RIETI Discussion Paper Series 18-E-032

Regional Employment and Artificial Intelligence in Japan

HAMAGUCHI Nobuaki
RIETI

KONDO Keisuke
RIETI

Research Institute of Economy, Trade & Industry, IAA

The Research Institute of Economy, Trade and Industry
https://www.rieti.go.jp/en/

RIETI Discussion Paper Series 18-E-032
May 2018

Regional Employment and Artificial Intelligence in Japan[*]

HAMAGUCHI Nobuaki [†]
RIEB, Kobe University
RIETI

KONDO Keisuke [‡]
RIETI

Abstract

This study investigates employment risk caused by new technology, such as artificial intelligence (AI) and robotics, using the probability of computerization by Frey and Osborne (2017) and Japanese employment data. The new perspective of this study is the consideration of regional heterogeneity in labor markets due to the uneven geographical distribution of occupations, which is especially observed between male and female workers. This study finds that female workers are exposed to higher risks of computerization than male workers, since they tend to be engaged in occupations with a high probability of computerization. This tendency is more pronounced in larger cities. Our results suggest that supporting additional human capital investment alone is not enough as a risk alleviation strategy against new technology, and policymakers need to address structural labor market issues, such as gender biases for career progression and participation in decision-making positions, in the AI era to mitigate unequal risk of computerization between workers.

JEL classification: J24, J31, J62, O33, R11
Keywords: Artificial intelligence, Computerization, Automation, Employment, Gender gap

[*] We thank Asao Ando, Veneziano Araujo, Masahisa Fujita, Hidehiko Ichimura, Kenta Ikeuchi, Arata Ito, Ryo Ito, Ayako Kondo, Tatsuhito Kono, Atsushi Nakajima, Tomoya Mori, Masayuki Morikawa, Se-il Mun, Hisamitsu Saito, Shintaro Yamaguchi, Makoto Yano, Dao-Zhi Zeng, Yang Zhang, and participants of RIETI DP seminar, of Regional Science Workshop at Tohoku University, of Urban Economics Workshop at Kyoto University, of 2017 Japanese Economic Association Autumn Meeting, of 64th Annual North American Meetings of the Regional Science Association International, and of Western Regional Science Association 57th annual meeting for their useful comments and suggestions. Naturally, any remaining errors are our own. This research was conducted under the project "Regional Economies in the New Era of Globalization and Informatization" and "Stable Development of Regional Economies under a Declining Population" at RIETI. We are grateful to the Ministry of Internal Affairs and Communications for providing the micro-data of the 2007 and 2012 Employment Status Surveys. We thank Hiromi Shimada for her assistance in applying for the micro-data. The views expressed in the paper are solely those of the authors, and neither represent those of the organization to which the authors belong nor the RIETI. The online appendix is available at https://sites.google.com/site/keisukekondokk/.
[†] Research Institute for Economics and Business Administration (RIEB), Kobe University: 2-1 Rokkodai-cho, Nada-ku, Kobe-shi, Hyogo, 657-8501, Japan. (E-mail: hamaguchi@rieb.kobe-u.ac.jp)
[‡] Research Institute of Economy, Trade and Industry (RIETI): 1-3-1 Kasumigaseki, Chiyoda-ku, Tokyo, 100-8901, Japan. (E-mail: kondo-keisuke@rieti.go.jp)

1 Introduction

Employment in the U.S. manufacturing sector has decreased since the Great Recession in 2009 despite GDP recovering in this sector. In the periods of jobless recovery, Jaimovich and Siu (2012) find that middle skills jobs are lost. During the 2016 U.S. presidential election, trade liberalization and immigration were focused on as possible causes of the jobless recovery. In turn, recent economic research has emphasized the impact of new technology on employment. Michaels et al. (2014) find that rather than the trade liberalization, the information and communication technology better explains a reason for jobless recovery. Graetz and Michaels (2015) find that industrial robots increase productivity and wages and reduce hours worked. Brynjolfsson and McAfee (2011, 2014) refer to a growing gap between GDP and employment as "the Great Decoupling," and their main message is that recent technological progress reduces employment.[1]

As such, there is growing concern that human jobs are being substituted by the rapid technological progress of artificial intelligence (AI), robotics, and automation.[2] Historically, this sort of concern has been repeatedly pointed out. For example, Keynes (1931) suggested the possibility of *technological unemployment* due to the rapid progress of labor-saving technology and machines in 1930.[3] In other words, the speed of technological progress surpasses that of human learning, which results in unemployment since workers cannot immediately find new jobs.

What are the key developments in the current discussion on AI and employment? The crucial difference from Keynes (1931) is that even white-collar workers can be substituted by the new technology. Whereas mechanization has so far only affected blue-collar workers, recent AI technology, which plays a similar role to the human brain, will mainly affect white-collar workers.[4] As AI already surpasses our human knowledge in a limited area such as playing *Shogi*, *Go*, and Chess, many human jobs are considered to be replaced by machines and robots combined with AI in near future. Pattern recognition and predictive analytics based on machine

[1]See also related studies: Autor et al. (2003), Acemoglu and Autor (2011), Acemoglu and Restrepo (2016), Acemoglu and Restrepo (2017), and Ikenaga and Kambayashi (2016).

[2]In this paper, we mainly use the terminology "computerization," which is used in Frey and Osborne (2017). Note that, in this paper, it broadly includes automation and mechanization. In particular, the core of our discussion relates to recent AI technology, such as image recognition, pattern recognition, and natural language processing by deep learning, which is further combined with robots. Currently, it is considered that even white-collar jobs can be replaced by machines and robots combined with AI.

[3]Mokyr et al. (2015) provide a historical review on anxiety arising from technological progress concerning employment.

[4]In Japan, Arai (2010) emphasized potential impacts of AI on the labor market in the early stages. To understand whether AI technology embodies our knowledge, in 2011, she began the Todai Robot Project, in which AI aims to pass the admission exam of the University of Tokyo, Japan (URL: `http://21robot.org/`).

learning, such as IBM Watson, already plays an important role in companies that collect big data.[5]

The fear of AI technology may stem from the great polarization between workers, implying that a relatively small proportion of white-collar workers account for a large share of earnings. In the next few decades, given the pace of automation, most workers will be faced with tough decisions regarding their choice of occupation. To investigate quantitative impacts of computerization on employment, Frey and Osborne (2017) estimate the probability of computerization for 702 occupations in the US using the O*NET database. Considering whether occupations can be automated from the perspective of technological capabilities, they conclude that 47% of employment is susceptible to automation in the US in the 2030s.

There is criticism against the view of Frey and Osborne (2017). For example, Autor (2015) argues that while some routinized tasks may be substituted by machines and robots, many jobs will not become redundant. Although there is continuous demand for many jobs, computerization changes the nature of the tasks involved. According to Bessen (2015), the introduction of bank ATMs did not induce mass unemployment of bank tellers. He found that while the number of bank tellers per branch decreased, the total number of branches increased. Consequently, the total number of bank tellers increased. Furthermore, he suggests that the introduction of bank ATMs changed the tasks of bank tellers. The skills required for bank tellers changed from cash-handling to marketing ability and interpersonal skills.

Arntz et al. (2016) argue that only part of tasks in each occupation will be substituted by machines, and demand for human employees will remain in the future. Their task-based approach reveals that the share of automatable jobs is 9% in 21 OECD counties. This number is much lower than that suggested Frey and Osborne (2017). Arntz et al. (2016) emphasize that even occupations with a high probability of computerization classified in Frey and Osborne (2017) include tasks that are difficult to automate, and thus their results are overestimated.

It should be emphasized that AI and robots are able not only to substitute, but also complement humans. Autor (2015) suggests that complementarity between labor and robots increases productivity. In addition, Davenport and Kirby (2016) argue that AI should be "Augmented Intelligence." Fujita (2017) also discusses that collaboration between human and AI enhances our creativity through mutual advantages. Their point is the coexistence between humans

[5]Pratt (2015) argues that rapid, short-term technological progress of AI and robotics, such as "Deep Learning" and "Cloud Robotics," is highly dependent on breaking through the limitations of hardware technology, such as computer processing speed, electrical energy storage, wireless communication, and data storage.

and machines, suggesting a new technology should be developed from the point of view of augmentation, not automation of tasks. Furthermore, Acemoglu and Restrepo (2018) provide a comprehensive view on the possible effects of automation on labor demand using the task-based framework, in which although automation has displacement effects on employment, labor demand simultaneously increases in non-automated tasks.

In spite of the criticism, we consider that Frey and Osborne's occupation-based approach may more accurately portray the reality of structural change in the job market. Although many occupations will not disappear because they involve tasks which are hard to automate and due to possible collaborations between human and AI, the characteristics of workers in charge of such occupations will be different from those of who previously occupied them. Hence, it may be more appropriate to say that these occupations are lost once, then recreated and performed by people with different skills.

Considering possible substitutability, policy-makers should strengthen the safety net in order to mitigate against risk of computerization in the future. For example, workers may consider switching from occupations susceptible to automation to those with a low probability of computerization. However, it is often difficult because occupations with a lower probability of computerization tend to require higher skills. As discussed in Brynjolfsson and McAfee (2011, 2015) and the U.S. Executive Office of the President (2016a), policies promoting additional human capital investment are necessary. If job mobility does not function properly in the labor market, as noted in Autor (2015) and Bessen (2016), employment polarization and wage disparity will accelerate.

Ford (2015) argues that acquiring high-level skills does not protect against automation. Ford (2009) criticizes the idea of many economists that the negative impact of automation on employment is short-term, and technology-driven economic growth increases employment in the long run. His point is that the impact of AI technology is completely different from that of technological progress so far, and he predicts that, in the future, a relatively large proportion of human jobs will be lost as a result of AI technology. The universal basic income is often referred to as a safety net for an economy with mass unemployment (e.g., the U.S. Executive Office of the President, 2016a, p. 40).

There is still no broad consensus on how automation related to AI technology affects labor markets. One of the main reasons is the difficulty in predicting the technological progress of AI and robotics. For example, using an original questionnaire survey for individuals in

Japan, Morikawa (2017b) clarifies that clerical and production-line workers strongly recognize the possibility of automation by AI and robots. In turns, he mentions that workers who studied natural science in graduate schools tend to be less afraid of the effect of computerization and automation.

In addition, Morikawa (2017a) investigates firms' expectations and concerns regarding AI and robots using an original questionnaire survey for approximately 3,000 Japanese firms. According to his results, most firms consider AI technology and robots to be labor-saving. On the other hand, firms hiring more high-skilled workers expect that AI technology and robots increase productivity and considers that AI-driven firm growth may increase employment, including new jobs that do not exist at the present moment. Morikawa (2017a) concludes that the prerequisite for AI-driven firm growth is skill formation for AI utilization, which depends on whether works are able to handle new technology skillfully.

AI technology will be fueled by the competitive innovations of science. As discussed by Morikawa (2017a), innovative, productive firms show a major interest in the use of AI in their business, which further accelerates the practical use of AI. Firms that successfully incorporate AI technology into their business flow will expand their market share. Hence, policy-makers simultaneously face two policy challenges of strengthening the global competitiveness of firms that use the AI technology and of mitigating the negative impact of computerization on employment. This study attempts to address the latter challenge.

To clarify which groups of workers should be targeted by policies as a priority, this study considers labor market heterogeneity in terms of gender (male and female) and city size (large and small cities). As discussed in the U.S. Executive Office of the President (2016a,b), it is important to draw implications for effective labor market and education policies in the era of AI and robotics. As a main result of this study, we find that female workers are exposed to higher risks than male workers, since female workers tend to be engaged in occupations susceptible to computerization, such as receptionist, clerical, and sales workers. This tendency is more prevalent in the labor market in larger Japanese cities. The important policy implication of this study is that supporting additional human capital investment alone is not enough as a means of alleviating risk against new technology, and policy-makers need to address structural labor market issues, especially the gender gap in the labor market (e.g., gender biases for career progression and participation in decision-making positions), which will amplify unequal risks of automation between male and females.

The remainder of this paper is organized as follows. Section 2 presents the data. Section 3 explains the empirical approach. Section 4 discusses estimation results. Finally, Section 5 presents the conclusions.

2 Data

2.1 Probability of Computerization

This study employs probabilities of computerization for occupations provided by Frey and Osborne (2017). These probabilities are estimated using the O*NET database, which is the online database of occupational information sponsored by the U.S. Department of Labor. Their main aim is to quantify the extent to which employment can be potentially substituted by computer capital from a technological capabilities point of view (Frey and Osborne, 2017, p. 268).

Frey and Osborne (2017) focus on occupations as a unit of empirical analysis. Merging occupational classifications of the 2010 Bureau of Labor Statistics with 903 occupations of the O*NET and keeping concordance between them reduces the number of occupations to 702.

Their calculation procedure of probability of computerization consists of three steps. First, collaborating with a group of machine learning researchers, Frey and Osborne (2017) label 70 occupations from a subjective perspective by assigning 1 if an occupation is automatable, and 0 if not. Second, they relate these dichotomous labels of automatability with score variables on knowledge, skill, and ability defined in the O*NET. They also consider three bottlenecks to computerization: (1) perception and manipulation, (2) creative intelligence, and (3) social intelligence. The first bottleneck includes three O*NET variables: Finger dexterity, Manual dexterity, and Cramped work space, awkward position. The second bottleneck includes two O*NET variables: Originality and Fine arts. The third bottleneck includes four O*NET variables: Social perceptiveness, Negotiation, Persuasion, and Assisting and caring for others. Using a probabilistic model with the labeled 70 occupations, Frey and Osborne (2017) estimate model parameters. Third, probabilities of computerization for all 702 occupations are predicted as a function of nine O*NET variables with estimated model parameters.

This study makes use of the table of probability of computerization for 702 occupations in Frey and Osborne (2017) and by connecting occupational classifications between Frey and Osborne (2017) and this study, we calculate the probability of computerization based on the Japanese occupational classifications.

The Japanese Standard Occupational Classification (JSOC, Rev. 5, December 2009) consists of 3 groups: major group (alphabet), minor group (2-digits), and unit group (3-digits). The major group includes 12 classifications, the minor group has 74 classifications, and the unit group contains 329 classifications.[6] The concordance of occupational classification between O*NET and JSOC and the calculation procedure of probability of computerization are provided in Appendix A.

2.2 Employment Data in Japan

This study employs two employment datasets in Japan. The first is taken from the 2010 Population Census (Statistical Bureau, Ministry of Internal Affairs and Communication), which is conducted every five years, and covers all people residing in Japan as of October 1. The second dataset is taken from the 2007 and 2012 Employment Status Surveys (Statistical Bureau, Ministry of Internal Affairs and Communication). The Employment Status Survey is also conducted every five years as a large sample survey (approximately one million people for each survey). This study makes use of prefecture-level data from the Population Census and workers' micro-data from the Employment Status Surveys.

The 2010 Population Census and the 2007 and 2012 Employment Status Surveys include 232 identical occupational classifications as a unit group (12 major groups, 57 minor groups, and 232 unit groups), which basically follow the JSOC (Rev. 5, December 2009). This study excludes other occupations not classified elsewhere at the unit group level, which reduces the number of occupations to 200.

This study uses employment data from the Population Census aggregated at the prefecture level, which is available from the Japan e-Stat website.[7] Detailed sample tabulation at the prefecture level includes the numbers of male and female workers by the unit group of occupational classification, which captures geographical distribution of occupations by gender.[8] However, a statistical issue is that this dataset is based on administrative units, and this study further focuses on regional labor markets using individual-level micro-data.

The micro-data of the Employment Status Surveys include the municipal information regarding residence. Note that workers do not necessarily work in the municipalities of their residence

[6]Ministry of Internal Affairs and Communications provides the information on the Japan Standard Occupational Classification (URL: `http://www.soumu.go.jp/english/dgpp_ss/seido/shokgyou/index09.htm`).

[7]e-Stat (URL: `http://www.e-stat.go.jp/SG1/estat/eStatTopPortalE.do`)

[8]Appendix B provides tables on within-prefecture employment shares by major group of the JSOC.

since they usually cross municipal borders to commute. To address this geographical mismatch issue, this study employs urban employment areas (UEAs) proposed by Kanemoto and Tokuoka (2002). The urban employment areas consist of multiple municipalities including the central and peripheral municipalities. Central municipalities are defined as those with densely inhabited districts where 10,000 or more people reside. Peripheral municipalities are defined as those from which more than 10% of workers commute to the central municipalities.[9]

Figure 1 presents the classification of large and small cities. Colored areas are classified as a group of large cities, which means UEAs including the 23 wards of Tokyo and Ordinance-Designated Cities. As of 2012, the Ordinance-Designated Cities include Sapporo, Sendai, Niigata, Shizuoka, Hamamatsu, Nagoya, Kyoto, Osaka, Kobe, Okayama, Hiroshima, Kitakyusyu, Fukuoka, and Kumamoto.[10] Non-colored areas are classified as a group of small cities, which include areas other than the 23 wards of Tokyo and Ordinance-Designated Cities.

[Figure 1]

Similar to Frey and Osborne (2017), this study employs variables on education and wage. The Employment Status Survey includes educational history as follows: "Primary and junior high school," "Senior high school," "Professional training college," "Junior college," "College or university," and "Graduate school." This study calculates years of schooling as 9 years for "Primary and junior high school," 12 years for "Senior high school," 14 years for "Professional training college" and "Junior college," 16 years for "College or university," and 18 years for "Graduate school."[11]

Daily wage is calculated as the annual income divided by annual days of work. The Employment Status Survey includes income information as follows: "0 to 0.49 million yen," "0.5 to 1 million yen," "1 to 1.49 million yen," "1.5 to 2 million yen," "2 to 2.5 million yen," "2.5 to 3 million yen," "3 to 4 million yen," "4 to 5 million yen," "5 to 6 million yen," "6 to 7 million yen," "7 to 8 million yen," "8 to 9 million yen," "9 to 10 million yen," "10 to 15 million yen," "15 million yen or more." This study uses these class values as annual income ("15 million yen or more" is defined as 15 million yen in the analysis). Furthermore, the Employment Status Survey

[9]Central municipalities identified at the first step might be classified as peripheral municipalities at the second step. Therefore, note that one urban employment area may include two or more central municipalities.

[10]These UEAs do not include suburban areas at the second level (i.e., peripheral municipalities of the peripheral municipalities of the central municipalities).

[11]The data limitation is that the level of human capital is captured only by educational history. This study cannot capture skills that workers have acquired in the labor market.

includes information on annual days of work as follows: “less than 50 days,” “50 to 99 days,” “100 to 149 days,” “150 to 199 days,” “200 to 249 days,” “250 to 299 days,” “300 days or more.” These class values are used as annual days of work (“300 days or more” is defined as 325 days). Thus, the daily wage is deflated by the Consumer Price Index (2010=1), and the uppermost 1% of real wage is excluded from the dataset.

Table 1 presents descriptive statistics of variables in integrated datasets from the 2007 and 2012 Employment Status Surveys. It not only presents descriptive statistics of the full sample but also those of samples divided into large and small cities. Table 1 shows that there is no significant difference in probability of computerization between large and small cities. In addition, average years of schooling in large cities are greater than those in smaller cities. Consistent with urban economics literature, wage is higher in larger cities.

[Table 1]

3 Empirical Approach

This section explains two empirical approaches to undertake a fact-finding analysis concerning the impacts of computerization on regional labor markets. First, this study proposes regional employment risk score of computerization using the probability of computerization and regional employment data. Second, this study uncovers how computerization varies across gender and city size.

3.1 Regional Employment Risk Score of Computerization

This study aims to quantify regional employment risk score of computerization by combining disaggregated occupational data with regional employment data. The risk score for gender g in prefecture a, $Score_a^g$, is calculated as follows:

$$Score_a^g = \sum_{i=1}^{N} Share_{ai}^g \cdot Prob_i, \qquad g \in \{\text{Male, Female}\}, \tag{1}$$

where N is the number of occupations (in this study, $N = 200$), $Share_{ai}^g$ is the share of occupation i in prefecture a for gender g, $Prob_i$ is the probability of computerization for occupation i based on Frey and Osborne (2017). Note that the probability of computerization does not differ between male and female. This study calculates probabilities of computerization for occupations defined in the JSOC after the occupation concordance between Frey and Osborne (2017) and this study.

This risk score takes a value between 0 and 100, with 0 indicating no employment risk of computerization and 100 indicating that all occupations are replaced. For example, when all workers are engaged in an occupation with probability of computerization 0 in a prefecture, the risk score takes the value 0. When all workers are engaged in an occupation with probability of computerization 1 in a prefecture, the risk score takes the value 100.[12]

A regional variation in risk score is discussed in terms of city size, which is measured by population density. As Bacolod et al. (2009) find that workers in large cities are more skilled than those in small cities, employment risk score may be lower in larger cities when there are occupations that require highly skilled workers in large cities or occupations with low probability of computerization. Using the employment risk score, this study aims to clarify how employment risk of computerization is related to gender and city size.

3.2 Education, Wage, and Probability of Computerization

Frey and Osborne (2017) find that education level and wages are negatively correlated with the probability of computerization in the US. Chang and Huynh (2016) also reaches the same conclusion using the datasets of the ASEAN countries. This study first confirms whether their findings also hold in Japan by estimating a simple regression as follows:

$$Education_i = \alpha_1 + \alpha_2 Prob_i + u_i, \tag{2}$$

where $Education_i^C$ is the variable of average years of schooling for occupation i, $Prob_i$ is the probability of computerization for occupation i, and u_i is an error term. Similarly, this study estimates a simple regression on wage as follows:

$$Wage_i = \beta_1 + \beta_2 Prob_i + v_i, \tag{3}$$

where $Wage_i$ is the variable of average wages for occupation i, and v_i is an error term. Note that this regression does not intend to estimate a causal relationship.[13]

[12] One limitation of this risk score is that unemployment is not considered. Further research should include information on previous occupations of the unemployed.

[13] If occupations with low probability of computerization require highly-skilled workers, $Prob_i$ partly captures skill differences across occupations. This relationship also affects the estimation of the coefficient of the probability of computerization.

A new aspect of this study derives from the idea that the geographical distribution of occupations is uneven. Some occupations are concentrated in urban areas, and other occupations are relatively concentrated in rural areas. In particular, this heterogeneity is most prevalent between male and female workers. Therefore, this study aims to capture how the effect of new technology differs in regional labor markets via this heterogeneity.

To capture heterogeneous impacts of computerization, this study proposes gap variables of years of schooling and wages between gender and city-size. In other words, this study considers gaps in terms of the following four categories: (i) gender gap within large cities, (ii) gender gap within small cities, (iii) city-size gap within males, and (iv) city-size gap within females. The gender gap is calculated as the values of males minus those of females. The city-size gap is calculated as the values of small cities minus those of large cities.

To investigate how computerization affects these gaps in years of schooling, this study estimates a simple regression as follows:

$$EducationGap_i^C = \gamma_1 + \gamma_2 Prob_i + e_i, \tag{4}$$

where $EducationGap_i^C$ is the gap variable of years of schooling for category C (i.e., the above-mentioned four categories) and e_i is an error term. Similarly, to investigate how computerization affects these gaps in wages, this study estimates a simple regression as follows:

$$WageGap_i^C = \delta_1 + \delta_2 Prob_i + \varepsilon_i, \tag{5}$$

where $WageGap_i^C$ is the gap variable of wages for category C and ε_i is an error term. Note that this regression does not intend to estimate a causal relationship.

Our aim is to assess how impacts of computerization are heterogeneous for gender and city-size. In both regression models, the constant term γ_1 and δ_1 capture the average gap in education and wage across occupations when $\gamma_2 = 0$ and $\delta_2 = 0$.

The slopes γ_2 and δ_2 capture the average gap related to the probability of computerization. When γ_2 and δ_2 are significantly different from 0, the gap expands with respect to the probability of computerization. For example, consider the case of gender gap of education in large cities. When γ_2 is negative and γ_1 is 0, occupations with higher probability of computerization show a larger gap in education level between male and female workers, meaning that females workers engaged in occupations with high probability of computerization are less educated than male workers.

This study attempts to undertake a fact-finding analysis on how computerization is related to the gender gap within the same city-size and with the city-size gap within the same gender via constant and slope parameters.

4 Estimation Results

4.1 Female Workers Are Exposed to Higher Risks of Computerization

Table 2 presents the employment risk scores by gender and prefecture based on Equation (1). Figure 2 illustrates geographical distribution of these risk scores by gender. There are some interesting findings. First, for male workers, Greater Tokyo and Osaka show relatively low employment risk scores. By contrast, these areas show relatively high employment risk scores for female workers. This finding is related to the fact that male workers in these areas tend to be engaged in administrative, managerial professional, and engineering occupations, whereas female workers in these areas tend to be engaged in clerical work. Second, for males, prefectures where manufacturing process workers are concentrated, especially Fukushima, Tochigi, Toyama, and Mie, tend to show high employment risk scores.[14] Third, within-prefecture employment risk score ratios tend be greater than one, which means that female workers are exposed to higher risks of computerization than male workers. Fourth, regional variation in employment risk score for female workers is smaller than for male workers, which means that geographical variation in occupations for male workers generates greater geographical variation in employment risk scores.

Figure 3 focuses on how employment risk scores are related to the city-size. Panel (a) of Figure 3 shows the negative correlation for male workers. By contrast, Panel (b) of Figure 3 shows the positive correlation for female workers. The employment risk score ratio in Panel (c) of 3 is calculated by dividing the female employment risk score by the male employment risk core. When the employment risk score ratio is 1, there is no gender gap in risk of computerization. When the employment risk score ratio is greater than 1, female workers are exposed to higher employment risks of computerization than male workers. When the employment risk score ratio is less than 1, male workers are exposed to higher employment risks of computerization than female workers. Our results show that the ratio of employment risk score between female and

[14] World Economic Forum (2016, Chapter 2) also suggests that whereas male workers tend to be engaged in production-line work, female workers tend to be engaged in clerical work, sales, and services.

male workers becomes greater in larger cities.

To summarize, our results show that the geographical distribution of different occupations leads to regional variation in employment risks of computerization. Clearly, regions where occupations with lower probability of computerization are concentrated show lower employment risks, and these occupations are generally concentrated in large cities. However, this study provides the new perspective that structural gender issues in labor markets generate contrasting results. In other words, female workers tend to have little opportunity to advance in career in the Japanese labor market and tend to be engaged in occupations with a high probability of computerization, such as a receptionist or sales worker. Consequently, larger cities show a greater gender gap in employment risk of computerization.

[Table 2; Figures 2 and 3]

4.2 Years of Schooling and Wages Are Negatively Correlated with Probability of Computerization

Figure 4 presents the correlations between average years of schooling and probability of computerization. For the four categories, a negative correlation is observed. Panels (a) and (c) of Figure 4 show a larger variation across occupations with low probability of computerization in large cities, implying that even workers with high-level education are engaged in occupations with low probability of computerization. Table 3 shows the estimation results of the simple regression, which also confirm that the coefficient of the probability of computerization is negative.

Figure 5 presents the correlations between average daily wages and the probability of computerization. Similar to average years of schooling, a negative correlation is observed for the four categories. However, note that some occupations with high probability of computerization show high wages in large cities. Table 4 shows the estimation results of the simple regression, which also confirm that the coefficient of the probability of computerization is negative.

[Figures 4 and 5; Tables 3 and 4]

Consistent with previous findings, such as Frey and Osborne (2017) in the US and Chang and Huynh (2016) in ASEAN countries, this study finds that workers engaged in occupations with high probability of computerization tend to be low-educated, and their wage is, on average, low. As claimed by Brynjolfsson and McAfee (2011, 2014), this finding suggests that additional human capital investment and facilitating job mobility can alleviate employment risks for low-educated workers engaged in occupations susceptible to computerization.[15]

4.3 Heterogeneous Impacts of Computerization for Gender and City-Size

Figure 6 presents four types of gaps in average years of schooling. Panel (a) shows the gender gap within large cities, Panel (b) shows the gender gap within small cities, Panel (c) shows the city-size gap within male workers, and Panel (d) shows the city-size gap within female workers. An interesting finding is Panel (a), in which the within-large-city gender gap in average years of schooling becomes larger for occupations with higher probability of computerization. This suggests that, relative to male workers, more additional human capital investment may be required for female workers when job mobility is necessary from occupations with high probability of computerization to those with low probability of computerization.

Table 5 presents estimation results of Regression (4). As discussed in Figure 6, the coefficient of the probability of computerization in Column (1) is significantly negative for the within-large-city gender gap. On the other hand, other gaps show significant negative constants. Column (2) shows that female workers have lower-level education than male workers within the same occupations. Columns (3) and (4) show that workers in large cities have a higher level of education than those in small cities within the same occupations.

Figure 7 presents four types of gaps in average daily wages. Panel (a) shows the gender gap within large cities, Panel (b) shows the gender gap within small cities, Panel (c) shows the city-size gap within male workers, and Panel (d) shows the city-size gap within female workers.

Panel (d) shows within-female-worker city-size gap in average daily wage becomes larger for occupations with lower probability of computerization. In other words, female workers engaged in occupations with lower probability of computerization in large cities earn higher wages than those in small cities, even within the same occupations. This finding suggests that the regional wage gap will expand within female workers group engaged in occupations with low probability of computerization.

Table 6 presents estimation results of Regression (5). Corresponding to Panel (d) of Figure 7, the coefficient of probability of computerization in Column (4) is significantly positive. In

[15]Considering the skill percentile ranked by occupational mean wage, Autor and Dorn (2013) find evidence of job polarization in the US labor market (i.e., a decline in employment for middle-skill occupation). Note that their measure of skills is different from the probability of computerization calculated by Frey and Osborne (2017), which is based on skills of perception and manipulation, creative intelligence, and social intelligence.

addition, as shown in Panels (a) and (b) of Figure 7, the coefficients of probability of computerization in Columns (1) and (2) are significantly negative, suggesting that male workers earn higher wages than female workers for occupations more susceptible to computerization. Furthermore, Columns (3) and (4) show significant negative constants, suggesting that workers in large cities earn higher wages than those in small cities. This is consistent with urban wage premium literature (Combes and Gobillon, 2015).

In summary, our findings suggest that new technology heterogeneously affects regional labor markets. In particular, gender issues in the Japanese labor market will generate an unequal gap in job opportunities between males and females when computerization begins in earnest.

[Figures 6 and 7; Tables 5 and 6]

5 Conclusion

This study has explored how new technology, such as AI and robotics, affects the Japanese labor market. A particular concern of this study is that geographical distribution of occupations is not even. Some occupations are relatively concentrated in urban areas, and others are concentrated in rural areas. In particular, this heterogeneity is most prevalent between male and female workers. Therefore, this study has aimed to undertake a fact-finding analysis of these issues by combining the probability of computerization discussed by Frey and Osborne (2017) with Japanese employment data.

This study has found that female workers are exposed to higher risks of computerization than male workers and this tendency becomes stronger in larger cities. The reason is that a majority of female workers in larger cities tend to be engaged in occupations with a high probability of computerization, such as receptionist, clerical worker, and sales worker. Our results suggest that the structural gender gap in the labor market affects the regional variation in employment risk of computerization.

Our policy implications emphasize that, although most of the previous studies emphasize that supporting additional human capital investment is necessary to mitigate future employment risk of computerization, this is not sufficient unless the structural labor market issues are addressed. In particular, policy-makers need to reduce the unequal gender gap in job opportunities (e.g., gender biases for career progression and participation in decision-making positions) in the era of AI and robotics. Moreover, we also find that some high-skilled workers face a high risk of computerization, and thus active labor market policies to facilitate job mobility are necessary. As Davenport and Kirby (2016) emphasize that AI should be "Augmented Intelligence," the important idea in policy-making is that AI technology can complement human activities, not only replace them. Fujita (2017) also discusses that collaboration between human and AI enhances our creativity through mutual advantages. Utilizing AI and robots supports business efficiency and better work-life balance, which can solve structural issues of long working hours in the Japanese labor market. Therefore, it is important, especially, for female workers, to consolidate the Japanese employment system at a fundamental level.

Finally, it should be noted that this study includes some limitations. This study specifically focuses on gender issues in the Japanese labor market. However, lifetime employment and seniority-based wage system, which are characterized as conventional employment practices in the Japanese labor market, may generate unequal risk of automation between generations. This should be also studied in future research. Furthermore, this study employs probabilities of computerization estimated at the occupational level. However, Autor (2015) and Arntz et al. (2016) emphasize the importance of task-based analysis, rather than occupation-based analysis. As a recent attempt, Acemoglu and Restrepo (2018) conceptualize effects of technological advances on labor demand based on their task-based model. In addition, the probability of computerization estimated by Frey and Osborne (2017) is based on the occupations in the US labor market. Even if the name of one occupation is identical between the US and Japan, the content and required skills of these jobs will be different. The occupational database should be developed in Japan for international comparison. Finally, occupations at high risk of automation may change in the near future since the technological progress of AI and robotics is unpredictable. This research field should continuously incorporate updated information.

References

[1] Acemoglu, Daron and David Autor (2011) "Skills, tasks and technologies: Implications for employment and earnings," in Card, David and Orley Ashenfelter eds. *Handbook of Labor Economics* Vol. 4: Elsevier, Chap. 12, pp. 1043–1171.

[2] Acemoglu, Daron and Pascual Restrepo (2016) "The race between machine and man: Implications of technology for growth, factor shares and employment." NBER Working Paper No. 22252.

[3] Acemoglu, Daron and Pascual Restrepo (2017) "Robots and jobs: Evidence from US labor markets." NBER Working Paper No. 23285.

[4] Acemoglu, Daron and Pascual Restrepo (2018) "Artificial intelligence, automation and work." NBER Working Paper No. 24196.

[5] Arai, Noriko (2010) *How computers can take our jobs*, Tokyo: Nikkei Publishing. (in Japanese).

[6] 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 Papers No. 189.

[7] Autor, David H. (2015) "Why are there still so many jobs? The history and future of workplace automation," *Journal of Economic Perspectives* 29(3), pp. 3–30.

[8] Autor, David H. and David Dorn (2013) "The growth of low-skill service jobs and the polarization of the US labor market," *American Economic Review* 103(5), pp. 1553–1597.

[9] Autor, David H., Frank Levy, and Richard J. Murnane (2003) "The skill content of recent technological change: An empirical exploration," *Quarterly Journal of Economics* 118(4), pp. 1279–1333.

[10] Bacolod, Marigee, Bernardo S. Blum, and William C.Strange (2009) "Skills in the city," *Journal of Urban Economics* 65(2), pp. 136–153.

[11] Bessen, James (2015) "Toil and Technology," *Finance and Development* 52(1), pp. 16–19.

[12] Bessen, James (2016) "How computer automation affects occupations: Technology, jobs, and skills." Boston University School of Law Law & Economics Working Paper No. 15-49.

[13] Brynjolfsson, Erik and Andrew McAfee (2011) *Race Against The Machine*, Lexington, MA: Digital Frontier Press.

[14] Brynjolfsson, Erik and Andrew McAfee (2014) *The Second Machine Age: Work, Progress, and Prosperity in a Time of Brilliant Technologies*, New York: W. W. Norton & Company.

[15] Brynjolfsson, Erik and Andrew McAfee (2015) "The Great Decoupling: An Interview with Erik Brynjolfsson and Andrew McAfee," *Harvard Business Review* June 2015, pp. 66–74. (Interviewes: Amy Bernstein and Anand Raman).

[16] Chang, Jae-Hee and Phu Huynh (2016) "ASEAN in transformation: The future of jobs at risk of automation." International Labour Organization Bureau for Employers' Activities, Working Paper No 9.

[17] Combes, Pierre-Philippe and Laurent Gobillon (2015) "The empirics of agglomeration economies," in Duranton, Gilles, J. Vernon Henderson, and William C. Strange eds. *Hand-*

book of Regional and Urban Economics Vol. 5, Amsterdam: Elsevier, Chap. 5, pp. 247–348.

[18] Davenport, Thomas H. and Julia Kirby (2016) *Only Humans Need Apply: Winners and Losers in the Age of Smart Machines*, New York: HarperBusiness.

[19] Ford, Martin (2009) *The Lights in the Tunnel: Automation, Accelerating Technology and the Economy of the Future*, New York: CreateSpace Independent Publishing Platform.

[20] Ford, Martin (2015) *Rise of the Robots: Technology and the Threat of a Jobless Future*, New York: Basic Books.

[21] Frey, Carl Benedikt and Michael Osborne (2017) "The future of employment: How susceptible are jobs to computerisation?" *Technological Forecasting and Social Change* 114, pp. 254–280.

[22] Fujita, Masahisa (2017) "AI and the future of the brain power society: When the descendants of Athena and Prometheus work together," *Review of International Economics*. forthcomming.

[23] Graetz, Georg and Guy Michaels (2015) "Robots at work." CEP Discussion Paper No. 1335.

[24] Ikenaga, Toshie and Ryo Kambayashi (2016) "Task polarization in the Japanese labor market: Evidence of a long-term trend," *Industrial Relations* 55(2), pp. 267–293.

[25] Jaimovich, Nir and Henry E. Siu (2012) "The trend is the cycle: Job polarization and jobless recoveries." NBER Working Paper No. 18334.

[26] Kanemoto, Yoshitsugu and Kazuyuki Tokuoka (2002) "Proposal for the standards of metropolitan areas of Japan," *Journal of Applied Regional Science* 7, pp. 1–15. (in Japanese).

[27] Keynes, John Maynard (1931) *Essays in Persuasion*, London: Macmillan.

[28] Michaels, Guy, Ashwini Natraj, and John Van Reenen (2014) "Has ICT polarized skill demand? Evidence from eleven countries over twenty-five years," *Review of Economics and Statistics* 96(1), pp. 60–77.

[29] 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* 29(3), pp. 31–50.

[30] Morikawa, Masayuki (2017a) "Firms' expectations about the impact of AI and robotics: Evidence from a survey," *Economic Inquiry* 55(2), pp. 1054–1063.

[31] Morikawa, Masayuki (2017b) "Who are afraid of losing their jobs to artificial intelligence and robots? Evidence from a survey." RIETI Discussion Paper No. 17-E-069.

[32] Pratt, Gill A. (2015) "Is a Cambrian explosion coming for robotics?" *Journal of Economic*

Perspectives 29(3), pp. 51–60.

[33] U.S. Executive Office of the President (2016a) "Artificial Intelligence, Automation, and the Economy," The White House President Barack Obama, Washington, D.C. `https://obamawhitehouse.archives.gov/sites/whitehouse.gov/files/documents/Artificial-Intelligence-Automation-Economy.pdf`.

[34] U.S. Executive Office of the President (2016b) "Preparing for the Future of Artificial Intelligence," The White House President Barack Obama, Washington, D.C. `https://obamawhitehouse.archives.gov/sites/default/files/whitehouse_files/microsites/ostp/NSTC/preparing_for_the_future_of_ai.pdf`.

[35] World Economic Forum (2016) *The Future of Jobs: Employment, Skills and Workforce Strategy for the Fourth Industrial Revolution*, Geneva: World Economic Forum.

Appendix A Probability of Computerization by Occupation

Table A.1 presents probabilities of computerization for occupations used in this study. The probability of computerization is based on Frey and Osborne (2017). There are three limitations regarding probability of computerization in this study.

First, Frey and Osborne (2017) includes 702 occupations from O*NET, whereas this study includes 232 occupations based on the Japanese Standard Occupation Classification (Rev. 5, December 2009). Therefore, probabilities of computerization for some occupations in Japan are calculated by aggregating multiple occupations in O*NET.

Second, particular occupations in Japan are difficult to keep concordance with those in U.S. For example, Roofing workers in Japan lay and replace tiles (*kawara*), slates, and roofing underlays as a Japanese traditional architecture. This occupation is matched with Roofers in O*NET. Plasterer (*Sakan*) in Japan coats walls with earth, mortar, plaster, and stucco as a Japanese traditional architecture. This occupation is matched with Cement masons and Concrete finishers in O*NET. *Tatami* is a Japanese traditional mat, which is generally made of rush (*igusa*). *Tatami* workers is matched with Carpet installers in O*NET.

Third, although Frey and Osborne (2017) include detailed information on researchers by research field, Population Census and Employment Status Survey in Japan include only two research fields: (i) natural science and (ii) humanities and social science. This study calculates probabilities of computerization for these two research fields by averaging disaggregated research fields of O*NET.

The Online Supplement includes the concordance table of occupational classification between this study and Frey and Osborne (2017).

[Table A.1]

Appendix B Share of Occupation

Tables B.1 and B.2 presents within-prefecture employment shares by major unit of occupational classification for male and female workers, respectively. Note that employment shares are calculated after the exclusion of other occupations not classified elsewhere.

There are two aspects of comparison in Tables B.1 and B.2. Concerning between-prefecture difference, administrative and managerial workers (major unit A), professional and engineering workers (major unit B), clerical workers (major unit C), and sales workers (major unit D) are relatively concentrated in Greater Tokyo and Osaka. By contrast, agriculture, forestry and fishery workers (major unit G) and manufacturing process workers (major unit H) are concentrated in rural areas.

Concerning between-gender difference, male workers occupy more administrative and managerial jobs (major unit A) than female workers. In general, male workers occupy manufacturing process workers (major unit H). Female workers occupy clerical workers (major unit C), sales workers (major unit D), and service workers (major unit E).

[Tables B.1–B.2]

Table 1 Descriptive Statistics of Employment Status Survey

Variables	Obs.	Mean	S.D.	Median	Min	Max
	Full Sample					
Probability of Computerization	1409531	0.661	0.308	0.760	0.004	0.990
Female Dummy	1409531	0.462	0.499	0.000	0.000	1.000
Average Years of Schooling	1409531	12.868	2.196	12.000	9.000	18.000
Daily Wage (Unit: 10,000 JPY)	1409531	1.254	0.972	1.004	0.076	5.450
	Sample: Large Cities					
Probability of Computerization	452973	0.652	0.322	0.797	0.004	0.990
Female Dummy	452973	0.455	0.498	0.000	0.000	1.000
Average Years of Schooling	452973	13.368	2.238	12.000	9.000	18.000
Daily Wage (Unit: 10,000 JPY)	452973	1.408	1.067	1.004	0.076	5.450
	Sample: Small Cities					
Probability of Computerization	956558	0.665	0.301	0.740	0.004	0.990
Female Dummy	956558	0.465	0.499	0.000	0.000	1.000
Average Years of Schooling	956558	12.632	2.135	12.000	9.000	18.000
Daily Wage (Unit: 10,000 JPY)	956558	1.181	0.914	0.989	0.076	5.450

Note: The dataset contains micro data of the 2007 and 2012 Employment Status Surveys (Statistical Bureau, Ministry of Internal Affairs and Communication). Daily wage is calculated as annual income divided by days worked per year. Daily wage is deflated by the consumer price index (2010=1). Uppermost 1% of the distribution in real daily wage is excluded from the sample.

Table 2 Employment Risk Score of Computerization by Prefecture

Prefecture	Risk Score (Male)	Risk Score (Female)	Risk Score Ratio	Population Density
Nation	64.262	67.506	1.050	69
Hokkaido	63.726	66.703	1.047	70
Aomori	65.123	65.566	1.007	142
Iwate	66.735	66.614	0.998	87
Miyagi	64.996	68.591	1.055	322
Akita	66.740	67.137	1.006	93
Yamagata	66.437	67.690	1.019	125
Fukushima	67.505	67.899	1.006	147
Ibaraki	65.398	68.345	1.045	487
Tochigi	66.649	68.294	1.025	313
Gunma	67.036	68.464	1.021	316
Saitama	64.973	69.628	1.072	1894
Chiba	63.672	68.960	1.083	1206
Tokyo	58.615	67.416	1.150	6016
Kanagawa	60.993	68.294	1.120	3745
Niigata	66.753	68.022	1.019	189
Toyama	66.827	67.749	1.014	257
Ishikawa	65.388	67.667	1.035	280
Fukui	66.163	67.365	1.018	192
Yamanashi	65.120	67.206	1.032	193
Nagano	65.671	67.328	1.025	159
Gifu	66.301	68.821	1.038	196
Shizuoka	66.163	69.607	1.052	484
Aichi	66.134	69.646	1.053	1435
Mie	67.670	68.511	1.012	321
Shiga	66.170	68.203	1.031	351
Kyoto	62.337	66.815	1.072	571
Osaka	64.145	67.938	1.059	4670
Hyogo	64.055	66.930	1.045	666
Nara	62.692	66.553	1.062	380
Wakayama	64.246	64.633	1.006	212
Tottori	64.813	65.177	1.006	168
Shimane	66.313	65.236	0.984	107
Okayama	66.245	66.124	0.998	274
Hiroshima	64.741	66.589	1.029	337
Yamaguchi	65.914	65.679	0.996	237
Tokushima	64.995	63.262	0.973	189
Kagawa	65.631	66.337	1.011	531
Ehime	65.564	65.315	0.996	252
Kochi	63.689	62.670	0.984	108
Fukuoka	64.308	66.181	1.029	1019
Saga	65.792	65.377	0.994	348
Nagasaki	63.138	63.804	1.011	348
Kumamoto	64.220	64.954	1.011	245
Oita	64.984	65.462	1.007	189
Miyazaki	65.074	65.661	1.009	147
Kagoshima	64.821	65.075	1.004	186
Okinawa	63.208	65.481	1.036	612

Note: Created by author using 2010 Population Census and probability of computerization computed by Frey and Osborne (2017). The risk score ration is calculated by dividing the female risk score by the male risk score. See Section 3.1 for more details of risk score calculation. Population density is calculated as the ratio of total population to area (in km^2) using 2010 Population Census.

Table 3 Average Years of Schooling and Probability of Computerization

	Dependent Variable: Average Years of Schooling			
	Male		Female	
	Large Cities	Small Cities	Large Cities	Small Cities
Explanatory Variables	(1)	(2)	(3)	(4)
Probability of Computerization	−2.284*	−2.360*	−2.460*	−2.485*
	(0.276)	(0.260)	(0.257)	(0.241)
Constant	14.889*	14.523*	14.795*	14.322*
	(0.190)	(0.179)	(0.173)	(0.165)
Number of Observations	193	196	168	176
Adjusted R^2	0.261	0.295	0.352	0.376

Note: Standard errors in parentheses. The unit of observation is occupation. * denotes statistical significance at the 1% level.

Table 4 Average Wages and Probability of Computerization

	Dependent Variable: Average Daily Wages (Unit: 10,000 JPY)			
	Male		Female	
	Large Cities	Small Cities	Large Cities	Small Cities
Explanatory Variables	(1)	(2)	(3)	(4)
Probability of Computerization	−0.432*	−0.426*	−0.715*	−0.622*
	(0.125)	(0.113)	(0.101)	(0.082)
Constant	2.043*	1.852*	1.513*	1.337*
	(0.086)	(0.078)	(0.068)	(0.056)
Number of Observations	193	196	168	176
Adjusted R^2	0.054	0.064	0.227	0.243

Note: Standard errors in parentheses. The unit of observation is occupation. * denotes statistical significance at the 1% level.

Table 5 Gaps in Average Years of Schooling and Probability of Computerization

	Dependent Variable: Gap in Average Years of Schooling			
	Gender Gap within Large Cities	Gender Gap within Small Cities	City-Size Gap within Males	City-Size Gap within Females
Explanatory Variables	(1)	(2)	(3)	(4)
Probability of Computerization	−0.431*	−0.137	0.005	0.094
	(0.132)	(0.108)	(0.090)	(0.084)
Constant	−0.094	−0.251*	−0.418*	−0.468*
	(0.090)	(0.074)	(0.062)	(0.056)
Number of Observations	162	173	192	165
Adjusted R^2	0.057	0.003	−0.005	0.002

Note: Standard errors in parentheses. The unit of observation is occupation. * denotes statistical significance at the 1% level. Gender gap in average years of schooling is calculated as the male value minus female value. City-size gap in average years of schooling is calculated as the values of small cities minus values of large cities.

Table 6 Gaps in Average Wages and Probability of Computerization

	Dependent Variable: Gap in Average Daily Wages (Unit: 10,000 JPY)			
	Gender Gap within Large Cities	Gender Gap within Small Cities	City-Size Gap within Males	City-Size Gap within Females
Explanatory Variables	(1)	(2)	(3)	(4)
Probability of Computerization	−0.296*	−0.224*	0.020	0.108*
	(0.066)	(0.060)	(0.041)	(0.036)
Constant	−0.486*	−0.451*	−0.201*	−0.166*
	(0.044)	(0.041)	(0.028)	(0.024)
Number of Observations	162	173	192	165
Adjusted R^2	0.107	0.069	−0.004	0.048

Note: Standard errors in parentheses. The unit of observation is occupation. * denotes statistical significance at the 1% level. Gender gap in average daily wages is calculated as the male value minus female value. City-size gap in average daily wages is calculated as the values of small cities minus values of large cities.

Table A.1 Probability of Computerization by Occupational Classification

Major Group	Unit Group	Occupation	Probability of Computerization
A	1	Management government officials	0.1117
A	2	Company officers	0.1600
A	4	Administrative and managerial workers of corporations and organizations	0.1600
B	6	Natural science researchers	0.1291
B	7	Humanities, social science, and other researchers	0.1372
B	8	Agriculture, forestry, fishery and food engineers	0.6268
B	9	Electrical, electronic, telecommunications engineers (except communication network engineers)	0.2963
B	10	Machinery engineers	0.3075
B	11	Transportation equipment engineers	0.1596
B	12	Metal engineers	0.0255
B	13	Chemical engineers	0.2935
B	14	Architectural engineers	0.2690
B	15	Civil engineers and surveyors	0.5763
B	16	System consultants and designers	0.2433
B	17	Software creators	0.0860
B	18	Other data processing and communication engineers	0.1958
B	20	Doctors	0.0042
B	21	Dental surgeons	0.0215
B	22	Veterinary surgeons	0.0380
B	23	Pharmacists	0.0120
B	24	Public health nurses	0.0450
B	25	Midwives	0.4000
B	26	Nurses (including assistant nurses)	0.0335
B	27	Diagnostic radiographers	0.2300
B	28	Clinical laboratory technicians	0.6850
B	29	Physiotherapists, occupational therapists	0.0123
B	30	Certified orthoptists, speech therapists	0.0049
B	31	Dental hygienists	0.6800
B	32	Dental technicians	0.0035
B	33	Nutritionists	0.0039
B	34	Masseurs, chiropractors, acupuncturists, moxacauterists and judo-orthopedists	0.2835
B	36	Childcare workers	0.0840
B	38	Judges, public prosecutors and attorneys	0.2783
B	39	Patent attorneys and judicial scriveners	0.7450
B	41	Certified public accountants	0.9400

(Continued on next page)

Major Group	Unit Group	Occupation	Probability of Computerization
B	42	Licensed tax accountants	0.9900
B	43	Certified social insurance and labor consultant	0.4700
B	45	Kindergarten teachers	0.0787
B	46	Elementary school teachers	0.0044
B	47	Junior high school teachers	0.1700
B	48	Senior high school teachers	0.0078
B	49	Special needs education school teachers	0.0119
B	50	University professors	0.0320
B	52	Workers in religion	0.0166
B	53	Authors	0.4640
B	54	Journalists, editors	0.0825
B	55	Sculptors, painters and industrial artists	0.0397
B	56	Designers	0.0992
B	57	Photographers, film operators	0.3105
B	58	Musicians	0.0445
B	59	Dancers, actors, directors and performers	0.1792
B	60	Librarians and curators	0.5994
B	61	Private tutors (for music)	0.1300
B	62	Private tutors (for dance, actor, direction, performance)	0.1300
B	63	Private tutors (for sports)	0.1300
B	64	Private tutors (for study)	0.1300
B	65	Private tutors (not classified elsewhere)	0.1300
B	66	Sports professionals	0.4243
B	67	Communication equipment operators	0.8600
C	69	General affairs and human affairs workers	0.9433
C	70	Reception and guidance clerical workers	0.9600
C	71	Telephone receptionists	0.9700
C	72	Comprehensive clerical workers	0.9600
C	74	Accountancy clerks	0.9775
C	75	Production-related clerical workers	0.9300
C	76	Sales clerks	0.8500
C	77	Money collectors	0.9500
C	78	Investigators	0.9400
C	80	Transport clerical workers	0.8533
C	81	Post clerical workers	0.9500
C	82	Personal computer operators	0.7800
C	83	Data entry device operators	0.9900
D	85	Retailers, retail manager	0.2800

(Continued on next page)

Major Group	Unit Group	Occupation	Probability of Computerization
D	86	Wholesalers, wholesale manager	0.0750
D	87	Shop assistants	0.9200
D	88	Home visit and mobile sales workers	0.9400
D	89	Recycled resources collection and wholesale workers	0.9300
D	90	Goods purchase canvassers	0.9800
D	91	Real estate agents and dealers	0.9700
D	92	Insurance agents and brokers	0.9200
D	94	Medicine sales workers	0.8500
D	95	Machinery, communication and system sales workers	0.8500
D	96	Finance and insurance sales workers	0.4680
D	97	Real estate sales workers	0.8600
E	99	Housekeepers, home helpers	0.6900
E	101	Care workers (medical and welfare facilities, etc.)	0.7400
E	102	Home visiting care workers	0.3900
E	103	Care assistants	0.6300
E	105	Hairdressers	0.8000
E	106	Beauticians	0.1100
E	107	Cosmetic service workers (except beauticians)	0.5100
E	108	Bath workers	0.6600
E	109	Launderers and fullers	0.7750
E	110	Cooks	0.6800
E	111	Bartenders	0.7700
E	112	Restaurateurs, restaurant managers	0.0830
E	113	Japanese inn owners and managers	0.0039
E	114	Food and drink service and personal assistance workers	0.8800
E	115	Customer entertainment workers	0.9700
E	116	Service workers in places of entertainment, etc.	0.7200
E	117	Condominiums, apartment buildings, lodging houses, hostel and dormitory management personnel	0.0039
E	118	Office building management personnel	0.8100
E	119	Car park management personnel	0.8700
E	120	Travel and tourist guides	0.4835
E	121	Left luggage handlers	0.4300
E	122	Commodity hire workers	0.9700
E	123	Advertisers	0.5400
E	124	Undertakers, crematorium workers	0.3700
F	126	Self-defense officials	0.0980
F	127	Police officers and maritime safety officials	0.2221

(Continued on next page)

Major Group	Unit Group	Occupation	Probability of Computerization
F	128	Prison guards and other judicial police staff	0.6000
F	129	Firefighters	0.0868
F	130	Security staff	0.8400
G	132	Crop farming workers	0.6400
G	133	Livestock farm workers	0.7600
G	134	Landscape gardeners, nursery workers	0.8600
G	136	Forest nursery workers	0.8700
G	137	Tree-felling, logging, and collecting workers	0.8800
G	139	Fishery workers	0.8300
G	140	Ships' captains, navigation officers, chief engineers, engineers (fishing boats)	0.8300
G	141	Seaweed and shellfish harvesting workers	0.8300
G	142	Aquaculture workers	0.8300
H	144	Pig-iron forging, steelmaking, non-ferrous metal smelting workers	0.8967
H	145	Cast metal manufacturing and forging workers	0.9000
H	146	Metal machine tools workers	0.8067
H	147	Metal press workers	0.8400
H	148	Ironworkers, boilermakers	0.6767
H	149	Sheet metal workers	0.9133
H	150	Metal sculpture and plating workers	0.9350
H	151	Metal welding and fusion cutting workers	0.7750
H	153	Chemical product manufacturing workers	0.8433
H	154	Ceramic, earth, and stone product manufacturing workers	0.7850
H	155	Food manufacturing workers	0.7971
H	156	Beverage and cigarette manufacturing workers	0.7850
H	157	Spinning, weaving, apparel, and fiber product manufacturing workers	0.7356
H	158	Wooden and paper product manufacturing workers	0.8400
H	159	Printing and bookbinding workers	0.8550
H	160	Rubber, plastic product manufacturing workers	0.8225
H	162	General-purpose, manufacturing, and business-use mechanical apparatus assembly workers	0.7350
H	163	Electro-mechanical apparatus assembly workers	0.8567
H	164	Automobile assembly workers	0.8100
H	165	Transportation machinery assembly workers (except automobiles)	0.7200
H	166	Weighing and measuring appliance, photo-optic mechanical apparatus assembly workers	0.8150
H	167	General-purpose, manufacturing, and business-use mechanical apparatus maintenance and repair workers	0.6700
H	168	Electro-mechanical apparatus maintenance and repair workers	0.6389

(Continued on next page)

Major Group	Unit Group	Occupation	Probability of Computerization
H	169	Automobile maintenance and repair workers	0.6950
H	170	Transportation machinery maintenance and repair workers (except automobiles)	0.7100
H	171	Weighing and measuring appliance, photo-optic mechanical apparatus maintenance and repair workers	0.7433
H	172	Metal product inspection workers	0.9800
H	173	Chemical product inspection workers	0.9800
H	174	Ceramic, earth, and stone product inspection workers	0.9800
H	175	Food inspection workers	0.9800
H	176	Beverage and cigarette inspection workers	0.9800
H	177	Spinning, weaving, apparel, and fiber product inspection workers	0.9800
H	178	Wooden and paper product inspection workers	0.9800
H	179	Printing and bookbinding inspection workers	0.9800
H	180	Rubber, plastic product inspection workers	0.9800
H	182	General-purpose, manufacturing, and business-use mechanical apparatus inspection workers	0.9800
H	183	Electro-mechanical apparatus inspection workers	0.9800
H	184	Automobile inspection workers	0.9800
H	185	Transportation machinery inspection workers (except automobiles)	0.9800
H	186	Weighing and measuring appliance, photo-optic mechanical apparatus inspection workers	0.9800
H	187	Painters, paint and signboard production workers	0.9200
H	188	Manufacturing-related workers (except painters, paint and signboard production)	0.9200
H	189	Quasi-manufacturing workers	0.6600
I	190	Railway drivers	0.8600
I	191	Motor vehicle drivers	0.8325
I	192	Ship captains, navigation officers, navigators (except fishing boats) and pilots	0.2700
I	193	Ships' chief engineers, engineers (except fishing boats)	0.0410
I	194	Aircraft pilots	0.3650
I	195	Conductors	0.8300
I	196	Deckhands, dual purpose crew and ships stokers	0.8300
I	198	Power plant and substation workers	0.8500
I	199	Boiler operators	0.8900
I	200	Crane, winch operators	0.7150
I	201	Construction, well-drilling machinery operators	0.9400
J	203	Molding box carpenters	0.9000

(Continued on next page)

Major Group	Unit Group	Occupation	Probability of Computerization
J	204	Scaffolding workers (Tobishoku)	0.9000
J	205	Steel reinforcement workers	0.8300
J	206	Carpenters	0.7200
J	207	Block and tile laying workers	0.7850
J	208	Roofing workers	0.9000
J	209	Plasterers	0.9400
J	210	Tatami workers	0.8700
J	211	Pipe laying workers	0.6200
J	212	Civil engineering workers	0.8800
J	213	Railway line construction workers	0.8900
J	215	Line hanging and laying workers	0.0970
J	216	Telecommunication equipment construction workers	0.3200
J	218	Gravel, sand and clay quarrying workers	0.9600
K	220	Mail and telegram collection and delivery workers	0.6800
K	221	Onboard and quayside cargo handlers	0.7200
K	222	Land-based cargo handling and carrying workers	0.7200
K	223	Warehouse workers	0.8500
K	224	Delivery workers	0.6900
K	225	Packing workers	0.3800
K	226	Building cleaning workers	0.6600
K	227	Waste treatment workers	0.5300
K	228	House cleaning workers	0.6900
K	230	Packaging workers	0.3800

Note: The 2010 Population Census and the 2007 and 2012 Employment Status Surveys include 232 occupations based on the Japan Standard Occupational Classification (Rev. 5, December 2009). Note that occupations not classified elsewhere at the unit group level are excluded from the analysis, which reduces the number of occupations to 200. Listed below is the classification of major group (A: Administrative and managerial workers, B: Professional and engineering workers, C: Clerical workers, D: Sales workers, E: Service workers, F: Security workers, G: Agriculture, forestry and fishery workers, H: Manufacturing process workers, I: Transport and machine operation workers, J: Construction and mining workers, K: Carrying, cleaning, packaging, and related workers, L: Workers not classified by occupation). This study aggregates the probability of computerization estimated by Frey and Osborne (2017) corresponding to the 200 occupations used in this study. Occupation correspondence table between Frey and Osborne (2017) and this study is available on Online Supplement (Excel file). Probability of computerization indicates whether an occupation is substitutable from the technological point of view.

Table B.1 Within-Prefecture Employment Share by Occupation for Male Workers

	Within-Prefecture Employment Share by Occupation (Unit: %)										
Prefecture	A	B	C	D	E	F	G	H	I	J	K
Nation	4.5	16.0	10.0	11.0	8.5	3.7	5.8	20.8	7.1	6.7	5.8
Hokkaido	4.8	13.6	9.3	10.3	9.0	6.5	9.6	13.7	9.4	8.1	5.5
Aomori	3.6	9.5	7.7	9.0	7.3	6.8	15.8	15.4	9.1	10.3	5.5
Iwate	4.2	11.1	8.1	9.4	7.0	3.0	15.4	19.2	8.4	9.1	5.2
Miyagi	4.3	13.8	9.6	11.5	8.5	4.2	7.2	18.2	8.7	7.8	6.2
Akita	4.0	10.8	8.7	9.1	7.2	3.6	13.3	20.1	7.8	10.3	5.1
Yamagata	4.1	10.9	7.5	9.4	6.9	3.5	13.3	23.7	6.6	8.9	5.2
Fukushima	4.0	11.0	8.3	9.5	7.1	3.0	10.2	25.3	7.8	8.6	5.2
Ibaraki	3.4	14.9	9.5	9.0	6.8	3.6	8.0	25.3	7.3	6.9	5.3
Tochigi	3.6	14.1	8.7	9.1	7.2	2.5	7.5	28.6	6.7	6.4	5.5
Gunma	3.8	13.1	8.9	9.8	7.9	2.5	7.2	28.0	6.4	6.8	5.6
Saitama	4.2	16.7	12.2	12.0	8.4	3.9	2.6	19.8	7.5	6.2	6.5
Chiba	4.4	17.8	12.5	12.2	8.6	4.3	4.3	16.0	7.6	5.9	6.3
Tokyo	6.6	24.9	12.6	13.1	10.8	3.4	0.7	11.9	6.0	4.1	5.8
Kanagawa	4.6	23.4	12.0	12.0	8.9	3.8	1.3	17.0	6.2	5.1	5.7
Niigata	4.5	11.9	8.4	9.4	7.8	2.9	8.3	23.4	8.2	9.8	5.4
Toyama	4.4	13.4	8.8	10.0	6.7	2.6	5.5	26.7	7.6	8.2	5.8
Ishikawa	4.4	13.9	8.6	10.8	8.6	3.4	4.8	24.6	7.1	8.3	5.4
Fukui	4.5	13.0	8.3	9.7	7.0	3.1	6.0	27.3	7.1	8.5	5.6
Yamanashi	3.9	14.0	8.6	9.8	9.8	3.0	9.8	22.9	5.5	7.9	4.9
Nagano	4.3	13.5	8.5	9.3	8.4	2.0	12.1	23.6	5.5	7.4	5.2
Gifu	4.6	13.1	9.8	9.9	7.6	3.1	4.3	27.8	6.3	7.9	5.8
Shizuoka	4.1	13.6	8.8	9.4	7.6	3.2	5.4	28.4	6.6	6.7	6.2
Aichi	4.0	15.5	9.8	10.7	7.4	2.6	2.8	29.3	6.4	5.2	6.3
Mie	3.6	12.3	9.3	8.6	6.7	3.3	5.6	31.1	6.8	7.0	5.8
Shiga	3.5	15.5	10.0	9.4	7.2	3.4	4.8	30.0	5.1	5.5	5.5
Kyoto	4.5	17.3	9.6	11.9	10.7	4.5	3.5	19.8	6.7	5.9	5.6
Osaka	5.0	16.7	11.1	13.3	10.2	3.2	1.0	20.0	7.2	5.3	6.9
Hyogo	4.5	16.7	10.9	11.9	8.8	3.6	3.3	22.2	6.6	5.5	6.0
Nara	5.1	18.1	12.5	12.9	8.8	3.9	4.3	18.3	5.3	5.6	5.2
Wakayama	3.8	12.7	9.2	10.3	8.9	3.4	12.2	18.9	6.9	7.7	6.0
Tottori	4.2	13.0	8.2	9.8	7.6	4.4	12.9	19.1	6.8	8.2	5.9
Shimane	4.5	12.2	8.3	9.1	7.8	3.9	11.8	19.5	7.4	10.2	5.3
Okayama	4.1	13.4	8.8	9.5	7.1	2.8	6.9	26.8	7.8	7.1	5.7
Hiroshima	4.3	14.4	9.5	10.7	7.8	4.6	4.6	24.4	7.6	6.3	5.7
Yamaguchi	4.1	12.0	8.3	9.3	6.7	4.6	7.9	25.0	8.1	8.4	5.6
Tokushima	4.1	13.5	7.8	9.5	7.9	3.5	11.2	22.5	6.8	8.2	5.2
Kagawa	4.5	12.7	9.6	10.9	8.0	3.3	7.7	23.3	7.2	6.8	6.0
Ehime	4.2	12.6	8.3	10.2	7.7	2.7	11.2	22.3	7.5	7.7	5.7
Kochi	4.0	13.3	6.4	10.2	9.2	3.5	16.5	15.1	7.3	9.2	5.4
Fukuoka	4.6	15.1	9.4	13.2	9.1	4.3	4.3	18.6	8.3	7.2	6.0
Saga	3.7	12.1	7.9	9.8	7.6	3.9	12.5	21.2	7.6	8.3	5.2
Nagasaki	3.8	12.6	7.1	9.9	8.5	6.5	11.5	17.9	8.2	8.8	5.1
Kumamoto	4.2	12.6	7.1	10.3	8.8	4.1	13.7	18.2	7.7	8.1	5.2
Oita	4.5	12.7	8.1	9.6	8.3	4.0	10.2	21.3	7.6	8.7	5.0
Miyazaki	3.9	12.2	7.2	9.8	8.1	4.1	16.0	17.7	6.8	9.1	5.1
Kagoshima	3.8	12.9	8.0	10.2	8.9	3.6	14.8	15.8	8.0	8.5	5.4
Okinawa	3.9	14.0	7.9	9.7	12.6	6.0	9.5	11.4	9.2	9.8	6.0

Note: Created by authors using the 2010 Population Census. Major group denotes A: Administrative and managerial workers, B: Professional and engineering workers, C: Clerical workers, D: Sales workers, E: Service workers, F: Security workers, G: Agriculture, forestry and fishery workers, H: Manufacturing process workers, I: Transport and machine operation workers, J: Construction and mining workers, K: Carrying, cleaning, packaging, and related workers, L: Workers not classified by occupation. The share is calculated except occupations not classified elsewhere.

Table B.2 Within-Prefecture Employment Share by Occupation for Female Workers

	Within-Prefecture Employment Share by Occupation (Unit: %)										
Prefecture	A	B	C	D	E	F	G	H	I	J	K
Nation	0.8	17.4	25.6	14.4	20.1	0.2	4.2	10.8	0.3	0.1	6.1
Hokkaido	0.8	16.5	22.0	14.4	22.0	0.3	7.1	8.8	0.3	0.2	7.5
Aomori	0.7	15.1	17.6	13.6	20.5	0.4	13.3	11.8	0.3	0.2	6.5
Iwate	0.7	15.6	19.1	12.8	19.3	0.1	11.8	14.5	0.2	0.2	5.7
Miyagi	0.8	15.8	25.0	15.6	19.7	0.3	4.5	12.1	0.3	0.1	5.9
Akita	0.6	15.5	20.5	13.2	21.6	0.2	8.3	14.3	0.2	0.1	5.4
Yamagata	0.7	14.9	20.1	12.9	19.4	0.2	9.0	17.2	0.2	0.1	5.2
Fukushima	0.7	15.1	20.3	13.2	19.7	0.2	8.2	16.6	0.3	0.2	5.4
Ibaraki	0.6	15.8	23.8	14.2	18.8	0.2	6.6	13.1	0.3	0.2	6.2
Tochigi	0.7	15.5	22.0	13.9	19.1	0.2	6.7	15.0	0.2	0.1	6.6
Gunma	0.6	15.6	22.7	13.6	20.1	0.2	5.5	15.1	0.2	0.1	6.1
Saitama	0.7	16.1	29.0	15.4	18.5	0.3	1.9	10.7	0.3	0.1	7.0
Chiba	0.7	16.7	28.5	15.9	19.8	0.3	3.6	7.4	0.3	0.1	6.6
Tokyo	1.5	20.1	33.0	14.6	18.9	0.3	0.3	5.9	0.2	0.1	5.0
Kanagawa	0.9	18.6	29.3	16.5	20.5	0.3	0.9	7.0	0.3	0.1	5.7
Niigata	0.6	15.2	22.8	13.4	20.6	0.2	5.9	13.9	0.3	0.2	7.0
Toyama	0.6	17.3	24.6	13.1	19.5	0.2	2.8	15.1	0.3	0.2	6.4
Ishikawa	0.7	17.5	24.6	13.9	20.5	0.2	2.4	13.8	0.2	0.1	6.1
Fukui	0.6	17.4	24.2	12.2	19.4	0.1	3.3	17.1	0.2	0.1	5.4
Yamanashi	0.7	16.4	21.5	13.0	22.1	0.2	8.1	12.5	0.2	0.1	5.3
Nagano	0.7	15.8	20.8	12.0	20.4	0.1	10.0	13.9	0.3	0.2	5.9
Gifu	0.7	15.8	24.2	13.5	19.3	0.2	2.9	16.2	0.3	0.2	6.8
Shizuoka	0.7	14.3	23.9	14.1	19.3	0.2	4.4	14.9	0.4	0.2	7.6
Aichi	0.7	15.5	27.0	14.0	18.9	0.2	2.8	13.3	0.3	0.1	7.1
Mie	0.6	16.2	24.2	14.2	20.7	0.2	3.4	13.7	0.3	0.1	6.4
Shiga	0.5	18.0	24.3	14.4	18.4	0.1	2.8	15.4	0.2	0.2	5.9
Kyoto	0.9	18.5	25.3	15.8	20.9	0.3	2.1	10.6	0.2	0.0	5.4
Osaka	0.9	17.9	30.4	14.6	20.2	0.2	0.4	8.8	0.2	0.1	6.2
Hyogo	0.8	18.8	26.4	15.4	20.0	0.2	1.8	10.4	0.2	0.1	5.8
Nara	0.8	20.0	27.3	15.7	18.7	0.3	2.5	9.7	0.2	0.1	4.8
Wakayama	0.6	17.8	22.5	14.0	20.8	0.2	9.7	8.3	0.2	0.1	5.8
Tottori	0.8	17.9	20.0	12.8	20.7	0.2	9.5	13.0	0.1	0.2	4.8
Shimane	0.8	18.6	21.8	12.9	21.1	0.2	7.1	12.0	0.3	0.1	5.0
Okayama	0.7	18.7	23.5	13.3	20.5	0.2	4.6	12.9	0.2	0.1	5.1
Hiroshima	0.8	18.6	25.6	14.4	20.6	0.3	3.4	10.3	0.3	0.1	5.6
Yamaguchi	0.7	18.3	23.0	14.3	21.7	0.3	5.3	10.3	0.3	0.2	5.6
Tokushima	1.0	20.4	21.4	12.9	20.1	0.2	8.9	10.3	0.2	0.1	4.6
Kagawa	0.8	18.4	25.9	13.7	19.7	0.1	4.9	10.9	0.1	0.1	5.4
Ehime	0.7	17.6	22.1	14.1	21.2	0.2	7.4	10.4	0.1	0.1	6.1
Kochi	0.8	20.0	19.9	13.4	21.9	0.2	10.9	7.5	0.2	0.1	5.2
Fukuoka	0.9	19.2	26.4	15.0	20.6	0.2	3.1	8.4	0.3	0.2	5.8
Saga	0.6	18.5	20.7	13.0	20.7	0.2	9.0	11.7	0.2	0.2	5.3
Nagasaki	0.7	19.4	20.7	13.9	23.6	0.3	6.9	8.8	0.2	0.2	5.3
Kumamoto	0.7	18.7	20.6	13.4	20.8	0.3	9.9	10.1	0.2	0.2	5.1
Oita	0.8	18.6	20.6	14.7	21.7	0.2	6.5	11.0	0.2	0.2	5.5
Miyazaki	0.5	17.3	20.1	12.5	20.7	0.2	10.9	11.9	0.2	0.2	5.4
Kagoshima	0.6	18.8	20.2	13.1	21.8	0.2	9.1	10.8	0.2	0.2	5.2
Okinawa	0.5	19.9	24.9	14.7	23.4	0.3	3.4	6.1	0.4	0.1	6.2

Note: Created by authors using the 2010 Population Census. Major group denotes A: Administrative and managerial workers, B: Professional and engineering workers, C: Clerical workers, D: Sales workers, E: Service workers, F: Security workers, G: Agriculture, forestry and fishery workers, H: Manufacturing process workers, I: Transport and machine operation workers, J: Construction and mining workers, K: Carrying, cleaning, packaging, and related workers, L: Workers not classified by occupation. The share is calculated except occupations not classified elsewhere.

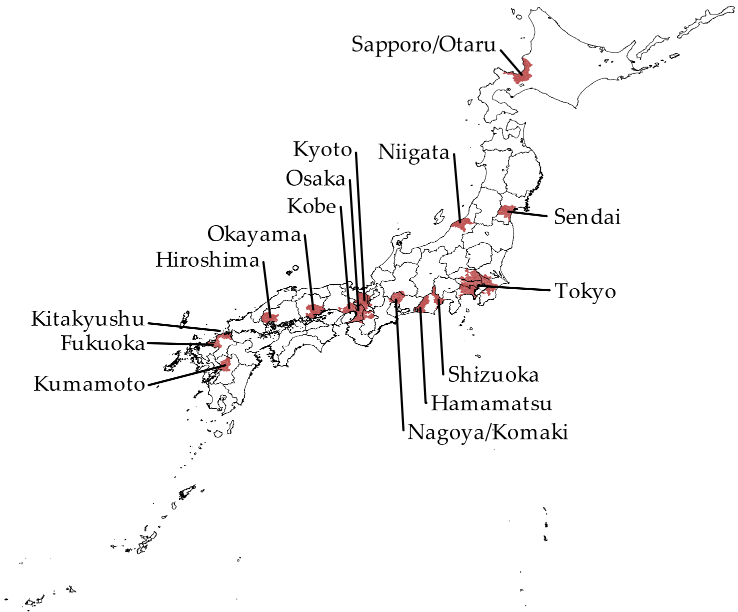
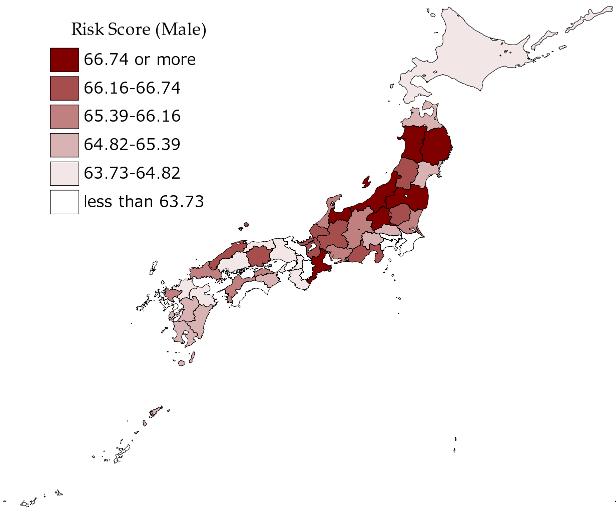
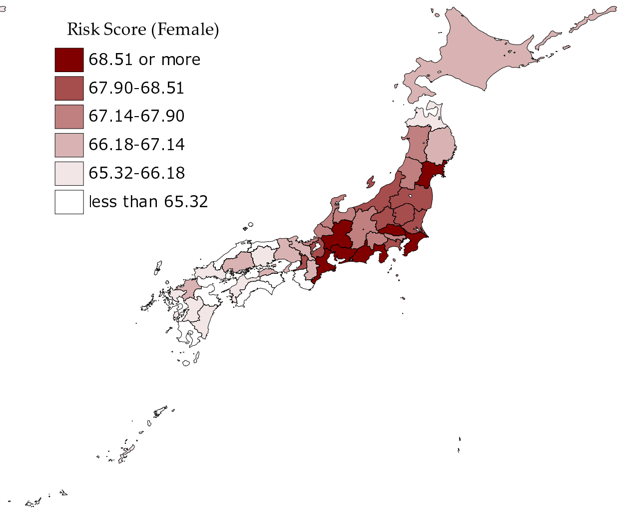


Figure 1: Classification of Large and Small Cities Based on Urban Employment Area

Note: Created by authors. The definition of urban employment area (UEA) is based on Kanemoto and Tokuoka (2002). Colored areas are classified as the group of large cities, which includes UEAs of the 23 wards of Tokyo and Ordinance-Designated Cities (as of 2012). The Ordinance-Designated Cities include Sapporo, Sendai, Niigata, Shizuoka, Hamamatsu, Nagoya, Kyoto, Osaka, Kobe, Okayama, Hiroshima, Kitakyusyu, Fukuoka, and Kumamoto. Non-colored areas are classified as the group of small cities, which includes the other areas except the 23 wards of Tokyo and Ordinance-Designated Cities.



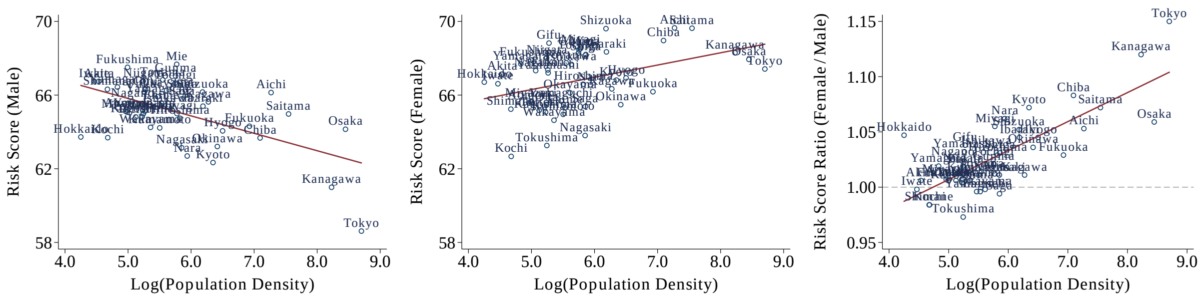
(a) Male



(b) Female

Figure 2: Geographical Distribution of Employment Risk Score of Computerization

Note: Created by authors using the 2010 Population Census and the probabilities of computerization computed by Frey and Osborne (2017). Risk scores by prefecture are in Table 2.



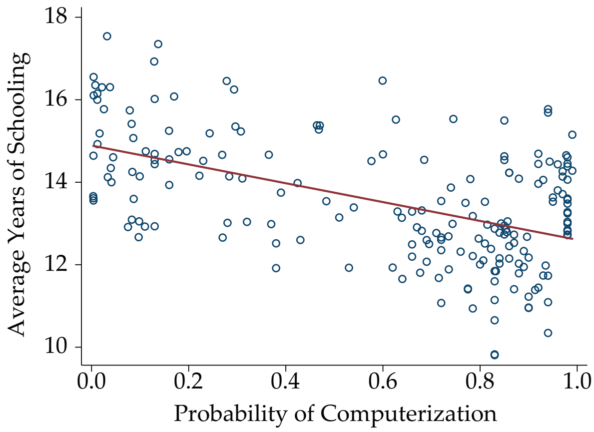
(a) Risk Score (Male)

(b) Risk Score (Female)

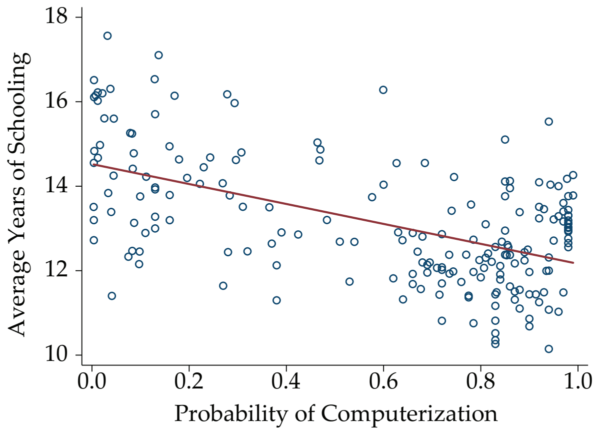
(c) Risk Score Ratio (Female/Male)

Figure 3: Employment Risk Score of Computerization and City size

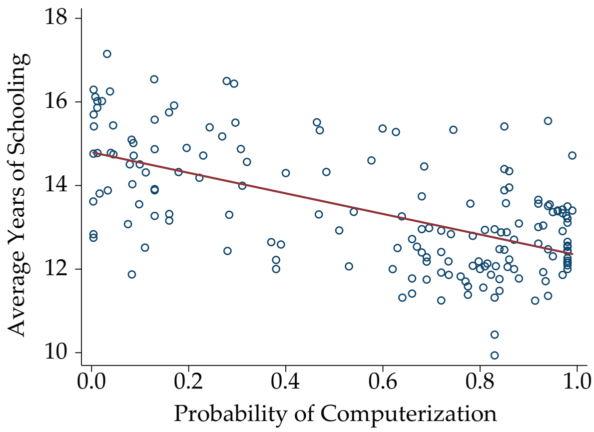
Note: Created by authors using the 2010 Population Census and probability of computerization by Frey and Osborne (2017). Risk scores by gender and prefecture are shown in Table 2. Risk score ratio in Panel (c) is calculated by dividing the female risk score by the male risk core. When the risk score is 1, there is no gender gap in risk of computerization. When the risk score is greater than 1, female workers are exposed to higher risks of computerization than male workers. When the risk score is less than 1, male workers are exposed to higher risks of computerization than female workers.



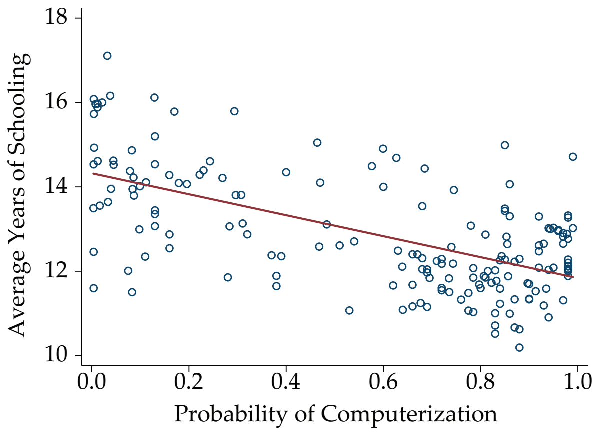
(a) Male, Large Cities



(b) Male, Small Cities



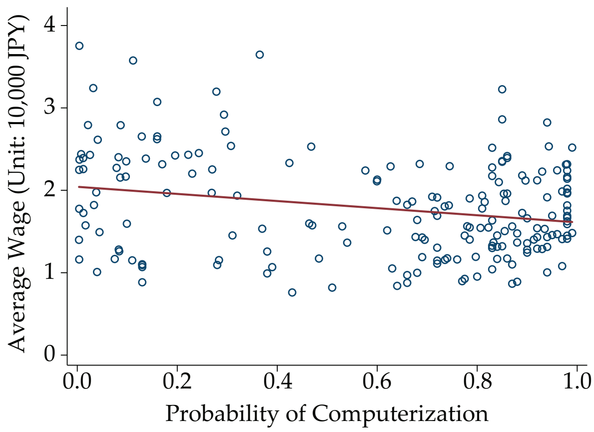
(c) Female, Large Cities



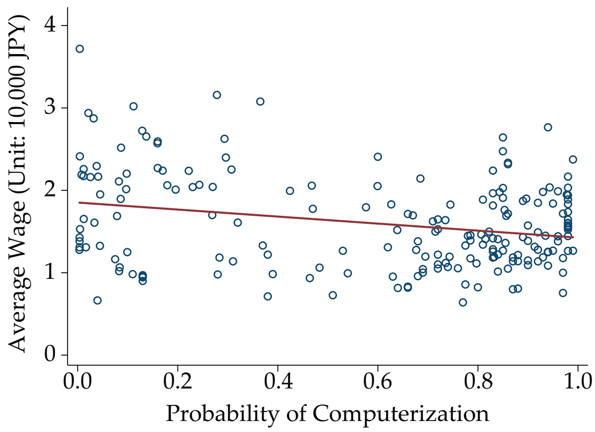
(d) Female, Small Cities

Figure 4: Average Years of Schooling and Probability of Computerization

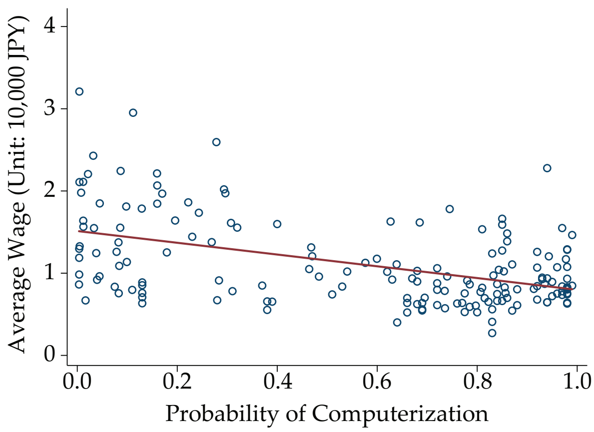
Note: Created by authors using micro data of the 2007 and 2012 Employment Status Surveys and the probability of computerization estimated by Frey and Osborne (2017). Occupations that do not include 20 workers and over by gender and city size are excluded from the sample.



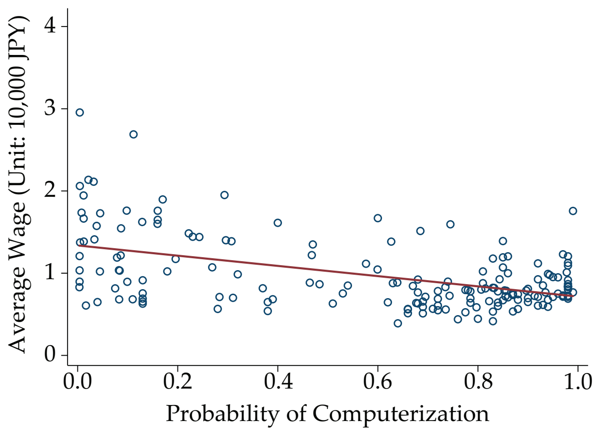
(a) Male, Large Cities



(b) Male, Small Cities



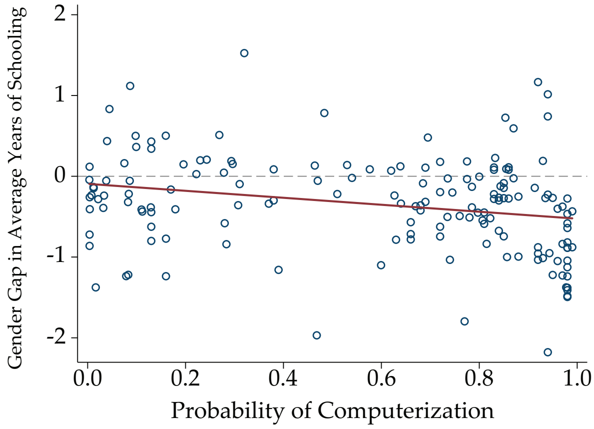
(c) Female, Large Cities



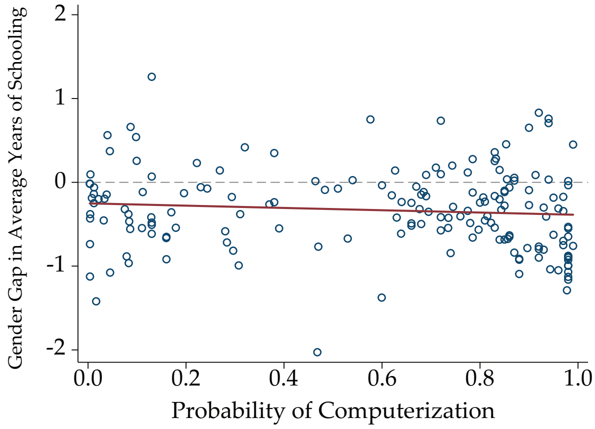
(d) Female, Small Cities

Figure 5: Average Wages and Probability of Computerization

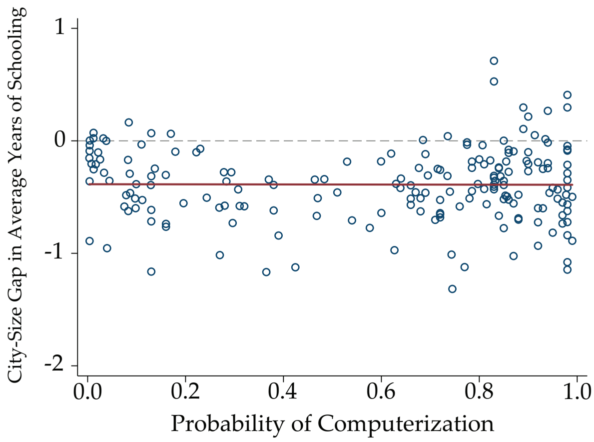
Note: Created by authors using micro data of the 2007 and 2012 Employment Status Surveys and the probability of computerization estimated by Frey and Osborne (2017). Occupations that do not include 20 workers and over by gender and city size are excluded from the sample.



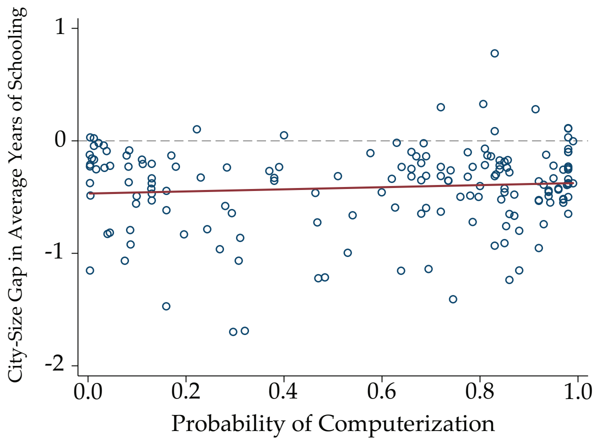
(a) Gender Gap within Large Cities



(b) Gender Gap within Small Cities



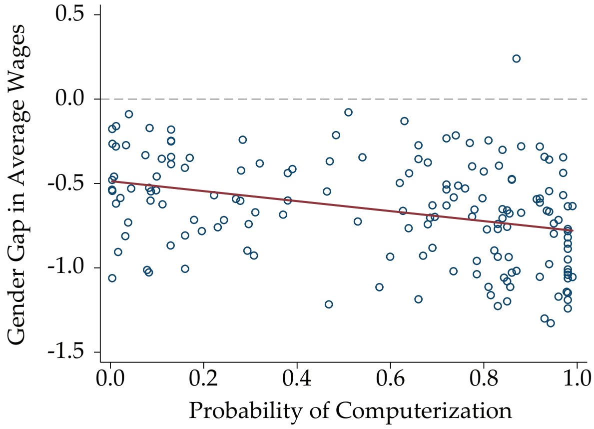
(c) City-Size Gap within Males



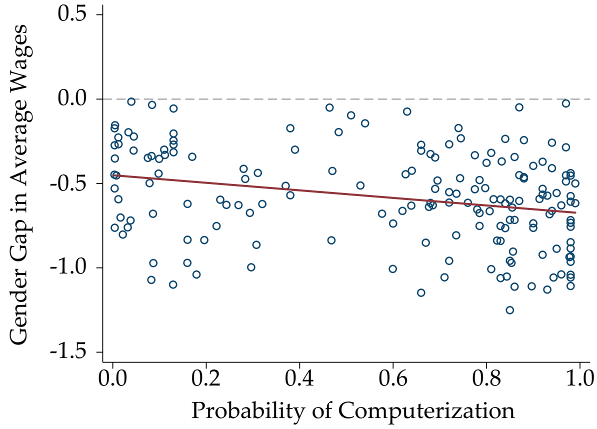
(d) City-Size Gap within Females

Figure 6: Gap in Average Years of Schooling and Probability of Computerization

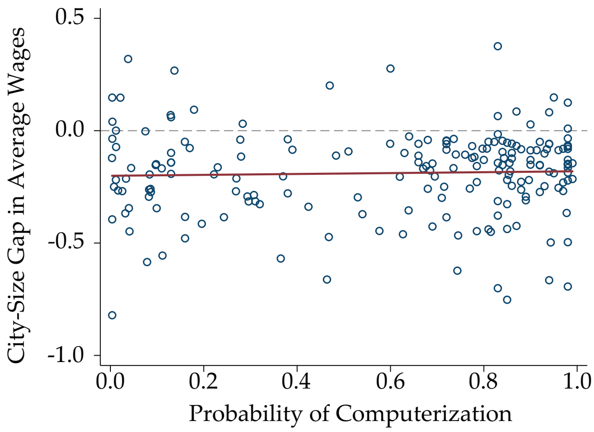
Note: Created by authors using micro data of the 2007 and 2012 Employment Status Surveys and the probability of computerization estimated by Frey and Osborne (2017). Occupations that do not include 20 workers and over by gender and city size are excluded from the sample. The gender gap is calculated as the values of males minus those of females. The city-size gap is calculated as the values of small cities minus those of large cities.



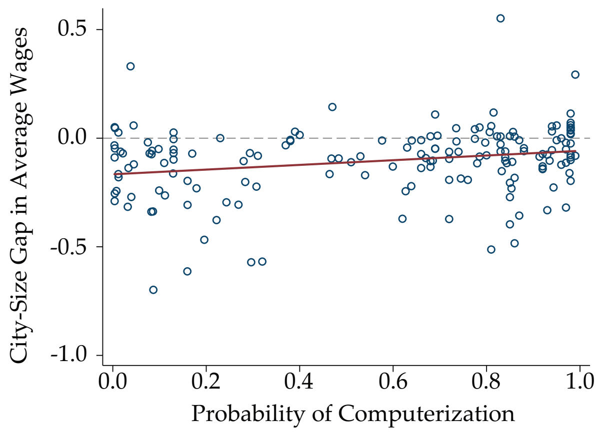
(a) Gender Gap within Large Cities



(b) Gender Gap within Small Cities



(c) City-Size Gap within Males



(d) City-Size Gap within Females

Figure 7: Gap in Average Wages and Probability of Computerization

Note: Created by authors using micro data of the 2007 and 2012 Employment Status Surveys and the probability of computerization estimated by Frey and Osborne (2017). Occupations that do not include 20 workers and over by gender and city size are excluded from the sample. The gender gap is calculated as the values of males minus those of females. The city-size gap is calculated as the values of small cities minus those of large cities.

Online Appendix for

Regional Employment and Artificial Intelligence in Japan

Nobuaki Hamaguchi* Keisuke Kondo†

Kobe University & RIETI RIETI

This online appendix provides additional results.

✜ Figures OA.1 and OA.2

Figure OA.1 presents the histogram of probability of computerization for occupations. Figure OA.2 presents disaggregated histograms into four categories.

✜ Figure OA.3

Figure OA.3 presents correlation between average years of schooling and probability of computerization, which corresponds to Figure 4 of the paper. Note that marker size represents the weight, which is proportional to the sample size of each occupation by gender and city size.

✜ Figure OA.4

Figure OA.4 presents correlation between daily wage and probability of computerization, which corresponds to Figure 5 of the paper. Note that marker size represents the weight, which is proportional to the sample size of each occupation by gender and city size.

*Research Institute for Economics and Business Administration (RIEB), Kobe University. 2-1 Rokkodai-cho, Nada-ku, Kobe-shi, Hyogo, 657–0013, Japan. (e-mail: `hamaguchi@rieb.kobe-u.ac.jp`).

†Research Institute of Economy, Trade and Industry (RIETI). 1-3-1 Kasumigaseki, Chiyoda-ku, Tokyo, 100–8901, Japan. (e-mail: `kondo-keisuke@rieti.go.jp`).

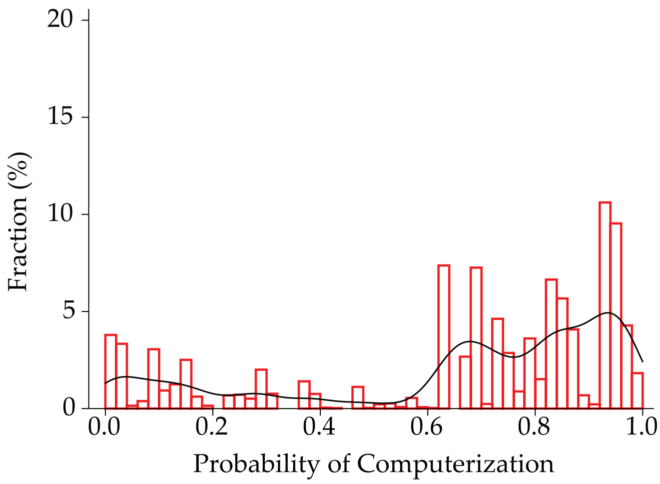
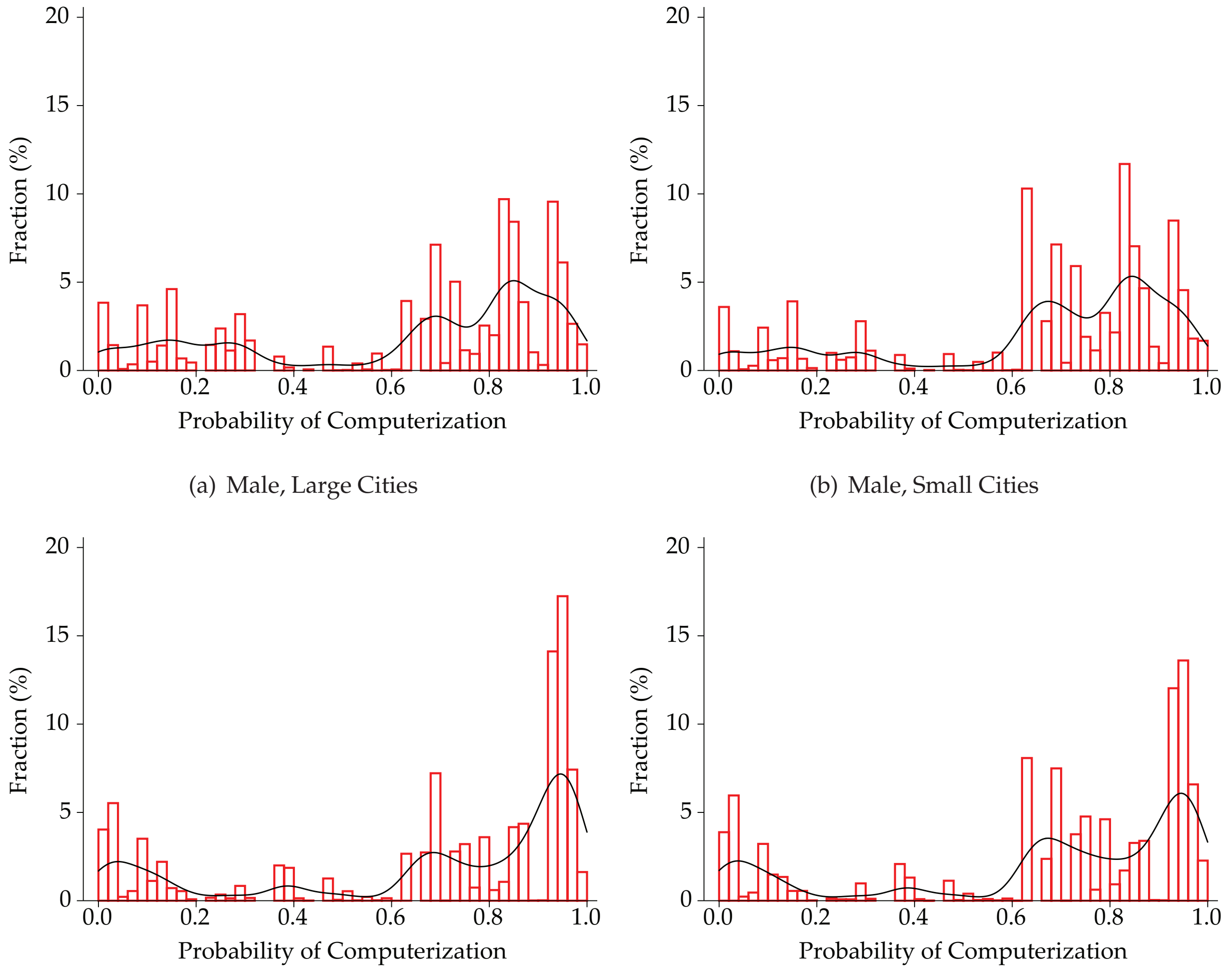


Figure OA.1: Distribution of Probability of Computerization

NOTE: Created by authors using micro data of the 2007 and 2012 Employment Status Surveys and the probability of computerization estimated by Frey and Osborne (2017). Fraction represents the share of the employed. The bin width is 0.02. Each panel includes the kernel density estimate with Gaussian kernel and band with 0.04.



(a) Male, Large Cities

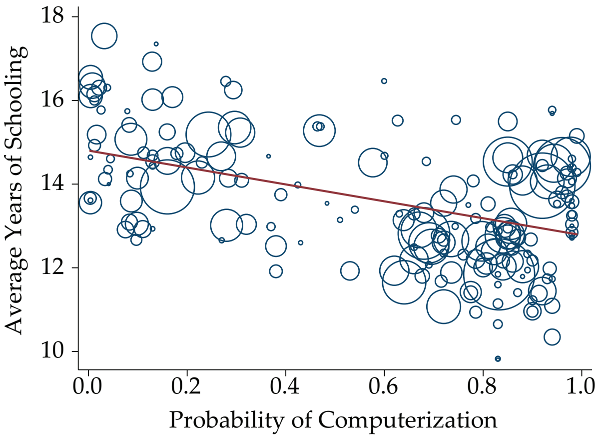
(b) Male, Small Cities

(c) Female, Large Cities

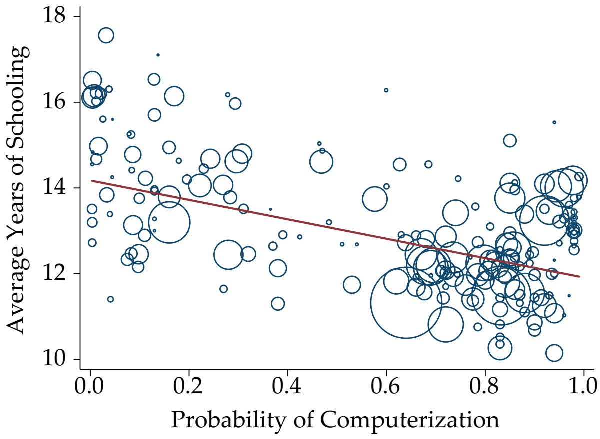
(d) Female, Small Cities

Figure OA.2: Distribution of Probability of Computerization by Gender and City Size

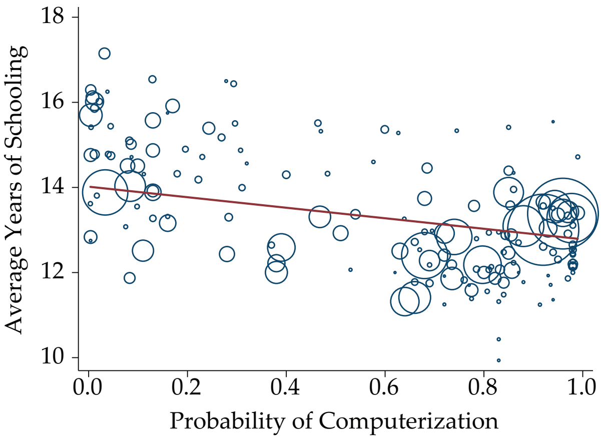
Note: Created by authors using micro data of the 2007 and 2012 Employment Status Surveys and the probability of computerization estimated by Frey and Osborne (2017). Fraction represents the share of the employed by gender and city size. The bin width is 0.02. Each panel includes the kernel density estimate with Gaussian kernel and band with 0.04.



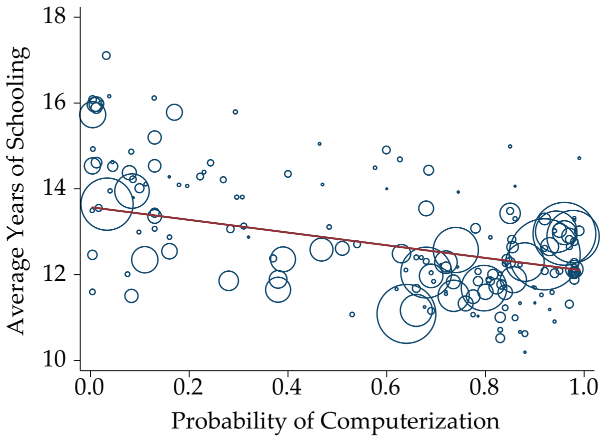
(a) Male, Large Cities



(b) Male, Small Cities



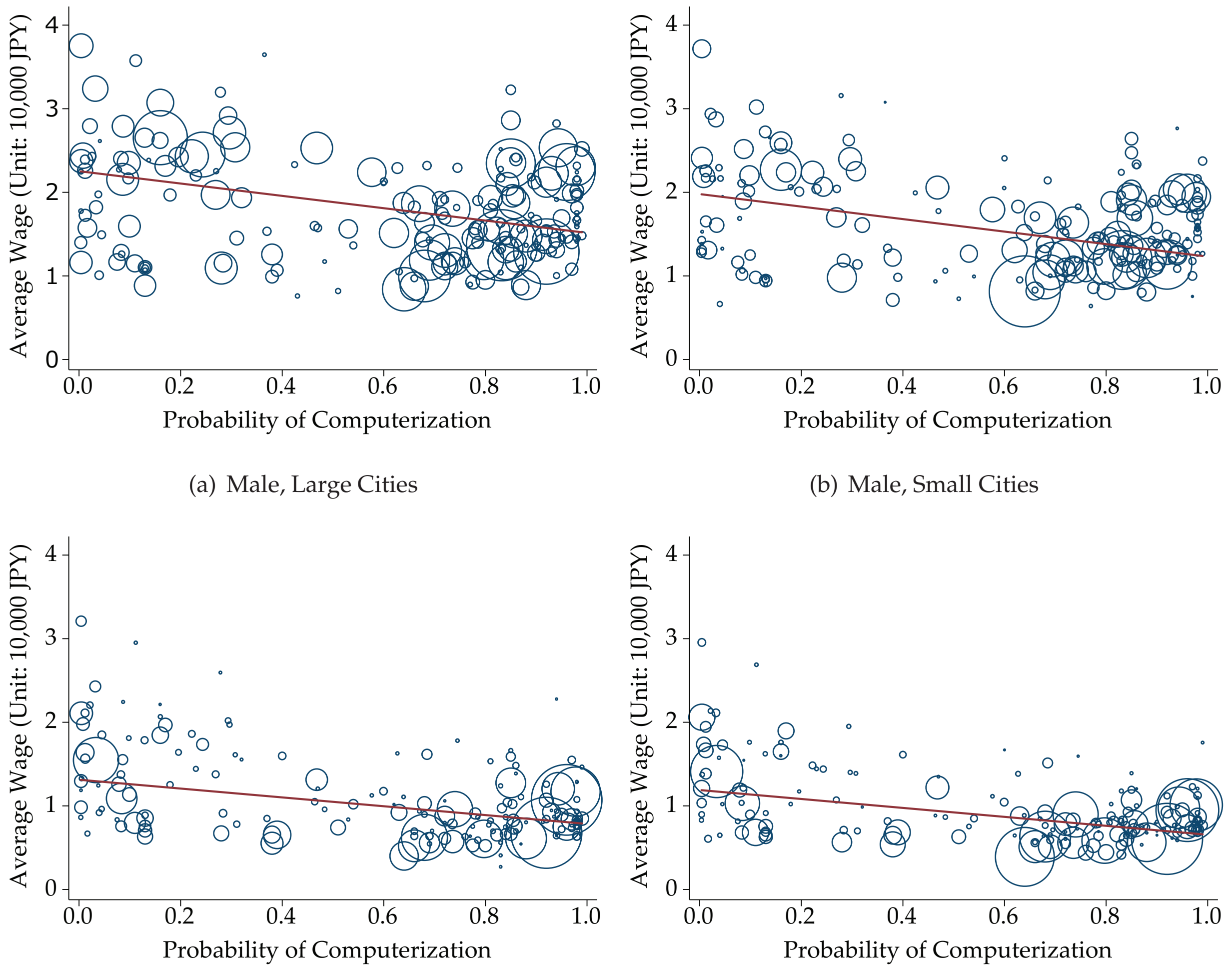
(c) Female, Large Cities



(d) Female, Small Cities

Figure OA.3: Average Years of Schooling and Probability of Computerization

Note: Created by authors using micro data of the 2007 and 2012 Employment Status Surveys and the probability of computerization estimated by Frey and Osborne (2017). Occupations that do not include 20 workers and over by gender and city size are excluded from the sample. Marker size represents the weight, which is proportional to the sample size of each occupation by gender and city size.



(a) Male, Large Cities

(b) Male, Small Cities

(c) Female, Large Cities

(d) Female, Small Cities

Figure OA.4: Average Wages and Probability of Computerization

Note: Created by authors using micro data of the 2007 and 2012 Employment Status Surveys and the probability of computerization estimated by Frey and Osborne (2017). Occupations that do not include 20 workers and over by gender and city size are excluded from the sample. Marker size represents the weight, which is proportional to the sample size of each occupation by gender and city size.