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Did COVID-19 Deteriorate Mismatch in the Japanese Labor Market?*

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Abstract: This study explores how the COVID-19 pandemic deteriorated the mismatch in the Japanese labor market. First, we focus on the differences in job flows by occupation and employment type, which differ according to the risk of infection. We then estimate the mismatch indices for distinct labor markets clustered by occupations that are more and less vulnerable to the pandemic using the method developed by Şahin et al. (2014). We find that the pandemic induced a mismatch for full-time workers in occupations with a high risk of infection, those in which it is easy to work remotely, and those in which it is particularly difficult to work remotely, as well as for part-time workers in occupations in which it is easy to work remotely.

JEL Classification Codes: J61, J62, J63
Keywords: Mismatch, O-NET data, COVID-19, Labor market tightness

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1. Introduction

In many countries, the effect of the COVID-19 pandemic on the labor market has been heterogeneous across dimensions such as industry, occupation, and worker attributes (e.g., Adams-Prassl et al. 2020; Crossley et al. 2021; Koebel and Pohler 2020). This heterogeneity is associated with job characteristics, including the intensity of face-to-face interactions (Avdiu and Nayyar 2020) and the feasibility of remote work (Dingel and Neiman 2020). Consequently, firms in sectors vulnerable to COVID-19 made employment adjustments by firing workers or requesting them to stay at home. Some workers chose to leave work until the pandemic was controlled. However, others decided to change jobs, leading to an increase in the number of job seekers with specific skills for jobs vulnerable to COVID-19.

Previous studies have shown that the COVID-19 pandemic changed job search behaviors. For example, job seekers in Sweden changed their search direction to occupations less affected by the pandemic (Hensvik et al. 2021). In the Netherlands, although the unemployed searched less during the recession caused by the pandemic than during other recessions, those who faced work situations that were exceptionally affected by the pandemic searched more intensely (Balgová et al. 2022). In the UK, as COVID-19 spread, some workers changed their search direction to expanding occupations, whereas others, especially non-employed and less-educated workers, searched for declining occupations (Carrillo-Tudela et al. 2023). Such evidence suggests that during the pandemic, occupations with a low risk of infection were relatively preferable, but occupations in which workers were required to have close contact with one another were avoided.

However, it is difficult for workers to quickly transfer to an occupation with a low

risk of infection because obtaining the necessary skills for a specific occupation is costly. Carrillo-Tudela et al. (2023) show that, although some workers from declining occupations preferred to search for jobs in expanding occupations, they were less likely to succeed in transferring their occupations. This suggests that those who were once employed in occupations vulnerable to infection had no choice but to search for similar occupations.

Simultaneously, firms vulnerable to COVID-19 decreased their demand for labor, leading to a decrease in job vacancies. For example, after the pandemic hit, vacancies in the leisure, hospitality, and non-essential retail sectors sharply decreased, whereas those in the essential retail sectors were hardly affected (Forsythe et al. 2020). Furthermore, vacancies in care and nursing increased (Arthur 2021). Firms that allowed their employees to work remotely even before the pandemic did not need to hold back on hiring new workers during the early stages of the pandemic (Fukui et al. 2020). Therefore, job matches were less likely to be fulfilled in an occupational labor market vulnerable to COVID-19, where there were many job seekers but fewer vacancies.

This misalignment between job seekers and vacancies is considered to have widened in some occupational labor markets but narrowed in others because of exposure to the pandemic. Although examining how the mismatch between job seekers and vacancies has evolved over time from the viewpoint of dynamic labor market policymaking is worthwhile, little is known about the effects of the COVID-19 pandemic on mismatch. Among the few studies on the subject, Pizzinelli and Shibata (2023) reveal that although the extent of mismatch across industries in the US and the UK rose sharply immediately after the start of the pandemic, it recovered to previous levels within a few quarters, suggesting that the pandemic had a limited effect on the job matching process in these

countries.

This study examines whether the COVID-19 pandemic deteriorated mismatch in the Japanese labor market. We adopt a twofold approach to answer this question, using the administrative data of public employment services and Japanese-style O-NET data. First, we focus on the variants in terms of measures relevant to matching in the Japanese labor market (i.e., labor market tightness and the job finding rate). Second, we estimate the mismatch across occupations. The method we use to calculate the mismatch index, developed by Şahin et al. (2014), involves calculating the counterfactual distribution of matches across distinct labor markets chosen by the social planner to maximize the number of matches in the entire labor market. The extent of the mismatch is measured as the difference between the actual and counterfactual distributions of the matches. This difference indicates the number of matches that would not have been lost if jobs had been allocated efficiently across distinct labor markets. This method allows us to measure mismatch indices, given that distinct labor markets are heterogeneous with respect to matching efficiency. Pizzinelli and Shibata (2023), who investigate the effect of COVID-19 on mismatch in the US and UK, follow this method.

In Japan, Kawata (2019) and Shibata (2020) use this method and confirm that a mismatch across occupations exists using the same administrative data we use but covering periods before the pandemic. Kawakami (2021), using the same administrative data from July 2017 to July 2020, reveals that in the early stages of the pandemic, the mismatch that already existed in Japan deteriorated due to the COVID-19 pandemic. Additionally, utilizing data on the characteristics of occupations from the Japanese-style O-NET, the author also finds that during the early days of the pandemic, there was an excess labor supply in occupations in which workers were required to work in close

contact with others. This finding is consistent with previous studies that show the adverse effects of COVID-19 to be heterogeneous in Japan with respect to individual and occupational characteristics.[1]

This study extends the length of the administrative data on public employment services to March 2023. In addition to using longer data, two features of this study distinguish it from previous literature and address a gap. First, we distinguish between occupations in which workers were more vulnerable to COVID-19. The Japanese-style O-NET dataset covers job characteristics of occupations and directly asks respondents engaging in each occupation about "whether or not workers are in close contact with others," "whether the risk of infection is high or low," and "whether or not workers are allowed to work remotely." Merging this dataset with administrative data by occupational code allows us to examine the differences in job flows and the extent of mismatch in distinct labor markets clustered by occupations at risk of infection and the availability of remote work. This approach is more direct than that used in the literature measuring occupations' vulnerability to COVID-19 in terms of the risk of infection and remote work feasibility based on job features in typical situations (e.g., Dingel and Neiman 2020).

Second, we focus on the effects of the pandemic on job flows and mismatch by employment type (full-time versus part-time), as well as the extent of vulnerability to COVID-19. We assume that labor markets segregated by employment type are

[1] In Japan, women, part-time workers, and workers belonging to the restaurant and bar sectors were more likely to be absent from work during the early days of the pandemic crisis (Fukai et al. 2021) and to be unemployed or out of the labor force by December 2020 (Fukai 2022). Workers in firms that the local government requested to temporarily suspend their business because workers engaged in frequent contact with others (Hoshi et al. 2022) and those who were not allowed to work a flexible schedule or remotely were also adversely affected by the pandemic (Kikuchi et al. 2021). The year-on-year increasing rate of the number of unemployed was similar in the second half of 2020 to that of the Great Recession, whereas the year-on-year decreasing rate of new hires in the restaurant and bar sectors was higher in the second half of 2020 than during the Great Recession (Kawata 2021).

independent of one another because workers do not typically alternate between these two employment types.

The two main findings are summarized as follows. First, the labor market worsened after March 2020 when the national government requested that all schools temporarily close because of an increase in the number of COVID-19 cases. We assume that the pandemic began this month in Japan. Both labor market tightness and job finding rate decreased. We observe the same patterns of job flow regardless of employment type (full-time or part-time) and occupation type (low or high risk of infection, and easy or difficult to work remotely). Labor market tightness gradually recovered in early 2021, approximately one year after the start of the pandemic. However, the job finding rate did not recover but remained at a lower level, suggesting that a mismatch occurred.

Second, we find that the mismatch rapidly increased after March 2020 for full-time workers in occupations with a high risk of infection, those in which it is easy to work remotely, those in which it is particularly difficult to work remotely, and part-time workers in occupations in which it is easy to work remotely. High-risk and difficult-to-work-remotely occupations can reflect those requiring face-to-face contact that were adversely affected by the pandemic. Easy-to-work-remotely occupations may have been preferred by workers during the pandemic. Thus, we consider that the mismatch in these types of occupations increased due to the pandemic.

The remainder of this paper is organized as follows. Section 2 provides details of the data we utilize. Section 3 describes the trends in the variables of interest, such as labor market tightness and the job finding rate. Section 4 presents the trends in mismatch. Finally, Section 5 presents concluding remarks.

2. Data

This section introduces the two datasets and explains their merging. We then explain which occupations are defined as low and high risk of infection and which are easy and difficult to work remotely.

2.1. Merging the two datasets

We begin by explaining the "Employment Referrals for General Workers (Report on Employment Service)" (ERGW/RES), which comprises administrative data on public employment services released by the Japanese Ministry of Health, Labour and Welfare (MHLW). The data include the number of job seekers, vacancies, and new hires registered at each local public employment security office nationwide.[2] These variables enable us to measure labor market tightness, job finding rates, and mismatch indices. We use monthly panel data aggregated at the small-classified occupation level based on the MHLW occupational classification (revised in 2011). The advantage of using the ERGW/RES dataset based on the small-classified occupations rather than the larger occupational classifications used by previous studies measuring mismatch indices for Japan through the method developed by Şahin et al. (2014) is that merging the dataset with the Japanese-style O-NET, containing one level smaller occupational classification, can be more precise.[3] The variables are separately available by employment type, namely full-time and part-time.[4] New graduates and vacancies targeting them are not included in

[2] In the original data, the number of "job seekers," "vacancies," and "new hires" are labeled as "monthly active applicants," "monthly active job openings," and "persons who found employment," respectively.

[3] To calculate the mismatch indices for Japan using the method of Şahin et al. (2014), previous studies that used the ERGW/RES dataset aggregate at occupations of large-classification (Kawata 2019; Shibata 2020) and middle-classification (Shibata 2020; Kawakami 2021).

[4] In the original data, "full-time workers" and "part-time workers" are labeled as "regular workers

the dataset. The dataset covers 369 occupations from June 2016 to March 2023, crossing the threshold of March 2020 when school closures were ordered owing to the spread of COVID-19 in Japan.[5]

Vacancies aggregated into small-classified occupations and employment types were calculated based on the information of firms registered with the local public employment security office. Job seekers registered their desired conditions, including occupation and employment type, when they registered themselves as job seekers. Based on this information, not only the number of vacancies but also the number of job seekers is available at the small-classified occupation level by employment type. Note that job seekers who wrote about their desired occupation in the middle classification or who did not write about their desired occupation in the application form are not included in the dataset.

A potential concern is whether the data on public employment services (ERGW/RES) are representative of the Japanese labor market. According to the 2016–2022 Survey on Employment Trends conducted by the MHLW, 14–18% of workers were hired by employers through public employment services. Other major channels were advertisements (approximately 30%), personal connections (approximately 20%), schools (approximately 7%), and private employment referral services (approximately 5%). Although the coverage of public employment services data is limited, we consider its use to be the best way to capture the job matching process in Japan because no

excluding part-timers" and "regular part-timers," respectively. According to the definition of the MHLW, "regular workers" are those whose employment contract stipulates no employment periods, or a four-month or longer period of employment. "Part-timers" indicates workers whose usual weekly working hours are less than other workers in the same establishment. See the website of the MHLW in detail (https://www.mhlw.go.jp/toukei/list/114-1_yougo.html (in Japanese) (accessed on November 6, 2023)).

[5] We do not use data after March 2023 because the occupational classification was changed in April 2023; thus, it is difficult to consistently connect with the data before and after this month.

comprehensive data on the number of job seekers, vacancies, and new hires for other channels are available. However, the data characteristics must be considered. Job seekers registered in public employment security offices tend to have disadvantageous characteristics, such as low education and longer unemployment periods, and experience a decrease in their wages after they find jobs through this service, suggesting that public employment services play a role in the safety net (JILPT 2015; Kodama et al. 2004). Although the data on public employment services do not necessarily reflect the Japanese labor market, we consider that the results from these data can have significant implications for employment policy since the workers and firms in these data seem to be the most vulnerable to negative shocks such as COVID-19, indicating that they are the prime policy targets.

The Japanese-style O-NET released by the Japanese Institute for Labour Policy and Training (JILPT) quantifies the characteristics of each occupation.[6] A large-scale survey was conducted in which registered workers engaged in each occupation were subjectively asked about occupational characteristics, such as the skills and knowledge necessary to perform tasks.[7] Workers responded to each question on a multiple-point scale, and the average score was calculated for each occupation. We use a version based on a survey administered from January 19 to February 15, 2021, which added information identifying which occupations were at risk of infection and which allowed workers to work remotely.

To explore the characteristics of labor markets clustered by occupation at a high or low risk of infection and those allowing remote work, we merge the two datasets. Note that this is possible because although the occupations in the Japanese-style O-NET follow their own classification, they provide the corresponding MHLW occupational

[6] The Japanese-style O-NET dataset is labeled as "job tag."
[7] See JILPT (2021) for details.

classification (revised in 2011) code at the sub-small classification level, which is one level smaller than the small classification. The version of the Japanese-style O-NET dataset that we use covers 497 occupations, 75 of which are omitted because of a lack of necessary information.[8] Some occupations in the Japanese-style O-NET dataset share MHLW occupational codes. To merge the two datasets based on the MHLW occupational classification, we convert the values of the variables in the Japanese-style O-NET dataset to the averages of the MHLW classification-based occupations. Finally, 422 occupations in the Japanese-style O-NET dataset are consolidated into 228. These occupations are merged into the ERGW/RES using occupational codes. As ERGW/RES cover 369 occupations, 141 occupations are deleted.[9]

There are two noteworthy points. First, the version of the Japanese-style O-NET data used in this study contain information on the occupational characteristics of infection risk and remote work availability collected from January 19 to February 15, 2021. We assume that the occupation characteristics remain unchanged over a long period and apply the occupational characteristics as of 2021 to any period from June 2016 to March 2023. Second, Japanese-style O-NET data do not distinguish occupational characteristics by employment type; therefore, we assume that there are no differences in occupational characteristics between full-time and part-time workers.

As mentioned previously, 141 of the 369 occupations are deleted from the ERGW/RES data because of a lack of information on occupational characteristics in Japanese-style O-NET data, leading to concerns about the problem caused by sample

[8] The MHLW occupational code corresponding to the O-NET occupational code is based on "Input Data for the occupational information network of Japan version 2.01," released by the JILPT, downloaded from the websites of the Japanese-style O-NET (http://shigoto.mhlw.go.jp/User/download) on August 2, 2021.

[9] See Figure OA.1 in the Online Appendix for the method to merge the two datasets in detail.

selection bias. Table OA.1 in the Online Appendix shows the differences in three variables (number of job seekers, vacancies, and new hires by employment type) between the 228 occupations with O-NET data and the remaining 141 occupations without O-NET data. We find that the averages of these variables are 6–13 times larger in the 228-occupation group than in the deleted 141-occupation group. These results indicate that the deleted 141-occupation group is far smaller in scale than the overall labor market. Additionally, Figure OA.2 in the Online Appendix shows that the trends of labor market tightness and the job finding rate for all 369 occupations and 228 occupations with O-NET data are very similar, whereas the trends of these variables for 144 occupations without O-NET data largely differ from those for all 369 occupations. Therefore, we interpret that the problem caused by sample selection bias is minor.

2.2. Which occupations are vulnerable to COVID-19?

This subsection presents two indices for identifying the occupations vulnerable to COVID-19. We explain two methods to distinguish between the two groups of occupations: whether the risk of infection is high or low in the workplace and how often workers are allowed to work remotely. Table OA.2 in the Online Appendix presents the groups under which each occupation is classified.

We begin with the first method of distinguishing between workers at high and low risk of infection. We compute the average of the scores from the two questions to measure the extent of infection risk. The first question is “How frequently do you leave yourself vulnerable to infectious diseases in your workplace?” Respondents answered this question on a five-point scale: (1) once a year or not at all, (2) once a year or more, (3) once a month or more, (4) once a week or more, and (5) almost every day. This score

indicates how seriously COVID-19 is endangering worker health in the workplace (infectious disease risk). The second question is "How closely do you and your colleagues generally contact each other in your workplace?" and answered on a five-point scale: (1) no contact with others or far away from others by 30 meters or more; (2) work with others but maintain a physical distance of 5 meters or more; (3) not close to or do not reach others when one extends an arm; (4) close to and reach others when one extends an arm; and (5) very close (shoulder-to-shoulder). We also use the second question because close contact (i.e., physical proximity to others) increases the risk of catching the virus, which is airborne and carried by droplets from infected individuals.[10]

We compute the arithmetic average of the two scores as a synthetic risk index to identify which occupations were at high or low risk of infection in the workplace.[11] Figure 1 shows the distributions of the indices for infectious disease risk and physical proximity to others, as well as the distribution of the synthetic risk index. When the synthetic risk index of an occupation is high, workers are more likely to be infected in the workplace. We employ two thresholds to distinguish between occupations at high and low risk of infection–the 50th or 75th percentile of the synthetic index–and define occupations above these thresholds as high risk.

[Insert Figure 1 about here]

The second index measures the frequency with which workers are allowed to work remotely. The Japanese-style O-NET additionally asked respondents the following

[10] See WHO website, "Coronavirus disease (COVID-19): How is it transmitted?" (https://www.who.int/news-room/questions-and-answers/item/coronavirus-disease-covid-19-how-is-it-transmitted#:~:text=Current%20evidence%20suggests%20that%20the,%2C%20speak%2C%20sing%20or%20breathe.)

[11] Because the two scores are within a range from 1 to 5, the synthetic index is also within a range from 1 to 5.

question: “How often do you think workers engaged in the same job as you were allowed to work remotely during the state of emergency (April–May 2020)? It should be noted that we would like you to respond to whether remote work is available not for you but for other workers in the same jobs.” Respondents answered on a six-point scale: (1) usually, no; (2) 20% of days of duty and below; (3) 20% or more but below 40% of days of duty; (4) 40% or more but below 60% of days of duty; (5) 60% or more but below 80% of days of duty; and (6) 80% of days of duty and more.

The Japanese-style O-NET contains the proportion of respondents to this question based on the six choices above.[12] To create a summarized index of the availability of remote work, we calculate the sum of the fraction of respondents weighted by the median range of the percentage of remote work availability for each choice, as shown in Figure 2.[13,14] This figure shows that the availability of remote work is low for most occupations. We define an occupation as difficult to work remotely if the magnitude of the availability of remote work, in order from the largest (i.e., from easy to difficult), is over the 50th or 75th percentile and as easy to work remotely otherwise.

[Insert Figure 2 about here]

Figure 3 plots the relationship between the synthetic index of risk of infection and the index of availability of remote work. The correlation coefficient is -0.47, indicating that the two indices exhibit a negative correlation, but its magnitude is not large. Occupations with a higher availability of remote work tend to face lower risks of infection. However, occupations with a lower risk of infection do not always exhibit higher

[12] Figure OA.3 shows these distribution.
[13] The median of each choice is: (1) = 0%; (2) = 10%; (3) = 30%; (4) = 50%; (5) = 70%; (6) = 90%.
[14] We also try another method to create the index of the availability of remote work. The Online Appendix contains the definition of this alternative index and some descriptive and estimation results based on it.

availability of remote work. This tendency suggests that the two different indices can capture different aspects of vulnerability to the COVID-19 pandemic.

[Insert Figure 3 about here]

3. Labor market tightness and job finding rate

This section presents the monthly moving average trends in labor market tightness (ratio of vacancies to job seekers) and job finding rates (ratio of new hires to job seekers) from May 2017 to March 2023, covering the period before and after the pandemic.[15]

Panels (a) and (b) of Figure 4 display the trends in labor market tightness and job finding rates by synthetic risk index (low versus high risk of infection) using two different thresholds (the 50th and 75th percentiles), respectively. These panels show the trends for full-time workers. Note that the extent of labor market tightness is measured on the left vertical line, and that of the job finding rate is measured on the right vertical line.

[Insert Figure 4 about here]

First, labor market tightness decreased after the pandemic emerged, regardless of whether the infection risk was high or low, leading to a decrease in the job finding rate for workers. However, labor market tightness increased in early 2021 and almost recovered in March 2023. At the same time, although the job finding rate also stopped decreasing in 2021, it did not recover and remained low, suggesting that a persistent mismatch across occupations occurred. Second, labor market tightness was always greater than one over the period, implying that the demand for labor (the number of vacancies) always exceeded the supply of labor (the number of job seekers). This reveals

[15] The data are available from June 2016 but the figures plots from May 2017 because the moving average is defined as the average of numbers obtained from the current month and the past 11 months (i.e., the 12-month backward moving averages).

that the Japanese labor market for full-time workers suffered from a chronic labor shortage even after negative shocks such as the COVID-19 pandemic.

Panels (c) and (d) for part-time workers show trends similar to those for full-time workers. That is, labor market tightness and the job finding rate decreased after the pandemic. These decreases in labor market tightness and job finding rates for high-risk occupations are steeper than those for low-risk occupations. However, labor market tightness showed an upward trend in early 2021, whereas the job finding rate continued to decrease.

We now examine these trends using the index of the availability of remote work. Panels (a) and (b) of Figure 5 display the moving average trends in labor market tightness and the job finding rate using the two thresholds (50th and 75th percentiles) to distinguish whether remote work is difficult for full-time workers. The trends in panel (a) are similar to those in panel (b); regardless of the thresholds, labor market tightness decreased for both easy- and difficult-to-work-remotely occupations since the pandemic, and the job finding rates also decreased. However, labor market tightness showed an upward trend in early 2021, while the job finding rates stopped decreasing sharply and remained low.

[Insert Figure 5 about here]

Panels (c) and (d) for part-time workers show that for both easy- and difficult-to-work-remotely occupations, labor market tightness decreased since the pandemic. They show an upward trend in early 2021. The job finding rates decreased over the sample period, except for easy-to-work-remotely occupations in panel (c), between early 2020 and mid-2021. These opposite trends, namely, an increase in labor market tightness and a decrease in the job finding rates after the pandemic, suggest that the mismatch arose due to the pandemic.

4. Mismatch

This section presents the transitions in the mismatch between workers and firms across distinct labor markets segmented by small-classified occupations over time. The mismatch indices developed by Şahin et al. (2014) are calculated. Their technique measures the fraction of actual matches to optimal matches; that is, it is the fraction of matches that would have been fulfilled if workers had searched for jobs in ideal distinct labor markets. Their model assumes that a social planner who maximizes the number of market-wide matches determines the optimal allocation of job seekers across distinct labor markets. An innovation of their technique is that the optimal number of matches is calculated by accounting for the heterogeneity of matching efficiencies across distinct labor markets. Appendix A presents the definition and calculation method of the mismatch index in detail.

From the sample, we delete data on occupations in which the number of new hires is zero for one or more periods because we cannot take the log of its value, which is necessary to calculate the mismatch indices.[16] Therefore, the number of occupations decreases from 228 to 207 in the sample of both employment types (i.e., aggregation of full-time and part-time workers), 202 in the sample of full-time workers, and 156 in the sample of part-time workers.[17] This exclusion of occupations is not expected to reduce the representativeness of the sample, as occupations with zero new hires for one or more periods across all public employment offices are relatively minor in Japan. Indeed, Figure OA.4 in the Online Appendix shows that the trends in labor market tightness and the job

[16] See Appendix A in detail.
[17] Occupations utilized to calculate the mismatch indices are listed in Table OA.2 in the Online Appendix.

finding rate for occupations included in the sample used to estimate the mismatch indices are quite similar to those in the full sample until the previous section. In contrast, the trends for occupations excluded from the sample differ markedly from those in the full sample.[18]

Subsection 4.1 first shows the mismatch indices nationwide. Additionally, as in Section 3, subsection 4.2 measures the mismatch indices across occupations according to the risk of infection. That is, we compare the mismatch across occupations in the labor market with low and high risks of infection. In other words, we assume that the mismatch occurs across occupations with a similar level of risk of infection but not across occupations with a largely different risk level. We consider a case in which there is little labor mobility across occupations with largely different risks of infection because there are broad variations in their job characteristics. For example, "food and drink service workers" and "Japanese Inn, hotel, and transportation customer service workers" are classified as high-risk occupations based on the 75th percentile threshold. "Telephone receptionists" is classified as a high-risk occupation based on the 50th percentile threshold. These workers may be able to change their occupations to "building cleaning workers," a low-risk occupation based on both the 50th and 75th percentile thresholds. However, many low-risk occupations seem to require high skills or qualifications of workers, such as "accountants business clerks," "software creators," and "electrical, electronic, telecommunications technicians." In subsection 4.3, the same procedure is used for occupational groups based on the availability of remote work. We also assume little labor

[18] Labor market tightness and job finding rate can be calculated for the excluded sample because these variables are calculated by aggregating all occupations in this sample. Additionally, even if the number of new hires is zero for some occupations in some periods, it is not zero for other occupations simultaneously in this sample. As a result, the total number of new hires for the entire excluded sample is not zero across all periods.

mobility across the largely different availabilities of remote work. For example, "food and drink service workers" and "building cleaning workers" are classified as difficult-to-work-remotely occupations based on the 75th percentile threshold. "Japanese Inn, hotel, and transportation customer service workers" is also classified as a difficult-to-work-remotely occupation based on the 50th percentile threshold. These workers can change their occupations to "telephone receptionists," an easy-to-work-remotely occupation based on the 50th percentile threshold. However, similar to low-risk occupations, many easy-to-work-remotely occupations seem to require high skills or qualifications from workers.

Finally, subsections 4.4 and 4.5 focus on the mismatch across different risks of infection and across different availabilities of remote work, respectively. These approaches allow us to measure the mismatch associated with labor mobility across these occupational attributes.

4.1. Overall mismatch

Before showing the mismatch by occupational group, we begin with Figure 6, which displays the trends in the overall mismatch across occupations, using an aggregated sample of full- and part-time workers. Panel (a) presents the mismatch index. Because the mismatch index fluctuates seasonally, we also show its moving average.[19] The mismatch index shows an overall upward trend. This trend accelerated immediately after the pandemic, and the extent of the mismatch remained high until early 2023.

[Insert Figure 6 about here]

[19] The data are available from June 2016, but the figures plot the original series and moving average series of mismatch indices from July 2016 and June 2017, respectively, because we took a one-period lag to calculate the indices. See Appendix A in detail.

Panel (b) shows actual, counterfactual, and mismatch unemployment rates. According to Şahin et al. (2014), the counterfactual unemployment rate, derived from the mismatch index, is the optimal unemployment rate in the absence of a mismatch.[20] The mismatch unemployment rate is the actual unemployment rate minus the counterfactual unemployment rate. This panel shows that actual and counterfactual unemployment rates increased after the onset of the pandemic. Consequently, the mismatch unemployment rate remained almost constant before and after the pandemic. This suggests that the mismatch indeed increased due to the pandemic but hardly resulted in an increase in the unemployment rate. We consider that the increase in the unemployment rate after the pandemic mainly came from labor demand shortages.

The labor market should be segmented into full-time and part-time workers. Figure 7 shows the trends in the mismatch indices according to employment type. In panel (a), we find that, although the variation in the mismatch index for full-time workers is larger than the overall trends (panel (a) of Table 6), their trends are very similar. In contrast, the mismatch index for part-time workers in panel (b) did not follow an upward trend but was almost constant before the pandemic. After the pandemic, the mismatch index for part-time workers increased. Overall, the pandemic increased the mismatch across occupations for both full-time and part-time workers. Note that we do not calculate the mismatch unemployment rate by employment type because no employment type can be attributed to the unemployed.

[Insert Figure 7 about here]

4.2. Occupational mismatch by high versus low infection risk occupation groups

[20] See Appendix A for the method of calculation of counterfactual unemployment rate, using the mismatch indices, in detail.

Next, we focus on exactly where the mismatch found in the previous subsection occurred within the labor market by dividing the labor market into high- and low-risk groups. As mentioned in the previous subsection, the overall mismatch increased but hardly induced an increase in the mismatch unemployment rate. Nevertheless, we explore the mismatch indices in detail because workers in some parts of the labor market, namely those in occupations that are vulnerable to the COVID-19 pandemic, might suffer from a large mismatch even if the overall mismatch unemployment rate does not seem to change.

Panels (a) and (b) of Figure 8 illustrate the trends in the mismatch indices using the synthetic risk index for both employment types (i.e., aggregation of full- and part-time workers). Panels (a) and (b) present the results of the 50th and 75th percentiles of the synthetic risk index as thresholds for occupational groups with a high risk of infection, respectively. We find similar results for both panels with different thresholds. Before the pandemic, the mismatch indices remained almost constant or increased slightly over time, regardless of the risk of infection. Immediately after March 2020, when the pandemic began in Japan, the mismatch indices sharply increased for high-risk occupations, whereas those for low-risk occupations gradually increased over the sample period.

[Insert Figure 8 about here]

Panels (c) and (d) of Figure 8 present trends in the mismatch indices for full-time workers. We obtain results similar to those in panels (a) and (b) for both employment types. After March 2020, the mismatch indices increased sharply in high-risk occupations, whereas the rate of increase in the mismatch indices for low-risk occupations was trivial. The mismatch across high-risk occupations due to the pandemic was gradually reconciled, but the level remained higher than before the pandemic. The mismatch indices began to increase gradually from mid-2020 for low-risk occupations and remained high until early

2023.

Panels (e) and (f) of Figure 8 present trends in the mismatch indices for part-time workers. Panel (e), using the 50th percentile as the threshold, shows that the mismatch index in low-risk occupations gradually increased from 2020 to 2022, although it temporarily decreased immediately after March 2020. The extent of change in the mismatch was small. For high-risk occupations, the mismatch index increased after March 2020; however, this increase was small. This trend did not continue, and the mismatch index decreased by 2021. When we employ the 75th percentile as the threshold, as shown in panel (f), the mismatch index in low-risk occupations increased from 2020 to mid-2021, although to a lesser extent. By contrast, the mismatch index in high-risk occupations was almost constant throughout the sample period. Thus, for part-time workers, the mismatch due to the pandemic was small.

4.3. Occupational mismatch by easy- versus difficult-to-work-remotely occupation groups

This subsection presents the trends in mismatch indices by occupational group based on the availability of remote work. In Figure 9, panels (a) and (b), which use the 50th and 75th percentiles, respectively, as thresholds to distinguish between the availability of remote work, present the results for both employment types (i.e., the aggregation of full-time and part-time workers). Easy-to-work-remotely occupations exhibited a steady increase in the mismatch indices after the pandemic. For difficult-to-work-remotely occupations, the mismatch indices increased slightly after the pandemic using the 50th percentile threshold. When we employ the 75th percentile threshold, the mismatch across difficult-to-work-remotely occupations increased sharply immediately after the pandemic

emerged. This extent of mismatch gradually decreased after mid-2020 but remained at a higher level than before the pandemic. This result suggests that a mismatch in the labor market for easy-to-work-remotely occupations arose because of the pandemic and continued to worsen. The mismatch due to the pandemic also increased in the labor market of occupations in which it is particularly difficult to work remotely (i.e., difficult-to-work-remotely occupations based on the 75 percentile threshold).

[Insert Figure 9 about here]

Panels (c) and (d) of Figure 9 display the trends in the mismatch indices for full-time workers using the 50th and 75th percentiles as thresholds, respectively. We obtain results similar to those in panels (a) and (b) for both employment types. We find that the mismatch increased for easy-to-work-remotely occupations and particularly difficult-to-work-remotely occupations.

Finally, panels (e) and (f) of Figure 9 present the trends in the mismatch indices for part-time workers using the 50th and 75th percentiles as thresholds, respectively. For both panels, the mismatch across easy-to-work-remotely occupations increased after March 2020, but to a small extent. In contrast, the mismatch across difficult-to-work-remotely occupations did not change much over time, even during the pandemic. Thus, we consider that the COVID-19 pandemic did not cause a severe mismatch in the part-time labor market, which was segmented by the availability of remote work.

4.4. Mismatch across occupational clusters with different infection risks

Subsections 4.2 and 4.3 evaluate the mismatch across small-classified occupations, assuming that the labor market was segmented by the risk of infection and the availability of remote work, respectively. These analyses enable us to identify the part of the labor

market affected by the mismatch. However, some job seekers may have searched for jobs in different labor markets due to the pandemic. Some high-risk occupations may have moved to low-risk occupations and vice versa. The same is true for mobility between easy- and difficult-to-work-remotely occupations. The following subsections describe the mismatch related to these types of mobility.

In this subsection, occupational clusters are defined on the basis of a synthetic risk index. As defined in Section 3, each occupation has a synthetic risk index score. We list the occupations in order of their scores and divide them into eight clusters. In other words, we reaggregate the small-classified occupations into eight clusters that are attributed to the risk of infection.[21] Furthermore, we compare the mismatch indices across clusters in the high- and low-risk labor markets using the 50th and 75th percentiles as thresholds. In this case, we assume that job seekers do not move to largely different labor markets in terms of the risk of infection but move to nearby markets. To measure mismatch indices, there must be at least two clusters. We adopt eight clusters because when the 75th percentile is employed as the threshold, the number of clusters in low- and high-risk occupations is six and two (i.e., the necessary minimum number of occupations), respectively.[22]

Panel (a) of Figure 10 illustrates the mismatch index across the eight occupational clusters with different levels of infection risk for both employment types. After March 2020, although the extent of the change in the mismatch index was small, the mismatch decreased, suggesting that labor mobility across occupational clusters with different risks was promoted. This result differs from that shown in Figure 6, which indicates an increase

[21] Table OA.2 in the Online Appendix presents eight occupational clusters.
[22] When the 50th percentile is employed as the threshold, the number of clusters for both low- and high-risk occupations is four.

in mismatch across small-classified occupations after the pandemic. However, a decrease in the mismatch index hardly affects the mismatch unemployment rate, as shown in panel (b) of Figure 10.[23]

[Insert Figure 10 about here]

Panel (a) of Figure 11 for full-time workers shows results similar to those for both employment types; that is, the mismatch index decreased after the pandemic began. For part-time workers, panel (b) shows that the mismatch index remained almost constant over time.

[Insert Figure 11 about here]

Overall, especially for full-time workers, we found conflicting results between the definitions of distinct labor markets; that is, the mismatch across small-classified occupations increased, whereas it decreased across occupational clusters with different risks. One possibility for the unstable results is that a mismatch occurred in some fractions of the labor market, while it did not occur in other fractions if most workers did not frequently move to largely different types of occupations, such as the risk of infection. This is because low-risk occupations are considered to require higher skills or qualifications than high-risk occupations, as mentioned at the beginning of this section. To detect where the mismatch occurred in the labor market, we compare the mismatch indices between the labor markets of low- and high-risk occupations.

Panels (a) and (b) of Figure 12 present the mismatch indices of low- and high-risk occupations for both employment types. Using the 50th percentile as the threshold, panel (a) shows that the mismatch for low-risk occupations decreased after March 2020, while

[23] The mismatch unemployment was negative in a few months, although this seems theoretically inconsistent. This is probably because the sources of data for the mismatch indices and the counterfactual unemployment rate are different. See also Appendix A in detail.

that for high-risk occupations remained almost constant over time. When we employ the 75th percentile as the threshold, as shown in panel (b), the mismatch for low-risk occupations decreased, whereas that for high-risk occupations increased immediately after March 2020. The mismatch for high-risk occupations was gradually eliminated, but it took approximately three years to recover to the pre-pandemic level. These results suggest that a mismatch due to the pandemic occurred in the riskiest occupational group.

[Insert Figure 12 about here]

For full-time workers, panels (c) and (d) provide suggestions similar to those for both employment types. The mismatch index for both low- and high-risk occupations decreased when the threshold was at the 50th percentile (panel (c)). Using the 75th percentile as the threshold, the mismatch for high-risk occupations increased immediately after March 2020 (panel (d)), suggesting that the pandemic caused a mismatch in the riskiest occupational group.

Panels (e) and (f) of Figure 12 show the mismatch indices for part-time workers. Using the 50th percentile as the threshold, panel (e) shows that the mismatch between low- and high-risk occupations decreased and increased after March 2020, respectively. However, these results are reversed when the 75th percentile is employed as the threshold, as shown in panel (f). The two relatively lower-risk occupational clusters among the four occupational clusters in the high-risk labor market under the 50th percentile threshold move to the low-risk labor market under the 75th percentile threshold. The mismatch between these two clusters and the four existing clusters in the low-risk labor market below the 50th percentile threshold may be large. However, in both panels, the extent of the change in the mismatch indices was small for both low- and high-risk occupations.

Altogether, when we separately measure the mismatch indices by high- and low-

risk occupations, we find that the mismatch across small-classification occupations (Table 8) and occupational clusters with different infection risks (Table 12) leads to similar evidence, although there are some different results. First, the extent of the mismatch in high-risk occupations for full-time workers increased after March 2020, suggesting that labor mobility in this market was discouraged due to the COVID-19 pandemic. High-risk occupations are in sectors requiring face-to-face contact. Such sectors were implicitly forced to suspend their businesses or shorten their working hours through voluntary bans on leaving their homes, resulting in a mismatch. Second, for part-time workers, the extent of the mismatch due to the pandemic was limited.

4.5. Mismatch across occupational clusters with different availability of remote work

Next, we define occupational clusters based on the availability of remote work in a manner similar to that described in the previous subsection. Specifically, occupations are divided into eight clusters after they are listed in order of the availability of remote work.

In Figure 13, for both employment types, panel (a) presents the mismatch index across the eight occupational clusters with different levels of remote work availability, whereas panel (b) displays the mismatch unemployment rate calculated by the mismatch index. The mismatch index slightly decreased immediately after March 2020 but hardly affected the mismatch unemployment rate. These results are similar to those using occupational clusters defined on the basis of a synthetic risk index (panels (a) and (b) of Figure 10).

[Insert Figure 13 about here]

Panel (a) of Figure 14 shows that the mismatch index for full-time workers decreased

after March 2020, although the extent of this change was small. By contrast, for part-time workers in panel (b), the extent of the mismatch was constant before the pandemic but increased after March 2020.

[Insert Figure 14 about here]

As in the previous subsections, Figure 15 measures the mismatch indices by labor market of easy- and difficult-to-work-remotely occupations. Panels (a) and (b) present the mismatch indices for both employment types, using the 50th and 75th percentiles as thresholds, respectively. For easy-to-work-remotely occupations, the mismatch increased after March 2020, regardless of the threshold. The mismatch for difficult-to-work-remotely occupations decreased after March 2020 using the 50th percentile threshold. Using the 75th percentile as the threshold, the mismatch index remained almost unchanged. Similar trends are confirmed for full-time workers (panels (c) and (d)), although the extent of the change in the mismatch indices is small.

For part-time workers (panel (e)), using the 50th percentile as the threshold, the result is similar to that for full-time workers; that is, the mismatch across occupational clusters for easy- and difficult-to-work-remotely occupations increased and decreased, respectively, after the pandemic. Using the 75th percentile as the threshold (panel (f)), the mismatch for easy-to-work-remotely occupations still increased after March 2020, but that for difficult-to-work-remotely occupations remained almost constant, regardless of the pandemic. These results suggest that the mismatch due to the pandemic is larger in the labor market, especially for easy-to-work-remotely occupations for part-time workers.

[Insert Figure 15 about here]

Consequently, based on the results of the mismatch across small-classified occupations (Figure 9) and across eight occupational clusters with different availabilities

of remote work (Figure 15), we consider the effects of the COVID-19 pandemic on the labor markets of easy- and difficult-to-work-remotely occupations as follows. First, the extent of mismatch in easy-to-work-remotely occupations increased among full-time workers after March 2020. For part-time workers, this result is confirmed for easy-to-work-remotely occupations when we focus on the mismatch across the occupational clusters. No results indicate that the mismatch indices decreased for part-time workers. These results suggest that the COVID-19 pandemic discouraged labor mobility in easy-to-work-remotely occupations. During the pandemic, workers may have preferred easy-to-work-remotely occupations, resulting in less mobility across occupations. This result does not conflict with previous results that the mismatch for full-time workers in high-risk occupations increased because our dataset indicates that some easy-to-work-remotely occupations are classified as high-risk (see Figure 3 in Section 2).

Second, for full-time workers, the mismatch in particularly difficult-to-work-remotely occupations increased due to the pandemic, according to the mismatch indices across small-classified occupations. This result is consistent with the increasing mismatch in the labor market for full-time workers in high-risk occupations.

5. Concluding remarks

This study explored how the labor market in Japan was adversely affected by the COVID-19 pandemic that began in March 2020, leading to temporary school closures. First, we focused on the differences in job flows of various occupations according to the extent of vulnerability to the pandemic. Second, using the method developed by Şahin et al. (2014), we estimated the mismatch indices for distinct labor markets clustered by occupations more and less vulnerable to the pandemic.

We employed two datasets: administrative data on public employment services from the MHLW and Japanese-style O-NET data released by the JILPT. The Japanese-style O-NET dataset directly asked respondents about "whether or not workers are in close contact with others," "whether the risk of infection is high or low," and "whether or not workers are allowed to work remotely." This allowed us to identify the occupations that were vulnerable to COVID-19. By merging the two datasets by occupational code, we explored how the pandemic affected the Japanese labor market depending on the extent of infection risk and the availability of remote work.

We derive the following two main findings. First, labor market conditions worsened after March 2020, the starting point of the pandemic. Labor market tightness, and in turn, the job finding rate, decreased for both full-time and part-time workers, regardless of whether their occupation types were vulnerable to infection. Labor market tightness gradually recovered in early 2021, while the job finding rate remained low. This suggests that a mismatch arose due to the pandemic.

Second, according to the mismatch indices, after March 2020, the mismatch increased for full-time workers in high-risk occupations. Similar trends were observed for full-time workers in occupations in which it was easy to work remotely. Additionally, some results indicated that the mismatch increased for full-time workers in occupations where it was particularly difficult to work remotely. The mismatch for part-time workers increased in easy-to-work-remotely occupations. We believe that high-risk and particularly difficult-to-work-remotely occupations in sectors requiring face-to-face contact were seriously affected by the pandemic, resulting in a mismatch in the labor market. Additionally, job seekers may have preferred easier remote work opportunities, resulting in a mismatch.

Finally, for future research, we discuss whether the Employment Adjustment Subsidy (EAS), a public grant aimed at protecting employment, could have influenced the mismatch during the pandemic. To protect employment in firms adversely affected by COVID-19, the Japanese government implemented a special measure to increase the EAS from April 2020 to March 2023.[24] Such a generous EAS might have mitigated the mismatch by reducing the number of unemployed job seekers. In contrast, it could have worsened the mismatch by making it more difficult for vacancies to be filled by suitable job seekers from a reduced unemployment pool due to the generous EAS, and vice versa. Whether the extent of the mismatch found in this study was mitigated or deteriorated by the generous EAS seems to be a significant issue in revealing the impact of the employment policy on labor mobility during the pandemic.

Appendix A. Mismatch index

This appendix describes the definition and calculation method of the mismatch index developed by Şahin et al. (2014). First, we briefly outline the theoretical framework of their study. Let the labor market be segmented by sector. Assuming that the labor market is segmented by occupation, we label the sectors as occupations. In each frictional labor market segmented by I occupations, the number of new hires, namely the number of matches between job seekers and vacancies, is assumed to be given by the following matching function:

$$h_{it} = \Phi_t \phi_i m(u_{it}, v_{it}), \qquad (A1)$$

[24] See the MHLW website for the normal EAS program (https://www.mhlw.go.jp/stf/seisakunitsuite/bunya/koyou_roudou/koyou/kyufukin/pageL07_20200515.html, in Japanese) and for the special EAS program to the COVID-19 (https://www.mhlw.go.jp/stf/seisakunitsuite/bunya/koyou_roudou/koyou/kyufukin/pageL07.html, in Japanese).

where h_{it} denotes the number of new hires in occupation i during period t; u_{it} and v_{it} are the number of job seekers and of vacancies in occupation i at the beginning of period t, respectively; and $m(\cdot)$ is the strictly increasing concave function in u_{it} and v_{it} and is homogeneous of degree one. $\Phi_t \phi_i$ represents the matching efficiency, where Φ_t and ϕ_i are the time-specific and the time-invariant occupation-specific components, respectively.[25,26] The matching efficiencies and vacancies that vary across occupational labor markets are presented. The matching function determines the number of new hires h_{it} once the number of job seekers u_{it} is allocated to the labor market.

Here, a social planner is assumed to allocate job seekers across occupational labor markets at no cost to maximize the number of new hires nationwide, given the matching efficiencies and number of vacancies. For all occupational labor markets i and j, the condition for maximizing is:

$$\phi_i m_{ui}\left(\frac{v_{it}}{u_{it}^*}\right) = \phi_j m_{uj}\left(\frac{v_{jt}}{u_{jt}^*}\right), \qquad (A2)$$

where $m_{ui}(\cdot)$ is a derivative of $m(\cdot)$ with respect to u_i and is written as a function of labor market tightness (i.e., the ratio of vacancies to job seekers) because $m(\cdot)$ follows a homogeneous degree of one. Consequently, u_{it}^* is the social planner's optimal allocation of job seekers.

Next, we describe the definition of the mismatch index. Here, the matching function of equation (A1) is assumed to follow the Cobb-Douglas specification:

$$h_{it} = \Phi_t \phi_i v_{it}^{\alpha} u_{it}^{1-\alpha}, \qquad (A3)$$

where $\alpha \in (0,1)$ is a parameter common across occupational labor markets. We obtain the optimal nationwide number of new hires h_{it}^* by aggregating equation (A3) for each

[25] Practically, we take a one-period lag for u_{it} and v_{it} in the dataset.
[26] Şahin et al. (2014) assume that ϕ follows ϕ_{it}, namely an idiosyncratic sectoral time effect. In this study, ϕ is assumed to follow ϕ_i, namely the time-invariant occupational effect.

occupational labor market, as follows:

$$h_t^* = \Phi_t v_t^{\alpha} u_t^{1-\alpha} \left[\sum_{i=1}^{I} \phi_i \left(\frac{v_{it}}{v_t} \right)^{\alpha} \left(\frac{u_{it}^*}{u_t} \right)^{1-\alpha} \right], \tag{A4}$$

where u_i and v_i are the aggregate numbers of job seekers and vacancies, respectively. Equation (A2) gives:

$$\frac{v_{it}}{u_{it}^*} = \left(\frac{\phi_j}{\phi_i} \right)^{\frac{1}{\alpha}} \frac{v_{jt}}{u_{jt}^*}. \tag{A5}$$

Substituting equation (A5) into equation (A4), the optimal number of new hires is given by

$$h_t^* = \bar{\phi}_t \Phi_t v_t^{\alpha} u_t^{1-\alpha}, where\ \bar{\phi}_t = \left[\sum_{i=1}^{I} \phi_i^{\frac{1}{\alpha}} \left(\frac{v_{it}}{v_t} \right) \right]^{\alpha}.$$

Finally, we obtain the following mismatch index, which measures the fraction of actual new hires to optimal new hires as a counterfactual:

$$\mathcal{M}_{\phi t} = 1 - \frac{h_t}{h_t^*} = 1 - \sum_{i=1}^{I} \left(\frac{\phi_i}{\bar{\phi}_t} \right) \left(\frac{v_{it}}{v_t} \right)^{\alpha} \left(\frac{u_{it}}{u_t} \right)^{1-\alpha}. \tag{A6}$$

The range of values that this index can take is between zero and one. The magnitude of this index represents the fraction of matches lost due to misallocation of job seekers. A significant feature of this index is that it accounts for the heterogeneity of matching efficiencies across occupational labor markets. When the matching efficiencies are identical across occupational labor markets, this mismatch index equals the conventional mismatch index proposed by Jackman and Roper (1987). This conventional index underestimates mismatch because it ignores the heterogeneity of matching efficiencies (Kawata 2019).

To calculate the mismatch index in equation (A6), we can use the data on "persons

who found employment," "active applicants," and "active job openings" for h_{it}, u_{it}, and v_{it}, respectively. These variables are obtained from the ERGW/RES provided by the MHLW. We obtain the matching efficiencies Φ_t and ϕ_i by estimating the matching function. By dividing both sides of equation (A3) by u_{it}, log-linearizing, and adding an error term ε_{it}, we obtain the following regression model.

$$\ln f_{it} = \gamma' trend_t + \ln \phi_i + \alpha \ln \theta_{it} + \varepsilon_{it}, \qquad (A7)$$

where $f_{it} \equiv h_{it}/u_{it}$ is the job finding rate; $\theta_{it} \equiv v_{it}/u_{it}$ is labor market tightness; and $trend_t$ is a vector of two elements for a quadratic time trend that captures Φ_t.[27] Following Kawata (2019), who estimates the mismatch index of Şahin et al. (2014) using the same Japanese data we use, we can obtain ϕ_i by estimating equation (A7) as a fixed effect model. Note that occupations that contain zero new hires for one or more periods are omitted from the sample because they cannot be logged. Following Şahin et al. (2014), we also assume the parameter $\alpha = 0.5$ for all occupational and both full-time and part-time workers' labor markets when we calculate the mismatch index of equation (A6). To estimate equation (A7), we utilize data from June 2016 to December 2019, before the COVID-19 pandemic.

Next, using the mismatch indices, Şahin et al. (2014) also propose a method to measure the counterfactual unemployment rate, u_t^*, which the social planner's optimal allocation excludes mismatch in the economy. Equation (A6) can induce the optimal job finding rate f_t^*, as follows:

$$f_t^* = f_t \frac{1}{1 - \mathcal{M}_{\phi t}} \left(\frac{u_t}{u_t^*} \right)^{\alpha},$$

where f_t is the actual job finding rate in the economy. Given the initial counterfactual unemployment rate u_0^*, the counterfactual unemployment rate is obtained in the

[27] We do not employ cubic or quartic time trends because they are omitted from the regressions.

following transition form:

$$u_{t+1}^{*} = s_t + (1 - s_t - f_t^{*})u_t^{*},$$

where s_t denotes the separation rate. We obtain the actual unemployment rate u_t, from the Labor Force Survey (LFS) conducted by the Statistics Bureau of the Ministry of Internal Affairs and Communications.[28] We assume that the initial counterfactual unemployment rate equals u_0^{*} the actual unemployment rate. The actual separation rate s_t and actual job finding rate f_t are calculated using the worker flow data in the LFS.[29,30] Finally, the gap between the actual and optimal unemployment rates $(u_t - u_t^{*})$ indicates the mismatch unemployment rate.

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[28] The LFS data for this study are obtained from the e-stat (https://www.e-stat.go.jp).

[29] The monthly LFS surveys the same households for two consecutive months, while half of the households are replaced in the sample. Thus, the data only capture the worker flows of half of the sample. As a result, the data on flow are not consistent with the data on stock that are made public each month. To deal with this problem, we adjust the flow data using the method proposed by Ministry of Labour (1986), following Lin and Miyamoto (2012).

[30] Job finding rates nationwide calculated by the ERGW/RES are lower than by the LFS probably because the job seekers registered in the public employment office have disadvantageous characteristics, as mentioned in Section 2. Consequently, the counterfactual unemployment rates using job finding rates from the ERGW/RES exhibit lower than the actual ones, resulting in negative unemployment rates. We thus use the job finding rates based on the LFS to calculate the counterfactual unemployment rates.

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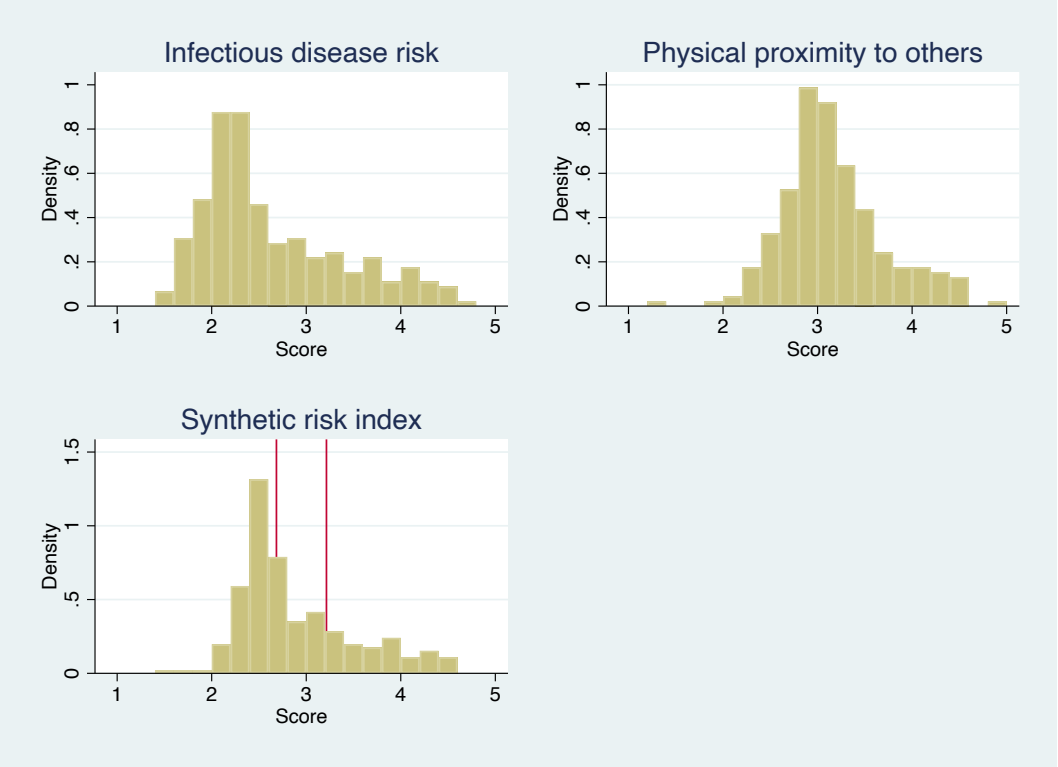
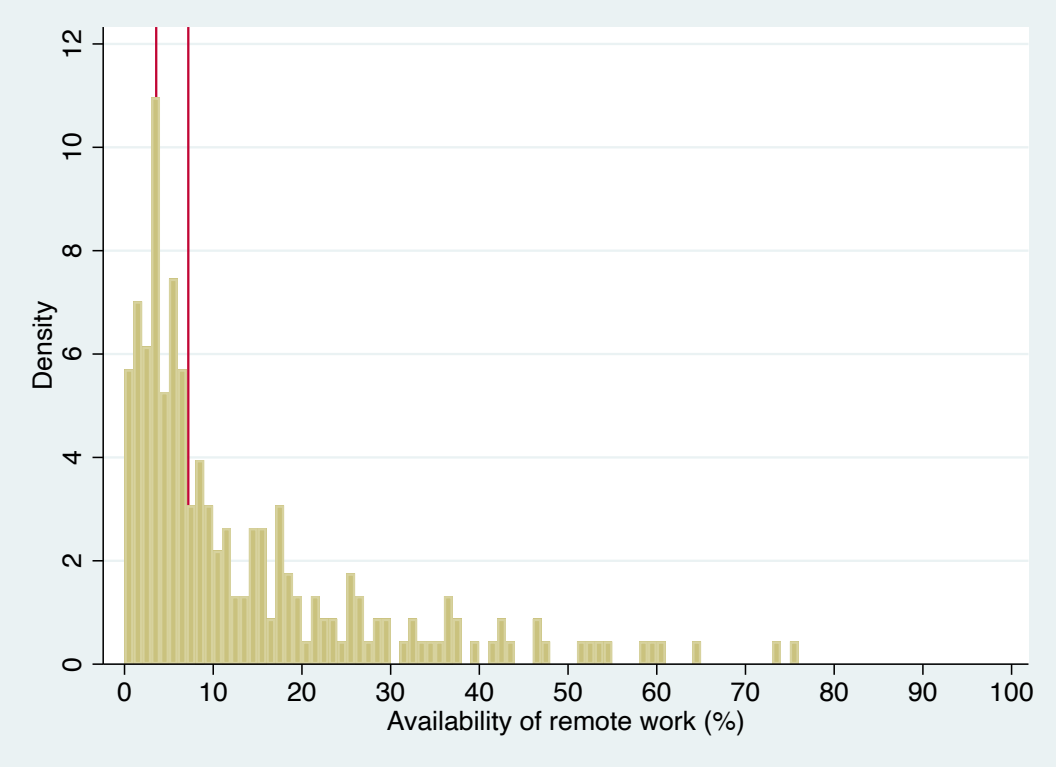
Figure 1: Distribution of Risk Indices



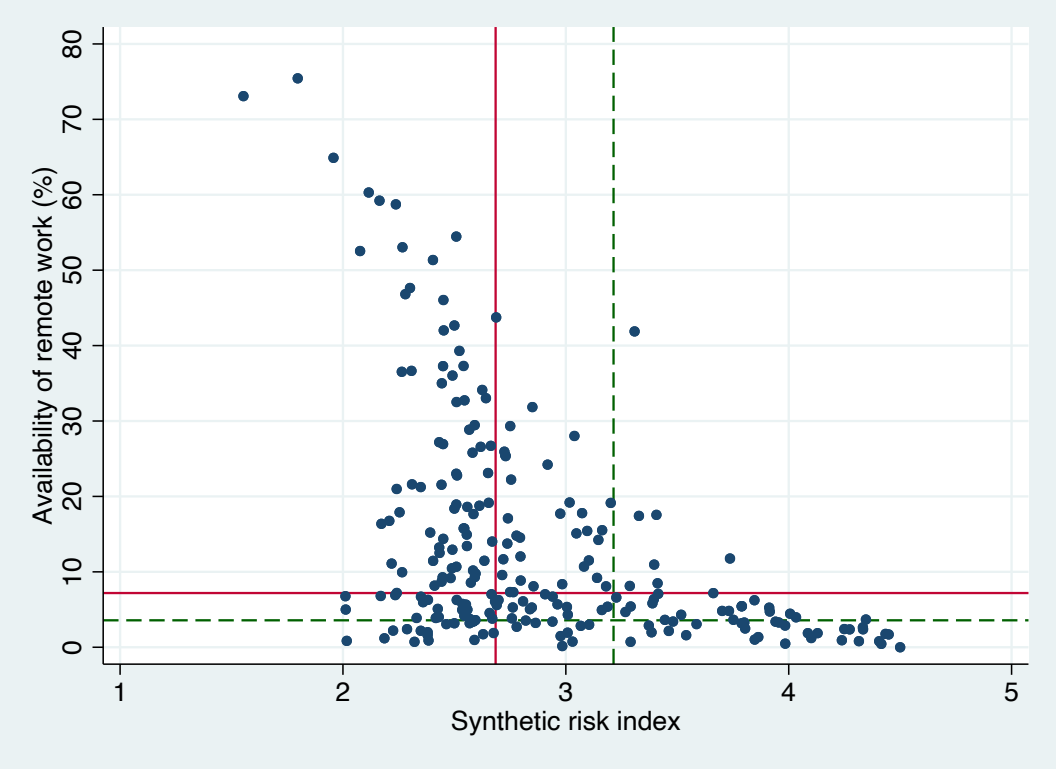
Notes: The "synthetic risk index" is the arithmetic mean of "infection disease risk" and "physical proximity." Vertical lines in the panel for the synthetic risk index indicate, from left to right, 50 and 75 percentile points, respectively.

Figure 2: Distribution of Availability of Remote Work



Notes: Availability of remote work is the sum of the proportion of respondents weighted by the median of the range of percentages of remote work availability for each choice. The median of each choice is: (1) = 0%; (2) = 10%; (3) = 30%; (4) = 50%; (5) = 70%; (6) = 90%. Vertical lines indicate, from right to left (from the largest), 50 and 75 percentile points, respectively.

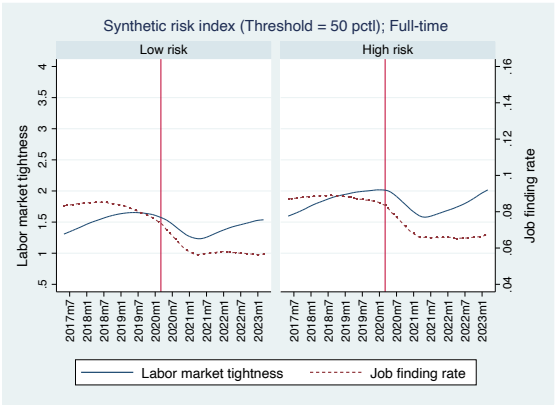
Figure 3: Scatter Plot of Synthetic Risk Index versus Availability of Remote Work



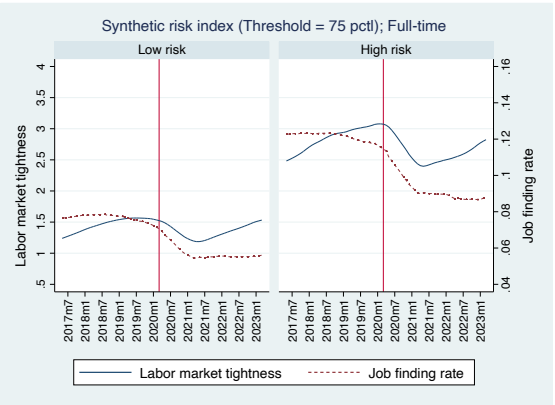
Notes: The solid red and dashed green vertical lines indicate 50 and 75 percentile points of the synthetic risk index, respectively. The solid red and dashed green horizontal lines indicate 50 and 75 percentile points of the availability of remote work, respectively.

Figure 4: Trends in Labor Market Tightness and Job Finding Rate by Low- and High-risk Occupational Group

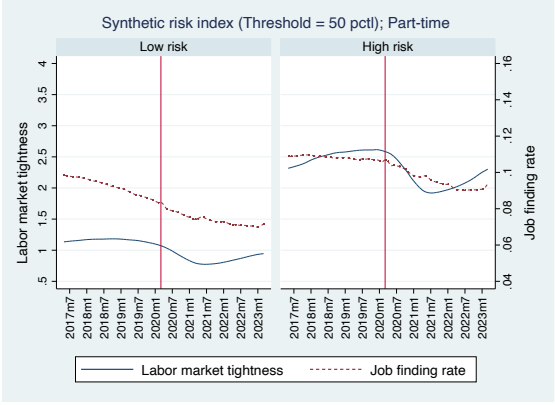
(a) Full-Time Workers (the 50th percentile of the synthetic risk index)



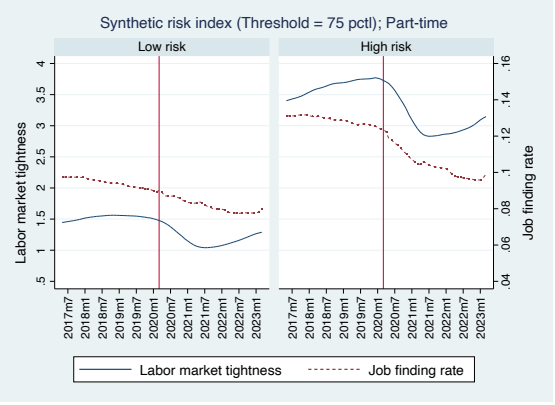
(b) Full-Time Workers (the 75th percentile of the synthetic risk index)



(c) Part-Time Workers (the 50th percentile of the synthetic risk index)



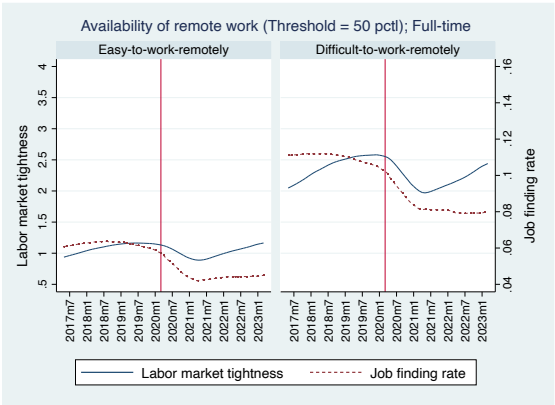
(d) Part-Time Workers (the 75th percentile of the synthetic risk index)



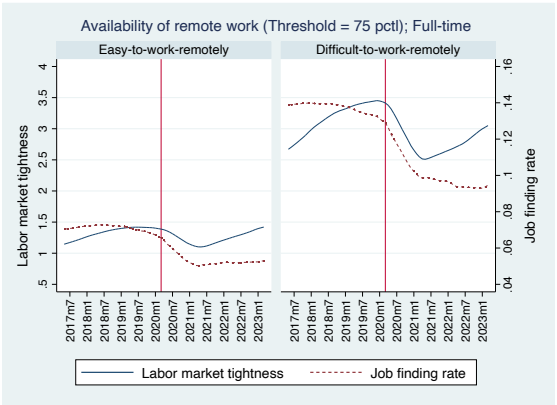
Notes: Job finding rate = new hires/job seekers. Labor market tightness = vacancies/job seekers. The 12-month backward moving averages of the mean values of the occupational groups are plotted. The vertical line indicates March 2020.

Figure 5: Trends in Labor Market Tightness and Job Finding Rate by Easy- and Difficult-to-Work-Remotely Occupational Group

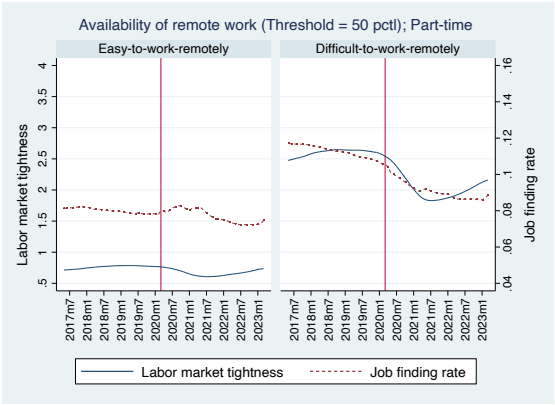
(a) Full-Time Workers (the 50th percentile of the availability of remote work)



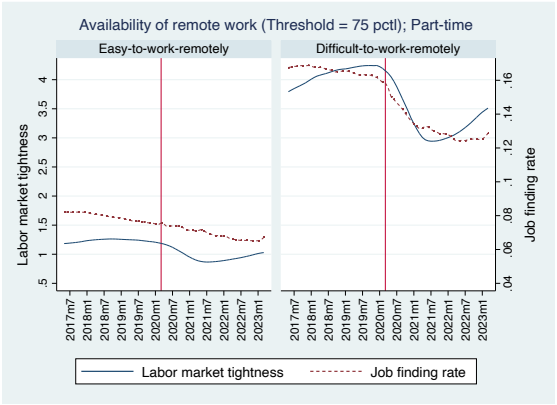
(b) Full-Time Workers (the 75th percentile of the availability of remote work)



(c) Part-Time Workers (the 50th percentile of the availability of remote work)



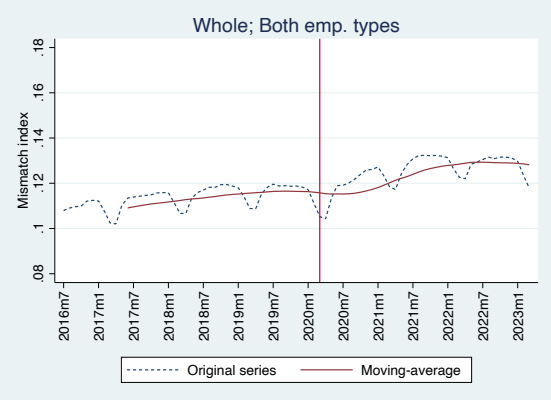
(d) Part-Time Workers (the 75th percentile of the availability of remote work)



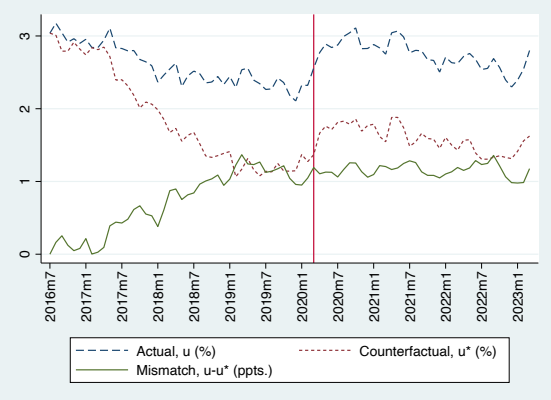
Notes: Job finding rate = new hires/job seekers. Labor market tightness = vacancies/job seekers. The 12-month backward moving averages of the mean values of the occupational groups are plotted. The vertical line indicates March 2020.

Figure 6: Mismatch across Occupations

(a) Mismatch index



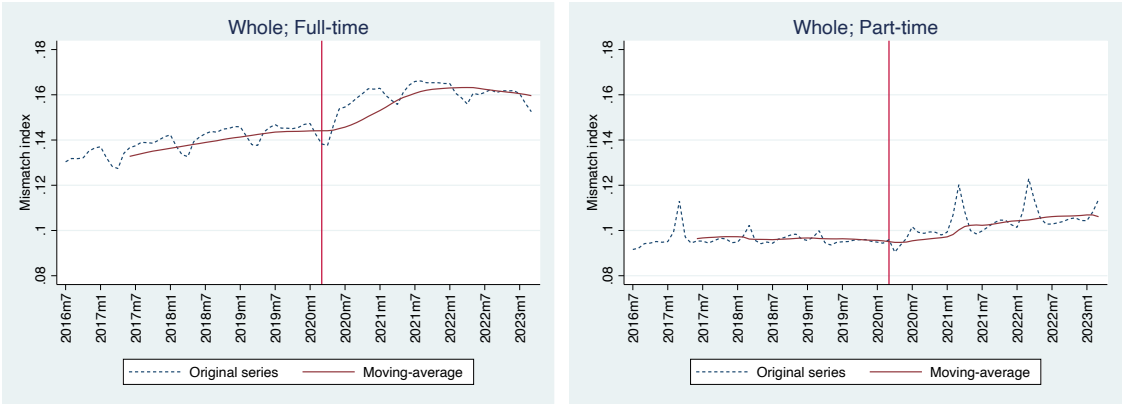
(b) Mismatch unemployment rate



Notes: The vertical line indicates March 2020.

Figure 7: Mismatch across Occupations for Full-time and Part-time Workers

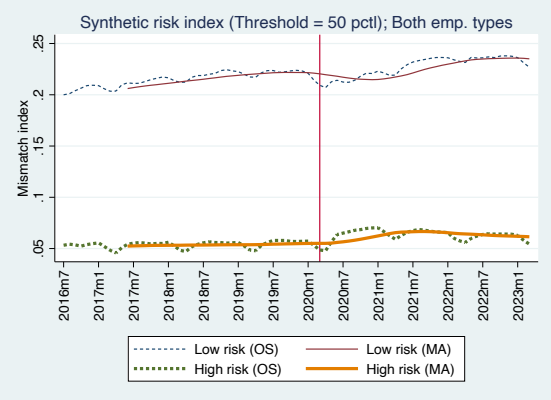
(a) Full-time workers (b) Part-time workers



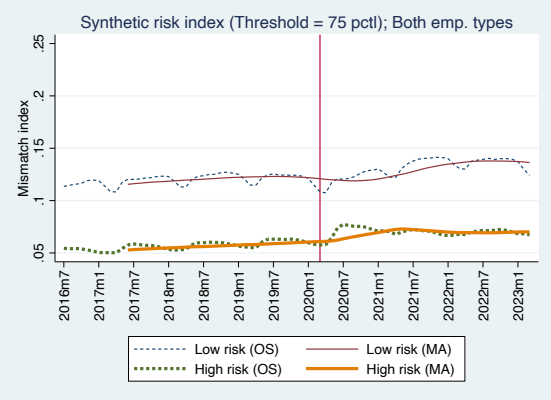
Notes: The vertical line indicates March 2020.

Figure 8: Mismatch across Occupations by Low- and High-risk Occupational Group

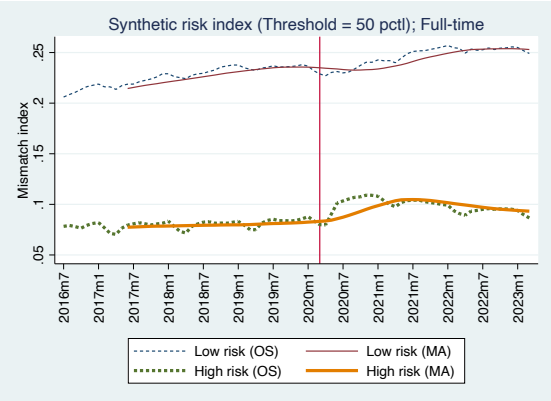
(a) Both employment types (the 50th percentile of the synthetic risk index)



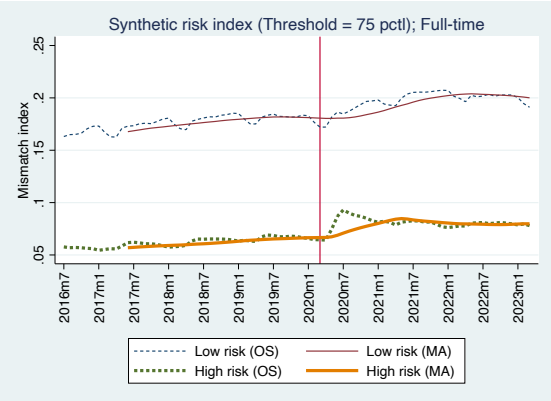
(b) Both employment types (the 75th percentile of the synthetic risk index)



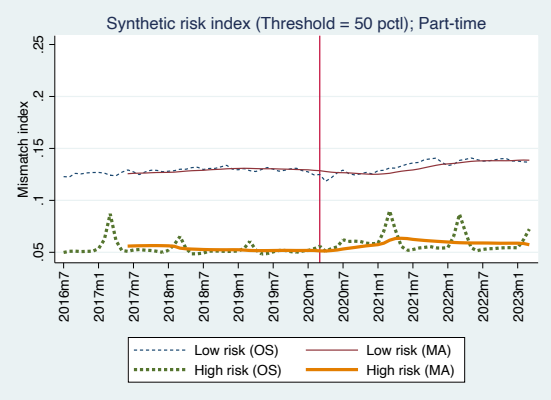
(c) Full-Time Workers (the 50th percentile of the synthetic risk index)



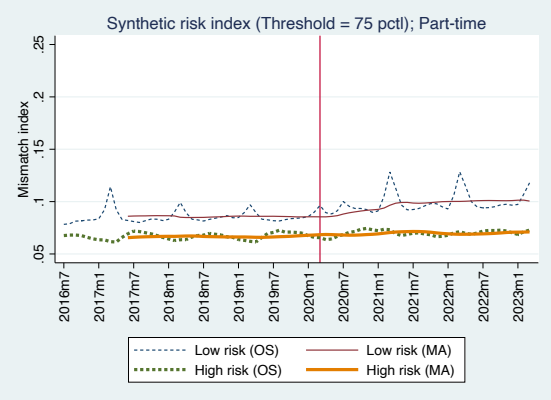
(d) Full-Time Workers (the 75th percentile of the synthetic risk index)



(e) Part-Time Workers (the 50th percentile of the synthetic risk index)



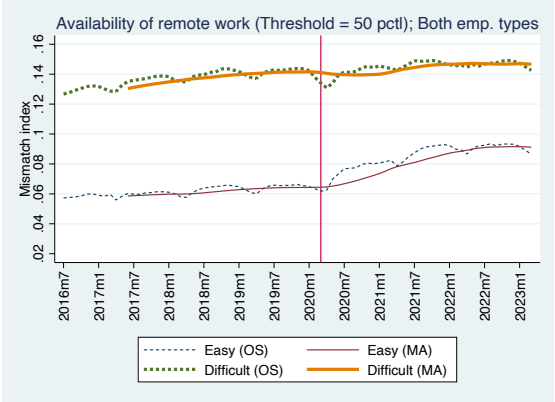
(f) Part-Time Workers (the 75th percentile of the synthetic risk index)



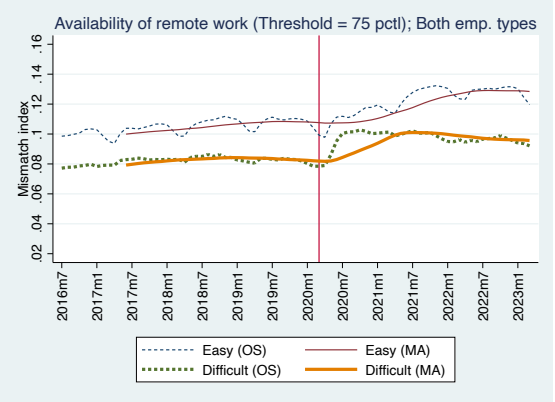
Notes: OS and MA are the original series and 12-month backward moving averages, respectively. The vertical line indicates March 2020.

Figure 9: Mismatch across Occupations by Easy- and Difficult-to-Work-Remotely Occupational Group

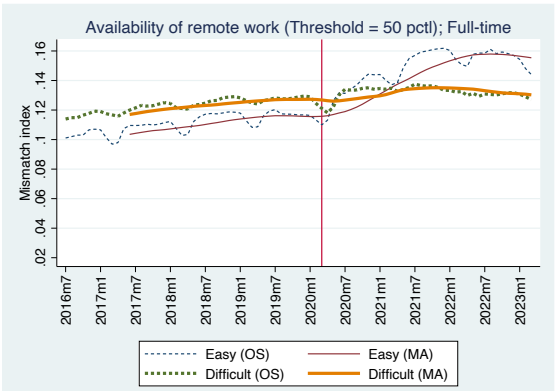
(a) Both employment types (the 50th percentile of the synthetic risk index)



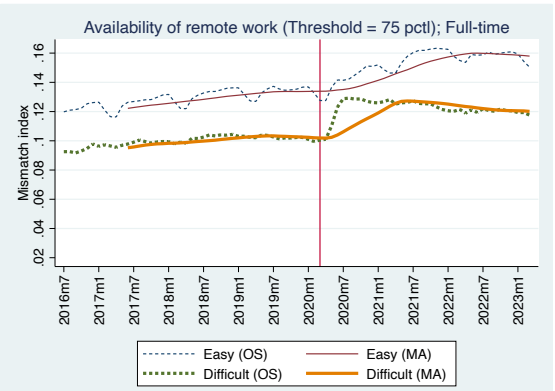
(b) Both employment types (the 75th percentile of the synthetic risk index)



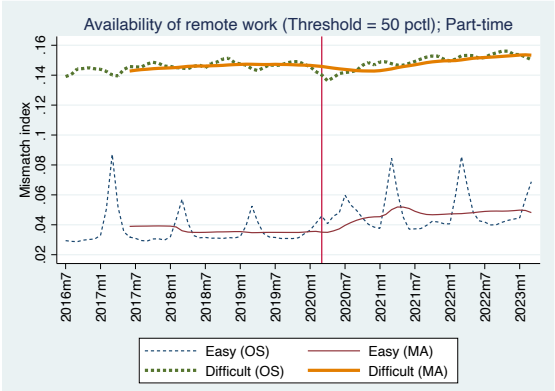
(c) Full-Time Workers (the 50th percentile of the synthetic risk index)



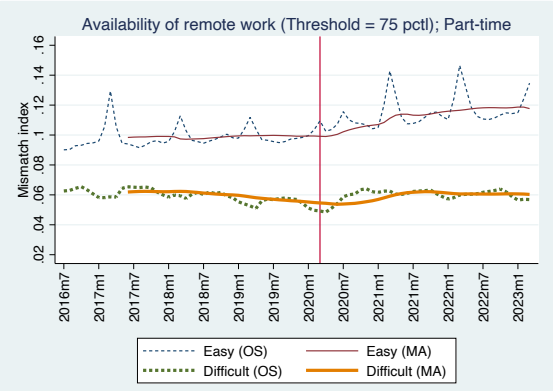
(d) Full-Time Workers (the 75th percentile of the synthetic risk index)



(e) Part-Time Workers (the 50th percentile of the synthetic risk index)



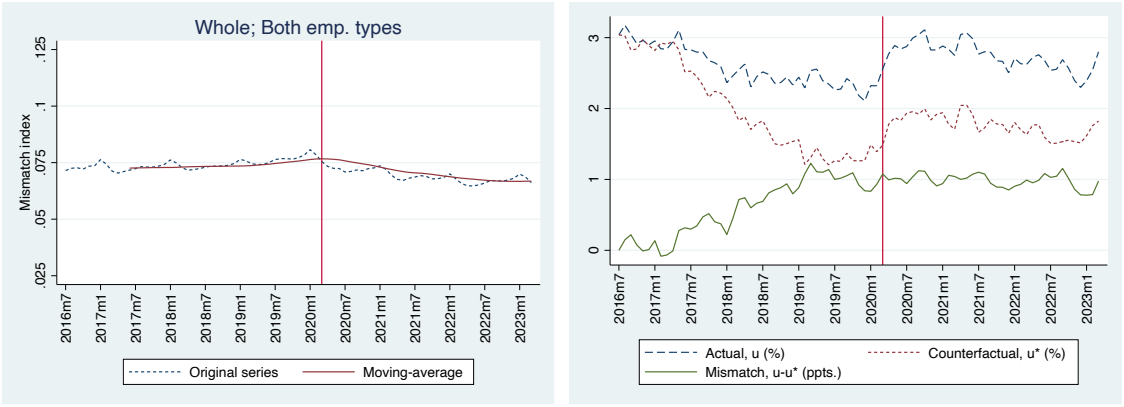
(f) Part-Time Workers (the 75th percentile of the synthetic risk index)



Notes: OS and MA are the original series and 12-month backward moving averages, respectively. The vertical line indicates March 2020.

Figure 10: Mismatch across Occupational Clusters with Different Infection Risks

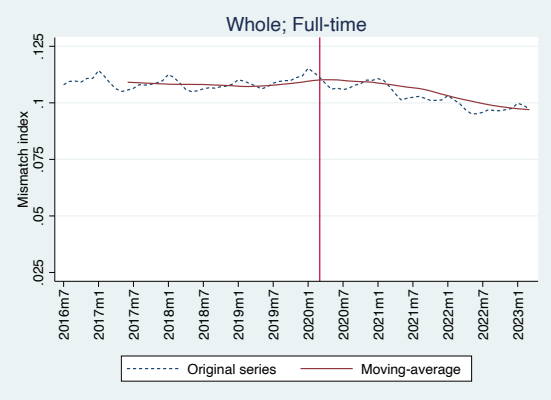
(a) Mismatch index (b) Mismatch unemployment rate



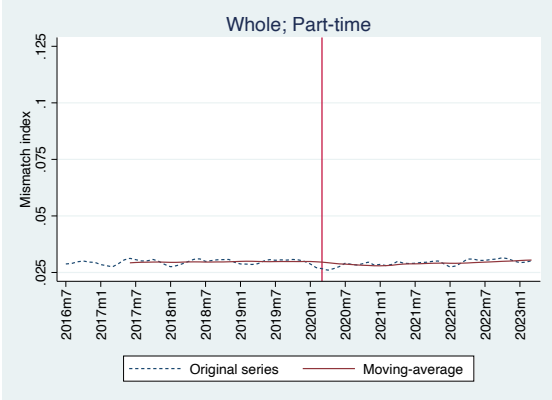
Notes: The vertical line indicates March 2020.

Figure 11: Mismatch across Occupational Clusters with Different Infection Risks for Full-time and Part-time Workers

(a) Full-time workers



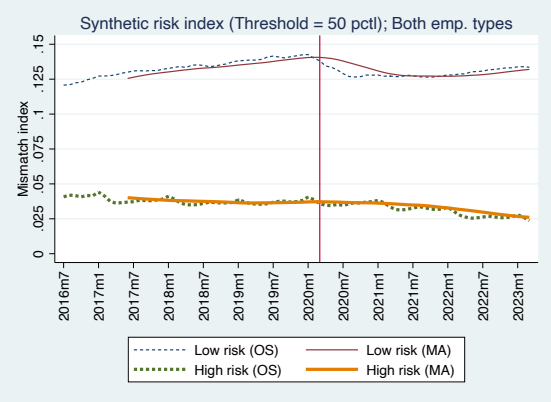
(b) Part-time workers



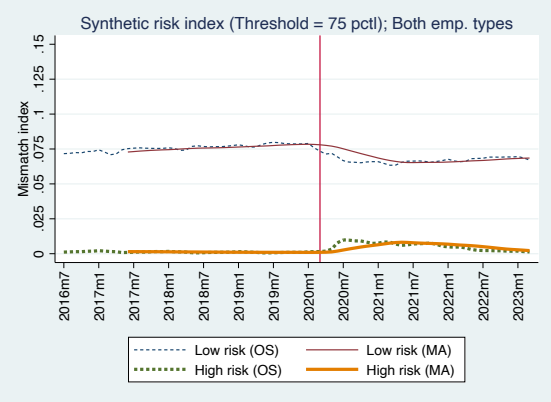
Notes: The vertical line indicates March 2020.

Figure 12: Mismatch across Occupational Clusters with Different Infection Risks by Low- and High-risk Occupational Group

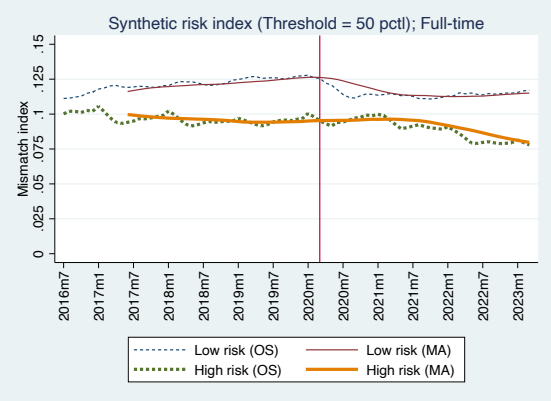
(a) Both employment types (the 50th percentile of the synthetic risk index)



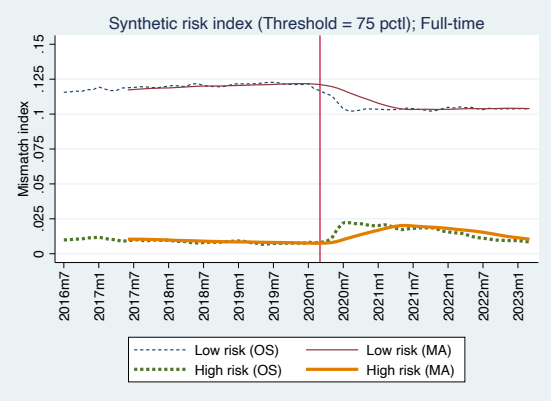
(b) Both employment types (the 75th percentile of the synthetic risk index)



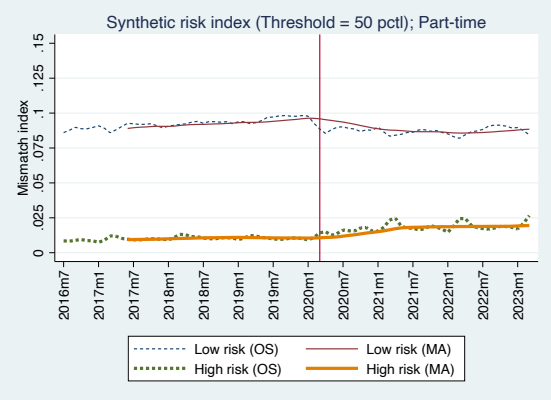
(c) Full-Time Workers (the 50th percentile of the synthetic risk index)



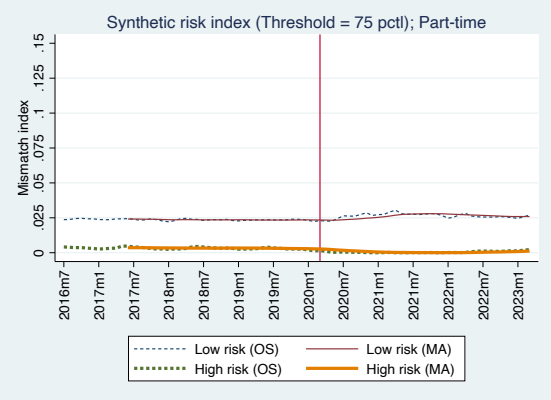
(d) Full-Time Workers (the 75th percentile of the synthetic risk index)



(e) Part-Time Workers (the 50th percentile of the synthetic risk index)



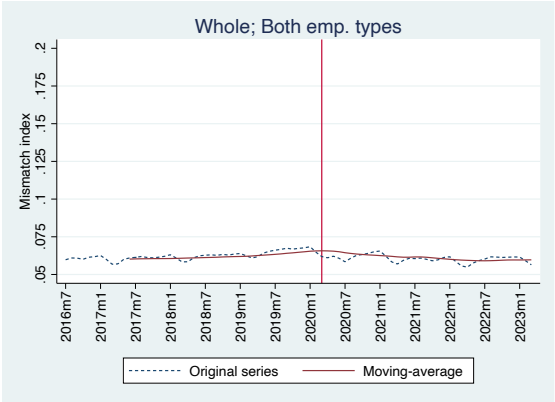
(f) Part-Time Workers (the 75th percentile of the synthetic risk index)



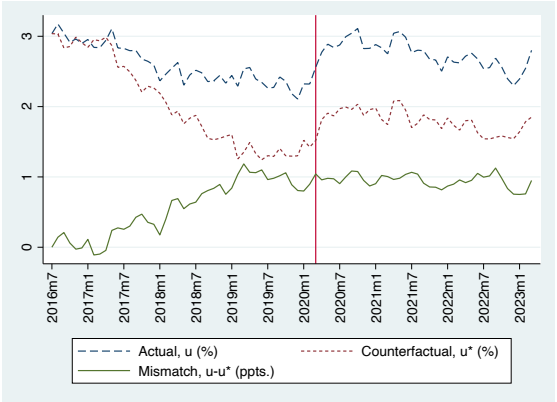
Notes: OS and MA are the original series and 12-month backward moving averages, respectively. Vertical line indicates March 2020.

Figure 13: Mismatch across Occupational Clusters with Different Availability of Remote Work

(a) Mismatch index



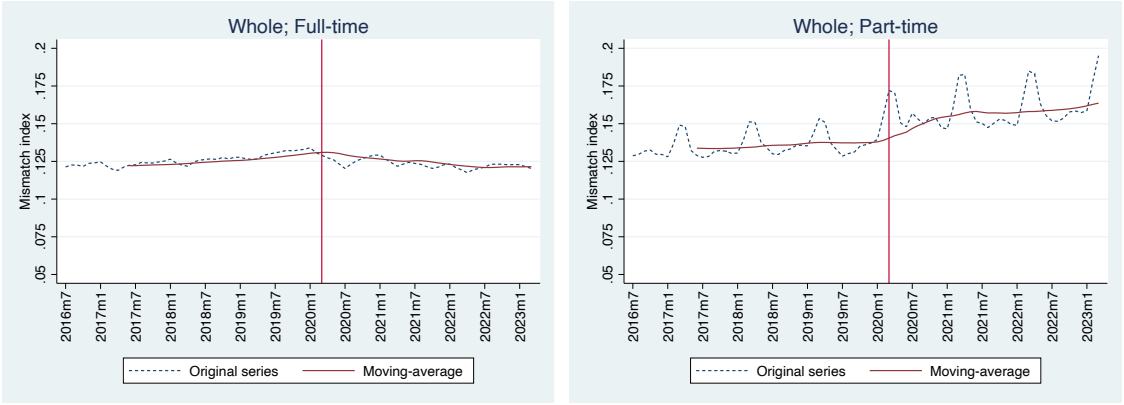
(b) Mismatch unemployment rate



Notes: The vertical line indicates March 2020.

Figure 14: Mismatch across Occupational Clusters with Different Availability of Remote Work for Full-time and Part-time Workers

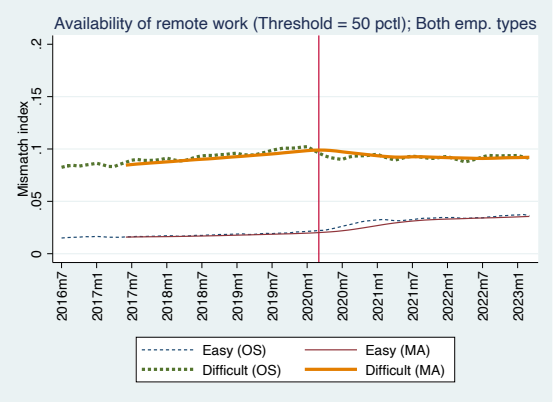
(a) Full-time workers (b) Part-time workers



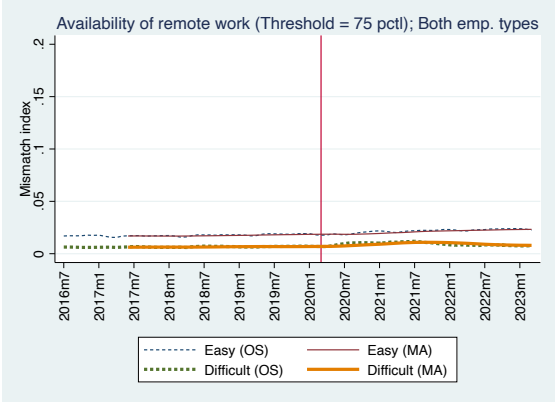
Notes: The vertical line indicates March 2020.

Figure 15: Mismatch across Occupational Clusters with Different Availability of Remote Work by Easy- and Difficult-to-Work-Remotely Occupational Group

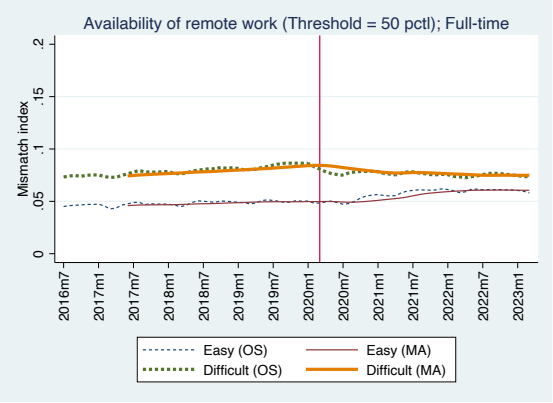
(a) Both employment types (the 50th percentile of the synthetic risk index)



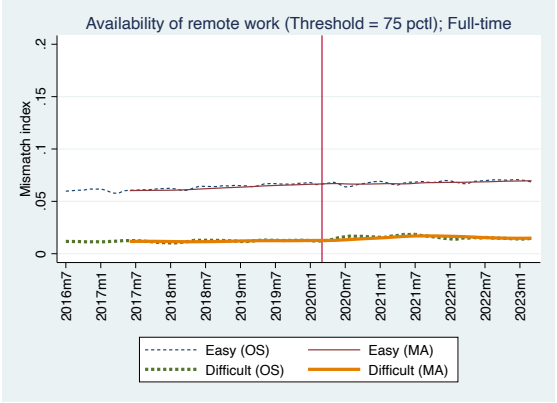
(b) Both employment types (the 75th percentile of the synthetic risk index)



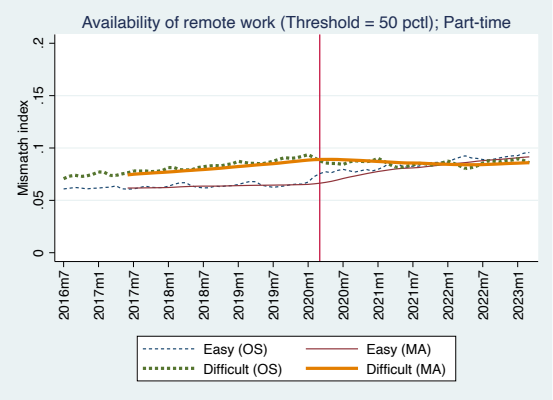
(c) Full-Time Workers (the 50th percentile of the synthetic risk index)



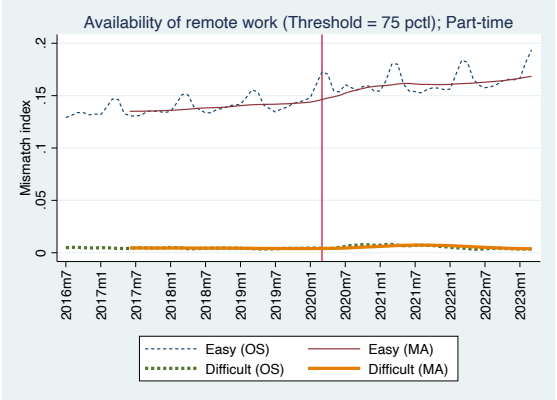
(d) Full-Time Workers (the 75th percentile of the synthetic risk index)



(e) Part-Time Workers (the 50th percentile of the synthetic risk index)



(f) Part-Time Workers (the 75th percentile of the synthetic risk index)



Notes: OS and MA are the original series and 12-month backward moving averages, respectively. The vertical line indicates March 2020.

Online Appendix for "Did COVID-19 Deteriorate Mismatch in the Japanese Labor Market?"

This Online Appendix provides supplemental tables and figures.

Table OA.1

This table shows the differences in three variables (number of job seekers, vacancies, and new hires by employment type) between 228 occupations with O-NET data, including the sample for this study, and the remaining 141 occupations without O-NET data, excluding from this study.

Table OA.2

This table shows the occupation list, indicating which occupations are classified as low-risk, high-risk, easy-to-work-remotely, and difficult-to-work-remotely. It also indicates the sample occupations used to measure the mismatch indices for both full-time and part-time workers.

Table OA.3

This table shows the three alternative thresholds for distinguishing between easy- and difficult-to-work-remotely occupations. The first threshold, labeled TW1, separates (1) from the remaining choices. If the proportion of (1) exceeds that of the sum of the rest of the choices in an occupation, the occupation is categorized as "difficult-to-work-remotely," and workers engaging in the occupation are defined as those not allowed to work remotely. Otherwise, we interpret that those workers engage in "easy-to-work remotely" occupations. The second threshold (TW2) extends the definition of "difficult-to-work-remotely." TW2 distinguishes (1) and (2) from the rest of the choices. The third threshold (TW3) further extends the definition of "difficult-to-work-remotely," namely (1), (2), and (3) versus (4), (5), and (6). We further narrow the standard for the availability of remote work by changing the threshold from TW1 to TW3. According to TW1, 171 out of 228 occupations are defined as "difficult-to-work-remotely" occupations, but the rest of them

(57 occupations) are categorized as “easy-to-work-remotely.” According to TW2 and TW3, the number of “easy-to-work-remotely” occupations is smaller, suggesting that fewer workers are allowed to work remotely.

Figure OA.1

This figure shows the method to construct the dataset.

Figure OA.2

This figure shows the comparison of trends of labor market tightness and job finding rate between occupations with and without O-NET data. It also shows the trends for all occupations in the Employment Referrals for General Workers (Report on Employment Service) as a benchmark.

Figure OA.3

This figure shows the distribution of respondents by each choice about availability of remote work in the O-NET questionnaire.

Figure OA.4

This figure shows the comparison of trends in labor market tightness and job finding rate between occupations included in and excluded from the sample for the mismatch indices. It also shows the trends for occupations in the full sample as a benchmark.

Figure OA.5

This figure shows trends in labor market tightness and job finding rate by easy- and difficult-to-remote-work occupational group based on alternative definition, show in Table OA.3. The results are similar to those in Figure 5 in the main text.

Figure OA.6

This figure shows that trends in mismatch indices by easy- and difficult-to-remote-work occupational group based on alternative definition, show in Table OA.3. The results are similar to those in Figure 9 in the main text.

Table OA.1: Comparison of Mean Values of New Hires, Job seekers, and Vacancies between Occupations Excluded from and Included in the Sample

Variable	(1) With O-NET (Obs=18,696 (=228 occ x 82 months))	(2) Without O-NET (Obs=11,562 (=141 occ x 82 months))	(1)/(2)
Panel A: Full-time			
New hires	262.68	40.70	6.45
Active applications	3489.44	498.91	6.99
Vacancies	5813.94	647.30	8.98
Panel B: Part-time			
New hires	183.34	20.63	8.89
Active applications	1942.31	226.70	8.57
Vacancies	3481.57	266.22	13.08

Notes: Occupations included in (excluded from) the sample represent those (not) included in the Japanese-style O-NET among occupations recorded in the Employment Referrals for General Workers (Report on Employment Service). However, occupations without necessary variables for the analyses are also excluded from the sample even if they are in the Japanese-style O-NET.

Table OA.2: List of Occupations in the Sample

Code	Occupation	Synthetic risk index (1–5)	Availabiliy of remote work (%)	Occupational group: Synthetic risk index: 50 pctl.	Synthetic risk index: 75 pctl.	Availabiliy of remote work: 50 pctl.	Availabiliy of remote work: 75 pctl.	Availabiliy of remote work (Alternative definition): TW1	TW2	TW3	Sample for mismatch indices: Both emp. types	Full-time	Part-time	Occupational clusters: Infectious risk	Availability of remote work
21	Company officers	2.35	21.24	Low	Low	Easy	Easy	Difficult	Difficult	Difficult				2	2
31	Company management staff	3.05	15.10	High	Low	Easy	Easy	Difficult	Difficult	Difficult	Y	Y		6	3
39	Other corporations, organization management staff	3.80	2.49	High	High	Difficult	Difficult	Difficult	Difficult	Difficult	Y	Y		8	7
51	Researchers	2.44	35.01	Low	Low	Easy	Easy	Easy	Easy	Difficult	Y	Y	Y	2	1
61	Agriculture, forestry, and fishery engineers	2.23	6.92	Low	Low	Difficult	Easy	Difficult	Difficult	Difficult	Y	Y		1	5
71	Food engineers (development)	2.67	14.02	Low	Low	Easy	Easy	Difficult	Difficult	Difficult	Y	Y		4	3
72	Electrical, electronic, telecommunications engineers (except communication network engineers) (development)	2.62	26.58	Low	Low	Easy	Easy	Easy	Difficult	Difficult	Y	Y		4	2
73	Machinery engineers (development)	2.51	32.52	Low	Low	Easy	Easy	Easy	Easy	Difficult	Y	Y	Y	3	1
77	Chemical engineers (development)	2.45	26.94	Low	Low	Easy	Easy	Easy	Difficult	Difficult				2	2
81	Food engineers (except development)	2.49	12.94	Low	Low	Easy	Easy	Difficult	Difficult	Difficult	Y	Y	Y	3	3
82	Electrical, electronic, telecommunications technicians (except communication network engineers) (except development)	2.50	42.67	Low	Low	Easy	Easy	Easy	Easy	Difficult	Y	Y	Y	3	1
87	Chemistry engineers (except development)	2.21	16.76	Low	Low	Easy	Easy	Easy	Difficult	Difficult	Y	Y		1	3
91	Architectural engineers	2.65	23.10	Low	Low	Easy	Easy	Easy	Difficult	Difficult	Y	Y	Y	4	2
92	Civil engineers	2.51	22.78	Low	Low	Easy	Easy	Easy	Difficult	Difficult	Y	Y	Y	3	2
93	Surveyors	2.59	9.32	Low	Low	Easy	Easy	Difficult	Difficult	Difficult	Y	Y	Y	4	4
101	System consultants	1.96	64.90	Low	Low	Easy	Easy	Easy	Easy	Easy	Y	Y		1	1
102	System designers	2.28	46.82	Low	Low	Easy	Easy	Easy	Easy	Easy	Y	Y		1	1
103	Data processing project managers	2.24	58.73	Low	Low	Easy	Easy	Easy	Easy	Easy				1	1
104	Software creators	2.27	53.04	Low	Low	Easy	Easy	Easy	Easy	Easy	Y	Y	Y	1	1
105	System operation managers	2.45	42.02	Low	Low	Easy	Easy	Easy	Easy	Difficult	Y	Y		2	1
106	Communication network engineers	2.64	33.03	Low	Low	Easy	Easy	Easy	Easy	Difficult	Y	Y		4	1
109	Other data processing and communication engineers	2.12	60.30	Low	Low	Easy	Easy	Easy	Easy	Easy	Y	Y	Y	1	1
119	Other engineers	2.66	26.71	Low	Low	Easy	Easy	Easy	Difficult	Difficult	Y	Y	Y	4	2
121	Doctors	4.03	3.97	High	High	Difficult	Easy	Difficult	Difficult	Difficult				8	6
122	Dental surgeons	4.50	0.00	High	High	Difficult	Difficult	Difficult	Difficult	Difficult				8	8
123	Veterinary surgeons	3.86	1.35	High	High	Difficult	Difficult	Difficult	Difficult	Difficult	Y			8	8
124	Pharmacists	3.91	5.25	High	High	Difficult	Easy	Difficult	Difficult	Difficult	Y	Y	Y	8	6
131	Public health nurses	3.52	4.31	High	High	Difficult	Easy	Difficult	Difficult	Difficult	Y	Y	Y	7	6
132	Midwives	4.45	1.70	High	High	Difficult	Difficult	Difficult	Difficult	Difficult	Y	Y	Y	8	8
133	Nurses (including assistant nurses)	4.35	3.68	High	High	Difficult	Easy	Difficult	Difficult	Difficult	Y	Y	Y	8	6
141	Diagnostic radiographers	4.42	0.45	High	High	Difficult	Difficult	Difficult	Difficult	Difficult	Y	Y	Y	8	8
142	Clinical engineers	4.13	1.87	High	High	Difficult	Difficult	Difficult	Difficult	Difficult	Y	Y		8	8
143	Clinical laboratory technicians	3.98	0.48	High	High	Difficult	Difficult	Difficult	Difficult	Difficult	Y	Y	Y	8	8
144	Physiotherapists	4.33	2.64	High	High	Difficult	Difficult	Difficult	Difficult	Difficult	Y	Y	Y	8	7
145	Occupational therapists	4.33	2.38	High	High	Difficult	Difficult	Difficult	Difficult	Difficult	Y	Y	Y	8	7
146	Certified orthoptists, speech therapists	4.25	2.42	High	High	Difficult	Difficult	Difficult	Difficult	Difficult	Y	Y	Y	8	7
147	Dental hygienists	4.09	1.87	High	High	Difficult	Difficult	Difficult	Difficult	Difficult	Y	Y	Y	8	8
148	Dental technicians	2.98	0.16	High	Low	Difficult	Difficult	Difficult	Difficult	Difficult	Y	Y		6	8
151	Nutritionists	3.39	6.37	High	High	Difficult	Easy	Difficult	Difficult	Difficult	Y	Y	Y	7	5
152	Masseurs, chiropractors, acupuncturists, and moxacauterists	4.10	1.23	High	High	Difficult	Difficult	Difficult	Difficult	Difficult	Y	Y	Y	8	8
153	Judo-orthopedists	4.43	1.77	High	High	Difficult	Difficult	Difficult	Difficult	Difficult	Y	Y	Y	8	8
159	Health care workers not classified elsewhere	3.41	17.56	High	High	Easy	Easy	Easy	Difficult	Difficult	Y	Y	Y	7	3
161	Welfare counseling guidance professionals	3.66	7.18	High	High	Difficult	Easy	Difficult	Difficult	Difficult	Y	Y	Y	7	5
162	Welfare facility guidance professionals	3.94	3.40	High	High	Difficult	Difficult	Difficult	Difficult	Difficult	Y	Y	Y	8	7
163	Childcare workers	4.32	0.81	High	High	Difficult	Difficult	Difficult	Difficult	Difficult	Y	Y	Y	8	8
169	Other social welfare specialist professionals	3.85	6.24	High	High	Difficult	Easy	Difficult	Difficult	Difficult	Y	Y	Y	8	5
173	Attorneys	2.43	27.19	Low	Low	Easy	Easy	Easy	Difficult	Difficult				2	2
174	Patent attorneys	2.16	59.22	Low	Low	Easy	Easy	Easy	Easy	Easy				1	1
175	Judicial scriveners	2.54	15.76	Low	Low	Easy	Easy	Difficult	Difficult	Difficult	Y	Y		3	3
179	Other legal workers	2.27	9.95	Low	Low	Easy	Easy	Difficult	Difficult	Difficult	Y	Y	Y	1	4
181	Certified public accountants	2.51	54.46	Low	Low	Easy	Easy	Easy	Easy	Easy				3	1
182	Licensed tax accountants	2.51	18.93	Low	Low	Easy	Easy	Easy	Difficult	Difficult	Y	Y		3	2
183	Certified social insurance and labor consultant	2.51	23.01	Low	Low	Easy	Easy	Easy	Difficult	Difficult	Y	Y	Y	3	2
184	Finance and insurance professionals	2.45	46.04	Low	Low	Easy	Easy	Easy	Easy	Easy				2	1
189	Other management, finance, and insurance professionals	2.54	37.30	Low	Low	Easy	Easy	Easy	Easy	Difficult	Y	Y		3	1
191	Kindergarten teachers	3.79	5.45	High	High	Difficult	Easy	Difficult	Difficult	Difficult	Y	Y	Y	7	5
192	Elementary school teachers	3.79	5.43	High	High	Difficult	Easy	Difficult	Difficult	Difficult	Y	Y	Y	7	5
193	Junior high school teachers	3.41	7.09	High	High	Difficult	Easy	Difficult	Difficult	Difficult	Y	Y		7	5
194	Senior high school teachers	3.33	17.42	High	High	Easy	Easy	Difficult	Difficult	Difficult	Y	Y	Y	7	3
196	Special needs education school teachers	3.74	11.77	High	High	Easy	Easy	Difficult	Difficult	Difficult	Y		Y	7	3
199	Other teachers	3.16	15.52	High	Low	Easy	Easy	Difficult	Difficult	Difficult	Y	Y	Y	6	3
211	Authors	1.80	75.44	Low	Low	Easy	Easy	Easy	Easy	Easy	Y			1	1
212	Journalists	2.30	47.64	Low	Low	Easy	Easy	Easy	Easy	Easy	Y	Y		1	1
213	Editors	2.40	51.35	Low	Low	Easy	Easy	Easy	Easy	Easy	Y	Y	Y	2	1
222	Painters, calligraphers	1.55	73.08	Low	Low	Easy	Easy	Easy	Easy	Easy				1	1
224	Designers	2.08	52.54	Low	Low	Easy	Easy	Easy	Easy	Easy	Y	Y	Y	1	1
225	Photographers, film operators	2.84	5.05	High	Low	Difficult	Easy	Difficult	Difficult	Difficult	Y	Y	Y	5	6
234	Producers and directors	3.10	15.42	High	Low	Easy	Easy	Difficult	Difficult	Difficult	Y	Y		6	3
241	Librarians	3.10	2.99	High	Low	Difficult	Difficult	Difficult	Difficult	Difficult	Y	Y	Y	6	7
242	Curators	2.73	25.47	High	Low	Easy	Easy	Easy	Difficult	Difficult	Y			5	2
243	Counselors (except medical and welfare facilities)	2.97	17.72	High	Low	Easy	Easy	Easy	Difficult	Difficult	Y	Y	Y	6	3
244	Private tutors	3.15	14.24	High	Low	Easy	Easy	Difficult	Difficult	Difficult	Y	Y	Y	6	3
246	Communication equipment operators	2.74	17.09	High	Low	Easy	Easy	Easy	Difficult	Difficult	Y	Y		5	3
249	Specialist professionals not classified elsewhere	2.52	39.30	Low	Low	Easy	Easy	Easy	Easy	Difficult	Y	Y	Y	3	1
251	General affairs workers	2.57	28.85	Low	Low	Easy	Easy	Easy	Difficult	Difficult	Y	Y	Y	3	2
252	Human affairs workers	2.63	34.12	Low	Low	Easy	Easy	Easy	Easy	Difficult	Y	Y	Y	4	1
253	Planning clerical workers	2.45	37.28	Low	Low	Easy	Easy	Easy	Easy	Difficult	Y	Y	Y	2	1
254	Reception and guidance clerical workers	3.16	4.94	High	Low	Difficult	Easy	Difficult	Difficult	Difficult	Y	Y	Y	6	6
255	Secretaries	2.49	36.03	Low	Low	Easy	Easy	Easy	Easy	Difficult	Y	Y	Y	3	1
256	Telephone receptionists	2.79	14.54	High	Low	Easy	Easy	Difficult	Difficult	Difficult	Y	Y	Y	5	3

257	Comprehensive clerical workers	2.73	25.35	High	Low	Easy	Easy	Easy	Difficult	Difficult	Y	Y	Y	5	2
258	Medical and care clerical workers	3.70	4.82	High	High	Difficult	Easy	Difficult	Difficult	Difficult	Y	Y	Y	7	6
259	Other general clerical workers	2.58	25.80	Low	Low	Easy	Easy	Easy	Difficult	Difficult	Y	Y	Y	4	2
261	Cash disbursement and receipt clerks	3.02	19.20	High	Low	Easy	Easy	Easy	Difficult	Difficult	Y	Y	Y	6	2
262	Deposit counter clerks	3.07	2.84	High	Low	Difficult	Difficult	Difficult	Difficult	Difficult	Y	Y	Y	6	7
263	Accountants business clerks	2.25	17.90	Low	Low	Easy	Easy	Difficult	Difficult	Difficult	Y	Y	Y	1	3
271	Production sites clerical workers	2.56	14.94	Low	Low	Easy	Easy	Easy	Difficult	Difficult	Y	Y	Y	3	3
281	Sales clerks	2.72	25.94	High	Low	Easy	Easy	Easy	Difficult	Difficult	Y	Y	Y	5	2
289	Other sales clerical workers	3.20	19.14	High	Low	Easy	Easy	Difficult	Difficult	Difficult	Y	Y	Y	6	2
299	Other outdoor service workers	2.24	7.20	Low	Low	Easy	Easy	Difficult	Difficult	Difficult	Y	Y	Y	1	4
301	Passenger / freight clerical workers	3.75	3.64	High	High	Difficult	Easy	Difficult	Difficult	Difficult	Y	Y	Y	7	6
302	Transportation management clerical workers	2.94	6.71	High	Low	Difficult	Easy	Difficult	Difficult	Difficult	Y	Y	Y	6	5
312	Data entry device operators	2.24	20.99	Low	Low	Easy	Easy	Difficult	Difficult	Difficult	Y	Y	Y	1	2
321	Retailers, retail manager	3.29	8.13	High	High	Easy	Easy	Difficult	Difficult	Difficult	Y	Y	Y	7	4
323	Shop assistants	3.19	5.38	High	Low	Difficult	Easy	Difficult	Difficult	Difficult	Y	Y	Y	6	5
325	Home visit and mobile sales workers	2.45	14.38	Low	Low	Easy	Easy	Difficult	Difficult	Difficult	Y	Y	Y	2	3
333	Stock dealers, Stock brokers, finance brokers	2.26	36.53	Low	Low	Easy	Easy	Easy	Difficult	Difficult				1	1
339	Other quasi-sales workers	2.91	7.03	High	Low	Difficult	Easy	Difficult	Difficult	Difficult	Y	Y	Y	5	5
343	Medicine sales workers	3.31	41.88	High	High	Easy	Easy	Easy	Easy	Difficult	Y	Y		7	1
344	Machinery sales workers (except communication equipment)	2.78	14.80	High	Low	Easy	Easy	Difficult	Difficult	Difficult	Y	Y		5	3
345	Communication and system sales workers	2.85	31.85	High	Low	Easy	Easy	Easy	Easy	Difficult	Y	Y		5	1
346	Finance and insurance sales workers	2.92	24.22	High	Low	Easy	Easy	Easy	Difficult	Difficult	Y	Y	Y	6	2
347	Real estate sales workers	3.07	17.79	High	Low	Easy	Easy	Easy	Difficult	Difficult	Y	Y	Y	6	3
349	Other sales workers	2.75	29.33	High	Low	Easy	Easy	Easy	Difficult	Difficult	Y	Y	Y	5	2
351	Housekeepers, home helpers	2.54	4.18	Low	Low	Difficult	Easy	Difficult	Difficult	Difficult	Y		Y	3	6
359	Other domestic support service workers	3.91	4.74	High	High	Difficult	Easy	Difficult	Difficult	Difficult	Y	Y	Y	8	6
361	Care workers (medical and welfare facilities, etc.)	4.24	0.93	High	High	Difficult	Difficult	Difficult	Difficult	Difficult	Y	Y	Y	8	8
362	Home visiting care workers	4.27	2.37	High	High	Difficult	Difficult	Difficult	Difficult	Difficult	Y	Y	Y	8	7
371	Care assistants	4.41	0.80	High	High	Difficult	Difficult	Difficult	Difficult	Difficult	Y	Y	Y	8	8
379	Other healthcare service workers	3.85	1.02	High	High	Difficult	Difficult	Difficult	Difficult	Difficult	Y	Y	Y	8	8
381	Hairdressers	3.98	2.88	High	High	Difficult	Difficult	Difficult	Difficult	Difficult	Y	Y	Y	8	7
382	Beauticians	3.80	3.28	High	High	Difficult	Difficult	Difficult	Difficult	Difficult	Y	Y	Y	8	7
383	Cosmetic service workers (except beauticians)	3.41	8.49	High	High	Easy	Easy	Difficult	Difficult	Difficult	Y	Y	Y	7	4
385	Launderers	3.01	4.32	High	Low	Difficult	Easy	Difficult	Difficult	Difficult	Y	Y	Y	6	6
391	Cooks	2.98	1.49	High	Low	Difficult	Difficult	Difficult	Difficult	Difficult	Y	Y	Y	6	8
392	Bartenders	3.37	2.88	High	High	Difficult	Difficult	Difficult	Difficult	Difficult				7	7
401	Restaurateurs, restaurant managers	3.44	3.63	High	High	Difficult	Easy	Difficult	Difficult	Difficult	Y	Y		7	6
402	Japanese inn owners and managers	3.29	5.41	High	High	Difficult	Easy	Difficult	Difficult	Difficult	Y	Y		7	5
403	Food and drink service workers	3.38	1.98	High	High	Difficult	Difficult	Difficult	Difficult	Difficult	Y	Y	Y	7	8
404	Japanese Inn, hotel, and transportation customer service workers	3.39	5.83	High	High	Difficult	Easy	Difficult	Difficult	Difficult	Y	Y	Y	7	5
406	Service workers in places of entertainment, etc.	3.48	3.41	High	High	Difficult	Difficult	Difficult	Difficult	Difficult	Y	Y	Y	7	7
411	Condominiums, apartment buildings, and lodging houses management personnel	2.42	3.88	Low	Low	Difficult	Easy	Difficult	Difficult	Difficult	Y	Y	Y	2	6
414	Car park management personnel	2.78	2.72	High	Low	Difficult	Difficult	Difficult	Difficult	Difficult	Y	Y	Y	5	7
421	Travel and tourist guides	3.40	10.97	High	High	Easy	Easy	Difficult	Difficult	Difficult	Y	Y	Y	7	4
423	Commodity hire workers	3.23	6.60	High	High	Difficult	Easy	Difficult	Difficult	Difficult	Y	Y	Y	7	5
425	Undertakers, crematorium workers	3.27	4.68	High	High	Difficult	Easy	Difficult	Difficult	Difficult	Y	Y	Y	7	6
426	Pet groomers	2.94	3.40	High	Low	Difficult	Difficult	Difficult	Difficult	Difficult	Y	Y	Y	6	7
429	Service workers not classified elsewhere	3.96	3.29	High	High	Difficult	Difficult	Difficult	Difficult	Difficult	Y	Y	Y	8	7
431	Self-defense officials	2.58	10.18	Low	Low	Easy	Easy	Difficult	Difficult	Difficult				4	4
441	Police officers	3.73	4.82	High	High	Difficult	Easy	Difficult	Difficult	Difficult				7	6
442	Maritime safety officials	2.75	7.32	High	Low	Easy	Easy	Difficult	Difficult	Difficult				5	4
451	Prison guards	3.54	1.60	High	High	Difficult	Difficult	Difficult	Difficult	Difficult				7	8
452	Firefighters	4.01	4.45	High	High	Difficult	Easy	Difficult	Difficult	Difficult	Y	Y		8	6
453	Security staff	3.03	0.75	High	Low	Difficult	Difficult	Difficult	Difficult	Difficult	Y	Y	Y	6	8
459	Other public security workers not classified elsewhere	2.82	3.55	High	Low	Difficult	Difficult	Difficult	Difficult	Difficult	Y	Y	Y	5	7
461	Crop farming workers	2.01	6.77	Low	Low	Difficult	Easy	Difficult	Difficult	Difficult	Y	Y	Y	1	5
462	Livestock farm workers	2.38	2.00	Low	Low	Difficult	Difficult	Difficult	Difficult	Difficult	Y	Y	Y	2	7
463	Landscape gardeners, nursery workers	2.22	2.21	Low	Low	Difficult	Difficult	Difficult	Difficult	Difficult	Y	Y	Y	1	7
471	Forest nursery workers	2.01	5.00	Low	Low	Difficult	Easy	Difficult	Difficult	Difficult	Y	Y	Y	1	6
481	Fishery workers	2.36	5.98	Low	Low	Difficult	Easy	Difficult	Difficult	Difficult	Y	Y		2	5
497	Metal sculpture and plating facility control and monitoring workers	2.70	6.26	High	Low	Difficult	Easy	Difficult	Difficult	Difficult	Y	Y		5	5
501	Chemical product manufacturing facility control and monitoring workers	2.59	17.67	Low	Low	Easy	Easy	Easy	Difficult	Difficult	Y	Y		4	3
505	Spinning, weaving, apparel, and fiber product manufacturing facility control and monitoring workers	2.33	3.88	Low	Low	Difficult	Easy	Difficult	Difficult	Difficult	Y	Y		2	6
507	Printing and bookbinding facility control and monitoring workers	2.41	8.17	Low	Low	Easy	Easy	Difficult	Difficult	Difficult	Y	Y		2	4
508	Rubber, plastic product manufacturing facility control and monitoring workers	2.59	29.46	Low	Low	Easy	Easy	Easy	Difficult	Difficult	Y	Y		4	2
512	Electro-mechanical apparatus assembly facility control and monitoring workers	2.75	22.23	High	Low	Easy	Easy	Difficult	Difficult	Difficult	Y	Y		5	2
523	Cast metal manufacturing workers	2.59	3.60	Low	Low	Difficult	Easy	Difficult	Difficult	Difficult	Y	Y	Y	4	6
524	Forging workers	2.51	6.27	Low	Low	Difficult	Easy	Difficult	Difficult	Difficult	Y	Y	Y	3	5
528	Numerical control metal machine tools workers	2.02	0.85	Low	Low	Difficult	Difficult	Difficult	Difficult	Difficult	Y	Y	Y	1	8
531	Metal press workers	2.46	3.07	Low	Low	Difficult	Difficult	Difficult	Difficult	Difficult	Y	Y	Y	3	7
532	Ironworkers, boilermakers	2.59	3.45	Low	Low	Difficult	Difficult	Difficult	Difficult	Difficult	Y	Y	Y	4	7
533	Sheet metal workers	2.32	0.72	Low	Low	Difficult	Difficult	Difficult	Difficult	Difficult	Y	Y	Y	1	8
536	Metal product manufacturing workers	2.38	6.29	Low	Low	Difficult	Easy	Difficult	Difficult	Difficult	Y	Y	Y	2	5
537	Metal welding and fusion cutting workers	2.35	6.71	Low	Low	Difficult	Easy	Difficult	Difficult	Difficult	Y	Y	Y	2	5
541	Chemical product manufacturing workers	2.50	18.39	Low	Low	Easy	Easy	Difficult	Difficult	Difficult	Y	Y	Y	3	2
542	Ceramic, earth, and stone product manufacturing workers	2.45	9.28	Low	Low	Easy	Easy	Difficult	Difficult	Difficult	Y	Y	Y	2	4
543	Cereal polishing, flour milling, and seasoned foods manufacturing workers	2.40	11.46	Low	Low	Easy	Easy	Difficult	Difficult	Difficult	Y	Y	Y	2	4
545	Bread and confectionery manufacturing workers	2.68	6.06	Low	Low	Difficult	Easy	Difficult	Difficult	Difficult	Y	Y	Y	4	5
546	Tofu, konjak jelly, wheat-gluten bread manufacturing workers	2.43	13.23	Low	Low	Easy	Easy	Difficult	Difficult	Difficult	Y	Y	Y	2	3
547	Canned and bottled foods manufacturing workers	2.80	12.04	High	Low	Easy	Easy	Difficult	Difficult	Difficult	Y	Y	Y	5	3

548	Milk and milk products manufacturing workers	2.56	18.61	Low	Low	Easy	Easy	Difficult	Difficult	Difficult	Y	Y	Y	3	2
551	Meat products manufacturing workers	2.43	5.09	Low	Low	Difficult	Easy	Difficult	Difficult	Difficult	Y	Y	Y	2	6
552	Fishery products manufacturing workers	2.49	10.47	Low	Low	Easy	Easy	Difficult	Difficult	Difficult	Y	Y	Y	3	4
553	Preserved foods manufacturing workers	2.44	8.70	Low	Low	Easy	Easy	Difficult	Difficult	Difficult	Y	Y	Y	2	4
554	Packed lunch products manufacturing workers	2.69	5.60	High	Low	Difficult	Easy	Difficult	Difficult	Difficult	Y	Y	Y	5	5
555	Vegetable pickle products manufacturing workers	2.57	3.80	Low	Low	Difficult	Easy	Difficult	Difficult	Difficult	Y	Y	Y	4	6
556	Beverage and cigarette manufacturing workers	2.56	13.43	Low	Low	Easy	Easy	Difficult	Difficult	Difficult	Y	Y	Y	3	3
558	Apparel and fiber product manufacturing workers	2.17	16.37	Low	Low	Easy	Easy	Difficult	Difficult	Difficult	Y	Y	Y	1	3
561	Wooden product manufacturing workers	2.22	11.10	Low	Low	Easy	Easy	Difficult	Difficult	Difficult	Y	Y	Y	1	4
562	Pulp, paper, and paper product manufacturing workers	2.59	3.43	Low	Low	Difficult	Difficult	Difficult	Difficult	Difficult	Y	Y	Y	4	7
563	Printing and bookbinding workers	2.60	9.77	Low	Low	Easy	Easy	Difficult	Difficult	Difficult	Y	Y	Y	4	4
565	Plastic product manufacturing workers	2.43	12.51	Low	Low	Easy	Easy	Difficult	Difficult	Difficult	Y	Y	Y	2	3
569	Other product manufacturing and processing workers (except metal products)	2.31	21.61	Low	Low	Easy	Easy	Difficult	Difficult	Difficult	Y	Y	Y	1	2
571	General-purpose, manufacturing, and business-use mechanical apparatus assembly workers	2.61	18.77	Low	Low	Easy	Easy	Difficult	Difficult	Difficult	Y	Y	Y	4	2
574	Electronic applied machinery and equipment assembly workers	3.04	28.02	High	Low	Easy	Easy	Easy	Easy	Difficult	Y	Y	Y	6	2
576	Semiconductor product manufacturing workers	2.48	9.18	Low	Low	Easy	Easy	Difficult	Difficult	Difficult	Y	Y		3	4
584	Automobile assembly workers	2.51	10.68	Low	Low	Easy	Easy	Difficult	Difficult	Difficult	Y	Y	Y	3	4
586	Weighing and measuring appliance assembly workers	2.63	11.47	Low	Low	Easy	Easy	Difficult	Difficult	Difficult	Y	Y	Y	4	4
587	Photo-optic mechanical apparatus assembly workers	2.54	15.75	Low	Low	Easy	Easy	Difficult	Difficult	Difficult	Y	Y		3	3
601	General-purpose mechanical apparatus maintenance and repair workers	2.65	19.16	Low	Low	Easy	Easy	Easy	Difficult	Difficult	Y	Y	Y	4	2
602	Electro-mechanical apparatus maintenance and repair workers	2.44	21.56	Low	Low	Easy	Easy	Difficult	Difficult	Difficult	Y	Y	Y	2	2
603	Automobile maintenance and repair workers	2.57	3.19	Low	Low	Difficult	Difficult	Difficult	Difficult	Difficult	Y	Y	Y	4	7
604	Transportation machinery maintenance and repair workers (except automobiles)	3.18	8.08	High	Low	Easy	Easy	Difficult	Difficult	Difficult	Y	Y	Y	6	4
612	Metal processing, welding, fusion cutting workers	2.56	4.99	Low	Low	Difficult	Easy	Difficult	Difficult	Difficult	Y	Y	Y	3	6
641	Painter	2.38	0.90	Low	Low	Difficult	Difficult	Difficult	Difficult	Difficult	Y	Y	Y	2	8
642	Painter, signboard production worker	2.31	36.65	Low	Low	Easy	Easy	Easy	Easy	Difficult	Y	Y		1	1
643	Drafting technicians	2.55	32.74	Low	Low	Easy	Easy	Easy	Difficult	Difficult	Y	Y	Y	3	1
651	Electric train drivers	3.01	1.94	High	Low	Difficult	Difficult	Difficult	Difficult	Difficult				6	8
661	Bus drivers	3.46	2.16	High	High	Difficult	Difficult	Difficult	Difficult	Difficult	Y	Y	Y	7	7
662	Passenger automobile drivers	3.79	3.18	High	High	Difficult	Difficult	Difficult	Difficult	Difficult	Y	Y	Y	7	7
663	Goods vehicle drivers	2.35	2.19	Low	Low	Difficult	Difficult	Difficult	Difficult	Difficult	Y	Y	Y	2	7
672	Navigation officers, navigators (except fishing boats), pilots	2.80	8.85	High	Low	Easy	Easy	Difficult	Difficult	Difficult				5	4
673	Ships' chief engineers, engineers (except fishing boats)	2.71	9.58	High	Low	Easy	Easy	Difficult	Difficult	Difficult				5	4
674	Aircraft pilots	3.08	10.70	High	Low	Easy	Easy	Easy	Difficult	Difficult				6	4
681	Conductors	3.59	3.07	High	High	Difficult	Difficult	Difficult	Difficult	Difficult				7	7
683	Deckhands, Ships stokers	3.14	9.20	High	Low	Easy	Easy	Difficult	Difficult	Difficult	Y	Y		6	4
684	Forklift operators	2.17	6.80	Low	Low	Difficult	Easy	Difficult	Difficult	Difficult	Y	Y	Y	1	5
689	Transport workers not classified elsewhere	2.69	43.74	High	Low	Easy	Easy	Easy	Easy	Easy	Y	Y	Y	5	1
691	Power plant and substation workers	2.39	15.21	Low	Low	Easy	Easy	Easy	Difficult	Difficult	Y	Y		2	3
692	Boiler operators	2.57	8.57	Low	Low	Easy	Easy	Difficult	Difficult	Difficult	Y	Y	Y	4	4
695	Construction, well-drilling machinery operators	2.19	1.19	Low	Low	Difficult	Difficult	Difficult	Difficult	Difficult	Y	Y		1	8
697	Building facility managers	2.86	3.23	High	Low	Difficult	Difficult	Difficult	Difficult	Difficult	Y	Y	Y	5	7
701	Molding box carpenters	2.55	5.66	Low	Low	Difficult	Easy	Difficult	Difficult	Difficult	Y	Y		3	5
702	Scaffolding workers	2.98	8.37	High	Low	Easy	Easy	Difficult	Difficult	Difficult	Y	Y	Y	6	4
703	Steel reinforcement workers	2.67	7.03	Low	Low	Difficult	Easy	Difficult	Difficult	Difficult	Y	Y		4	5
711	Carpenters	2.63	1.73	Low	Low	Difficult	Difficult	Difficult	Difficult	Difficult	Y	Y	Y	4	8
712	Block and tile laying workers	2.38	1.60	Low	Low	Difficult	Difficult	Difficult	Difficult	Difficult	Y	Y		2	8
714	Plasterers	2.29	2.40	Low	Low	Difficult	Difficult	Difficult	Difficult	Difficult	Y	Y		1	7
716	Pipe laying workers	2.85	5.27	High	Low	Difficult	Easy	Difficult	Difficult	Difficult	Y	Y		5	6
717	Interior finishers	2.66	4.54	Low	Low	Difficult	Easy	Difficult	Difficult	Difficult	Y	Y		4	6
718	Waterproofers	2.76	5.28	High	Low	Difficult	Easy	Difficult	Difficult	Difficult	Y	Y		5	5
721	Power line hanging and laying workers	2.72	11.67	High	Low	Easy	Easy	Difficult	Difficult	Difficult	Y	Y		5	3
725	Other electric construction workers	2.96	5.69	High	Low	Difficult	Easy	Difficult	Difficult	Difficult	Y	Y	Y	6	5
731	Civil engineering workers	2.54	5.75	Low	Low	Difficult	Easy	Difficult	Difficult	Difficult	Y	Y	Y	3	5
732	Railway line construction workers	2.86	8.09	High	Low	Easy	Easy	Difficult	Difficult	Difficult	Y	Y		5	4
752	Onboard and quayside cargo handlers	2.74	13.75	High	Low	Easy	Easy	Difficult	Difficult	Difficult	Y	Y		5	3
753	Land-based cargo handling and carrying workers	3.01	5.34	High	Low	Difficult	Easy	Difficult	Difficult	Difficult	Y	Y	Y	6	5
754	Warehouse workers	2.68	1.89	Low	Low	Difficult	Difficult	Difficult	Difficult	Difficult	Y	Y	Y	4	8
755	Delivery workers	2.76	3.84	High	Low	Difficult	Easy	Difficult	Difficult	Difficult	Y	Y	Y	5	6
756	Packing workers	2.43	4.00	Low	Low	Difficult	Easy	Difficult	Difficult	Difficult	Y	Y	Y	2	6
761	Building cleaning workers	2.59	0.97	Low	Low	Difficult	Difficult	Difficult	Difficult	Difficult	Y	Y	Y	4	8
762	House cleaning workers	2.81	6.09	High	Low	Difficult	Easy	Difficult	Difficult	Difficult	Y	Y	Y	5	5
764	Garbage and human waste treatment workers	3.29	0.72	High	High	Difficult	Difficult	Difficult	Difficult	Difficult	Y	Y	Y	7	8
765	Industrial waste treatment workers	2.76	7.31	High	Low	Easy	Easy	Difficult	Difficult	Difficult	Y	Y	Y	5	4
769	Other cleaning workers	3.10	11.51	High	Low	Easy	Easy	Difficult	Difficult	Difficult	Y	Y	Y	6	4
771	Packaging workers	2.67	3.80	Low	Low	Difficult	Easy	Difficult	Difficult	Difficult	Y	Y	Y	4	6
781	Sorters	2.50	3.18	Low	Low	Difficult	Difficult	Difficult	Difficult	Difficult	Y	Y	Y	3	7
782	Light-duty workers	2.53	4.96	Low	Low	Difficult	Easy	Difficult	Difficult	Difficult	Y	Y	Y	3	6

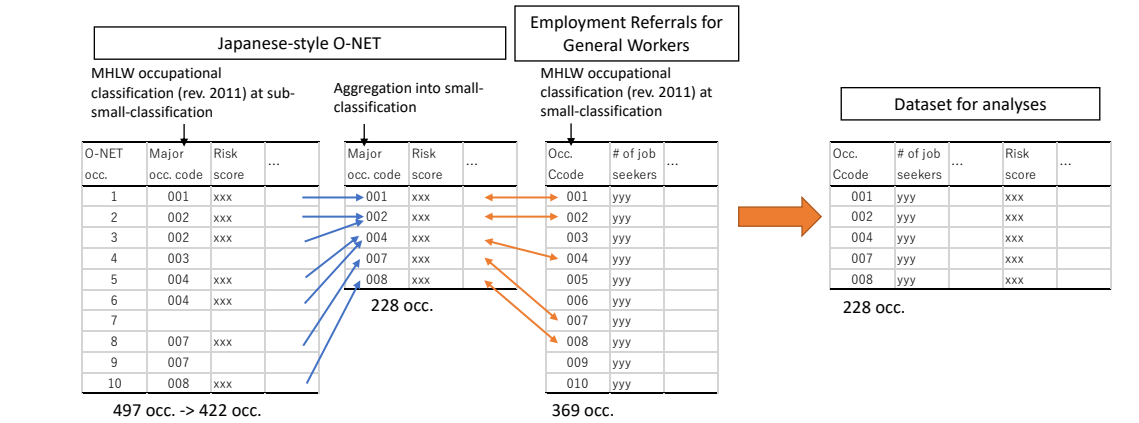
Notes: Occupation names are translated from Japanese into English by the authors referencing the Japan Standard Occupational Classification (Rev. 5th, December 2009) (https://www.soumu.go.jp/english/dgpp_ss/seido/shokgyou/co09-4a.htm), released by the Ministry of Internal Affairs and Communications, which is similar to the MHLW occupational classification. The value of occupational clusters represents that the occupations belong to the corresponding clusters: 1 = [0, 12.5] pctl.; 2= (12.5, 25] pctl.; 3 = (25, 37.5] pctl. 4 = (37.5, 50] pctl.; 5= (50, 62.5] pctl.; 6 = (62.5, 75] pctl.; 7 = (75, 87.5] pctl.; 8 = (87.5, 100] pctl.

Table OA.3: Occupational Group Defined by Remote Work Availability Based on Alternative Thresholds

Occupational group definition	Definition of difficult-to-work-remotely occupation	Number of occupations	
		Easy-to-work-remotely	Difficult-to-work-remotely
TW1	If the fraction of respondents is "(1)>(2)+(3)+(4)+(5)+(6)"	57	171
TW2	If the fraction of respondents is "(1)+(2)>(3)+(4)+(5)+(6)"	28	200
TW3	If the fraction of respondents is "(1)+(2)+(3)>(4)+(5)+(6)"	14	214

Notes: The values in parentheses indicate choices in the questionnaire: (1) usually, no; (2) 20% of days of duty and below; (3) 20% or more but below 40% of days of duty; (4) 40% or more but below 60% of days of duty; (5) 60% or more but below 80% of days of duty; and (6) 80% of days of duty and more.

Figure OA.1: Method to Construct the Dataset



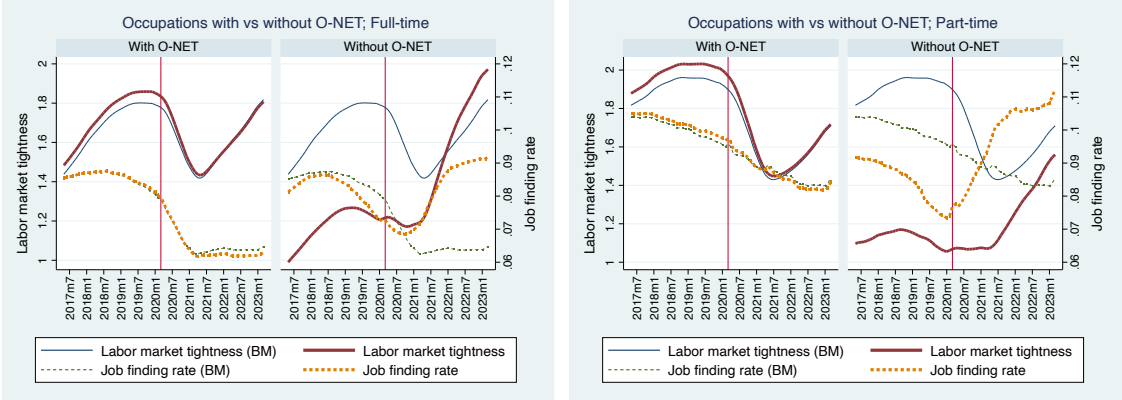
Aggregate occupations based on "major occupational classification code"
- Variables are transformed into arithmetical mean
- Seven occupations lacking "major occupational classification code" and 69 occupations without necessary variables for the analyses are excluded from the sample (one occupation lacks both of them).

Merge the two data based on occupational code (small-classification)
- Occupations that have no corresponding ones in the Japanese-style O-NET are excluded from the sample

Dataset (occupational panel)
- Scores in the Japanese-style O-NET are constant over time; thus, different periods of same occupation are assigned to the same scores.

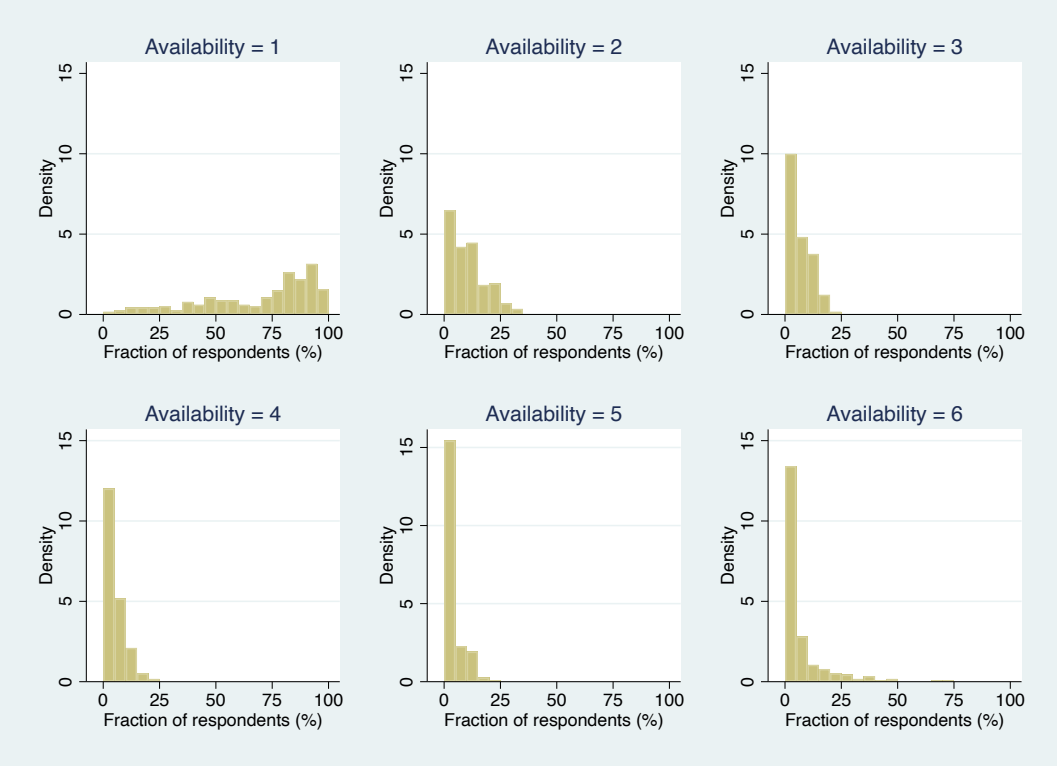
Figure OA.2: Trends in Labor Market Tightness and Job Finding Rate for Occupations with and without O-NET Data

(a) Full-time workers (b) Part-time workers



Notes: Job finding rate = new hires/job seekers. Labor market tightness = vacancies/job seekers. The 12-month backward moving averages of the mean values of the occupational groups are plotted. The vertical line indicates March 2020. BM indicates the benchmark, including all occupations in the Employment Referrals for General Workers (Report on Employment Service).

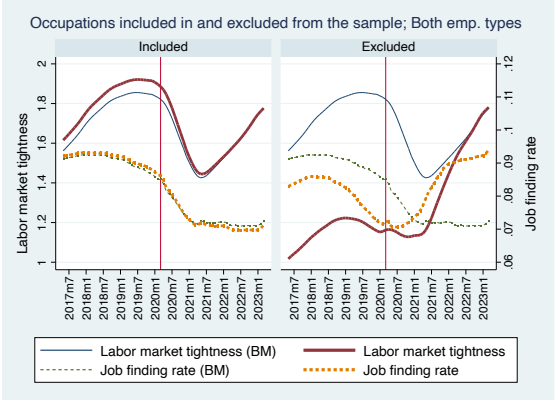
Figure OA.3: Distribution of Respondents by Each Choice about Availability of Remote Work



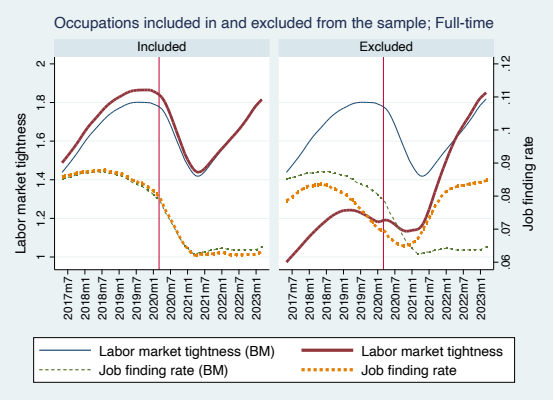
Notes: The value of availability for each panel indicates a choice in the questionnaire: (1) usually, no; (2) 20% of days of duty and below; (3) 20% or more but below 40% of days of duty; (4) 40% or more but below 60% of days of duty; (5) 60% or more but below 80% of days of duty; and (6) 80% of days of duty and more.

Figure OA.4: Trends in Labor Market Tightness and Job Finding Rate for Occupations Included and Excluded from the Sample for the Mismatch Indices

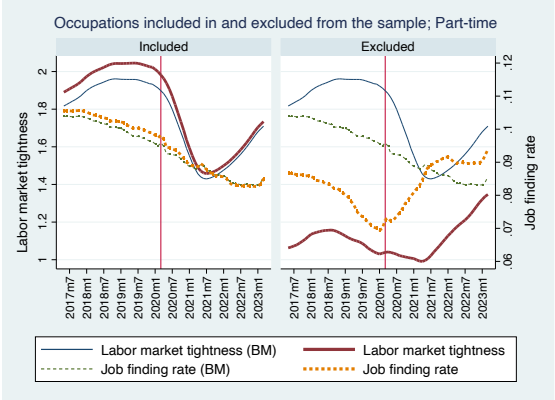
(a) Both employment types



(b) Full-time workers



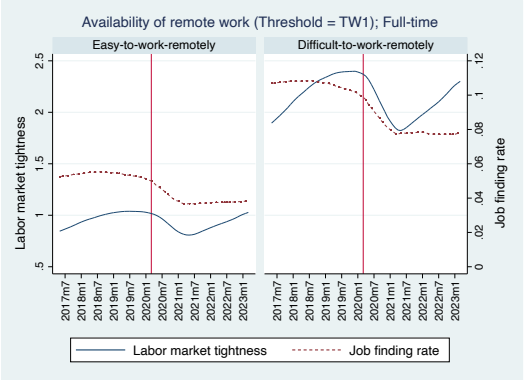
(c) Part-time workers



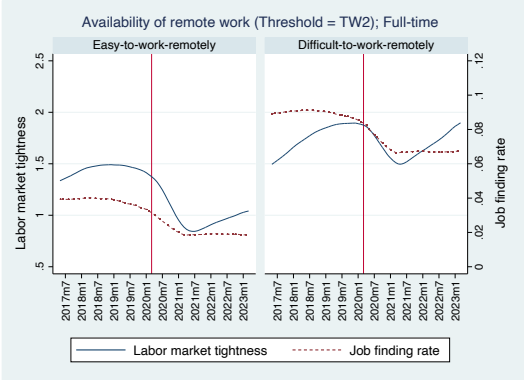
Notes: Job finding rate = new hires/job seekers. Labor market tightness = vacancies/job seekers. The 12-month backward moving averages of the mean values of the occupational groups are plotted. The vertical line indicates March 2020. BM indicates the benchmark, including occupations in the full sample merged with the Japanese-style O-NET. The full sample is divided into the occupations included and excluded from the sample to estimate the mismatch indices. The excluded occupations have zero new hires for one period or more. Labor market tightness and job finding rate can be calculated for the excluded sample because these variables are calculated by aggregating all occupations in this sample. Additionally, even if the number of new hires is zero for some occupations in some periods, it is not zero for other occupations simultaneously in this sample. As a result, the total number of new hires for the entire excluded sample is not zero across all periods.

Figure OA.5: Trends in Labor Market Tightness and Job Finding Rate by Easy- and Difficult-to-Work-Remotely Occupational Group Based on Alternative Definition

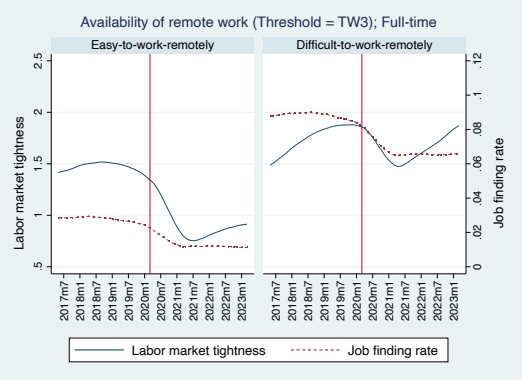
(a) Full-Time Workers (TW1 as the threshold of remote work availability)



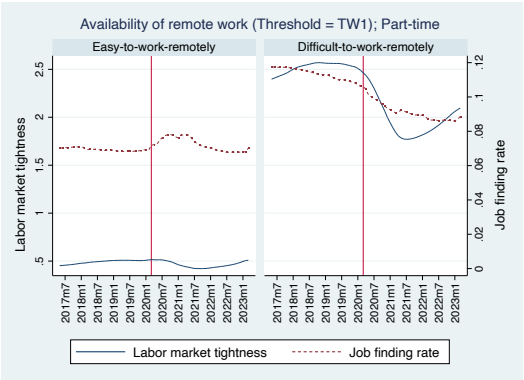
(b) Full-Time Workers (TW2 as the threshold of remote work availability)



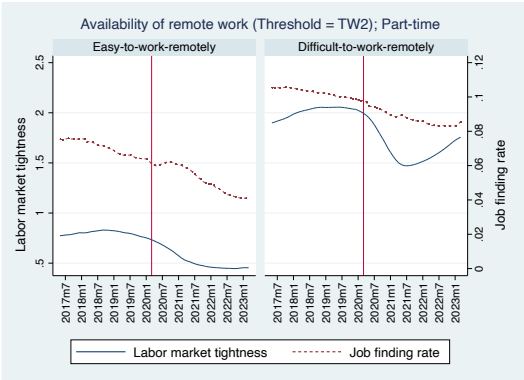
(c) Full-Time Workers (TW3 as the threshold of remote work availability)



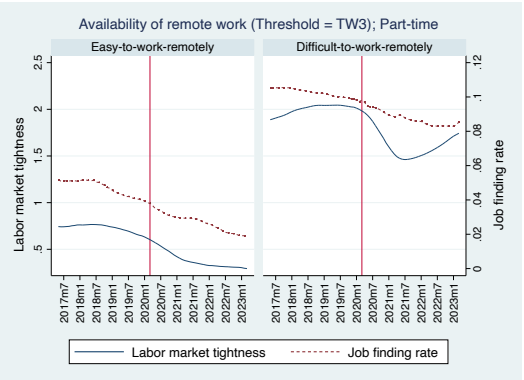
(d) Part-Time Workers (TW1 as the threshold of remote work availability)



(e) Part-Time Workers (TW2 as the threshold of remote work availability)



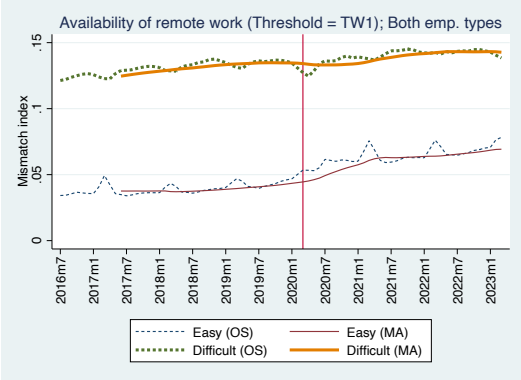
(f) Part-Time Workers (TW3 as the threshold of remote work availability)



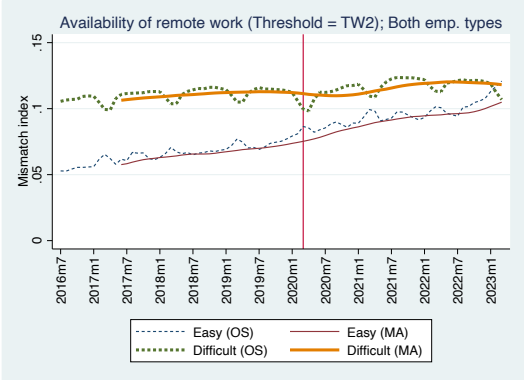
Notes: Job finding rate = new hires/job seekers. Labor market tightness = vacancies/job seekers. The 12-month backward moving averages of the mean values of the occupational groups are plotted. The vertical line indicates March 2020.

Figure OA.6: Mismatch across Occupations by Easy- and Difficult-to-Work-Remotely Occupational Group Based on Alternative Definition

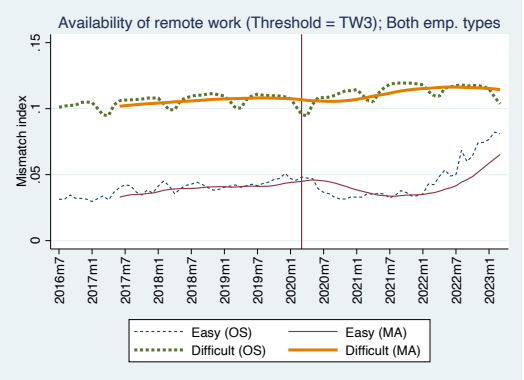
(a) Both employment types (TW1 as the threshold of remote work availability)



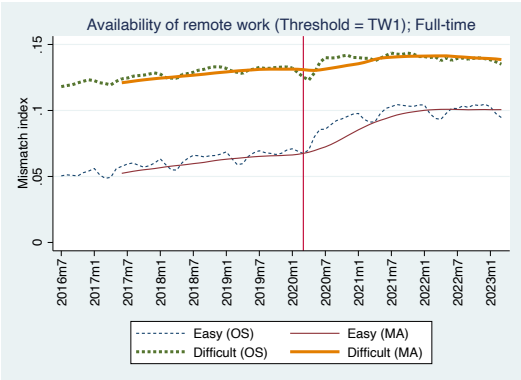
(b) Both employment types (TW2 as the threshold of remote work availability)



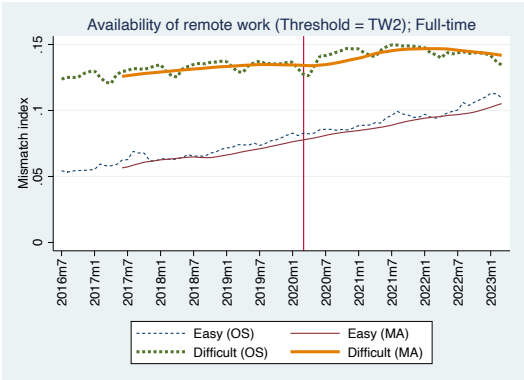
(c) Both employment types (TW3 as the threshold of remote work availability)



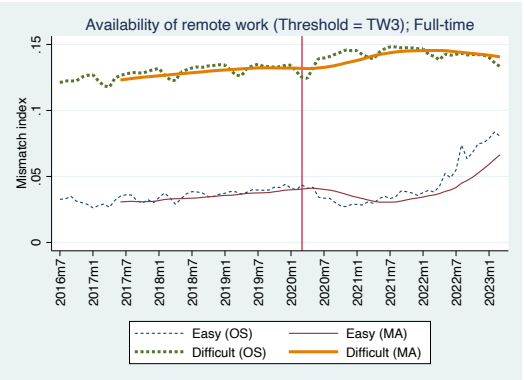
(d) Full-Time Workers (TW1 as the threshold of remote work availability)



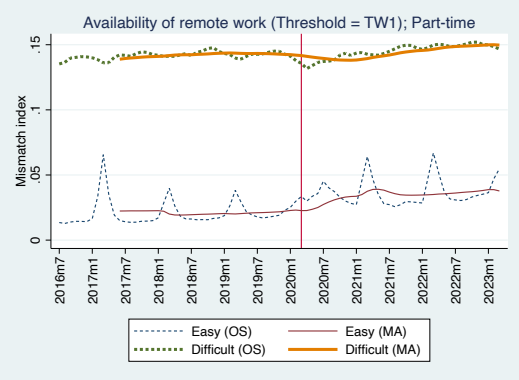
(e) Full-Time Workers (TW2 as the threshold of remote work availability)



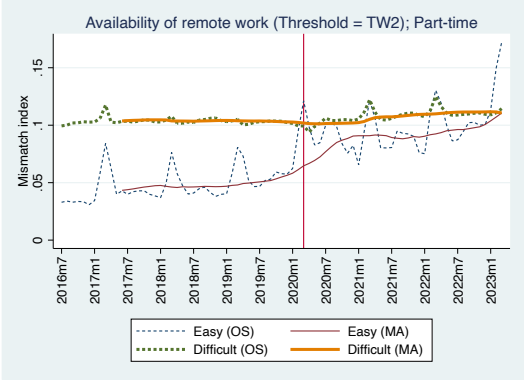
(f) Full-Time Workers (TW3 as the threshold of remote work availability)



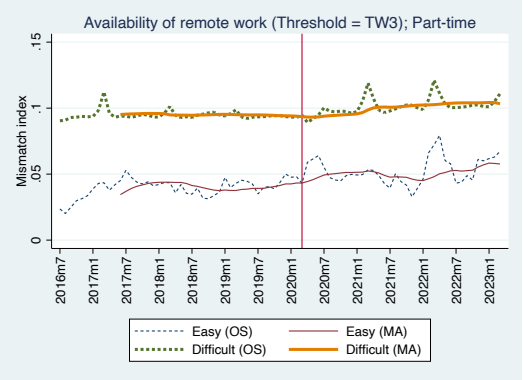
(g) Part-Time Workers (TW1 as the threshold of remote work availability)



(h) Part-Time Workers (TW2 as the threshold of remote work availability)



(i) Part-Time Workers (TW3 as the threshold of remote work availability)



Notes: OS and MA are the original series and 12-month backward moving averages, respectively. The vertical line indicates March 2020.