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ARE SOFTWARE AUTOMATION AND TELEWORKERS SUBSTITUTES? PRELIMINARY EVIDENCE FROM JAPAN

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ABSTRACT

Digital technology is reshaping workplaces by enabling spatial separation of offices, known as telework, or remote intelligence (RI), and by facilitating automation of service sector tasks via artificial intelligence (AI). This paper is a first attempt to empirically investigate whether AI and RI are complements or substitutes in the service sector. It uses a worker-level panel of surveys collected from around 10,000 workers from pre-COVID-19 pandemic to late 2022, we find preliminary evidence that suggests that AI and RI are complements rather than substitutes. The evidence comes first from the positive correlation of investments in AI-promoting and RI-promoting software at the firm and worker level, and second from the positive correlation of workers' expectations regarding telework and software automation. The evidence is far from definitive but suggests that the complement-substitution question is a fruitful line for future research.

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1 Introduction

Digital technology is reshaping workplaces in ways that were unimaginable just a few years ago. This is happening in two distinct ways. First, digitech is unbundling offices in the sense that some service tasks that were traditionally performed by workers sitting physically close to each other can now be undertaken at a distance. Second, digitech is allowing many more service sector tasks to be automated by software.

Telework is one name for the first impact of digital technology and the key point is that digital technology is making remote work increasingly easy. Of course, teleworking is not a new phenomenon and first appeared in the 1970s (Nilles, 1975; Aguilera et al. 2016). There were always some workers who worked remotely – 'road warriors' was one name for service workers who routinely participated in office work while travelling via laptops, emails, and mobile phones (Bloom et al. 2018). Since the Covid-19 restrictions required or encouraged workers to work from home, this sort of telework has become far more common (Kahn, 2020). The key technical innovations include improved collaborative software suites, videoconferencing apps, and secure, cloud-based document sharing and editing. To date much of the telework is done by domestic workers, but the trend towards using foreign remote workers is well underway – a phenomenon that can be called telemigration.

The second major impact of digital technology on work patterns concerns automation of many tasks related to service jobs. The recent breakthroughs in generative AI, such as ChatGPT, are transforming many office and professional jobs. But even before ChatGPT, software such as Robotic Process Automation (RPA), chatbots, and automatic translation apps were automating many tasks traditionally performed by office workers and professionals. Collectively, such software might be called software robots, or white-collar robots (to distinguish these from the more familiar industrial robots).

The key innovation here was the rapid advance of machine learning. Before 2017 (the year Fortune Magazine called the year of AI), computers could only perform tasks the automated human thinking of the analytic, conscious type – what Daniel Kahneman calls 'thinking slow' (Kahneman, 2011). The reason was due to the nature of computer programming. Writing code requires the coder to understand the mental process that is being taught to the computer. Computers could not do intuitive, unconscious thinking – like recognizing faces in photos, or translating languages – since humans did not understand how humans think intuitively (we still do not). A new way of writing computer programs relaxed this constraint. A form of AI, called machine learning, allowed data scientists to estimate very large and very complex statistical models that mimic human unconscious thinking – or what Kahneman (2011) calls 'thinking fast'. Since 2017, computers are as good or better than humans in some instinctual, unconscious mental tasks—things like recognizing speech, reading handwriting, and identifying objects in photos. The rate of advance in this field is astounding.

The merger of these two emergent trends – globalisation and robotisation of service sector tasks – has been collectively referred to as the "Globotics Upheaval" (Baldwin, 2019). In 2022, the possibility of digital technology disrupting workplaces and displacing jobs is no longer a conjecture. Moreover, in economies where jobs are the foundation of economic prosperity and social standing, the disruptive nature of competition from distant teleworkers and nearby service task automation software is a real concern.

The dual nature of the digitech impact on the future of work prompts an important question about the relationship between service sector automation and offshoring: are they complements or substitutes? Is AI applied in offices a substitute for remote intelligence (RI) employed in offices? Or to put it more directly, will teleworking make it more likely that your employer will automate part or all of your job? One example where they are clearly substitutable is in the domain of call centers where automation is replacing remote workers. Call centers, an integral part of many service-sector businesses, often deliver essential support services using workers located in lower cost places within the same country or even in other countries. In recent years, however, many of the jobs in these call centers are replacing workers with chatbots, which are just AI-drive automation software. An example presented in the MIT Technology Review (Hao, 2020) relates how the local government in Otsego County New York used IBM's 'Watson Assistant for Citizens' to respond to the surge in routine questions about Covid-19 while cutting staff by half. During the pandemic, IBM saw a two-fifths boost in the use of its Watson Assistant. The emergence of very capable chat bots has led to a reduction of humans employed in call centers in the Philippines and India. As usual it is not a full substitution, since humans still like to talk to humans, and chat bots do not have the answer to every question but as chat bots advance, the number of humans needed will fall.

Another type of worker-substituting automation is called 'Robotic Process Automation' (RPA). As Jason Kingdon, who chairs an RPA company, Blue Prism, describes them: "They mimic a human. They do exactly what a human does. If you watch one of these things working.… you see it typing. Screens pop-up, you see it cutting and pasting." RPAs are designed to work as an automated office worker which is why Blue Prism calls the software robots. The commercial interest in RPA lies in the way it can reduce the number of workers in back-office processes. RPAs are also more consistent than workers and they create a digital record of their activity. RPAs need human backup for difficult cases, but the number of workers is reduced. As many of these 'assembly line' information processing jobs were shifted to telework during the pandemic, RPA can be thought of as being a substitute of RI.

On the complement side, one obvious automation software that boosts the use of remote workers is automatic translation. With the widespread adoption of machine translation technology, remote work has become increasingly accessible to non-English speaking workers. For many service tasks, all that is needed is access to the internet connection, a laptop, and the requisite skills. With software like Google Translate, DeepL Translator, or Bing Microsoft Translator, workers living in countries where $5 an hour affords a middle-class living can potentially be workmates with office workers in wealthier nations. Here AI is a complement to RI since the AI is making the RI easier to do for workers without language skills. In essence, the AI makes it easier for foreign based freelancers and remote workers to deliver content in English even when they are not native speakers.

Literature Review

The literature on the impact of Computers/Robots/ICT/AI on labor has been growing in the last decades (Acemoglu, 2007; Autor et al. 2013; Acemoglu and Restrepo, 2018). The theoretical work has focused on the impact of technological advances such as ICT and robots on employment and wages. Autor et al.(2003), for instance, modelled unskilled workers as performing mostly routine tasks, and skilled workers as performing mostly non-routine tasks. The impact of automation on the two types of labor depends upon whether the technology is substitutable for or complementary to the two types of tasks. Assuming automation is a substitute for routine tasks but a complement to non-routine tasks, automation raises the gap between job opportunities and wages for unskilled versus skilled labor. This accounts for polarization in the US labor market. Goos et al.(2007, 2009, 2014) found that unskilled labor shifted from replaceable jobs by automation to non-replaceable but low-income jobs in technological change in Europe. Beyond this, as shown in Brynjolfsson and McAfee (2014) and Ford (2016), automation is deeply spread over the labor market in many dimensions. Frey and Osborne (2013) predicted around half of occupations will be disrupted by automation in the future.

Turning to remote intelligence (RI), there are already some studies on remote work before the pandemic in worker-level analysis of labor economics. Remote work has several advantages such as improving work-life balance (Dutcher, 2012; Coenen and Kok, 2014; Kazekami, 2020) and productivities (Bartik et al. 2020). With the spread of Covid-19, studies on the impact of teleworking on economies increased (Adams-Prassl, et al. 2022; 2023; Alipour et al. 2021; 2023; Bonacini et al., 2021; Kawaguchi and Motegi, 2021; Morikawa, 2022; Mongey et al. 2021; Okubo, 2022; Okubo et al. 2021). Dingel and Neiman (2021) suggested that there are some specific occupations suitable for remote work. Their derived remote workable index by occupation based on O*NET information found that 37% of jobs in the United States can be performed entirely at home.

As far as we know, no studies have investigated the nexus of automation by AI and remote work by RI in their long-run aspects. Our paper is aimed at investigating the substitutability of AI and RI to labor at occupational level and providing evidence from Japanese worker-level surveys. Furthermore, the survey we use is unique in that it directly asked workers about their use and their company's use of AI and RI as well as their expectations concerning the impact of AI and RI on their own jobs in the future, and whether they see AI and RI as substitutes or complements to their jobs. In addition, the survey gathers extensive information on the workers' basic characteristics, the tasks their job involves, and information on their firm.

Plan of paper

This paper investigates the substitutability of AI and RI at the occupational level in the context of Japan using a unique panel of surveys collected from about 10,000 workers with a start date that was just before the Covid-19 shock and continued until late 2022.

The investigation starts by examining the technical teleworkability and automatability of occupations as a first step to looking at the actual co-movement of telework and software automation. This is based on ex ante evaluation of the occupation descriptions. The most famous of these is Dingel and Neiman (2020) which examines the job descriptions on the US's O*NET. A similar exercise has been done using Japan's O*NET by Kotera (2021). When it comes to automatability, we look at the famous Frey-Osbourne index of automatability to gauge how automatability of various occupations in US. Equivalently, Frey and Osbourne (2015) calculated the index of automatability for case of Japan in collaboration with NRI (Nomura Research Institute).

To summarize the technical feasibility for various occupations, we introduce the "Globotics quadrant diagram," which maps occupations into a two-dimensional chart based on their automatability and teleworkability. The scatter chart is used to illustrate data for both the United States and Japan. The central argument is that while some occupations are both automatable and teleworkable, many others are suited to only one or neither, as determined by standard measures such as the Dingel-Neiman index for telework and the Frey and Osborne index for automatability.

The subsequent section of the paper examines the impact of the COVID-19 pandemic in Japan on the relationship between AI and RI using data from the survey, which was conducted by Toshihiro Okubo (Keio University) and NIRA (Nippon Institute for Research Advancement). While the survey provides detailed information on the number of workers who switched to teleworking, it lacks data on the number of workers who were replaced by white-collar robots. Thus, a direct test of the substitution-versus-complementarity question cannot be assessed. However, the survey does provide information on firms' use of software that facilitates telework and automation of office tasks, respectively.

Using information on firms' usage of pro-RI and pro-AI software (as reported by the workers), and the exogeneity of the COVID-19 shock, the paper examines whether firms' investments in AI-promoting software and RI-promoting software were positively or negatively correlated. Given that the rise in telework was directly induced by the pandemic, while the adoption of automation software was not, a positive correlation would suggest that AI and RI are complements, while a negative correlation would suggest substitution. In short, we study whether companies that used more telework invested in more or less service-task software automation, like RPA.

The final substantive section turns to another indirect proxy for substitution and complementary behavior. The survey includes questions to workers about their expectations about future use of telework and software automation. This evidence strand provides additional insight into the relationship between RI and AI.

While the evidence presented in this paper is not conclusive, what is clear is that on the whole telework and automation do not seem to be substitutes. We show that telework and automation are technically possible for many occupations, but there is no clear evidence that automation was less used in occupations where telework rose the most. We take this as preliminary evidence that in the context of the Covid-19 shock, AI and RI are either independent or complements not substitutes.

2 Teleworkability and automatability in the US and Japan: The globotics quadrant diagram

Things can be substitutable, complementary, or independent. The idea of substitutability means two things can be replaced by one another; complementarity means two things are used together. It is also possible that the two things are independent and have nothing to do with each other. These definitions are important when we think about office automation and telework because not all jobs can be automated and not all can be done via telework.

The possibility that automation and remote work are substitutes or complements arises for occupations where both automation and telework are feasible. In contemplating their impact, we must first determine which occupations are capable of being automated and performed remotely. To classify occupations based on this suitability, we introduce the "globotics quadrant" diagram. It allows us to assess the teleworkability and automatability of each occupation, thus determining the potential for automation to substitute for remote work and vice versa.

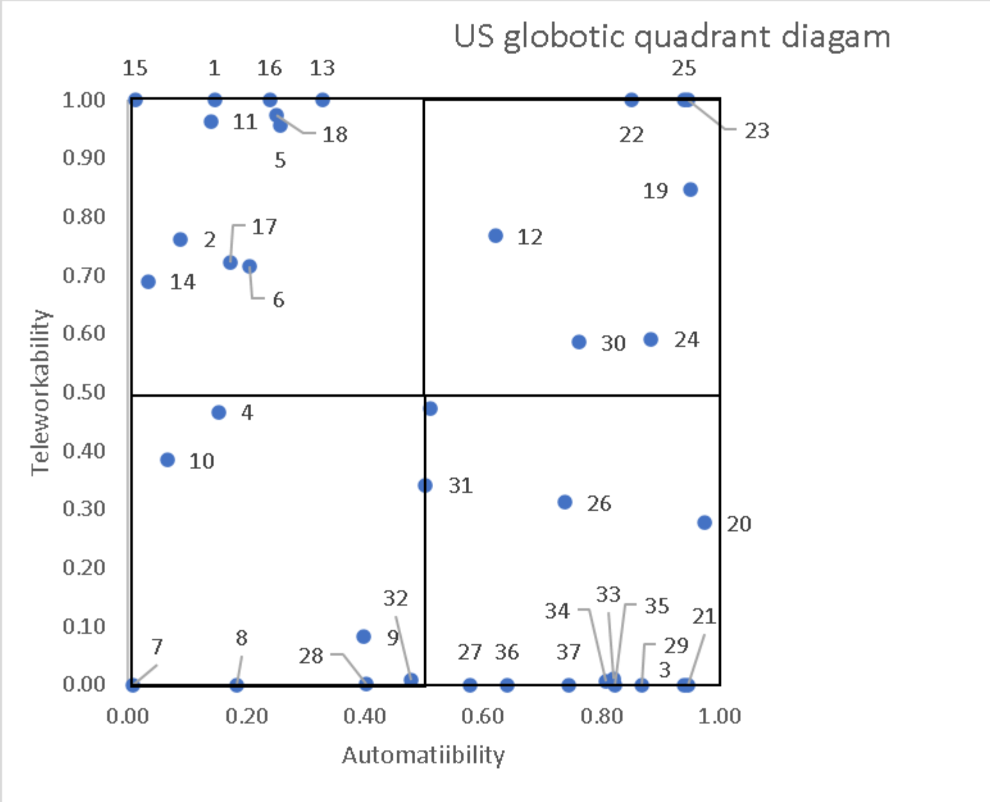
2.1 Which service jobs are offshore and automatable?

Since the onset of the pandemic in 2019, economists have made several attempts to classify occupations into teleworkable and non-teleworkable categories. The most famous was by Dingle and Neiman (2020) for the US, whilst the best-known effort was by Frey and Osborne (2013). These are the measures we use in the first instance when looking at the US.

We plot occupations in a quadrant diagram, what we call the Globotics Quadrant (Figure 1)[3]. The horizontal and vertical lines are drawn at the mean value for all occupations, so occupations to the left of the vertical line are less than average automatable and those below the horizontal line are less than average teleworkable. While the original Frey-Osborne and Dingle-Neiman estimates were done at the BLS occupation level, it would be too cluttered to present all in a single diagram, so we have aggregated the BLS occupations into Japan's 38 occupations (NIRA classification) weighted by occupational labor force in Japan (Population Census)(See Appendix Table). We first focus only on US data. Below we contrast these results with similar measures for Japan.

[3] Original idea and basic concept of the diagram on policy perspective were firstly proposed by Okubo (2022c).

Figure 1: The US globotics quadrant: occupations by automatability and teleworkability



Source: Authors' elaboration of data from Dingel-Neiman (telework), and Frey-Osbourne (automatability). Note: Each point represents an occupation; x-axis shows the automatability score (from 0 to 1), and y-axis is teleworkable Score (0 to 1). Occupations grouped into Japan's NIRA38 aggregates.

To read the diagram, keep in mind the fact that occupations in the Northeast quadrant are exposed to above average offshorability (taking teleworkability as a rough indicator of offshorability) and to above average automation. Those in the Southwest are exposed to below average teleworkability and automatability. In the other two quadrants, the occupations have above average exposure to teleworkability or automatability but below average exposure to the other. The labels in the diagram show the number of US workers with occupations in each of the quadrants.

The key takeaways are simple. First, occupations are spread across all four quadrants, so the impact of advancing digital technology will vary greatly by occupation. There can be no universal answer to the question of whether AI and RI are complements or substitutes. For particular occupations, AI and RI can be substitutes or complements, but not as a general statement about all occupations.

Second, there are about 12 million workers in the occupations found in the Northeast quadrant, which is about 10% of occupations classified (Table 1). These are jobs where AI and RI are both relevant and thus potentially complements or substitutes to each other. The occupations in the quadrant are general clerical, outdoor service, and office appliance workers.

There are about 21 million workers in occupations in the Northwest quadrant (Table 1). These jobs are difficult to automate but easily undertaken in remote places. The occupations are accountancy clerks, production related clerical, agricultural forestry and fishery engineers, food and drink cooking staff and serving customers, transportation and machine operation, agriculture forestry and fishery, manufacturing process, carrying cleaning packaging and related, sales, construction and mining, family life support and care service.

Table 1: US occupations and jobs (millions) in US globotics quadrants

Quadrant	Jobs	Quadrant	Jobs
Northwest total	**20.7**	**Northeast total**	**11.7**
Accountancy clerks	2.5	General clerical	1
Production-related clerical	0	Outdoor service	1.4
Agriculture, forestry, and fishery engineers	0.6	Office appliance operators	4.6
Food and drink cooking, staff serving customers	6.6	Transport and post clerical	0.9
Transport and machine operation	1.7	Salesclerks	1.8
Agriculture, forestry and fishery	0.8	Manager of residential facilities and buildings	1.4
Manufacturing process	1.6	Finance and insurance professionals	0.6
Carrying, cleaning, packaging, and related	5.4		
Sales	0.1		
Construction and mining	0.2		
Family Life Support and Care Service	1.1		

Source: Authors' elaboration of data from Dingel-Neiman (telework), and Frey-Osbourne (automatability). Note: Each point represents an occupation; x-axis shows the automatability score (from 0 to 1), and y-axis is teleworkable Score (0 to 1).

Occupations in the Southwest corner are both difficult to automate and difficult to undertake from a remote location so the issue of substitutability and complementarity does not really arise. Many of these are in fact listed as having zero teleworkability, so the issue of substitutes versus complements does not arise.

Third, there is no clear correlation between teleworkability and automatability. For instance, we do not see most professions in the Northeast and Southwest quadrants as would be the case if automation and teleworkability were positively correlated across professions. This stresses the need for nuance when thinking about the impact of digital technology on the future of work.

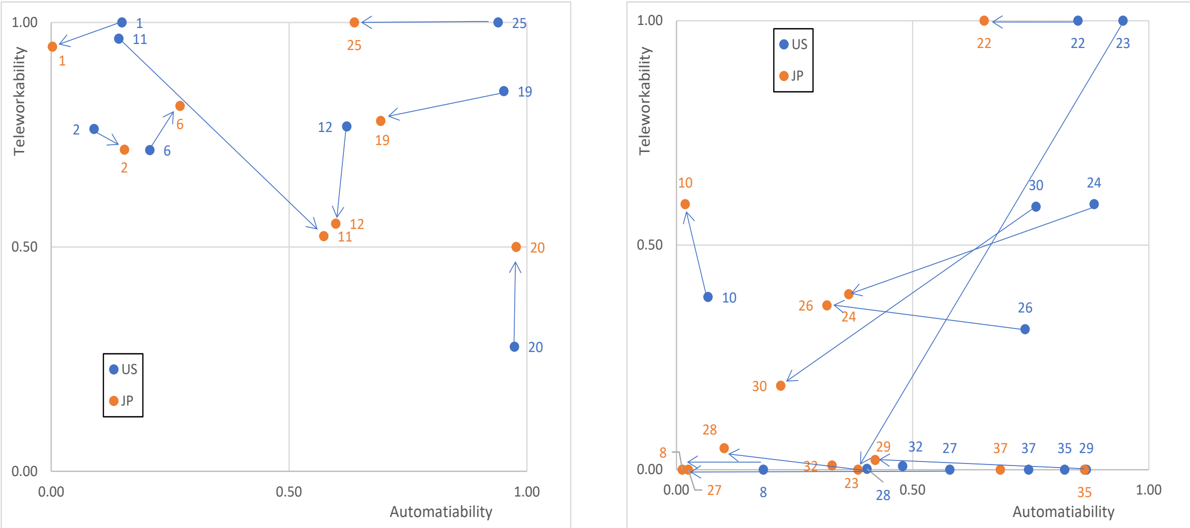
Fourth, the lack of a clear positive or negative correlation is suggestive of a lack of economy-wide substitutability or complementarity. If all the occupations had lined up in a positively sloped line, we could say that in a reduced-form sense, telework and automatability tended to be done together. When you see a lot of teleworkability, you see a lot of automatability. By contrast, a clear negative correlation would have suggested a reduced-form substitutability. Occupations tended to be either automatable and not very teleworkable, or vice versa.

2.2 Japanese quadrant contrast with US

The scores in Figure 1 are based on an analysis of the tasks involved in the various occupations analyzed in the US. A similar analysis has been done for Japan. Specifically, we use the teleworkability index of Kotera (2020) based on recalculating Dingel Neiman's remote work index by using the Japan's O*NET. We also use the automatability index by Frey and Osbourne (2015, NRI report), recalculated as the Japanese case.

Overall, Japanese occupations are judged as both less teleworkable and less automatable. On the scale of zero to one, the US average automatable score is 0.51 while it is 0.32 in Japan. For teleworkability, the averages are 0.47 and 0.41.

Figure 2: Automatability and Teleworkable, office and walking service occupations: US vs Japan



#	Office Work Occupations
1	Administrative and managerial workers
2	Researchers
6	Data processing and communication engineers
12	Finance and insurance professionals
19	General clerical workers
20	Accountancy clerks
25	Office appliance operators

#	Walking Service Occupations
8	Public health nurses, midwives, and nurses
10	Professional social welfare workers
22	Salesclerks
23	Outdoor service workers
24	Transport and post clerical workers
26	Sales workers
27	Workers in Family Life Support and Care Service
28	Occupational health and hygiene service workers
29	Food and drink cooking, staff serving customers
30	Manager of residential facilities and buildings
32	Security workers
35	Transport and machine operation workers
37	Carrying, cleaning, packaging, and related workers

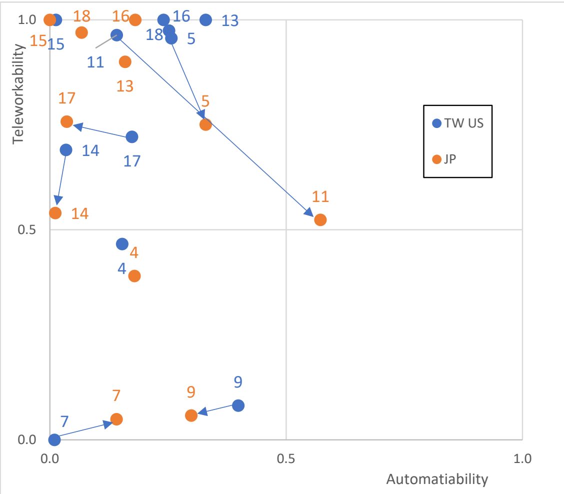
Source: Authors' elaboration of data from Dingel-Neiman (telework), and Frey-Osbourne (automatability).
Note: Each point represents an occupation; x-axis shows the automatability score (from 0 to 1), and y-axis is teleworkable Score (0 to 1).

Figures 2 and 3 compare US and Japanese teleworkability and automatability scores by distinguishing occupations by three broad categories of service occupations: office workers, professional service workers, and walking service workers (see list under the figures).

Figure 2 (left panel), shows the comparison for office workers, it indicates that the results for the US and Japan are not very different when it comes to office-based occupations. All but two of the occupations are in the same quadrant for both the US and Japanese case. Moreover, there is not a pervasive difference in either dimension. For example, three of the eight occupations are reported as more teleworkable in Japan, and four are more automatable, but two are both more automatable and teleworkable, and three have lower scores in Japan on both dimensions. By contrast, the right-panel of Figure 2 results for walking service workers like nurses, salesclerks, transport, and postal workers, etc., are quite different. Here most occupations in Japan are both less automatable and less teleworkable.

When it comes to professional occupations, as shown in Figure 3, the picture is more mixed. Three occupations are more automatable in Japan: manufacturing engineers, architects, civil engineers, surveyors, and medical professionals. In particular, the legal professions are judged to be far more automatable in Japan than in the US, but far less conducive to teleworking. However, for most professions, US occupations are rated as more conducive to teleworking.

Figure 3: Automatability and Teleworkable, professionals: US vs Japan



#	Professional Occupations
4	Manufacturing engineers
5	Architects, civil engineers, and surveyor
7	Doctors, dentists, veterinarians, and pharmacists
9	Medical Technology and Healthcare Professionals
11	Legal
13	Management and business consultants
14	Teachers
15	Workers in religion
16	Authors, journalists, editors
17	Artists, designers, photographers, film operators
18	Other specialist professionals

Source: Authors' elaboration of data from Dingel-Neiman (telework), and Frey-Osbourne (automatability). Note: Each point represents an occupation; x-axis shows the automatability score (from 0 to 1), and y-axis is teleworkable Score (0 to 1).

3 Evidence from software investments

This section leverages Covid-19 as an exogenous shock that induced changes in telework and office automation to investigate whether artificial intelligence (AI) and remote intelligence (RI) are substitutes or complements for teleworkers. The data comes from the Okubo-NIRA survey (Okubo and NIRA, 2020a,b,c, 2021a,b, 2022, a, b), a set of comprehensive surveys of around 10,000 workers (in a randomly stratified sample) that was undertaken in Japan in seven waves (as of November 2022). The first came in March 2020 just before the onset of the pandemic and the first state of emergency (April to May 2020) and the last in June 2022 (as of November 2022).

Although the survey provides us with direct and meticulous information on the number of workers who have transitioned to teleworking, it is lacks information on the number of workers who have been replaced by white collar robots, so we cannot directly compare the impact of AI and RI on jobs. Instead, we use information in the survey result on firms' adoption of two types of software: software that facilitates telework, and software that enables the automation of office tasks. By leveraging this information and the exogeneity of the Covid-19 shock, we examine whether firms' investment in AI-promoting software and RI-promoting software were positively or negatively correlated.

It is important to note that while the rise in telework was quite directly forced by the pandemic, the adoption of automation software was not. Thus, a positive correlation would suggest that AI and RI are complements to teleworking, while a negative correlation would suggest substitutes. We start, however, with some background on Japan's rather unique experience with the disease.

3.1 Covid in Japan

Japan, given its proximity to China, was the second country to record a case of COVID-19 (in January 2020). Its first death was in February 2020. Japanese public health authorities learned first-hand about the virus from the experiences of passengers quarantined on the cruise liner Diamond Princess, which arrived in Yokohama on 3 February 2020 (after having reported one passenger test positive for Covid-19). Eventually, 712 of the 3,711 people on board were infected.

One important learning, that was embraced early on in Japan, was that the virus seemed to be spread by airborne particles and droplets from infected people. This led to early and widespread adoption of the "3 Cs" policies whereby citizens avoid situations involving Closed spaces, Crowded spaces, and Close-contact, especially situations involving two or more of the three. Unlike the US and Europe, which were hit hard by the pandemic in the early months, Japan was initially able to keep the number of cases low. This may have been due to the country's experience with previous pandemics, like SARS (2003) as well as its culture of mask-wearing and 3-C's behavior which has been widely spread since the Spanish flu (1918-1920).[4] Despite this, the virus did spread, and the government reacted.

Figure 1 shows the daily number of new cases of COVID-19 in Japan, including the dates of government-declared states of emergency. Importantly, the chart also shows the timing of the various waves of the Okubo-NIRA survey we use.

On 7 April 2020, the Japanese government declared a state of emergency, urging citizens to avoid nonessential travel and work from home, while also shutting down or shortening the hours of retail shops, department stores, and restaurants. This led to a slowdown of economic activity, but the lockdown was relatively soft, allowing for the public transport system to operate normally and people to commute. After the lifting of the first state of emergency on May 25, economic activity resumed, and in June 2020, the government announced daily-life guidelines to combat COVID-19. However, the government's focus then shifted from reducing the spread of new infections to economic countermeasures, such as the "Go To Travel" and "Go To Eat" campaigns aimed at boosting revenues in the hard-hit hotel and accommodation sectors (see Okubo (2022b) about econometric analysis on

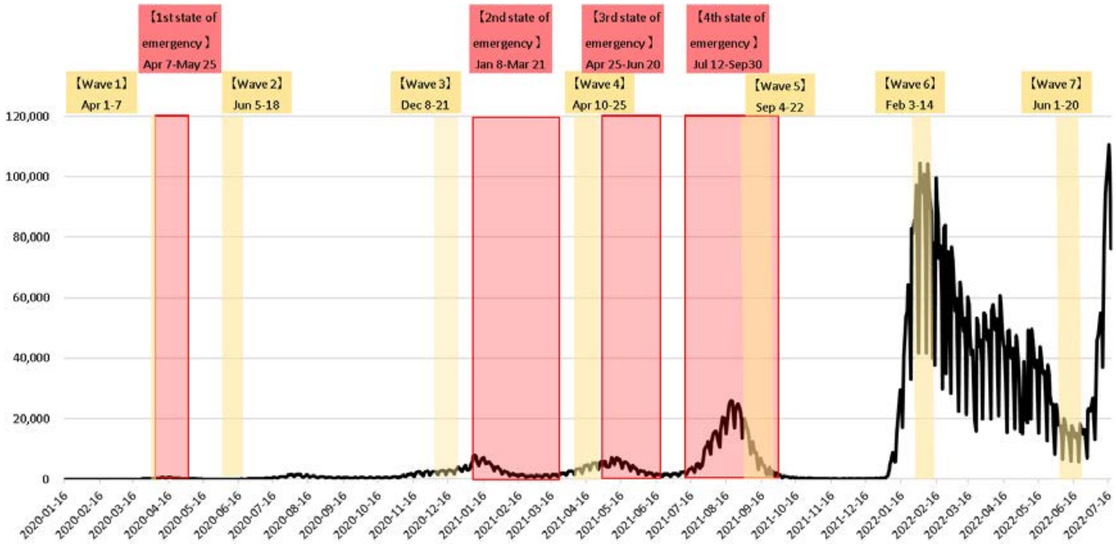
[4] See Noy et al. (2023).

these “Go To” campaign policies). When the third wave stuck in December 2020, the government refocused on containing the spread of new infections and eventually stopped the "Go To" policies.

On January 8, 2021, the second state of emergency was declared, which was again a "soft" lockdown with no legal restrictions or penalties for noncompliance. This state of emergency was applied to only 11 out of 47 prefectures. The third and fourth states of emergency were declared in April and July respectively of 2021 (a period that covered the Summer Olympics in Tokyo). Vaccinations started in mid-2021 and by the end of that year, the vaccination rate reach a high level. This helped contain the spread of infections, allowing for the eventual lifting of the state of emergency in September 2021. The sixth and seventh waves – by far the worst in terms of number of infections – did not trigger emergency declarations.

Note that due to constitutional restrictions, the Japanese government never mandated lockdowns or telework. The “lockdowns” were request-based, involving no legal restrictions, sanctions, or punishments.

Figure 4: COVID-19 deaths in Japan March 2020 to July 2022,



Source: OWID, https://ourworldindata.org/coronavirus/country/japan.

3.2 Our data and survey design

As mentioned, the data in this paper comes from an original survey-based dataset, Okubo-NIRA telework survey (‘Questionnaire Survey on the Effects of the Spread of COVID-19 on Telework-based Work Styles, Lifestyle, and Awareness’), that was collected to track the impact of COVID-19 on Japanese workers and workplace practices. It is a rich, worker-level survey that collects data on the traits of the workers, their jobs, their companies, their workplaces, and their residences. The survey was conducted by Toshihiro Okubo (Keio University) and NIRA (Nippon Institute for Research Advancement).

3.2.1 Timing of the survey

The timings of seven waves of our surveys were, as shown if Figure 4, interspersed among the five waves of the disease (as measured by peak deaths) and the four states of emergency declarations (Figure 2.1). As the surveys were done remotely, the pandemic did not significantly disrupt survey implementation.

The survey was implemented by NIRA and Okubo (Okubo and NIRA, 2020a, b, c, 2021a, b, 2022a, b). It was conducted on the website constructed by the professional research company, Nikkei Research Co., a purpose-built website which took a stratified random sampling strategy of approximately more than 10,000 workers. The survey targets workers and thus excludes unemployed people, housewives/husbands, and students. Many respondents continuously joined the survey for several waves. 3,162 respondents in the whole sample until wave 5 repeatedly joined the survey for all seven waves, in which 30% of respondents in the first wave survived and joined all waves. The sample stratified Japan into five regional classification and six age groups for each gender, so there are 60 gender-age-region groups per region. The number of participants in each of the 60 cells was determined by population shares (based on data from the Population Census, Ministry of Internal Affairs and Telecommunication).

The survey collects information on respondents' individual characteristics, including age, gender, income, educational background, residential place, working place, occupation, industry, and job status. The occupation categories used are the 38 NIRA occupational categories which are based on the Japan Standard Occupational Category (see Appendix Table). It also collects workplace information including company size (measured by number of employees), and establishment size.

As the central focus is on working environments, it asked about detailed task characteristics (routine, manual, team tasks), working environments (e.g., flexible working time), and whether teleworking is practiced. It also collects information on the kinds of digital tools available at the workplace, and how working environment changed during the Covid-19 (see Okubo, 2022a). The fifth wave of the survey also asked several more detailed questions on digitalization.

3.2.2 Description of the sample

Our sample includes more than 10,000 employed persons in each survey wave, with only partial overlap of subjects across waves. The sample is randomly selected but stratified according to aggregate demographics. Respondents are classified into five age groups: 15–29 (15%), 30-39 (18%), 40-49 (24%), 50-64 (29%), and over 65 (14%). About half the respondents are married, and about half hold university degree; approximately 45% are female. In terms of employment status, 53% are regular employees, 31% are non-regular employees, and 10% are self-employed.

As a comparison, according to the Population Census 2020, the percentage of women in the Japanese workforce is 44%: the percentage of workers in each of the above age groups is 17%, 18%, 23%, 29%, and 13%, respectively; the percentage of workers who are married is 63%, and 32% have graduated from university. In employment status, 51% are regular employees, 28% are non-regular employees, and 12% are self-employed. Thus, the demographics of our sample are broadly like those from the Population Census.

The median of the incomes in the seven waves varies between 3 to 3.5 million yen, and 4 to 4.5 million yen is mean. Workers earning less than 4 million yen (around 28,000 USD) account for about 58% or respondents. According to the Statistical Survey of Actual Status for Salary in the Private Sector by the National Tax Agency the average income of Japanese workers is 4.33 million yen in 2020, so again our sample is broadly representative of the overall population.

In terms of occupations, clerks and sales workers account for 33%, while administrative and managerial workers account for 9%. Ten percent of our sample is made up of cleaning workers with other services occupations amounting to 19%. In the industrial sectors, people in manufacturing sector for 17%, while wholesale and retails occupations account for 12%.

When it comes to firm size, employees in firms with more than 500 employees account for 28%, while employees of small and medium businesses (those with fewer than 100 employees) add up to 48% of respondents. Self-employed make up the balance.

The place of residence of our sample is, at prefectural level, 15% in Tokyo, and another 19% in Greater Tokyo other than Tokyo (Kanagawa, Chiba, and Saitama prefectures). Greater Osaka (Osaka, Kyoto and Hyogo prefectures) accounts for 15%, and Aichi prefecture (Nagoya) is 6%. The rest of the sample is spread across the remaining prefectures broadly in line with population shares.

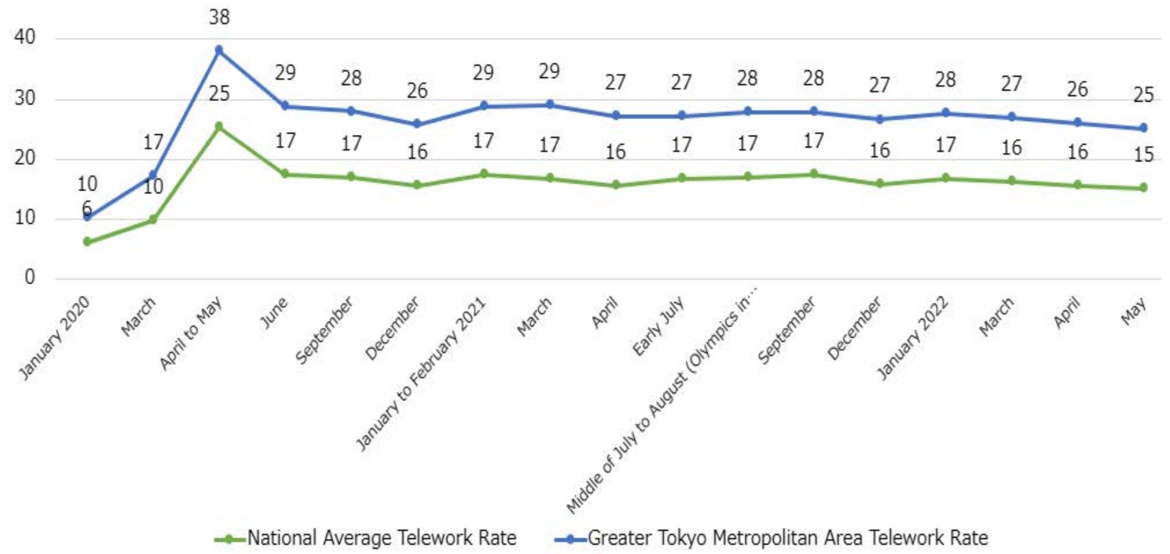
Our sample distinguishes between place of residence and place of work. When it comes to the latter, 20% of workers work in Tokyo and 13% in other parts of Greater Tokyo; many people in Greater Tokyo commute to Tokyo from neighboring prefectures.

Of particular interest is the share of respondents who are teleworkers (17%). We also asked our respondents about their use of communication tools, collaboration IT tools, and administration IT tools. The corresponding share of respondents that said they used these are 28%, 16%, and 19%, respectively. Thus, telework and IT usage is widespread in our sample but not pervasive.

The survey clearly defines telework as remote working for certain hours. Our definition, therefore, does not include the use of ICT devices at locations such as stations, airports, transportation facilities, and the premises of business partners. In addition, our definition does not include working from home without ICT devices. Therefore, whereas previous studies investigated "remote work" regardless of using or not using ICT devices, telework in our paper is more limited in the sense of working remotely using ICT devices.

Figure 5 plots the percentage of telework use over time. Before Covid-19 this only 6% in total and 10% in Greater Tokyo. When the first state of emergency was lifted, the percentage increased to 25% in total and 38% in Greater Tokyo. After the first state of emergency, the percentages are stagnant over time. On average the percentages work are around 16-17% in total and around 26-29% in Greater Tokyo.

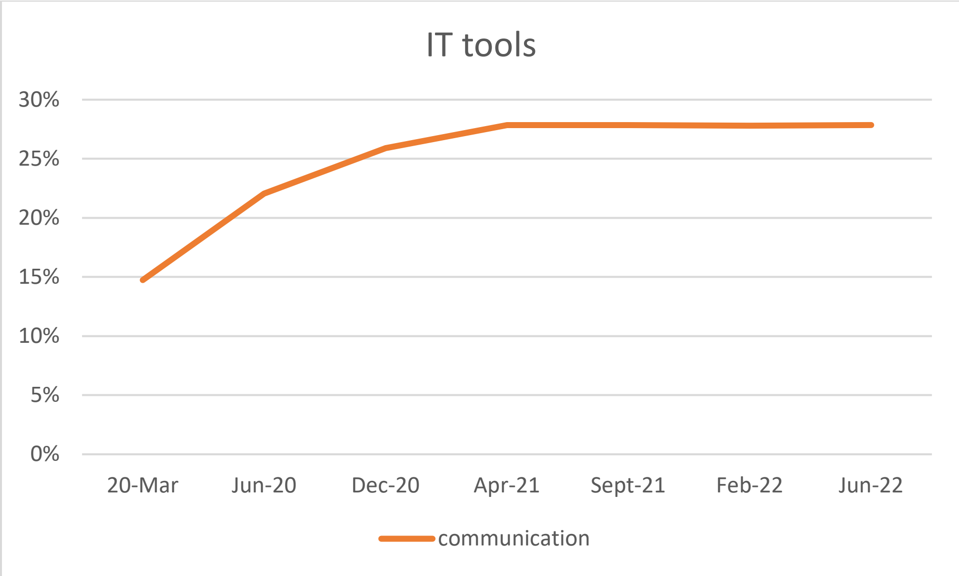
Figure 5: Telework usage over time.



Source: Okubo-NIRA dataset.

Figure 6 plots use of IT collaboration and teleconference systems (e.g. Zoom, Skype, Dropbox, and Slack) (items 1, 2, and 4 in Table 2)over time. The share is those who use at least one IT tool for working. The survey asked whether respondents use specific IT tools or not in every wave. The percentage of workers using IT tools increased early in the period and then steadily increased over time.

Figure 6: IT tool usage over time.



Source: Okubo-NIRA dataset.

3.3 Firms' usage of AI-facilitating and RI-facilitating software

One interesting set of questions included in the survey asked workers about the specific types of software their companies use. The list was selected to focus on software that could be used to automate service sector tasks, as well as software that could facilitate remote work. The list included 16 types of software, ranging from teleconferencing systems like Zoom to explicit office automation tools like Robotic Process Automation (RPA). See Appendix for the list of 16 types of software. Broadly speaking, the software can be classified into four types (see "function categories" in Table 2): those explicitly aimed at: automating service sector tasks, automating the administration of workers in offices, such as HR information systems, those aimed at facilitating communication between remote workers and the office, and lastly, those that facilitate collaboration among remote team members.

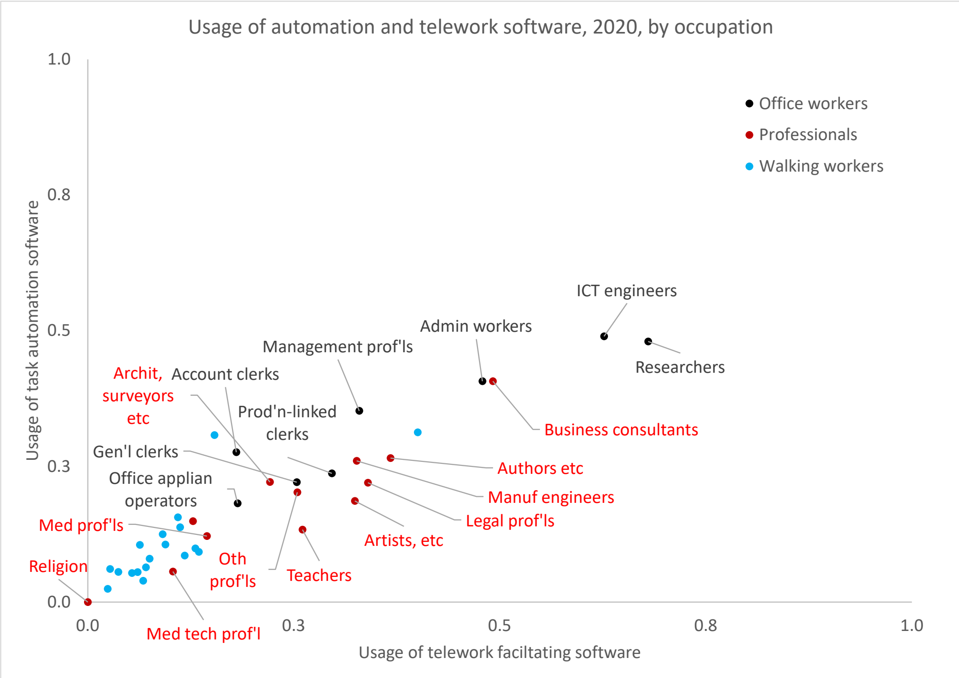
Table 2: Classification of specific software.

<table>
<tr><th></th><th>IT-tool categories and examples in the survey questionnaire</th><th>Function categories</th><th>Pro-AI and pro-RI categories</th></tr>
<tr><td>1</td><td>teleconference and web conference system (e.g. Zoom, Skype)</td><td rowspan="3">Facilitating communication</td><td rowspan="5">Pro-telework software (pro-RI)</td></tr>
<tr><td>2</td><td>information share (e.g. Slack, Line)</td></tr>
<tr><td>3</td><td>virtual office (e.g. Sococo, Remo)</td></tr>
<tr><td>4</td><td>sharing file (e.g. Dropbox, One drive)</td><td rowspan="2">Facilitating collaboration</td></tr>
<tr><td>5</td><td>remote access (e.g. SWANStor, Platform V system)</td></tr>
<tr><td>6</td><td>task project management (e.g. Trello, Backlog)</td><td rowspan="9">Office Management Automation</td><td rowspan="11">Pro-office automation software (pro-AI)</td></tr>
<tr><td>7</td><td>electric payment (e.g. Creat!Web flow)</td></tr>
<tr><td>8</td><td>attendance management (Office365, Cybozu)</td></tr>
<tr><td>9</td><td>mental health management (e.g. jinjer work vital, onsei kokoro bunseki service (voice mental analysis service, MIMOSYS))</td></tr>
<tr><td>10</td><td>business management (e.g. Sales cloud, kintone)</td></tr>
<tr><td>11</td><td>sale management, production management, stock management (e.g. Rakusho, Arajin Office)</td></tr>
<tr><td>12</td><td>employment management system (e.g. HRMOS Kanri, Jobukan Saiyo Kanri)</td></tr>
<tr><td>13</td><td>human resource management (e.g. Smart HR, OBIC7)</td></tr>
<tr><td>14</td><td>accounting management (e.g. Yayoi Kaikei, Super-Stream NX)</td></tr>
<tr><td>15</td><td>RPA (robotic process automation)(e.g. WinActor, Robotic Crowd)</td><td rowspan="2">Service Task automation</td></tr>
<tr><td>16</td><td>contactless technology (e.g. robot for automatic operation, automated checkout)</td></tr>
</table>

Source: Authors' elaboration based on Okubo-NIRA dataset.

We aggregated the responses into two indices (see "pro-AI" and "pro-RI" categories in Table 2): one that measures the usage of software that facilitates remote work (pro-telework software) and another that measures the usage of software that automates service sector tasks (pro-office automation software). The question on pro-telework software was administered in all waves of the survey, including the pre-COVID wave. However, the question on pro-office automation software was only included in the second survey, which was conducted in mid-2020 after the first COVID-19 emergency. The most recent set of responses we have is from September 2022 (wave 7).

Figure 7: Usage in 2020 of software facilitating telework and task automation



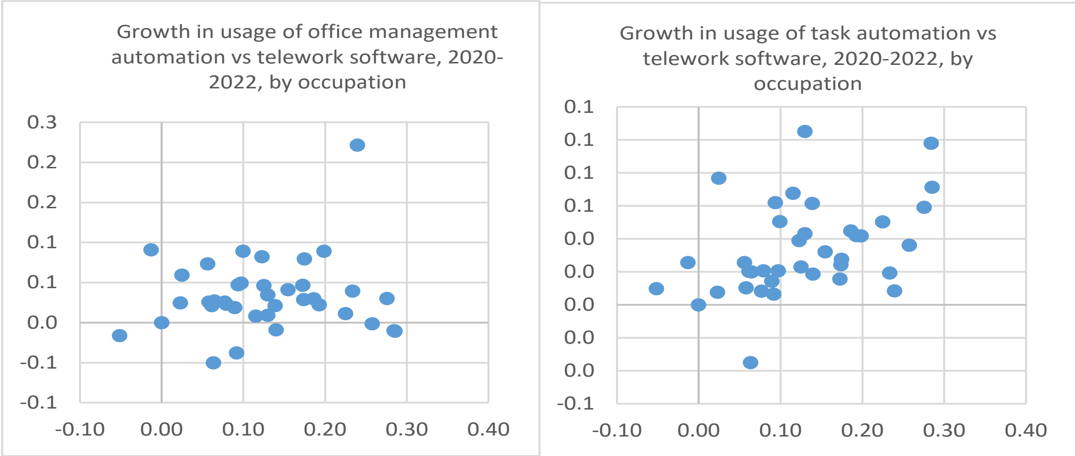
Source: Authors' elaboration of data from Okubo-NIRA data set.
Note: the indices are coded to be 1 or 0 at the respondent level and then averaged over workers with that occupation in all industries.

The results are shown, by occupation, in Figure 7. Occupations are segmented into three broad categories (office workers, professionals, and walking workers). The chart shows a clear and strong positive correlation between the level of usage of both types of software across occupations. In certain occupations, especially those in the office and professional categories, respondents were already widely exposed to AI-promoting and RI-promoting software. The top users in both types of software are ICT engineers and Research. Many other occupations, especially those in the walking workers category did not use much of either.

To further investigate this negative correlation, we divided the overall office automation index into direct service task automation software (such as robotic process automation) and automation of office management systems (which are often related to handling information concerning workers in the office; see function categories of Table 2). The findings are displayed in Figure 8.

Taking Covid-19 as an exogenous shock it is revealing to look at how the use of pro-AI and pro-RI software moved from March 2020 (before the pandemic) to June 2022. A positive correlation would suggest that firms would find it advantageous to invest in more office automation software as the degree of teleworking rose. This is indicative of a complementarity between AI and RI. A negative correlation would be indicative of substitutability. Figure 8 shows the results.

Figure 8: Growth in usage of pro-telework software versus management automation and service task automation software (2020 to 2022).



Source: Authors' elaboration of data from Okubo-NIRA data set.
Note: Growth in pro-teleworking software usage is on x-axis of both charts; the y-axis for the left chart is the change in usage of office management software while the y-axis of the right chart shows changes in usage of repetitive service task automation like RPA

In both panels, the horizontal axis plots the change in usage of software that promotes telework (pro-telework software, e.g., zoom, slack, cloud-base file sharing, etc.). The left panel shows the automation software related to managing workers (management automation software, items 6 to 14 in Table 2) (e.g., HR management tools). Here we see that the correlation is close to zero. If we leave aside the outlier, which is for Transport and post clerical workers, the correlation is slightly negative, suggesting a slight substitutability. Thus, there is weak evidence for substitution of AI and RI for software which automates some management tasks related to workers – like attendance management software (e.g., Cybozu), mental health management (e.g., Jinger Work Vital), business management (e.g., Sales Cloud), employment management (e.g., HRMOS Kanri), human resource management (e.g., Smart HR), and accounting management (e.g., Yayoi Kaikei). Further research would be needed to establish the reason for the negative correlation, but it is certainly in line with the notion that less management-facilitating software is needed when there are fewer workers in the office. The left panel shows a mild negative correlation, or no correlation at all, between usage of management automation software and pro-telework software that supports remote work. This is not unexpected since the need to expand usage of management software might not be augmented as the share of workers actually in the office falls (as it did between 2020 and 2022 in almost all occupations). The right panel shows the automation software related to service task automation such as RPA and contactless technology (e.g. robot for automatic operation and automated checkout). The right panel shows a positive correlation. The complementarity between service task automation and telework-facilitating software, by contrast, suggests there is little evidence that firms are choosing to automate jobs with software and promote teleworking. Quite the contrary, it seems that, at the occupation level, firms do more of both at the same time.

In summary, evidence from firms' investment in AI-promoting and RI-promoting software broadly suggests some forms are AI-promoting software – applications, like RPA platforms, that are very directly aimed at replacing repetitive information processing services tasks – are positively correlated with investment in telework-facilitating software. This suggests that this type of AI is complementary with RI. For other forms of automation software, there is some weak evidence of substitution.

4 Evidence from workers' expectations

The final strand of evidence we can shed light on the question as to whether labor-saving AI is a complement or substitute for teleworking comes from a unique set of questions included in the fifth wave of the survey in September 2021 and thus was well into the pandemic; with more than 1 year having passed since the first national emergency, workers had abundant experience with how their employers were reacting to the shock.

The specific questions were with respect to the future of their jobs, and on each they could choose their answer among five choices disagree, slightly disagree, neutral, slightly agree, agree. The questions were: Will you be able to telework in the future? Will your work be assisted by automation technology such as AI and robots in the future? Will your work be replaced by automation technology such as AI and robots in the future? (See Appendix for more details)

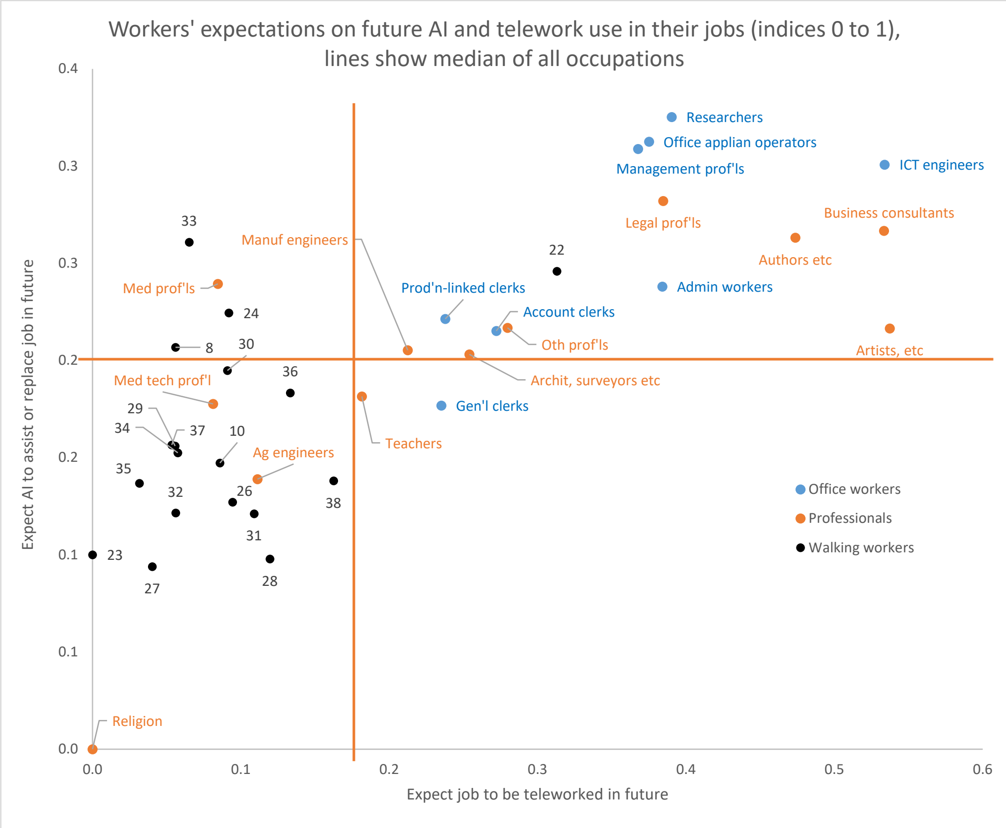
Figure 9 presents a scatter plot of the two answers coded such that the answer is 1 for those who agree or slightly agree and zero otherwise. The reported indices are averages of respondents in all sectors in each occupation and thus the indices run from 1 to 0. The horizontal axis plots the expected future teleworkability and the vertical axis the expected future automation.

The dominant feature of the data is the positive correlation. Specifically, the answer share of respondents answering positively on future AI-use was highly correlated across occupation with positive answers on the future telework question (correlation coefficient of 86%). We take this as indicating that the job was automatable and thus it would both assist workers and displace some workers.

Tellingly, the occupations where the responses to the two separate AI-automation questions (AI will assist and AI will replace) are highly divergent, the share answering positively on the replacement answer being much lower than the answer on AI assist. The occupation where this occurred involves tasks where humans must be physically close to machinery (agricultural engineers, outdoor service workers, and office appliance operators).

The chart shows a marked positive correlation which goes against the idea that AI and RI are substitutes. Workers who expect to telework in the future also expect to see AI being used in their jobs in the future. A few points are worth highlighting. First, the level of the expectation of telework is fairly high for Japan. In the median occupations (for example, architects, civil engineers, and surveyors) 20% of respondents expect to telework in the future. The median for expectations of future software automation is only slightly lower at 18%. Second, the variation in expectations line up relatively well with our three-way classification of occupations (office workers, professionals, and walking workers). The office-worker occupations (see note to Figure 2 for a list) show above median expected use of automating AI software, and all but one expects above average teleworking. By contrast, the walking-worker occupations are mostly in the southwest quadrant with below median expectations of future telework and software automation. Neither of these is surprising given the nature of the occupations and focus on AI-automation software companies on office-based tasks. What is somewhat less expected is the wide range of expectations of professional workers. Most expect to use automating AI (exceptions are teachers, medical technology professionals, and agricultural engineers), but some expect below average teleworking (e.g., religious workers).

Figure 9: Workers' expectations of telework and task automation in their jobs.



Source: Authors' elaboration of data from Okubo-NIRA data set.

Note: the indices are coded to be 1 or 0 at the respondent level and then averaged over workers with that occupation in all industries. Agri workers, 33; Carrying, cleaning etc, 37; Construction workers, 36; Food services, 29; Buildings managers, 30; Manuf workers, 34; Occ'l health workers, 28; Other, 38; Other service workers, 31; Outdoor serv workers, 23; Social work prof'l, 10; Nurses etc, 8; Sales clerks, 22; Sales workers, 26; Security workers, 32; Transport workers, 35; Transport workers, 24; Family care workers, 27 (see Appendix Table)

This evidence, however, needs careful handling, since the answers are from workers who still have jobs (recall the survey was done in September 2021 which was well into the Covid-19 shock). One scenario that could be consistent with an AI-RI substitutes hypothesis is that the workers who retain their jobs will be both teleworking more and using more AI, but the number of workers falls as AI raises the productivity of remaining workers. But at least at the level of occupations, the chart provides clear evidence that occupations that are the most teleworkable are also those that are most susceptible to automation.

5 Summary and concluding remarks

The ongoing digital technology revolution is transforming workplaces in two significant ways. First, it is enabling the 'unbundling' or spatial separation of offices in ways that allow service tasks to be completed remotely that were traditionally performed by workers close to each other. This trend, known as telework, has been facilitated by advancements in collaborative software suites, videoconferencing applications, and secure, cloud-based document sharing and editing. Second, machine learning and generative AI have facilitated the automation of various service sector tasks, allowing white-collar robots or software robots to automate jobs previously done by office workers and professionals.

The convergence of these two trends, termed the "Globotics Upheaval," has sparked concerns about the future of work and potential job displacement. It is too early to evaluate whether either of these trends are displacing or creating more jobs, but we can investigate the more pointed question of how task automating software (AI) and remote work (RI) are related. Are they working in the same direction – amplifying each other since they are complements or are they replacing each other since they are substitutes?

In 'Consumer Theory 101' complementarity and substitutability are a matter of cross price elasticities: if purchases of B rise when the relative price of A rises, then B is a substitute for A; if the purchases of B move in the opposite direction, they are complements. In the absence of prices that would allow estimation of cross-price elasticities, we can lean on the correlation of purchase behavior. Typically, the correlation of purchases of A and B is positive when they are complements but negative when they are substitutes.

Drawing on this mapping between correlation and substitutability/complementarity, this paper investigates the substitutability of AI and RI at the occupational level in Japan, using a unique panel of surveys collected from approximately 10,000 workers from just before the COVID-19 pandemic up to late 2022. The Dingel-Neiman index for telework and the Frey-Osbourne index of automatability are used to evaluate the technical feasibility of telework and automatability of occupations. The Globotics quadrant diagram is employed to map occupations based on their automatability and teleworkability, with the key argument being that while some occupations are suited to both, others are suited to only one or neither.

The paper proceeds to examine the impact of the COVID-19 pandemic on the relationship between AI and RI, using data from the survey to explore the potential substitution or complementarity between the two forms of intelligence. The survey provides information on firms' use of software that facilitates telework and automation of office tasks. The paper investigates whether firms' investments in AI-promoting software and RI-promoting software were positively or negatively correlated, to determine whether AI and RI are complements or substitutes.

The paper also looks at workers' expectations regarding the use of telework and software automation, providing additional insight into the relationship between AI and RI. Overall, this paper provides a comprehensive investigation of the substitutability of AI and RI in Japan, offering valuable insights into the future of work in an increasingly digitized world.

While the evidence is suggestive rather than conclusive, it seems clear that while telework and automation are technically possible for many occupations, there is no clear evidence that automation was less used in occupations where telework rose the most. We take this as preliminary evidence that in the context of the Covid-19 shock, AI and RI are complements not substitutes.

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Appendix: Okubo-NIRA Telework Survey

Survey and Sampling

This paper employs 'Questionnaire Survey on the Effects of the Spread of COVID-19 on Telework-based Work Styles, Lifestyle, and Awareness' (Okubo=NIRA Telework Survey), the survey was conducted by NIRA and Keio University (Okubo and NIRA, 2020a,b,c, 2021a,b). See https://nira.or.jp/paper/data/2022/26.html for the data link. See Okubo (2022a) about data and survey for more details.

The survey was conducted on a website constructed by Nikkei Research Co. It uses a stratified random sampling strategy. Japan is stratified into five regions by regional classification and six age groups for each gender (i.e., 12 age groups per region). The number of samples for 60 region-age groups is determined by population ratio from the Population Census (Ministry of Internal Affairs and Telecommunication).

The survey conducted seven waves in the spread of Covid-19: March (first wave of the survey), June (second wave), and December (third wave) 2020, April 2021 (fourth wave), September 2021 (fifth wave), February 2022 (sixth wave), and June 2022 (seventh wave) as of November 2022. The panel data was composed of seven waves with sample sizes of 10,516, 12,138, 10,523, 9,796, 10,644, 10113, and 10595, respectively. Many respondents continuously joined the survey for several waves. 3,162 respondents in the whole sample repeatedly joined the survey for all waves, in which 30% of respondents in the first wave survived.

Individual characteristics include age, gender, income, educational background, residential place, working place, occupation, industry, job status, employment size of companies and establishments of his/her working place. The central interest of the survey is in working environments. The survey asked about task characteristics (routine, manual, team tasks), working environments (e.g., flexible working time), whether to use telework, what kind of digital tools are available at workplace and how working environments changed during the Covid-19. The fifth wave asked several questions on digitalization, as mentioned below.

Usage of ICT software

The questionnaire asked respondents to choose from 16 items on ICT tools with raising some representative tools available in Japan if they usually use them at workplace: teleconference and web conference system (e.g. Zoom, Skype); information sharing (e.g. Slack, Line); sharing file (e.g. Dropbox, One drive); remote access (e.g. SWANStor, Platform V system); task project management (e.g. Trello, Backlog); electric payment (e.g. Creat!Web flow); attendance management (Office365, Cybozu); mental health management (e.g. jinjer work vital, onsei kokoro bunseki service (voice mental analysis service, MIMOSYS); business management (e.g. Sales cloud, kintone); sale management, production management, stock management (e.g. Rakusho, Arajin Office); employment management system (e.g. HRMOS Kanri, Jobukan Saiyo Kanri); human resource management (e.g. Smart HR, OBIC7); accounting management (e.g. Yayoi Kaikei, Super-Stream NX); RPA (robotic process automation)(e.g. WinActor, Robotic Crowd); virtual office (e.g. Sococo, Remo); contactless technology (e.g. robot for automatic operation, automated checkout).

Future expectation

The fifth wave includes some questions on an individual’s perspective on the impact of digitalization on his/her job in the near future. In detail, the survey asked several questions on his/her future job and task.

Question: Recently, it is often said that many task are workable remotely due to the development of information technology. Based on this point, what do you expect of your own job and task in the near future?

1. You will be able to work by teleworking
2. Some tasks will be replaced by freelance workers remotely
3. Some tasks will be replaced by other domestic companies remotely
4. Some tasks will be replaced by oversea companies remotely
5. Your tasks will be replaced by automation technology such as AI and robots
6. Your tasks will be supported by automation technology such as AI and robots

7. You can work by using virtual technology such as AR and VR
8. You can work by telework (remote work) for side business

Answer: Strongly agree, agree, neutral, disagree, and strongly disagree.

For our calculation, strongly agree and agree are 1, while others are zero. In this paper, we take mean values in each item and calculate the percentage of respondents who take positive attitudes to digitalization in each item. Item 1 is regarded as the percentage of future teleworking, that is, the future telework use ratio. Item 2 is deep teleworking. Items 3 and 4 asked about the future outsourcing by telework. Item 3 is regarded as domestic task outsourcing by telemigration. Item 4 is regarded as foreign task outsourcing by telemigration. Items 5 and 6 are regarded as replacement or substitute to the job by automation technology. Item 7 is regarded as support by VR and AR. Item 8 is telework use by side business.

Occupation categories of US and Japanese O*NET

They make an index based on the occupational information of US O*NET. However, the occupational characteristics are different between US and Japan in some occupations. Thus, we employ Kotera (2020), which recalculated Dingel's index, based on Japanese O*Net. For our calculation for 38 occupations (see Appendix Table), we take average weighted by labor force in each occupation (2015 Population Census, Ministry of Internal Affair and Telecommunication). We note that DN index measures remote workability, while ours is to measure teleworkability, that is, working ICT tools at remote work.

Frey's automation index

NRI (Nomura Research Institute), jointly worked with Frey and Osborne, calculated Frey's automation probability index in case of Japan. We use the automation index of NRI (Frey and Osborne, 2015). For our calculation for 38 occupations, we take average weighted by labor force in each occupation (2015 Population Census, Ministry of Internal Affair and Telecommunication). We note that Frey's index measures the probability of replacement by the automation of AI and robot.

Appendix Table: NIRA occupation category (Okubo and NIRA, 2020a,b,c).

NIRA38 code	Occupation	Occupation Abbreviation
1	Administrative and managerial	Admin workers
2	Researchers	Researchers
3	Agricultural engineers	Ag engineers
4	Manufacturing engineers	Manuf engineers
5	Architects, civil engineers	Archit, surveyors etc
6	Data processing	ICT engineers
7	Doctors, dentists	Med prof'ls
8	Public health nurses	Nurses etc
9	Medical Technology Professionals	Med Tech prof'l
10	Social welfare workers	Social work prof'l
11	Legal Professionals	Legal Prof'ls
12	Finance and insurance	Finance prof'ls

13	Management Business consultants	Business consultants
14	Teachers	Teachers
15	Religions	Religions
16	Authors, journalists, editors	Authors etc
17	Artists, designers, photographers	Artists etc
18	Other specialist professionals	Other prof'ls
19	General clerical	Gen'l clerks
20	Accountancy	Account
21	Production-related clerical	Prod'n-linked clerks
22	Sales clerks	Sales clerks
23	Outdoor service	Outdoor serv workers
24	Transport and post clerical	Transport workers
25	Office appliance operators	Office applian operators
26	Sales workers	Sales workers
27	Family Life Support and Care Service	Family care workers
28	Occupational health and hygiene	Occ'l health workers
29	Food and drink cooking	Food services
30	Residential facilities and buildings	Buildings managers
31	Other service workers	Other service workers
32	Security workers	Security worker
33	Agriculture, forestry and fishery	Agri workers
34	Manufacturing process	Manuf workers
35	Transport and machine operation	Transport workers
36	Construction and mining	Construction workers
37	Carrying, cleaning, packaging	Carrying, cleaning etc
38	Other	Other