RIETI Discussion Paper Series 17-E-069

Who Are Afraid of Losing Their Jobs to Artificial Intelligence and Robots? Evidence from a survey

MORIKAWA Masayuki
RIETI

RIETI
Research Institute of Economy, Trade & Industry, IAA
The Research Institute of Economy, Trade and Industry
http://www.rieti.go.jp/en/

RIETI Discussion Paper Series 17-E-069
May 2017

Who Are Afraid of Losing Their Jobs to Artificial Intelligence and Robots? Evidence from a survey*

MORIKAWA Masayuki (RIETI)

Abstract

This study, using original survey data of 10,000 individuals, analyzes the possible impacts of artificial intelligence (AI) and robotics on employment. The first interest of this study is to ascertain, from the viewpoint of workers, what types of worker characteristics are associated with the perception of risk of jobs being replaced by the development of AI and robotics. The second interest is to identify, from the viewpoint of consumers, what types of services are likely to be replaced by AI and robotics. The results suggest that malleable/adaptable high skills acquired through higher education, particularly in science and engineering, are complementary with new technologies such as AI and robotics. At the same time, occupation-specific skills acquired by attending professional schools or holding occupational licenses, particularly those related to human-intensive services, are less likely to be replaced by AI and robotics.

Keywords: Artificial intelligence, Robotics, Skill, Household production
JEL Classification：J24, O33, D12

* I would like to thank Yoshiyuki Arata, Kenta Ikeuchi, Seiichiro Inoue, Arata Ito, Yoko Konishi, Atsushi Nakajima, Takanori Okuda, Ryohei Yoshida, Hiroyuki Yoshiya, and the seminar participants at RIETI for their helpful comments and suggestions. I take responsibility for any errors. This research is supported by the JSPS Grants-in-Aid for Scientific Research (26285063, 16H06322).

Who Are Afraid of Losing Their Jobs to Artificial Intelligence and Robots? Evidence from a Survey

1. Introduction

This study, using data from an original survey on individuals, presents new evidence on the possible impacts of artificial intelligence (AI) and robotics on employment. Major interests of this study are what type of individuals are concerned about losing their jobs, and what type of jobs are likely to be replaced by the development and diffusion of AI and robotics.

Amid conditions of stagnant productivity and potential growth rates in major advanced economies, policy makers expect the "Fourth Industrial Revolution" such as AI and robotics to drive the future economic growth. On the other hand, negative impacts of AI and robotics, especially loss of human jobs, have been actively discussed (Brynjolfsson and McAfee, 2011, 2016; Frey and Osborne, 2017). This issue is a natural extension of a large number of studies on the substitution between information technology (IT) and labor (e.g., Krueger, 1993; Doms *et al.*, 1997; Autor *et al.*, 1998; Bresnahan *et al.*, 2002; Autor *et al.*, 2006, 2008; Goos and Manning, 2007; Van Reenen, 2011; Goos *et al.*, 2014). An estimated result by Frey and Osborne (2017), which states that about 47% of total US employment faces the risk of being computerized, attracted attention from the researchers and policy makers around the world. David (2017) applies a similar methodology to Japan to estimate that 55% of employment is susceptible to be replaced by computers.

On the other hand, Arntz *et al*. (2016), based on a task-based approach, estimate that the share of automatable jobs in the 21 OECD countries is only 9%, which is far smaller than the figure derived from the occupation-based approach employed by Frey and Osborne (2017). The point of their study is that some of the tasks contained in high-risk occupations cannot be easily computerized. In addition, computers and robots may create new products and services, and these product innovations will result in unimaginable new occupations (Mokyr *et al*., 2015). Furthermore, new automation technologies and some types of labor are highly complementary (Autor, 2015).

In spite of widespread interest regarding the impact of AI and robotics on the labor market, studies in economics are still in the initial stages and quantitative empirical studies have been very limited.[1] A major reason for this delay is the lack of statistical data on AI and robotics, as the

[1] Rare examples include an international comparison of AI-related patent applications (Lechevalier *et al*., 2014) and a cross-country empirical study on the impacts of industrial robots on productivity (Graetz and Michaels, 2015).

technologies are in the phase of development and early diffusion. A possible approach to overcome the unavailability of statistical data is to conduct surveys on firms or individuals to collect subjective assessment of the impacts of these new technologies. A recent example of this line of study is Morikawa (2017), who conducts a survey for a large number of Japanese firms to analyze the possible impact of AI and robotics on employment. The study detects technology-skill complementarity at the firm level. In particular, the complementarity with AI-related technologies is more prominent for employees with postgraduate education. However, the individual characteristics used in the analysis are aggregated data at the firm level.

The analysis of this study is based on an original survey on individuals, which is different from the firm-level study of Morikawa (2017). Specifically, this study analyzes the relationship between various individual characteristics (such as age, educational attainment, and occupation) and their perception about the impact of AI and robotics on their own employment prospect. The main hypothesis of this study is that the highly skilled individuals tend to perceive the impact of AI and robotics positively, and vice versa. Regarding the individual skills, we distinguish malleable/adaptable general skills formed through higher education (university and postgraduate school) and occupation-specific skills acquired from vocational schooling or embodied as holding occupational licenses.[2]

In addition, this study assesses the substitutability of human jobs by AI and robots from the viewpoint of user/consumer of personal services. Amid the trend of population aging in major advanced countries including Japan, diffusion of labor-saving AI-related technologies to improve productivity of labor-intensive personal services such as health, elderly, and nursery care is highly expected. However, the degree of mechanization of personal services depends not only on the supply-side factors such as technological progress and cost reduction but also on the acceptability of the service robots by consumers. If consumers' preference for services provided by human work is strong, personal service jobs are hard to be replaced by low-cost service robots equipped with AI-related technologies.

The results of this study suggest that malleable general skills acquired through higher education, particularly in science and engineering, are complementary with new technologies such as AI and robotics. At the same time, occupation-specific skills acquired by completing professional schools or holding occupational licenses are perceived to be less likely to be replaced by AI and robots. Analysis of consumers' preference indicates that human-intensive services such as child care, health care, and education are difficult to be substituted by robots.

The remainder of this paper is organized as follows. Section 2 explains the survey data used in

[2] Literature on vocational education suggests a trade-off between short-term benefit of school-to-work transition and long-term cost of adaptability to new technologies (Krueger and Kumar, 2004; Brunello and Rocco, 2017; Hanushek *et al*., 2017).

this study and the method of analysis. Section 3 reports the results of the analysis from the survey data, and Section 4 summarizes the study's conclusions and discusses the policy implications.

2. Survey Design and Method of Analysis

The data used in this study originate from the "Survey of Life and Consumption Under the Changing Economic Structure and Policies" designed by the author of this study and conducted by the Rakuten Research, Inc., contracted out by the Research Institute of Economy, Trade and Industry (RIETI) in 2016. The number of sample individuals is just 10,000, randomly chosen from the 2.3 million registered monitors in Rakuten Research, Inc., stratified by gender, age, and region (prefecture) in accordance with the Population Estimates in 2014 (Statistics Bureau, Ministry of Internal Affairs and Communications). The distribution of the sample by individual characteristics (gender, age categories, education, and working status) is shown in **Table 1**.

The questionnaires of the survey are wide-ranging, but this study uses responses to the questionnaire regarding the impact of AI and robotics and data on individual characteristics, including gender, age, education, and annual income of the households. Specific wordings of the multiple-choice questions and the choices are as follows. The question on the impact on employment is "what do you think about the impact of AI and robotics on the future of your job?" The choices are 1) "I might lose my job," 2) "I don't think I will lose my job," and 3) "I don't know."

There are two questions from the viewpoint of potential consumer of services using AI and robots. The first question is "which housework listed below is desirable to be conducted by AI and robots?" The specific house jobs listed are "general housework (cooking, cleaning, washing, etc.)," "child rearing," "elderly care and sick care," and "shopping." The second question is "which services listed below are necessary to be provided by human workers rather than robots?" The specific personal services listed are "child care services," "elderly and sick care services," "medical care (diagnosis and treatment)," "haircutting and beauty salon services," "education," and "vehicle driving services." For these two questions, respondents are asked to choose all house jobs/services he/she thinks as desirable/necessary, and there is a provision to select the choice "nothing."

The method of analysis is basically a simple totaling and cross-tabulation by individual characteristics. When necessary, probit and ordered-probit estimations will be applied to control for the influence of other characteristics. The individual characteristics considered are gender, age, and education for all respondents, and industry, type of employment, and occupation are included in the estimation for the subsample of those who are working. In some estimations, "marital status," “whether or not having children,” and “whether or not having family member needing elderly care” are included as explanatory variables.

Among these individual characteristics, age is categorized into 10-year intervals: 1) 20–29, 2) 30–39, 3) 40–49, 4) 50–59, and 5) 60 or older. Educational attainment is grouped into six classes: 1) primary school or junior high school, 2) senior high school, 3) vocational school, 4) junior (2-year) college, 5) (4-year) college or university, and 6) graduate school.[3] In addition, the major field of study for those who graduated from university or higher is classified into 1) natural science, 2) social science and humanities, and 3) other fields. For those who are working, the term “industry” is further categorized into 14 industries.[4] Type of employment is grouped into nine categories: executive of company, self-employed, family-worker, regular employee, part-time employee, temporary employee, temporary agency worker, contract employee, and entrusted employee. Occupation is grouped into seven categories: administrative and managerial, professional and engineering, sales, clerical, manufacturing process, service, and other.

In the regression analysis, age 30–39, senior high school, manufacturing industry, clerical worker, and regular employee are used as the reference categories. Regarding the major field of study, a dummy for natural science is used.

3. Results

3-1. Impact of AI and Robotics on Employment

The response to the question on the impact of AI and robotics on employment is summarized in **Table 2-A**. Aggregated percentage figure and cross-tabulation results by gender and education are reported in this table. In this calculation, the denominator is the number of those who are working (N=6,579). The percentages of respondents choosing “I might lose my job,” “I don’t think I will lose my job,” and “I don’t know” are 29.9%, 38.8%, and 31.3%, respectively. While a relatively large number of respondents do not fear about losing jobs, about 30% people perceive the risk of their jobs being replaced by AI and robotics. By gender, a male worker is somewhat optimistic relative to female workers. By education, workers with postgraduate education are least

---

[3] In the survey, graduate school is separated into masters and doctoral degrees. However, as the number of those who graduated from doctoral course is small, these two categories are combined as “graduate school.”

[4] The industries are 1) agriculture, forestry, and fishery, 2) construction, 3) manufacturing, 4) information and communications, 5) transport, 6) wholesale and retail, 7) finance and insurance, 8) real estate, 9) accommodations, eating and drinking services, 10) medical, health care, and welfare, 11) education, 12) services not elsewhere classified, 13) government, and 14) other industries.

pessimistic about the prospect of their job, followed by university graduates and those who graduated from vocational school.

The cross-tabulation result by age classes is shown in **Table 2-B**. It is obvious that younger generations tend to perceive a risk of losing jobs. It is a natural result as the development and diffusion of AI and robotics will be advancing gradually.

However, these cross-tabulation results do not account for the confounding effects of the other individual characteristics. We run ordered-probit estimation to explain risk perception by the dummies for various individual characteristics, including gender, age, and education. The estimation is conducted only for those who are working (N=6,579). The discrete dependent variable is defined as "I don't think I will lose my job" =3, "I don't know"=2, and "I might lose my job"=1. Thus, the positive coefficients mean optimistic perception about the prospect of job relative to the reference categories. The reference categories are male, age 40–49, and senior high school. We include a dummy for natural science major for those who graduated from university or graduate school, because even among highly educated individuals, natural science graduates may have different skills.[5] In addition to this baseline specification, we use a dummy for those who hold occupation licenses, which can be interpreted as a proxy for occupation-specific skills. This dummy is assigned for those who hold occupational licenses and use them for their current jobs.

Furthermore, dummies for industry (14 industries), type of employment (9 types), and occupation (7 occupations), alternatively, are used as additional variables. The reference categories of these additional variables are manufacturing, regular employee, and clerical workers.

The estimation results are presented in **Table 3**. According to the result obtained from baseline specification (column (1)), female and younger employees tend to perceive risk of their jobs to be replaced by AI and robotics. However, while not reported in the table, the coefficient for female dummy loses statistical significance once type of employment or occupation are controlled, which means that the higher subjective perception of losing a job reflects the fact that the share of females is relatively large in non-regular employment and clerical jobs.[6]

The result reconfirms the aforementioned age profile that younger workers tend to exhibit a higher subjective risk, indicating that a large number of current jobs will be lost with the development and diffusion of AI-related technologies. The coefficient for postgraduate education is a large positive figure and highly significant: Those who have postgraduate education are less

---

[5] Recent studies indicate that those who graduated from fields of natural science (STEM workers) make an important contribution to the productivity growth of a country or a region (Winters, 2014; Peri *et al*., 2015).

[6] When including dummies for the type of employment or dummies for occupation as an explanatory variable, the p-values of the coefficient for females are 0.650 and 0.417, respectively.

likely to perceive their jobs to be lost. Although the coefficient for university is insignificant, the coefficient for natural science major is positive and significant as expected. Our interpretation is that those who studied natural science in higher education have better analytical skills, which are less likely to be replaced by the new technologies. Interestingly, the coefficient for vocational school is positive and significant at the 1% level. These people perceive that their occupation-specific skills, which are not necessarily numerical or analytical, cannot be easily substituted by AI and robotics. This result is related to the literature on the trade-off between short-term and long-term costs and benefits of general and vocational education (e.g., Hanushek *et al*., 2017; Brunello and Rocco, 2017) from the viewpoint of the new AI-related technologies.

When adding a dummy for occupational license, the coefficient for this variable is positive and significant at the 5% level (column (2)), indicating that those who hold and use occupational licenses in their current job perceive their risk of losing jobs to be lower.[7] One interpretation is that the holding of occupational licenses reflects high-level occupation-specific skills. Another possibility is that the labor markets of licensed occupations are protected by laws and regulations and the restrictions on new entry leads to monopolistic powers for the incumbents. When we split occupational licenses into 1) certifications (holding of certification represents the skills but conducting the job is anyway legally possible) and 2) monopolistic licenses (holding of licenses is the prerequisite to conduct jobs), both of the estimated coefficients are positive, but only the coefficient for monopolistic license is statistically significant (column (3)). The result supports the second interpretation and suggests that a legal framework of the labor markets may influence the impact of AI and robotics in the future.

The ordered-probit estimation presented above includes the response “I don’t know” as a dependent variable. In order to check the robustness, a simple probit model excluding this category is estimated (the number of observations is 4,725). In this specification, the dependent variable is defined as “I don’t think I will lose my job”=1 and “I might lose my job”=0. The results are presented in **Appendix Table A1**. The sign and statistical significance for most of the explanatory variables are the same as those obtained from the ordered-probit estimations. An exception is that the coefficient for university is positive and significant in the baseline specification (column (1)), although the significance level is 10%. The probit estimation results are generally consistent with the ordered-probit estimation results including the category “I don’t know” as a choice.

The estimation results adding industry, type of employment, and occupation dummies are reported in **Table 4**. As mentioned previously, individual characteristics used as explanatory variables such as gender and age are the same with the baseline specification, but industry (14

---

[7] This dummy is assigned for those who hold occupational licenses and use them for their current jobs.

categories), type of employment (9 categories), or occupation (7 categories) are added alternatively. Column (1) of the table is the result for industry, where the coefficients for agriculture, construction, real estate, accommodations and restaurants, health care, and education are positive and significant at least at the 10% level. In particular, those who are working in health care and education are less concerned with their jobs to be replaced by AI and robotics.

By type of employment, the coefficients for part-time employee, temporary agency workers, and entrusted employee are negative and statistically significant (column (2)). On the other hand, the subjective risk of an executive of a company and self-employed is statistically indistinguishable from that of regular employee. Interestingly, the result of the non-regular employees' higher subjective risk perception is consistent with the results of the study by David (2017) which assesses the risk of job destructions induced by computer technology in Japan from a technical viewpoint.

By occupation (the base category is clerical occupation), the coefficients for administrative and managerial, professional and engineering, and other occupations are positive and significant and those for manufacturing process occupation are negative and significant (column (3)).

The results of a simple probit model excluding the response "I don't know" are presented in **Appendix Table A2**. The results are generally consistent with those obtained from the ordered-probit model.

To summarize, the analysis suggests a complementarity between very high level of schooling, in particular postgraduate education and natural science majors, and AI-related technologies, which is consistent with the results from a firm-level survey (Morikawa, 2017) and past studies on the technology-skill complementarity. However, a notable finding from this study is that not only widely applicable malleable skills formed through higher education but also job-specific skills represented by graduation from vocational school and holding of occupational license are related to the perception of job security. As described in the next subsection, consumers' preference for services provided by human workers is strong in currently human-intensive services such as child care, health care, and education. Those who are working in these jobs may recognize the importance of human contact and perceive the risk of substitution to be small.

3-2. Substitutability of Human Works by AI and Robotics: From Users' Viewpoint

In this subsection, we report results of the survey questions from the viewpoint of potential users (consumers) of AI and robots. Our emphasis is on 1) what sort of housework is regarded as desirable to be conducted by AI and robots, and 2) what sort of market services are difficult to be replaced by robots from the viewpoint of consumers of these services. Theoretically, the answers depend on the elasticity of substitution in consumers' preferences, or utility functions.

The percentages of chosen responses to the question "which housework listed below is desirable to be conducted by AI and robots?" are as follows: general housework (cooking, cleaning, washing, etc.) 58.6%, elderly and sick care 47.1%, shopping 28.9%, and child rearing 8.5%. Demand for substitution of daily housework and elderly/sick care is relatively strong, but child rearing is not expected to be replaced by machines.

The results of probit estimations to explain the responses (choose=1 and do not choose=0) by individual characteristics are shown in **Table 5**. The explanatory variables are gender (female dummy), age categories, marriage status, working status, dummies for children—1) senior high school or higher, 2) primary or junior high school, 3) preschool children—, and the existence of family members needing care. The figures reported in the table are the marginal effects.

With an exception of elderly/sick care, the coefficients for females are negative, which means that males are relatively positive for the substitution by AI and robots. The coefficients of age 60 or over for elderly and sick care as well as for general housework are positive and significant. Since the existence of family members needing care is controlled, it can be construed that elderly people themselves have a desire to be cared by robots. On the other hand, those who have family members needing care have a generally negative view on the care to be replaced by robots.

Next, we report results of the question about the six market services necessarily to be provided by human workers rather than robots. The proportion for those who prefer human workers is: child care services 58.9%, medical care 56.3%, education 47.5%, elderly and sick care services 37.9%, haircutting and beauty salon services 29.7%, and vehicle driving services 21.8%. The stronger preferences for human workers in child care, medical care, and education from the consumers' viewpoint are consistent with the result of the previous subsection from the viewpoint of workers that those who are working in industries of medical care and education perceive lower risk of their jobs to be replaced by AI and robotics.

According to Frey and Osborne (2017), analyzing the risk of occupations to be computerized from the pure technical aspect, physicians and surgeons, registered nurses, childcare workers, preschool teachers, and elementary school teachers, and secondary school teachers are low-risk occupations. In contrast, the risks of occupations such as barbers and taxi drivers are ranked very high.[8] The result of this study from consumers' side is consistent with the supply-side analysis of Frey and Osborne (2017).

The results of probit estimation to explain the responses (necessary to be provided by human

[8] According to Frey and Osborne (2017), computerizable probabilities of physicians and surgeons, registered nurses, childcare workers, preschool teachers, elementary school teachers, and secondary school teachers are less than 3%. In contrast, the probabilities of barbers and taxi drivers are higher than 80%.

workers=1) by individual characteristics are shown in **Table 6**. The explanatory variables are the same with **Table 5** and the figures reported in the table are the marginal effects. After accounting for the other individual characteristics, females generally have a preference for human workers with an exception of elderly and sick care services. By age classes, elderly people (50–59 and 60 or over) generally have a preference for human workers; however, the coefficients of these age categories for elderly and sick care are positive but insignificant. Those who have preschool or junior school children have a strong preference for human workers. Working status of the respondents is generally uncorrelated with the preferences for human/robots.

4. Conclusion

This study, using data obtained from an original survey on Japanese individuals, analyzes the possible impacts of the development and diffusion of AI and robotics on employment. The major findings can be summarized as follows.

According to the worker-side analysis, about 30% of workers are afraid of their jobs being replaced by AI and robotics in the future. In particular, the young generation (age in 20s and 30s), non-regular employees, and those working in the clerical and manufacturing process occupations tend to perceive higher subjective risk. In contrast, those who graduated with higher education, particularly in science and engineering, tend to show lower subjective risk of losing their jobs. At the same time, occupation-specific skills acquired by attending professional schools or holding occupational license are perceived to be less likely to be replaced by AI and robotics. Consumer-side analysis suggests that personal services such as child care, medical care, and education are less likely to be replaced by AI and robotics, because consumers have strong preference for these services to be provided by human workers. This result is consistent with the findings from worker-side analysis that those who are working in the health care and education industries evaluate the risk of losing their jobs to be low. The findings suggest that the technology-skill complementarity cannot be analyzed by focusing only on educational attainments.

The results suggest that malleable/adaptable high skills acquired through higher education, particularly in science and engineering, are complementary with new technologies such as AI and robotics. At the same time, occupation-specific skills acquired by attending professional schools or holding occupational license, particularly those related to human-intensive personal services, are not easy to be replaced by AI and robots. From the policy perspective, investments in developing malleable high skills through postgraduate education and personal skills specific to human-intensive services are both important.

However, the analysis of this study depends on a cross-sectional subjective data and the classification of occupations is not finely disaggregated. Along with the development and diffusion of AI and robotics, further research needs to be conducted by gathering objective and more detailed data.

References

Arntz, Melanie, Terry Gregory, and Ulrich Zierahn (2016), "The Risk of Automation for Jobs in OECD Countries: A Comparative Analysis," OECD Social, Employment and Migration Working Paper, No. 189.

Autor, David H. (2015), "Why Are There Still So Many Jobs? The History and Future of Workplace Automation," *Journal of Economic Perspectives*, Vol. 29, No. 3, pp. 3-30.

Autor, David H., Lawrence F. Katz, and Alan B. Krueger (1998), "Computing Inequality: Have Computers Changed the Labor Market?," *Quarterly Journal of Economics*, Vol. 113, No. 4, pp. 1169-1213.

Autor, David H., Lawrence F. Katz, and Melissa S. Kearney (2006), "The Polarization of the U.S. Labor Market," *American Economic Review*, Vol. 96, No. 2, pp. 189-194.

Autor, David H., Lawrence F. Katz, and Melissa S. Kearney (2008), "Trends in U.S. Wage Inequality: Revising the Revisionists," *Review of Economics and Statistics*, Vol. 90, No. 2, pp. 300-323.

Bresnahan, Timothy F., Erik Brynjolfsson, and Lorin M. Hitt (2002), "Information Technology, Workplace Organization, and the Demand for Skilled Labor: Firm-Level Evidence," *Quarterly Journal of Economics*, Vol. 117, No. 1, pp. 339-376.

Brunello, Giorgio and Lorenzo Rocco (2017), "The Labor Market Effects of Academic and Vocational Education over the Life Cycle: Evidence Based on a British Cohort," *Journal of Human Capital*, Vol. 11, No. 1, pp. 106-166.

Brynjolfsson, Erik and Andrew McAfee (2011), *Race Against the Machine: How the Digital Revolution is Accelerating Innovation, Driving Productivity, and Irreversibly Transforming Employment and the Economy*, Digital Frontier Press.

Brynjolfsson, Erik and Andrew McAfee (2016), *The Second Machine Age: Work, Progress, and Prosperity in a Time of Brilliant Technologies*, W.W. Norton & Co Inc.

David, Benjamin (2017), "Computer Technology and Probable Job Destructions in Japan: An Evaluation," *Journal of the Japanese and International Economies*, Vol. 43, March, pp. 77-87.

Doms, Mark, Timothy Dunne, and Kenneth R. Troske (1997), "Workers, Wages, and Technology," *Quarterly Journal of Economics*, Vol. 112, No. 1, pp. 253-290.

Frey, Carl Benedikt and Michael A. Osborne (2017), "The Future of Employment: How Susceptible Are Jobs to Computerisation?," *Technological Forecasting & Social Change*, Vol. 114, January, pp. 254-280.

Goos, Maarten and Alan Manning (2007), "Lousy and Lovely Jobs: The Rising Polarization of Work in Britain," *Review of Economics and Statistics*, Vol. 89, No. 1, pp. 118-133.

Goos, Maarten, Alan Manning, and Anna Salomons (2014), "Explaining Job Polarization: Routine-Biased Technological Change and Offshoring," *American Economic Review*, Vol. 104, No. 8, pp.

2509-2526.

Graetz, Georg and Guy Michaels (2015), "Robots at Work," CEPR Discussion Paper, No. 10477.

Hanushek, Eric A., Guido Schwerdt, Ludger Woessmann, and Lei Zhang (2017), "General Education, Vocational Education, and Labor-Market Outcomes over the Lifecycle," *Journal of Human Resources*, Vol. 52, No. 1, pp. 48-87.

Krueger, Alan B. (1993), "How Computers Have Changed the Wage Structure: Evidence from Microdata, 1984-1989," *Quarterly Journal of Economics*, Vol. 108, No. 1, pp. 33-60.

Krueger, Dirk and Krishna B. Kumar (2004), "Skill-Specific rather than General Education: A Reason for US-Europe Growth Differences?" *Journal of Economic Growth*, Vol. 9, No. 2, pp. 167-207.

Lechevalier, Sébastien, Junichi Nishimura, and Cornelia Storz (2014), "Diversity in Patterns of Industry Evolution: How an Intrapreneurial Regime Contributed to the Emergence of the Service Robot Industry," *Research Policy*, Vol. 43, No. 10, pp. 1716-1729.

Mokyr, Joel, Chris Vickers, and Nicolas L. Ziebarth (2015), "The History of Technological Anxiety and the Future of Economic Growth: Is This Time Different?," *Journal of Economic Perspectives*, Vol. 29, No. 3, pp. 31-50.

Morikawa, Masayuki (2017), "Firms' Expectations about the Impact of AI and Robotics: Evidence from a Survey," *Economic Inquiry*, Vol. 55, No. 2, pp. 1054-1063.

Peri, Giovanni, Keven Shih, and Chad Sparber (2015), "STEM Workers, H-1B Visas, and Productivity in US Cities," *Journal of Labor Economics*, Vol. 33, No. 3, Pt. 2, pp. S225-S255.

Van Reenen, John (2011), "Wage Inequality, Technology and Trade: 21st Century Evidence," *Labor Economics*, Vol. 18, No. 6, pp. 730-741.

Winters, John V. (2014), "STEM Graduates, Human Capital Externalities, and Wages in the U.S.," *Regional Science and Urban Economics*, Vol. 48, September, pp. 190-198.

Table 1

Distribution of respondents' individual characteristics

Individual characteristics		%
Gender	Male	49.3%
	Female	50.7%
Age class	20-29	13.2%
	30-39	16.6%
	40-49	19.6%
	50-59	16.4%
	60 or over	34.1%
Education	Primary school or junior high school	2.4%
	Senior high school	28.3%
	Vocational school	10.5%
	Junior (2-year) college	12.1%
	(4-year) college or university	41.4%
	Graduate school	5.4%
Major	Natural science	36.4%
	Social science and humanities	59.5%
	Other fields	4.2%
Working status	Working	65.8%
	Not working	34.2%

(Notes) The sample size is 10,000. The major fields comprise those who graduated from university and postgraduate school. Working status is based on whether currently earning from market work or not.

Table 2

Impact of AI and robotics on employment

A. By gender and education

	I might lose my job	I don’t think I will lose my job	I don't know
All	29.9%	38.8%	31.3%
Male	29.5%	41.9%	28.5%
Female	30.3%	34.4%	35.2%
Primary school or junior high school	29.6%	31.9%	38.5%
Senior high school	29.7%	33.6%	36.7%
Vocational school	28.8%	39.1%	32.2%
Junior (2-year) college	28.7%	35.4%	35.9%
(4-year) college or university	31.1%	40.2%	28.7%
Graduate school	26.1%	55.2%	18.6%

(Notes) Sample comprises those who are working (N=6,579).

B. By age class

	I might lose my job	I don’t think I will lose my job	I don't know
20-29	41.8%	28.6%	29.5%
30-39	36.3%	29.8%	33.8%
40-49	30.7%	34.1%	35.2%
50-59	23.9%	33.1%	43.0%
60 or over	19.9%	29.8%	50.2%

(Notes) Sample comprises those who are working (N=6,579).

Table 3

Impact of AI and robotics on employment (ordered-probit estimation results)

	(1)		(2)		(3)	
Female	-0.0746	**	-0.0690	**	-0.0688	**
	(0.0300)		(0.0301)		(0.0301)	
20-29	-0.2419	***	-0.2388	***	-0.2392	***
	(0.0462)		(0.0462)		(0.0462)	
30-39	-0.1075	***	-0.1095	***	-0.1101	***
	(0.0420)		(0.0420)		(0.0420)	
50-59	0.2061	***	0.2063	***	0.2053	***
	(0.0422)		(0.0422)		(0.0422)	
60 or over	0.3653	***	0.3664	***	0.3651	***
	(0.0420)		(0.0420)		(0.0420)	
Primary or junior high school	-0.0074		-0.0057		-0.0063	
	(0.1002)		(0.1002)		(0.1002)	
Vocational school	0.1456	***	0.1361	***	0.1338	***
	(0.0498)		(0.0499)		(0.0500)	
Junior college	0.0605		0.0564		0.0553	
	(0.0522)		(0.0523)		(0.0523)	
University	0.0600		0.0584		0.0579	
	(0.0377)		(0.0377)		(0.0377)	
Graduate school	0.3472	***	0.3477	***	0.3465	***
	(0.0694)		(0.0694)		(0.0695)	
Natural science	0.0845	**	0.0770	*	0.0749	*
	(0.0426)		(0.0427)		(0.0428)	
Occupational license			0.0670	**		
			(0.0295)			
Certification					0.0543	
					(0.0406)	
Monopolistic license					0.0822	**
					(0.0351)	

(Note) Ordered-probit estimation results with standard errors in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The reference categories are male, age in 40s, senior high school, majors other than natural science. The sample comprises those who are working (N=6,579).

Table 4

Impact of AI and robotics on employment by industry, type of employment, and occupation (ordered-probit estimation results)

(1) Industry			(2) Type of employment			(3) Occupation		
Agriculture, forestry,	0.3022	**	Executive of	0.0802		Managerial	0.2712	***
and fishery	0.1437		company	0.0619			0.0534	
Construction	0.1219	*	Self-employed	0.0297		Professional and	0.2282	***
	0.0695			0.0500		engineering	0.0414	
Information and	-0.0225		Family-worker	0.1130		Sales	0.0888	
communications	0.0767			0.1080			0.0578	
Transport	-0.0499		Part-time	-0.1956	***	Manufacturing	-0.1000	*
	0.0790		employee	0.0452		process	0.0601	
Wholesale and retail	0.0768		Temporary	-0.0763		Service	0.0398	
	0.0545		employee	0.0619			0.0427	
Finance and insurance	0.0979		Temporary	-0.1879	**	Other	0.1404	*
	0.0769		agency workers	0.0860			0.0794	
Real estate	0.1785		Contract	-0.0416				
	0.0941		employee	0.0622				
Accommodations and	0.1603	*	Entrusted	-0.2913	***			
restaurants	0.0898		employee	0.1036				
Medical, health care,	0.2524	*						
and welfare	0.0580							
Education	0.2224	***						
	0.0675							
Services, NEC	-0.0176	***						
	0.0468							
Government	0.0899							
	0.0655							
Other industries	0.0573							
	0.0769							

(Note) Ordered-probit estimation results with standard errors in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The reference categories are manufacturing, regular employee, and clerical occupation, respectively. All estimations include gender, age, education, and major as explanatory variables. The sample comprises those who are working (N=6,579).

Table 5

Housework desirable to be conducted by AI and robotics AI (probit estimation results)

	(1) General housework		(2) Child care		(3) Elderly and sick care		(4) Shopping	
Female	-0.0129		-0.1837	***	0.0188		-0.1389	***
	(0.0290)		(0.0421)		(0.0289)		(0.0305)	
20-29	0.1476	***	0.3732	***	-0.1166	**	0.3073	***
	(0.0555)		(0.0737)		(0.0554)		(0.0576)	
30-39	0.1156	**	0.2381	***	-0.0532		0.2082	***
	(0.0489)		(0.0674)		(0.0488)		(0.0513)	
50-59	-0.0026		-0.1080		0.0350		0.1390	***
	(0.0495)		(0.0748)		(0.0494)		(0.0529)	
60 or over	0.1283	***	-0.1480	**	0.2226	***	0.0751	
	(0.0463)		(0.0692)		(0.0461)		(0.0497)	
Married	0.1189	***	0.0266		0.0126		0.0046	
	(0.0388)		(0.0553)		(0.0387)		(0.0410)	
Working	0.0852	***	0.0436		-0.0142		0.0804	**
	(0.0328)		(0.0482)		(0.0326)		(0.0347)	
Children, senior	-0.0066		-0.0188		-0.0054		-0.0424	
high school or over	(0.0352)		(0.0547)		(0.0351)		(0.0378)	
Children, primary	0.0308		-0.0697		-0.0416		0.0017	
or junior high	(0.0469)		(0.0668)		(0.0467)		(0.0491)	
Preschool children	0.0803		0.0257		-0.1632	***	0.1473	***
	(0.0498)		(0.0665)		(0.0496)		(0.0510)	
Family member	-0.0047		-0.2746	***	-0.2219	***	0.0339	
needing care	(0.0577)		(0.0761)		(0.0577)		(0.0613)	

(Notes) Probit estimation results indicating marginal effects with standard errors in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Reference categories are male, age in 40s, unmarried, and non-worker. The sample comprises all respondents (N=10,000).

Table 6

Market services essentially provided by human workers rather than robots (probit estimation results)

	(1) Child care services		(2) Elderly and sick care services		(3) Medical care (diagnosis and treatment)		(4) Haircutting and beauty salon services		(5) Education		(6) Vehicle driving services	
Female	0.0711	**	-0.1185	***	0.0110		0.1967	***	0.0789	***	0.1575	***
	(0.0292)		(0.0293)		(0.0290)		(0.0304)		(0.0289)		(0.0322)	
20-29	0.0848		-0.0156		0.0149		0.2013	***	0.1238	**	0.1706	***
	(0.0554)		(0.0559)		(0.0550)		(0.0579)		(0.0553)		(0.0610)	
30-39	0.0570		-0.0767		-0.0317		0.1379	***	0.0441		-0.0280	
	(0.0490)		(0.0495)		(0.0485)		(0.0514)		(0.0488)		(0.0552)	
50-59	0.1531	***	0.0437		0.1751	***	0.1347	***	0.2406	***	0.1390	**
	(0.0497)		(0.0500)		(0.0495)		(0.0525)		(0.0496)		(0.0553)	
60 or over	0.3005	***	0.0313		0.3156	***	0.1313	***	0.3471	***	0.1241	**
	(0.0465)		(0.0468)		(0.0463)		(0.0491)		(0.0463)		(0.0518)	
Married	0.1629	***	0.0612		0.1259	***	-0.0047		0.1068	***	-0.0010	
	(0.0388)		(0.0394)		(0.0387)		(0.0407)		(0.0388)		(0.0431)	
Working	0.0096		0.0564	*	-0.0174		0.0506		0.0160		-0.0119	
	(0.0330)		(0.0331)		(0.0328)		(0.0342)		(0.0326)		(0.0361)	
Children, senior	0.0480		0.0092		0.0646	*	-0.0141		0.0117		-0.0147	
high school or over	(0.0356)		(0.0355)		(0.0355)		(0.0370)		(0.0350)		(0.0389)	
Children, primary	0.1380	***	-0.0282		0.0684		0.0710		0.1446	***	0.1010	*
or junior high	(0.0472)		(0.0471)		(0.0466)		(0.0490)		(0.0465)		(0.0517)	
Preschool children	0.2225	***	0.1679	***	0.0645		-0.0004		0.1446	***	0.0664	
	(0.0500)		(0.0496)		(0.0491)		(0.0516)		(0.0491)		(0.0547)	
Family member	0.0812		-0.0844		0.0107		0.0261		0.0017		-0.0391	
needs care	(0.0577)		(0.0578)		(0.0579)		(0.0607)		(0.0574)		(0.0632)	

(Notes) Probit estimation results indicating marginal effects with standard errors in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Reference categories are male, age in 40s, unmarried, and non-worker. The sample comprises all respondents (N=10,000).

Appendix Table A1

Impact of AI and robotics on employment (probit estimation results)

	(1)		(2)		(3)	
Female	-0.0323	**	-0.0296	*	-0.0298	*
	(0.0161)		(0.0162)		(0.0162)	
20-29	-0.1232	***	-0.1214	***	-0.1217	***
	(0.0246)		(0.0246)		(0.0246)	
30-39	-0.0560	**	-0.0566	**	-0.0567	**
	(0.0225)		(0.0225)		(0.0225)	
50-59	0.1088	***	0.1095	***	0.1091	***
	(0.0218)		(0.0218)		(0.0219)	
60 or over	0.1853	***	0.1868	***	0.1862	***
	(0.0205)		(0.0205)		(0.0205)	
Primary or junior high school	-0.0009		0.0006		0.0005	
	(0.0566)		(0.0566)		(0.0566)	
Vocational school	0.0757	***	0.0708	***	0.0701	***
	(0.0261)		(0.0262)		(0.0263)	
Junior college	0.0302		0.0281		0.0279	
	(0.0285)		(0.0286)		(0.0286)	
University	0.0339	*	0.0334		0.0333	
	(0.0205)		(0.0205)		(0.0205)	
Graduate school	0.1394	***	0.1398	***	0.1393	***
	(0.0316)		(0.0316)		(0.0317)	
Natural science	0.0367	*	0.0330		0.0327	
	(0.0216)		(0.0217)		(0.0218)	
Occupational license			0.0360	**		
			(0.0154)			
Certification					0.0293	
					(0.0214)	
Monopolistic license					0.0400	**
					(0.0180)	

(Notes) Probit estimation results indicating marginal effects with standard errors in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The reference categories are male, age in 40s, senior high school, majors other than natural science. The sample comprises those who are working, excluding those who responded as “I don’t know” (N=4,517).

Appendix Table A2

Impact of AI and robotics on employment by industry, type of employment, and occupations (probit estimation results)

(1) Industry			(2) Type of employment			(3) Occupation		
Agriculture, forestry, and fishery	0.1830 (0.0688)	**	Executive of company	0.0353 (0.0326)		Managerial	0.1200 (0.0260)	***
Construction	0.0681 (0.0366)	*	Self-employed	0.0161 (0.0266)		Professional and engineering	0.1108 (0.0211)	***
Information and communications	-0.0153 (0.0398)		Family-worker	0.0703 (0.0600)		Sales	0.0512 (0.0299)	*
Transport	-0.0319 (0.0434)		Part-time employee	-0.1148 (0.0259)	***	Manufacturing process	-0.0692 (0.0341)	**
Wholesale and retail	0.0355 (0.0292)		Temporary employee	-0.0595 (0.0345)	*	Service	0.0169 (0.0236)	
Finance and insurance	0.0366 (0.0390)		Temporary agency workers	-0.1119 (0.0482)	**	Other	0.0806 (0.0436)	*
Real estate	0.0822 (0.0491)		Contract employee	-0.0282 (0.0339)				
Accommodations and restaurants	0.0734 (0.0481)		Entrusted employee	-0.1664 (0.0560)	***			
Medical, health care, and welfare	0.1272 (0.0286)	***						
Education	0.0965 (0.0328)	***						
Services, NEC	-0.0136 (0.0251)							
Government	0.0432 (0.0339)							
Other industries	0.0345 (0.0411)							

(Notes) Probit estimation results indicating marginal effects with standard errors in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The reference categories are manufacturing, regular employee, and clerical occupation, respectively. All estimations include gender, age, education, and major as explanatory variables. The sample comprises those who are working, excluding those who responded as “I don’t know” (N=4,517).