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The Japanese Labor Market During the COVID-19 Pandemic

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The Japanese Labor Market During the COVID-19 Pandemic

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ABSTRACT: This paper investigates labor market dynamics in Japan during the COVID-19 pandemic drawing on macro and micro data. The pandemic and related containment measures had a large negative impact on employment, labor force participation, earnings, and labor market mobility, although policy support through furlough schemes partially mitigated the rise in unemployment. Our results indicate that industry effects were a crucial driver of labor market outcomes for different groups of employees — women, younger age groups, non-regular, self-employed, and low-income workers accounted for a disproportional share of employment in the hardest hit industries. We also find empirical evidence for the need to improve childcare and related support, training and upskilling offerings, and teleworking availability, and the role of skill mismatches in reducing labor market mobility and resource reallocation.

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Glossary

DML	Double Machine Learning
EAS	Employment Adjustment Subsidy
EI	Employment Insurance
GFC	Global Financial Crisis
JPSED	Japanese Panel Study of Employment Dynamics
MHLW	Ministry of Health, Labor, and Welfare
NILF	Not In the Labor Force
VET	Vocational Education and Training
WSR	Work Style Reform

1. Introduction

The COVID-19 pandemic and related containment measures hit labor markets worldwide hard, with highly unequal effects across workers (IMF 2021a). Japan is no exception despite comparatively low cases and fatalities. The number of employed persons decreased by about 1 million (equal to about a 1 percent drop in the ratio of employment to population) during the initial pandemic shock, and average earnings declined by 1.4 percent in 2020 due to lower overtime and bonus payments. The employment impacts on Japanese workers have varied greatly across industries and attributes including skill level, gender, and employment type. A granular analysis of the COVID-19 labor market shock is important for policy design and insights into more permanent implications of the shock for labor market and human capital development.

This paper contributes to the understanding of labor market dynamics in Japan during the COVID-19 shock drawing on macro and micro data. Relative to the existing literature, our study covers more aspects of the labor market impact and goes beyond the initial period of the COVID-19 shock. A large micro panel data set containing various labor indicators, including employment status and conditions, earnings, and working hours, allows us to examine the impact of the COVID-19 shock in detail, with particular attention to heterogeneity across the labor force, and to uncover new results. We study the key attributes associated with labor income and employment changes in 2020, the benefits of telework and human capital development during the crisis and suggest policy implications. Our empirical approach relies on machine learning techniques that are more agnostic of variable selection than traditional econometric approaches. This has advantages over selecting variables based on the literature or theory given that the COVID -19 labor market impact has no precedence.

Our results indicate that sectoral differences are a crucial driver of labor market outcomes for different groups of employees during the pandemic. While women, younger age groups, non-regular, self-employed, and low-income workers experienced greater declines in earnings and had a higher risk of losing employment, this is primarily driven by their greater relative representation in the most affected industries, especially in contact-intensive services sectors. In addition to industry effects, we find that for employment outcomes part-time workers were disproportionally affected — women, young, and low-income workers account for a large share of part-timers. For earnings outcomes we find that small firms, low education, working while studying and part-time work are associated with worse outcomes and again these groupings tend to have higher than average employment shares among women, young, and low-income workers. We also find empirical evidence for the need to improve childcare and related support offerings, reduced labor market mobility and resource allocation due to skill mismatches, the general beneficial effects of more training and upskilling, and the importance of being able to telework. We discuss the policy implications of our results in section 5.

This paper is related to research examining the pandemic's impact on the Japanese labor market. Hoshi et al. (2021) investigate the impact of mobility on work absences, working hours, and unemployment using micro data from February to June 2020. They find women, specific age groups (31-45 years for work absences, 60-65 years for unemployment), non-regular, self-employed, and low-educated workers more affected. Kikuchi et al. (2021) construct a life-cycle model of heterogeneous agents and simulate that the most severely affected groups are female, non-regular, low-skilled, engaged in social jobs, and not able to work remotely. Similarly, Kikuchi et al. (2020) argue that the crisis would hit low-income groups disproportionally and exacerbate inequality. Fukai et al. (2020) adopt machine learning techniques to examine the impact on employment status (employed or not) using individual data until June 2020. They show that unemployed or part-time workers in the hotel and restaurant industry and services occupation, as well as younger and female workers are more affected. Based on a May 2020 labor market survey by Keio University, Yamamoto et al. (2021) find that employment status (regular or non-regular) and firm size were the main determinants of employment outcome differences. Drawing on additional Keio University surveys, Sumita (2021) does not find significant increases in unemployment and job changes due to the pandemic, although household income decreased, especially for women.

Given the importance of teleworking during the pandemic, several studies investigate the implications for the Japanese labor market. Okubo (2020) reports an increase in teleworking from 6% in January to 17% in June 2020. Following the approach in Dingel and Neiman (2020), Kotera (2020) estimates that potentially about 30% of workers could work from home in Japan. Survey results by Morikawa (2021a) show that workers' reported productivity of work from home improved from 2020 to 2021, but on average is lower than working in the office. Kitagawa et al. (2021) report that poor home office and communication technology setups are the main reasons for productivity losses with work from home. Empirical analysis by Ishii et al. (2021) that addresses reverse causality concerns indicates that telework mitigated the reduction of income and working hours during April and May 2020.

The remainder of the paper is organized as follows. The second section provides background on pandemic developments and labor market policies in Japan. The third section presents an overview of the Japanese labor market during the pandemic drawing on macro data. The fourth section analyzes labor market developments drawing on micro panel data. The last section concludes.

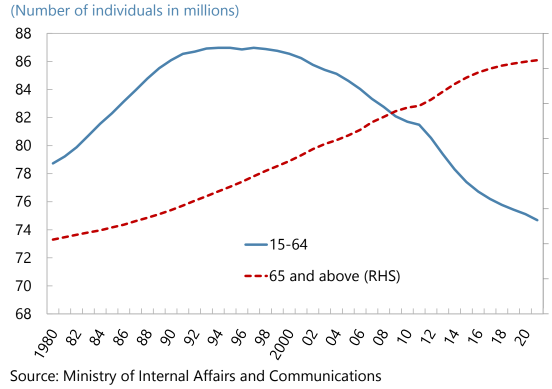
2. COVID-19 and Labor Market Policies

2.1 General Background on the Japanese Labor Market

This section provides a brief overview of key characteristics of the Japanese labor market before the pandemic. Demographic developments have been important in shaping the Japanese labor market in the last decades. The working-age (15-64) population has declined by slightly more than 12 million since 2000, from 87 million to 75 million (Figure 1). At the same time, the number of employed individuals has slightly increase (Figure 2, upper left). This expansion of employment despite a rapid decline in the working-age population reflects fast increases in the employment rate (share of the population with jobs) of working-age women (Figure 2, upper right). The Japanese employment rate for women stood at 71.5 percent as of end 2019, above the OECD average of 61.5 percent. In addition, more recently, employment rates of the elderly (65+) rebounded to levels in the 1990s. Meanwhile, the Japanese labor market has been relatively tight prior to the pandemic, with a low unemployment rate of 2.4 percent in 2019 and a job offer to applicant ratio of 1.6 in 2019.

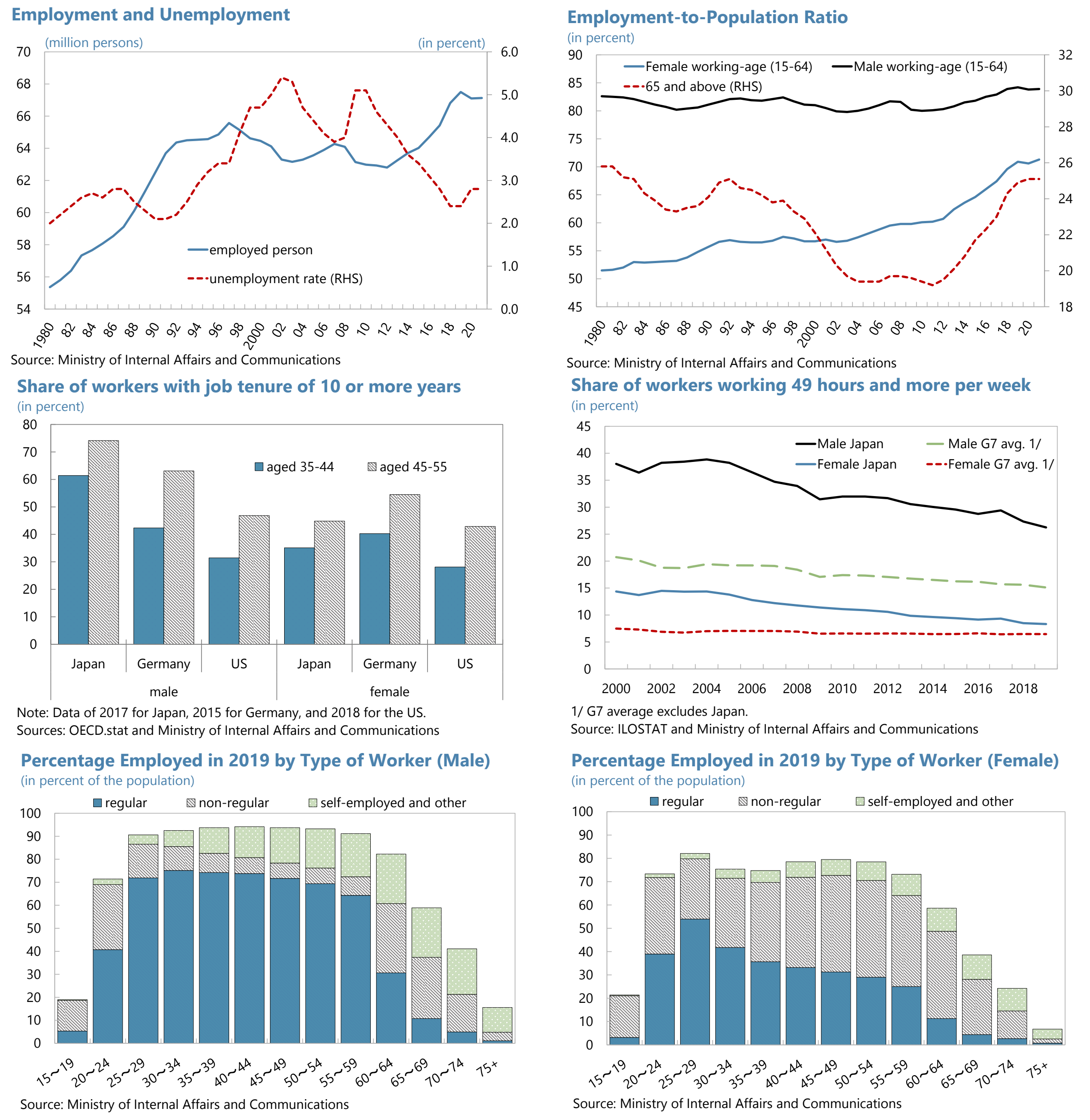
Figure 1. Working-age (15-64) and 65+ Population

(Number of individuals in millions)



Source: Ministry of Internal Affairs and Communications

Figure 2. Overview of the Japanese Labor Market



The Japanese labor market is traditionally centered around lifetime employment. Under this system, employers recruit new graduates annually with an implicit promise of employment until mandatory retirement. While the importance of lifetime employment has diminished in the last decades (Kawaguchi and Ueno, 2013) it remains an important employment model (Figure 2, middle left). The share of male workers employed by the same company for 10 years or more for those aged 35-45 stands at more than 60 percent in Japan, about twice the share in the US. However, for women the share of long-tenured employees in Japan is not higher than in other countries. The lifetime employment system is associated with seniority-based promotion and pay structures. Lifetime employment can provide incentives to employers and employees to invest in firm-specific human capital, but it has also been associated with high gender inequality and lack of diversity.[1] The system mainly applies to regular male workers, reflecting traditional gender roles and the typically required long working hours (Figure 2, middle right). Various other factors keep women out of life-time employment arrangements including insufficient childcare support and a need for more flexibility and shorter working hours due to family obligations. In addition, even among regular workers, many large firms tend to adopt a dual-track system with a career and a non-career tack. Women tend to be strongly underrepresented in career tracks.

In contrast to lifetime employment, non-regular employment contracts typically include fixed-term, part-time, and dispatched workers. The share of non-regular workers in total employment has risen from 16% in 1995 to 32% in 2019 (Figure 2, bottom). Women account for about 70 percent of non-regular workers. For men, non-regular employment is particularly prevalent among young and older workers. Firms have less incentive to invest in training and human capital of non-regular workers, which can negatively affect productivity (Randall and Haruki, 2019). Non-regular employment is also associated with lower wages and lower job security.

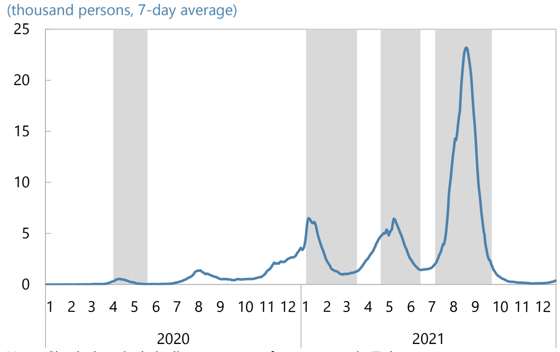
The Japanese government acknowledges the need to reform the traditional employment system.[2] In 2016, the government began discussions of Work Style Reform (WSR) and legislation was passed in 2018. WSR aims to increase employment opportunities and productivity through measures such as caps on excessive overtime, promotion of flexible working styles, equal pay for equal work, and shifting the focus from working hours to output. Japan has also continued to make progress on other reforms to improve gender equality including an expansion of childcare and nursing facilities and skills training to increase female workforce participation and employment (IMF, 2020).

2.2 COVID-19 Developments

Labor market developments and policies in Japan during 2020 and 2021 evolved against the backdrop of an unprecedented shock stemming from the COVID-19 pandemic. The following provides a brief review of major pandemic developments (Figure 3). After the first COVID-19 case was confirmed in Japan on January 15, 2020, cases rose slowly between March and April. To contain the virus, the government requested the cancellation or postponement of major events and the temporary closure of schools at the end of February. On April 7, a state of emergency was declared, initially in 7 prefectures including the Tokyo metropolitan area, and extended to the entire country on April 16. During the state of emergency, the government requested prevention measures including refraining from going out, temporary business closure, and reducing the number of commuters. To mitigate the economic impact of the containment policies, the government decided to provide economic support measures on April 20,

Figure 3. New infection cases in Japan

(thousand persons, 7-day average)



Note: Shaded periods indicate a state of emergency in Tokyo.
Source: NHK

[1] See Moriguchi (2014) for the history of the Japanese human resource management system. IMF (2017) discusses details of the lifetime employment system and gender inequality.

[2] Cabinet Office (2019) states that the traditional Japanese-style employment system prevents diversity and limits innovation, and that the system does not have a sound economic rational in the current rapidly changing business and technology environment.

totaling 117 trillion yen (about 21% of GDP)[3]. The state of emergency was gradually lifted from mid-May depending on prefectures' infection rates, and was entirely lifted on May 25. In July, the government started a tourism promotion program for the country excluding Tokyo. A new wave of infections peaked in early August. The tourism promotion campaign was extended to Tokyo in October but suspended entirely in December, as new infections started to rise again from the end of October. On December 8, the government adopted another economic stimulus package worth 73.6 trillion yen (about 13% of GDP)[4], focused on promoting digitalization and green technologies and an extension of ongoing support measures.

Japan suffered from three major infection waves in 2021 that necessitated repeated behavioral and economic restrictions. In response to rising infection cases since late 2020, the government declared a second state of emergency in Tokyo and neighboring regions as well as seven other prefectures in January. The state of emergency was lifted in all areas on March 21, but as case numbers rose again, the government declared a third state of emergency on April 25 in four prefectures, including Tokyo, and an additional six prefectures shortly after. Requested prevention measures included shorter operating hours for restaurants and similar businesses, closure of large commercial facilities such as malls, and banning spectators from events. The state of emergency was lifted between June 21 to July 11 except for one prefecture (Okinawa). However, new infections soared again from late July, prompting the government to place 21 prefectures under a state of emergency in August. New cases peaked around late August and the emergency declaration was lifted in all prefectures on September 30. Covid-19 infections remained at a low level until the emergence of the Omicron variant at the end of 2021. On November 19, the government adopted additional economic measures totaling 78.9 trillion yen (about 14% of GDP)[5], including special benefits to households with children.

2.3 Labor Market Policies During COVID-19

The main instrument to mitigate the pandemic impact on labor markets is the Employment Adjustment Subsidy (EAS). This scheme provides financial assistance to businesses if they maintain their employment by placing their employees on temporary leave, similar to furlough schemes employed in many European countries during COVID-19. Firms are required to pay a leave allowance to such employees[6], but EAS reimburses a percentage (grant rate) of this leave allowance with a cap. Leave eligible under the scheme can be as short as 1 hour.[7] The scheme was originally established during the 1974 oil crisis, and although its importance had diminished during the 1990s, the subsidy was extensively used during the global financial crisis (GFC) when the government relaxed EAS requirements considerably (Hamaguchi, 2020). During the pandemic, starting in April 2020, the government implemented more generous EAS terms than during the GFC, including by expanding coverage to all employees[8] and raising the grant rate and

[3] The package titled "Emergency Economic Measures to Cope with COVID-19" https://www5.cao.go.jp/keizai1/keizaitaisaku/2020/20200420_economic_measures_all.pdf

[4] The package titled "Comprehensive Economic Measures to Secure People's Lives and Livelihoods toward Relief and Hope" https://www5.cao.go.jp/keizai1/keizaitaisaku/2020-2/20201208_economic_measures_all.pdf

[5] The package titled "Economic Measures for Overcoming Coronavirus Infections and Opening Up a New Era" https://www5.cao.go.jp/keizai1/keizaitaisaku/2021/20211119_economic_measures.pdf

[6] The company needs to pay 60% or more of the average wage.

[7] In response to COVID-19 the flexibility of the scheme was increased to accommodate shorter leave periods.

[8] Initially, EAS only applied to employees enrolled in the employment insurance (those who work 20 hours or more per week). During the pandemic the government established the Emergency Employment Safety Subsidy to cover all other employees.

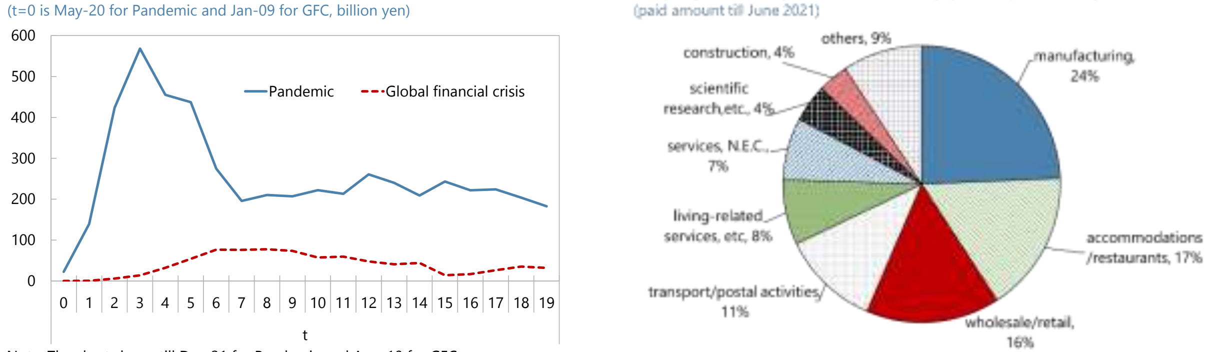
reimbursement cap[9]. Additionally, EAS flexibility was increased by allowing firms to place employees in vocational education and training (VET) programs instead of leave, and the subsidized amount and requirements of this VET scheme were also relaxed.[10] Further, the Ministry of Health, Labor, and Welfare (MHLW) simplified the application procedures to accelerate disbursements.

Total EAS payments during this pandemic far exceeded those during the GFC, reaching a peak of close to 600 bn yen in August 2020 (Figure 4, left).[11] Payments decreased to roughly 200 billion yen per month in December 2020, and have remained at a similar level until late 2021. During FY2020, the total cumulative amount of 3.1 trillion yen was provided, about seven times higher than the EAS payments during the entire GFC period. Among industries, manufacturing, accommodation and restaurants, and wholesale and retail were the main recipients, receiving more than half of EAS payments (Figure 4, right). According to Japanese government estimates, EAS lowered the unemployment rate by about 2.6 percentage points during April to October 2020 (MHLW, 2021).

Figure 4. Employment Adjustment Subsidy (EAS)

Employment adjustment subsidy paid each month
(t=0 is May-20 for Pandemic and Jan-09 for GFC, billion yen)

Employment adjustment subsidy paid by industry
(paid amount till June 2021)



Note: The chart shows till Dec-21 for Pandemic and Aug-10 for GFC.
Source: Ministry of Health, Labour and Welfare

Source: Ministry of Health, Labour and Welfare

The support from EAS is related to the large increase in “employed persons not at work” (temporarily on leave) across all age groups in the first months of the pandemic. As figure 5 shows, the increase in employed persons not at work happened primarily in April and May of 2020. Workers on leave jumped by over 4 million persons relative to the previous year in April 2020, but the number declined fast, settling at a level only slightly higher than pre-crisis from around June.[12] This contrasts with EAS payments continuing to remain substantially above pre-pandemic levels through 2020 and 2021 (Figure 4, left). The discrepancy suggests that firms continue to use EAS to put employees on short-term leave (to be classified as employed

[9] The grant rate became 1/2 to 2/3 for large companies and 2/3 to 4/5 for SMEs. If companies make no dismissal, the rate became 3/4 for large companies and 9/10 for SMEs. The upper limit of subsidy also increased from 8,330 yen to 13,500 or 15,000 yen per day.

[10] Initially, an additional 1,200 yen was disbursed per worker for one day VET, but during the pandemic, the amount increased to 2,400 yen for SMEs and 1,800 yen for large companies. Furthermore, VET coverage was expanded, and days can be split between VET and leave.

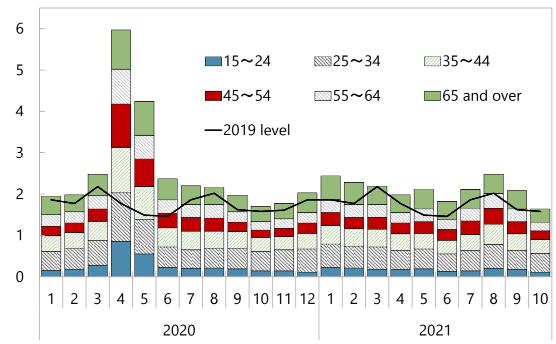
[11] Data on the number of employees benefitting from EAS is not available. We therefore need to rely on EAS payments to firms as a proxy for EAS usage.

[12] This is a much higher number compared with the GFC. On an annual average, workers on leave increased by 213 thousand from 2007 to 2009, but by 807 thousand from 2019 to 2020.

persons not at work requires at least one week of leave in a given month). Furthermore, EAS payments are likely higher due to more generous terms and the additional disbursements for training.

Figure 5. Employed person not at work

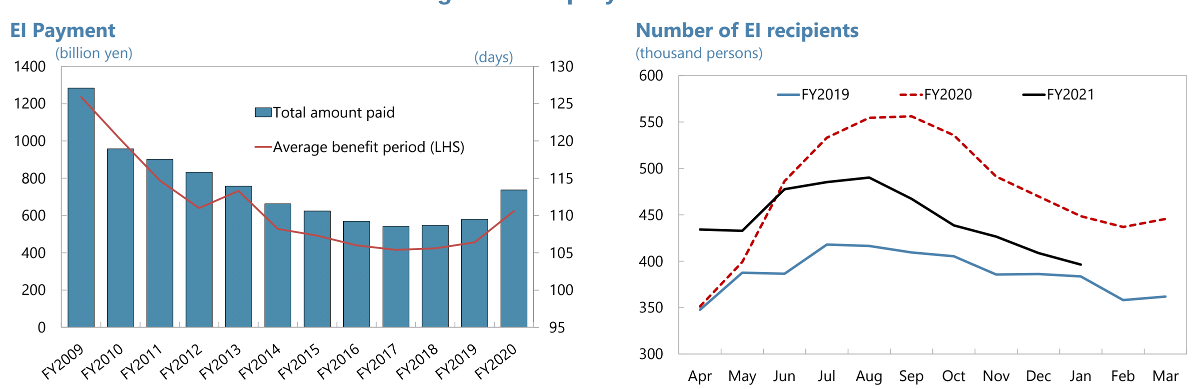
(million persons, not seasonally adjusted)



Source: Ministry of Internal Affairs and Communications

While EAS helped to maintain employment, the government also expanded the employment insurance (EI) benefits to protect those losing their jobs. Prior to the pandemic, the unemployed received basic benefits equivalent to 50-80% of their previous income with a cap for 90-330 days depending on their age, the duration of contributions, and the reason for becoming unemployed.[13] Employees working at least 20 hours per week, including non-regular workers, are eligible for EI coverage. In response to COVID-19, EI benefit payments were temporarily extended by an additional 60 days.[14] In FY2020, the total payment of EI basic benefits increased by about 27 percent compared with the previous fiscal year, due to more recipients and a longer average benefit period (Figure 6). The average number of beneficiaries increased from 387 thousand persons in FY2019 to persons in FY2020. However, the total payment for FY2020 is about 42 percent lower than FY2009, which implies that compared with the GFC, EI is less important in this crisis due to the generous EAS support during the pandemic which helped prevent a large increase in unemployment.

Figure 6. Employment Insurance



Note: Data for basic allowance.
Source: Ministry of Health, Labour and Welfare

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Source: Ministry of Health, Labour and Welfare

Apart from EAS and EI, the government implemented other measures to support the labor market. For example, individuals who cannot receive the leave allowance for some reason can directly apply for grants and allowances. Some assistance measures were created for people who are forced to take leave due to childcare obligations. In addition, the career counseling support system through *Hello Work* (public

[13] The benefits here refer to the basic allowance of EI which includes the most common benefits of the unemployment insurance. Depending on the circumstances, people can apply for other unemployment benefits such as the skill acquirement allowance, injury and sickness allowance, and old-age job applicant benefit.

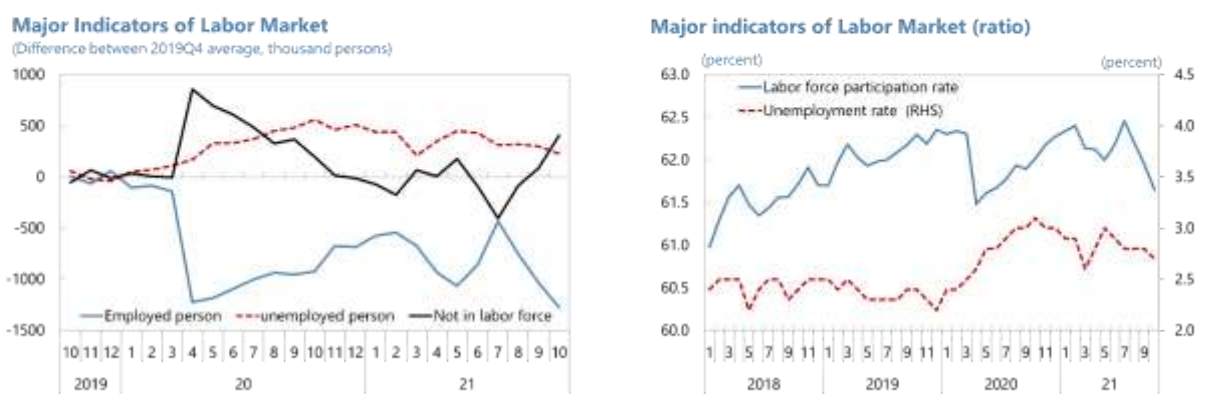
[14] The scope of eligible workers varies depending on whether the unemployment date is before, during, or after a state of emergency. A person receives additional 30 days instead of 60 if one is aged 35 to 44 and initially eligible for 270 days of benefits or is aged 45 to 59 and initially eligible for 330 days of benefits.

employment security service) was strengthened for non-regular workers, and eligibility for job-seeker support training was expanded.

3. Labor Market Developments During the Pandemic – Evidence from Macro Data

The initial pandemic shock to the labor market was large and instant. The number of employed persons decreased by about 1 million from March to April 2020. Many people left the labor market instead of filing as unemployed, leaving the unemployment rate initially almost unchanged (Figure 7).[15] After the initial shock, the number of people not in the labor force (NILF) gradually declined reaching the pre-pandemic level in November 2020. However, in 2021, the number of people not in the labor force increased again during COVID-19 infection waves in May/June and in the Fall. The number of employed persons recovered gradually after the sharp initial drop in April 2020, but as of late 2021 remains substantially below the pre-crisis level with major damage resulting from renewed COVID-19 waves. Meanwhile, the number of people registered as unemployed rose gradually until leveling off in late 2020 and remains about 1.3 times higher than before the pandemic.

Figure 7. Employment during the Pandemic



Source: Ministry of Internal Affairs and Communications

Source: Ministry of Internal Affairs and Communications

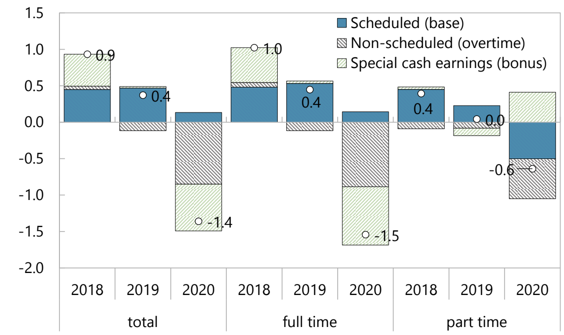
Average annual earnings declined by 1.4 percent in 2020 due to reduced overtime and bonus payments (Figure 8). For full-time workers the average annual earnings change was -1.5 percent. Part-timer workers experienced a smaller reduction of -0.6 percent, but this may reflect compositional effects as part-time workers with a lower-wage level lost their jobs, as well as special bonuses for part-time workers in a few sectors in 2020 including healthcare and education. Reflecting the more flexible nature of temporary workers' contracts, temporary workers experienced a decline in base pay, partially offset by bonus payments.

[15] Potential reasons for the sharp increase in people not in the labor force while unemployment was relatively stable include (1) workers dropping out of the labor force due to fear of COVID-19 or family obligations; (2) part-time workers dropping out who do not qualify for unemployment benefits (work less than 20 hours per week); (3) people may indicate in the household survey data presented in the figure that they are not looking for work while still receiving unemployment benefits (Japan relies on the survey data for unemployment, as EI does not cover workers with less than 20 hours per week).

There is significant heterogeneity of the pandemic impact across industries. Contact-intensive services, such as accommodation and restaurants and living-related and amusement services were most affected (Figure 9, left). Manufacturing and transport services were also hit, especially through lower earnings. Real estate and information services experienced rising employment but falling earnings. Only medical care and finance and insurance saw rising earnings and in the former employment also rose.

Figure 8. Changes in total cash earnings

(year-on-year, in percent)

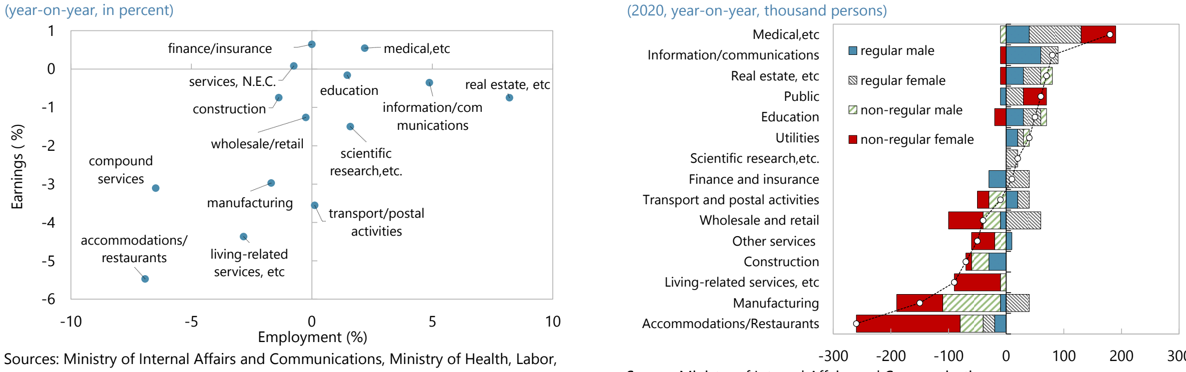


Source: Ministry of Health, Labor, and Welfare

Zooming into employment changes by gender and regular/non-regular status also reveals substantial differences across industries (Figure 9, right). Non-regular workers bore the brunt of the COVID-19 shock to the labor market: in 2020, the number of regular workers grew by 360 thousand persons while the number of non-regular workers fell by 750 thousand. Contact-intensive services industries saw large declines in nonregular workers, with especially women affected reflecting their greater employment share in these industries. Substantial losses of non-regular positions in manufacturing were evenly split between men and women. New jobs in industries that added employment (health care, information/communication services, real estate, public sector, education) were mostly regular positions, although there was also a significant number of new non-regular positions in health care and the public sector filled by women.

Figure 9. Labor Market by Industry

Employment and Earnings Changes in 2020 (year-on-year, in percent) | **Employment Changes by Industry by Worker Type** (2020, year-on-year, thousand persons)



Sources: Ministry of Internal Affairs and Communications, Ministry of Health, Labor, and Welfare

Source: Ministry of Internal Affairs and Communications

Table 1 provides a granular look at changes in employment for the full year of 2020 and 2020Q4 broken down by gender and age. For the full year, the number of employed persons dropped by 240 thousand persons for each male and female. There are, however, important compositional differences by gender. While the reduction in male employment was mostly due to full time employees ("mainly at work"), female employment losses stemmed predominantly from women working part-time ("work while attending school or housekeeping"). Employment losses for both genders were concentrated in younger age groups. As discussed in the previous section, the support from EAS is visible in the large increase in the category "employed persons not at work" (temporarily on leave) across all age and gender groups. Turning to unemployment, the increase in unemployed persons was close to double for men compared to women, suggesting that more women dropped out of the workforce rather than register as unemployed. As of 4Q of 2020, 1.2 million males and 0.8 million females remained unemployed. For those not in the labor force, there was a big increase for women but not for men. Especially young workers ages 15 to 24 dropped out of the workforce, although the reason changed from attending school to "other".[16]. Females aged 65 and over stand out for dropping out of the labor force in large numbers, possibly to avoid infections or because employment opportunities in services disappeared.

Table 1. Labor Market Changes by Gender and Age

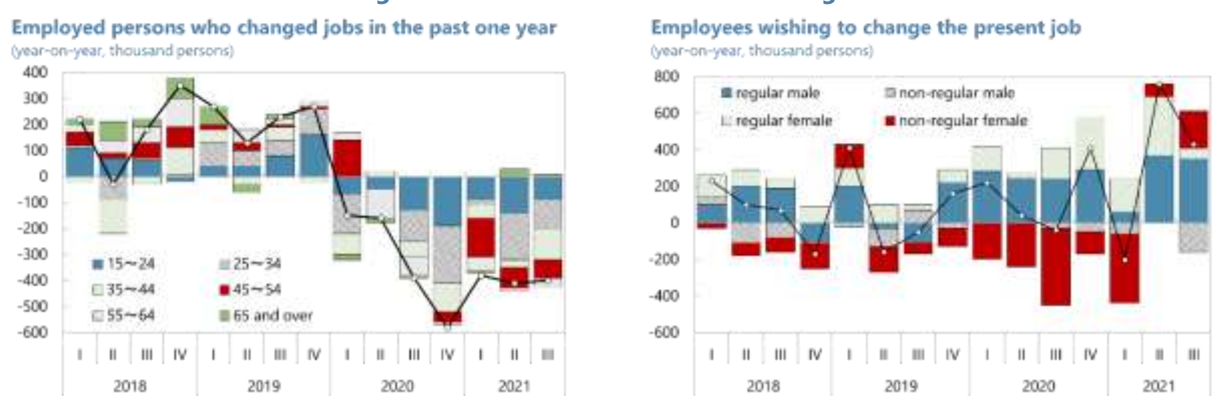
Year-on-year Changes (thousand persons)

		2020 average						Q4 2020					
		Employed person			Unemployed person	Not in labor force		Employed person			Unemployed person	Not in labor force	
		Mainly at work	Work while attending school or house-keeping	Not at work		Attending school	House-keeping & other	Mainly at work	Work while attending school or house-keeping	Not at work		Attending school	House-keeping & other
male	15～24	-45	-73	40	28	-75	80	-10	-110	-10	30	10	10
	25～34	-143	18	50	43	3	3	-110	10	20	60	-10	-20
	35～44	-338	8	53	33	0	3	-300	10	20	70	0	-20
	45～54	5	18	45	28	0	0	-40	20	-10	60	0	20
	55～64	-13	3	58	43	0	-53	30	-10	10	80	0	-60
	65 and over	-35	5	108	15	0	50	-20	20	40	20	0	90
	total	-570	-20	350	190	-70	70	-460	-70	80	320	0	10
female	15～24	-25	-118	53	13	-43	75	-20	-80	0	10	10	30
	25～34	-40	-93	85	40	-10	-60	40	-90	40	60	-20	-110
	35～44	-148	-170	78	3	-5	3	-30	-140	-10	10	0	-60
	45～54	85	-155	88	28	3	38	110	-180	0	40	0	60
	55～64	33	-48	68	18	0	-38	60	-20	-10	40	0	-10
	65 and over	-10	-10	75	3	0	103	20	-10	40	0	0	120
	total	-110	-580	450	100	-50	110	180	-520	70	150	0	20

Sources: Ministry of Internal Affairs and Communications

The frequency of job changes declined for all age groups during the pandemic and remains depressed through the end of 2021 (Figure 10, left). This reflects a less favorable job market with fewer open positions during the pandemic. Prior to COVID-19, job switching had become more common in Japan against the backdrop of shortages of workers and competition for qualified human resources.

Figure 10. Actual and Desired Job Changes



Source: Ministry of Internal Affairs and Communications
Source: Ministry of Internal Affairs and Communications

At this point, there is no evidence of a "great resignation" in Japan, unlike the US, where the number of employees quitting their job reached a record high in September 2021. However, there has been an increase in the number of employees expressing the wish to change jobs, especially among men on regular work contracts (Figure 10, right). A possible interpretation is that Japanese workers were prompted by

[16] See figure 11 for detail on the drivers of dropping out of the workforce.

COVID-19 to reevaluate their career preferences, similar to workers in the U.S., but labor mobility in Japan is generally lower as discussed in section 2.1 and opportunities for job changes during the pandemic are more limited. That said, with the labor market recovery under way in Japan, the number of job switchers may increase, but given the data on desired job changes it is unlikely to reach the proportions of the U.S. “great resignation”.

During the pandemic, people not in the labor force became less interested in finding employment. The number of people not wishing to work increased, particularly for the age group 15 to 24 and females aged 65 and over (Figure 11, left). Before the crisis, the labor force was on an increasing trend due to the higher labor force participation rates of older people and women. The pandemic has arrested the trend of increasing labor force participation, at least in the short run. Reasons for those who left their previous job and became NILF vary with some pronounced gender differences (Figure 11, right). Looking at changes in Q4 2020 relative to the prior year, more women indicated marriage, childbirth, or childcare, suggesting that the burden of school closures and other pandemic restrictions fell especially on women.

Figure 11. People Not in the Labor Force (NILF)

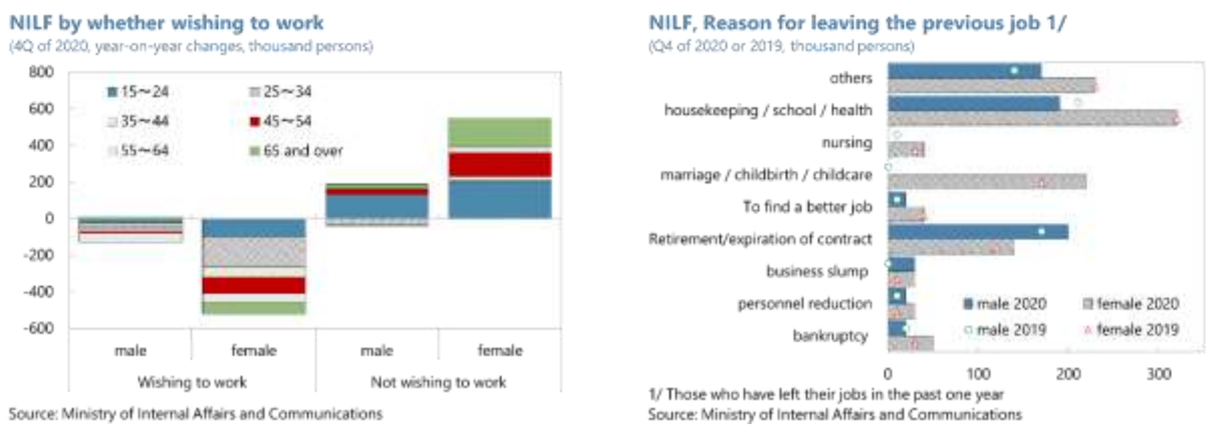
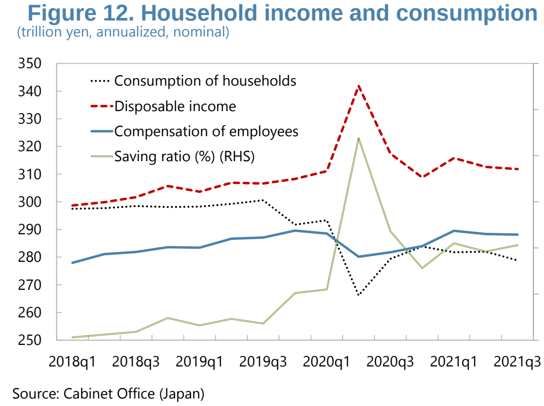


Figure 12. Household income and consumption



Despite reduced employment and earnings, household disposable income increased substantially at the macro level in 2020 (Figure 12). The aggregate compensation of employees dropped by around 8 trillion yen (annualized) in 2Q 2020, but disposable income spiked at the same time due to the government's unconditional cash transfer of 100,000 yen per person and other support programs. Nonetheless, household consumption fell, resulting in an increase in the saving ratio from 6% to 22% in 2Q 2020. However, this does not mean that government aid offset the pandemic's adverse effects for every household, as the impact differed significantly depending on the households' work situation.

In summary, the macro data tells us that the impact of the pandemic on the labor market varies substantially across gender, age, regular vs non-regular, and industry, pointing to the importance of accounting for workers’ heterogeneous attributes in analyzing the pandemic impact. There is a limit as to how far macro data can provide insights into the heterogeneity, so we are using a rich micro data set for the analysis in the next section.

4. Labor Market Developments During the Pandemic – Evidence from Micro Panel Data

4.1. Panel Data Set

We use individual-level data from the Japanese Panel Study of Employment Dynamics (JPSED) provided by the Recruit Works Institute. JPSED is an internet monitoring panel survey conducted every January since 2016. The sample includes men and women aged 15 years and over. The sampling is designed to be representative of the Japanese population for attributes such as gender, age, type of employment, district block, and educational background.[17] Each year, the survey asks roughly 100 questions about basic attributes and the previous year's labor indicators, including employment status and dynamics, working hours, and annual earned income. The sample size fluctuates with approximately 50,000 to 60,000 individual observations collected each year. In the 2021 survey, 56,064 individual observations are available, 45,192 of which are continuous from previous years, 5,809 are new individuals, and 5,065 were in previous samples but not continuously.

We divide the sample into three groups based on their employment status dynamics taking advantage of the availability of employment status data for every month (Figure 13 and Table 2). First, we restrict the sample to persons employed (at work) from November of year t-1 to January of year t to examine the pandemic's effects on employment more clearly.[18] Then, depending on the labor status during February to December of year t, we classify the sample into 3 groups. Group 1 is for those who kept working during the year. This group can be further divided into 2 categories: job stayers (group 1-1) and job switchers (group 1-2). Group 2 includes respondents that became unemployed or left the labor market for at least one month during the year. We further break group 2 down into two categories (group 2-1: find a job again, group 2-2: still unemployed or NILF). Lastly, we classify those who are employed but not at work at least one month during February to December to group 3.[19] The data period covers t = 2018 to

Figure 13. Targeted Sample

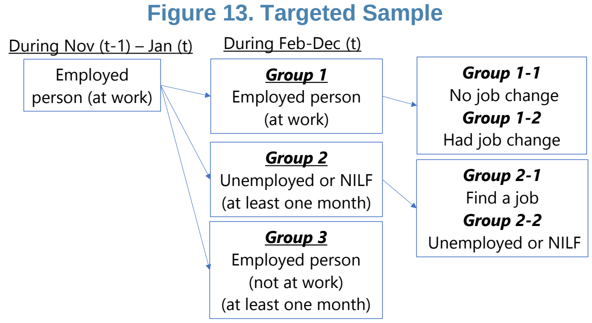


Table 2. Sample size

		2018	2019	2020	Total
Group	1-1	20,369	26,082	23,890	70,341
	1-2	2,180	2,668	2,158	7,006
	2-1	549	721	793	2,063
	2-2	553	695	811	2,059
	3	576	742	1,320	2,638
		24,227	30,908	28,972	84,107

[17] The population data is the Labor Force Survey by the Ministry of Internal Affairs and Communications. Since the sample does not fully match the population data structure, the Recruit Work Institute provides the sampling weights to adjust for this bias.

[18] This restriction also aims to remove noisy observations who are in and out of the labor market frequently.

[19] An observation is classified as group 3 if they did not work at all during a month. If an observation has both unemployment (or NILF) and not at work periods, we include the observation in group 2.

2020, allowing us to analyze pandemic effects on the labor market in 2020 relative to the previous two years. Descriptive statistics are presented in Appendix 1.

4. 2 Employed Persons at Work (group 1)

This group includes those working continuously during the pandemic without any periods of unemployment, NILF, or absence. For those who did not change jobs (group 1-1), earnings changes are our primary concern. Our focus for job switchers (group 1-2) are signs of labor reallocation during 2020, motivated by suggestions that the reallocation of labor could mitigate the loss of TFP (total factor productivity) during the recession (IMF, 2021b).

4. 2. 1. Earnings Developments for Employees with no Job Change (group 1-1)

The large number of observations for this group allows us to use regression analysis to identify factors affecting earnings changes in 2020. Our dependent variable is the log transformation of annual earnings (w_{it}) expressed as $\Delta y_{it} = LN(w_{it}) - LN(w_{it-1})$.[20] We analyze three categories of employees based on working hours (as of December, year t-1): 1) full sample (63,305 observations), 2) full-time workers (35 hours or more per week) (50,643 observations), and 3) part-time worker(less than 35 hours per week) (12,662 observations).

Table 3. Selected result of DML analysis

		Coefficient: all	Coefficient: full-time	Coefficient: part-time
d20*female		–	–	–
d20*age(t-1)		–	+	–
d20*education(t-1)	junior high school	-3.5 **	-1.6 ***	-11.2 ***
	at school	-3.5 *	-5.2 ***	-7.1 *
d20*employment status(t-1)	regular worker	-3.0 **	–	–
	non-regular worker	-2.6 *	–	–
	self-employed	-2.8 *	–	–
d20*industry(t-1)	manufacturing	-2.3 **	–	-3.7 *
	wholesale/retail	-2.1 **	–	–
	accommodation/restaurants	-3.9 ***	-2.3 *	-6.0 **
	living-related service	-3.3 **	-3.0 *	–
d20*occupation (t-1)	security	-3.1 ***	-2.7 **	–
	transportation/communications	-4.5 ***	-4.1 ***	–
	production	-1.8 **	-2.0 **	–
	professional job	-1.6 **	-1.7 **	–
d20*working hour (t-1)	～19h	-3.0 *	N/A	+
	20～29h	-4.1 **	N/A	+

		Coefficient: all	Coefficient: full-time	Coefficient: part-time
d20*firm size (t-1)	～9 persons	-3.5 ***	–	-9.4 ***
	10～99	-2.3 *	–	-8.4 ***
d20*various tasks		–	–	–
d20*job level change (t)	job level up	-3.2 *	–	–
	job level down	-4.3 **	-4.0 **	–
	job same level	-2.9 *	–	–
d20* annual earnings (t-1)	less than 1M yen	-4.7 ***	–	–
	3-4M yen	-7.2 ***	-1.9 *	-6.6 ***
	over 8M yen	-8.8 ***	-3.0 ***	-7.8 **
d20*spouse's employment	executives	-3.0 ***	-	-4.1 *
can telework (t)		0.8 ***	1.0 ***	–
d20*can telework (t)		–	–	–
self-development (t-1)		–	–	–
d20*self-development (t-1)		–	–	–
Number of obs		63,305	50,643	12,662

The dependent variable is annual earnings change (in percent). The table shows the DML analysis's selected results, where significant results are found. The hyphen indicates the results are not significant at the 10% level. The plus indicates all items are significant. See Appendix 4 for the full detailed results. *** p<0.001, ** p<0.05, * p<0.1

To identify the main drivers of earnings changes, we employ the Double Machine Learning (DML) technique (cross-fit partialing-out) developed by Chernozhukov et al. (2018). The primary advantage of DML over traditional regression analysis is the data-based method of covariate selection aiming to avoid selecting the wrong controls or omitting relevant ones. Since the pandemic is an unprecedented crisis and relevant variables are therefore a priori unknown, we include many potential variables in the initial model selection (see Appendix 2 for a list of variables). We conducted multiple DML regressions by changing our variables of interest (d_{i20}), which are feature variables multiplied by a 2020-year dummy to capture

[20] Observations are excluded as outliers if $|\Delta y_{it}|$ is higher than 60%, with the threshold based on the 2.5 percentile of the sample.

movements in the pandemic year. If the coefficients of d_{i20} are significant, workers with those features experienced lower or higher percentage points of earnings growth in 2020 compared with the previous two years. This analysis employs rigorous lasso linear regression for covariate selection, where all variables except d_{i20} are candidates for controls. See Appendix 3 for technical details.

Controlling for other factors, the adverse impact of the pandemic on earnings is more concentrated among specific industries and occupations[21], small firms, and those with junior high school education only, working while studying and working part-time (Table 3). As for industries, significant earnings declines are found in manufacturing, wholesale and retail, accommodation and restaurants, and living-related services.[22] Part-time workers in the accommodation and restaurants sector were particularly hard hit. On an occupational level, earnings declines are bigger for transport/communication and security occupations, likely due to people refraining from going out. Although in general we do not find people with higher education to be less affected, workers with junior high school education only and those working while attending school saw a larger reduction of earnings. People working at smaller firms or working less than 29 hours per week also experienced less earnings growth.

Another noticeable feature is that workers whose job level was downgraded in 2020 saw lower earnings growth than usual, especially for full-time workers. Table 4 shows that more people answered that their job level was downgraded in 2020 compared to the previous two years, possibly due to companies' efforts to maintain employment. In addition, fewer workers were promoted in 2020, which also limited earnings increases in 2020.

Table 4. Job Level Change (%)

	2018	2019	2020
Level up	21.9	23.9	20.3
Level down	8.4	8.2	11.8

In contrast with previous studies, after controlling for factors such as industry, there is no strong evidence that women, younger age groups, non-regular, self-employed, and low-income earners experienced larger earnings declines. The gender dummy variable is not significant across all sample categories. Age dummies only imply greater earnings declines for 65+ aged full-time workers, but no clear differences exist for other age groups. Similar earnings declines are found for regular, non-regular, and self-employed workers; only executives saw smaller earnings declines than others. Lastly, earnings growth was lower for all income levels, with larger reductions for high income earners.

Table 5. Characteristics of affected industries

		Gender	Status			Age		Working hour		Firm size	
	average of 2018 and 2019	female	regular	non-regular	self-employed	15-24	65-	male	female	1-29 persons	500 persons -
	Total	44%	52%	32%	10%	9%	13%	42.5	32.1	29%	33%
	Manufacturing	30%	67%	24%	4%	7%	9%	43.6	35.1	19%	38%
	Wholesale and retail	52%	43%	43%	7%	11%	12%	42.7	30.7	29%	40%
	Accommodations and restaurant	62%	21%	63%	13%	25%	15%	40.2	27.3	35%	33%
	Living-related, amusement, etc	60%	31%	43%	22%	12%	18%	41.3	31.8	37%	24%
Ranking	Manufacturing	13	5	11	11	10	12	3	4	12	7
Out of 18	Wholesale and retail	6	13	2	9	4	9	6	14	9	6
Industries	Accommodations and restaurant	2	17	1	5	1	6	13	18	6	8
	Living-related, amusement, etc	3	15	3	3	3	4	10	11	5	13

The table shows the ratio relative to total employed persons. Working hour is weekly average hours. The top (bottom) three industries of each feature are shaded as orange (blue).
Source: Ministry of Internal Affairs and Communications

[21] JPSED's categories for industry and occupation do not exactly much Japanese official classifications.

[22] Living related services include for example laundry, beauty salon, bathhouse, housekeeping, bridal, and funeral service.

Although the above results suggest gender, age, and regular vs non-regular status in themselves are not drivers of annual earnings changes, we know from the macro data that these groups are more affected. The reason is that they are overrepresented in hard-hit industries. The DML analysis suggests that earnings in four industries (manufacturing, wholesale and retail, accommodation and restaurants, and living-related services) are especially affected (hereafter, affected industries). Macro data shows that the three service industries tend to have a higher female employee ratio, a higher non-regular worker ratio, and a higher ratio of employees aged 15-24 (Table 5). The DML analysis also implies lower earnings growth for workers with short hours, and women's working hours in accommodation and restaurants are the lowest among 18 industries. The bottom line is that women, non-regular, and youth workers experienced larger earnings declines because they are overrepresented in affected industries.

Lastly, employees in jobs conducive to remote work tend to have higher earnings increases regardless of the pandemic[23], suggesting that teleworking is often associated with in-demand skills and professions (Table 3). In our sample, the ratio of people who indicate that they can telework was less than 5% in 2019, but it tripled in 2020 to 14.5%. This is a welcome change for the Japanese labor market, as the government had struggled to promote telework before the crisis.

4. 2. 2. Job Changes for Employees Continuously at Work Through 2020 (group 1-2)

The reallocation of labor between industries was limited during the pandemic. As shown in the macro data section (Figure 10), the total number of employees switching jobs decreased in the pandemic. Looking at industry transitions for job switchers reveals the expected result that workers tend to move less to industries affected by the pandemic in 2020, but it also shows that workers move less out of affected industries (Table 6 (1)).[24] However, more job changes happened between non-affected industries during the pandemic. Estimated average annual earnings changes after controlling for various factors (see note in table 6) show that job changes to non-affected industries were associated with higher earnings increases than job changes into affected industries (Table 6 (2)). While this is unsurprising for 2020, it was also the case before the pandemic, suggesting that industries most affected by the pandemic experienced lower earnings growth before COVID-19.

Table 6. Employees switching jobs

		(1) reallocation of labor (in percent)		(sample size)		(2) earnings changes (in percent)	
From	To	2019/18	2020	2019/18	2020	2019/18	2020
non-affected	non-affected	52.7%	57.2%	1295	1231	4.5	1.7
	affected	8.5%	7.5%	208	161	-3.5	-6.7
affected	non-affected	13.9%	14.0%	342	300	6.9	2.7
	affected	24.9%	21.3%	612	459	0.0	-2.6
		100%	100%	2458	2150		

Note: Based on the analysis of job stayers (group 1-1), the affected industries are manufacturing, wholesale and retail, accommodation and restaurants, and life-related service. The wage changes are estimates based on a simple linear regression controlling for gender, age, employment status, income level, and job level change.

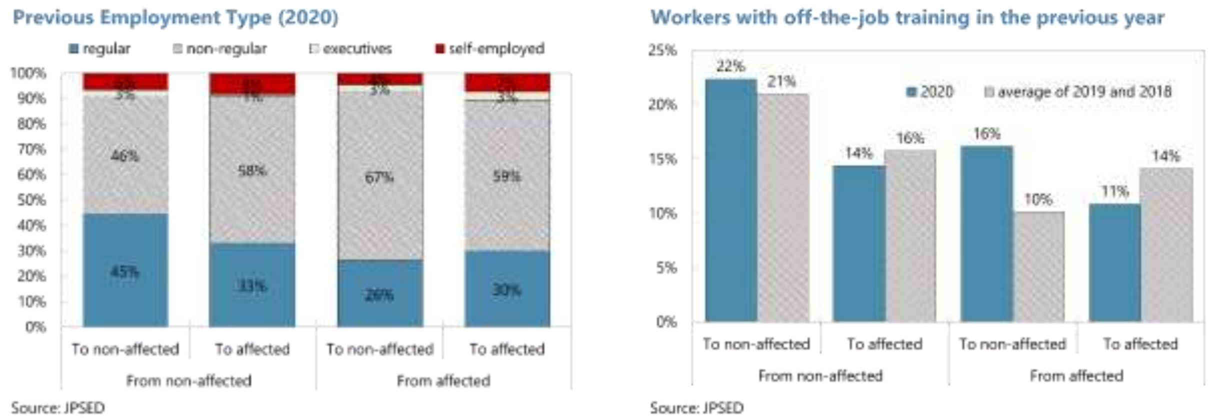
For job changes between non-affected industries regular and non-regular workers accounted for a similar percentage, while for job changes to/from affected industries non-regular workers accounted for close to twice as many cases as regular workers (Figure 14, left). Off-the-job training is also associated with job transition opportunities during the crisis (Figure 14, right). The percentage of workers who had off-

[23] Telework eligibility is associated with higher annual earnings in 2018, 2019, and 2020, and the magnitude does not change in 2020.

[24] The ratio of workers moving to the affected industries was 29% (33%) in 2020 (2018 and 2019 average), while the ratio of workers moving from the affected industries was 35% (39%) in 2020 (2018 and 2019 average).

the-job training in 2019 is higher for workers who switch between non-affected industries and from affected to non-affected industries.

Figure 14. Employees switching jobs



4. 3. Unemployed or Dropping out of the Workforce (group 2)

We analyze those experiencing unemployment or dropping out of the labor force for at least one month from February to December 2020 (group 2) in two steps. First, we identify the main factors causing workers to lose their jobs. Then we study the main traits of this group and identify factors that are associated with finding a new job.

We employ DML analysis again to identify the main attributes of workers who became unemployed or left the labor market in 2020. The regression settings are almost the same as in the previous section, with a few differences. The main change is that the setup is now with a binary dependent variable, which takes the value one if an observation is in group 2 (unemployed or NILF) and zero if it is in group 1-1 (job stayers). Since the outcome is binary, the regression can be run using a logit lasso instead of a linear regression. We limit the number of potential variables of interest (d_{i20}) for the analysis, based on the earnings analysis in the previous section.[25] Again, the lasso will choose the control variables from the list in Appendix 2.

With control variables, we obtain statistically significant results only for two industries and for workers working less than 20 hours per week (Table 7). We do not find strong evidence that women, young or old age groups, non-regular, self-employed, and low-income earners have a higher risk of unemployment or leaving the workforce during the pandemic after controlling for

Table 7. Selected result of DML analysis

		Odds ratio
Gender		–
Age (t-1)		–
Education (t-1)		–
Employment status (t-1)		–
Industry	manufacturing(t-1)*d20	1.3 **
	wholesale/retail(t-1)*d20	–
	accommodation/restaurants(t-1)*d20	1.6 **
	living-related service(t-1)*d20	–
Occupation (t-1)		–
Working hour	working hour (～19h) (t-1)*d20	1.3 *
	working hour (20～29h) (t-1)*d20	–
Firm size (t-1)		–
Annual earnings (t-1)		–
Telework	can telework (t-1)	–
	can telework (t-1)*d20	–
Self-development	work related self-learning (t-1)	0.9 **
	d20*work related self-learning (t-1)	–
	Number of obs	72,399

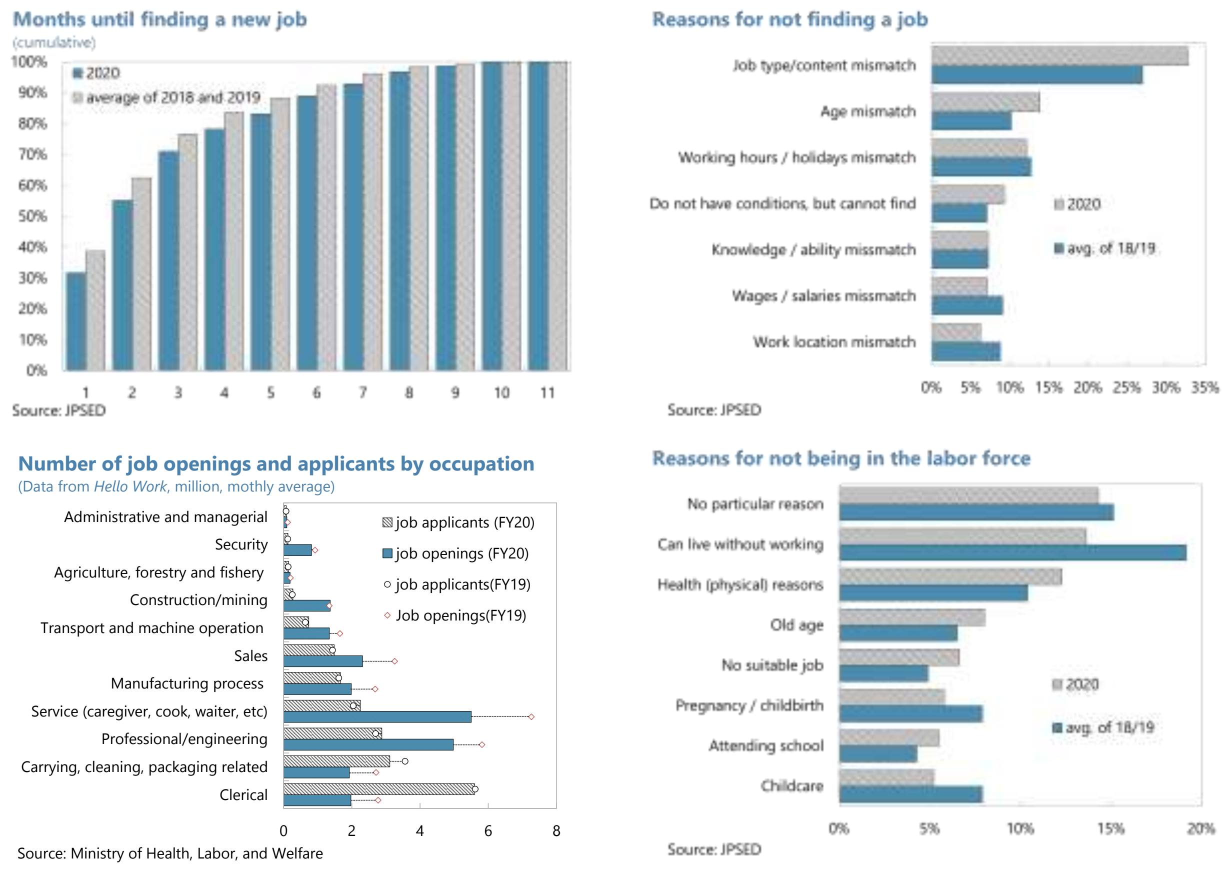
The dependent variable is one if a sample is in group 2 (unemployed or NILF) and zero in group 1-1 (job stayers). The table shows the DML analysis's selected results. The hyphen indicates the results are not significant at the 10% level. See Appendix 5 for the full results.** p<0.05, * p<0.1

[25] Another reason for this is the limited sample size of group 2 compared with group 1-1 (Group 1-1: 70,341 vs. Group 2: 3,863). Observations reaching mandatory retirement during year t are excluded from this analysis.

confounding factors such as industry. Among the affected industries, workers in manufacturing and accommodation and restaurants are at higher risk of losing their jobs in 2020. As discussed in the previous section, the accommodation and restaurants sector has a higher share of female, young, and irregular workers, and as a result these groups are harder hit in the pandemic. The important message from this analysis and the previous section on annual earnings is that labor market impacts of the pandemic are predominantly driven by industry effects.

For the ability to telework we do not find significant effects in this analysis. Telework is not associated with a lower risk of job loss in 2020 or previous years. Employees engaged in self-learning activities however have a lower risk of unemployment or dropping out of the labor force in general, although this effect is not stronger in 2020 compared to previous years.

Figure 15. Persons becoming unemployed or leaving the workforce

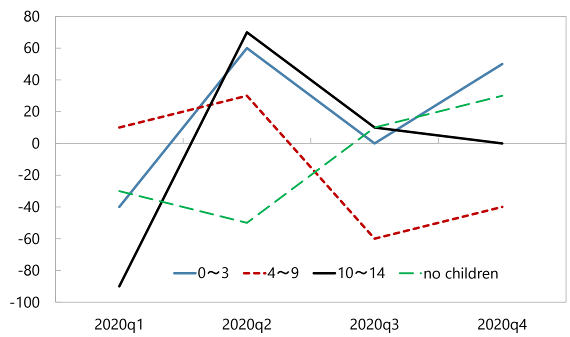


Turning to the time it takes to find a new job, about 50% in the sample are re-employed by year end in 2018, 2019, and 2020. However, it took slightly longer to find a new job in 2020 (Figure 15, upper left): on average, it took 3.0 months to find a new job in 2020, while it took 2.6 months in both 2018 and 2019. A major factor are of course fewer job openings during the pandemic, but skill mismatches also appear to play a role. The top reason for not finding a job are mismatches of job type or content (Figure 15, upper right). Skill (job-type/content) mismatches are mentioned as a hinderance more frequently in 2020 than in previous years. This is intuitive given that the pandemic hit industries to very different degrees. To put it simply, service workers in the restaurant industry may not have the right skillset to move to health care which saw greater labor demand in 2020.

Further evidence for labor market mismatches comes from job-to-applicants data from Hello Work (public employment service). The ratio of jobs-to-applicants decreased from 1.6 to 1.2 in 2020, meaning that there were still more job openings than job applicants during the pandemic in aggregate. However, job openings and applications continue to have large gaps for some occupations (Figure 15, lower left), notably for clerical (3.6 million higher applicants), service (3.2 million higher openings), and professional and engineering (2.1 million higher openings). In addition, although the job-to-applicants ratio stayed above one for the whole country, the ratio dipped below one in Tokyo in July 2020, indicating regional mismatches in labor supply and demand.

Figure 16. NILF female by the youngest child age

(females aged under 55 who have spouse, year-on-year, thousand persons)



Source: Ministry of Internal Affairs and Communications

The reasons for people leaving the labor force (NILF) changed in 2020 relative to previous years (Figure 15, lower right). The top reason for NILF was 'can live without working' in 2018 and 2019. In 2020, this reason remained important, but 'no particular reason' became the most common answer. Health, old age, no suitable job, and attending school also became more important reasons for dropping out of the labor force in 2020. Meanwhile, pregnancy/childbirth and childcare were mentioned less frequently in 2020. This likely reflects the date of the survey which is December. By then, schools had reopened after being closed during the first state of emergency.[26] In macro data we also see that women with young children drop out of the labor force disproportionally more in 2Q of 2020 but there is no clear difference to women without children in 3Q or 4Q of 2020 (Figure 16). In summary, it is likely that school closures in 2Q of 2020 forced women to leave the labor market during the first state of emergency. Women with young children returned to the labor force later in the year.

Table 8. Workers who reach the compulsory retirement age

	Find a job	Unemployed	NILF
2020	17%	11%	72%
avg. of 18/19	25%	7%	67%

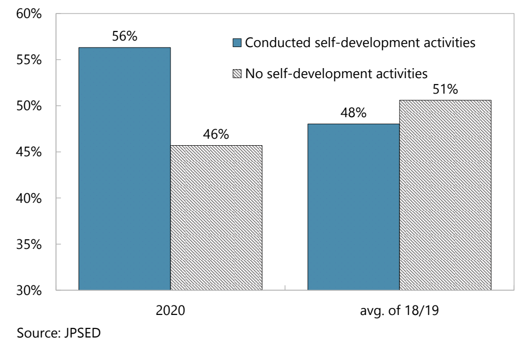
Among those who left their job due to reaching the mandatory retirement age,[27] fewer people were reemployed in 2020 than in previous years (Table 8). Only 17% found a job in the pandemic year, compared to 25% for the previous two years' average. Given the higher unemployed or NILF ratio in 2020, more retired people seem to have been discouraged from working or having difficulties finding a job again. A logistic regression analysis also shows that retired people have a significantly higher probability of being unemployed or NILF in 2020 even after controlling for other factors (Appendix 6).

[26] Our regression results also indicates that having an infant significantly decreases the probability of being re-employed (by December), but we did not observe any significant increase in this probability in 2020 relative to previous years. See appendix 6 for the statistical table.

[27] According MHLW, about 74% of firms set the mandatory retirement age at 60 in 2017. However, those firms have reemployment systems, which allow retired employees to continue working if they wish, often with lower wages. We focus here on people who left their job due to reaching mandatory retirement (i.e. they did not take advantage of reemployment opportunities).

Lastly, people engaged in self-development activities (e.g., self-study and upskilling) had a higher chance finding a job during the pandemic (Figure 17). In 2018 and 2019, self-development activities in the previous year appear to have little association with finding a new job. However, in 2019 the share of people finding a new job and engaging in self-development activities was 10 percentage points higher than those not engaging in such activities. Logistic regression analysis confirms this result (Appendix 6). This underscores the importance of vocational training and upskilling for people to stay in or come back to the labor market, especially during crisis episodes.

Figure 17. Ratio of people finding a new job



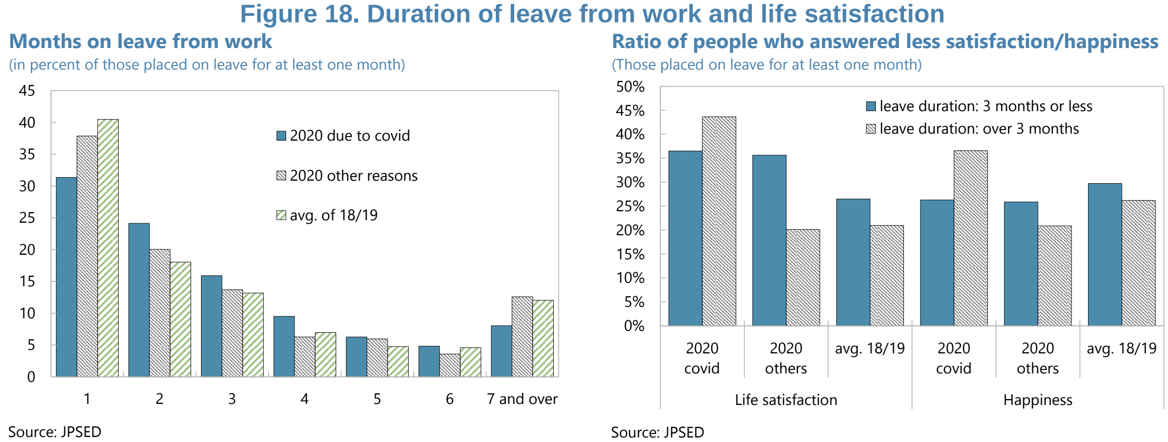
Source: JPSED

4. 4. Employees Placed on Temporary Leave in 2020 (group 3)

The EAS program, outlined in section 2, provides employers with a subsidy when they place employees on temporary leave while maintaining employment. As shown in section 3, the EAS program was instrumental in protecting employment during the pandemic. The number of employed persons not at work spiked in 2Q of 2020, but it declined to a slightly higher than normal level after 3Q of 2020.[28] In this section, we provide additional insights into being placed temporarily on leave and examine the key determinants relative to those employed and not being placed on leave (group 1-1).

On average, workers were temporarily on leave for 2.9 months due to the pandemic in 2020, conditional on being placed on leave for at least 1 month (Figure 18, left).[29] Although the duration of leave is similar to previous years (the average is 3.0 months in both 2018 and 2019), there are differences in the distribution of leave length. During the pandemic, more employees were placed on leave for between 2-4 months, while fewer were on 1 month or 7 month plus leave.

Figure 18. Duration of leave from work and life satisfaction



[28] As discussed in section 3, based on disbursements use of the EAS scheme continues to be substantial, but usage appears to have shifted to shorter leave periods which do not register as 'Employed not at work'.

[29] The data does not capture leave of less than a month. If this data would be available, the average leave duration in 2020 would be higher.

Forced leave during the pandemic could be associated with dissatisfaction or less happiness which may impact motivation or productivity in the future. There is no difference for the percentage of workers who answered less life satisfaction or happiness in 2020 between those on leave because of COVID-19 related reasons and others if the leave duration is three months or less (Figure 18, right). However, for those on leave longer than three months there is more dissatisfaction among those on leave due to COVID-19. This suggest that long pandemic-related leave jeopardizes motivation and potentially mental health.

For those placed on leave, EAS seems to have cushioned earnings reductions to some extent in 2020. Although the average reduction rate of annual earnings is larger in 2020, the earnings changes for pandemic leave workers are less than for those on leave for other reasons (Table 9).

Table 9.Average annual earnings changes (%)

2020		2019	2018
due to COVID	other reasons		
-7.5	-11.8	-4.4	-4.0

To identify key attributes of workers on leave, we employ DML with logistic lasso regressions similar to the analysis for group 2 (unemployed or NILF). The binary dependent variable takes the value one if an observation is in group 3 (employed but on leave) and zero if it is in group 1-1 (job stayers). Control variables are listed in Appendix 2.

Controlling for various factors, the results suggest that non-regular, self-employed, restaurant and accommodation workers, and jobs in production had a higher tendency to be on leave during 2020 (Table 10). It appears that companies arranged leave more frequently for non-regular employees than for regular ones. This may have cushioned the employment impact of the pandemic on non-regular worker, likely a reason for not finding significant effects for non-regular workers in the analysis of people losing their jobs (group 2). The dummy for accommodation and restaurants is significant in all cases, underscoring the considerable adverse pandemic impact on this industry. The higher odds ratio of production workers is consistent with the substantial industrial production decline during 2Q 2020. Age, education, gender, and income do not appear to have affected the probability of being placed on leave after controlling for industry and regular vs non-regular work arrangement.

Table 10. Selected result of DML analysis

		Odds ratio
Gender		–
Age (t-1)		+
Education (t-1)		+
Status	regular worker (t-1)*d20	–
	non-regular worker (t-1)*d20	2.1 *
	self-employed (t-1)*d20	1.9 *
Industry	manufacturing (t-1)*d20	–
	wholesale/retail (t-1)*d20	–
	accommodation/restaurants (t-1)*d20	2.7 ***
	living-related service (t-1)*d20	–
Occupation	security job(t-1) *d20	–
	transportation/communications job(t-1)*d20	–
	production job(t-1)*d20	2.7 ***
	professional job(t-1)*d20	–
Working hour (t-1)		–
Firm size (t-1)		–
Annual earnings (t-1)		–
Telework	can telework (t)	–
	can telework (t)*d20	0.7 *
	Number of obs	71,053

The dependent variable is one if a sample is in group 3 (employed but on leave) and zero in group 1-1 (job stayers). The table show s the DML analysis's selected results. The hyphen indicates the results are not significant at the 10% level. The plus indicates all items are significant. See Appendix 7 for the full detailed results.
*** p<0.001, ** p<0.05, * p<0.1

Employees who were able to telework had a significantly lower probability of being placed on leave in 2020. During normal times, there is no relationship between ability to telework and being on leave, but in the pandemic year, telework was of critical importance to continue working.

5. Conclusion and Policy Implications

The COVID-19 pandemic had a severe impact on the Japanese labor market. Employment remained substantially below the pre-pandemic level as of late 2021, and average earnings declined in 2020 due to reduced overtime and bonus payments. Strong government support cushioned the hit to labor markets, most importantly the EAS furlough scheme which provides subsidies to firms if they maintain employment. As a result, the increase in unemployment was limited although it remained above pre-pandemic levels as of end 2021. At the same time, job mobility decreased during the pandemic including from the most affected industries, reflecting fewer job openings but also skill mismatches and the emphasis of policy support on maintaining employment. Labor force participation dropped, especially for older people and women, groups that had been driving the upward trend in the participation rate prior to the pandemic.

A defining feature of the pandemic shock to labor markets is that the impact across industries varied widely. Contact-intensive services (e.g., restaurants) and manufacturing were hardest hit both in terms of employment and earnings. Meanwhile, other industries including medical, financial and IT services fared relatively well and even added employment. The pandemic impact also varied across different groups of employees. Our analysis complements earlier studies by disentangling the drivers of different labor market outcomes for different groups and uncovering important nuances relevant to policy makers. Most importantly, we show that industry effects are a crucial driver of different employment and earnings outcomes across groups in 2020. While women, younger age groups, non-regular, self-employed, and low-income workers experienced greater declines in earnings and had a higher risk of losing employment, this is primarily driven by their greater relative representation in the most affected industries, especially in the contact-intensive services sectors. In addition to industry effects, we find that for employment outcomes part-time workers were disproportionally affected — women, young, and low-income workers account for a large share of part-timers. For earnings outcomes we find that small firms, low education, working while studying and part-time work are associated with worse outcomes and again these groupings tend to have higher than average employment shares among women, young, and low-income workers.

Our results imply several lessons for policy design. First, short-term support measures should be well targeted to the most affected industries and occupations, small firms, and part-time workers. Second, women, young, and non-regular workers were hard hit during the pandemic because they are overrepresented in vulnerable industries and occupations that typically offer less stable working conditions and fewer training and growth opportunities. This points to structural inequities and impediments for female, young, and non-regular workers that should be addressed irrespective of the pandemic.[30] In addition, our analysis of high frequency labor market developments shows that women with children dropped out of the workforce disproportionally during the school closures of the first state of emergency. This underscores the need to continue to improve childcare offerings and support as well as employer flexibility. Third, the emphasis on policy support to maintain employment as opposed to a greater reliance on direct support for

[30] Empirical analyses by Hara (2016) and Yamaguchi (2016) indicate that gender gaps in wages and share of managers are only partially explained by differences in human capital, suggesting discriminatory practices. Aoyagi and Ganelli (2015) report that labor market duality (regular and non-regular) in Japan reduces TFP through firms' disincentive to train non-regular workers. Recommendations in IMF (2018) include labor market reforms to provide a productivity boost for disadvantaged workers (i.e., non-regular and female) via training and education, enhancing product market competition and firm dynamism, the elimination of disincentives to full-time and regular work from the tax and social security system, and better availability of childcare and nursing facilities.

the unemployed has been successful in maintaining employment and potentially helped limit scaring. However, the continued high usage rates of EAS support suggest that some workers' skills and abilities have been underutilized for extended periods. Long periods of forced leave could cause skills to atrophy and surveys suggests that they reduce motivation and happiness. Therefore, over time a recalibration of support seems warranted to encourage the reallocation of labor from unviable firms to new growth sectors. Active labor market policies and strong unemployment and transition support could be helpful in protecting the vulnerable while enabling more frequent job transitions. In this context, strengthening the EI scheme by expanding its eligibility could also be considered. Relatedly, Morikawa (2021b) and Hoshi et al. (2021) indicate that firms with lower productivity or low credit scores before the pandemic are more likely to receive support measures, which also underscores the need for resource reallocation. Fourth, our results show that skill mismatches have hindered labor reallocation, while employee training and education is associated with better labor outcomes in general and during the pandemic. Policies and programs to support skill updating and training are therefore essential. The inclusion of training into eligible activities for EAS support during the pandemic is a welcome step to upgrade and maintain skills. Fifth, telework has played an important role in keeping people at work and mitigating earnings declines, and the government should continue to promote flexible work styles and to address obstacles to telework such as the use of physical seals and paper documents. Evidence for a shift in preferences toward teleworkable jobs among job seekers also underscore the importance of facilitating telework or remote work access (Duval et al., 2022). The government's ongoing digitalization efforts should contribute to greater feasibility of telework.

Appendices

Appendix 1: Descriptive statistics of JPSED

		group1		group2		group3	
		avg. 18/19	2020	avg. 18/19	2020	avg. 18/19	2020
gender	male	58.6%	58.9%	41.2%	41.7%	35.5%	33.0%
	female	41.4%	41.1%	58.8%	58.3%	64.5%	67.0%
age (t)	15～24	4.8%	4.6%	11.0%	11.5%	10.6%	11.1%
	25～34	15.5%	14.9%	19.3%	16.1%	26.4%	19.8%
	35～44	23.2%	23.1%	16.7%	14.2%	21.3%	18.3%
	45～54	25.4%	25.9%	16.4%	17.4%	15.0%	18.4%
	55～64	19.1%	19.0%	17.3%	16.7%	14.1%	15.5%
	65～	12.1%	12.5%	19.3%	24.1%	12.8%	16.8%
status (t-1)	regular	53.3%	55.0%	28.8%	24.7%	40.5%	25.3%
(as Dec)	non-regular	31.0%	30.4%	62.4%	62.1%	44.5%	55.4%
	executives	5.1%	4.8%	2.7%	2.9%	2.9%	2.5%
	self-employed	10.6%	9.8%	6.1%	10.3%	12.1%	16.8%
education(t)	junior high school	2.4%	2.5%	2.5%	2.9%	3.6%	2.9%
	high school	37.7%	37.0%	38.3%	37.4%	33.2%	33.7%
	junior college etc	28.5%	28.4%	28.6%	28.9%	30.6%	32.3%
	university	29.6%	30.4%	25.8%	24.6%	26.9%	24.3%
	at school	1.8%	1.8%	4.8%	6.1%	5.7%	6.9%
firm size (t-1)	-9	21.1%	19.7%	15.9%	19.3%	18.3%	24.1%
	10～99	29.2%	29.4%	35.9%	34.1%	33.0%	32.8%
	100-999	23.6%	24.0%	24.9%	23.8%	25.0%	23.3%
	1000-	19.6%	20.1%	17.4%	17.3%	18.3%	16.1%
	public	6.5%	6.8%	6.0%	5.5%	5.4%	3.7%
working hour	-19h	11.7%	11.7%	22.4%	26.9%	21.2%	28.2%
(t-1)	20-29h	9.4%	9.1%	16.9%	17.7%	14.0%	18.4%
	30-40	16.2%	16.2%	19.5%	17.9%	19.8%	18.4%
	40-50	44.9%	46.3%	32.4%	29.9%	34.9%	27.8%
	50-	17.8%	16.6%	8.8%	7.6%	10.0%	7.3%
annual earnings	-2M yen	28.9%	27.5%	53.8%	56.6%	44.6%	55.1%
(t-1)	2-3M yen	15.5%	15.1%	20.3%	18.8%	17.8%	16.0%
	3-4M yen	16.1%	16.1%	11.9%	10.4%	15.8%	12.4%
	4-5M yen	12.7%	13.1%	6.3%	5.3%	9.1%	8.2%
	5-6M yen	9.1%	9.8%	2.8%	2.4%	5.3%	3.5%
	6-8M yen	10.8%	11.2%	2.9%	3.6%	5.1%	3.0%
	8M- yen	6.9%	7.2%	2.0%	2.8%	2.2%	1.8%
LN(earnings(t)/earnings(t-1)), average		6.4%	4.0%	-25.0%	-30.9%	-4.2%	-9.6%
Industry (t-1)	agriculture etc	1.0%	1.0%	0.7%	0.9%	1.2%	0.4%
	construction	5.8%	5.6%	3.2%	2.5%	3.9%	3.1%
	manufacturing	16.9%	17.2%	12.1%	14.2%	11.5%	10.1%
	utility	1.4%	1.4%	1.1%	0.7%	1.1%	0.3%
	information and communication	5.8%	5.9%	4.3%	4.0%	4.7%	2.8%
	transportation/postal	6.3%	6.4%	5.0%	5.9%	6.2%	4.7%
	wholesale/retail	12.0%	11.8%	14.6%	12.3%	13.2%	12.6%
	finance/insurance	3.5%	3.6%	4.0%	2.8%	1.9%	2.1%
	real estate	2.6%	2.6%	2.2%	1.9%	1.4%	1.2%
	restaurants/accommodation	4.6%	4.0%	7.5%	9.3%	7.0%	16.0%
	medical/welfare	10.3%	10.9%	11.8%	10.7%	14.3%	8.2%
	education/learning support	4.2%	4.3%	5.5%	5.0%	7.7%	8.6%
	living-related service	2.6%	2.6%	2.5%	2.3%	4.0%	4.9%
	professional service	2.6%	2.5%	1.9%	3.6%	1.9%	3.0%
	other service	6.0%	6.1%	5.8%	5.3%	4.9%	5.4%
	public	5.8%	6.1%	5.2%	4.8%	4.3%	2.8%
	other industries	8.5%	8.2%	12.7%	13.9%	10.7%	13.8%
sample size		25,650	26,048	1,259	1,604	659	1,320

Classification: Group 1: Employed at work, Group 2: Unemployed or Not in the Labor Force, Group 3: Employed not at work

Appendix 2: Variables used for the DML

Gender(t-1)	female
Having infant (t)	have infant
Age(t-1)	age, ～24
	age, 25～29
	age, 30～34
	age, 35～39
	age, 40～44
	age, 45～49
	age, 50～54
	age, 55～59
	age, 60～64
	age, 65-
Education (t-1)	edu, junior high school
	edu, high school
	edu, junior college etc
	edu, university
	edu, at school
Living area (t)	area, Hokkaido
	area, Tohoku
	area, S.Kanto
	area, N.Kanto
	area, Hokuriku
	area, Tohoku
	area, Kinki
	area, Chugoku
	area, Shikoku
	area, Kyushu
living expenses (t-1)	living expenses, myself
	living expenses, myself & spouse
	living expenses, saving
	living expenses, parents & child
	living expenses, public assitance
Breadwinner,(t-1)	breadwinner, myself
	breadwinner, parents
	breadwinner, spouse
	breadwinner, others
Income source (t-1)	other faimily member
Employment status(t-1)	status,regular worker
	status,non-regular worker
	status,executives
	status,self-employed
	status,unemployed
	status,NLF
Firm size (t-1)	firm size, -9
	firm size, 10～99
	firm size, 100-999
	firm size, 1000-
	firm size, public
Job Title (t-1)	title, board member
	title, director /manager
	title, chief
	no title
Working hour per week (t-1)	working hour, -19h
	working hour, 20-29h
	working hour, 30-40
	working hour, 40-50
	working hour, 50-60
	working hour, 60-
Occupation (t-1)	job, service
	job, security
	job, agriculture related
	job, transportation/communications
	job, production
	job, management
	job, clerk
	job, sales
	job, professional job
	job, other occupation
Job level change (t)	job level up
	job level down
	job same level

Industry(t-1)	ind, agriculture etc
	ind, construction
	ind, manufacturing
	ind, utility
	ind, information and communication
	ind, transportation/postal
	ind, wholesale/retail
	ind, finance/insurance
	ind, real estate
	ind, restaurants/accommodation
	ind, medical/welfare
	ind, education/learning support
	ind, living-related service
	ind, professional service
	ind, other service
	ind, public
	ind, other industries
Can choose work place or time (t-1)	flexible
	rather flexible
	somewhat flexible
	less flexible
	not flexible
Did telework(t)	at least 1 hour per week
Can telework(t)	applied to myself
Responsible for various tasks (t-1)	task, various
	task, rather various
	task, somewhat various
	task, less various
	task, no various
Have discretionary at work (t-1)	task, discretionary
	task, rather discretionary
	task, somewhat discretionary
	task, less discretionary
	task, no discretionary
Have OJT (t-1)	OJT-educational program
	OJT-guidance
	OJT-observe others
	OJT-read manual
	no OJT
Have Off-JT (t-1)	no chance for Off-JT
	did not take Off-JT
	Off-JT, - 5H
	Off-JT, 5-9H
	Off-JT, 10-19H
	Off-JT, 20-49H
	Off-JT, 50H-
Self-development (t-1)	work related self-learning
Learning activity (t-1)	took online/distance course, etc
annual earnings (t-1)	earnings, less than 1M yen
	earnings, 1-2M yen
	earnings, 2-3M yen
	earnings, 3-4M yen
	earnings, 4-5M yen
	earnings, 5-6M yen
	earnings, 6-8M yen
	earnings, over 8M yen
% of paid leave took (t-1)	paid leave, 100%
	paid leave, 75%
	paid leave, 50%
	paid leave, 25%
	paid leave, few %
	no paid leave
Employment status of spouse (t-1)	no spouse
	spouse,regular worker
	spouse,non-regular worker
	spouse,executives
	spouse,self-employed
	spouse,not working
Doing side business(t)	have side business

Appendix 3: DML with a linear Lasso

The rough idea of DML here can be described as follows. For the simple linear regression, we can run the following regression:

$$\Delta y_{it} = \alpha_0 + X_{it}(\beta_1 + \theta D_{20}) + \ D_t\beta_2 + D_i\beta_3 + \varepsilon_{it}$$

where X_{it} are feature variables as listed in Appendix 2[31], D_{20} is a year dummy of 2020, D_t are year dummies, and D_i are dummies of samples' answered years[32]. θ are our interested coefficients, and if they are significantly different from zero, it indicates some features affected differently in the pandemic year compared with the previous two years.

The challenge to adopting the above traditional approach is that researchers must decide which covariates to include. However, we could pick up the wrong controls or omit variables, especially for analyzing an unprecedented case like the pandemic or regressing with too many potential control variables to consider, leading to a biased estimator of θ. DML can be helpful to address this issue, as the machine can perform variable selection based on the data patterns. Instead of running the above regression, DML runs the following regression, which is regressing residuals on residuals.

$$\left(\Delta y_{it} - \widetilde{Z_y}\hat{\beta}\right) = \theta\left(d_{i20} - \widetilde{Z_d}\hat{\gamma}\right)$$

where d_{i20} are our variables of interest (feature variables multiplied by D_{20}), $\widetilde{Z_y}$ and $\widetilde{Z_d}$ are set of control variables for Δy_{it} and d_{i20}, respectively, and they are automatically selected by the machine learning (in our case, Lasso). In each DML exercise, we only used one category of the Appendix 2 list (e.g., gender, age, status, industry, and occupation) for d_{i20}, and we conducted multiple DML regressions by changing d_{i20}. Both $\widetilde{Z_y}$ and $\widetilde{Z_d}$ are Another important trick for DML is that selecting the control variables and calculating the residuals must be conducted using a different subsample to avoid overfitting. With all these techniques, it was proved that θ are the unbiased estimator.

The following is the algorithm of DML with a linear lasso model, where y is a dependent variable, Z are control variables, and d are variables of interest.

- Step 1: Divide the data randomly into K subsamples called folds (K=10 in our case)
- Step 2: For k=1…K
  - 2-1: Using observations not in fold k, run Lasso for y on Z to select a subset $\tilde{Z}_{yk} \in Z$ that best predicts y
  - 2-2: Run OLS for y on the selected $\tilde{Z}_{yk}$, and estimate their coefficients $\hat{\beta}_{yk}$
  - 2-3: Using observations in fold k, calculate the residuals $\tilde{y} = y - \tilde{Z}_{yk}\hat{\beta}_{yk}$
- Step 3: For k=1…K
  - 3-1: Using observations not in fold k, run Lasso for d on Z to select a subset $\tilde{Z}_{dk} \in Z$ that best predicts d
  - 3-2: Run OLS for d on the selected $\tilde{Z}_{dk}$, and estimate their coefficients $\hat{\beta}_{dk}$
  - 3-3: Using observations in fold k, calculate the residuals $\tilde{d} = d - \tilde{Z}_{dk}\hat{\beta}_{dk}$
- Step 4: Regress residuals on residuals: run OLS for $\tilde{y}$ on $\tilde{d}$

[31] All feature variables are converted to binary.

[32] The dummies are to capture any biases coming from the number of times answered and which surveys answered. They have six categories: a sample appears on 1)2020/2019 only, 2)2019/2018 only, 3) 2018/2017 only, 4) 2020/2019 and 2019/2018, 5) 2019/2018 and 2018/2017, and 6) 2020/2019, 2019/2018, and 2018/2017.

The linear Lasso above solves the following problem,

$$\hat{\beta} = arg \min_b \frac{1}{n}\sum_{i=1}^{n}\left(y_i - \sum_{j=1}^{p} z_{i,j} b_j\right)^2 + \frac{\lambda}{n}\sum_{j=1}^{p}\left|b_j\right|\kappa_j$$

where n is the number of observations, p is the number of covariates, λ (>0) is the lasso penalty parameter, and κ_j is the penalty loadings (coefficient-level weights). When $\lambda = 0$, the result is identical to OLS. When λ is large enough, all coefficient estimates are zero. When λ takes a value between these two extremes, some of the estimated coefficients are exactly equal to zero (and some are not zero). Hence, Lasso can perform variable selection, as the covariates with coefficients of zero are excluded from the model. The penalty loadings are chosen to accommodate regressors with uneven variance and can also be selected to address heteroskedasticity.

Both λ and κ_j are called tuning parameters and must be selected before performing variable selection. We adopted "rigorous" approach for choosing these parameters, where the term "rigorous" indicates that the framework is theoretically grounded. Belloni et al. (2012) showed the optimal values for λ^* and estimators for κ_j under heteroskedasticity as follows,

$$\lambda^* = 2c\sqrt{n}\Phi^{-1}\left(1 - \frac{\gamma}{2p}\right)$$

$$\kappa_j = \sqrt{\frac{1}{n}\sum\nolimits_i z_{ij}^2 \epsilon_i^2}$$

where c is a constant slack parameter (set at 1.1), Φ^{-1} is the inverse of the cumulative standard normal distribution, and γ is the probability level of not removing a variable when it has a coefficient of zero (set at 0.1/ln(n)). The unobserved disturbances ϵ_i are estimated using the iterative algorithm adopted from Belloni et al. (2014).

Appendix 4: DML result of the Earnings Analysis of Job stayers (Group 1-1)

		All sample			Full time worker			Part time worker		
		Coefficient	std.err.	controls	Coefficient	std.err.	controls	Coefficient	std.err.	controls
d20*female(t)		-0.58	0.38	46	-0.10	0.39	60	-1.54	1.07	30
d20*age(t-1)	～24	-0.16	1.29	34	-3.57	1.43 **	35	-2.09	3.13	15
	25～29	0.07	1.11	37	-3.72	1.19 ***	28	0.78	2.52	13
	30～34	0.34	1.04	31	-3.42	1.12 ***	29	0.06	2.30	12
	35～39	-0.54	1.04	16	-4.54	1.13 ***	16	0.57	2.33	9
	40～44	-0.09	1.04	15	-4.21	1.12 ***	11	1.44	2.21	8
	45～49	-0.18	1.03	21	-4.08	1.10 ***	20	-0.16	2.24	10
	50～54	-0.13	1.04	23	-4.22	1.11 ***	21	0.88	2.25	12
	55～59	-0.14	1.04	26	-4.23	1.11 ***	25	0.78	2.27	10
	60～64	-0.48	1.14	27	-3.55	1.23 ***	26	-1.23	2.41	17
	65～	-0.42	1.15	34	-6.14	1.31 ***	27	2.99	2.38	29
d20*education (t-1)	junior high school	-3.52	1.54 **	20	-1.62	1.43 ***	19	-11.21	3.93 ***	18
	high school	-1.30	1.25	29	-0.88	1.50 ***	28	-3.02	3.20	14
	junior college etc	-1.50	1.25	17	-1.11	1.69 ***	20	-3.30	3.20	13
	university	-1.44	1.25	34	-2.11	1.61 ***	32	-2.13	3.19	14
	at school	-3.54	1.87 *	17	-5.18	1.97 ***	10	-7.09	3.81 *	13
d20*living area (t)	Hokkaido	-8.56	1.61 ***	13	-4.89	1.61 ***	12	-2.73	5.43	5
	Tohoku	-7.72	1.60 ***	11	-3.84	1.59 **	10	-3.55	5.38	6
	S.Kanto	-7.80	1.56 ***	15	-4.31	1.55 ***	15	-1.94	5.27	9
	N.Kanto	-7.02	1.59 ***	8	-3.93	1.59 **	8	-0.22	5.30	6
	Hokuriku	-7.65	1.63 ***	10	-4.02	1.63 **	8	-2.48	5.39	4
	Tohoku	-8.41	1.58 ***	6	-5.16	1.57 ***	5	-1.83	5.29	5
	Kinki	-7.90	1.58 ***	6	-4.26	1.57 ***	5	-2.93	5.33	4
	Chugoku	-8.59	1.61 ***	8	-4.63	1.61 ***	8	-4.95	5.45	6
	Shikoku	-7.76	1.69 ***	10	-3.56	1.70 **	7	-5.59	5.50	5
	Kyushu	-7.27	1.58 ***	8	-3.61	1.57 **	7	-2.44	5.31	4
d20*employment status(t-1)	regular worker	-3.02	1.31 **	32	-1.62	1.43	24	3.74	3.43	35
	non-regular worker	-2.58	1.36 *	46	-0.88	1.50	30	3.31	3.39	38
	executives	-2.28	1.65	18	-1.11	1.69	17	2.30	3.93	7
	self-employed	-2.78	1.46 *	35	-2.11	1.61	32	5.05	3.36	21
d20*iIndustry(t-1)	agriculture etc	-0.74	2.22	30	0.17	2.22	30	2.33	4.33	5
	construction	-1.04	1.06	34	-0.45	1.08	31	-1.26	2.59	10
	manufacturing	-2.35	1.00 **	34	-1.51	1.02	30	-3.72	2.23 *	13
	utility	-0.91	1.28	25	0.28	1.32	25	-2.96	3.24	10
	information and communication	-0.98	1.06	33	-0.38	1.07	32	-0.65	2.66	12
	transportation/postal	-0.49	1.14	27	-0.36	1.15	23	-0.03	2.32	15
	wholesale/retail	-2.15	1.01 **	31	-1.26	1.04	34	-2.54	2.01	14
	finance/insurance	-1.76	1.10	37	-0.94	1.12	35	-3.34	2.54	15
	real estate	-1.08	1.30	29	-2.51	1.30 *	29	5.53	2.86 *	12
	accommodation/restaurants	-3.94	1.30 ***	30	-2.34	1.40 *	22	-6.00	2.49 **	13
	medical/welfare	-0.68	1.05	39	0.01	1.07	36	-0.68	2.18	18
	education/learning support	0.18	1.16	34	0.80	1.18	31	0.15	2.44	14
	living-related service	-3.27	1.48 **	28	-2.98	1.54 *	28	-1.94	3.24	11
	professional service	-1.50	1.34	29	-1.16	1.37	30	-0.19	3.24	14
	other service	-1.08	1.10	24	-0.07	1.11	22	-2.49	2.37	18
	public	-2.00	1.59	37	-0.92	1.68	36	-2.94	3.00	19
	other industries	-1.32	1.16	33	-0.72	1.23	25	-1.54	2.23	9
Number of obs				63,305			50,643			12,662
Number of folds in cross-fit			10			10			10	
Number of controls			285 - 302			285 - 302			285 - 302	

Dependent variable is annual earnings change (in percent). The controls column reports the median number of control variables selected by Lasso among 10 folds. *** p<0.001, ** p<0.05, * p<0.1***.

		All sample			Full time worker			part time worker		
		Coefficient	std.err.	controls	Coefficient	std.err.	controls	Coefficient	std.err.	controls
d20*occupation (t-1)	service	-0.84	0.93	37	-0.78	0.95	27	2.86	2.26	16
	security	-3.11	1.06 ***	32	-2.65	1.08 **	34	-2.16	3.71	23
	agriculture related	-1.36	2.35	16	1.27	2.50	18	-5.32	5.13	17
	transportation/communications	-4.46	1.09 ***	32	-4.06	1.11 ***	28	-3.57	2.94	13
	production	-1.82	0.85 **	43	-2.03	0.88 **	37	2.46	2.21	20
	management	-1.42	0.94	18	-1.33	0.94	16	1.29	3.11	8
	clerk	-1.21	0.80	32	-1.40	0.80 *	23	2.59	2.06	21
	sales	-0.24	0.91	29	-0.20	0.92	28	3.84	3.03	13
	professional job	-1.60	0.80 **	41	-1.69	0.80 **	40	0.25	2.20	28
	other occupation	-1.32	0.92	23	-2.01	0.96 **	17	3.05	2.23	10
d20*working hour per week (t-1)	～19h	-2.99	1.75 *	19				-14.33	4.15 ***	10
	20～29h	-4.07	1.77 **	24				-15.02	4.22 ***	7
	30～40h	-2.28	1.65	23	-6.19	1.60 ***	19	-13.72	4.19 ***	7
	40～50h	-2.41	1.62	16	-6.23	1.56 ***	8			
	50～60h	-2.21	1.65	23	-6.26	1.57 ***	15			
	60h～	-2.31	1.66	23	-6.45	1.59 ***	17			
d20*firm size (t-1)	～9 persons	-3.49	1.35 ***	28	0.55	1.36	28	-9.35	3.28 ***	22
	10～99	-2.29	1.32 *	21	1.68	1.31	21	-8.39	3.23 ***	17
	100～999	-1.88	1.33	15	2.05	1.30	15	-7.02	3.21 **	12
	1000～	-1.49	1.34	34	2.45	1.32 *	34	-7.55	3.17 **	19
	public	-0.07	1.52	24	3.10	1.76 *	24	-0.49	4.09	25
d20*responsible for various tasks (t-1)	various	0.62	1.31	22	1.21	1.26	19	-2.98	3.56	8
	rather various	0.18	1.27	20	0.35	1.22	18	-1.07	3.28	12
	somewhat various	0.20	1.27	12	0.40	1.22	12	-1.03	3.30	7
	less various	-0.18	1.28	12	0.23	1.23	11	-2.04	3.33	9
	no various	0.46	1.31	21	0.96	1.27	17	-1.47	3.33	12
d20*job level change (t)	job level up	-3.18	1.70 *	24	-2.71	1.69	24	-7.31	4.68	11
	job level down	-4.30	1.73 **	7	-3.96	1.73 **	7	-7.60	4.82	6
	job same level	-2.92	1.68 *	12	-2.70	1.67	10	-6.12	4.62	11
d20* annual earnings (t-1)	less than 1M yen	-4.66	1.39 ***	40	2.27	2.43	19	-2.65	2.58	9
	1-2M yen	-4.78	1.25 ***	26	-0.48	1.29	35	-2.59	2.55	5
	2-3M yen	-6.15	1.17 ***	28	-0.89	1.13	28	-3.82	2.53	2
	3-4M yen	-7.21	1.15 ***	28	-1.88	1.09 *	22	-6.58	2.57 ***	4
	4-5M yen	-7.19	1.15 ***	17	-1.75	1.07	15	-4.51	2.65 *	5
	5-6M yen	-7.91	1.16 ***	24	-2.43	1.08 **	20	-7.36	2.72 ***	5
	6-8M yen	-8.46	1.17 ***	33	-2.85	1.10 ***	30	-7.40	2.75 ***	9
	over 8M yen	-8.81	1.22 ***	40	-3.02	1.17 ***	52	-7.76	3.18 **	6
d20*employment status of spouse (t-1)	regular worker	-0.22	0.42	20	-0.09	0.43	21	-0.61	1.37	24
	non-regular worker	0.11	0.42	23	0.16	0.43	20	0.74	1.35	12
	executives	-3.00	1.17 ***	18	-1.60	1.35	16	-4.11	2.45 *	10
	self-employed	0.31	0.85	16	0.23	0.95	16	0.64	1.85	11
	not working	-0.27	0.42	25	0.08	0.42	26	-1.26	1.41	16
can telework (t)		0.82	0.29 ***	69	1.05	0.29 ***	64	0.18	1.33	34
d20*can telework (t)		0.00	0.43	45	-0.48	0.44	40	1.12	1.71	28
work related self-learning (t-1)		0.00	0.17	42	0.04	0.18	37	0.07	0.51	30
d20*work related self-learning (t-1)		0.36	0.29	33	0.21	0.29	32	1.11	0.86	27
Number of obs				63,305			50,643			12,662
Number of folds in cross-fit			10			10			10	
Number of controls			285 - 302			285 - 302			285 - 302	
clusters			No			No			Yes	

Dependent variable is annual earnings change (in percent). The controls column reports the median number of control variables selected by Lasso among 10 folds. *** p<0.001, ** p<0.05, * p<0.

Appendix 5: DML result of Unemployed or NILF (Group 2)

		Odds ratio	std.err.		controls
Gender	female(t)*d20	0.81	0.11		44
Age	under 30 years old (t-1)*d20	0.87	0.17		39
	65 years old or over (t-1)*d20	1.11	0.19		71
Education	junior high school (t-1)*d20	0.88	0.25		19
	at school (t-1)*d20	0.82	0.21		54
Status	non-regular worker (t-1)*d20	0.80	0.19		44
	self-employed (t-1)*d20	1.31	0.42		55
Industry	manufacturing (t-1)*d20	1.30	0.14	**	43
	wholesale/retail (t-1)*d20	0.94	0.10		29
	restaurants/accommodation (t-1)*d20	1.61	0.31	**	36
	living-related service (t-1)*d20	0.75	0.30		35
Occupation	security job(t-1) *d20	0.92	0.21		33
	transportation/communications job(t-1)*d20	0.93	0.28		35
	production job(t-1)*d20	0.74	0.14		57
	professional job(t-1)*d20	1.21	0.14		37
Working hour	working hour (～19h) (t-1)*d20	1.27	0.17	*	31
	working hour (20～29h) (t-1)*d20	1.05	0.15		27
Firm size	size(～99 persons) (t-1)*d20	0.86	0.10		27
Annual earnings	less than 1M yen (t-1)*d20	0.80	0.17		49
	1-2M yen (t-1)*d20	0.95	0.18		27
Spouse	(spouse' status) executives (t-1)*d20	1.02	0.26		18
Telework	can telework (t-1)	1.13	0.08		49
	can telework (t-1)*d20	0.84	0.13		42
Self-learning	work related self-learning (t-1)	0.89	0.05	**	48
	d20*work related self-learning (t-1)	1.11	0.10		43
	Number of obs	72399			
	Number of folds in cross-fit	10			
	Number of controls	278-295			

The dependent variable is one if the sample is in group 2 (unemployed or not in the labor force) and zero in group 1-1 (job stayers). The controls column reports the median number of control variables selected by Lasso among 10 folds.

** p<0.05, * p<0.1

Appendix 6: Logistic regression result of Group 2 (Unemployed or NILF)

		Coefficient	Std. err.	z-score	
Female		-0.15	0.11	-1.31	
D20*Female		0.18	0.17	1.05	
Age(t)	25 ~ 34	0.26	0.22	1.21	
(base 15-24)	35 ~ 44	0.56	0.22	2.52	**
	45 ~ 54	0.38	0.22	1.74	*
	55 ~ 64	0.96	0.22	4.36	***
	65+	1.38	0.23	6.01	***
D20*Age(t)	15 ~ 24	0.32	0.49	0.65	
	25 ~ 34	0.18	0.58	0.31	
	35 ~ 44	-0.09	0.58	-0.16	
	45 ~ 54	0.34	0.58	0.59	
	55 ~ 64	0.07	0.58	0.12	
	65+	-0.24	0.57	-0.42	
Education(t)	junior college etc	-0.11	0.12	-0.95	
(base:high school or lower)	university	-0.08	0.12	-0.65	
	at school	0.51	0.30	1.69	*
D20*Education(t)	high school or lower	-0.07	0.44	-0.16	
	junior college etc	-0.08	0.45	-0.18	
	university	-0.37	0.43	-0.85	
Have infant(t)		0.98	0.18	5.35	***
D20*Have infant(t)		-0.36	0.30	-1.17	
Self development(t-1)		0.15	0.11	1.41	
D20*Self development(t-1)		-0.64	0.16	-3.87	***
Compulsory retirement(t)		0.75	0.23	3.25	***
D20*Compulsory retirement(t)		0.72	0.37	1.93	*
Occupation(t-1)	production/manual job	-0.13	0.17	-0.74	
(base:service)	clerk	0.04	0.15	0.25	
	sales	0.17	0.19	0.91	
	professional	-0.05	0.16	-0.32	
	Others	0.08	0.18	0.42	
D20*Occupation(t-1)	service	-0.14	0.28	-0.49	
	production/manual job	0.17	0.30	0.58	
	clerk	0.19	0.26	0.72	
	sales	0.03	0.32	0.11	
	professional	0.16	0.28	0.56	
Responsible for various tasks(t-1)		0.05	0.04	1.31	
D20*Responsible for various tasks(t-1)		-0.07	0.06	-1.14	
Working hours(t-1)		-0.15	0.04	-3.98	***
D20 * Working hours(t-1)		0.09	0.06	1.44	
2019 Dummy		-0.06	0.09	-0.64	
Constant		-0.36	0.30	-1.19	
Number of obs			4071		
Pseudo R2			0.06		

The dependent variable is one for unemployed or NILF and zero for re-employed (till December of year t). All independent variables are dummy variables except the "responsible for various tasks" and "working hours," which are 5 and 6 level ordinal variables, respectively. A sample is responsible for various tasks if the variable takes a lower value, and a sample's working hour is longer if the variable takes a higher value.
Robust standard errors are reported. *** p<0.001, ** p<0.05, * p<0.

Appendix 7: DML result of employed person not at work (Group 3)

		Odds ratio	std.err.		controls
Gender	female(t)*d20	0.89	0.13		44
Age	under 30 years old (t-1)*d20	9.98	1.96	***	39
	30-44 years old (t-1)*d20	6.39	0.88	***	27
	45-64 years old (t-1)*d20	7.86	1.20	***	30
	65 years old or over (t-1)*d20	8.69	1.62	***	33
Education	junior high school (t-1)*d20	2.25	0.70	***	18
	high school (t-1)*d20	2.68	0.57	***	28
	junior college (t-1)*d20	2.78	0.62	***	17
	university (t-1)*d20	2.77	0.67	***	35
Status	regular worker (t-1)*d20	1.49	0.46		47
	non-regular worker (t-1)*d20	2.09	0.86	*	44
	self-employed (t-1)*d20	1.94	0.74	*	64
Industry	manufacturing (t-1)*d20	1.04	0.13		36
	wholesale/retail (t-1)*d20	1.14	0.12		35
	accommodation/restaurants (t-1)*d20	2.71	0.62	***	48
	living-related service (t-1)*d20	1.08	0.46		37
Occupation	security job(t-1) *d20	1.04	0.13		32
	transportation/communications job(t-1)*d20	1.14	0.12		41
	production job(t-1)*d20	2.71	0.62	***	58
	professional job(t-1)*d20	1.08	0.46		38
Working hour	working hour (〜19h) (t-1)*d20	0.96	0.19		28
	working hour (20〜29h) (t-1)*d20	1.06	0.18		25
Firm size	〜99 persons (t-1)*d20	1.52	0.93		27
	100〜999 persons) (t-1)*d20	1.58	1.06		22
	1000 persons 〜 (t-1)*d20	1.62	1.00		37
Annual earnings	less than 1M yen (t-1)*d20	0.94	0.15		55
	1-2M yen (t-1)*d20	1.01	0.16		25
Telework	can telework (t-1)	1.11	0.11		49
	can telework (t-1)*d20	0.75	0.13	*	42
	Number of obs	71053			
	Number of folds in cross-fit	10			
	Number of controls	285-302			

The dependent variable is one if the sample is in group 3 (employed person not at work) and zero in group 1-1 (job stayers). The controls column reports the median number of control variables selected by Lasso among 10 folds.
*** p<0.001, ** p<0.05, * p<0.

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