I Z A Institute of Labor Economics

Initiated by Deutsche Post Foundation

DISCUSSION PAPER SERIES

IZA DP No. 15917

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

Yudai Higashi
Masaru Sasaki

FEBRUARY 2023

I Z A Institute
of Labor Economics

Initiated by Deutsche Post Foundation

DISCUSSION PAPER SERIES

IZA DP No. 15917

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

Yudai Higashi
Okayama University

Masaru Sasaki
Okayama University and IZA

FEBRUARY 2023

Any opinions expressed in this paper are those of the author(s) and not those of IZA. Research published in this series may include views on policy, but IZA takes no institutional policy positions. The IZA research network is committed to the IZA Guiding Principles of Research Integrity.

The IZA Institute of Labor Economics is an independent economic research institute that conducts research in labor economics and offers evidence-based policy advice on labor market issues. Supported by the Deutsche Post Foundation, IZA runs the world's largest network of economists, whose research aims to provide answers to the global labor market challenges of our time. Our key objective is to build bridges between academic research, policymakers and society.

IZA Discussion Papers often represent preliminary work and are circulated to encourage discussion. Citation of such a paper should account for its provisional character. A revised version may be available directly from the author.

ISSN: 2365-9793

IZA – Institute of Labor Economics

Schaumburg-Lippe-Straße 5–9
53113 Bonn, Germany

Phone: +49-228-3894-0
Email: publications@iza.org

www.iza.org

ABSTRACT

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

This study explores how the COVID-19 pandemic deteriorated the mismatch in the Japanese labor market. We first focus on differences in job flows and reservation wages by occupation and employment type, which differ according to the risk of infection. We next estimate the mismatch indices for local labor markets clustered in by occupations vulnerable and not vulnerable to COVID-19 using the method developed by Şahin et al. (2014). We find that the pandemic induced an overall mismatch, regardless of whether the occupations were vulnerable to infection. The mismatch for high-risk occupations was gradually eliminated in 2021, suggesting that the Japanese labor market adapted gradually but successfully to the new normal. However, the mismatch for low-risk occupations increased in 2021, indicating that labor mobility had been discouraged.

JEL Classification: J61, J62, J63

Keywords: mismatch, O-NET data, COVID-19, labor market tightness, desired wage

Corresponding author:
Yudai Higashi
Faculty of Humanities and Social Sciences
Okayama University
3-1-1 Tsushima-naka
Kita-ku
Okayama 700-8530
Japan
E-mail: yudai.higashi@okayama-u.ac.jp

* The authors would like to thank the Japanese Ministry of Health, Labour and Welfare (MHLW) and the Japan Institute for Labour Policy and Training (JILPT) for the data used in this research. The authors are also grateful to the members of the COVID-19 and O-NET Data Research Group and participants at the Asian and Australasian Society of Labour Economics 2022 Conference for their valuable comments. An earlier version of this paper was written in Japanese and included in JILPT Document Series No. 256. All remaining errors are our own.

1. Introduction

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

Indeed, some studies have shown that COVID-19 has changed job search behaviors. For example, jobseekers in Sweden changed their search direction to occupations that were less affected by COVID-19 (Hensvik et al. 2021). In the Netherlands, although the unemployed, on average, searched less during the recession caused by COVID-19 than during other recessions, those who faced work situations 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, while others, especially non-employed and less-educated ones, searched for declining occupations (Carrillo-Tudela et al. 2023). Such evidence suggests that, in the post-COVID-19 environment, jobs at low risk of infection were relatively preferable, but jobs in which workers were required to contact one another closely were avoided.

However, it is difficult to immediately transfer to sectors with a low risk of infection in the short run, because it is costly to obtain the skills appropriate for a specific sector.

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 ultimately, those who used to engage in a job vulnerable to the infection could not but search for a similar job in the same sector.

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

Indeed, this misalignment widened in some local labor markets, but narrowed in others. The heterogeneity of such differences across local labor markets arose because of the exposure to the pandemic. It is rational to examine how the mismatch between jobseekers and vacancies across the local labor market evolved over time from the viewpoint of dynamic labor market policymaking. However, little is known about the effect of the COVID-19 pandemic on the mismatch between workers and firms. Exceptionally, Pizzinelli and Shibata (2023) reveal that although the extent of mismatch in the US and the UK rose sharply immediately after the pandemic hit, it recovered to previous levels within a few quarters, suggesting a limited effect of the pandemic on the job matching process in these countries.

This study examines whether the COVID-19 pandemic deteriorated mismatches in the Japanese labor market. We adopt a two-fold approach to answer this question. First, we focus on the variants in terms of measures relevant to matching in the Japanese labor market (i.e., labor market tightness, job finding rate, and reservation wages) based on the public employment services administrative data and Japanese-style O-NET data. Second, using the method developed by Şahin et al. (2014), we estimate the mismatch indices for each local labor market by type of occupation and then compare the extent of mismatch in the local labor markets between occupations vulnerable to the risk of COVID-19 infection with those not so vulnerable. The essence of this method, developed by Şahin et al. (2014), is to calculate the counterfactual distribution of matches across local labor markets chosen by the social planner to maximize the number of matches in the entire labor market. The extent of the mismatch is then measured by the difference between the actual and counterfactual distributions of matches. This difference indicates the number of mismatches that would not have been lost if jobs were efficiently allocated across local labor markets. This method, notably, allows us to measure the mismatch indices, given that the local labor markets are heterogeneous with respect to matching efficiency. The above-mentioned Pizzinelli and Shibata (2023), who investigated the effect of COVID-19 on mismatches in the US and the UK, followed this method.

In Japan, following this method, the mismatch across large-classification occupations (Kawata 2019; Shibata 2020) and that across middle-classification occupations (Shibata 2020) are confirmed, using the same administrative data as we use, but covering periods before the pandemic. In the early stages of the pandemic, using the same administrative data from July 2017 to July 2020, Kawakami (2021) revealed that the mismatch that had already existed in Japan deteriorated because of the pandemic. He calculated mismatch indices across local labor markets, simultaneously classified by occupational type (middle classification), employment type (full-time versus part-time), and prefectures. Additionally, he regressed the mismatch indices across occupations on occupational characteristics obtained from the Japanese-type O-NET data and found that during the early days of the pandemic, there was an excess labor supply in occupations where workers were required to work in close contact. His finding is consistent with past studies that found 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 administrative data on public employment services to October 2021. In addition to the fact that we used longer length of data, three features of this study distinguish it from the previous literature and address a gap. First, the administrative data utilized for this study are classified into 369 types of occupations within a certain range from June 2016 to October 2021 at a monthly frequency. We use small-classified occupations data from the administrative data of public employment services, unlike previous studies that used larger classifications. Even if we had employed middle-classified data, we would have been likely to have underestimated the extent of mismatches because a local labor market clustered by the middle-classified occupations is so large that few workers change their jobs across local labor markets.

---

[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 be unemployed or out of the labor force by December 2020 (Fukai 2022). Firms in which they worked were requested temporarily to suspend their business by the local government because workers needed to contact one another frequently (Hoshi et al. 2022). Workers 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).

Second, the Japanese-style O-NET dataset covers job characteristics of 497 occupations and directly asks respondents engaging in each occupation about "whether or not workers contact closely with others," "whether the risk of infection is high or low," and "whether or not workers are allowed to work remotely." We are then allowed to distinguish between occupations vulnerable and invulnerable to COVID-19 infection. By merging the O-NET data and the administrative data by each occupational code, we can examine the differences in job flows and extent of mismatch in local labor markets clustered by occupations at the risk of infection. This approach is more direct than the literature measuring occupations' vulnerability to COVID-19 in terms of remote work feasibility and risk of infection based on job features under usual situations (e.g., Dingel and Neiman 2020).

Third, 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 the risk of infection. We assume that local labor markets segregated by employment type are independent of one another because workers usually do not alternate between these two local labor markets.

The three main findings are summarized below. First, the labor market condition 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 started this month in Japan. Both labor market tightness and job finding rate became lower. We observe the same patterns of job flows, regardless of employment type and occupation type (low- or high-risk). However, the labor market gradually recovered from January 2021, approximately one year after the pandemic began. More jobs became available, and therefore, many jobseekers succeeded in finding a new job, which suggests that the labor market adapted properly and dynamically to the post-pandemic "new normal."

Second, jobseekers' desired wage, which we interpret as reservation wage, was on a upward trend before the pandemic. This trend continued even during the pandemic, regardless of employment type. For full-time workers engaged in an occupation at a high risk of infection, the rate of increase in the desired wage was markedly higher after the pandemic. We employed the model of the compensating wage differentials to explain the strongly upward trend in desired wages. We believe workers demanded higher wages to compensate for the increase in their perceived risk of getting an infection as the pandemic raged.

Finally, we find that the mismatch rapidly worsened after March 2020, regardless of whether jobs in a local labor market were vulnerable to infection risk. After January 2021, the mismatch for high-risk occupations was gradually eliminated, but its level was still higher than that before the pandemic. Voluntary bans on leaving home to avoid direct contact implicitly forced restaurants and bars to suspend their businesses or shorten working hours. Hence, the mismatch worsened in the local labor markets of restaurant and bars. We consider that many workers left these markets, which partially resulted in the mismatch resolution in 2021. For low-risk occupations, the extent of mismatch increased in 2021. Overall, regardless of the risk of infection, the extent of the mismatch was larger over the sample period than that before the pandemic. One possible factor inducing a large mismatch is the generous Japanese subsidy for job protection discouraging labor mobility.

The remainder of this paper is organized as follows. Section 2 provides the details of the data we utilized—the public employment services administrative data and Japanese-style O-NET data—and explains the method of merging the two datasets. Section 3 describes the trends in the variables of interest, such as labor market tightness, job finding rate, and jobseekers' desired wages, both before and after March 2020. Section 4 presents the trends in mismatches based on the extent of infection risk in local labor markets. Section 5 discusses the factors causing the mismatch trend in Japan, which are different from those in the US and the UK, and Section 6 presents the concluding remarks.

2. Data

This section introduces the two datasets and explains how they were merged. We then explain which occupations are defined as low- and high-risk of infection, and 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), the administrative data of public employment services, released by the Japanese Ministry of Health, Labour and Welfare (MHLW). The dataset include data on the number of jobseekers, vacancies, and new hires registered in each local employment service office across the country. We used monthly panel data at the occupational level, in which registered vacancies are classified by the small category. The data tell us whether a jobseeker is looking for a full-time or part-time job. Note that new graduates and vacancies targeting them are excluded because new graduates are not eligible for the provision of unemployment insurance. The dataset covers June 2016 to October 2021, crossing the threshold of March 2020, when school closure was ordered.

The Japanese-style O-NET dataset, released by the Japanese Institute for Labour

Policy and Training (JILPT), quantifies each occupation's characteristics. A large-scale survey was conducted in which some registered workers engaged in each occupation were subjectively asked about occupational characteristics, such as the skills and knowledge necessary to perform tasks.[2] These workers responded to each question on a multiple-point scale, and the average score was then calculated for each occupation. The new version was administered from January 19 to February 15, 2021, adding new questions to identify which occupation was at risk of infection or in which occupation workers were allowed to work remotely.

To explore the characteristics of labor markets clustered by occupations at high or low risk of infection and by those allowing remote work, we merged the two datasets. This was possible because both datasets share the same occupation codes according to the 2011 occupational classifications determined by the MHLW.[3]

The Japanese-style O-NET dataset covers 497 occupations, 75 of which were missing. We observed that some occupations coincided with others, allowing us to share the same occupation code in cases where the occupations are integrated. We calculated the average scores quantified based on the characteristics of similar occupations. Finally, we consolidated the 422 occupations into 228. These 228 occupations were then merged into the administrative data of public employment services using occupational codes. As the public employment services administrative data cover 369 occupations, we can say that 141 occupations were deleted.[4]

There are two points to note here. First, the version of Japanese-style O-NET data this study uses contain information on the occupational characteristics of infection risk

---

[2] See JILPT Document Series No. 240 for details.
[3] See the websites of the Japanese-style O-NET. The lists of occupational classifications can be downloaded (http://shigoto.mhlw.go.jp/User/download).
[4] See Figure OA.1 in the Online Appendix.

and remote work availability, collected from January 19 to February 15, 2021. We assumed that the occupation characteristics remain unchanged over a long period of time and apply occupational characteristics as of 2021 to any period from June 2016 to October 2021. Second, the Japanese-style O-NET data do not distinguish occupational characteristics by employment type; therefore, we assumed that there are no differences in occupation characteristics between full-time and part-time workers.

As mentioned before, 141 out of 369 occupations were deleted from the administrative data because of a lack of information on occupational characteristics in the Japanese-style O-NET data, leading to concern about the problem caused by sample selection bias. Table OA.1 in the Online Appendix shows the differences in various variables (number of jobseekers, vacancies, and new hires by employment type) between 141 occupations and the remaining 228 occupations. We found that the averages of these variables were 6–13 times larger for the 228-occupation group than for the deleted 144-occupation group. These results mean that the deleted 114-occupation group is far smaller in scale relative to the overall labor market. Therefore, we interpret that the problem caused by the sample selection bias is minor.

2.2. Who is vulnerable to COVID-19?

This subsection presents two indices for identifying those vulnerable to the COVID-19 infection. We explain the two ways of distinguishing 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 to distinguish between workers at a high or low risk of infection. We computed the average of the scores from two questions to measure the extent of the infection risk, the first score being from the question: “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 and over, (3) once a month and over, (4) once a week and over, and (5) almost every day. This score indicates how seriously COVID-19 endangers workers’ health at their workplace (infectious disease risk).

The second question was, “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). This is because close contact (physical proximity to others) increases the risk of catching the virus, which is airborne and carried by droplets from the infected (physical proximity to others).[5]

We computed the arithmetic average of the two scores as a synthetic risk index to determine who was at a high or low risk of infection at the workplace.[6] When an occupation’s synthetic index is higher, workers are more likely to become infected at the workplace. We employed two thresholds to distinguish between workers at high and low risk of infection, the 50th or the 75th percentile of the synthetic index, and maintain that

---

[5] 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.)

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

occupations above these thresholds are associated with a higher risk of COVID-19. Figure 1 shows the distributions of the indices for infectious disease risk and physical proximity to others, and the distribution of the synthetic risk index.

[Insert Figure 1 about here]

The second index seeks to measure the frequency at which workers are allowed to work remotely. The Japanese-style O-NET additionally asked the respondents the following question: "How often do you think workers engaging in the same job as yours were allowed to work remotely during the state of emergency (April–May 2020)? It should be noted that we would like you to respond whether remote work is available not for you, but for other workers in the same jobs." The 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% and over 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. This allowed us to determine the proportions of the categories of workers in each occupation.

We employed three thresholds to determine who is allowed to work remotely, as shown in Table 1. The first threshold (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," that is, TW2 distinguishes (1) and (2) from the rest of the choices. The third threshold (TW3) further extends the definition of "difficult-to-work-remotely": (1), (2), and (3) versus (4), (5), and (6). We further narrowed down the standard of availability of remote work by changing the threshold from TW1 to TW3.

[Insert Table 1 about here]

Table 1 shows that three-quarters of the occupations are categorized as (1), implying that the majority of workers responded that they could not work remotely in their occupations.[7] 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 2 shows the distribution of the proportion of respondents in each category by occupation. For example, in the upper-left panel, the bar at 100 indicates the proportion of occupations in which all respondents answered (1), and in the lower-right panel, the bar at 0 indicates the proportion of occupations in which all respondents answered (6). We find that the majority of the respondents could not work remotely.

[Insert Figure 2 about here]

3. Labor market tightness, job finding rate, and jobseekers' desired wages

This section presents the monthly moving-average trends in labor market tightness, job finding rates, and jobseekers' desired wages from June 2016 to October 2021, covering the periods before and after the pandemic.[8]

Panels (a) and (b) of Figure 3 display trends in labor market tightness, job finding rates by the synthetic risk index (low versus high risk of infection) using two different thresholds (50^{th} and 75^{th} percentiles), respectively. We restrict both figures to the trends

---

[7] See Table OA.2 in the Online Appendix. In many occupations, the respondents answered that they were not usually allowed to work remotely.

[8] The moving-average is defined as the average of numbers obtained from the current month and the past 11 months.

for full-time workers. Note that the extent of labor market tightness is measured in the left vertical line and that of the job finding rate is measured in the right vertical line.

[Insert Figure 3 about here]

We find that, first, labor market tightness deteriorated after the pandemic, regardless of whether the infection risk was high or low, which indicates a decrease in the job finding rate for workers. However, labor market tightness improved in 2021, and so did the job finding rate. When we employ the 75^{th} percentile of the synthetic risk index for the threshold to separate occupations with high and low risk of infection, labor market tightness sharply worsens for occupations with high risk of infection after the pandemic. Second, labor market tightness and the job finding rate were consistently higher in occupations with a higher risk of infection, which means that the local labor market is more flexible at high risk. Finally, labor market tightness was always more than one over the period, which implies that the demand for labor (the number of vacancies) always exceeded the number of jobseekers. This reveals that the Japanese labor market has suffered from a chronic labor shortage, even after negative shocks such as the COVID-19 pandemic.

Thus, we can infer that many workers have gradually adjusted to a new post-pandemic normal since January 2021, when the third wave of the pandemic hit. Expecting the pandemic to be prolonged, some workers, who were in a job with high risk of infection, such as restaurants and bars, had left the labor market due to COVID-19. This led to an upward trend in labor market tightness for occupations with a high risk of infection.

Panels (c) and (d) of Figure 3 show similar moving-average trends in the synthetic risk index for part-time workers. We obtained similar results for full-time workers; labor market tightness had worsened after the pandemic and the job finding rate had decreased.

However, both indicators show an upward trend in January 2021. For occupations with a low risk of infection, both labor market tightness and job finding rate were low overall, with very small variations. For occupations with a high risk of infection, the labor market tightness was at least 2.5 under the COVID-19 crisis according to panel (d), in which the 75th percentile of the synthetic risk index was used as the threshold to distinguish between jobs with high and low infection risk. This result implies that many firms are actively willing to hire workers or a few jobseekers are searching for high-risk jobs.

We now look at the trends using another index for the availability of remote work. Panels (a) to (c) of Figure 4 display moving-average trends in labor market tightness and job finding rate by the three thresholds (TW1, TW2, and TW3) to distinguish whether remote work is available for full-time workers. The trends in panel (a) are similar to those in panels (b) and (c); that is, regardless of the thresholds, labor market tightness worsens for any occupation since the pandemic, and the job finding rate has also decreased. However, both labor market tightness and job finding rate turned out to have an upward trend in 2021.

[Insert Figure 4 about here]

To be comparable, Panels (d) to (f) of Figure 4 display moving-average trends in labor market tightness and job finding rate by the three thresholds (TW1, TW2, and TW3) for part-time workers. For occupations that did not allow workers to work remotely, labor market tightness had deteriorated since the pandemic, and therefore, the job finding rate also decreased with COVID-19 cases. Similar to previous findings, both labor market tightness and job finding rate showed an upward trend in 2021. For occupations that allowed workers to work remotely, as shown in panel (d), with TW1 as threshold, the job finding rate increased after the pandemic, but overall, the variations in the job finding rate for before and after the pandemic were relatively small.

Next, we look at jobseekers' desired wages, which we interpret as the reservation wage. The desired wage is defined as the wage that a jobseeker fills out on the form, asking, "How much do you desire to accept a job offer?" We assume that the desired wage mentioned is equivalent to the lowest wage that a worker accepts, so it can be interpreted as the reservation wage. We calculated the desired wage averaged by occupation.[9]

Panels (a) and (b) of Figure 5 show the moving-average trends in the desired wages for full-time workers. Panel (a) employs the 50th percentile of the synthetic risk index as the threshold to distinguish between occupations with high and low risk of infection. Panel (b) uses another threshold: the 75th percentile of the synthetic risk index. From both panels, the desired wages showed monotonically increasing trends both before and after the pandemic, regardless of the extent of infection risk. This again points to the chronic labor force shortage in the Japanese labor market.

[Insert Figure 5 about here]

We emphasize that the desired wages fluctuated more dramatically and increased faster right after the pandemic for occupations with low as well as high risk of infection. Based on the model of compensating wage differentials, we infer that workers who engaged in jobs demanded much higher wages to compensate for an increase in their perceived risk of infection. In particular, workers in the restaurant and bar sectors were not concerned about the frequency of close contact with others, and thus the risk to them, before the pandemic, but they did afterward, with a greater concern, prompting them to desire higher wages to compensate for the risk.

[9] The mean values of the desired wage are weighted by the number of respondents by occupation. Note that no respondent answers the desired wage for some occupations in some periods. In this case, the weight is zero.

Panels (c) and (d) of Figure 5 reveal the moving-average trends in the desired wages for part-time workers, using the 50th and 75th percentiles of the synthetic risk index to distinguish between high- and low-risk occupations, respectively. Similar to the trends for full-time workers, the desired wages for part-time workers show an upward trend over the entire period. However, we observed an increase in the desired wage, with a decreasing rate, immediately after the pandemic. Additionally, the desired wage for part-time workers did not fluctuate, unlike the case for full-time workers. It appears that part-time workers did not demand much higher wages to compensate for the increased risk of infection, and perhaps even quit the labor market.

Panels (a) to (c) of Figure 6 display the moving-average trends in the desired wages for full-time workers, using another index with three thresholds (TW1, TW2, and TW3) to find out whether remote work was available for full-time workers. Regardless of the feasibility of remote work, desired wages had gradually increased before the pandemic and continued to increase for any threshold. Sharp jumps in the trend of the desired wages were observed after the pandemic, but only in Panel (a). Additionally, the desired wages were consistently higher for occupations that allowed workers to work remotely than for those that did not allow them to do so for any threshold. This implies that labor productivity, and thus wages, were higher for workers allowed to work remotely than for those who were not. Thus, we can confirm that workers who are more productive were at lower risk of infection.

[Insert Figure 6 about here]

Panels (d) to (f) of Figure 6 show the moving-average trends in the desired wages for part-time workers using the three thresholds (TW1, TW2, and TW3). Similar to the case of full-time workers, the desired wages were on an upward trend before the pandemic.

These trends continued, regardless of the feasibility of remote work. The desired wage for part-time workers was consistently higher for occupations that allowed workers to work remotely than for those that did not allow so for all thresholds.

4. Mismatch

This section presents the transitions of mismatches between workers and firms across local labor markets, segmented by small-classified occupations over time. As in Section 3, we compare the mismatch indices across occupational groups based on the extent of risk of infection and availability of remote work. That is, we evaluate the mismatch across occupations with a low and high risks of infection. To do so, we assume that the mismatch occurs across occupations with a common risk level of infection, but not across occupations with a largely different risk. Although labor mobility across occupations with largely different risks of infection can arise, we do not focus on the mismatch caused by labor mobility but on whether the effect of the pandemic on occupational mismatch is heterogeneous with respect to the extent of the risk. 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. Calculating the indices of mismatch across these occupations might allow us to evaluate the extent of mismatch that practically cannot be eliminated, which is the purpose, and significance, of our approach to separately calculate the mismatch indices by the risk of infection. The same procedure was used for occupational groups, based on availability of remote work.

The mismatch indices developed by Şahin et al. (2014) were calculated. Briefly, their technique measures the fraction of actual matches to optimal matches, that is, it is the fraction of the matches that would have been fulfilled if workers had searched for jobs in ideal local labor markets. Their model assumes that the optimal allocation of jobseekers across local labor markets is determined by a social planner who maximizes the number of market-wide matches. An innovation of their technique is that the optimal number of matches is calculated by accounting for the heterogeneity of the matching efficiencies across local labor markets. Appendix A presents a discussion on the mismatch index.

From the sample, we delete data on occupations in which the number of hires is zero for one period or longer because we cannot take a log of its value, necessary to calculate the mismatch indices.[10] Therefore, the number of occupations decreases from 228 to 207 in the sample of full-time workers and from 228 to 158 in the sample of part-time workers.

Before showing the mismatch by occupational group, we begin with Figure 7, which displays trends in the overall mismatch indices from 2016 to 2021. Panels (b) and (c) show the trends for full-time and part-time workers, respectively, and Panel (a) is obtained from the sum of these panels. Although the mismatch indices fluctuate seasonally, we observe that the mismatch indices are overall on the upward trends in panels (a) and (b) but not on the upward or downward trend in panel (c). Panel (a) shows that the upward trend for full-time workers accelerated after the pandemic. The mismatch was still high as of October 2021, one and a half years after the pandemic emerged according to panels (a) and (b); this result is different from those obtained by Pizzinelli and Shibata (2023) using US and UK data.

[Insert Figure 7 about here]

As shown in Panel (c), mismatches had been gradually eliminated in early 2020, even before the pandemic began, and there seems to be no difference in the extent of the mismatch before and after March 2020. One possible explanation might be that part-time

[10] See Appendix A in detail.

workers who were risk-averse to infection at the workplace decided to exit from the labor market, and did not contribute to the deteriorating mismatch.

Panels (a) and (b) of Figure 8 illustrate the trends in the mismatch indices using the synthetic risk index for both full-time and part-time workers. As the number of segmented local labor markets (i.e., occupations in this study) increases, the extent of the mismatch index tends to increase. In our sample, the number of occupations differed across occupational groups and between full-time and part-time workers in each occupational group. These differences make it difficult to directly compare mismatch indices. Thus, in addition to the monthly change rates of mismatch in 2020 and 2021, the Online Appendix compares with 2019, the year before the pandemic, as a benchmark. Panels (a) and (b) show the results for the 50th and 75th percentiles, respectively, of the synthetic risk index as the thresholds for the occupational groups with a high risk of infection. We find similar results for both panels with different thresholds. Before the pandemic, the mismatch indices changed significantly 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 the rate of increase in the mismatch indices for low-risk occupations was not large. The former increased slowly in late 2020 and decreased in 2021, but were approximately 5% higher in October 2021 than in October 2019. We can conclude that the occupational mismatch across high-risk occupations due to the pandemic has gradually recovered, although the level of mismatch remains high.

[Insert Figure 8 here]

These trends suggest that the pandemic affected high-risk occupations, resulting in a large mismatch in the corresponding labor market. As the desired wage, or reservation wage, had increased immediately after March 2020, one of the possible factors causing the mismatch is that wage adjustment was not completed in the early stages of the pandemic. Thereafter, some workers might have adapted to the situation and started searching for jobs. Labor mobility within the market composed of high-risk occupations accelerated, resulting in labor adjustments. However, some structural changes in this market because the mismatch level was still worse than in pre-pandemic times.

The mismatch indices for low-risk occupations were lower in 2020 than in 2019, implying that the mismatch was not as serious in 2020 as in 2019. However, the mismatch indices steadily increased in 2021. The time of the mismatch for the low-risk occupations lagged behind that for the high-risk occupations by one year. This implies that the labor market is less flexible in low-risk occupations than in high-risk occupations. Financial support to firms, such as the Employment Adjustment Subsidy, might have discouraged labor mobility in low-risk occupations.

Panels (c) and (d) of Figure 8 present the trends in the mismatch indices for full-time workers. We obtain similar results in panels (a) and (b). After March 2020, the mismatch indices sharply increased in high-risk occupations, while the rate of increase in the mismatch indices for low-risk ones was trivial. The mismatch indices for the former declined in late 2020 and continued to decrease until 2021, but were still 10–20% higher in October 2021 than in October 2019. The occupational mismatch across high-risk occupations due to the pandemic has gradually reconciled, but the level is still serious. The mismatch indices began to increase from mid-2020 for low-risk occupations, continuing steadily in 2021. The overall rate of increase for low-risk occupations was lower than that for high-risk occupations.

Panels (e) and (f) of Figure 8 present the trends in the mismatch indices for part-time workers. Regardless of the threshold to distinguish infectious risk, the mismatch indices in low-risk occupations in March 2020 were lower at any monthly level than in 2019. After March 2020, the mismatch indices increased immediately. This trend has continued during 2020 and 2021, suggesting that labor mobility has not been promoted in the market for low-risk occupations. In terms of high-risk occupations, the mismatch indices did not start to increase immediately after March 2020, but only after July 2020. This trend did not continue, and the mismatch indices decreased in 2021, suggesting that the labor market was adjusted due to labor mobility. For low-risk, the mismatch indices first decreased in 2020 and increased in 2021.

Next, we considered the results based on occupational groups by availability of remote work. Panels (a) to (c) of Figures 9 show the trends in the mismatch indices for all full-time and part-time workers, by occupational group based on the three thresholds to distinguish between difficult- and easy-to-work-remotely. In panel (a), occupations are classified as difficult-to-work-remotely if half or more answered "usually, no" to available to work remotely (TW1). Based on this definition, occupations in which workers can work remotely even for one day are classified as easy-to-work-remotely. For difficult-to-work-remotely occupations, the mismatch index slowly increased after the pandemic. It has not recovered, but remains at a high level. The easy-to-work-remotely occupations also exhibited an increase in the mismatch index in 2020 and 2021. However, this trend started in January 2020, two months before the pandemic.

[Insert Figure 9 about here]

We expect that easy-to-work-remotely occupations correspond to low-risk ones because workers are not frequently required for face-to-face contact. However, the results show that the monthly change rates of the mismatch index are much larger for the easy-to-work-remotely occupations than for difficult-to-work-remotely ones (see Figure OA.3

in the Online Appendix), indicating that the mismatches for low-risk ones are more serious than for the high-risk ones. This result seems to conflict with the results in panels (a) and (b) of Figure 8, where the threshold is defined by risk of infection.

A possible explanation for this inconsistency is that the easy-to-work-remotely group defined by TW1 in panel (a) of Figure 9 might include some high-risk occupations because this definition covers a wide range of occupations. Another possibility is that the variance of the mismatch index for the easy-to-work-remotely occupations might increase over time because the number of occupations in this group is small. The mismatch index for such occupations started to increase before the pandemic (see Figure OA.3 in the Online Appendix), which we have difficulty interpreting, and could also be attributed to the small sample size.

Panels (b) and (c) show the change in mismatch indices by occupational groups that classify a narrower range of occupations as easy-to-work-remotely compared to panel (a). In panel (b), occupations are defined as easy-to-work-remotely if the workers can work remotely for 20% of days of duty and below (TW2), while panel (c) is for those where workers can work remotely for 40% of days and below (TW3). For both panels (b) and (c) of Figure 9, the mismatch indices for difficult-to-work-remotely occupations steadily increased immediately after March 2020 and continued to be at high. This result suggests that a mismatch in the labor market of this occupational group arose due to the pandemic, did not recover in October 2021 to the March-2020 level For the easy-to-work-remotely occupations, we find that the change rate of the mismatch index is smaller in panel (b) than in panel (a) and that the mismatch started to increase even before the pandemic. Panel (c) shows that the mismatch was eliminated after the pandemic.

Panels (d) to (f) of Figures 9 display the trends in the mismatch indices for full-time workers by the three thresholds. We obtained similar results for panels (a) to (c). Regardless of which threshold is employed, we find that the mismatch deteriorated for difficult-to-work-remotely occupations, and gradually eliminated in the easy-to-work-remotely ones.

Finally, panels (g) to (i) of Figures 9 present the trends in mismatch indices for part-time workers by three types of occupational classification based on availability of remote work. According to Panel (g), in which TW1 is used as the threshold, the mismatch for the easy-to-work-remotely occupations sharply increased after March 2020 but improved from July 2020 onward. In contrast, the mismatch for difficult-to-work-remotely occupations has not changed over time, even during the pandemic. Panel (h) shows the results for the occupational groups based on TW2, which classifies the narrower extent of occupations into easy-to-work-remotely ones. The mismatch index increased for easy-to-work-remotely occupations during the pandemic between 2020 and 2021, continuing from before March 2020. For difficult-to-work-remotely occupations, the level of mismatch in 2020 was lower than that in 2019. This trend increased immediately after the pandemic.

According to panel (i), based on the narrowest classification of the easy-to-work-remotely occupations (TW3), the easy-to-work-remotely occupations do not exhibit an apparent change in the mismatch over time. For difficult-to-work-remotely occupations, the result is similar to that of panel (h). We thus consider that the COVID-19 pandemic has not caused a severe mismatch in the labor market of easy-to-work-remotely occupations, but the labor market of difficult-to-work-remotely occupations is narrower.

5. Discussion

Section 4 showed that, regardless of the risk of infection, mismatch remained sufficiently high even in 2021, although on a downward trend for workers at a high risk of infection. This result is different from those obtained by Pizzinelli and Shibata (2023), who showed that mismatches were eliminated quickly in the US and UK. One reason for the difference is that the Employment Adjustment Subsidy (EAS), a public grant to protect employment, was more generous in Japan than in any other country.

The purpose of EAS was to compensate the wage loss to workers who are forced to be absent from work, because their firms must suspend business or shorten business hours. The EAS targeted workers who lost the opportunity to earn, but the subsidy is paid directly to firms that apply for the EAP program. The firms then deliver the subsidies to their workers. Before the pandemic, the EAS program was implemented in such a way that the daily limit of the subsidy was 8,265 Japanese Yen (58.45 US dollars)[11] at the rate of two-thirds of the wages for small and medium firms and half for large firms.

As the number of COVID-19 cases increased in early 2020, more workers had to be absent from work because of business suspension. The government delivered the EAS to workers who lost earnings, with 15,000 JPY (106.12 USD) as the daily limit and 100% of the subsidy rate in April 2020. The special measure was effective until May 2021, and the daily limit was then slightly reduced to 13,500 JPY (95.51 USD) in May 2021. The generous provision of the EAS continued until October 2021, the last month of the data covered in our study. The daily limit of the subsidy was reduced to 11,000 JPY (77.82 USD) in January 2022 and to 9,000 JPY (63.67 USD) in March 2022.[12] The generous subsidy to protect employment discouraged workers from moving to new jobs even invulnerable to infection, which implies the persistence of inefficient allocation of

[11] We use the exchange rate of 141.35 Japanese Yen for one US dollar.
[12] The EAS daily limit remained at 15,000 Japanese Yen in areas severely affected by the pandemic.

workers in the new normal.

There are subsidies to protect employment, similar to EAS in other countries. For example, the Paycheck Protection Program (PPP) was implemented nationwide in the US for workers who had to be absent from work because of the pandemic. Many researchers are investigating whether PPP has been effective for employment protection.

According to Hubbard et al. (2020), firms that received PPP or qualified for it and had 500 or fewer employees increased employment by 1.4% to 1.8% more than those that had 501 or more and 1000 or fewer. PPP had a significant effect on employment protection, given that the average employment at establishments with 1–1,000 employees declined by 1.6% between November and August 2020.

However, Autor et al. (2022) argue that this result might capture the effect of firm size heterogeneity rather than the effect of PPP. To overcome the identification problem, they compared similar firms in size and found that PPP increased employment in firms with 500 or fewer employees by 2–5% as of May 2020, compared to firms that did not apply for PPP. However, this effect gradually declined and became statistically insignificant in December. They found that the implementation of PPP protected 3.6 million jobs in mid-May and 1.4 million jobs in December, at an estimated PPP cost ranging from 3.4–5.2 times the median salary of full-time workers. The cost of PPP to protect employment at the extensive margin is much higher than that of salaries. We can say that it was not cost-effective at all, but necessary because PPP was widely implemented to prioritize quick dissemination to the employees in vulnerable firms.

Granja et al. (2022) also showed that the impact of the first and second rounds of PPPs on employment was small, noting that this may be because PPPs did not necessarily reach severely affected firms or because the firms that received PPPs might have kept the money as security against future crises.

The UK also implemented a subsidy program for employment protection called the Coronavirus Job Retention Scheme (CJRS). Crossley et al. (2021) found that the CJRS did not affect the unemployment rate in the UK between February and May 2020; however, 50% of the working-age population worked zero hours. This implies that this scheme did not encourage workers to move from a sector vulnerable to the pandemic to a sector invulnerable to it, but that the scheme was effective in preventing a decline in household income. At the same time, we observed an income decline for younger workers or those without guaranteed working hours, but they were searching for new jobs or applied for universal credit. The hours to work for minorities and low-income groups also decreased on average because some of them became unemployed, but they staved of the crisis by borrowing from family and friends.

In Japan, some studies have measured the effect of the EAS program on employment during the pandemic. Kobayashi (2021) and Fukuda and Yamamoto (2021) used monthly panel data of firms collected by the JILPT from February 2020 to January 2021. They found that EAS was used by firms whose performance deteriorated because of the pandemic. In addition, firms that applied for and/or received EAS succeeded in reducing the burden of labor costs for 1–3 months, suggesting that the subsidies were effective in reducing labor costs in the long run and undertaking employment and wage adjustments (Fukuda and Yamamoto, 2021). In fact, we confirm that firms receiving EAS tended not to implement personnel cuts for several (1–6) months (Kobayashi, 2021).

As shown in Pizzinelli and Shibata (2023), the mismatch was very serious in the early stages of the pandemic in the US and the UK but was quickly eliminated. In Japan, we observed a similar trend of mismatch for workers at a high risk of infection; that is, the mismatch rapidly increased in labor markets in early 2020 but was on a downward trend in 2021, although its level was still higher than the pre-pandemic level.

We infer that the reason for what happened in the US and UK as well as in Japan was that subsidies for employment protection such as PPP, CJRS, and EAS did not reach each and every vulnerable firm or low-skilled, young, or minority worker. These workers, who did not benefit from the subsidy, left firms affected the pandemic and searched for low-risk jobs. The labor mobility of these workers increased rapidly, but after a short while, they were allocated efficiently to firms not vulnerable to COVID-19, resulting in the elimination of mismatch.

While EAS provided in Japan was relatively generous, and firms were allowed to apply for the EAS program at any time, not all firms and micro enterprises, in particular, applied for it. Employees in these firms are more likely to lose the opportunity to receive EAS. Similar to vulnerable workers in the US and the UK, they quit their jobs and searched for new jobs. This temporarily raised the mismatch, but after a while, the mismatch was eliminated to achieve a more efficient allocation of workers.

We observed a different trend in the mismatch among workers at a low risk of infection in Japan. Mismatches were originally low before the pandemic and gradually increased in 2020 as well as in 2021. These workers were more likely to receive EAS and were on leave until the pandemic decreased slightly if their firms requested them to stay home. Therefore, the provision of EAS suppressed the increase in mismatch in the short term. However, some workers decided to change their jobs, expecting the pandemic to be prolonged, leading to a gradual increase in the mismatch.

We evaluated the advantages and disadvantages of subsidies for employment protection. The subsidy temporarily protected employment during the early days of the pandemic, thereby suppressing an increase in mismatch. However, in the long term, the subsidy induced workers to stay in vulnerable firms that could not carry on, which discouraged the efficient allocation of workers.

6. 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 a temporary school closure. We paid attention to the differences in job flows and the desired wage (or reservation wage) of various occupations according to the extent of the infection risk. Using the method developed by Şahin et al. (2014), we estimated the mismatch indices for local labor markets clustered in by occupations vulnerable and invulnerable to COVID-19.

To do so, we employed two datasets: administrative data on public employment services from the MHLW and Japanese-style O-NET data released by JILPT. The administrative data included information on 369 types of occupations from June 2016 to October 2021 at the monthly level, and the O-NET dataset covered the job characteristics of 497 occupations. We emphasize that each dataset had several notable features. The administrative data cover occupations by small classifications that cluster in the local labor market. The local labor market clustered in by these occupations is not very large, so we can avoid underestimating the job transfers of workers across local labor markets. The Japanese-style O-NET dataset directly asked respondents about “whether or not workers contact closely 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 occupations vulnerable to the COVID-19 infection. By merging the two datasets by occupational code, we explore how the pandemic affected the Japanese labor market, depending on the extent of infection risk.

We derive three main findings. First, the labor market condition 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 occupation types were vulnerable to infection. However, the labor market conditions gradually recovered in January 2021. This suggests that the Japanese labor market well reconciled with the new normal after the crisis, as more vacancies were posted and more jobseekers found work.

Second, jobseekers' desired wage, defined here as the reservation wage, was rising before the pandemic hit, and this upward trend continued for both full-time and part-time workers even afterward. We found that the desired wages for full-time workers engaging in an occupation at a high risk of infection increased faster just after the pandemic starting point. Under the model of compensating wage differentials, we assumed that workers demanded higher wages to compensate for the increase in the extent of perceived infectious risk.

Finally, the overall mismatch rapidly worsened since March 2020. After late 2020, however, some results showed that mismatches for high-risk occupations were gradually eliminated, but their levels were still higher than before the pandemic hit. The restaurant and bar sectors, in particular, suffered several adverse impacts. The mismatch for low-risk occupations increased in 2021, while the timing of the increase lagged that for high-risk occupations. We consider that such a larger extent of mismatch for both high- and low-risk occupations compared to before the pandemic occurred because the generous government subsidy offered for job protection might have discouraged labor mobility.

We predict that with new variants of the virus emerging, new waves of sickness would occur. Notwithstanding such eventualities, our overview of the dynamic changes in the Japanese labor market over the past two years concludes that the market has adapted gradually but successfully to the new post-COVID-19 normal.

Appendix A: Mismatch index

This appendix describes the calculation of the mismatch index developed by Şahin et al. (2014). First, we briefly outline their theoretical framework. Let the labor market be segmented by sectors. Here, assuming that the labor market is segmented by small classified occupations, we label the sectors as occupations. In each local labor market segmented by I occupations that are frictional, the number of new hires, namely, the number of matches between workers and firms, is assumed to be given by the following matching function.

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

where h_{it} denotes the number of new hires in occupation i in period t; u_{it} and v_{it} are the number of job seekers and of vacancies in occupation i in 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.[13] 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 jobseekers u_{it} is allocated to the labor market.

Here, a social planner is assumed to allocate jobseekers across occupational labor

[13] 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.

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 to maximize is

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

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 jobseekers) because $m(\cdot)$ follows a homogeneous degree of one. Consequently, u_{it}^* is the social planner's optimal allocation of jobseekers.

Next, we show the definition of the mismatch index. We here assume that the matching function of equation (A1) follows a Cobb-Douglas specification:

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

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 local 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 jobseekers and vacancies, respectively. Equation (A2) yields:

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

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

$$h_t^* = \bar{\phi}_t \Phi_t v_t^{\alpha} u_t^{1-\alpha}, where\ \bar{\phi}_t = \left[\sum_{i=1}^{I} \phi_i^{\frac{1}{\alpha}}\left(\frac{v_{it}}{v_t}\right)\right]^{\alpha}. \tag{A6}$$

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

$$\mathcal{M}_{\phi t} = 1 - \frac{h_t}{h_t^*} = 1 - \sum_{i=1}^{I} \left(\frac{\phi_i}{\bar{\phi}_t}\right) \left(\frac{v_{it}}{v_t}\right)^{\alpha} \left(\frac{u_{it}}{u_t}\right)^{1-\alpha}. \qquad (A7)$$

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 because of the misallocation of jobseekers. A significant feature of this index is that it accounts for the heterogeneity of matching efficiencies across occupational labor markets. When 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 the mismatch because it ignores the heterogeneity of the matching efficiencies (Kawata 2019).

To calculate the mismatch index in equation (A7), 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 taken from the Employment Referrals for General Workers (Report on Employment Service), 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.

$$\ln f_{it} = \gamma' \, trend_t + \ln \phi_i + \alpha \ln \theta_{it} + \varepsilon_{it}, \qquad (A8)$$

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.[14] Following Kawata (2019), who estimates the mismatch index of Şahin et al. (2014) using

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

the same Japanese data as we do, we can obtain ϕ_i by estimating equation (A8) as a fixed effect model. Note that occupations that contain zero new hires for one period or over are omitted from the sample because we cannot log them. 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 (A7), implying an upper bound for mismatch indices. To estimate equation (A8), we utilized data from June 2016 to December 2019, before the COVID-19 pandemic.

References

Adams-Prassl, Abi, Teodora Boneva, Marta Golin, and Christopher Rauh. 2020. "Inequality in the Impact of the Coronavirus Shock: Evidence from Real Time Surveys." *Journal of Public Economics* 189 (September): 104245. https://doi.org/10.1016/j.jpubeco.2020.104245.

Autor, David, David Cho, Leland D. Crane, Mita Goldar, Byron Lutz, Joshua Montes, William B. Peterman, David Ratner, Daniel Villar, and Ahu Yildirmaz. 2022. "An Evaluation of the Paycheck Protection Program Using Administrative Payroll Microdata." *Journal of Public Economics* 211 (July): 104664. https://doi.org/10.1016/j.jpubeco.2022.104664.

Arthur, Rudy. 2021. "Studying the UK Job Market during the COVID-19 Crisis with Online Job Ads." Edited by Siew Ann Cheong. *PLOS ONE* 16 (5): e0251431. https://doi.org/10.1371/journal.pone.0251431.

Avdiu, Besart, and Gaurav Nayyar. 2020. "When Face-to-Face Interactions Become an Occupational Hazard: Jobs in the Time of COVID-19." *Economics Letters* 197 (December): 109648. https://doi.org/10.1016/j.econlet.2020.109648.

Balgová, Mária, Simon Trenkle, Christian Zimpelmann, and Nico Pestel. 2022. "Job Search during a Pandemic Recession: Survey Evidence from the Netherlands." *Labour Economics* 75 (April): 102142. https://doi.org/10.1016/j.labeco.2022.102142.

Carrillo-Tudela, Carlos, Alex Clymo, Camila Comunello, Annette Jäckle, Ludo Visschers, and David Zentler-Munro. 2023. "Search and Reallocation in the COVID-19 Pandemic: Evidence from the UK." *Labour Economics* 81 (April): 102328. https://doi.org/10.1016/j.labeco.2023.102328.

Crossley, Thomas F., Paul Fisher, and Hamish Low. 2021. "The Heterogeneous and Regressive Consequences of COVID-19: Evidence from High Quality Panel Data." *Journal of Public Economics* 193 (January): 104334. https://doi.org/10.1016/j.jpubeco.2020.104334.

Dingel, Jonathan I., and Brent Neiman. 2020. "How Many Jobs Can Be Done at Home?" *Journal of Public Economics* 189 (September): 104235. https://doi.org/10.1016/j.jpubeco.2020.104235.

Forsythe, Eliza, Lisa B. Kahn, Fabian Lange, and David Wiczer. 2020. "Labor Demand in the Time of COVID-19: Evidence from Vacancy Postings and UI Claims." *Journal of Public Economics* 189 (September): 104238. https://doi.org/10.1016/j.jpubeco.2020.104238.

Fukai, Taiyo. 2022. "Employment under COVID-19 in Japan in 2020: An Examination of the Heterogeneity of the Effects on Workers Using the Labor Force Survey" *Japanese Journal of Labour Studies*, No. 738: 14–27 (in Japanese).

Fukai, Taiyo, Hidehiko Ichimura, and Keisuke Kawata. 2021. "Describing the Impacts of COVID-19 on the Labor Market in Japan until June 2020." *Japanese Economic Review* 72 (3): 439–70. https://doi.org/10.1007/s42973-021-00081-z.

Fukuda, Akira and Isamu Yamamoto. 2021. "Corona-ka no seihu niyoru kigyoshiensaku to koyoiji, koyosakugen eno kakukoka (Measures for supporting firms by the government and their effects on maintaining and reducing employment)." In *Corona-ka niokeru kojin to kigyo no henyo: Hatarakikata, seikatsu, kakusa to shiensaku (Changes in individuals and firms: Work style, livelihood, disparities, and supporting measures)*, edited by Yoshio Higuchi and JILPT, pp. 75–92 (Chapter 3), Tokyo: Keio University Press (in Japanese).

Fukui, Masao, Shinnosuke Kikuchi, and Goalist Co. Ltd. 2020. "Job Creation during the COVID-19 Pandemic in Japan." CREPE Discussion Paper, No. 73.

Granja, João, Christos Makridis, Constantine Yannelis, and Eric Zwick. 2022. "Did the Paycheck Protection Program Hit the Target?" *Journal of Financial Economics* 145 (3): 725–61. https://doi.org/10.1016/j.jfineco.2022.05.006.

Hensvik, Lena, Thomas Le Barbanchon, and Roland Rathelot. 2021. "Job Search during the COVID-19 Crisis." *Journal of Public Economics* 194 (February): 104349. https://doi.org/10.1016/j.jpubeco.2020.104349.

Hoshi, Kisho, Hiroyuki Kasahara, Ryo Makioka, Michio Suzuki, and Satoshi Tanaka. 2022. "The Heterogeneous Effects of COVID-19 on Labor Markets: People's Movement and Non-Pharmaceutical Interventions." *Journal of the Japanese and International Economies* 63: 101170. https://doi.org/10.1016/j.jjie.2021.101170.

Hubbard, Glenn and Michael R. Strain. 2020. "Has the Paycheck Protection Program Succeeded?" *Brookings Papers on Economic Activity*, Fall, 335-390.

Jackman, Richard A. and Stephen Roper. 1987. "Structural Unemployment." *Oxford Bulletin of Economics and Statistics* 49 (1): 9–36.

Kawakami, Atsushi. 2021. "Corona Shock niyoru Rodoshijo no Henka (Changes in Labor

Market due to the Corona Shock).” In *Corona Shock no Keizaigaku (Economics of the Corona Shock)*, edited by Tsutomu Miyagawa, pp. 115–138 (Chapter 7), Tokyo: Chuokeizai-Sha (in Japanese).

Kawata, Keisuke. 2019. “Measuring Mismatch in Japanese Labor Market” *Economic Analysis (ESRI)*, No. 199: 122–151 (in Japanese).

Kawata, Keisuke. 2021. “The Impact of COVID-19 on the Japanese Labor Market” the *Japanese Journal of Labour Studies*, No. 729: 2–7 (in Japanese).

Kikuchi, Shinnosuke, Sagiri Kitao, and Minamo Mikoshiba. 2021. “Who Suffers from the COVID-19 Shocks? Labor Market Heterogeneity and Welfare Consequences in Japan.” *Journal of the Japanese and International Economies* 59: 101117. https://doi.org/10.1016/j.jjie.2020.101117.

Kobayashi, Toru. 2021. “Corona-ka no kigyogyoseki no henka to juyokankisaku, koyoijisaku no koka (The changes in corporate performance and the effects of policies to boost demand and to maintain employment amid the COVID-19 pandemic).” In *Corona-ka niokeru kojin to kigyo no henyo: Hatarakikata, seikatsu, kakusa to shiensaku (Changes in individuals and firms: Work style, livelihood, disparities, and supporting measures)*, edited by Yoshio Higuchi and JILPT, pp. 45–73 (Chapter 2), Tokyo: Keio University Press (in Japanese).

Koebel, Kourtney, and Dionne Pohler. 2020. “Labor Markets in Crisis: The Double Liability of Low‐Wage Work During COVID‐19.” *Industrial Relations: A Journal of Economy and Society* 59 (4): 503–31. https://doi.org/10.1111/irel.12269.

Pizzinelli, Carlo, and Ippei Shibata. “Has COVID-19 Induced Labor Market Mismatch? Evidence from the US and the UK.” *Labour Economics*, January 2023, 102329. https://doi.org/10.1016/j.labeco.2023.102329.

Şahin, Ayşegül, Joseph Song, Giorgio Topa, and Giovanni L. Violante. 2014. "Mismatch Unemployment." *American Economic Review* 104 (11): 3529–64. https://doi.org/10.1257/aer.104.11.3529.

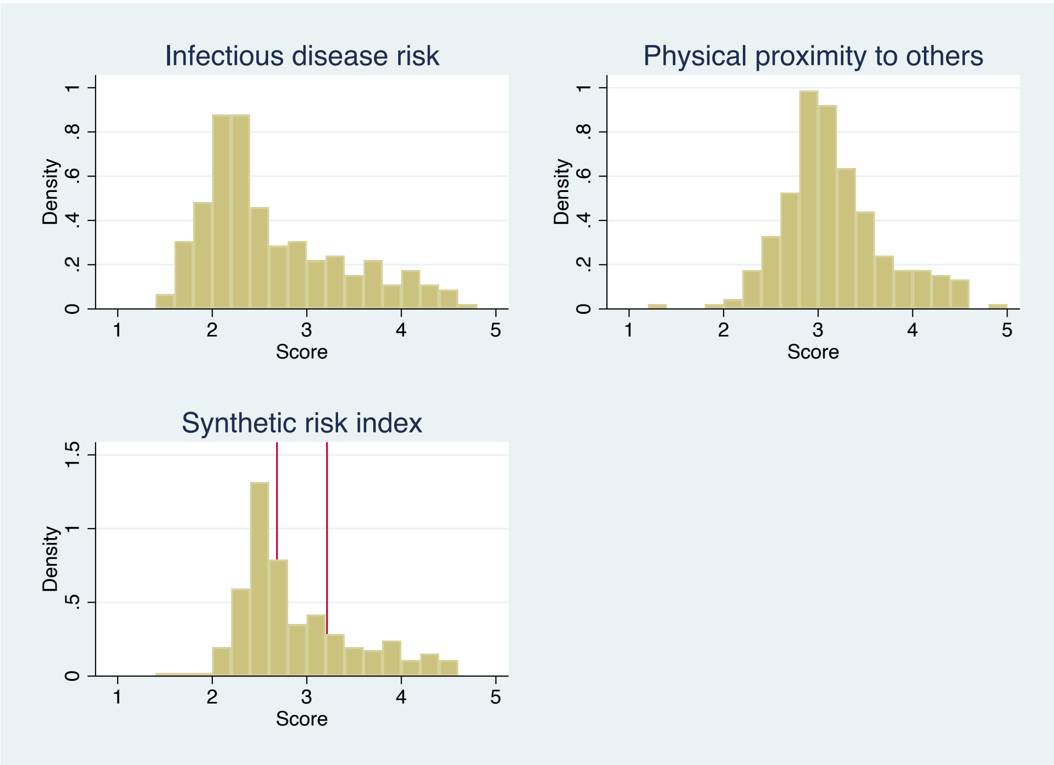
Shibata, Ippei. 2020. "Is Labor Market Mismatch a Big Deal in Japan?" *The B.E. Journal of Macroeconomics* 20 (2): 20160179. https://doi.org/10.1515/bejm-2016-0179.

Table 1: Occupational Group Defined by Remote Work Availability

Occupational group definition	Definition of easy-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

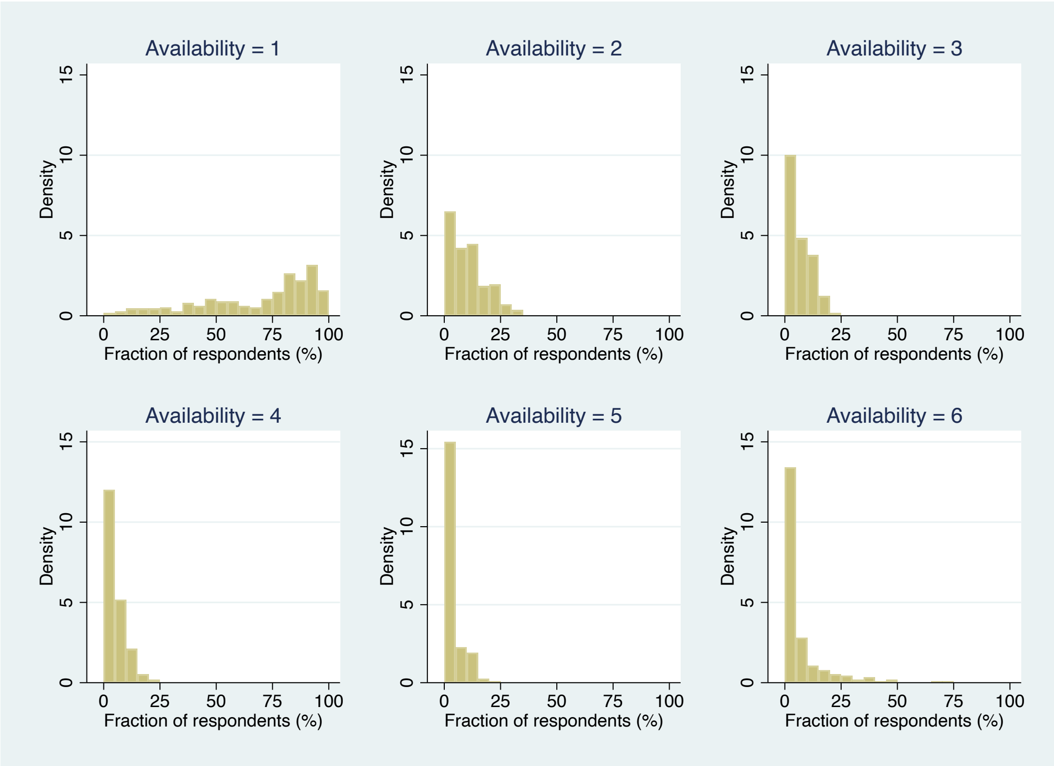
Notes: Values in parentheses correspond to the choices for the question about availability of remote work under an infectious diseases epidemic.

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.

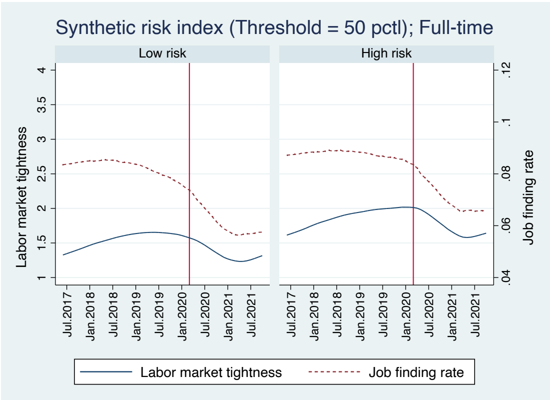
Figure 2: Distribution of Availability of Remote Work



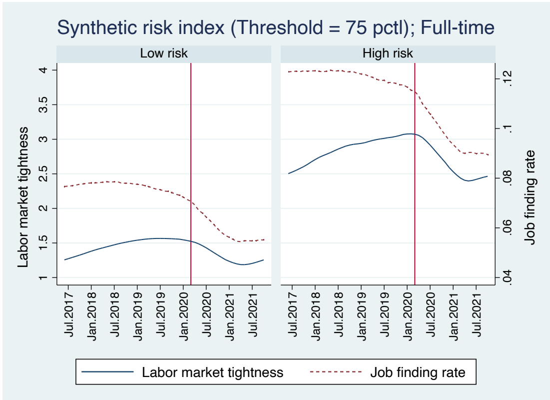
Notes: The value of availability for each panel indicates a choice in the questionnaire: 1 = usually, no; 2 = 20% of days of duty and below; 3 = 20% and over, below 40% of days of duty; 4 = 40% and over, below 60% of days of duty; 5 = 60% and over, below 80% of days of duty; 6 = 80% of days of duty and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

Figure 3: Trends in Labor Market Tightness and Job Finding Rate by Occupational Group Defined by Risk of Infection

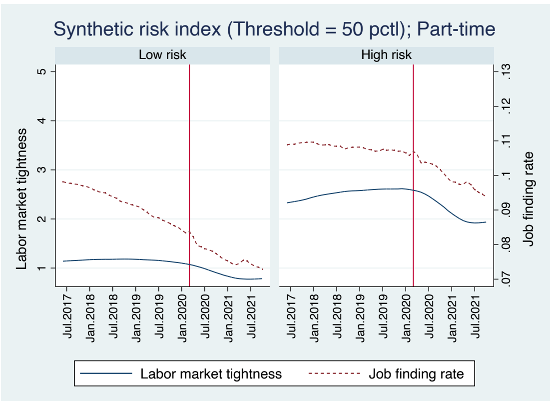
(a) Full-Time Workers (the 50th percentile of the synthetic risk index)



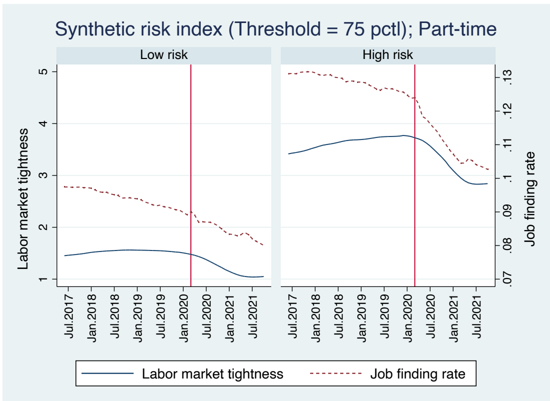
(b) Full-Time Workers (the 75th percentile of the synthetic risk index)



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



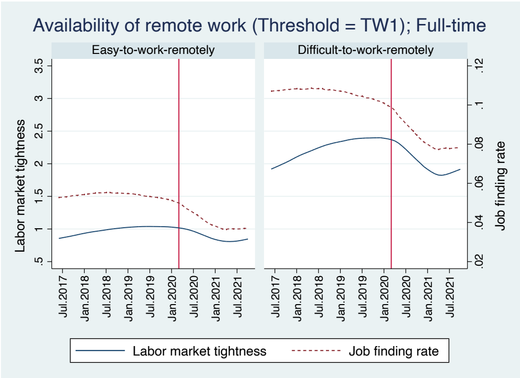
(d) Part-Time Workers (the 75th percentile of the synthetic risk index)



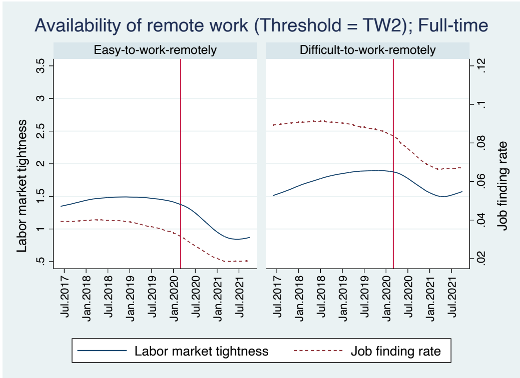
Notes: Job finding rate = new hires/jobseekers. Labor market tightness = vacancies/jobseekers. The 12-month backward moving averages of the occupational group's mean values are plotted. The vertical line indicates March 2020.

Figure 4: Trends in Labor Market Tightness and Job Finding Rate by Occupational Group Defined by Availability of Remote Work

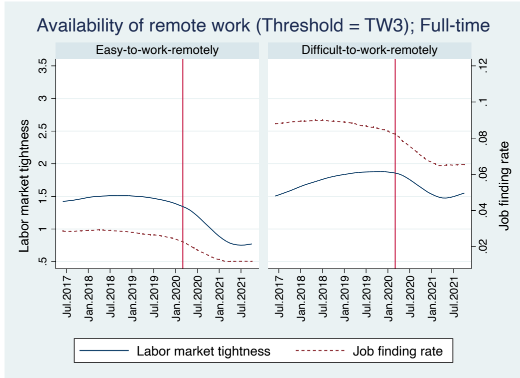
(a) Full-Time Workers (TW1 as the threshold of remote work availability)



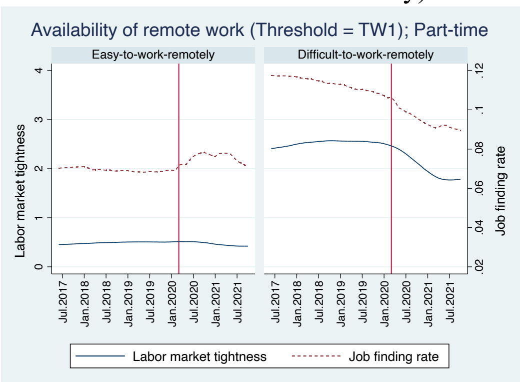
(b) Full-Time Workers (TW2 as the threshold of remote work availability)



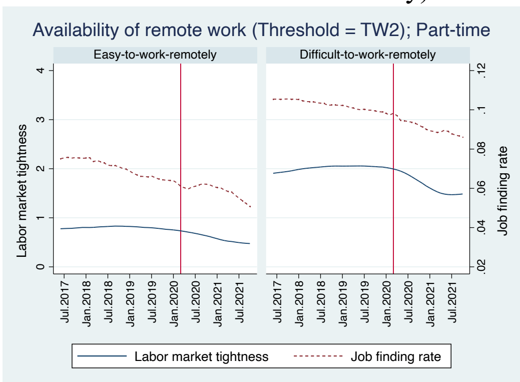
(c) Full-Time Workers (TW3 as the threshold of remote work availability)



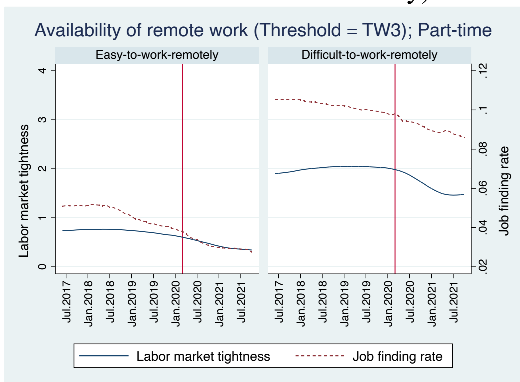
(d) Part-Time Workers (TW1 as the threshold of remote work availability)



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



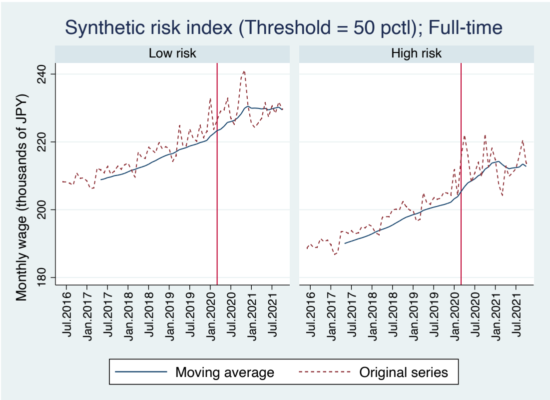
(f) Part-Time Workers (TW3 as the threshold of remote work availability)



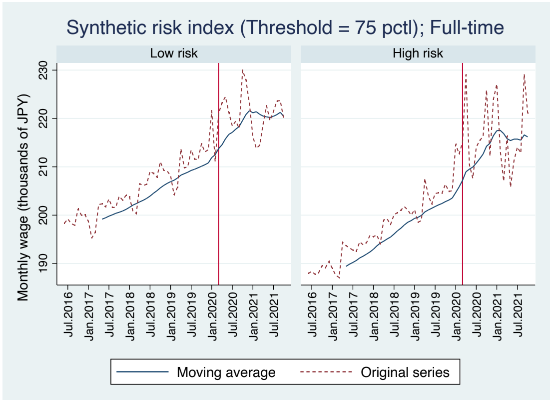
Notes: Job finding rate = new hires/jobseekers. Labor market tightness = vacancies/jobseekers. The 12-month backward moving averages of the occupational group's mean values are plotted. The vertical line indicates March 2020.

Figure 5: Trends in the Desired Wages by Occupational Group Defined by Risk of Infection

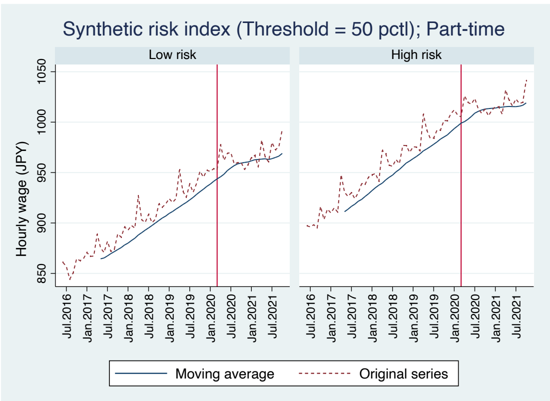
(a) Full-Time Workers (the 50th percentile of the synthetic risk index)



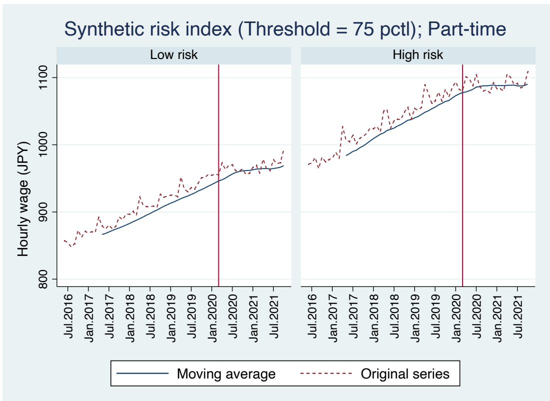
(b) Full-Time Workers (the 75th percentile of the synthetic risk index)



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



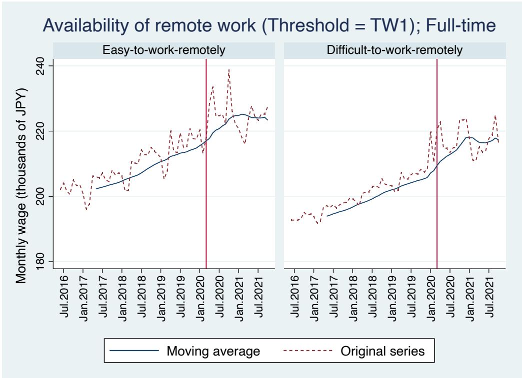
(d) Part-Time Workers (the 75th percentile of the synthetic risk index)



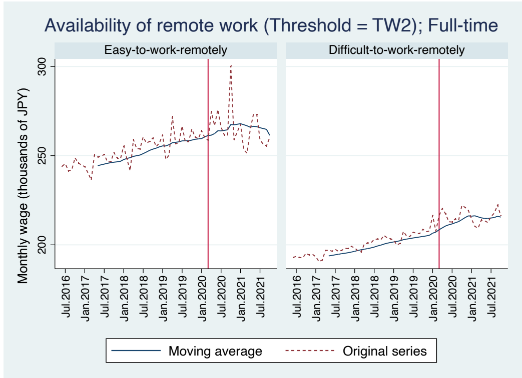
Notes: The desired wages are adjusted using the 2020 base Consumer Price Index from the Japanese Statistics Bureau, Ministry of Internal Affairs and Communications. The original series and the 12-month backward moving average of occupational group mean values weighted by the number of respondents are plotted. The vertical line indicates March 2020.

Figure 6: Trends in the Desired Wages by Occupational Group Defined by Availability of Remote Work

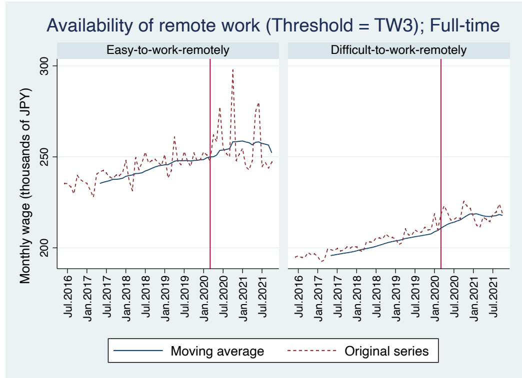
(a) Full-Time Workers (TW1 as the threshold of remote work availability)



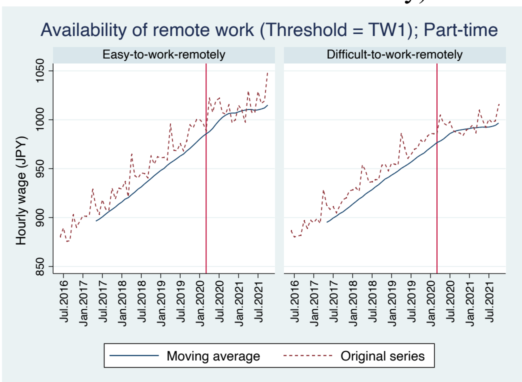
(b) Full-Time Workers (TW2 as the threshold of remote work availability)



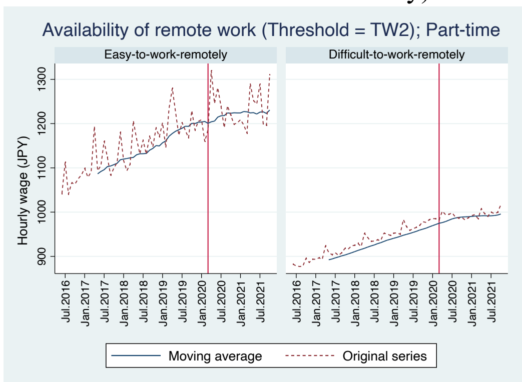
(c) Full-Time Workers (TW3 as the threshold of remote work availability)



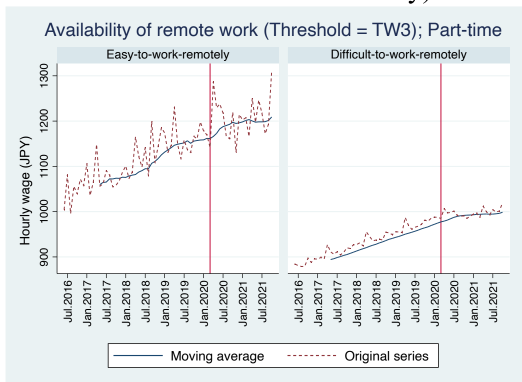
(d) Part-Time Workers (TW1 as the threshold of remote work availability)



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



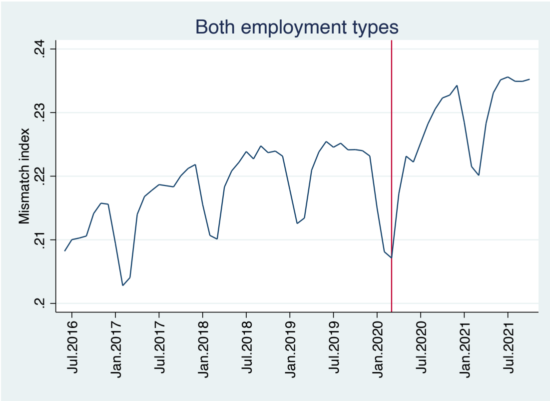
(f) Part-Time Workers (TW3 as the threshold of remote work availability)



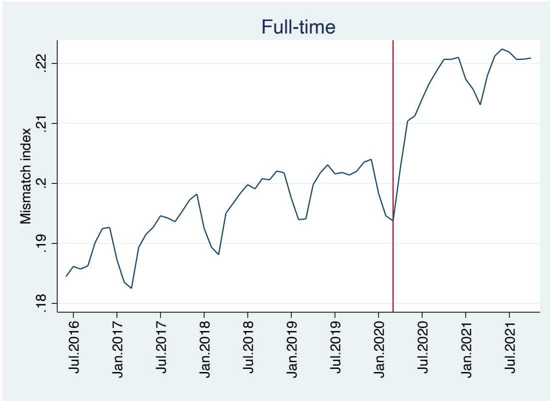
Notes: The desired wages are adjusted using the 2020 base Consumer Price Index from the Japanese Statistics Bureau, Ministry of Internal Affairs and Communications. The original series and the 12-month backward moving average of occupational group mean values weighted by the number of respondents are plotted. The vertical line indicates March 2020.

Figure 7: Trends in the Mismatch Indices

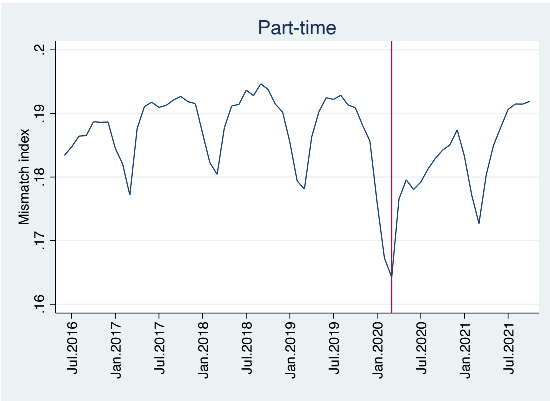
(a) Both employment types



(b) Full-time workers



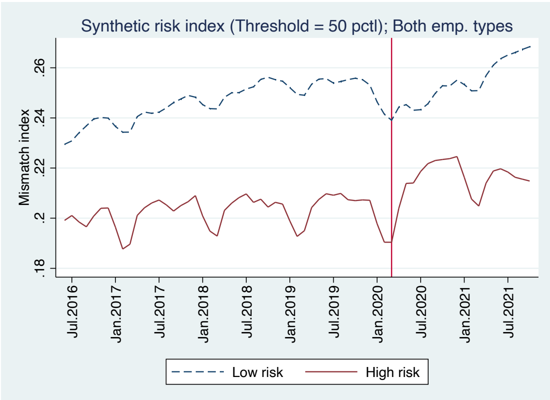
(c) Part-time workers



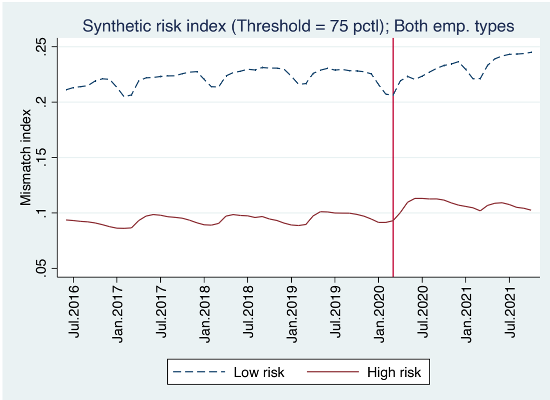
Notes: The vertical line indicates March 2020.

Figure 8: Trends in the Mismatch Indices by Occupational Group Defined by Risk of Infection

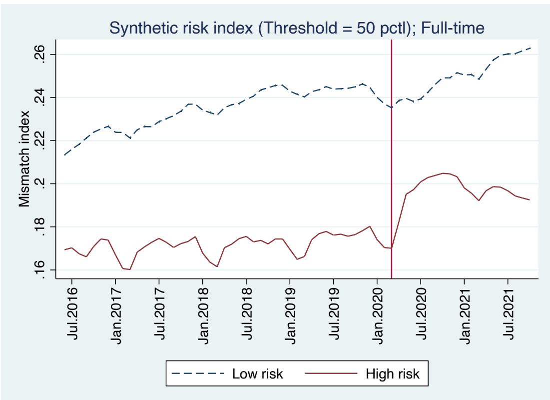
(a) Both employment types (the 50th percentile of the synthetic risk index)



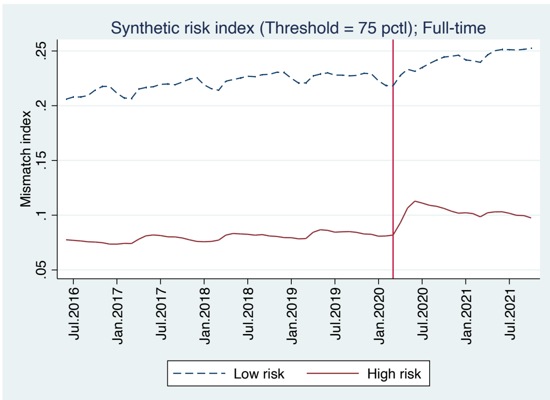
(b) Both employment types (the 75th percentile of the synthetic risk index)



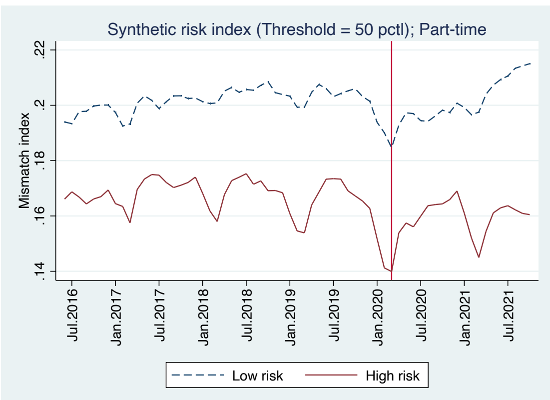
(c) Full-Time Workers (the 50th percentile of the synthetic risk index)



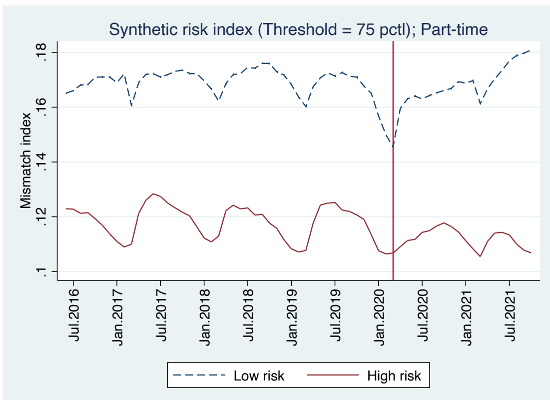
(d) Full-Time Workers (the 75th percentile of the synthetic risk index)



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



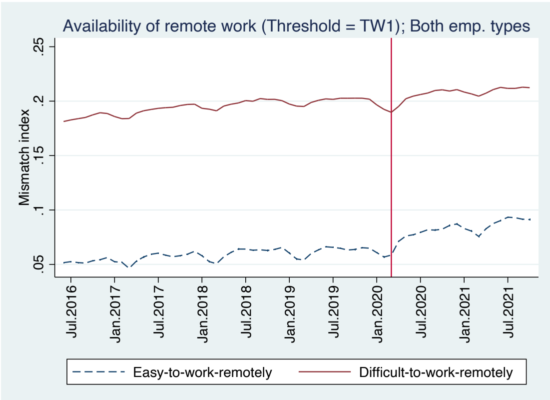
(f) Part-Time Workers (the 75th percentile of the synthetic risk index)



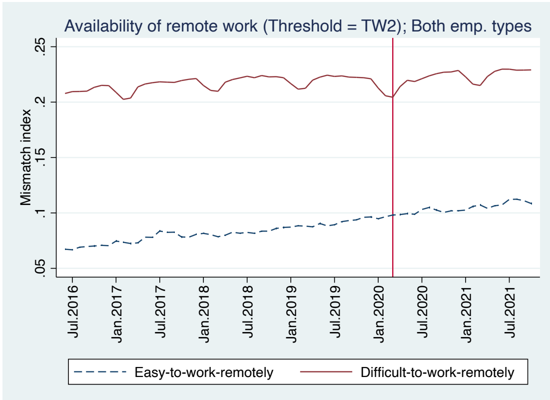
Note: The vertical line indicates March 2020.

Figure 9: Trends in the Mismatch Indices by Occupational Group Defined by Availability of Remote Work

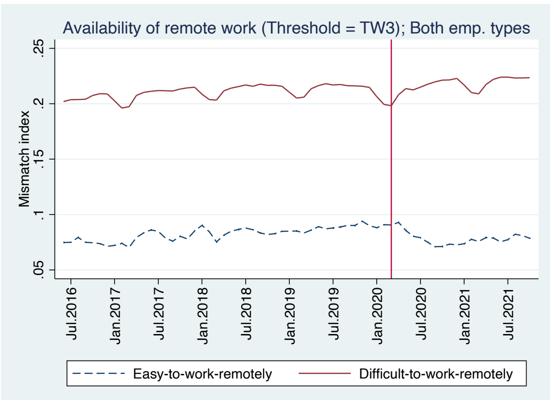
(a) Both employment types (TW1 as the threshold of remote work availability)



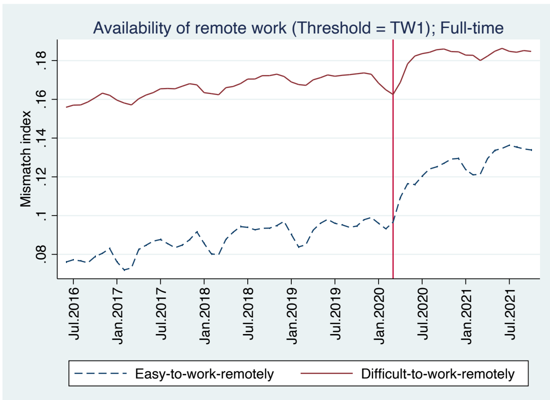
(b) Both employment types (TW2 as the threshold of remote work availability)



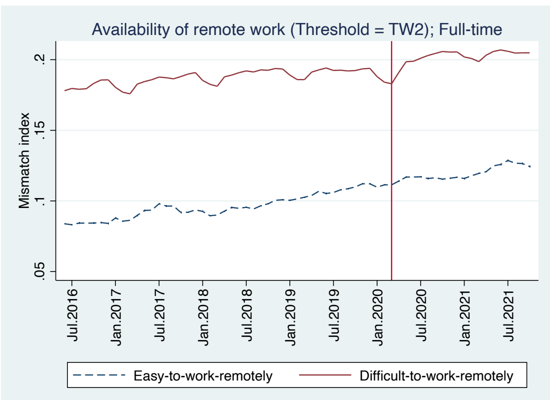
(c) Both employment types (TW3 as the threshold of remote work availability)



(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)

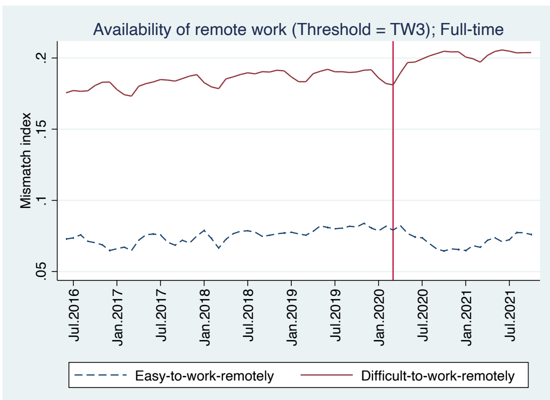
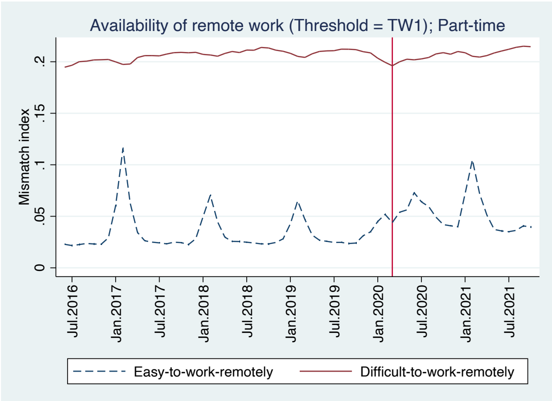
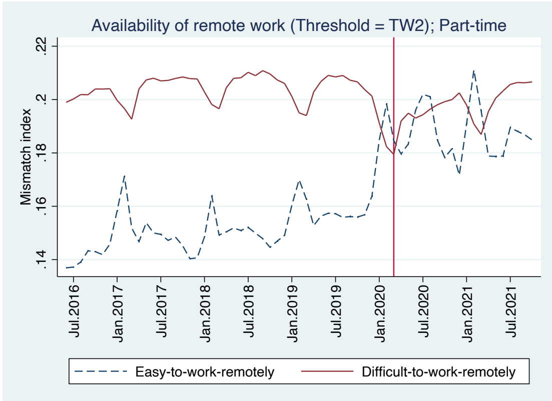


Figure 9 (continued)

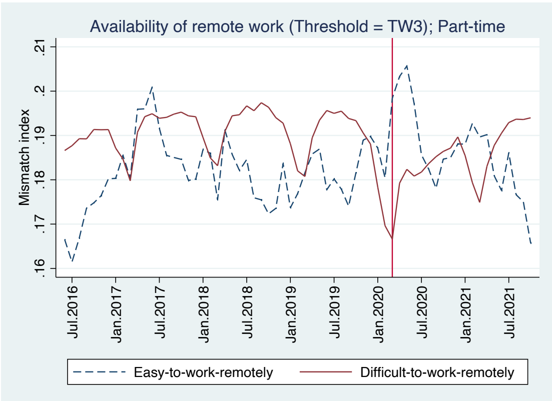
(g) Part-Time Workers (TW1 as the threshold of remote work availability)



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



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



Note: The vertical line indicates March 2020.

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

By Yudai Higashi and Masaru Sasaki

This Online Appendix provides supplemental tables and figures.

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

Variable	(1) Occupations included in the sample (Obs: 14,820 (=228 occ × 65 months))	(2) Occupations excluded from the sample (Obs: 9,165 (=141 occ × 65 months))	(1)/(2)
Panel A: Full-time			
New hires	277.55	42.86	6.48
Jobseekers	3543.99	536.51	6.61
Vacancies	5818.90	637.90	9.12
Panel B: Part-time			
New hires	187.36	21.23	8.83
Jobseekers	1929.10	242.37	7.96
Vacancies	3512.91	269.69	13.03

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. 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 (small-classification)	Occupational group					Sample restriction for mismatch indices	
		Risk of infection		Availability of remote work				
		Threshold = 50 pctl	Threshold = 75 pctl	Threshold = TW1	Threshold = TW2	Threshold = TW3	Full-time	Part-time
21	Corporate officers	Low	Low	Difficult	Difficult	Difficult		
31	Corporate management staff	High	Low	Difficult	Difficult	Difficult	Y	
39	Other corporate management staff, etc.	High	High	Difficult	Difficult	Difficult	Y	
51	Researchers	Low	Low	Easy	Easy	Difficult	Y	Y
61	Agricultural, forest, fisheries engineers	Low	Low	Difficult	Difficult	Difficult	Y	
71	Food development engineers	Low	Low	Difficult	Difficult	Difficult	Y	
72	Electrical and electronic development engineers, etc.	Low	Low	Easy	Difficult	Difficult	Y	
73	Mechanical development engineer	Low	Low	Easy	Easy	Difficult	Y	Y
77	Chemical development engineers	Low	Low	Easy	Difficult	Difficult	Y	
81	Food manufacturing engineers	Low	Low	Difficult	Difficult	Difficult	Y	Y
82	Electrical and electronic manufacturing engineers	Low	Low	Easy	Easy	Difficult	Y	Y
87	Chemicals manufacturing engineers	Low	Low	Easy	Difficult	Difficult	Y	
91	Architectural engineer	Low	Low	Easy	Difficult	Difficult	Y	Y
92	Civil engineers	Low	Low	Easy	Difficult	Difficult	Y	Y
93	Surveying technicians	Low	Low	Difficult	Difficult	Difficult	Y	Y
101	Systems consultants	Low	Low	Easy	Easy	Easy	Y	
102	System design engineers	Low	Low	Easy	Easy	Easy	Y	
103	Project managers	Low	Low	Easy	Easy	Easy		
104	Software development engineers	Low	Low	Easy	Easy	Easy	Y	Y
105	Systems operations manager	Low	Low	Easy	Easy	Difficult	Y	
106	Telecommunications network engineer	Low	Low	Easy	Easy	Difficult	Y	
109	Other information processing engineers, etc.	Low	Low	Easy	Easy	Easy	Y	Y
119	Other engineers	Low	Low	Easy	Difficult	Difficult	Y	Y
121	Physicians	High	High	Difficult	Difficult	Difficult		
122	Dentists	High	High	Difficult	Difficult	Difficult		
123	Veterinarians	High	High	Difficult	Difficult	Difficult		
124	Pharmacists	High	High	Difficult	Difficult	Difficult	Y	Y
131	Public health nurses	High	High	Difficult	Difficult	Difficult	Y	Y
132	Midwives	High	High	Difficult	Difficult	Difficult	Y	Y
133	Nurses, assistant nurses	High	High	Difficult	Difficult	Difficult	Y	Y
141	Radiologic technologists	High	High	Difficult	Difficult	Difficult	Y	Y
142	Clinical engineers	High	High	Difficult	Difficult	Difficult	Y	
143	Medical technologists	High	High	Difficult	Difficult	Difficult	Y	Y
144	Physiotherapists	High	High	Difficult	Difficult	Difficult	Y	Y

145	Occupational therapists	High	High	Difficult	Difficult	Difficult	Y	Y
146	Optometrists, speech-language-hearing therapists	High	High	Difficult	Difficult	Difficult	Y	Y
147	Dental hygienists	High	High	Difficult	Difficult	Difficult	Y	Y
148	Dental technicians	High	Low	Difficult	Difficult	Difficult	Y	Y
151	Nutritionists, Registered Dietitians	High	High	Difficult	Difficult	Difficult	Y	Y
152	*Anma*, massage, *shiatsu* practitioners, etc.	High	High	Difficult	Difficult	Difficult	Y	Y
153	Judo therapists	High	High	Difficult	Difficult	Difficult	Y	Y
159	Healthcare not elsewhere classified	High	High	Easy	Difficult	Difficult	Y	Y
161	Welfare consultation and guidance specialists	High	High	Difficult	Difficult	Difficult	Y	Y
162	Welfare facility consulting specialists	High	High	Difficult	Difficult	Difficult	Y	Y
163	Nursery school teachers	High	High	Difficult	Difficult	Difficult	Y	Y
169	Other social welfare professions	High	High	Difficult	Difficult	Difficult	Y	Y
173	Lawyers	Low	Low	Easy	Difficult	Difficult		
174	Patent attorneys	Low	Low	Easy	Easy	Easy		
175	Judicial scriveners	Low	Low	Difficult	Difficult	Difficult	Y	
179	Other legal professions	Low	Low	Difficult	Difficult	Difficult	Y	Y
181	Certified public accountants	Low	Low	Easy	Easy	Easy		
182	Tax accountants	Low	Low	Easy	Difficult	Difficult	Y	
183	Social insurance and labor consultants	Low	Low	Easy	Difficult	Difficult	Y	Y
184	Finance and insurance professionals	Low	Low	Easy	Easy	Easy		
189	Other professions related to management, finance, etc.	Low	Low	Easy	Easy	Difficult	Y	
191	Kindergarten teachers	High	High	Difficult	Difficult	Difficult	Y	Y
192	Elementary school teachers	High	High	Difficult	Difficult	Difficult	Y	Y
193	Middle school teachers	High	High	Difficult	Difficult	Difficult	Y	
194	High school teachers	High	High	Difficult	Difficult	Difficult	Y	Y
196	Special needs school teachers	High	High	Difficult	Difficult	Difficult	Y	Y
199	Other education professions	High	Low	Difficult	Difficult	Difficult	Y	Y
211	Writers	Low	Low	Easy	Easy	Easy	Y	
212	Journalists	Low	Low	Easy	Easy	Easy	Y	
213	Editors	Low	Low	Easy	Easy	Easy	Y	Y
222	Painters, calligraphers, manga artists	Low	Low	Easy	Easy	Easy	Y	
224	Designers	Low	Low	Easy	Easy	Easy	Y	Y
225	Photographers, videographers	High	Low	Difficult	Difficult	Difficult	Y	Y
234	Producers, directors	High	Low	Difficult	Difficult	Difficult	Y	
241	Librarians	High	Low	Difficult	Difficult	Difficult	Y	Y
242	Curators	High	Low	Easy	Difficult	Difficult		
243	Counselors	High	Low	Easy	Difficult	Difficult	Y	Y
244	Tutors	High	Low	Difficult	Difficult	Difficult	Y	Y
246	Telecommunications equipment operators	High	Low	Easy	Difficult	Difficult	Y	
249	Specialties not elsewhere classified	Low	Low	Easy	Easy	Difficult	Y	Y
251	Administrative clerks	Low	Low	Easy	Difficult	Difficult	Y	Y
252	Personnel clerks	Low	Low	Easy	Easy	Difficult	Y	Y

253	Planning and research clerks	Low	Low	Easy	Easy	Difficult	Y	Y
254	Receptionists and information clerks	High	Low	Difficult	Difficult	Difficult	Y	Y
255	Secretaries	Low	Low	Easy	Easy	Difficult	Y	Y
256	Telephone receptionists	High	Low	Difficult	Difficult	Difficult	Y	Y
257	General office clerks	High	Low	Easy	Difficult	Difficult	Y	Y
258	Medical and long-term care clerks	High	High	Difficult	Difficult	Difficult	Y	Y
259	Other general clerical personnel	Low	Low	Easy	Difficult	Difficult	Y	Y
261	Cash tellers	High	Low	Easy	Difficult	Difficult	Y	Y
262	Bank, etc. counter clerks	High	Low	Difficult	Difficult	Difficult	Y	Y
263	Accounting clerks	Low	Low	Difficult	Difficult	Difficult	Y	Y
271	Production clerks	Low	Low	Easy	Difficult	Difficult	Y	Y
281	Marketing/Sales clerks	High	Low	Easy	Difficult	Difficult	Y	Y
289	Other marketing/sales clerical personnel	High	Low	Difficult	Difficult	Difficult	Y	Y
299	Other outdoor service personnel	Low	Low	Difficult	Difficult	Difficult	Y	Y
301	Passenger/freight clerical personnel	High	High	Difficult	Difficult	Difficult	Y	Y
302	Operations clerk	High	Low	Difficult	Difficult	Difficult	Y	Y
312	Data entry clerk	Low	Low	Difficult	Difficult	Difficult	Y	Y
321	Retail store owners and managers	High	High	Difficult	Difficult	Difficult	Y	Y
323	Retail store salespersons	High	Low	Difficult	Difficult	Difficult	Y	Y
325	Home visit and mobile sales agents	Low	Low	Difficult	Difficult	Difficult	Y	Y
333	Securities, commodities, and financial services sales agents	Low	Low	Easy	Difficult	Difficult		
339	Other sales and similar workers	High	Low	Difficult	Difficult	Difficult	Y	Y
343	Pharmaceutical sales worker	High	High	Easy	Easy	Difficult	Y	
344	Machinery, equipment, and supplies sales agents	High	Low	Difficult	Difficult	Difficult	Y	
345	Telecommunications and information systems sales agents	High	Low	Easy	Easy	Difficult	Y	
346	Finance and insurance sales agents	High	Low	Easy	Difficult	Difficult	Y	Y
347	Real estate sales agents	High	Low	Easy	Difficult	Difficult	Y	Y
349	Other sales agents	High	Low	Easy	Difficult	Difficult	Y	Y
351	Housekeeper, domestic workers	Low	Low	Difficult	Difficult	Difficult	Y	Y
359	Other domestic support service worker	High	High	Difficult	Difficult	Difficult	Y	Y
361	Facility caregivers	High	High	Difficult	Difficult	Difficult	Y	Y
362	Home-visit caregivers	High	High	Difficult	Difficult	Difficult	Y	Y
371	Nursing assistants	High	High	Difficult	Difficult	Difficult	Y	Y
379	Other healthcare service workers	High	High	Difficult	Difficult	Difficult	Y	Y
381	Barbers	High	High	Difficult	Difficult	Difficult	Y	Y
382	Beauticians	High	High	Difficult	Difficult	Difficult	Y	Y
383	Beauty service professionals	High	High	Difficult	Difficult	Difficult	Y	Y
385	Cleaners	High	Low	Difficult	Difficult	Difficult	Y	Y
391	Cooks	High	Low	Difficult	Difficult	Difficult	Y	Y
392	Bartenders	High	High	Difficult	Difficult	Difficult		
401	Restaurant owners and managers	High	High	Difficult	Difficult	Difficult	Y	
402	*Ryokan* and hotel managers	High	High	Difficult	Difficult	Difficult	Y	

403	Food and beverages servers	High	High	Difficult	Difficult	Difficult	Y	Y
404	Inn, hotel, and transportation service personnel	High	High	Difficult	Difficult	Difficult	Y	Y
406	Customer service personnel at entertainment venues, etc.	High	High	Difficult	Difficult	Difficult	Y	Y
411	Condominium managers, etc.	Low	Low	Difficult	Difficult	Difficult	Y	Y
414	Car/bicycle parking managers	High	Low	Difficult	Difficult	Difficult	Y	Y
421	Tour conductors, tour guides	High	High	Difficult	Difficult	Difficult	Y	Y
423	Lessors	High	High	Difficult	Difficult	Difficult	Y	Y
425	Funeral directors, crematory operators	High	High	Difficult	Difficult	Difficult	Y	Y
426	Pet groomers	High	Low	Difficult	Difficult	Difficult	Y	Y
429	Service personnel not elsewhere classified	High	High	Difficult	Difficult	Difficult	Y	Y
431	Members of the Self-Defense Forces of Japan	Low	Low	Difficult	Difficult	Difficult		
441	Police officers	High	High	Difficult	Difficult	Difficult		
442	Maritime security officer	High	Low	Difficult	Difficult	Difficult		
451	Prison guards	High	High	Difficult	Difficult	Difficult		
452	Firefighters	High	High	Difficult	Difficult	Difficult	Y	
453	Security guards	High	Low	Difficult	Difficult	Difficult	Y	Y
459	Other security and law enforcement personnel not elsewhere classified	High	Low	Difficult	Difficult	Difficult	Y	Y
461	Agricultural workers	Low	Low	Difficult	Difficult	Difficult	Y	Y
462	Livestock farm worker	Low	Low	Difficult	Difficult	Difficult	Y	Y
463	Gardeners, landscapers	Low	Low	Difficult	Difficult	Difficult	Y	Y
471	Forest workers	Low	Low	Difficult	Difficult	Difficult	Y	Y
481	Fishermen and fisherwomen	Low	Low	Difficult	Difficult	Difficult	Y	
497	Metal plating and polishing facility workers	High	Low	Difficult	Difficult	Difficult	Y	
501	Chemical product manufacturing facility workers	Low	Low	Easy	Difficult	Difficult	Y	
505	Spinning and weaving, garment manufacturing facility workers	Low	Low	Difficult	Difficult	Difficult	Y	
507	Printing and bookbinding facility workers	Low	Low	Difficult	Difficult	Difficult	Y	
508	Rubber manufacturing facility workers	Low	Low	Easy	Difficult	Difficult	Y	
512	Electrical machinery and equipment assembly facility workers	High	Low	Difficult	Difficult	Difficult	Y	
523	Foundry workers	Low	Low	Difficult	Difficult	Difficult	Y	Y
524	Forge workers	Low	Low	Difficult	Difficult	Difficult	Y	Y
528	Computer numerical control machinists	Low	Low	Difficult	Difficult	Difficult	Y	Y
531	Metal press operators	Low	Low	Difficult	Difficult	Difficult	Y	Y
532	Ironworkers, cannery workers	Low	Low	Difficult	Difficult	Difficult	Y	Y
533	Tinsmiths	Low	Low	Difficult	Difficult	Difficult	Y	Y
536	Metal product manufacturing facility workers	Low	Low	Difficult	Difficult	Difficult	Y	Y
537	Metal welding and cutting facility workers	Low	Low	Difficult	Difficult	Difficult	Y	Y
541	Chemical product manufacturing facility workers	Low	Low	Difficult	Difficult	Difficult	Y	Y
542	Ceramic, earth, and stone product manufacturing facility workers	Low	Low	Difficult	Difficult	Difficult	Y	Y
543	Flour and grain mill workers, etc.	Low	Low	Difficult	Difficult	Difficult	Y	Y
545	Bread and confectionery manufacturing facility workers	Low	Low	Difficult	Difficult	Difficult	Y	Y
546	*Tofu*- and *konnyaku*-based product manufacturing facility workers	Low	Low	Difficult	Difficult	Difficult	Y	Y

547	Canned and bottled product manufacturing facility workers	High	Low	Difficult	Difficult	Difficult	Y	Y
548	Dairy product manufacturing facility workers	Low	Low	Difficult	Difficult	Difficult	Y	Y
551	Meat processing facility workers	Low	Low	Difficult	Difficult	Difficult	Y	Y
552	Marine product processing facility workers	Low	Low	Difficult	Difficult	Difficult	Y	Y
553	Preserved food production facility workers	Low	Low	Difficult	Difficult	Difficult	Y	Y
554	Packed lunch production facility workers	High	Low	Difficult	Difficult	Difficult	Y	Y
555	Vegetable pickle production facility workers	Low	Low	Difficult	Difficult	Difficult	Y	Y
556	Beverage and tobacco manufacturing facility workers	Low	Low	Difficult	Difficult	Difficult	Y	Y
558	Clothing and textile manufacturing facility workers	Low	Low	Difficult	Difficult	Difficult	Y	Y
561	Wood product manufacturing workers	Low	Low	Difficult	Difficult	Difficult	Y	Y
562	Pulp, paper, and paper product manufacturing workers	Low	Low	Difficult	Difficult	Difficult	Y	Y
563	Printing and bookbinding facility workers	Low	Low	Difficult	Difficult	Difficult	Y	Y
565	Plastic product manufacturing facility workers	Low	Low	Difficult	Difficult	Difficult	Y	Y
569	Other product manufacturing facility workers	Low	Low	Difficult	Difficult	Difficult	Y	Y
571	General machinery and equipment assembly workers	Low	Low	Difficult	Difficult	Difficult	Y	Y
574	Electronic applied machinery and equipment assembly workers	High	Low	Easy	Easy	Difficult	Y	Y
576	Semiconductor product manufacturing facility workers	Low	Low	Difficult	Difficult	Difficult	Y	
584	Automotive assembly workers	Low	Low	Difficult	Difficult	Difficult	Y	Y
586	Weighing and measuring instrument assembly workers	Low	Low	Difficult	Difficult	Difficult	Y	Y
587	Optical instrument assembly workers	Low	Low	Difficult	Difficult	Difficult	Y	
601	General machinery repairmen and repairwomen	Low	Low	Easy	Difficult	Difficult	Y	Y
602	Electrical machinery repairmen and repairwomen	Low	Low	Difficult	Difficult	Difficult	Y	Y
603	Auto mechanics	Low	Low	Difficult	Difficult	Difficult	Y	Y
604	Transportation machinery maintenance workers	High	Low	Difficult	Difficult	Difficult	Y	Y
612	Metalworking and welding inspectors	Low	Low	Difficult	Difficult	Difficult	Y	Y
641	Painters	Low	Low	Difficult	Difficult	Difficult	Y	Y
642	Artists, signboard makers	Low	Low	Easy	Easy	Difficult	Y	Y
643	Draftsmen	Low	Low	Easy	Difficult	Difficult	Y	Y
651	Train drivers	High	Low	Difficult	Difficult	Difficult		
661	Bus drivers	High	High	Difficult	Difficult	Difficult	Y	Y
662	Passenger vehicle drivers	High	High	Difficult	Difficult	Difficult	Y	Y
663	Truck drivers	Low	Low	Difficult	Difficult	Difficult	Y	Y
672	Navigation officers, pilots	High	Low	Difficult	Difficult	Difficult		
673	Ship's chief engineers, other ship engineers	High	Low	Difficult	Difficult	Difficult		
674	Aircraft pilots	High	Low	Easy	Difficult	Difficult		
681	Train conductors	High	High	Difficult	Difficult	Difficult		
683	Deckhands, steersmen	High	Low	Difficult	Difficult	Difficult	Y	
684	Forklift operators	Low	Low	Difficult	Difficult	Difficult	Y	Y
689	Other transport workers not elsewhere classified	High	Low	Easy	Easy	Easy	Y	Y
691	Electrical generators and substation workers	Low	Low	Easy	Difficult	Difficult	Y	
692	Boiler operators	Low	Low	Difficult	Difficult	Difficult	Y	Y
695	Construction machinery operators	Low	Low	Difficult	Difficult	Difficult	Y	

697	Building facility managers	High	Low	Difficult	Difficult	Difficult	Y	Y
701	Formwork carpenters	Low	Low	Difficult	Difficult	Difficult	Y	
702	Scaffolders	High	Low	Difficult	Difficult	Difficult	Y	Y
703	Reinforcing-bar workers	Low	Low	Difficult	Difficult	Difficult	Y	
711	Carpenter	Low	Low	Difficult	Difficult	Difficult	Y	Y
712	Brick and stone masons and tile setters	Low	Low	Difficult	Difficult	Difficult	Y	
714	Plasterers	Low	Low	Difficult	Difficult	Difficult	Y	
716	Pipefitters	High	Low	Difficult	Difficult	Difficult	Y	
717	Interior finishers	Low	Low	Difficult	Difficult	Difficult	Y	
718	Waterproofers	High	Low	Difficult	Difficult	Difficult	Y	
721	Electrical power-line installers	High	Low	Difficult	Difficult	Difficult	Y	
725	Construction electricians	High	Low	Difficult	Difficult	Difficult	Y	Y
731	Construction workers	Low	Low	Difficult	Difficult	Difficult	Y	Y
732	Railroad track construction workers	High	Low	Difficult	Difficult	Difficult	Y	
752	Port crane operators	High	Low	Difficult	Difficult	Difficult	Y	
753	Land freight forwarding workers	High	Low	Difficult	Difficult	Difficult	Y	Y
754	Warehouse workers	Low	Low	Difficult	Difficult	Difficult	Y	Y
755	Delivery persons	High	Low	Difficult	Difficult	Difficult	Y	Y
756	Packing and forwarding agents	Low	Low	Difficult	Difficult	Difficult	Y	Y
761	Janitors and Building Cleaners	Low	Low	Difficult	Difficult	Difficult	Y	Y
762	Housekeeping cleaners	High	Low	Difficult	Difficult	Difficult	Y	Y
764	Garbage and human waste treatment workers	High	High	Difficult	Difficult	Difficult	Y	Y
765	Industrial waste treatment workers	High	Low	Difficult	Difficult	Difficult	Y	Y
769	Other cleaning workers	High	Low	Difficult	Difficult	Difficult	Y	Y
771	Packaging operators	Low	Low	Difficult	Difficult	Difficult	Y	Y
781	Sorters	Low	Low	Difficult	Difficult	Difficult	Y	Y
782	Light-duty workers	Low	Low	Difficult	Difficult	Difficult	Y	Y

Note: Y = Occupation in the sample.

Figure OA.1: Method of Construction of the Dataset

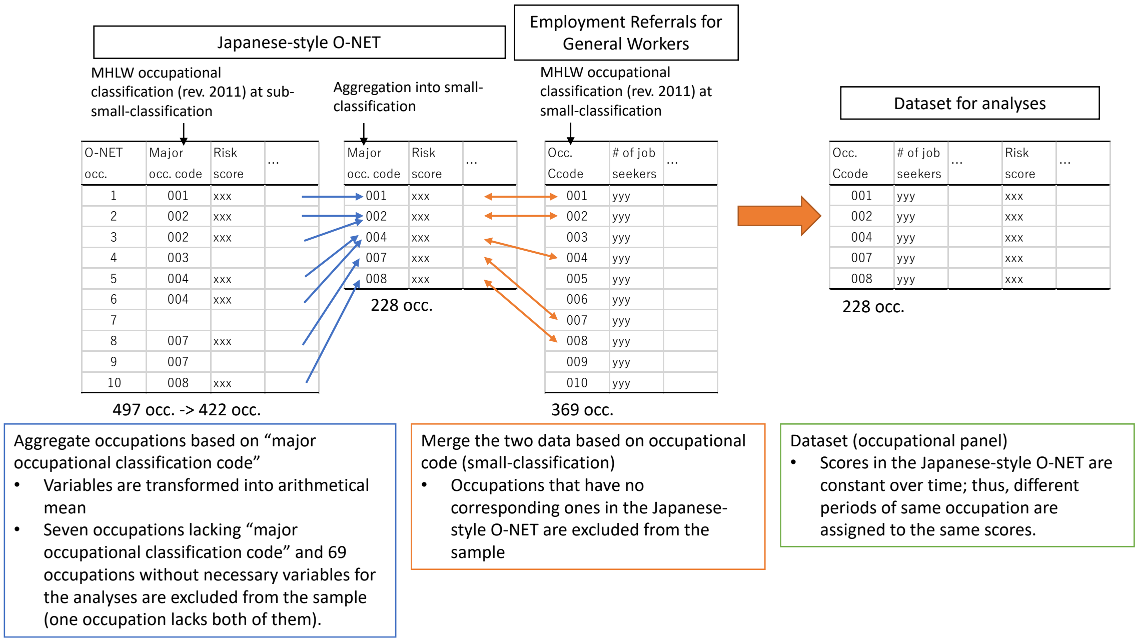
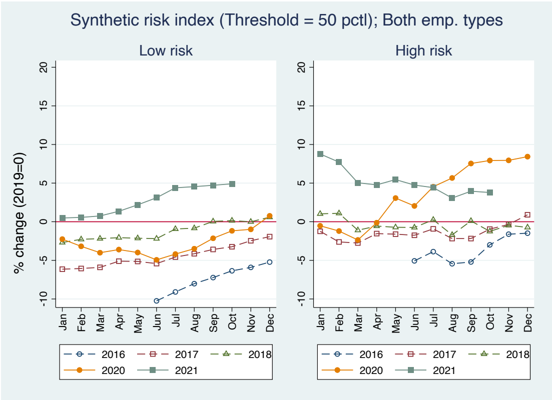
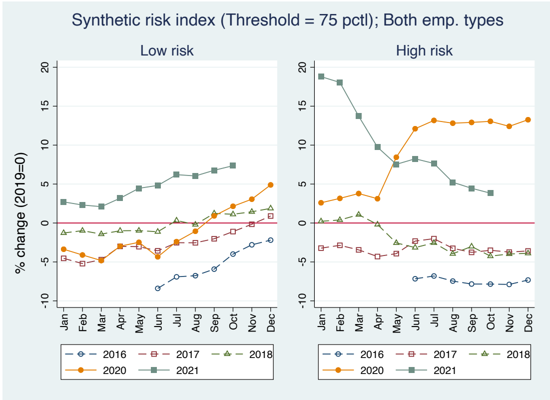


Figure OA.2: Percentage Changes in the Mismatch Indices by Occupational Group Defined by Risk of Infection

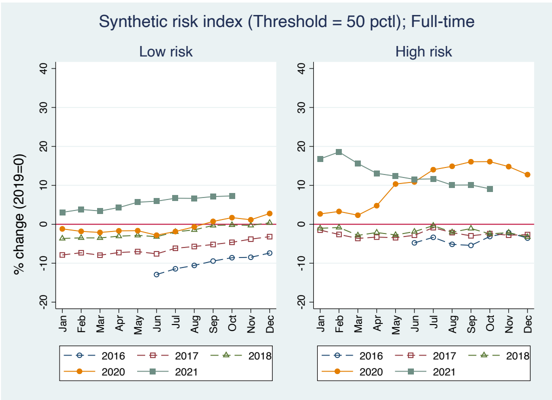
(a) Both employment types (the 50th percentile of the synthetic risk index)



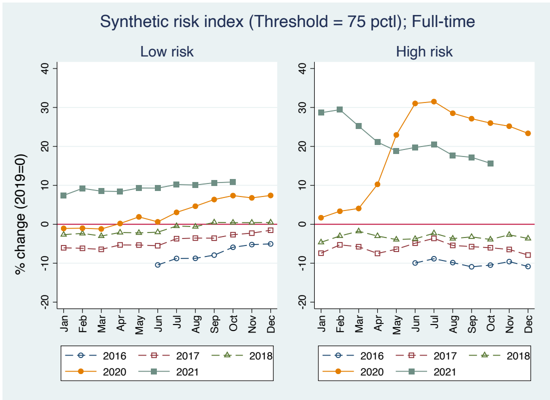
(b) Both employment types (the 75th percentile of the synthetic risk index)



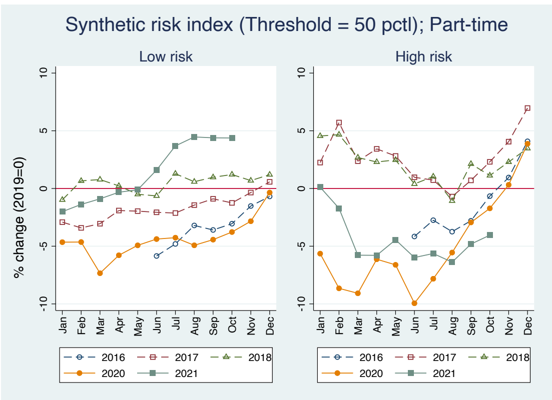
(c) Full-Time Workers (the 50th percentile of the synthetic risk index)



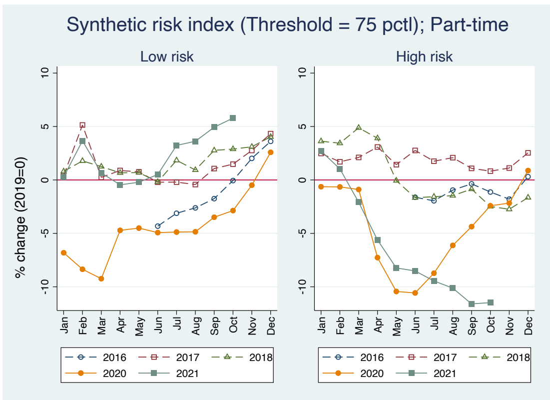
(d) Full-Time Workers (the 75th percentile of the synthetic risk index)



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



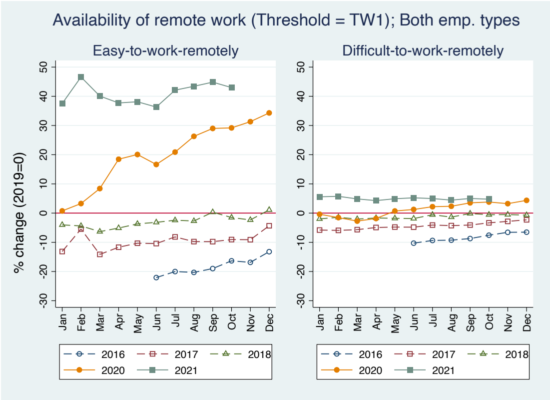
(f) Part-Time Workers (the 75th percentile of the synthetic risk index)



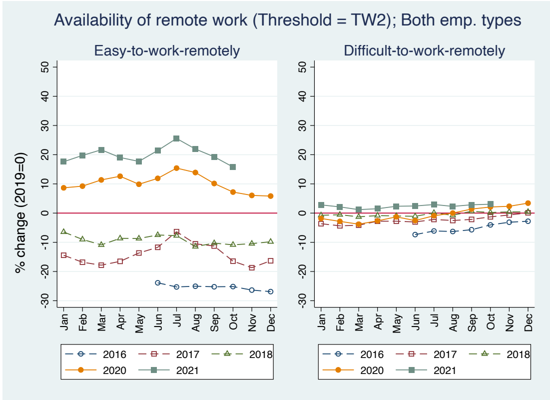
Notes: The vertical line indicates March 2020. The horizontal line at zero represents the mismatch level standardized in the corresponding month of 2019 as the benchmark.

Figure OA.3: Percentage changes in the Mismatch indices by Occupational Group Defined by Availability of Remote Work

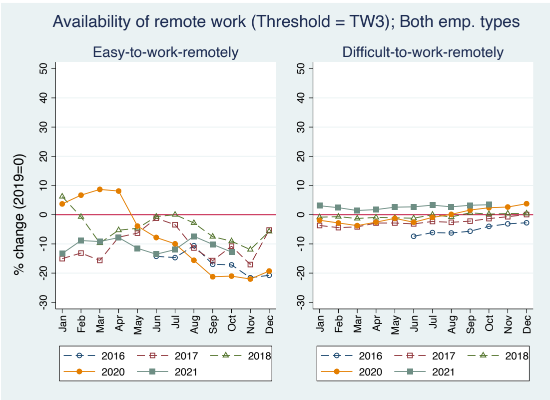
(a) Both employment types (TW1 as the threshold of remote work availability)



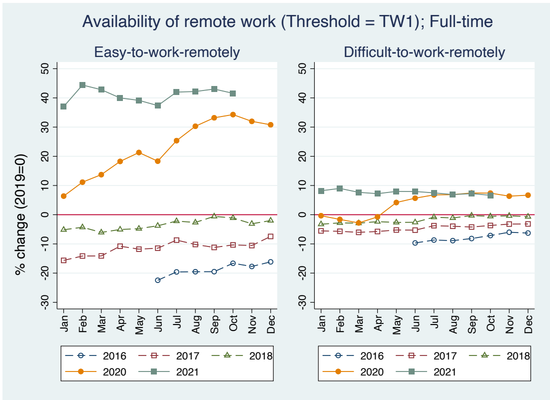
(b) Both employment types (TW2 as the threshold of remote work availability)



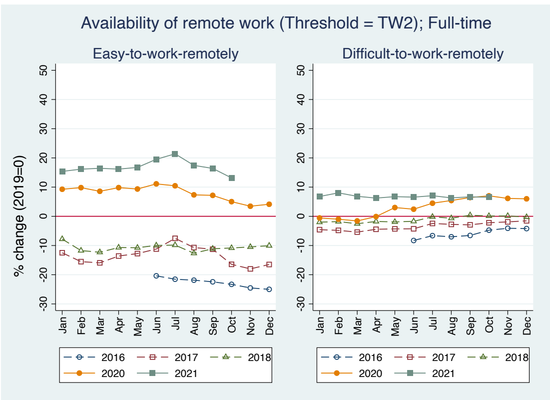
(c) Both employment types (TW3 as the threshold of remote work availability)



(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)

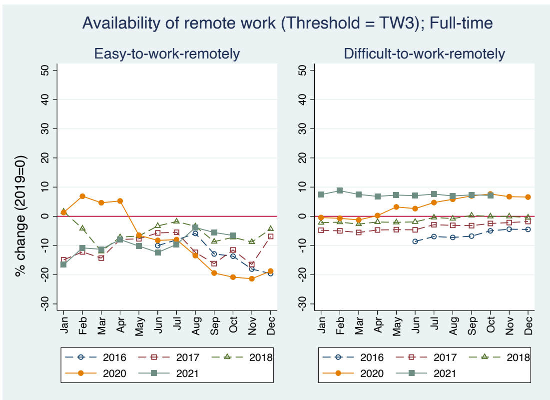
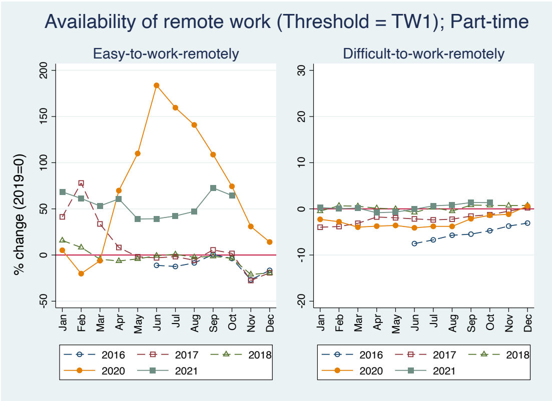
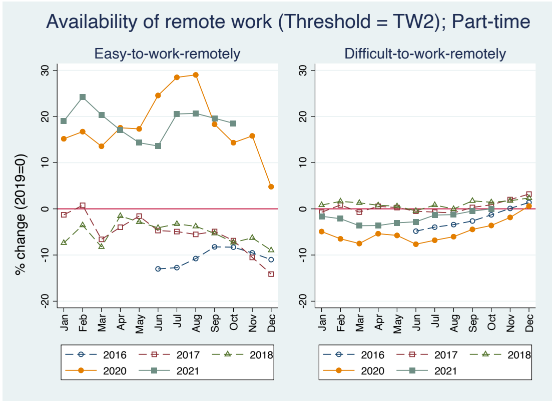


Figure OA.3 (continued)

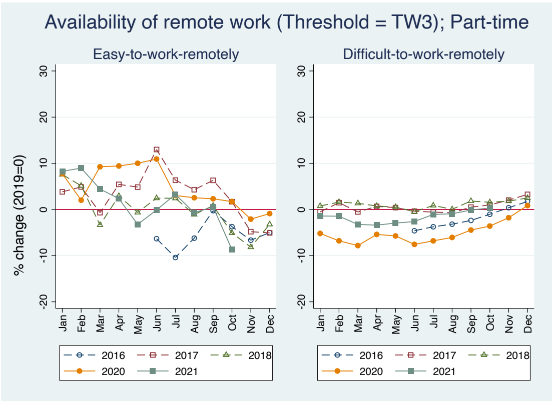
(g) Part-Time Workers (TW1 as the threshold of remote work availability)



(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: The vertical line indicates March 2020. The horizontal line at zero represents the mismatch level standardized in the corresponding month of 2019 as the benchmark.