[Draft] Do Digital Technologies Complement or Substitute for Human Labor?*

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ABSTRACT

Digital technologies such as artificial intelligence (AI) have been advancing rapidly and are increasingly being used in practice. However, few empirical studies have examined whether they complement or substitute for human labor. Exceptions are studies which predict the probability that certain jobs will be replaced by automation over the next two decades or so. In this study, using an original online survey of workers in Japan, we conduct difference-in-differences analyses on the effect of the introduction of AI on hours worked, employment, and the non-routineness of tasks for five occupations that previous studies have identified as being likely to be negatively affected by AI. Our estimation results for workers overall show that the introduction of AI reduced hours worked, increased the non-routineness of jobs in terms of the repetitiveness of tasks, and required more regular employees, even though it had no significant effect on total employment. Further, the estimation results by occupation differ across occupations. Overall, the results suggest that AI acts as both a complement to and a substitute for human labor.

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* We thank Hisashi Dobashi, Yuko Harayama, Masahiro Hori, Masaki Ichikawa, Shuichiro Itakura, Daiji Kawaguchi, Teppei Koguchi, Koichi Kume, Fumihira Nishizaki, Takashi Omori, Norimichi Ukita, Isamu Yamamoto, Minoru Yonekura, and other ESRI colleagues for excellent comments that helped to improve the paper. Special thanks are due to Eric Gower and Ralph Paprzycki for their excellent English editing services. The views expressed in this paper are those of the authors and do not necessarily reflect those of the Economic and Social Research Institute, the Cabinet Office, or the Government of Japan.

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1. INTRODUCTION

Recent years have seen growing concerns that human labor might increasingly be replaced by digital technologies such as artificial intelligence (AI), the internet of things (IoT), and robotics.[1] Although such technologies have made considerable progress and are increasingly being adopted in practice, there are relatively few empirical studies examining the impact of their introduction on the demand for labor. While theoretical studies on digital technologies[2] suggest that the effects of technological change depend on the tasks in which workers are engaged, the actual impact on the labor market remains unclear. Does the adoption of digital technologies increase or decrease employment? Do digital technologies act as complements to or substitutes for human labor? How does the introduction of AI change the tasks that workers are engaged in? In this study, using an original online survey, we conduct difference-in-differences (DID) analyses of the effect of the introduction of AI on hours worked, employment, and the non-routineness of jobs to answer these questions.

The adoption of digital technologies such as AI has only just begun and sufficient data on the impact are not yet available. Due to such data constraints, empirical research so far has focused on the effects of information and communication technology (ICT) other than AI. The extant literature about the effects of AI is limited to predictions using machine learning,[3] and the prediction of studies on the extent of those effects differs considerably. This paper is the first step toward an empirical analysis of the effects of AI on the labor market.[4] We conducted an online

[1] See, for example, Brynjolfsson and McAfee (2011).

[2] The effects of automation on labor are discussed in, for example, Autor, Levy, and Murnane (2003), Acemoglu and Autor (2011), and Acemoglu and Restrepo (2018a, 2018b).

[3] See, for example, Frey and Osborne (2017), Arntz, Gregory, and Zierahn (2016) and Nedelkoska and Quintini (2018).

[4] Among digital technologies, we focus on AI. However, it is difficult to clearly distinguish between AI-driven technologies and other technologies. The reason is that AI is a kind of computer program and can be loaded onto various devices and equipment such as computers and robots. Therefore, our online survey includes these devices and equipment. In addition, the survey does not exclude robotics process automation (RPA).

survey in which respondents were divided into two groups: (1) a treatment group consisting of those into whose workplace AI had been introduced, and (2) a control group consisting of those into whose workplace AI had not been introduced. In addition, we develop an original measure of the degree of the non-routineness of jobs, which we call the ”non-routine task intensity” (NRTI). NRTI is constructed by regarding jobs as consisting of different tasks along the following three dimensions: repetition, decision-making, and communication. Tasks are then scored in terms of their non-routineness, and NRTI is constructed by aggregating the non-routineness scores of the different tasks. For example, an increase in NRTI in terms of the extent to which a job involves repetition implies that the job becomes more non-routine in that it involves less and/or fewer repetitive tasks.

We then construct a task-based model for estimation that essentially follows Acemoglu and Restrepo (2018b). The model consists of firms that produce output by combining labor services and households that supply labor. Using DID estimation, we find that the introduction of AI reduced hours worked by 0.287 hours, that is, 17.2 minutes per day, increased NRTI in terms of repetition, that is, made jobs involve less and/or fewer repetitive tasks, and required more regular employees, while the effect on total employment was insignificant. Furthermore, the estimation results by occupation differ across occupations.

We begin by reviewing recent developments in the attempt to devise a theoretical framework for the secular income inequality that has arisen over the past several decades. Since around the 1960s, in the United States labor market, the real wage premium of college graduates vis-à-vis non-college graduates has been rising despite the increase in the relative supply of college graduates. This so-called "college premium" was interpreted as the result of the adoption of ICT, which favors more skilled labor (or those with higher educational attainment), and therefore induces a skill-biased demand shift (i.e., as shift in demand toward those with a college education). [5] This ”skill-biased technical change” (SBTC) hypothesis

[5] See, for example, Tinbergen (1974, 1975).

successfully accounted for developments in the wage gap during the 1970s and 1980s, and most research carried out during that period -- both theoretical and empirical -- was based on this SBTC hypothesis. In the 1990s, however, the college premium started to lag behind technological progress, and researchers started to look for other explanations.

Autor, Levy, and Murnane (2003) argued that the effects of ICT on workers was linked to the tasks they are engaged in rather than the skills they are endowed with and formulated a task-based model. Their model is a two-factor model consisting of a production function whose inputs are imperfectly substitutable non-routine tasks (carried out by high-skill labor) and routine tasks (carried out by low-skill labor or ICT capital). They tested how the rapid adoption of ICT changed the tasks performed by workers at their jobs and ultimately the demand for human labor. Their findings brought a paradigm shift in the theoretical framework from SBTC to "task biased technical change (TBTC)". However, although the task-based model by Autor, Levy, and Murnane (2003) was able to explain the decline of the college premium, it was unable to explain the polarization of employment[6] observed since around the 1990s. Acemoglu and Autor (2011) therefore proposed a refined version of the task-based model that comprises three factors and successfully explains the polarization of employment.

While theoretical work has developed along the lines just presented, empirical work[7] has been limited to the analysis of the impact of ICT other than AI. However, since what AI can perform is no longer confined to routine tasks,[8] there has been growing concern that human labor might be replaced by AI. Since state-of-the-art technologies employing AI have only just started to be used in practice, there is little data on the effects of AI, which has resulted in a lack of empirical research. A

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[6] The polarization of employment was first noted in Acemoglu (1999).

[7] Examples of recent empirical analyses on the impact of the introduction of AI and robotics in Japan are the studies by Adachi, Kawaguchi, and Saito (2019), Kume *et al.* (2017), and Yamamoto and Kuroda (2019).

[8] See, for example, Brynjolfsson and McAfee (2011).

seminal study in this context is that by Frey and Osborne (2017),[9] which has recently opened up a new field of research. The study differs from the traditional empirical literature in that the authors proposed a new methodology to estimate the susceptibility of employment to computerization using machine learning. They argued that, “Following recent technological advances, ..., computerisation is now spreading to domains commonly defined as non-routine” (Frey and Osborne, 2013: 259).[10] Following the task-based model by Autor, Levy, and Murnane (2003), Frey and Osborne (2013) built a model comprising several factors, such as computer capital and two types of labor input, which is either susceptible or non-susceptible to computerization. Non-susceptible labor is related to three types of engineering bottlenecks to computerization they identified, namely, bottlenecks with regard to (1) perception and manipulation; (2) creative intelligence; and (3) social intelligence. Using 70 original hand-labelled occupations as training data, they calculated the probability of job automation for 702 occupations and then classified occupations based on these probabilities to estimate the expected impact of automation on the US labor market. Their estimates suggest that 47 percent of jobs in the US were at a "high risk" (of more than 70 percent) of being replaced by computerization within the next one or two decades. However, their study has some limitations. For example, they only take technological factors into account, and the estimates depend on training data of 70 hand-labelled occupations to which they assigned values of 0 or 1 to represent the likelihood that they can be computerized based on their subjective assessment.

Another study using machine learning to predict the impact of automation and digitalization on employment is Arntz, Gregory, and Zierahn (2016), who estimated the risk of automation and digitalization for jobs based on the approach by Frey and Osborne (2013) while taking the heterogeneity of workers’ tasks within occupations into account. They found that, when examined at the task level, an average of 9

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[9] The first version of the study appeared in 2013 as an Oxford Martin School Working Paper.

[10] Note that they refer to the replacement of labor by technology as “computerization” rather than “automation.”

percent of jobs across the 21 OECD countries are automatable. Their task-based approach suggested that the threat to jobs from technological advances is much less pronounced than the results of the occupation-based approach implies.

The remainder of this study is organized as follows. Section 2 introduces the dataset we use in our analysis, including how we conducted our online survey and created the variables. In addition, it provides descriptive statistics and describes the relationship among variables. Section 3 presents our task-based model of the effect of AI on hours worked, employment, and non-routineness. Section 4 presents our empirical estimation results. Finally, Section 5 concludes and presents remarks on possible future extensions.

2. DATA

This section introduces the data we use in our empirical analysis, describes the construction of the index we use for measuring the non-routineness of tasks, and provides basic descriptive statistics.

2.1. Data Collection

Since there is no major existing dataset combining data on the introduction of AI and hours worked, employment, or the routineness of jobs, we conducted our own original online survey (see Appendix 1). Our survey framework consists of two types of survey:

- Survey A: for employees engaged in particular occupations.
- Survey B: for managers in any occupation.

Both surveys were designed to analyze and compare two groups: (1) a treatment group consisting of those into whose workplace AI[11] had been introduced, and (2) a control group consisting of those into whose workplace AI had not been introduced.

[11] In our online survey, respondents were asked to answer whether or not their current job involved "new technology or machines" such as AI for natural language processing, AI for image processing, AI for speech processing, AI for control, or robotic process automation (RPA).

In Survey A, we targeted specific occupations that were ranked as high risk by Frey and Osborne (2017) and then selected five occupations:[12] receptionists and information clerks, account clerks, quality control technicians, retail salespersons, and human resource coordinators. We asked workers engaged in these occupations about their current working conditions[13,14] and their working conditions five years or so ago (e.g., hours worked), and whether AI had been introduced into their workplace within the last three years, i.e., in 2016, 2017 or 2018. Note that respondents to Survey A are bound to have little to do with the management of their company because of their job status and therefore know little about their company's employment strategy. Therefore, to complement Survey A, we conducted Survey B, in which we asked managers about the current and past situation of their subordinates, and whether AI had been introduced or not. The industry distribution of respondents to our survey is almost the same as in the Employment Status Survey, a national survey for Japan.

2.2. Construction of Non-Routine Task Intensity Measure

Following Arntz, Gregory, and Zierahn (2016), we examine how the introduction of AI into the workplace changed the tasks of workers. To this end, we develop

[12] We selected these five occupations among those labeled "high risk" based on the large number of workers they employ. There are two reasons. First, the more workers are employed in a particular occupation, the more likely it is that this occupation will be affected by the introduction of AI, and the larger is the likely economic impact. Second, since AI has not been widely adopted yet, this ensures that we have a sufficient number of ofservations for the treatment group to conduct DID analyses.

[13] Our survey is retrospective, that is, respondents were asked to answer questions about their past working conditions as well as their current ones. From the dataset, we constructed the data for estimation. We refer it as "panel data" for simplicity.

[14] Since our dataset is based on a retrospective survey, there may be some reflection bias, that is, answers about past working conditions may be incorrect or imprecise. To examine whether this is the case, we compared out data to nationwide statistics. We found that in our survey hours worked per day dropped by 1.7 percent (see Table 2), while in the Monthly Labour Survey, the hours worked index dropped by 2.1 percent from 2013 to 2018. Thus, the trend in our survey does not appear to be substantially different from the national trend, so that we used our survey data without making any adjustments.

our measure of the non-routine task intensity (NRTI) of jobs along the three dimensions mentioned earlier, i.e., repetition, decision-making, and communication. Let volume, Vol, be the percentage of hours worked for each task and let intensity, Int, be the degree of non-routineness of each task. Then let NRTI be the volume-weighted aggregate intensity of routineness at the individual level. Suppose a worker i is engaged in a set of tasks j in period t. The worker's NRTI can then be defined as follows:

$$NRTI_{i,k,t} = \sum_{j} Vol_{i,j,t} \times Int_{i,j,k,t} \qquad (1)$$

where k denotes one of the three dimensions, repetition, decision-making, or communication.[15] We refer to the NRTI for these three dimensions as NRTI1 (repetition), NRTI2 (decision-making) and NRTI3 (communication).

2.2.1. Survey Design for Quantification

When collecting data at the task level, we notified respondents of the following two points. First, we broke down each occupation into tasks to obtain standardized data at the task level. In Japan, companies expect employees to work flexibly and rarely provide a clear job description. Consequently, a notable feature of Japan's labor market is that there is little accurate information on job contents. Referring to job information websites, we decomposed each occupation into clear and specific tasks,[16] as shown in Table 1. Second, to measure the volume and intensity of each task, we asked respondents about the percentage of hours worked spent on each

[15] The three dimensions we selected – repetition, decision-making, and communication – correspond roughly to the three engineering bottlenecks identified by Frey and Osborne (2017) with regard to perception and manipulation, creative intelligence, and social intelligence.

[16] Acording to ISCO-08, "a *job* is defined in ISCO-08 as 'a set of tasks and duties performed, or meant to be performed, by one person, including for an employer or in self employment'. *Occupation* refers to the kind of work performed in a job. The concept of occupation is defined as a 'set of jobs whose main tasks and duties are characterized by a high degree of similarity'." (International Labour Organization, 2008: 11)

task and about the degree of non-routineness of tasks with regard to the three dimensions mentioned above – repetition, decision-making, and communication – on an ordinal scale (e.g., true, somewhat true, somewhat not true, not true).

2.2.2. Calculation of Non-Routine Task Intensity

Let us define that $Int_{i,j,1,t} = Int1_{i,j,t}$ for $k = 1$, $Int_{i,j,2,t} = \left(5 - Int2_{i,j,t}\right)$ for $k = 2$ and $Int_{i,j,3,t} = \left(4 - Int3_{i,j,t}\right)$ for $k = 3$. Note that $Int1_{i,j,t}$, $Int2_{i,j,t}$ and $Int3_{i,j,t}$ are converted from raw data as depicted in Figure 1. Using the data obtained, we calculate NRTIs along the three dimensions based on equation (1). For simplicity, the intervals of the scale are assumed to be equal. Based on this assumption, we convert the intensity data obtained on an ordinal scale into integral numbers to construct Int, where a lower value means that the more a particular statement applies (is “true”), as shown in Figure 1. Hours worked is represented by Vol. We then calculate the volume-weighted average intensity and designate this index as the NRTI. A higher NRTI value means that a job is more non-routine task intensive.

Therefore, while for repetition Int is used as it is, for decision-making and communication the inverse is used. That is, regarding repetition ($k = 1$),

$$NRTI_{i,1,t} = \sum_{j} (Vol_{i,j,t} \ * \frac{1}{100}) \times Int1_{i,j,t}$$

and regarding decision-making and communication ($k = 2,3$),

$$NRTI_{i,2,t} = \sum_{j} (Vol_{i,j,t} \ * \frac{1}{100}) \ \times (5 - Int2_{i,j,t})$$
$$NRTI_{i,3,t} = \sum_{j} (Vol_{i,j,t} \ * \frac{1}{100}) \ \times (4 - Int3_{i,j,t})$$

2.3. Descriptive Statistics

Table 2 presents summary statistics of the variables.

2.3.1. Histograms

Figure 2(a) shows a histogram for the frequency distribution (percentage) of differences in hours worked between the past and the present for the treatment group. Figure 2(b) shows the histogram for the control group.

The distribution for the treatment group is skewed slightly more to the left than that for the control group, which means that the introduction of AI appears to have reduced workers' hours worked. Similarly, Figures 3(a) and (b) show the frequency distribution of differences in NRTI1 (repetition) for the two groups. NRTI1 (repetition) for the treatment group is distributed more to the right than for the control group. This suggests that the introduction of AI resulted in workers doing more non-routine (less and/or fewer repetitive) tasks. As for NRTI2 (decision-making) and NRTI3 (communication), the distributions for the two groups appear to be almost identical, which differs from the pattern for NRTI1 (repetition).

2.3.2. Crosstables

Tables 3(a) and (b) are crosstables of the relationship between variables and the presence (+) or absence (-) of AI. They show that the rate of introduction of AI seems to be correlated to gender (higher for men than for women), educational attainment, firm size, and income, while the rate is not correlated to age. These observations indicate that, for the estimation, we should take these variables into account so as to neither overestimate nor underestimate the impact of the introduction of AI.

3. THE MODEL

In the previous section, we outlined how the dataset was constructed and provided an intuitive understanding of the data through the use of histograms and crosstables. In this section, we construct a task-based model for estimation. The model consists of firms that produce output by combining labor services and households that supply labor. Our model closely follows the model developed by Acemoglu and Restrepo (2018b).

Firms: A Task-Based Model

Assume that aggregate output is produced by combining the services of a unit measure of tasks $x \in [N-1, N]$ according to the following Cobb-Douglas aggregator:

$$\ln Y = \int_{N-1}^{N} \ln y(x) dx, \tag{1}$$

where Y denotes aggregate output and $y(x)$ is the output of task x.

Each task can be produced by human labor, $l(x)$, or by machines, $m(x)$, depending on whether it has been automated or not. We set the frontier of automation possibilities, I. For $x \in [N-1, I]$, tasks have been technologically automated. Then, tasks can be produced either by labor or by machines. For $x \in (I, N]$, tasks, which are not technologically automated, must be produced with labor. Thus, we have

$$y(x) = \begin{cases} \gamma_L(x) l(x) + \gamma_M(x) m(x) & if \;\; x \in [N-1, I] \\ \gamma_L(x) l(x) & if \;\; x \in (I, N]. \end{cases} \tag{2}$$

In the above equation, $\gamma_L(x)$ and $\gamma_M(x)$ are the productivity of human labor and machines, respectively. We assume that $\gamma_L(x)/\gamma_M(x)$ is increasing in x, meaning that labor has a comparative advantage in higher-indexed tasks. For simplicity, we set physical capital, K, to be fixed and inelastic. Firms minimize the cost to produce each task with equilibrium wage rate w and the equilibrium cost of capital r, since we assume perfect competition.

Households

Suppose that we have households $j = 0, \dots, J$ with reservation utility $\bar{u}_j$, where

$\bar{u}_{j+1} > \bar{u}_j$ in the economy and households provide labor $l_j \in [0,1]$. Households' utility function is $u = u_j(c_j, l_j)$, where $\partial u/\partial c > 0$, $\partial^2 u/\partial c^2 < 0, \partial u/\partial l < 0$, $\partial^2 u/\partial l^2 < 0$. Each household decides whether to work or not only in one period, with w given, and there is no saving; that is, all earnings are consumed in this period. Then, household j's maximization problem is as follows:

$$\max U_j = \begin{cases} \max\limits_{c_j, l_j} u_j(c_j, l_j) \quad s.t. \quad c_j = wl_j, l_j \leq 1 \quad if \;\; l_j > 0 \\ \\ \bar{u}_j \qquad\qquad\qquad\qquad\qquad\qquad\qquad if \;\; l_j = 0. \end{cases} \tag{3}$$

Given this setting, a marginal increase in w is likely to lead incumbent employees to reduce their labor supply and induces those who are unemployed to participate in the labor market. Different from Acemoglu and Restrepo (2018), we assume that labor supply is flexible.

Equilibrium

As stated above, in equilibrium, firms minimize the cost to produce each task and households maximize their utility. The labor market, capital market, and goods market all clear.

Central to our focus is not only the impact of new technologies on the productivity of labor but also on the demand for labor. Appendix 3 shows that the demand for labor can be expressed as

$$w = (N - I)\frac{Y}{L} \; . \tag{4}$$

Equation (4) can be inverted to obtain a downward-sloping labor demand curve as a function of the wage:

$$L = (N - I)\frac{Y}{w} \; . \tag{5}$$

The Displacement Effect and the Productivity Effect

As for labor demand, a marginal increase of the frontier of automation possibilities,

I, creates a displacement effect that reduces labor demand but is also counteracted by a productivity effect that pushes toward greater labor demand.

Specifically, from equation (5) we directly obtain

$$\frac{d\ln L}{dI} = \underbrace{\frac{d\ln(N-I)}{dI}}_{\substack{\text{Displacement} \\ \text{Effect (-)}}} + \underbrace{\frac{d\ln(Y/w)}{dI}}_{\substack{\text{Productivity} \\ \text{Effect (+ or -)}}} . \qquad (6)$$

Note that L in the above equation has two meanings, hours worked and employment. As discussed in this section, a marginal increase of I has a displacement effect, that is, it leads to the replacement of labor by AI, and has a productivity effect, that is, it leads to a demand shift toward labor because of the rise in productivity that affects both hours worked and employment.

Estimation Framework

We employ DID estimation to examine the effect of the introduction of AI on hours worked and employment. Our estimation equation for hours worked and employment is as follows:

$$L_{i,t} = \alpha + \beta_1(Treat_{i,t} * After_{i,t}) + \beta_2 Treat_{i,t} + \beta_3 After_{i,t} + \sum_k \gamma_k X_{k,i,t} + \varepsilon_{i,t} \qquad (7)$$ [17]

where $Treat_{i,t}$ is a treatment dummy that takes a value of one if AI has been introduced into the workplace where individual i works at time t, and takes a value of zero otherwise. $After_{i,t}$ is a time dummy that takes a value of one in the present, i.e., t=1, and a value of zero in the past, i.e., t=0, and $X_{k,i,t}$ is a matrix of respondents' characteristics such as their age, gender, educational attainment, income, and size of the firm that they work for. The value of β_1 allows us to examine

[17] It should be noted that equation (7) is a labor supply equation, while equation (6) is a labor demand equation.

the DID effect.

As discussed above, we estimate the effect of the introduction of AI on hours worked and employment separately. As is well known, in Japan firms tend to rely on adjusting hours worked rather than employment levels when their demand for labor changes, since regulations for laying off workers are strict and fixed cost for workers, such as social security premiums, are very high. Therefore, we expect the impact of the introduction of AI on hours worked to be more pronounced than that on employment.

In the next section, using equation (7),[18] we estimate the impact of the introduction of AI while controlling for workers' characteristics. Moreover, for the estimation of the impact of the introduction of AI on NRTIs, we use the same estimation equation as for hours worked and employment, since NRTIs are also likely to be affected by workers' characteristics.

4. ESTIMATION RESULTS

In this section, we examine the effects of the introduction of AI on hours worked and employment using equation (7) controlling for factors related to the introduction of AI. In addition, we also estimate the direct effect of the introduction of AI on the non-routineness of jobs and discuss the differences in the effects by type of tasks. As shown in Section 2, the rate of introduction of AI appears to be correlated to gender, firm size, and income level. These factors are controlled for employing panel data analysis and propensity scoring matching.[19] That is, we conduct our estimation using a random effect model. Since there are some

[18] Note that we do not control for wage differences in the estimation, since our online survey does not provide satisfactory data. According to the Basic Survey on Wage Structure, the average salary in Japan hardly changed over the five-year period. Specifically, the overall average salary increased at an annual rate of only 0.23 pcercent. Regarding jobs related to our five occupations, the salaries of department store clerks and other shop clerks increased 0.04 percent and 0.44 percent, respectively, while the salaries of metallic materials inspection workers and machine inspection workers changed -2.30% and 0.19%, respectively.

[19] We tried various, although not all, combinations with the five variables, as shown in Table 7.

observations in the dataset that can be regarded as outliers, we exclude such outliers based on various criteria.[20]

4.1. Effect on Hours Worked

Table 4 shows the results for hours worked based on the DID using panel data. The results in column (1) indicate that the introduction of AI reduced hours worked by 0.287 hours, that is, 17.2 minutes per day.

We conduct two alternative estimations, one with and one without income as one of the independent variables, since income itself may be affected by the introduction of AI. As shown in Table 3(a), there is a positive correlation between workers' income and the rate of introduction of AI. Comparing the results in column (2) in Table 4, which includes income, with those in column (1), we find little difference between the estimation results.

The propensity score matching estimation results are shown in Table 5. The results are consistent with those of the panel data analysis, that is, the introduction of AI reduced hours worked.

4.2. Effect on Non-Routine Task Intensity

Table 6 shows the estimation results for NRTI using the panel data. The results are mixed. In the estimations for NRTI1 (repetition), the coefficient is positive and statistically significant (columns (1) and (2)), while in the estimations for NRTI2 (decision-making) and NRTI3 (communication), the coefficients are statistically insignificant (columns (3) to (6)). These results imply that the introduction of AI affects different tasks differently; that is, while tasks that involve repetition are likely

[20] We eliminate outliers based on the following criteria. Survey A: respondents who worked more than fifteen hours per day on average, who had worked at their current firm for less than five years, and/or whose answers on educational attainment, income, and/or firm size were invalid; respondents who answered that AI had been introduced into their workplace, but the introduction of AI was over three years ago. Survey B: respondents whose answers on their position, income, and/or firm size were invalid; and respondents where the number of workers in the section they manage had increased or decreased by more than 50 percent.

to be affected by the introduction of AI, tasks that involved decision-making or communication are unlikely to be affected. This result coincides with the general notion that AI is good at predictable and codifiable tasks with given rules but is not good at putting knowledge into context or form without predefined rules. Furthermore, the result is in line with the prediction by Frey and Osborne (2017).[21]

The propensity score matching estimation results are shown in Table 5. The results are consistent with the panel data analysis, that is, the coefficient for NRTI1 (repetition) is positive and significant in some cases, while the coefficients for NRTI2 (decision-making) and NRTI3 (communication) are insignificant.

4.3. Effect on Employment

Table 7 shows the results for the impact on employment levels. The results indicate that the impact on the number of regular employees is positive and weakly significant, suggesting that the introduction of AI resulted in an increase in the number of regular employees of 2.4 percent, while the impact on total employment and other types of employees is insignificant. This implies that the introduction of AI may require more regular employees, who are likely to be more skilled, but has little impact on total employment.

The propensity score matching estimation results in Table 8 show that the introduction of AI has little impact on employment. The reason is that for the employment analysis, Survey B data is used for the estimation, and the diversity of respondents' occupations is much larger than in Survey A in which respondents are limited to only five occupations. This makes it difficult to find appropriate matches, given the limited sample size.

[21] Frey and Osborne (2017) argued that their findings suggest that the timeline for the computerization of occupations mainly depends on the pace at which the engineering bottlenecks can be overcome. Their prediction implicitly suggests that technological improvements are likely to enter the domains of perception and manipulation first, followed by the domains of creative intelligence and social intelligence in the long-run.

4.4. Estimation Results by Occupation

Next, we conduct the same estimations by including a dummy variable for each of the five occupations. Table 9(a) shows the results for the effects of the introduction of AI on hours worked. They indicate that for account clerks and human resource coordinators, the effects are negative and significant, in line with the overall results in Table 4. On the other hand, the effects for the other occupations, that is, receptionists and information clerks, quality control technicians, and retail salespersons, are insignificant.

Next, Table 9(b) shows the results for the effects on NRTI. For NRTI1 (repetition), the coefficients for quality control technicians and human resource coordinators are positive and significant, while for the other occupations they are insignificant. For NRTI2 (decision-making), the coefficient for quality control technicians is positive and significant, while coefficients for the other occupations are insignificant. Meanwhile, for NRTI3 (communication), the coefficient for human resource coordinators is positive and significant, while those for the other occupations are insignificant. On the whole, the effects are always positive when significant, suggesting the introduction of AI increased the non-routineness of jobs.

Based on the estimation results by occupation with regard to hours worked and NRTI, we can classify the five occupations into two categories: (a) occupations for which the impact is consistently insignificant, namely, receptionists and information clerks, and retail salespersons; and (b) occupations for which the impact is significant in some cases, namely, account clerks, quality control technicians, and human resource coordinators. Note that the rate of introduction of AI is higher in (b) than in (a).[22] These estimation results can be interpreted as follows. The occupations in group (a) have not been affected by the introduction of AI so far; this is due to the lower rate of introduction of AI in occupations in this category. An alternative interpretation is that the occupations in group (a) have been affected by

[22] The rate of the introduction of AI by occupation is as follows: receptionists and information clerks, 5.1 percent; account clerks, 8.3 percent; quality control technicians, 10.6 percent; retail salespersons, 2.4 percent; and human resource coordinators, 19.7 percent

the introduction of AI and/or other recent technologies to such an extent that workers have changed their occupations and can no longer answer this online survey, that is, the results are subject to selection bias.

Therefore, the estimation results by occupation do not necessarily contradict the estimation results overall in that the introduction of AI decreased the hours worked and increased NRTI1 (repetition) for some occupations.

Let us briefly summarize the estimation results. We found that the introduction of AI reduced hours worked; moreover, it increased NRTI1 both in the overall estimations and in the estimations by occupation, albeit only for quality control technicians and human resource coordinators. In addition, in the estimation by occupation, we found that the introduction of AI decreased hours worked for account clerks and human resource coordinators, while it increased NRTI1 (repetition) for quality control technicians and human resource coordinators, NRTI2 (decision making) for quality control technicians, and NRTI3 (communication) for human resource coordinators. Furthermore, in the overall estimation, we found that the introduction of AI increased the employment of regular employees.

It should be noted that these estimation results may be affected by the capabilities of current AI, which, as discussed in the previous subsection, is good at predictable and codifiable tasks with given rules, that is, repetitive tasks. However, current AI is neither good at putting knowledge into context, namely, communication tasks, nor is it good in contexts without predefined rules, that is, decision-making tasks. Our estimation results that the effects of AI on tasks differ depending on the nature of the task involved therefore suggest that the impact of the introduction of AI reflects current limitations in the capabilities of AI. Furthermore, our estimation results suggest that AI is both a substitute for labor by reducing hours worked and a complement by partially increasing employment. Finally, we do not find a large negative effect on employment, but the longer-term effects still remain to be seen.

5. CONCLUSION

In this study, we discussed the effects of the introduction of AI on the labor market to examine whether AI acts as a substitute for or complement to human labor. We analyzed the issue empirically using an extended version of a task-based model. Frey and Osborne (2017) predicted the probability of automation for different occupations using machine learning. They showed that about half of US jobs could be replaced by computerization. Arntz, Gregory, and Zierahn (2016) followed the machine learning framework developed by Frey and Osborne (2017) to predict the impact of AI but took heterogeneity in workers' tasks within occupations into account. Their results suggested that on average only about 9 percent of jobs in OECD countries are automatable. Against this background, we conducted an online survey to empirically examine the impact of the introduction of AI in Japan. Using the dataset obtained from the survey, we calculated the non-routine task intensity of jobs to examine the effect on jobs.

We then presented a theoretical model consisting of firms and households to conduct an empirical analysis of the impact on hours worked, employment, and NRTI. Conducting estimations for workers overall and by occupation, we found that the introduction of AI reduced hours worked and increased NRTI1 (repetition) in the estimations for workers overall. In addition, in the estimations by occupation, we found that the introduction of AI decreased hours worked for account clerks and human resource coordinators, while it increased NRTI1 (repetition) for quality control technicians and human resource coordinators, NRTI2 (decision making) for quality control technicians, and NRTI3 (communication) for human resource coordinators. In the estimations for workers overall, the estimation results for employment suggest that the introduction of AI increased the employment of regular employees.

An interpretation of our estimation results with regard to hours worked and employment is that AI is both a complement to and substitute for human labor. Next, an interpretation of the estimation results with regard to NRTI is that the adoption of AI is now spreading in the domain of repetition, which corresponds to tasks related to perception and manipulation identified by Frey and Osborne (2017), while the adoption of AI is not yet spreading in the domains of decision-making and communication, which correspond to tasks related to creative intelligence and social intelligence. In the short-term, these estimation results with regard to NRTI are in line with the timeline regarding the development of AI capabilities predicted by Frey and Osborne (2017). In the long run, we do not find a large negative effect on employment as predicted by Frey and Osborne (2017), but the longer-term effects still remain to be seen.

To evaluate the effects of the introduction of AI on employment more broadly, we need a larger-scale online survey or use public statistics capturing the introduction of AI if they become available. Other than data limitations, a major remaining issue is to examine the shift in wages or changes in the income distribution brought about by the introduction of AI, using a combination of official labor statistics and surveys on machinery that include information on the adoption of AI. Such statistics would allow us to examine the “reinstatement effect,"[23] that is, the wage increase brought about by the creation of new tasks in which labor has a comparative advantage. Further research is needed in this area.

[23] See Acemoglu and Restrepo (2018b).

REFERENCES

Acemoglu, D. (1999) “Changes in Unemployment and Wage Inequality: An Alternative Theory and Some Evidence,” *American Economic Review*, Vol. 89, pp. 1259–1278.

Acemoglu, D. and D. H. Autor (2011) “Skills, Tasks and Technologies: Implications for Employment and Earnings,” *Handbook of Labor Economics*, Ch. 11, Elsevier, pp. 1043–1171.

Acemoglu, D. and P. Restrepo (2018a) “The Race between Man and Machine: Implications of Technology for Growth, Factor Shares, and Employment,” *American Economic Review*, Vol. 108, pp. 1488–1542.

Acemoglu, D. and P. Restrepo (2018b) “Artificial Intelligence, Automation and Work,” *NBER Working Paper*, No. 24196.

Arntz, M., T. Gregory and U. Zierahn (2016) “The Risk of Automation for Jobs in OECD Countries: A Comparative Analysis,” *OECD Social, Employment and Migration Working Papers*, No. 189.

Autor, D. H. and D. Dorn (2013) “The Growth of Low-Skill Service Jobs and the Polarization of the US Labor Market,” *The American Economic Review*, Vol. 103, pp. 1553–1597.

Autor, D. H., F. Levy and R. J. Murnane (2003) “The Skill Content of Recent Technological Change: An Empirical Exploration,” *The Quarterly Journal of Economics*, Vol. 118, pp. 1279–1333.

Brynjolfsson, E. and A. McAfee (2011) *Race Against the Machine: How the Digital Revolution Is Accelerating Innovation, Driving Productivity, and Irreversibly Transforming Employment and the Economy*, Lexington, MA: Digital Frontier Press.

De La Rica, S. and L. Gortazar (2016) “Differences in Job De-Routinization in OECD Countries: Evidence from PIAAC,” *IZA Discussion Paper Series*, No. 9736.

Frey, C. B. and M. A. Osborne (2017) “The Future of Employment: How Susceptible Are Jobs to Computerisation?” *Technological Forecasting and Social Change*, Vol. 43, pp. 254–280.

International Labour Organization (2008) ”International Standard Classification of Occupations 2008.”

Adachi, D., D. Kawaguchi and Y. U. Saito (2019) “Robot, Employment, and Population: Evidence from Articulated Robot in Japan’s Local Labor Markets,” *forthcoming*.

Kume, K., H. Chuma, S. Hayashi and A. Toda (2017) “Self-Evolvability and Attitude toward Technological Changes: An Empirical Analysis Using a Survey,” *RIETI Discussion Paper Series,* 17-J-053.

Nedelkoska, L. and G. Quintini (2018) “Automation, Skills Use and Training,” *OECD Social, Employment and Migration Working Papers*, No. 202.

Tinbergen, J. (1974) “Substitution of Graduate by Other Labor,” *Kyklos*, Vol. 27, pp. 217–226.

Tinbergen, J. (1975) *Income Difference: Recent Research*, Amsterdam: North-Holland Publishing Company.

Yamamoto, I. and S. Kuroda (2019) “Use of New Information Technology such as AI and Worker Well-Being: Evidence from Panel Data,” *RIETI Discussion Paper Series,* 19-J-012.

Figure 1: Conversion of Ordinal Intensity Data into Integral Numbers, $Int1$

Occupation: Receptionists and information clerks				
Task	Answers: Past degree of repetition (Norminal)			
	True	Somewhat true	Somewhat not true	Not true
Communicate with customers directly	☐	☐	☑	☐
Communicate with customers indirectly (via phone or email)	☐	☑	☐	☐
Compile, copy, sort, and file records	☑	☐	☐	☐
Other	☐	☐	☐	☑

Task	*Int* : Past degree of repetition (Integral)
Communicate with customers directly	3
Communicate with customers indirectly (via phone or email)	2
Compile, copy, sort, and file records	1
Other	4

Figure 2(a): Difference in Hours Worked from Past to Present in the Treatment Group

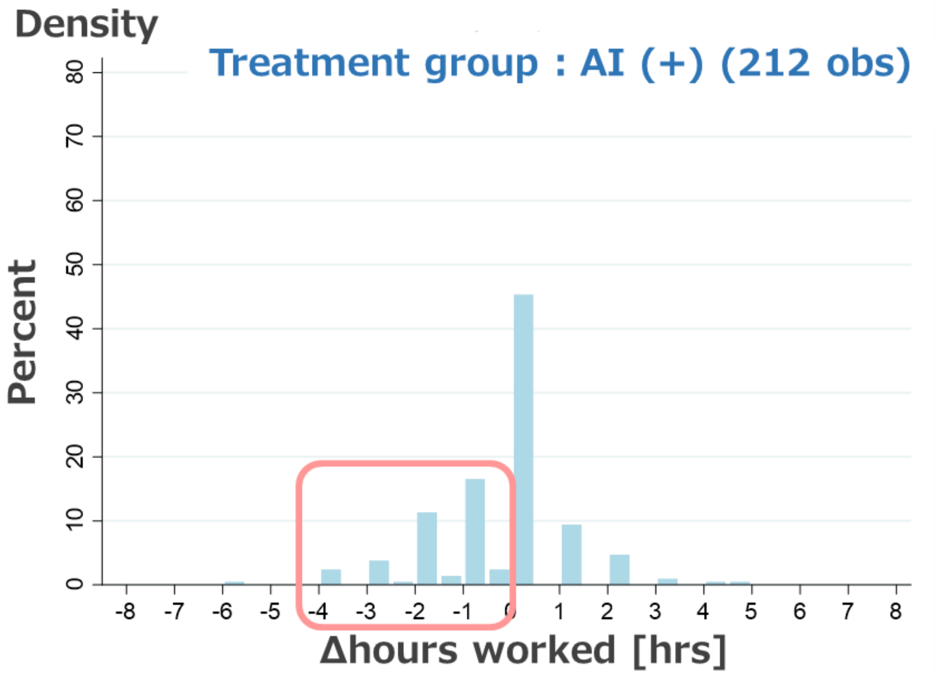

Figure 2(b): Difference in Hours Worked from Past to Present in the Control Group

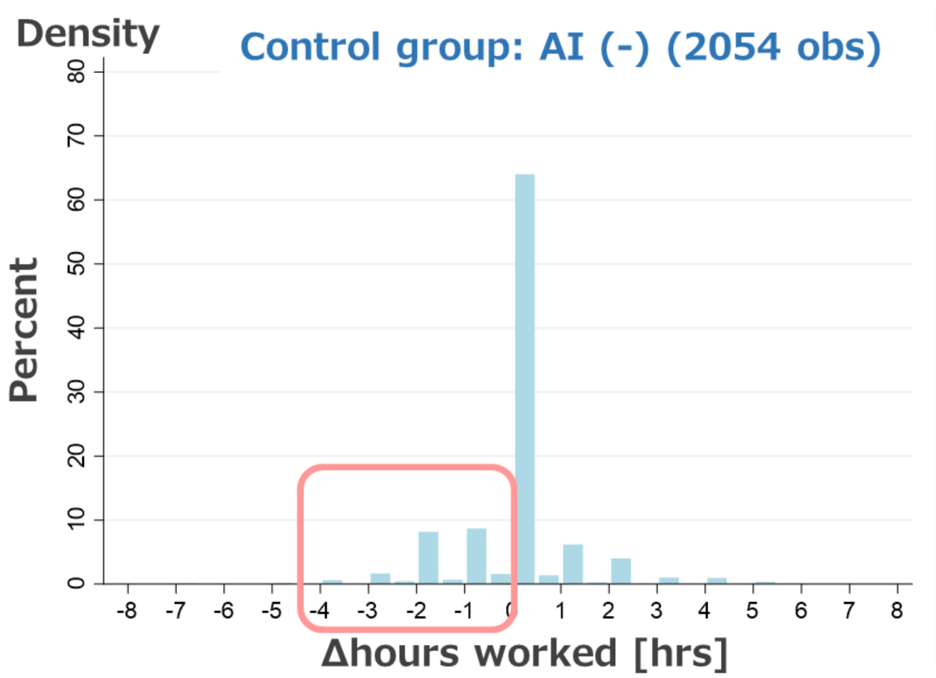

Figure 3(a): Difference in NRTI1 (Repetition) from Past to Present in the Treatment Group

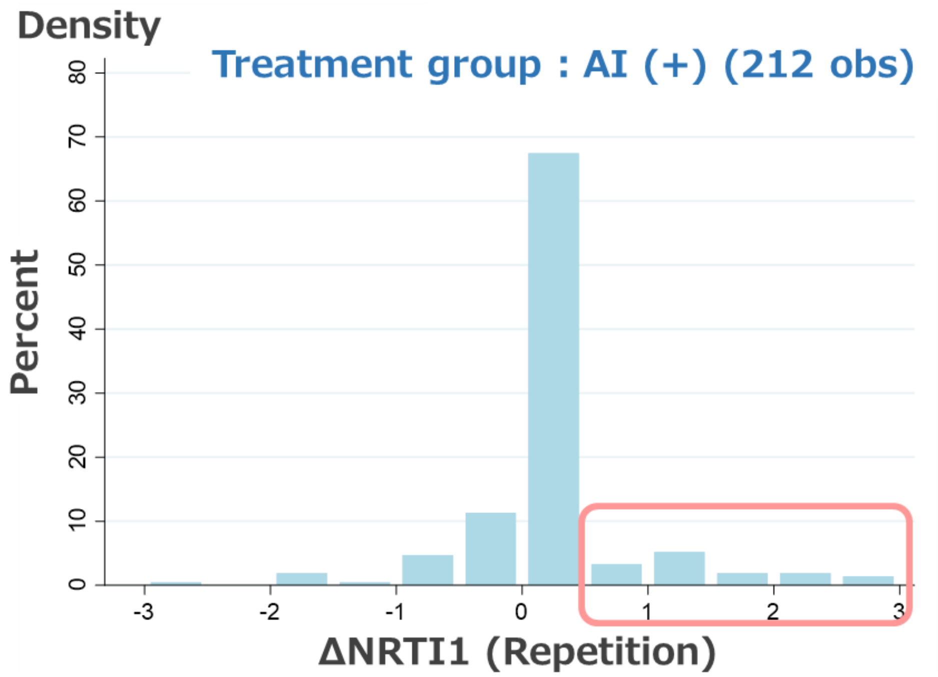

Figure 3(b):
Difference in NRTI1 (Repetition) from Past to Present in the Control Group

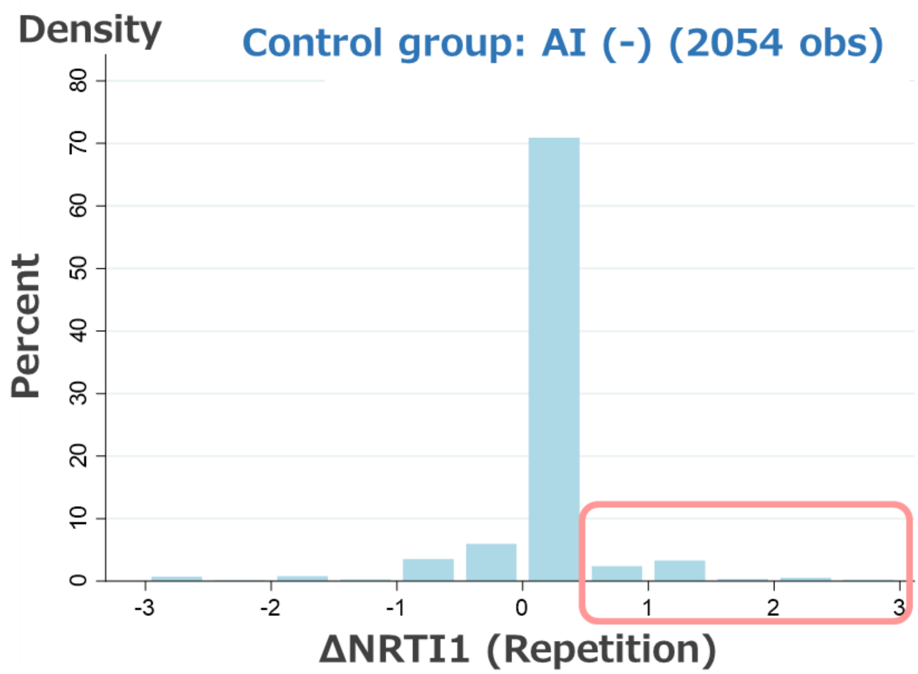

Table 1: Specific Tasks Making up the Five Occupations

Occupation	Tasks
Receptionists and information clerks	Communicate with customers directly
	Communicate with customers indirectly (via phone or email)
	Compile, copy, sort, and file records
	Other
Account clerks	Perform daily accounting clerical work
	Perform monthly accounting clerical work
	Perform annual accounting clerical work
	Other
Quality control technicians	Inspect products visually
	Inspect products using chemical agents
	Inspect the surfaces of products
	Inspect products with sensory organs
	Support inspection procedures
	Determine acceptance or rejection of products
	Pack and ship products
	Improve the environment for inspection
	Prepare documents
	Other
Retail salespersons	Communicate with customers directly
	Communicate with customers indirectly (via phone or email)
	Manage inventory
	Assist sales
	Other
Human resource coordinators	Plan human resources policies
	Recruit and hire new employees
	Educate and train employees
	Conduct personnel evaluation
	Execute personnel management
	Other

Table 2: Summary Statistics

Variable (Level)		Obs.	Mean	Std. Dev.	Min.	Max.
Hours worked	Past	2,266	8.73	1.49	2	14
	Current	2,266	8.58	1.29	1	14
NRTI1 (Repetition)	Past	2,266	1.78	0.92	1	4
	Current	2,266	1.78	0.92	1	4
NRTI2 (Decision making)	Past	2,266	3.27	0.78	1	4
	Current	2,266	3.48	0.65	1	4
NRTI3 (Communication)	Past	2,266	2.25	0.75	1	3
	Current	2,266	2.23	0.76	1	3
Employment	Past	1,982	411.0	3377.9	1	80,000
	Current	1,982	434.4	3775.8	1	100,000

Variable (Diff.)	Obs.	Mean	Std. Dev.	Min.	Max.
ΔHours worked	2,266	-0.15	1.19	-7	6
ΔNRTI1 (Repetition)	2,266	-0.0021	0.51	-3	3
ΔNRTI2 (Decision making)	2,266	-0.16	0.69	-3	3
ΔNRTI3 (Communication)	2,266	0.019	0.38	-2	2
ΔEmployment	1,982	0.029	0.17	-0.50	0.50

Table 3(a): Rate of Introduction of AI by Variable, Survey A

Gender

Gender \ Introduction of AI +/-		AI(-)		AI(+)		Total	
		Count	Rate	Count	Rate	Count	Rate
1	Male	1,289	0.63	164	0.77	1,453	0.64
2	Female	765	0.37	48	0.23	813	0.36
Total		2,054	1.00	212	1.00	2,266	1.00

Age

Age \ Introduction of AI +/-		AI(-)		AI(+)		Total	
		Count	Rate	Count	Rate	Count	Rate
1	23-24	4	0.00	0	0.00	4	0.00
2	25-29	64	0.03	6	0.03	70	0.03
3	30-34	172	0.08	21	0.10	193	0.09
4	35-39	291	0.14	32	0.15	323	0.14
5	40-44	377	0.18	31	0.15	408	0.18
6	45-49	396	0.19	39	0.18	435	0.19
7	50-54	372	0.18	45	0.21	417	0.18
8	55-59	249	0.12	28	0.13	277	0.12
9	60-64	129	0.06	10	0.05	139	0.06
Total		2,054	1.00	212	1.00	2,266	1.00

Educational attainment

Education \ Introduction of AI +/-		AI(-)		AI(+)		Total	
		Count	Rate	Count	Rate	Count	Rate
1	Lower secondary school	13	0.01	0	0.00	13	0.01
2	Upper secondary school	496	0.24	33	0.16	529	0.23
3	Specialized training college	241	0.12	11	0.05	252	0.11
4	Junior college or college of technology	161	0.08	11	0.05	172	0.08
5	University	1,090	0.53	141	0.67	1,231	0.54
6	Graduate school	53	0.03	16	0.08	69	0.03
Total		2,054	1.00	212	1.00	2,266	1.00

Firm size (Number of employees working for the firm)

Firm size	Introduction of AI +/-	AI(-) Count	AI(-) Rate	AI(+) Count	AI(+) Rate	Total Count	Total Rate
1	Fewer than 3	49	0.02	0	0.00	49	0.02
2	3-5	111	0.05	1	0.00	112	0.05
3	6-9	105	0.05	0	0.00	105	0.05
4	10-19	147	0.07	3	0.01	150	0.07
5	20-29	84	0.04	2	0.01	86	0.04
6	30-39	79	0.04	3	0.01	82	0.04
7	40-49	52	0.03	4	0.02	56	0.02
8	50-99	172	0.08	7	0.03	179	0.08
9	100-299	285	0.14	25	0.12	310	0.14
10	300-499	105	0.05	15	0.07	120	0.05
11	500-999	165	0.08	16	0.08	181	0.08
12	1,000-2,999	211	0.10	27	0.13	238	0.11
13	3,000-4,999	111	0.05	29	0.14	140	0.06
14	5,000-9,999	120	0.06	20	0.09	140	0.06
15	10,000+	258	0.13	60	0.28	318	0.14
	Total	2,054	1.00	212	1.00	2,266	1.00

Income (Million JPY) (per year)

Income	Introduction of AI +/-	AI(-) Count	AI(-) Rate	AI(+) Count	AI(+) Rate	Total Count	Total Rate
1	Less than 2	108	0.05	2	0.01	110	0.05
2	2-3	280	0.14	10	0.05	290	0.13
3	3-4	384	0.19	20	0.09	404	0.18
4	4-5	321	0.16	19	0.09	340	0.15
5	5-6	286	0.14	27	0.13	313	0.14
6	6-7	205	0.10	29	0.14	234	0.10
7	7-8	153	0.07	20	0.09	173	0.08
8	8-10	167	0.08	41	0.19	208	0.09
9	10-12	85	0.04	27	0.13	112	0.05
10	12-15	47	0.02	8	0.04	55	0.02
11	15-20	13	0.01	7	0.03	20	0.01
12	20+	5	0.00	2	0.01	7	0.00
	Total	2,054	1.00	212	1.00	2,266	1.00

Table 3(b): Rate of Introduction of AI by Variable, Survey B

Gender

Gender \ Introduction of AI +/-		AI(-) Count	AI(-) Rate	AI(+) Count	AI(+) Rate	Total Count	Total Rate
1	Male	1,656	0.93	173	0.90	1,829	0.92
2	Female	134	0.07	19	0.10	153	0.08
	Total	1,790	1.00	192	1.00	1,982	1.00

Age

Age \ Introduction of AI +/-		AI(-) Count	AI(-) Rate	AI(+) Count	AI(+) Rate	Total Count	Total Rate
1	23-24	1	0.00	0	-	1	0.00
2	25-29	8	0.00	4	0.02	12	0.01
3	30-34	61	0.03	12	0.06	73	0.04
4	35-39	100	0.06	23	0.12	123	0.06
5	40-44	281	0.16	33	0.17	314	0.16
6	45-49	427	0.24	37	0.19	464	0.23
7	50-54	434	0.24	38	0.20	472	0.24
8	55-59	337	0.19	30	0.16	367	0.19
9	60-64	141	0.08	14	0.07	155	0.08
	Total	1,790	1.00	191	1.00	1,981	1.00

Firm size (Number of employees working for the firm)

Firm size \ Introduction of AI +/-		AI(-) Count	AI(-) Rate	AI(+) Count	AI(+) Rate	Total Count	Total Rate
1	less than 5	127	0.07	6	0.03	133	0.07
2	5-20	184	0.10	14	0.07	198	0.10
3	21-50	173	0.10	15	0.08	188	0.09
4	51-100	170	0.09	16	0.08	186	0.09
5	101-300	253	0.14	32	0.17	285	0.14
6	301-1,000	277	0.15	22	0.11	299	0.15
7	1,001-3,000	213	0.12	33	0.17	246	0.12
8	3,001+	393	0.22	54	0.28	447	0.23
	Total	1,790	1.00	192	1.00	1,982	1.00

Income (Million JPY) (per year)

Income \ Introduction of AI +/-		AI(-) Count	AI(-) Rate	AI(+) Count	AI(+) Rate	Total Count	Total Rate
1	Less than 4	162	0.09	18	0.09	180	0.09
2	4-6	481	0.27	42	0.22	523	0.26
3	6-8	434	0.24	45	0.23	479	0.24
4	8-10	323	0.18	37	0.19	360	0.18
5	10-12	186	0.10	18	0.09	204	0.10
6	12-15	106	0.06	16	0.08	122	0.06
7	15-20	57	0.03	7	0.04	64	0.03
8	20+	41	0.02	9	0.05	50	0.03
Total		1,790	1.00	192	1.00	1,982	1.00

Position

Position \ Introduction of AI +/-		AI(-) Count	AI(-) Rate	AI(+) Count	AI(+) Rate	Total Count	Total Rate
1	Chairperson	4	0.00	2	0.01	6	0
2	Deputy chair	0	-	0	-	0	-
3	Representative director and president	142	0.08	11	0.06	153	0
4	Representative director or vice-president	8	0.00	2	0.01	10	0
5	Senior managing director, managing director, or board member	114	0.06	13	0.07	127	0
6	Consultant or auditing director	4	0.00	1	0.01	5	0
7	Division director	27	0.02	6	0.03	33	0
8	General manager	256	0.14	38	0.20	294	0
9	Acting general manager	94	0.05	11	0.06	105	0
10	Manager	493	0.28	46	0.24	539	0
11	Acting manager	101	0.06	9	0.05	110	0
12	Senior staff	195	0.11	17	0.09	212	0
13	Chief (Lowest managerial rank)	322	0.18	36	0.19	358	0
14	Branch manager or factory manager	30	0.02	0	-	30	0
Total		1,790	1.00	192	1.00	1,982	1.00

Table 4: Changes in Hours Worked After the Introduction of AI

	(1)		(2)	
$Treat_{i,t} \times After_{i,t}$	-0.287	***	-0.287	***
	(0.086)		(0.086)	
$Treat_{i,t}$	0.284	***	0.227	**
	(0.096)		(0.096)	
$After_{i,t}$	-0.122	***	-0.122	***
	(0.026)		(0.026)	
Age	0.039		0.026	
	(0.025)		(0.025)	
Age^2	-0.001	*	0.000	
	(0.000)		(0.000)	
Female	-0.848	***	-0.733	***
	(0.060)		(0.063)	
Constant	9.828	***	9.712	***
	(0.594)		(0.739)	
Education	Yes		Yes	
Firm size	Yes		Yes	
Income	No		Yes	
Obs.	2,266		2,266	
R^2	0.141		0.159	

(Note) Standard errors are in parentheses. Figures are given in hours.

*, **, and *** denotes statistical significance at the 10, 5, and 1 percent level respectively.

Table 5: Changes in Hours Worked and NRTI based on Propensity Score Matching

Dependent Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
d(Hours worked)											
DID	-0.148	-0.230 **	-0.119	-0.270 **	-0.200	-0.204 *	-0.105	-0.260 **	-0.158	-0.181 *	-0.178 *
S.E.	(0.133)	(0.112)	(0.115)	(0.110)	(0.133)	(0.116)	(0.118)	(0.102)	(0.104)	(0.100)	(0.103)
d(NRTI 1) Repetition											
DID	0.041	0.079	0.070	0.089 *	0.073	0.102 *	0.095	0.118 **	0.035	0.051	0.070
S.D.	(0.063)	(0.057)	(0.056)	(0.054)	(0.060)	(0.053)	(0.063)	(0.057)	(0.053)	(0.051)	(0.050)
d(NRTI 2) Decision making											
DID	-0.051	0.018	-0.013	-0.013	-0.032	-0.028	0.055	0.007	0.003	-0.013	-0.013
S.D.	(0.074)	(0.061)	(0.064)	(0.059)	(0.070)	(0.060)	(0.067)	(0.055)	(0.058)	(0.054)	(0.054)
d(NRTI 3) Communication											
DID	0.000	-0.016	0.011	0.000	-0.033	-0.013	0.017	-0.003	-0.016	0.001	0.006
S.D.	(0.043)	(0.033)	(0.035)	(0.031)	(0.039)	(0.034)	(0.039)	(0.030)	(0.033)	(0.030)	(0.030)
Variables Used for Matching											
Age	○	○	○	○	○	○	○	○			
Gender	○	○	○	○	○	○	○	○			
Edu	○	○	○	○							
Income	○	○			○	○			○	○	
Firm size	○		○		○		○		○		○
Obs.	2,266	2,266	2,266	2,266	2,266	2,266	2,266	2,266	2,266	2,266	2,266

(Note) Standard errors are in parentheses.

*, **, and *** denotes statistical significance at the 10, 5, and 1 percent level respectively.

Table 6: Changes in Non-Routine Task Intensity After the Introduction of AI

	NRTI1 (Repetition)				NRTI2 (Decision making)				NRTI3 (Communication)			
	(1)		(2)		(3)		(4)		(5)		(6)	
$Treat_{i,t} \times After_{i,t}$	0.087	**	0.087	**	-0.007		-0.007		0.010		0.010	
	(0.037)		(0.037)		(0.049)		(0.049)		(0.028)		(0.028)	
$Treat_{i,t}$	0.063		-0.003		-0.060		-0.090	*	0.008		-0.013	
	(0.066)		(0.066)		(0.053)		(0.053)		(0.055)		(0.055)	
$After_{i,t}$	-0.004		-0.004		0.210	***	0.210	***	-0.021	**	-0.021	**
	(0.011)		(0.011)		(0.015)		(0.015)		(0.008)		(0.008)	
Age	-0.002		-0.014		-0.003		-0.009		-0.014		-0.007	
	(0.018)		(0.018)		(0.014)		(0.014)		(0.016)		(0.016)	
Age^2	0.000		0.000		0.000		0.000		0.000		0.000	
	(0.000)		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)	
Female	-0.123	***	-0.035		-0.011		0.027		-0.108	***	-0.145	***
	(0.044)		(0.047)		(0.033)		(0.035)		(0.037)		(0.040)	
Constant	2.350	***	2.773	***	3.125	***	3.851	***	2.918	***	2.851	***
	(0.438)		(0.543)		(0.325)		(0.407)		(0.369)		(0.460)	
Education	Yes		Yes		Yes		Yes		Yes		Yes	
Firm size	Yes		Yes		Yes		Yes		Yes		Yes	
Income	No		Yes		No		Yes		No		Yes	
Obs.	2,266		2,266		2,266		2,266		2,266		2,266	
R^2	0.086		0.113		0.044		0.544		0.048		0.066	

(Note) Standard errors are in parentheses.

*, **, and *** denotes statistical significance at the 10, 5, and 1 percent level respectively.

Table 7: Changes in Employment After the Introduction of AI

	ln(Total)		ln(Regular employees)		ln(Contract employees)		ln(Temporary staff)		ln(Casual employees)	
	(1)		(2)		(3)		(4)		(5)	
$Treat_{i,t} \times After_{i,t}$	0.020		0.024	*	0.001		0.030		-0.018	
	(0.013)		(0.013)		(0.016)		(0.023)		(0.025)	
$Treat_{i,t}$	0.780	***	0.656	***	0.242		0.077		0.347	
	(0.141)		(0.142)		(0.198)		(0.279)		(0.463)	
$After_{i,t}$	0.027	***	0.016	***	0.004		0.001		0.005	
	(0.004)		(0.004)		(0.006)		(0.009)		(0.015)	
Age	0.007		0.013	**	0.001		-0.011		-0.006	
	(0.006)		(0.006)		(0.009)		(0.014)		(0.024)	
Female	-0.1461		-0.1082		-0.3051		-1.1929	***	-1.2516	*
	(0.1617)		(0.1670)		(0.2398)		(0.4254)		(0.7407)	
Income	0.106	***	0.126	***	0.032		0.060		0.262	**
	(0.031)		(0.031)		(0.050)		(0.073)		(0.130)	
Firm size	0.189	***	0.165	***	0.257	***	0.180	***	0.105	
	(0.024)		(0.024)		(0.040)		(0.070)		(0.114)	
Position	-0.041	**	-0.013		-0.019		-0.044		0.127	
	(0.019)		(0.018)		(0.030)		(0.054)		(0.085)	
Constant	1.639	***	0.825	*	1.333	**	3.075	***	0.967	
	(0.436)		(0.433)		(0.651)		(1.170)		(1.766)	
Obs.	1,982		1,895		851		351		91	
R^2	0.091		0.086		0.085		0.065		0.160	

(Note) Standard errors are in parentheses. Figures are given in log natural employment.

*, **, and *** denotes statistical significance at the 10, 5, and 1 percent level respectively.

Table 8: Changes in Employment based on Propensity Score Matching

Dependent Variable

dln(Total)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	1	2	3	4	5	6	7
DID	-0.003	-0.002	-0.005	-0.002	0.001	-0.017	-0.008
S.E.	(0.024)	(0.022)	(0.022)	(0.020)	(0.019)	(0.021)	(0.022)
Obs.	1,305	1,305	1,305	1,305	1,305	1,305	1,305

dln(Regular employees)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	1	2	3	4	5	6	7
DID	0.008	0.007	0.004	-0.004	0.002	0.008	0.008
S.E.	(0.024)	(0.022)	(0.021)	(0.020)	(0.020)	(0.022)	(0.024)
Obs.	1,246	1,246	1,246	1,246	1,246	1,246	1,246

dln(Contract emplyees)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	1	2	3	4	5	6	7
DID	0.016	0.019	0.016	0.003	0.011	0.019	0.026
S.E.	(0.027)	(0.028)	(0.030)	(0.026)	(0.026)	(0.029)	(0.028)
Obs.	520	520	520	520	520	520	520

dln(Temporary staff)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	1	2	3	4	5	6	7
DID	0.061	0.061 *	0.028	0.010	0.015	0.049	0.052
S.E.	(0.041)	(0.035)	(0.038)	(0.037)	(0.033)	(0.037)	(0.045)
Obs.	230	230	230	230	230	230	230

dln(Casual employees)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	1	2	3	4	5	6	7
DID	-0.037	-0.074	0.000	-0.074 *	-0.005	0.012	-0.006
S.E.	(0.048)	(0.051)	(0.104)	(0.042)	(0.063)	(0.045)	(0.104)
Obs.	45	45	45	45	45	45	45

Variables used for matching

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Age	○	○	○	○		○	○
Gender	○	○	○	○			
Firm size	○		○		○		○
Income	○	○				○	○

(Note) Standard errors are in parentheses.

*, **, and *** denotes statistical significance at the 10, 5, and 1 percent level respectively.

Table 9(a): Changes in Hours Worked by Occupation after the Introduction of AI

	(1)		(2)	
$Treat_{i,t} \times After_{i,t}$				
	1. Receptionists and information clerks			
	-0.235		-0.268	
	(0.322)		(0.323)	
	2. Account clerks			
	-0.375	**	-0.393	***
	(0.147)		(0.147)	
	3. Quality control technicians			
	0.181		0.162	
	(0.208)		(0.209)	
	4. Retail salespersons			
	0.160		0.115	
	(0.286)		(0.286)	
	5. Human resource coordinators			
	-0.428	***	-0.403	***
	(0.114)		(0.114)	
$Treat_{i,t}$	0.224	**	0.284	***
	(0.096)		(0.096)	
$After_{i,t}$	-0.122	***	-0.122	***
	(0.026)		(0.026)	
Age	0.027		0.040	
	(0.025)		(0.025)	
Age^2	0.000		-0.001	*
	(0.000)		(0.000)	
Female	-0.729	***	-0.846	***
	(0.063)		(0.060)	
Constant	9.706	***	9.805	***
	(0.739)		(0.595)	
Education	Yes		Yes	
Firm size	Yes		Yes	
Income	No		Yes	
Obs.	2,266		2,266	
R^2	0.160		0.141	

(Note) Standard errors are in parentheses. Figures are given in hours.

*, **, and *** denotes statistical significance at the 10, 5, and 1 percent level respectively.

Table 9(b): Changes in NRTI by Occupation After the Introduction of AI

	NRTI1 (Repetition)				NRTI2 (Decision making)				NRTI3 (Communication)			
	(1)		(2)		(3)		(4)		(5)		(6)	
$Treat_{i,t} \times After_{i,t}$												
1. Receptionists and information clerks												
	-0.059		-0.074		0.073		0.059		0.132		0.129	
	(0.149)		(0.149)		(0.181)		(0.181)		(0.112)		(0.112)	
2. Account clerks												
	0.083		0.082		-0.097		-0.088		-0.055		-0.054	
	(0.067)		(0.067)		(0.083)		(0.083)		(0.050)		(0.050)	
3. Quality control technicians												
	0.194	**	0.185	*	0.259	**	0.250	**	-0.106		-0.109	
	(0.096)		(0.096)		(0.117)		(0.117)		(0.072)		(0.072)	
4. Retail salespersons												
	-0.098		-0.124		-0.217		-0.240		-0.095		-0.099	
	(0.132)		(0.132)		(0.161)		(0.161)		(0.099)		(0.099)	
5. Human resource coordinators												
	0.102	**	0.110	**	-0.006		-0.004		0.078	**	0.079	**
	(0.051)		(0.051)		(0.064)		(0.064)		(0.038)		(0.038)	
$Treat_{i,t}$	-0.002		0.064		-0.090	*	-0.059		-0.012		0.008	
	(0.065)		(0.065)		(0.053)		(0.053)		(0.055)		(0.055)	
$After_{i,t}$	-0.004		-0.004		0.210	***	0.210	***	-0.021	**	-0.021	**
	(0.011)		(0.011)		(0.015)		(0.015)		(0.008)		(0.008)	
Age	-0.014		-0.002		-0.009		-0.003		-0.007		-0.014	
	(0.018)		(0.018)		(0.014)		(0.014)		(0.016)		(0.016)	
Age^2	0.000		0.000		0.000		0.000		0.000		0.000	
	(0.000)		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)	
Female	-0.034		-0.122	***	0.028		-0.009		-0.147	***	-0.109	***
	(0.046)		(0.044)		(0.035)		(0.033)		(0.039)		(0.037)	
Constant	2.783	***	2.362	***	3.850	***	3.118	***	2.848	***	2.916	***
	(0.541)		(0.436)		(0.407)		(0.325)		(0.460)		(0.369)	
Education	Yes		Yes		Yes		Yes		Yes		Yes	
Firm size	Yes		Yes		Yes		Yes		Yes		Yes	
Income	No		Yes		No		Yes		No		Yes	
Obs.	2,266		2,266		2,266		2,266		2,266		2,266	
R^2	0.115		0.088		0.056		0.045		0.067		0.049	

(Note)　Standard errors are in parentheses.

*, **, and ***　denotes statistical significance at the 10, 5, and 1 percent level respectively.

APPENDIX 1

Summary of Our Survey

Method	Online Questionnaire Survey
Period	December 28th, 2018 - January 23rd, 2019
Respondent	Survey A: Employees engaged in the following five occupations: receptionists and information clerks, account clerks, quality control technicians, retail salespersons, and human resource coordinators Survey B: Managers

Survey	Number of respondents
Survey A (Employees)	2,266
Receptionists and information clerks	216
Account clerks	689
Quality control technicians	254
Retail salespersons	583
Human resource coordinators	524
Survey B (Managers)	1,982

Note: Our online survey was conducted as follows. We first set target number for the number of observations of 5,000, that is, 1,000 for each occupation, for Survey A, and of 2,500 for Survey B. Number of participants is 13,937 for Survey A and 5,879 for Survey B. Since our survey system accepts respondents whose occupations or positions are not in our scope, then, we sorted out and filtered respondents to fit with our targeting samples. We collected raw data of 4,595 observations in Survey A and 3,480 observations in Survey B. We eliminated observations with missing values or invalid answers to obtain 3,858 and 2,595 observation, respectively. Finally, we dropped observations based on the criteria outlined footnote 18, we ended up with 2,266 observations from Survey A and 1,982 observations from Survey B, as shown in the table above.

APPENDIX 2

This appendix provides an example of the calculation of non-routine task intensity.

Let us give a specific example. Assuming that respondent 1 ($i = 1$) works as a receptionist and answers as shown below, the NRTI1 turns out to be:

$$NRTI1_{1,0} = \sum_j (Vol_{1,j,0} * \frac{1}{100}) \times (Int1_{1,j,0})$$

$$=0.2*3+0.4*2+0.3*1+0.1*4=2.1$$

$$NRTI1_{1,1} = \sum_j (Vol_{1,j,1} * \frac{1}{100}) \times (Int1_{1,j,1})$$

$$=0.5*4+0.2*2+0.1*1+0.2*4=3.3$$

$$\Delta NRTI1_1 = NRTI1_{1,1} - NRTI1_{1,0} = 3.3\text{-}2.1 = 1.2$$

Occupation: Receptionists and information clerks				
Task	*Vol* : Percentage of time allocation		*Int* : Degree of repetition	
	Past (*t=0*)	Current (*t=1*)	Past (*t=0*)	Current (*t=1*)
Communicate with customers directly	20	50	3	4
Communicate with customers indirectly (via phone or email)	40	20	2	2
Compile, copy, sort, and file records	30	10	1	1
Other	10	20	4	4

APPENDIX 3

Appendix 3 is basically the same as in Acemoglu and Restrepo (2018b).

For simplify the discussion, we impose Assumption A1 as follows. The first inequality implies that the introduction of new tasks will increase aggregate output. The second inequality implies that all tasks in $[N-1, I]$ will be produced by machines by the nature of the model.

$$\frac{\gamma_L(N)}{\gamma_M(N-1)} > \frac{W}{R} > \frac{\gamma_L(I)}{\gamma_M(I)}.$$

Suppose that Assumption A1 holds. We can derive the demand for factors, i.e. smart machines and labor in the following manner.
Denote by $p(x)$ the price of task x. Assumption A1 implies

$$p(x) = \begin{cases} \dfrac{R}{\gamma_M(x)} & if \;\; x \in [N-1, I] \\ \dfrac{W}{\gamma_L(x)} & if \;\; x \in [I, N] \end{cases}$$

In addition, the demand for task x is given by

$$y(x) = \frac{Y}{p(x)}$$

Thus, the demand for smart machines in task x is

$$k(x) = \begin{cases} \dfrac{Y}{r} & if \;\; x \in [N-1, I] \\ 0 & if \;\; x \in (I, N] \end{cases},$$

and the demand for labor in task x is

$$l(x) = \begin{cases} 0 & if \;\; x \in [N-1, I] \\ \dfrac{Y}{w} & if \;\; x \in (I, N] \end{cases}.$$

Aggregating the demand for machines from this expression and setting it equal to the supply of capital, K, we have the following market clearing condition for capital:

$$K = \frac{Y}{r}(I - N + 1).$$

Similarly, aggregating the demand for labor and setting it equal to its inelastic supply,

L, we obtain the market clearing condition for labor:

$$L = \frac{Y}{w}(N - I).$$

Rearranging these two equations, the equilibrium rental rate and wage is given by

$$r = \frac{Y}{K}(I - N + 1) \text{ and } w = \frac{Y}{L}(N - I).$$