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Implications of artificial intelligence and robots for employment and labor productivity: Firm-level evidence from the Republic of Korea

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IMPLICATIONS OF ARTIFICIAL INTELLIGENCE AND ROBOTS FOR EMPLOYMENT AND LABOR PRODUCTIVITY

FIRM-LEVEL EVIDENCE FROM THE REPUBLIC OF KOREA

Donghyun Park and Kwanho Shin

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Implications of Artificial Intelligence and Robots for Employment and Labor Productivity: Firm-Level Evidence from the Republic of Korea

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ABSTRACT

We examine the implications of robots and artificial intelligence (AI) for employment and productivity, using a rich firm-level database from the Survey of Business Activities provided by Statistics Korea. While previous studies have explored the effects of robots and AI separately, we investigate their effects jointly within a unified framework. We deploy 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 patterns of adopting robots and AI differ significantly across industries. Additionally, although the overall share of firms adopting robots is larger, AI adoption is more concentrated among bigger firms. Our main finding is that, while adopting robots and adopting AI both increase employment, only adopting AI improves labor productivity. However, such productivity gains are accompanied by a decrease in the labor share of income, suggesting a potential shift in value distribution favoring capital income. Furthermore, we find that the immediate impact of adopting both robots and AI is an increase in temporary but not permanent employment. Finally, there is no evidence that firms adopting both robots and AI improve their labor productivity, potentially reflecting a lack of synergy.

Keywords: artificial intelligence, robots, employment, productivity

JEL codes: O33, O40, J21, J24, D22

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I. INTRODUCTION

There are widespread concerns about the impacts artificial intelligence (AI) and robots will have on the labor market. These center in particular around the potential displacement of workers and hence their contribution to higher unemployment. At the same time, the two technologies offer the promise of higher labor productivity. That is, workers who work with AI and robots are likely to be more productive than their counterparts who do not. An additional issue of interest is whether there is synergy between using the two technologies in improving labor productivity.

A large and growing empirical literature, covered in the next section, has sprung up to examine the impacts of AI and robots on employment and labor productivity. However, such studies have looked at the labor market impact of the two technologies separately. In contrast, we explore their effects jointly. To do so, we use a rich firm-level database, the Survey of Business Activities from Statistics Korea. Notably, the database allows us to directly identify firms that use AI or robots because the survey asks firms about the use of the two technologies since 2017. The database also includes many other firm-specific variables. We deploy propensity score matching (PSM) to control for firm characteristics, which allows us to perform a causal interpretation of the differential labor market impacts of robots and AI.

The Republic of Korea (ROK) is a global leader in the use of both AI and robots. According to the International Federation of Robotics, the ROK led the world in robot intensity in 2022 by a substantial margin, with 1,012 operational robots per 1,000 employees. It was followed by Singapore and Germany, which had corresponding figures of 730 and 415 robots. Furthermore, the ROK ranked sixth on the Global AI Index, behind only the United States, the People's Republic of China (PRC), Singapore, the United Kingdom, and France.¹ The index is the first to benchmark countries on their level of investment in, innovation with, and implementation of AI. The fact that both technologies are a significant feature of the Korean economy adds further value to our use of Korean firm-level data to analyze labor market implications.

The data indicate that patterns of 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 is the frontrunner in AI adoption. Additionally, while the share of firms adopting robots is higher overall, AI adoption is more concentrated among larger firms. Furthermore, the relatively low correlation coefficient of around 0.2 between robot and AI adoption points to a potential lack of synergy between the two. We also observe that firms with larger sales, higher research and development (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 differ significantly. While both adopting robots and adopting AI increase employment, either permanent or temporary, only adopting AI improves labor productivity. However, these productivity gains lead to a decrease in the labor share of income, 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 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 increase either permanent employment or labor productivity, potentially reflecting a lack of synergy between the two technologies. It should be noted that our findings cannot be generalized to the entire economy without considering additional factors such as the effects on other firms through input-output linkages.

¹ www.tortoisemedia.com/intelligence/global-ai

The rest of the paper is organized as follows. The next section reviews the relevant literature and spells out our contribution. Section III lays out the data we use for our empirical analysis. Section IV analyzes the characteristics of the firms that adopt robots and AI. In Section V, we investigate the impacts of robot and AI adoption on employment and productivity. Section VI concludes.

II. LITERATURE REVIEW AND CONTRIBUTION TO THE LITERATURE

The influence of 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 for workers in routine cognitive tasks. Similarly, Webb finds that AI can substitute for workers in 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 will displace workers permanently, leading to reduced employment levels. The Luddite movement of the early 19th century epitomized such fears, under which 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.² 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 because of 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.³ 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 impacts of robots on employment across US 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 for rather than complement workers, further exacerbating concerns about job displacement.⁴ Acemoglu and Restrepo (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.

² According to the U.S. Bureau of Labor Statistics, the employment–population ratio in the United States reached its peak at 64.7% in 2000. However, it has been on a declining trend throughout the 21st century.

³ 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.

⁴ Brynjolfsson and McAfee (2014) distinguish the Second Machine Age, which involves the automation of cognitive tasks, from the First Machine Age, or the Industrial Revolution, which was characterized by complementarity between labor and machines.

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—(i) own-industry effects, (ii) indirect upstream and downstream effects in linked sectors, and (iii) 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 17 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, Manuylov, and Smolka (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 in the PRC, often referred to as “The World Factory,” reveal that robotization, specifically the “machine substitution” policy, encourages funded firms to expand their labor demand primarily because of 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, Babina 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 skills and technologies. Furthermore, Georgieff and Hye (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.⁵ Song, Choi, and Cho (2024), focusing on the ROK’s experience, find no significant impact of AI adoption on employment at the firm level.⁶

Another important issue is the impact of adopting robots or AI 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 17 countries from 1993 to 2007 and new instrumental variables based on robots’ comparative advantage in specific tasks, found that increased robot use contributed

⁵ 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.

⁶ Song, Choi, and Cho (2024) utilized the same dataset as we did. 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 PSM to achieve better matching between control and treatment groups, the impact of AI on employment becomes positive.

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 United States. Furthermore, Li et al. (2024) identify a positive causal effect of robot adoption on firm productivity based on firm-level data from the PRC.

Studies are even more optimistic about the positive impact of AI on productivity. Babina 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 has become the fastest-spreading technology platform in history, amassing an estimated 100 million monthly users just 2 months after its launch. Praising its success, Hatzius et al. (2023), in a Goldman Sachs report, argue that generative AI could raise annual US 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 gross domestic product. 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) 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 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 an interesting and significant question. Are there differences between robots and AI in terms of their effects on employment and productivity? Second, rather than indirectly identifying robot or AI adoption through patents, job postings, or other indicators, we directly identify firms that adopt either robots or AI based on survey questions. This improves the precision of our analysis. Finally, instead of relying on regional or macro-level data, we employ firm-level data to investigate the labor market impact of robot and AI adoption. Firm-level analysis allows us to match treated and control firms using propensity scores. This minimizes the potential non-equivalence of characteristics between the treatment and control groups and mitigates the bias introduced by covariates when estimating the treatment effect. Although some studies in the literature also use firm-level data, relatively few incorporate matching between treated and control groups.

III. DATA

The data used in this study are derived from the Survey of Business Activities, conducted annually by Statistics Korea. This survey targets firms in all industries in the ROK with at least 50 regular employees and a capital of at least W300 million (approximately \$220,000), covering 13,824 corporations as of year 2022 across all industries.⁷ While every firm is classified in an industry, if a firm is involved in multiple industrial activities, it is classified in the main industry sector, and the sales from other sectors are included in the main industry. Industry classification follows the

⁷ In retail and other services sectors, firms with fewer than 50 regular employees are included in the survey if their capital exceeds W1 billion.

Korean Standard Industrial Classification (KSIC), which closely resembles the International Standard Industrial Classification (ISIC), revision 4. The survey is conducted principally 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 enterprises, including management performance, diversification, affiliation, performance management systems, and changes in business strategies and industrial structures.⁸ 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 is 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: AI; robots; Internet of Things; cloud computing; big data; mobile technologies and services (including 5G); blockchain; 3D printing; and augmented reality/virtual reality.

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 have identified indirectly firms using related patents or job advertisements.⁹ As Song and Cho (2021) note, if a firm's use of AI is measured based on the possession of AI-related patents, there is a strong correlation with whether it 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.¹⁰

Employees are categorized as either permanent or temporary workers. Permanent workers are those who have an employment contract with their employer for at least 1 year or who work as permanent staff without a fixed term of employment. In contrast, temporary workers have an employment contract for less than 1 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% 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. R&D expenses include all costs associated with the company's R&D activities, such as labor, 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:¹¹ "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

⁸ The explanation on the survey is based on the Survey of Business Activities 2022.

⁹ For example, Alderucci et al. (2020) and Damioli, Van Roy, and Vertesy (2021) identify firms using AI by employing machine learning algorithms to analyze the text of US 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.

¹⁰ Song and Cho (2021) used the same data as we did.

¹¹ The tables and figures are available in the Appendix (<http://dx.doi.org/10.22617/WPS250038-2>).

“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; we revisit these issues more rigorously in the next section.

In Figures 1.1 to 1.3, 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*, from 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 significant growth, 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.

Figures 2.1 to 2.3 illustrate the shares of firms adopting robots, AI, or both, along with the corresponding employment shares, categorized into 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 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 with 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%

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.

in 2021. This indicates that, compared with 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 shows 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 into 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.

Figures 5.1 to 5.3 illustrate 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 Ordinary Least Square (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 revisit this issue in Section IV.

IV. WHICH FIRMS ADOPT ROBOTS AND ARTIFICIAL INTELLIGENCE?

In this section, we explore the firm-specific characteristics that influence the adoption of robots and AI. Koch, Manuylov, and Smolka (2021), using 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 5-year university degree, are less likely to adopt robots.

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

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

where the dependent variable is an indicator variable for robot use for firm i during the sample period; ϕ_{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, Manuylov, and Smolka (2021) define the base year as the first year that the firm appears in the sample. We define the base year as year 2016, which is 1 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 number of employees), R&D intensity (deflated R&D expenditure divided by deflated total sales), share of manufacturing employment, and average wage (deflated total labor costs divided by 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.

Tables 2.1 to 2.3 present 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% ($=0.007 \times 1.49$). 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 driven primarily by domestic factors.¹⁴ Additionally, while the coefficient for labor productivity is negative, the coefficient for average wage is positive and statistically 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.

Tables 3.1 to 3.3 report the probit estimation results of the same equation as in Table 2. Table 3.1 presents the results for robot adoption and Table 3.2 those for AI adoption. 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.

V. IMPACTS OF ROBOT AND ARTIFICIAL INTELLIGENCE ADOPTION ON EMPLOYMENT AND LABOR PRODUCTIVITY

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

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

where $Employment_{it}$ represents the log of employment for firm i , $Robot_{it}$ is an indicator variable that takes 1 if the firm i adopts robots at time t and 0 otherwise, and α_i and α_t are firm and time fixed effects, respectively. Goodman-Bacon (2021) illustrates that the estimated

¹³ This finding stands in clear contrast to that of Koch, Manuylov, and Smolka (2021), which reports positive and highly statistically significant coefficients for the share of manufacturing workers. However, in the ROK, 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.

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 and d'Haultfœuille (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 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 4 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 2 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 2 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 4 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 TWFE regressions for base year t :

$$Employment_{itp} = \alpha + \beta_1 Year_{tp} + \beta_2 Robot_{it} + \beta_3 Year_{tp} * Robot_{it} + \gamma X_{itp} + \epsilon_{itp} \quad (3)$$

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 1 if the firm i adopted robots in the treatment year and 0 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.

¹⁵ This approach is also employed by Song, Choi, and Cho (2024) to examine the impact of AI on employment, who conclude that AI's effect on employment is negligible. Another potential method is the approach proposed by Callaway and Sant'Anna (2021), which is frequently applied to estimate treatment effects in staggered treatment settings. Although not reported here, the results derived from this method are very similar to those obtained through our approach of analyzing each pair of observations separately.

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'Haultfœuille (2022) for a survey of this literature to overcome this problem.

Tables 4.1 to 4.3 present the impact of robot adoption on employment and labor productivity using the 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, 1 year after, 2 years after, 3 years after, and 4 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 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 the 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 the ROK’s unique context, where the primary motivation for adopting robots may not be to replace labor or improve labor productivity. Given the ROK’s highly active labor unions, firms may introduce robots as a strategic response to alleviate union pressures by reducing the need to hire additional workers.

Tables 5.1 to 5.3 report the impact of AI adoption on employment and labor productivity using the 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

¹⁷ Including other firm characteristics such as firm size does not change the qualitative results.

¹⁸ This finding is consistent with Song, Choi, and Cho (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 2 years.

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 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-treatment characteristics.

Tables 7.1 to 7.4 present 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 2017.²²

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

²⁰ See Rosenbaum and Rubin (1983).

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.

²² In this way, we avoid the need to assume no anticipation, which is a critical assumption for interpreting the estimation results from Callaway and Sant’Anna (2021). When we applied the approach proposed by Callaway and Sant’Anna, we rarely found statistically significant estimates.

for a comprehensive analysis of the evolving impacts of robot adoption on employment. To assess the balance of covariates after PSM, we report the average Standardized Mean Difference (SMD) both before and after matching. Note that, as in Table 7.2, if matching is 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 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 the treatment firms. Similarly, we estimated the impacts on employment for subsequent years using the same methodology.

In Table 7.1, column (1) reports the ATT for robot adoption in 2017, analyzing the effects on permanent employment across the year T (the year of adoption), and the subsequent 4 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 3 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 the matching was appropriately performed across the table.²³ 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.

Tables 8.1 to 8.4 assess 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

²³ This holds true for the remaining tables throughout the paper. Therefore, we do not explicitly discuss the validity of matching in subsequent sections.

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 2 to 3 years for the labor productivity to go up. 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, Tables 9.1 to 9.4 report 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 is 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.

VI. CONCLUSION

In principle, AI and robots can have either positive or negative impacts on the labor market. In particular, the two technologies have the potential to cause higher unemployment as well as to promote higher labor productivity. A large and growing number of studies empirically examine the effect of AI and robots on employment and labor productivity. However, these typically focus solely on the impact of AI or the impact of robots but not the impact of both AI and robots. The main contribution of our paper to the literature is that we investigate the role of both AI and robots in employment and labor productivity within a unified framework. This enables us to address the interesting and significant question of whether the two technologies have different impacts on labor market outcomes. Another big contribution is that we use a rich Korean firm-level database that directly identifies firms that use AI and robots. Furthermore, the ROK is a global leader in the use of both technologies.

Our central finding is that AI and robots differ in their impact on employment and labor productivity. AI has a more positive overall impact on labor market outcomes. More specifically, while both adopting AI and adopting robots increase employment, only adopting AI improves labor productivity. However, those productivity gains are associated with a decrease in the labor share of income. In addition, there is no evidence that firms adopting both robots and AI improve their labor productivity, potentially reflecting a lack of synergy. Using PSM to control for firm characteristics allows us to potentially causally interpret the differential impacts of robots and AI on employment and labor productivity.

It is important to recognize that our findings cannot be generalized to the entire economy without considering additional factors. As Autor and Salomons (2018) highlight, there are at least two broader effects of robot or AI adoption that must be taken into account if we are to assess its economy-wide impact. First, there are significant effects related to input-output linkages. While our analysis focuses on the immediate impacts on firms that have already adopted robots or AI, other firms interconnected through input-output linkages may also be affected. Such effects

include increased demand for upstream firms and productivity change for downstream firms. Second, increases in income resulting from robot or AI adoption can boost aggregate demand, thereby affecting even firms outside input-output relationships. To comprehensively assess the impact of AI and robots on the employment and labor productivity of the entire economy, these additional effects must be incorporated. Finally, it would be interesting and significant to replicate our analysis for other countries in the future if and when the required data become available.

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Implications of Artificial Intelligence and Robots for Employment and Labor Productivity

Firm-Level Evidence from the Republic of Korea

This paper examines the implications of robots and artificial intelligence (AI) for employment and productivity, using a rich firm-level database from the Survey of Business Activities provided by Statistics Korea. Using propensity score matching to control for firm characteristics, the results show that, while adopting robots and adopting AI both increase employment, only adopting AI improves labor productivity accompanied by a decrease in the labor share of income. Adopting both robots and AI increased employment temporarily and there is no evidence on the firms' labor productivity improvement, potentially due to lack of synergy.

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