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Heterogeneous Relationships between Automation Technologies and Skilled Labor: Evidence from a Firm Survey*

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Abstract

Based on an original survey of Japanese firms, this study presents evidence of the use of recent automation technologies—artificial intelligence (AI), big data analytics, and robotics—and discusses the relationship between these technologies and skilled employees at the firm-level. The result indicates that while the number of firms already using these technologies is small, the number of firms interested in using them is large. The use of AI and big data is positively associated with the share of highly educated employees, particularly those with a postgraduate degree; however, such a relationship is absent in the case of the use of industrial robots in the manufacturing industry. Studies have not distinguished between robotics and other automation technologies, such as AI, but the result suggests a heterogeneous complementarity with high-skilled employees for each type of automation technology.

Keywords: Automation; Artificial intelligence; Big data; Robots; Skill

JEL Classification: O33, J23, J24

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1. Introduction

The economic and social impacts of recent automation technologies, such as artificial intelligence (AI) and robotics, have been attracting the attention of researchers and policymakers. The potential of these technologies to accelerate productivity and economic growth as well as the negative impacts of AI and robotics—the loss of human jobs and the polarization of the labor market—have been actively discussed.[1]

Numerous studies discuss the impacts of information and communications technology (ICT) on the labor market. These studies conclude that ICT has replaced middle- and low-skilled routine jobs and that computerization has led to job polarization and rising wage inequality (e.g., Autor *et al*., 2003, 2006; Goos and Manning, 2007; Van Reenen, 2011; Goos *et al*., 2014; Burstein *et al*., 2019). However, studies on the labor market impact of AI and robotics are at an infant stage. Although the development of theoretical models has been advancing rapidly (e.g., Acemoglu and Restrepo, 2018, 2019; Aghion *et al*., 2019), empirical studies are far lagging owing to the lack of adequate data on the adoption and diffusion of recent automation technologies.

Among the automation technologies, industrial robots are an exception. Several studies have explored the impacts of robots on employment using industry-level robot shipment data compiled by the International Federation of Robotics (IFR) (e.g., Dauth *et al*., 2017; Graetz and Michaels, 2018; Borjas and Freeman, 2019; Acemoglu and Restrepo, 2019; Kromann *et al*., 2019; Destefano *et al*., 2019; Adachi *et al*., 2019). Although the results on the impact on aggregate employment are not uniform across studies, these studies reveal the negative impact on low- and middle-skilled workers.

However, an important limitation of these studies is the lack of firm- or establishment-level

[1] Some studies estimate the future risk of the loss of human jobs by computerization, from the viewpoint of technological substitutability (e.g., Frey and Osborne, 2017; David, 2017; Arntz *et al*., 2017).

microdata on the use of robots. Raj and Seamans (2019) stress the necessity of firm-level data in a survey on empirical findings on the adoption of robotics and AI and its impacts on productivity and the labor market. To address data unavailability, the U.S. Census Bureau started a survey on the use of robotics in the U.S. manufacturing establishments in 2018 (Buffington *et al*., 2018) as well as an annual business survey to collect rich information on the use of various production technologies, including AI, cloud-based computing systems, and robotics, for the production of goods or services.[2] Since 2015, in China, a group of researchers have been collecting information on the adoption of industrial robots by Chinese manufacturers (Cheng *et al*, 2019), which indicates that the manual task intensity is positively associated with the adoption of robots at the firm-level. However, still there are limited empirical studies on the impacts of robots using firm-level data. Furthermore, a firm-level study on the substitutability or complementarity of automation technologies, other than industrial robots, such as machine learning and big data analytics, with human workers is almost nonexistent.

An exception is Morikawa (2017); it uses data from a survey of about 3,000 Japanese firms conducted in 2015 and presents suggestive evidence that the adoption of recent automation technologies is positively associated with the skill level of the firms' employees. However, his study does not explicitly distinguish among AI, big data analytics, and robotics. Accordingly, this study fails to explore the heterogeneity among automation technologies. The rapid development and diffusion of various automation technologies highlight the need for updating studies. Brynjolfsson and McElheran (2016) is another example of such studies. They document the diffusion of data-driven decision-making (DDD) in the United States and the factors influencing its adoption, by using data from the Management and Organizational Practices Survey conducted by the U.S. Census Bureau. They show that a majority of educated workers adopt DDD, and hence establish a correlation between education and DDD adoption. However, the coverage of their study is limited to DDD.

Against the background, using an originally designed survey conducted in 2019, this study contributes to the literature by presenting new findings on the use of automation technologies in Japanese firms and its relationship with the skill composition of firms' workforce. It also allows

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[2] For more information, see https://www.census.gov/programs-surveys/abs.html.

a distinction among AI, big data analytics, and robotics.

In summary, although the number of firms already adopting these technologies is small, a large number of firms intend to use AI and big data analytics for their businesses. Importantly, we observe a strong positive relationship between the use of AI and big data and the skill level of firm employees, but such positive association is absent in the case of the use of industrial robots in the manufacturing industry. In other words, the empirical results on the possible impacts of automation technologies on employment obtained from industrial robots cannot necessarily be generalized to AI and big data analytics.

The remainder of this paper is structured as follows. Section 2 explains the firm survey used in this study. Section 3 reports results on the use of recent automation technologies and the relationship of these technologies with skilled employees. Section 4 summarizes the study's conclusions and implications.

2. Survey Design

This study's data originated from the Survey of Corporate Management and Economic Policy (SCMEP) designed by the author and conducted by the Research Institute of Economy, Trade and Industry in 2019. The survey questionnaire was mailed to 15,000 Japanese firms operating in both manufacturing and service industries between January and February 2019. The firms were randomly sampled from about 30,000 firms registered in the Basic Survey of Japanese Business Structure and Activities (BSJBSA) conducted by the Ministry of Economy, Trade and Industry since 2017.[3] The BSJBSA is a representative official firm survey in Japan that accumulates annual statistics for all Japanese firms with 50 or more regular employees engaged in mining, manufacturing, electricity and gas, wholesale, retail, and several service industries. The SCEMP collected responses from 2,535 firms (response rate of 16.9%), with 52.7%, 5.4%, 18.0%, 10.6%, 9.3%, and 3.3% firms engaged in manufacturing, ICT, wholesale, retail, services, other industries, respectively. [4]

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[3] Firms classified in mining and utilities industries are excluded in the SCMEP.
[4] A small number of respondent firms (0.7%) does not report the industry classification.

The specific multiple-choice question on the use of automation technologies is “What does your firm think about AI, big data, and robots?” The four possible answer choices are as follows: 1) “already using for business,” 2) “intend to use in the future business,” 3) “not related to our business,” and 4) “unsure.” The question is asked separately for the use of AI, big data, and robots.

The SCMEP asked about various firm characteristics, including industry classification (one digit), firm size (total number of regular employees), and the composition of the employees—gender, age, education, and employment type as shares to the total number of regular employees. Among these individual characteristics, the study categorized age into 10-year intervals—1) 20–29, 2) 30–39, 3) 40–49, 4) 50–59, and 5) 60 or older—and surveyed the percentages of employees in each category. Regarding educational attainment, it surveyed the percentages of 1) employees with a 4-year college/university degree or higher and 2) those with a postgraduate degree. We calculated the percentage of undergraduate employees by subtracting the percentage of postgraduate employees from those with a university degree or higher. The number of regular employees was categorized into standard and non-standard employees.[5]

Using this dataset, first we tabulated the use of automation technologies by industry. Subsequently, we make cross-tabulations to observe the relationship between the use of automation technologies and the percentages of regular employees with higher education. Finally, we conducted ordered probit estimations to explain the use of automation technologies by firm characteristics. In the ordered probit estimations, firms that chose the response “unsure” were removed from the sample. The dependent variable denotes the use of each automation technology: “already using for business” = 3, “intend to use in future business” = 2, and “not related to our business” = 1. Accordingly, positive coefficients imply that the characteristics are associated with a positive response on the use of automation technologies. Explanatory variables comprise firm size (log number of employees); one-digit industry dummies; the shares of employees with undergraduate and postgraduate education; and the ratios of young employees (age 39 or younger), female employees, and non-standard employees. Summary statistics of the explanatory variables are presented in **Table 1**.

We aim to determine the education level of the employees through this regression. The positive

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[5] Non-standard employees include part-time employees, temporary employees, and contract employees.

coefficient of higher education can be interpreted as a suggestive evidence of complementarity between the use of automation technologies and the high cognitive skills of employees.

3. Results

Table 2 presents the tabulation result of the adoption of automation technologies. The percentages of firms already using AI and big data for their businesses are small (3.1% and 3.3%, respectively), but a relatively large number of firms exhibit an intention to use AI and big data in their future business (43.2% and 34.7%, respectively). However, the use of robots is already prevalent among a large number (16.3%) of the respondents. Concerning robotic use, about half of the respondent firms chose the response "already using for business" or "intend to use in the future business."

By industry, the ICT industry receives the highest number of positive responses concerning the use of AI and big data—more than 10% of the firms in this industry already use AI and big data, and more than half of the firms intend to use them in the future business. However, the positive responses are also prevalent among firms in wholesale, retail, and service industries. For example, about 5% of the wholesale and retail firms already use big data for their businesses. However, the diffusion of robots stands out in the manufacturing industry—26.2% of the manufacturing firms already use robots. This result is in line with expectations because industrial robots have been used for a long time by Japanese manufacturers. However, it is interesting to find that non-negligible percentages of non-manufacturing firms (26.7%, see column (3) of the table) are interested in using robots in their future business. The result suggests that firms in the service sector have a strong desire to adopt service robots or multi-purpose robots to tackle the serious labor shortage.

Table 3 presents the cross-tabulation result on the relationship between the use of the three types of automation technologies and the percentages of employees with higher education. The percentages are the ratios of undergraduate (column (1)) and postgraduate employees (column (2)). The statistical significance levels in this table indicate t-test results relative to firms' response as "not related to our business." Concerning AI and big data, the percentages of highly educated employees are the highest in firms already using these technologies, followed by firms that intend to use them in the future business (rows A and B of the table). The differences among firms choosing the response “not related to our business” are statistically significant at the 1% level. [6]

Interestingly, the association between the use of robots and the education of employees is significantly different (row C of the table). The percentage of employees with undergraduate education is the lowest in firms already using robots, followed by those intending to use them in the future business, and it is the highest in firms that do not plan to use them in their business. When focusing on the ratio of employees with postgraduate education, firms using robots and those intending to use robots exhibit slightly higher percentages than firms without an intention to use robots. However, as reported later, the differences are statistically insignificant after accounting for the other firm characteristics.

From the viewpoint of complementarity with cognitive skills measured as educational attainments, this result suggests that automation technologies, such as AI and big data analytics, used for prediction and white-collar tasks are very different from robots used in manufacturing. Although these technologies are often categorized under one heading of automation technologies, we should be careful about the difference when considering their impacts on the labor market.

However, even among robots, service robots or general-purpose robots expected to be adopted in the service industries may characteristically differ from industrial robots prevalent in the manufacturing industry. In considering this possibility, we divide the sample into manufacturing and non-manufacturing firms (rows C-1 and C-2 of **Table 3**). The relationship between the use of robots and education level is very different by industry. The relationship in non-manufacturing industry is similar to that existing for the use of AI and big data. However, industrial robots used in the manufacturing industry are not positively associated with undergraduate employees.

Table 4 presents the ordered probit estimation results to explain the use of automation technologies.[7] The coefficients of higher education—the main interest of this study—are positive

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[6] The positive association between the use of big data and education is consistent with the result reported in Morikawa (2017).

[7] We also conduct simple probit estimations where the dependent variable denotes whether the firm is already using automation technologies or not. The results are reported in **Appendix Table A1**. Since the number of firms using AI and big data is small, the explanatory power drops substantially, but the results are qualitatively consistent with the ordered probit estimations reported in **Table 4**.

and highly significant in firms using AI and big data (columns (1) and (2)). It is obvious that firms with a large share of highly educated employees use (or intend to use) AI and big data.[8] It should be noted that the coefficient of postgraduate education is much larger than that of undergraduate education, suggesting the relatively high threshold of complementary skills required for adopting AI and big data. Although AI and big data analytics are different technologies, they often have mutually reinforcing role in business applications. Therefore, the similar results for AI and big data is unsurprising. The result suggests that complementary investments in human capital is needed in order to realize the benefits from the development of AI and big data analytics.

Conversely, in the case of robots, the estimated coefficients of undergraduate and postgraduate education are small and statistically insignificant (column (3)). We run the same estimations by splitting the firms into manufacturing and non-manufacturing subsamples. In the subsample of manufacturing firms, the coefficient of undergraduate is negative and significant at the 1% level, while the coefficient of postgraduate is positive and insignificant (column (3-A)). However, in the non-manufacturing subsample, the coefficient for postgraduate education is positive and statistically significant at the 5% level (column (3-B)). This result confirms the finding reported in **Table 3** that industrial robots used in the manufacturing industry and service robots have different relationships with the cognitive skill of the employees.

To summarize, our findings from the SCMEP have a similar implication with those of Agrawal *et al*. (2019), which states that "we caution on drawing broad inferences from the research on factory automation in forecasting the net near-term consequences of artificial intelligence for labor markets."

The coefficients of the ratio of younger employees are positive and highly significant for all technologies; it implies that firms with a large share of young employees exhibit a positive attitude while adopting recent automation technologies. This result suggests a possibility that the development and diffusion of automation technologies may lead to the replacement of senior or elderly workers. The coefficients of female ratio are negative for all technologies, but the statistical significance is weak. The coefficients for the ratio of non-standard employees are small and insignificant for all the automation technologies examined in this study. The coefficients for

[8] The size of the coefficients of education for the use of big data is similar to those reported in Morikawa (2017), which employs 2015 survey data for examining the use of big data.

firm size are positive and significant at the 1% level for all the technologies. In other words, larger firms exhibit a more positive attitude when adopting automation technologies, which implies economies of scale through the use of recent automation technologies.

4. Conclusion

Using data from an original survey of Japanese firms, this study presents new findings on the adoption of AI, big data, and robots as well as discusses the relationships between these automation technologies and the skill composition of employees.

The results can be summarized as follows. First, although the number of firms already adopting AI and big data analytics are very small, a large number of firms exhibit an intention to use these technologies in their businesses. Larger firm and firms in the ICT industry exhibit a positive attitude when adopting these automation technologies. Second, firms' use of AI and big data is significantly associated with the education level of their employees, but such positive association is absent in the case of the use of industrial robots in the manufacturing industry. In other words, we should be cautious about generalizing the results of studies on the impacts of industrial robots on employment to other automation technologies including AI.

Although this study contributes to the literature by presenting novel findings on the heterogeneous relationship between various automation technologies and firm characteristics, particularly skill composition of the workforce, the survey data used in this study do not contain information about the quantity or monetary value of the automation technologies. Hence, the reported findings are based solely on qualitative information on the use of automation technologies. Furthermore, the cross-sectional relationships presented in this study cannot be interpreted as causality in an econometric sense. In order to conduct rigorous econometric analysis on the impacts of AI and big data analytics, it would be crucial to develop a method to collect quantitative data. Additionally, it would be important for the government statistical agencies to conduct periodical surveys in order to construct rich panel data.

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Table 1.

Variables and Summary Statistics.

	Mean	Std. Dev.	Min.	Max.	Obs.
Undergraduate	0.3085	0.2415	0.0000	1.0000	2,121
Postgraduate	0.0248	0.0585	0.0000	0.8200	2,139
Young	0.4064	0.1545	0.0000	1.0000	2,229
Female	0.3066	0.2010	0.0000	0.9821	2,460
Non-standard	0.2427	0.2436	0.0000	1.0000	2,406
Firm size (log employees)	5.0605	0.9703	0.6931	10.7251	2,460

Notes: With an exception of firm size, the figures present the share to total regular employees. “Young” is the share of employees below the age of 40 years.

Table 2.

Use and Intention to Use Automation Technologies.

	(1) All	(2) Manufacturing	(3) Non-manufacturing	(3-A) ICT	(3-B) Wholesale	(3-C) Retail	(3-D) Service
A. AI							
1) Using for business	3.1%	2.3%	4.0%	11.9%	2.7%	2.3%	3.9%
2) Intend to use in future business	43.2%	46.1%	39.9%	57.5%	38.5%	34.3%	37.1%
3) Not related to our business	23.7%	21.6%	26.2%	11.2%	27.0%	28.3%	31.5%
4) Unsure	30.0%	30.1%	29.9%	19.4%	31.9%	35.1%	27.6%
B. Big data							
1) Using for business	3.3%	2.0%	4.7%	12.6%	2.4%	4.9%	5.6%
2) Intend to use in future business	34.7%	33.0%	36.7%	50.4%	33.1%	38.3%	33.5%
3) Not related to our business	26.0%	27.6%	24.2%	17.0%	26.5%	18.4%	28.3%
4) Unsure	36.0%	37.4%	34.4%	20.0%	38.0%	38.3%	32.6%
C. Robot							
1) Using for business	16.3%	26.2%	5.0%	6.7%	6.2%	1.9%	3.9%
2) Intend to use in future business	33.5%	39.4%	26.7%	38.5%	26.7%	18.1%	29.3%
3) Not related to our business	23.6%	13.7%	34.9%	31.1%	35.1%	35.8%	35.3%
4) Unsure	26.7%	20.8%	33.4%	23.7%	32.0%	44.2%	31.5%

Note: Non-manufacturing industry (column (3)) includes “other industries.”

Table 3.

Use of Automation Technologies and Education of Employees.

		(1) Undergraduate	(2) Postgraduate
A. AI	1) Using for business	46.6% ***	5.5% ***
	2) Intend to use in future business	33.3% ***	3.5% ***
	3) Not related to our business	28.0%	1.3%
B. Big data	1) Using for business	39.8% ***	7.1% ***
	2) Intend to use in future business	35.0% ***	3.2% ***
	3) Not related to our business	28.2%	1.9%
C. Robot	1) Using for business	25.0% ***	3.1% ***
	2) Intend to use in future business	30.8% ***	3.2% ***
	3) Not related to our business	35.2%	1.7%
C-1. Robot Manufacturing	1) Using for business	20.8% **	3.0% **
	2) Intend to use in future business	23.6%	3.4% ***
	3) Not related to our business	24.5%	1.8%
C-2. Robot Non-manufacturing	1) Using for business	53.6% ***	3.6% **
	2) Intend to use in future business	44.1% *	3.0% ***
	3) Not related to our business	40.2%	1.6%

Notes: The statistical significance levels indicate t-test results relative to firms' response as "not related to our business." ***: $p<0.01$, **: $p<0.05$, and *: $p<0.1$.

Table 4.

Use of Automation Technologies and Firm Characteristics (Ordered Probit Estimations).

	(1) AI		(2) Big data		(3) Robot		(3-A) Robot Manufacturing		(3-B) Robot Non-manufacturing	
Undergraduate	0.7584	***	0.5085	***	-0.2308		-0.7126	***	0.2021	
	(0.1641)		(0.1657)		(0.1520)		(0.2370)		(0.1994)	
Postgraduate	2.2014	***	2.0687	**	0.4907		-0.5020		2.1238	**
	(0.4748)		(0.6867)		(0.5570)		(0.7144)		(0.8300)	
Young	0.6951	***	0.6427	***	0.9635	***	1.0307	***	0.7117	**
	(0.2347)		(0.2328)		(0.2140)		(0.3024)		(0.3040)	
Female	-0.1734		-0.1134		-0.3358	*	-0.5491	**	-0.2036	
	(0.2198)		(0.2126)		(0.1964)		(0.2577)		(0.3058)	
Non-standard	0.1913		-0.0578		-0.0325		-0.1178		0.2196	
	(0.2168)		(0.1917)		(0.1708)		(0.2375)		(0.2513)	
ln(employment)	0.3071	***	0.3509	***	0.3220	***	0.3938	***	0.2386	***
	(0.0416)		(0.0399)		(0.0376)		(0.0552)		(0.0555)	
Industry dummies	yes		yes		yes		no		yes	
Nobs.	1,400		1,277		1,496		882		614	
Pseudo R^2	0.0911		0.0843		0.1341		0.0586		0.0487	

Notes: Results of the ordered probit estimation with robust standard errors in parentheses. ***: p<0.01, **: p<0.05, and *: p<0.1. Firms that chose the response "unsure" were removed from the sample.

Appendix Table A1.

Use of Automation Technologies and Firm Characteristics (Probit Estimations).

	(1) AI	(2) Big data	(3) Robot	(3-A) Robot Manufacturing	(3-B) Robot Non-manufacturing
Undergraduate	0.0625 ***	0.0082	-0.0722	-0.2851 ***	0.0404
	(0.0163)	(0.0226)	(0.0505)	(0.0995)	(0.0325)
Postgraduate	0.0631	0.1844 ***	-0.1609	-0.4811	0.1681
	(0.0440)	(0.0543)	(0.1987)	(0.3299)	(0.1354)
Young	0.0251	0.0232 ***	0.2970 ***	0.3908 ***	0.0909 **
	(0.0247)	(0.0310)	(0.0696)	(0.1235)	(0.0475)
Female	-0.0291	-0.0153	-0.1098 *	-0.3120 ***	0.0662
	(0.0276)	(0.0295)	(0.0654)	(0.1040)	(0.0531)
Non-standard	0.0170	-0.0158	-0.0678	-0.0091	-0.0967 *
	(0.0269)	(0.0281)	(0.0573)	(0.0929)	(0.0494)
ln(employment)	0.0167 ***	0.0225 ***	0.0803 ***	0.1320 ***	0.0244 ***
	(0.0044)	(0.0046)	(0.0121)	(0.0220)	(0.0091)
Industry dummies	yes	yes	yes	no	yes
Nobs.	1,414	1,289	1,507	887	620
Pseudo R^2	0.1281	0.1374	0.1523	0.0726	0.0807

Notes: Marginal effects from probit estimations. Robust standard errors are reported in parentheses. ***: p<0.01, **: p<0.05, and *: p<0.1. Firms that chose the response “unsure” were removed from the sample.