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Use of Artificial Intelligence and Productivity: Evidence from firm and worker surveys *

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Abstract

With the rapid diffusion of artificial intelligence (AI), its effects on economic growth and the labor market have attracted the attention of researchers. However, the lack of statistical data on the use of AI has restricted empirical research. Based on original surveys, this study provides an overview of the use of AI and other automation technologies in Japan, the characteristics of firms and workers who use AI, and their views on the impact of AI. According to the results, first, the number of firms using AI is increasing rapidly and firms with a larger share of highly educated workers have a greater tendency to use AI. Robot-using firms are also increasing, but the relationship between their use and workers' education is weakly negative, suggesting that the impact on the labor market is different for each technology. Second, AI-using firms have higher productivity, wages, and medium-term growth expectations. Third, AI-using firms expect that while it will increase productivity and wages, it may decrease their employment. Fourth, at the worker level, more-educated workers are more likely to use AI, suggesting that AI and education are complementary. Currently, AI may favor high-skill workers in the labor market. Fifth, workers who use AI evaluate their work productivity to have increased by approximately 20% on average, suggesting that AI could potentially have a fairly large productivity enhancing effect.

Keywords: artificial intelligence, big data, robot, productivity, wage, employment
JEL Classification: D24, J23, J24, J31, O33

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1. Introduction

The use of artificial intelligence (AI) is increasing rapidly. As AI is a general-purpose technology (GPT) with a wide range of applications, its development and diffusion have the potential to dramatically increase productivity throughout the economy. A theoretical possibility of exploding acceleration in the economic growth rate when the development of AI reaches a singularity has been noted (e.g., Fernald and Jones, 2014); however, at present, singularity is considered to be a distant future (Aghion et al., 2019; Nordhaus, 2021).

There were many empirical studies of the effects of the "IT revolution" in the late 1990s and early 2000s on productivity, indicating that the productivity of "IT-using industries" such as the financial, retail, and transportation sectors increased significantly (e.g., Stroh, 2002; Pilat *et al*., 2002). The effects of AI are also likely to be more significant in AI-using industries than in AI-producing industries.

However, empirical studies of the economic effects of AI are limited.[1] The main reason for this is a lack of firm-level data on AI use (Raj and Seamans, 2019; Furman and Seamans, 2019). Although there is a growing body of empirical research on robots, as discussed in the next section, a survey of the economic effects of AI (Agrawal *et al*., 2019) noted that one should be cautious about analogizing the impact of AI from research on factory automation (industrial robots). Restrepo (2024), in a recent survey of the economic effects of automation technologies, described the impact of AI on the labor market and workforce as an important area for future research. Acemoglu (2024), who quantitatively assessed the medium-term economic impact of AI based on currently available data, estimates that the effect on total factor productivity (TFP) over the next 10 years will be approximately 0.7% or less, and states that "there is huge uncertainty about which tasks will be automated or complemented, and what the cost savings will be."

Against this background, this study provides an overview of the use of AI and other automation technologies and analyzes the characteristics of firms and workers who use them based on surveys of Japanese firms conducted three times in FY 2018, FY 2021, and FY 2023, and a survey of workers in FY 2023.

The major findings are summarized as follows. First, the number of firms using AI is increasing rapidly, and firms with a larger share of highly educated workers, particularly those with a

[1] Abrardi *et al*. (2022) for a recent survey of studies of the economic impacts of AI.

postgraduate education, tend to use AI. Robot-using firms are also increasing, but the relationship between their use and workers' education is weakly negative, suggesting that the impact on the labor market is different for each technology. Second, AI-using firms have higher productivity, wages, and medium-term growth expectations. Third, AI-using firms expect that while it will increase productivity and wages, it may decrease their employment in the long run. Fourth, even at the worker level, more-educated workers are more likely to use AI, suggesting that AI and education are complementary. Fifth, workers who use AI evaluate their work productivity to have increased by approximately 20% on average, suggesting that AI could potentially have a fairly large productivity enhancing effect.

The remainder of this paper is organized as follows. Section 2 provides a brief overview of related literature. Section 3 presents the results of a survey of Japanese firms, showing recent trends in the use of AI and other automation technologies as well as firms' long-term outlook on the effects of AI. Section 4 presents the results of the use of AI at the worker level and its effect on job productivity, based on a survey of workers. Finally, Section 5 summarizes the main findings of this study and discusses the limitations of the analysis and future issues.

2. Literature on the Impacts of Automation Technologies

Among automation technologies, numerous studies have been conducted of industrial robots and their effects on employment. According to a task-based theoretical model of the effects of automation technologies (Acemoglu and Restrepo, 2018, 2019, 2020), the total effects of automation technologies on employment can be decomposed into negative employment displacement effects, positive productivity effects, and positive compositional effects (reinstatement effect). Therefore, the total effect can be either positive or negative depending on the relative strength of these effects. Since the International Federation of Robotics (IFR) data on robot utilization by country and industry became available, several empirical studies have been conducted using these data (e.g., Autor and Salomons, 2018; Blanas *et al*., 2019; Acemoglu *et al*., 2020; Acemoglu and Restrepo, 2019, 2020, 2022; de Vries *et al*., 2020; Dauth *et al*., 2021; Chung and Lee, 2023; Mann and Püttmann, 2023).

Blanas et al. (2019), Acemoglu et al. (2020), Acemoglu and Restrepo (2019, 2020, 2022), and de Vries et al. (2020) show that robots have negatively impacted employment, especially for production and low-skilled workers. In contrast, Dauth et al. (2021) and Mann and Püttmann (2023) find that employment growth in the service sector offsets the manufacturing employment decline. Chung and Lee (2023) indicate that robots reduced employment in the early years, but have recently had a positive effect on employment through new task creation and spillover effects on other industries. Japanese studies, such as those by Dekle (2020) and Adachi *et al*. (2024), report that the use of robots has a positive effect on employment. In summary, the effects of robots on the labor market have not yet reached consensus.[2] In parallel, many empirical studies of the effects of robots on productivity have been conducted, and most have reported positive effects on productivity (e.g., Kromann and Sørensen, 2019; Kromann *et al*., 2020; Park *et al*., 2021; Cette *et al*., 2021; Koch *et al*., 2021).

By contrast, empirical research on AI is scarce because, unlike robots, data on its use are unavailable. However, in recent years, several countries have begun to collect such data, and firms' adoption of AI has gradually become clearer.[3] According to studies based on data from the U.S. Annual Business Survey (ABS) in 2019, 3.2% of US firms were using AI (Zolas *et al*., 2020; Acemoglu *et al*., 2022; McElheran *et al*., 2024). The Business Trend and Outlook Survey of the U.S. Census Bureau also began surveying firms' AI utilization in 2023 and 2024. Using these data, Bonney *et al*. (2024) indicate that the AI utilization rate was 3.7% in September 2023 and still less than 10% in fall 2024.

Similar surveys have begun to be conducted in Europe. Using German data (2018) from the European Innovation Survey (CIS), Czarnitzki *et al*. (2023) find that approximately 7% of firms use AI and that there is a significant positive relationship between firm AI use and productivity.[4] Using data from the EU Commission's survey of European firms, Hoffreumon *et al*. (2024) show the use of AI in applications such as natural language processing, image recognition, and forecasting. Using EUROSTAT's 2021 survey, Brey and Van der Marel (2024) show that countries and industries with higher levels of human capital are more likely to use AI.

Regarding the impact on employment, media attention was drawn to the estimation by Frey

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[2] Dekle (2020) and Adachi *et al*. (2024) use data from the Japan Robot Association (JARA) rather than IFR.

[3] From a relatively early stage, data from AI-related patents have been employed in empirical studies (e.g., Webb *et al*., 2018; Venturini, 2022). In Japan, firm-level AI patent data are used to analyze the relationship with productivity (e.g., Ikeuchi, 2021; Ikeuchi *et al*., 2023; Kim and Inui, 2021). Using patent data is one valid empirical approach because it is objective and quantitative, but it is information from the development and production side of AI technology and is not suitable for analysis from the AI user side.

[4] According to Engberg *et al*. (2024), in Portugal, Denmark, and Sweden, 17%, 24%, and 10% of firms with 10 or more employees were using AI in 2021, respectively.

and Osborne (2017) that 47 % of all U.S. jobs are at risk from computerization. David's (2017) similar analysis for Japan finds that approximately 55% of jobs could be replaced. However, Arnts *et al*. (2017) show that the figure in Frey and Osborne (2017) is overestimated when considered at the task-level rather than at the occupation-level, and that, on average, in OECD countries, only 9% of jobs are at risk of being lost through automation. Morikawa (2017) analyzes the effects of AI-related technologies using data from an original firm survey in 2015, finding that many Japanese firms expect AI to have positive effects on business and negative effects on employment, and that firms' use of big data is positively associated with their employees' education level.

Several recent studies have employed AI-related job posting data (e.g., Alekseeva *et al*., 2021; Acemoglu *et al*., 2022; Bonfiglioli *et al*., 2023). Alekseeva *et al*. (2021) use large data of online job postings in the U.S. (2010-2019) to measure demand for AI professionals by occupation, industry, and firm, finding that demand for AI skills is growing rapidly in most industries and occupations, and that there is a wage premium for AI skills. Acemoglu *et al*. (2022) also use data of AI job postings in the U.S. and report that AI is currently replacing humans in some tasks but that there is no visible impact on the macro labor market. Bonfiglioli *et al*. (2023), based on information on the demand for software skills, such as machine learning in job postings, find that exposure to AI has a negative impact on regional (commuting area) employment.

Studies have also emerged on the effects of AI on firm performance. Czarnitzki *et al*. (2023) use German data on firms' adoption of AI technology to estimate productivity effects using a production function approach and find a significant positive relationship between AI use and firm productivity. Babina *et al*. (2024) analyze the effects of AI technology use on the productivity of U.S. firms. Because firm-level data on AI use did not exist, they constructed a firm-level measure of AI investment by combining employee resume information and job posting data. The results reveal that firms investing in AI have higher growth rates in terms of sales, employment, and market value. Although firm-level empirical studies are still in their infancy, they are expected to rapidly develop.

Studies using worker-level data to identify the causal effects of AI on productivity are also emerging (e.g., Kanazawa *et al*., 2022; Brynjolfsson *et al*., 2023; Noy and Zhang, 2023). Kanazawa *et al*. (2022) estimate the effect of AI on productivity using data from Japanese taxi drivers. They find that by reducing the time spent finding passengers, productivity of drivers improved by approximately 5% on average, with the productivity effect greater for less skilled drivers. Brynjolfsson *et al*. (2023) estimate the effects of introducing generative AI conversation support tools using employee-level data from a large software company. They find that generative AI increases physical productivity by an average of 13.8%, with productivity effects particularly large for low-skilled workers. Noy and Zhang (2023) analyze the productivity effects of generative AI (ChatGPT) on writing tasks of highly educated professional workers through an online randomized experiment. They find that generative AI significantly increases labor productivity; the average time taken decreases by 40% and output quality increases by 18%.

In summary, research on the economic impact of AI using a variety of data is progressing rapidly; however, it remains far less developed than studies of industrial robots. Given this situation, this study presents evidence on recent trends in AI use in Japan and its economic effects using originally constructed firm- and worker-level datasets. The contributions of this study are (1) to collect firm-level panel data from 2018 to 2023 to show trends in AI use over time; (2) to analyze differences in firm characteristics using three automation technologies: AI, big data, and robots; and (3) to show the characteristics of workers who use AI and the effects on their self-assessed productivity.

3. Trends and Characteristics of Firms Using AI

3.1. Outline of the Survey of Firms

The survey of firms used in this study is the Survey of Corporate Management and Economic Policy (SCMEP) designed by the author and conducted by the Research Institute of Economy, Trade, and Industry, contracted to Tokyo Shoko Research, Inc.

We use data from three surveys–FY 2018, FY 2021, and FY 2023–which include questions on AI use. While there is a wide range of survey questions, the main questions used in this study are (1) questions on the use of AI, big data, and robots, and (2) qualitative questions on the impact of AI on productivity, employment, and wages. The specific wording of the questions is explained later. As questions related to AI are asked throughout the three surveys, changes over time could be observed.

The SCMEP covers both manufacturing and non-manufacturing firms with 50 or more regular employees, including listed and non-listed firms. The FY 2018 and FY 2021 surveys cover 15,000 firms, selected from approximately 30 thousand firms that responded to the Basic Survey of Japanese Business Structure and Activities (BSJBSA), an official statistical survey conducted annually by the Ministry of Economy, Trade, and Industry. The FY 2023 SCMEP is a follow-up survey of the firms that responded to the FY 2021 SCMEP. [5]

The timing of the surveys is (1) January-February 2019 for the FY 2018 survey, (2) October-December 2021 for the FY 2021 survey, and (3) December 2023-January 2024 for the FY 2023 survey (hereinafter referred to as the "2018 survey," "2021 survey," and "2023 survey"). The number of responding firms is (1) 2,535, (2) 3,125, and (3) 1,377. The number of "panel firms" that responded continuously to the three surveys is 647. The industry distribution of the responding firms and the mean, standard deviation, and median firm size are shown in **Table 1**.

3.2. Trends in the Use of Automation Technologies

The question on the use of AI and other automation technologies is "Does your firm use the following technologies in its business?" The technologies listed are (1) artificial intelligence (AI), (2) big data, and (3) robots.[6] **Table 2** shows the percentage of firms using these technologies. The number of firms using AI, big data, and robots is increasing. A similar pattern is observed when we select the panel firms that responded to all three surveys (Column B of **Table 2**). **Table 3** shows simple probit estimation results for the relationship between the use of these automation technologies and firm characteristics (industry, firm size (log of the number of employees), and educational composition of employees (ratios of university graduates and postgraduates)). The wholesale industry is the reference category. The figures reported in the table indicate marginal effects.

Firms in the information and communications industry, larger firms, and those with a higher percentage of highly educated employees (college and graduate school graduates) tend to use AI. Big data users generally show a similar pattern to AI, but many firms in the retail industry use big data, possibly because they possess and utilize point of sales (POS) data. By contrast, the characteristics of firms that use robots are very different. As expected, manufacturing firms are the most frequent users, and the coefficients for firm size are much larger than those for AI and big data. The relationship with the educational composition of employees is weak, with the coefficient of the percentage of university graduates being nonsignificantly negative, the coefficient of the percentage of postgraduate education being negative and approaching significance.

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[5] The SCMEP is answered by the president themself or by a person who is able to state the opinion of the president.

[6] The 2023 survey explicitly indicates that "artificial intelligence includes generative AI."

Table 4 compares the total factor productivity (TFP) and mean wages of firms using automation technology with those of non-users. TFP and mean wages, both expressed as logarithms, are calculated from the BSJBSA data. TFP is calculated non-parametrically for each three-digit industry of the BSJBSA using the index number method, with real value-added as output, and tangible fixed asset stock and labor input (hours) as inputs.[7] At this time, since the BSJBSA data through FY2022 are available, TFP and wages in FY2022 are applied to FY2023. After adjusting for industry, firm size, and survey year, TFP was 8.8% higher for firms using AI, 8.0% higher for firms using big data, and 2.9% higher for firms using robots than for non-users. Firms that use these technologies also have significantly higher wages. Note that these figures indicate only cross-sectional correlations.[8]

The SCMEP asks for mid-term (5 years) projected sales and the number of employees of the firms surveyed. The specific questions are "By what percentage do you expect your sales to increase or decrease over the next five years compared to last year's sales?" and "By what percentage do you expect the number of employees in your firm to increase or decrease over the next five years compared to the end of the previous year?" **Table 5** compares the medium-term expected growth rates of firms that use new technologies with those of non-users. After adjusting for industry, firm size, and survey year, firms using AI and big data have 9.4% and 7.4% higher expected medium-term growth rates of sales, respectively. The expected growth rate in the number of employees is also 4.5% and 3.3% higher than that of the non-user firms. By contrast, the expected growth rate of robot-using firms is not significantly higher than that of non-users.

3.3. Firms' Outlook on the Impact of AI on Productivity, Employment, and Wages

The 2023 survey asks firms about their views on the long-term effects of AI on productivity, employment, and wages. The specific question is "What do you think of the effect of the spread of AI on your firm's productivity over the long term?" There are five response options: (1) "Significant positive impact," (2) "Positive impact," (3) "Cannot say either," (4) "Negative

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[7] Since data on working hours are not available in the BSJBSA, labor input was calculated using data on working hours (full-time and part-time workers) for each industry from the Monthly Labour Survey (Ministry of Health, Labour and Welfare), and multiplied by the number of full-time workers and part-time workers in each firm.

[8] When estimates include firm fixed-effects, coefficients for AI, big data, or robot use are statistically insignificant.

impact," and (5) "Significant negative impact." **Figure 1** shows the aggregation results for all of the responding firms and a subsample of firms using AI. Most firms see the effect on productivity as positive, with almost no firms responding that it has a negative impact, although approximately half of the firms answered "cannot say either." Not surprisingly, firms that are already using AI evaluate its effect on productivity more positively, with fewer responding "cannot say either."

The question regarding the effect on the employment is "What do you think of the effect of the spread of AI on the employment of your firm over the long term?" There are four response options: (1) "Increase in employment," (2) "Decrease in employment," (3) "Nothing to do with employment," and (4) "Unsure." The aggregation results are shown in **Figure 2**. Approximately half of the firms answered "unsure," but a small percentage answered that it would lead to an increase in employment, while nearly a quarter answered that it would lead to a decrease in employment. A relatively large percentage of firms expect a decrease in employment than those that expect an increase in employment. For the subsample of firms using AI, the qualitative pattern is the same, although the percentage of firms that answered "unsure" is small.

The question regarding the effect on wages is "What do you think is the effect of the future spread of AI on wages of your firm's employees over the long term?" There are four response options: (1) "Increase in wages," (2) "Decrease in wages," (3) "Nothing to do with wages," and (4) "Unsure." **Figure 3** shows the aggregation results, with more respondents expecting wages to increase than to decrease, which is more pronounced among AI-using firms. As noted previously, firms using AI tend to expect positive long-term effects from AI on productivity. A positive expectation regarding wages is a natural outcome if wages reflect productivity. In addition, as we have seen, there is complementarity between the use of AI and the share of highly educated employees. Therefore, it is possible that firms using AI anticipate long-term improvements in employee skills associated with the use of AI.

4. Workers' Use of AI and Productivity

4.1. Outline of the Survey of Workers

This section reports the results of the survey of workers conducted in September 2023. The data were retrieved from the "Follow-up Survey of Life and Consumption under the Changing Economic Structure" designed by the author of this paper, conducted by Rakuten Insight, Inc. The target population comprises registered individuals aged 20 years or older who were working at the time of the survey. The sample was drawn so that the composition of respondents by gender and age categories corresponds to that of the “Employment Status Survey” in 2022 (Ministry of Internal Affairs and Communications). The composition of the 13,150 respondents according to gender and age group is shown in **Table 6**.

The question regarding AI usage in this survey is “We would like to ask you about your use of AI. Are you using AI?” The question notes that “AI includes generative AI.” The answer choices are (1) “I use it in my work,” (2) “I use it, but not in my work,” and (3) “I do not use it.” Those who answered (1) were asked about the effects of AI use on subjective productivity. The question is “How does using AI in your work improve your work efficiency (productivity) compared to not using AI?” The answer choices are (1) “Using AI increases work efficiency by about __%” and (2) “Using AI is not related to work efficiency.”

4.2. Characteristics of Workers Using AI

Aggregating the use of AI, 5.8% of respondents used AI for work and 16.1% if those who use AI outside of work are included. Looking at the percentage of respondents who used AI for work according to major individual characteristics, the value is high for males, young adults, and highly educated individuals. By industry, the information and communications industry stands out with a high percentage (14.2%), while the professional services industry (9.7%) and the finance/insurance industry (8.9%) also have relatively high percentages. In contrast, the number of AI users in jobs in food and beverage/accommodation services and medical care/welfare is low, at c. 2 to 3%. The use of artificial intelligence is increasing in industries with many highly skilled white-collar workers.

Table 7 shows the results of simple probit estimations that explain AI use according to various individual characteristics (e.g., gender, age, and education). The reference categories are male, age 40s, and less than a high school graduate.[9] Column (1) of the table shows the results for those who use AI for work or other purposes, and Column (2) shows the results for those who use AI for work = 1. The figures indicate the marginal effects of the explanatory variables.

Workers in their 20s and 30s are more likely to use AI. Highly educated workers tend to use

[9] Among the explanatory variables, annual income from work (18 categories ranging from “less than 500 thousand yen” to “more than 20 million yen”) was used by log-transforming the median value for each category (minimum category was treated as 250 thousand yen and maximum category as 22.5 million yen).

AI. Similar to the results of the firm survey in the previous section, the results suggest a complementarity between skills measured by educational background and AI use. As explained in Section 2, some studies estimating the effect of AI on worker productivity for specific tasks find that the productivity effect is greater for relatively low-skilled workers engaged in specific tasks (Kanazawa *et al*., 2022; Brynjolfsson *et al*., 2023). However, that highly educated workers are more likely to use AI suggests that AI may increase overall inequality in the labor market.

The coefficient of annual income from work is also positive at a high significance level, with higher wage earners having a higher probability of using AI. Adjusting for other individual characteristics, the quantitative relationship is that a doubling of annual income is associated with approximately a 1% higher probability of using AI at work.

4.3. Use of AI and Productivity

Finally, we report the effects of AI use on work productivity. The mean was calculated by treating the response "AI use has no relationship to work efficiency" as zero. On average, across all industries, the increase in subjective productivity at work due to the use of AI is quite large, at +21.8%. Differences in gender, age, and education are small.

Because the number of people using AI outside of work is nearly twice that of those using AI for work, if such people were to also start using AI for work, it would increase the productivity of the economy as a whole by 2-3%. Because Japan's economic growth rate remains low, this has a fairly large potential effect. However, it should be noted that there could be a selection effect, with those with larger productivity effects already using AI for work, and that the macroeconomic effects would be constrained by tasks for which AI is technically difficult to use.

5. Conclusion

Based on an original survey of Japanese firms and workers, this study presents evidence on the use of AI and other automation technologies, the characteristics of the firms and workers who use them, and their views on the effects of AI. The main results are summarized as follows. First, the number of firms using AI is increasing rapidly, and firms with a larger share of highly educated workers, particularly those with a postgraduate education, tend to use AI. Robot-using firms are also increasing, but the relationship between their use and workers' education is weakly negative, suggesting that the impact on the labor market is different for each technology. Second, AI-using firms have higher productivity, mean wages, and expected medium-term growth rates. Third, AI-using firms expect that while it will increase their productivity and wages in the long run, it may decrease their number of employees. Fourth, even at the worker level, more-educated workers are more likely to use AI, suggesting that AI and education are complementary. Currently, AI may favor high-skill workers' positions in the labor market. Fifth, workers who use AI evaluate their work productivity to have increased by approximately 20% on average, suggesting that AI could potentially have a fairly large productivity enhancing effect.

The result that AI is complementary to high-skilled labor at this time is similar to that of Morikawa (2017). However, the use of generative AI is expanding rapidly and this situation may change as the scope of AI applications expands. To increase the economic benefits of AI, it is necessary to apply it to various tasks beyond the scope of deskwork for highly educated white-collar workers.

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Table 1. Characteristics of firms that responded to the survey.

		2018	2021	2023
Industry	Manufacturing	53.1%	51.4%	54.0%
	I&C	5.4%	5.6%	5.2%
	Wholesale	18.1%	18.7%	18.4%
	Retail	10.6%	10.8%	10.2%
	Service	9.4%	10.2%	9.2%
	Other	3.3%	3.3%	3.0%
ln Employees	Mean	5.059	5.041	4.897
	SD	0.968	0.964	0.844
	p50	4.868	4.860	4.762
Obs.		2,527	3,123	1,377

Note: I&C denotes information and communications industry.

Table 2. Trends in the use of automation technologies.

A. All respondents			
	(1) AI	(2) Bigdata	(3) Robot
2018	3.0%	3.3%	16.2%
2021	7.8%	7.1%	19.5%
2023	10.0%	6.6%	21.0%
B. Panel firms			
	(1) AI	(2) Bigdata	(3) Robot
2018	1.1%	2.5%	15.0%
2021	5.6%	4.2%	18.5%
2023	8.2%	6.0%	23.5%

Note: Panel firms are those that responded to all three surveys.

Table 3. Characteristics of firms using automation technologies.

	(1) AI		(2) Bigdata		(3) Robot	
Manufacturing	0.007		0.005		0.187	***
	(0.008)		(0.005)		(0.014)	
Retail	0.013		0.039	***	-0.114	***
	(0.012)		(0.011)		(0.014)	
I & C	0.092	***	0.035	***	0.031	
	(0.021)		(0.012)		(0.027)	
Service	0.007		0.017	**	-0.089	***
	(0.011)		(0.009)		(0.016)	
ln (employees)	0.028	***	0.017	***	0.081	***
	(0.003)		(0.002)		(0.006)	
Share of university graduates	0.046	***	0.045	***	-0.015	
	(0.011)		(0.008)		(0.025)	
Share of postgraduates	0.192	***	0.157	***	-0.164	*
	(0.032)		(0.022)		(0.094)	
Year dummies	yes		yes		yes	
Nobs.	5,932		8,815		5,925	
Pseudo R2	0.137		0.112		0.136	

Note: Probit estimation results with robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.10. The figures indicate marginal effects. The wholesale industry is the reference category. I & C denotes the information and communications industry.

Table 4. Productivity and wage premium of firms using automation technologies.

	(1) TFP	(2) Wage
AI	9.0% ***	6.1% **
Bigdata	7.4% ***	9.3% ***
Robot	1.6%	5.7% ***

Notes: The values are productivity and wage premiums compared with each technology non-user firm, adjusting for industry, firm size (log number of employees), and year. *** p<0.01, ** p<0.05.

Table 5. Mid-term growth expectation of firms using automation technologies.

	(1) Sales	(2) Employment
AI	9.4% ***	4.5% ***
Bigdata	7.4% ***	3.3% **
Robot	0.1%	0.7%

Notes: The values are the expected sales and employment growth over the next 5 years compared with firms not using any automation technology, adjusting for industry, firm size (log number of employees), and year. *** p<0.01, ** p<0.05.

Table 6. Composition of workers who responded by gender and age categories.

	N	
Male	7,210	54.8%
Female	5,940	45.2%
20s	1,960	14.9%
30s	2,336	17.8%
40s	3,016	22.9%
50s	2,939	22.3%
60s	2,479	18.9%
70 or older	420	3.2%
Obs.	13,150	

Table 7. Individual characteristics of AI users.

	(1) Using AI			(2) Using AI for Work		
Female	-0.0541	(0.0076)	***	-0.0067	(0.0041)	
20s	0.0980	(0.0125)	***	0.0416	(0.0078)	***
30s	0.0454	(0.0103)	***	0.0235	(0.0062)	***
50s	-0.0423	(0.0081)	***	-0.0105	(0.0044)	**
60s	-0.0533	(0.0086)	***	-0.0114	(0.0048)	**
70 or older	-0.0128	(0.0185)		0.0173	(0.0135)	
Vocational school	0.0194	(0.0124)		0.0087	(0.0071)	
Junior college, technical college	0.0184	(0.0137)		-0.0044	(0.0070)	
University	0.0494	(0.0087)	***	0.0167	(0.0048)	***
Master	0.1071	(0.0194)	***	0.0232	(0.0097)	***
Ph.D	0.2426	(0.0401)	***	0.1172	(0.0296)	***
ln Annul income	0.0340	(0.0054)	***	0.0147	(0.0030)	***
Type of employment	yes			yes		
Industry	yes			yes		
Occupation	yes			yes		
Firm size	yes			yes		
Nobs.	13,150			13,150		
Pseudo R2	0.1118			0.1246		

Note: Marginal effects from probit estimations with robust standard errors are in parentheses. *** p<0.01, ** p<0.05. The reference categories are male, age 40s, and high school education or less.

Figure 1. Long-term impact of AI on productivity.

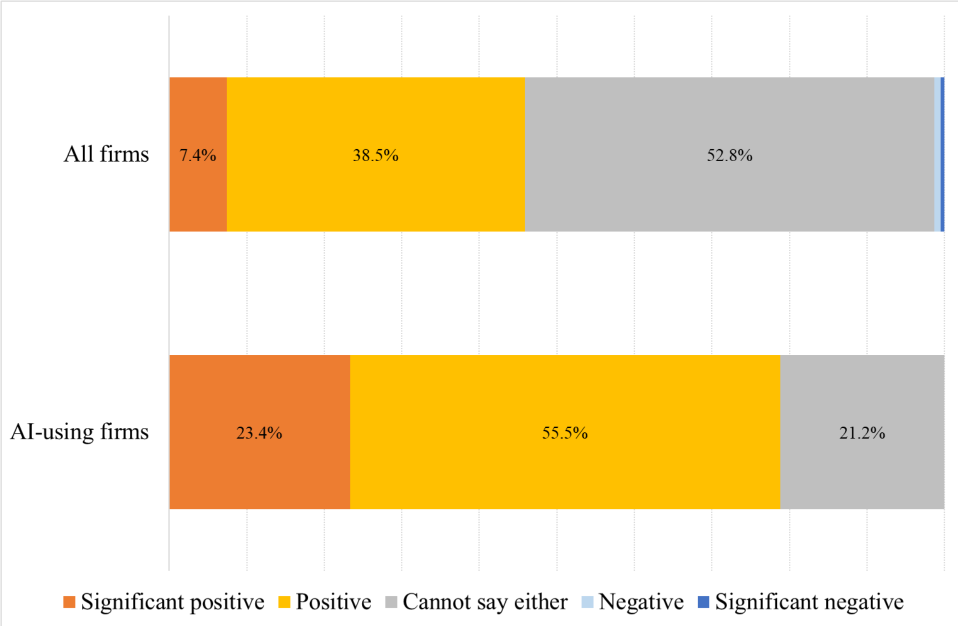

Figure 2. Long-term impact of AI on employment.

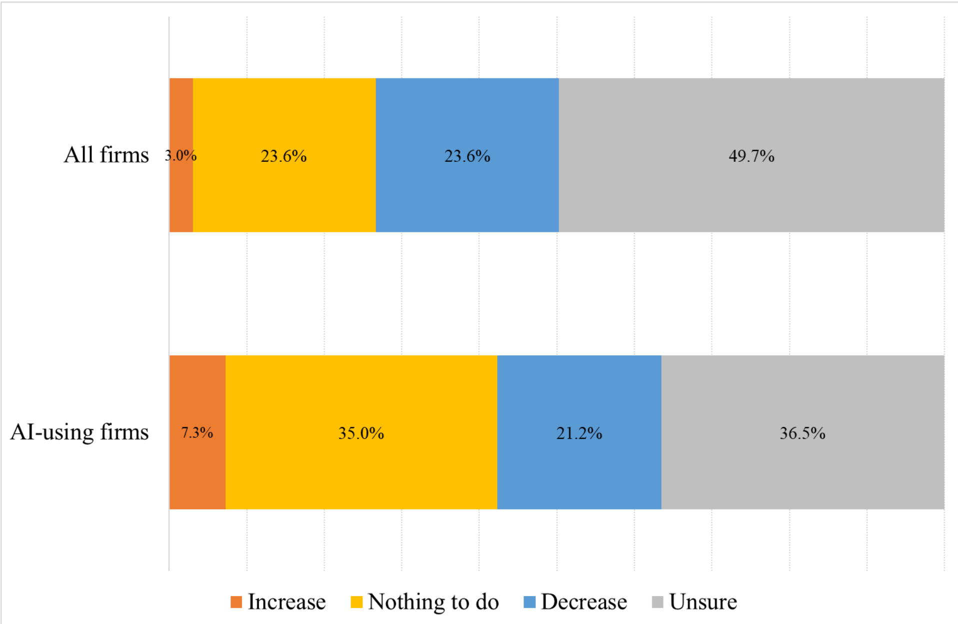

Figure 3. Long-term impact of AI on the employees' wages.