching was not satisfactory for the firms that first employed robots in 2017. A counterfactual group was constructed using a logit regression model to estimate the likelihood of adopting robots in 2017. This model incorporated key regressors, including total employment (both permanent and temporary workers), labor productivity, a parent company dummy, and industry dummies. We then analyzed changes in employment for these matched pairs by comparing employment differences from 2017 to 2018 (T). For subsequent analyses, such as the impact in 2019 (T+1), we retained the same matched groups and calculated the treatment effect based on differences in employment from 2017 to 2019, and so forth. To ensure the analysis accounted for variances in the impact of robot adoption from one year to the next, we repeated the procedure for firms adopting robots in 2019 under Initial Year 2019, and similarly for subsequent years. To assess the balance of covariates after propensity score matching, we report the average Standardized Mean Difference (SMD) both before and after matching. Significance levels are indicated by asterisks: * for 10%, ** for 5%, and *** for 1%.

Sources: Authors' calculations.

Table 8. The Impact of AI Adoption: Propensity Score Matching

Table 8.1. The Impact of AI Adoption on Permanent Employment

Dependent Variable: Permanent Employment					
AI	(1) Initial Year 2017	(2) Initial Year 2018	(3) Initial Year 2019	(4) Initial Year 2020	(5) Initial Year 2021
T	-0.06	0.02	0.02	0.16*	0.05
	(0.06)	(0.03)	(0.04)	(0.1)	(0.04)
Observations	5020	9723	11383	11088	11464
SMD Before	0.469	0.462	0.431	0.375	0.193
SMD After	0.161	0.120	0.080	0.009	0.048
T+1	-0.04	-0.01	0.09	0.10*	
	(0.08)	(0.06)	(0.07)	(0.06)	
Observations	4806	9313	10535	10547	
SMD Before	0.456	0.455	0.418	0.365	
SMD After	0.123	0.088	0.102	0.065	
T+2	0.05	-0.11	0.14*		
	(0.1)	(0.07)	(0.07)		
Observations	4604	8672	10050		
SMD Before	0.449	0.447	0.410		
SMD After	0.177	0.090	0.078		
T+3	0.12	0.03			
	(0.17)	(0.05)			
Observations	4295	8302			
SMD Before	0.439	0.442			
SMD After	0.152	0.130			
T+4	0.12				
	(0.16)				
Observations	4124				
SMD Before	0.431				
SMD After	0.114				

Notes: We report the impact of AI adoption on permanent employment for the year 2017 under Initial Year 2017, marking the year a firm first employed robots. A counterfactual group was constructed using a logit regression model to estimate the likelihood of adopting robots in 2016. This model incorporated key regressors, including total employment (both permanent and temporary workers), labor productivity, a parent company dummy, and industry dummies. We then analyzed changes in employment for these matched pairs by comparing employment differences from 2016 to 2017 (T). For subsequent analyses, such as the impact in 2018 (T+1), we retained the same matched groups and calculated the treatment effect based on differences in employment from 2016 to 2018, and so forth. To ensure the analysis accounted for variances in the impact of robot adoption from one year to the next, we repeated the procedure for firms adopting robots in 2018 under Initial Year 2018, and similarly for subsequent years. To assess the balance of covariates after propensity score matching, we report the average Standardized Mean Difference (SMD) both before and after matching. Significance levels are indicated by asterisks: * for 10%, ** for 5%, and *** for 1%.

Sources: Authors' calculations.

Table 8.2. The Impact of AI Adoption on Temporary Employment

Dependent Variable: Temporary Employment					
AI	(1) Initial Year 2017	(2) Initial Year 2018	(3) Initial Year 2019	(4) Initial Year 2020	(5) Initial Year 2021
T	-0.11	0.61***	0.09	0.48	0.36
	(0.43)	(0.22)	(0.20)	(0.37)	(0.38)
Observations	1909	1878	1894	1685	1949
SMD Before	0.500	0.529	0.544	0.436	0.277
SMD After	0.177	0.132	0.275	0.155	0.094
T+1	-0.47	0.60*	-0.34	0.43*	
	(0.49)	(0.35)	(0.42)	(0.24)	
Observations	1691	1409	1496	1562	
SMD Before	0.517	0.480	0.547	0.366	
SMD After	0.343	0.192	0.219	0.101	
T+2	-0.13	0.71	-1.26***		
	(0.63)	(0.47)	(0.42)		
Observations	1376	1172	1492		
SMD Before	0.663	0.620	0.424		
SMD After	0.115	0.196	0.064		
T+3	1.61*	0.47			
	(0.96)	(0.48)			
Observations	1244	1153			
SMD Before	0.722	0.515			
SMD After	0.276	0.229			
T+4	0.03				
	(0.54)				
Observations	1199				
SMD Before	0.798				
SMD After	0.066				

Notes: We report the impact of AI adoption on temporary employment for the year 2017 under Initial Year 2017, marking the year a firm first employed robots. A counterfactual group was constructed using a logit regression model to estimate the likelihood of adopting robots in 2016. This model incorporated key regressors, including total employment (both permanent and temporary workers), labor productivity, a parent company dummy, and industry dummies. We then analyzed changes in employment for these matched pairs by comparing employment differences from 2016 to 2017 (T). For subsequent analyses, such as the impact in 2018 (T+1), we retained the same matched groups and calculated the treatment effect based on differences in employment from 2016 to 2018, and so forth. To ensure the analysis accounted for variances in the impact of robot adoption from one year to the next, we repeated the procedure for firms adopting robots in 2018 under Initial Year 2018, and similarly for subsequent years. To assess the balance of covariates after propensity score matching, we report the average Standardized Mean Difference (SMD) both before and after matching. Significance levels are indicated by asterisks: * for 10%, ** for 5%, and *** for 1%.

Sources: Authors' calculations.

Table 8.3. The Impact of AI Adoption on Labor Productivity

Dependent Variable: Labor Productivity					
AI	(1) Initial Year 2017	(2) Initial Year 2018	(3) Initial Year 2019	(4) Initial Year 2020	(5) Initial Year 2021
T	-0.01	-0.01	0.06	-0.11	0.04
	(0.10)	(0.06)	(0.06)	(0.13)	(0.06)
Observations	4458	9578	11253	10907	11311
SMD Before	0.620	0.459	0.428	0.373	0.201
SMD After	0.253	0.137	0.102	0.094	0.087
T+1	0.24	-0.05	0.04	0.13	
	(0.23)	(0.07)	(0.14)	(0.11)	
Observations	4734	9171	10343	10379	
SMD Before	0.450	0.454	0.416	0.363	
SMD After	0.081	0.103	0.198	0.069	
T+2	0.31**	-0.05	0.22*		
	(0.16)	(0.08)	(0.13)		
Observations	4545	8502	9871		
SMD Before	0.502	0.447	0.409		
SMD After	0.297	0.140	0.095		
T+3	0.08	0.24**			
	(0.18)	(0.10)			
Observations	4213	8156			
SMD Before	0.492	0.434			
SMD After	0.227	0.088			
T+4	0.14				
	(0.31)				
Observations	4050				
SMD Before	0.429				
SMD After	0.061				

Notes: We report the impact of AI adoption on labor productivity for the year 2017 under Initial Year 2017, marking the year a firm first employed robots. A counterfactual group was constructed using a logit regression model to estimate the likelihood of adopting robots in 2016. This model incorporated key regressors, including total employment (both permanent and temporary workers), labor productivity, a parent company dummy, and industry dummies. We then analyzed changes in employment for these matched pairs by comparing employment differences from 2016 to 2017 (T). For subsequent analyses, such as the impact in 2018 (T+1), we retained the same matched groups and calculated the treatment effect based on differences in employment from 2016 to 2018, and so forth. To ensure the analysis accounted for variances in the impact of robot adoption from one year to the next, we repeated the procedure for firms adopting robots in 2018 under Initial Year 2018, and similarly for subsequent years. To assess the balance of covariates after propensity score matching, we report the average Standardized Mean Difference (SMD) both before and after matching. Significance levels are indicated by asterisks: * for 10%, ** for 5%, and *** for 1%.

Sources: Authors' calculations.

Table 8.4. The Impact of AI Adoption on Labor Share

Dependent Variable: Labor Share					
AI	(1) Initial Year 2017	(2) Initial Year 2018	(3) Initial Year 2019	(4) Initial Year 2020	(5) Initial Year 2021
T	0.06	0.04	-0.06	0.16	-0.92
	(0.14)	(0.03)	(0.04)	(0.38)	(0.65)
Observations	4677	9723	11383	11086	11464
SMD Before	0.431	0.442	0.410	0.365	0.193
SMD After	0.114	0.130	0.078	0.065	0.050
T+1	-0.32*	0.01	0.02	-0.03	
	(0.18)	(0.03)	(0.32)	(0.06)	
Observations	4806	9313	10532	10547	
SMD Before	0.439	0.447	0.418	0.375	
SMD After	0.095	0.052	0.118	0.019	
T+2	-0.43	-0.02	-0.46*		
	(0.26)	(0.22)	(0.25)		
Observations	4604	8671	10050		
SMD Before	0.449	0.455	0.431		
SMD After	0.177	0.088	0.080		
T+3	-0.40	-0.02			
	(0.55)	(0.07)			
Observations	4294	8302			
SMD Before	0.456	0.462			
SMD After	0.123	0.120			
T+4	0.16				
	(0.66)				
Observations	4124				
SMD Before	0.540				
SMD After	0.270				

Notes: We report the impact of AI adoption on labor share for the year 2017 under Initial Year 2017, marking the year a firm first employed robots. A counterfactual group was constructed using a logit regression model to estimate the likelihood of adopting robots in 2016. This model incorporated key regressors, including total employment (both permanent and temporary workers), labor productivity, a parent company dummy, and industry dummies. We then analyzed changes in employment for these matched pairs by comparing employment differences from 2016 to 2017 (T). For subsequent analyses, such as the impact in 2018 (T+1), we retained the same matched groups and calculated the treatment effect based on differences in employment from 2016 to 2018, and so forth. To ensure the analysis accounted for variances in the impact of robot adoption from one year to the next, we repeated the procedure for firms adopting robots in 2018 under Initial Year 2018, and similarly for subsequent years. To assess the balance of covariates after propensity score matching, we report the average Standardized Mean Difference (SMD) both before and after matching. Significance levels are indicated by asterisks: * for 10%, ** for 5%, and *** for 1%.

Sources: Authors' calculations.

Table 9. The Impact of Adopting Both: Propensity Score Matching

Table 9.1. The Impact of Adopting Both on Permanent Employment

Dependent Variable: Permanent Employment					
Both	(1) Initial Year 2017	(2) Initial Year 2018	(3) Initial Year 2019	(4) Initial Year 2020	(5) Initial Year 2021
T	0.09	-0.04	-0.14	-0.15**	0.18**
	(0.05)	(0.07)	(0.24)	(0.06)	(0.08)
Observations	5264	9666	10185	11703	11931
SMD Before	0.489	0.872	0.876	0.548	0.448
SMD After	0.290	0.094	0.178	0.122	0.073
T+1	0.02	-0.00	-0.13**	-0.13	
	(0.19)	(0.11)	(0.06)	(0.08)	
Observations	5053	9280	9478	11150	
SMD Before	0.482	0.868	0.867	0.539	
SMD After	0.471	0.130	0.154	0.212	
T+2	0.07	0.00	0.07		
	(0.16)	(0.13)	(0.08)		
Observations	4845	8683	9072		
SMD Before	0.482	0.862	0.863		
SMD After	0.437	0.200	0.086		
T+3	0.25	0.04			
	(0.28)	(0.11)			
Observations	4531	8323			
SMD Before	0.477	0.859			
SMD After	0.343	0.279			
T+4	0.19				
	(0.40)				
Observations	4356				
SMD Before	0.475				
SMD After	0.059				

Notes: We report the impact of adopting both robots and AI on permanent employment for the year 2017 under Initial Year 2017, marking the year a firm first employed robots. A counterfactual group was constructed using a logit regression model to estimate the likelihood of adopting robots in 2016. This model incorporated key regressors, including total employment (both permanent and temporary workers), labor productivity, a parent company dummy, and industry dummies. We then analyzed changes in employment for these matched pairs by comparing employment differences from 2016 to 2017 (T). For subsequent analyses, such as the impact in 2018 (T+1), we retained the same matched groups and calculated the treatment effect based on differences in employment from 2016 to 2018, and so forth. To ensure the analysis accounted for variances in the impact of robot adoption from one year to the next, we repeated the procedure for firms adopting robots in 2018 under Initial Year 2018, and similarly for subsequent years. To assess the balance of covariates after propensity score matching, we report the average Standardized Mean Difference (SMD) both before and after matching. Significance levels are indicated by asterisks: * for 10%, ** for 5%, and *** for 1%.

Sources: Authors' calculations.

Table 9.2. The Impact of Adopting Both on Temporary Employment

Dependent Variable: Temporary Employment			
Both	(1) Initial Year 2018	(2) Initial Year 2019	(3) Initial Year 2021
T	-0.07	1.05**	0.57*
	(0.30)	(0.50)	(0.30)
Observations	1624	2007	2132
SMD Before	1.268	1.307	0.712
SMD After	0.461	0.303	0.103
T+1	0.08	0.16	
	(0.49)	(0.35)	
Observations	1239	1618	
SMD Before	1.260	1.128	
SMD After	0.253	0.388	
T+2	0.39	0.89	
	(0.36)	(0.64)	
Observations	1078	1624	
SMD Before	1.203	1.134	
SMD After	0.296	0.165	
T+3	-0.22		
	(0.53)		
Observations	1062		
SMD Before	1.179		
SMD After	0.112		

Notes: We report the impact of adopting both robots and AI on temporary employment for the year 2017 under Initial Year 2017, marking the year a firm first employed robots. A counterfactual group was constructed using a logit regression model to estimate the likelihood of adopting robots in 2016. This model incorporated key regressors, including total employment (both permanent and temporary workers), labor productivity, a parent company dummy, and industry dummies. We then analyzed changes in employment for these matched pairs by comparing employment differences from 2016 to 2017 (T). For subsequent analyses, such as the impact in 2018 (T+1), we retained the same matched groups and calculated the treatment effect based on differences in employment from 2016 to 2018, and so forth. To ensure the analysis accounted for variances in the impact of robot adoption from one year to the next, we repeated the procedure for firms adopting robots in 2018 under Initial Year 2018, and similarly for subsequent years. To assess the balance of covariates after propensity score matching, we report the average Standardized Mean Difference (SMD) both before and after matching. Significance levels are indicated by asterisks: * for 10%, ** for 5%, and *** for 1%.

Sources: Authors' calculations.

Table 9.3. The Impact of Adopting Both on Labor Productivity

Dependent Variable: Labor Productivity				
Both	(1) Initial Year 2018	(2) Initial Year 2019	(3) Initial Year 2020	(4) Initial Year 2021
T	-0.12	0.06	0.06	-0.11
	(0.10)	(0.08)	(0.17)	(0.16)
Observations	9253	11524	11510	11872
SMD Before	0.871	0.874	0.547	0.444
SMD After	0.117	0.246	0.019	0.092
T+1	-0.12	0.14	-0.15	
	(0.08)	(0.10)	(0.12)	
Observations	8905	10678	10972	
SMD Before	0.867	0.866	0.538	
SMD After	0.300	0.185	0.310	
T+2	-0.06	-0.25*		
	(0.14)	(0.14)		
Observations	8327	10243		
SMD Before	0.861	0.888		
SMD After	0.300	0.082		
T+3	-0.03			
	(0.14)			
Observations	8009			
SMD Before	0.786			
SMD After	0.250			

Notes: We report the impact of adopting both robots and AI on labor productivity for the year 2017 under Initial Year 2017, marking the year a firm first employed robots. A counterfactual group was constructed using a logit regression model to estimate the likelihood of adopting robots in 2016. This model incorporated key regressors, including total employment (both permanent and temporary workers), labor productivity, a parent company dummy, and industry dummies. We then analyzed changes in employment for these matched pairs by comparing employment differences from 2016 to 2017 (T). For subsequent analyses, such as the impact in 2018 (T+1), we retained the same matched groups and calculated the treatment effect based on differences in employment from 2016 to 2018, and so forth. To ensure the analysis accounted for variances in the impact of robot adoption from one year to the next, we repeated the procedure for firms adopting robots in 2018 under Initial Year 2018, and similarly for subsequent years. To assess the balance of covariates after propensity score matching, we report the average Standardized Mean Difference (SMD) both before and after matching. Significance levels are indicated by asterisks: * for 10%, ** for 5%, and *** for 1%.

Sources: Authors' calculations.

Table 9.4. The Impact of Adopting Both on Labor Share

Dependent Variable: Labor Share					
Both	(1) Initial Year 2017	(2) Initial Year 2018	(3) Initial Year 2019	(4) Initial Year 2020	(5) Initial Year 2021
T	-0.03	0.05	0.01	0.05	0.44*
	(0.55)	(0.05)	(0.02)	(0.04)	(0.24)
Observations	4937	9370	11638	11700	12031
SMD Before	0.523	0.872	0.876	0.548	0.448
SMD After	0.409	0.094	0.178	0.080	0.073
T+1	-0.47***	0.08*	0.20	0.05	
	(0.17)	(0.05)	(1.72)	(0.05)	
Observations	5096	9016	10859	11150	
SMD Before	0.482	0.868	0.867	0.539	
SMD After	0.471	0.130	0.141	0.212	
T+2	-1.25	0.10	-1.52		
	(0.97)	(0.08)	(1.51)		
Observations	4887	8474	10402		
SMD Before	0.482	0.862	0.863		
SMD After	0.437	0.200	0.086		
T+3	-7.02***	-0.07			
	(2.45)	(0.12)			
Observations	4568	8130			
SMD Before	0.477	0.859			
SMD After	0.267	0.279			
T+4	4.53				
	(3.88)				
Observations	4391				
SMD Before	0.475				
SMD After	0.059				

Notes: We report the impact of adopting both robots and AI on labor share for the year 2017 under Initial Year 2017, marking the year a firm first employed robots. A counterfactual group was constructed using a logit regression model to estimate the likelihood of adopting robots in 2016. This model incorporated key regressors, including total employment (both permanent and temporary workers), labor productivity, a parent company dummy, and industry dummies. We then analyzed changes in employment for these matched pairs by comparing employment differences from 2016 to 2017 (T). For subsequent analyses, such as the impact in 2018 (T+1), we retained the same matched groups and calculated the treatment effect based on differences in employment from 2016 to 2018, and so forth. To ensure the analysis accounted for variances in the impact of robot adoption from one year to the next, we repeated the procedure for firms adopting robots in 2018 under Initial Year 2018, and similarly for subsequent years. To assess the balance of covariates after propensity score matching, we report the average Standardized Mean Difference (SMD) both before and after matching. Significance levels are indicated by asterisks: * for 10%, ** for 5%, and *** for 1%.

Sources: Authors' calculations.