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HOSHI, Kisho
University of British Columbia

KASAHARA, Hiroyuki
University of British Columbia

MAKIOKA, Ryo
RIETI

SUZUKI, Michio
Economic and Social Research Institute (ESRI) / Tohoku University

TANAKA, Satoshi
University of Queensland

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The Heterogeneous Effects of COVID-19 on Labor Markets: People's Movement and Non-Pharmaceutical Interventions*

Kisho Hoshi†, Hiroyuki Kasahara‡, Ryo Makioka§, Michio Suzuki**, Satoshi Tanaka††

Abstract

The paper investigates the heterogeneous effect of a policy-induced decline in people's mobility on the Japanese labor market outcome during the early COVID-19 period. Regressing individual-level labor market outcomes on prefecture-level mobility changes using policy stringency index as an instrument, our two-stage least squares estimator presents the following findings. First, the number of people absent from work increased for all groups of individuals, but the magnitude was greater for workers with non-regular employment status, low-educated people, females, and those aged 31 to 45 years. Second, while work hours decreased for most groups, the magnitude was especially greater for business owners without employees and those aged 31 to 45. Third, the negative effect on unemployment was statistically significant for older males who worked as regular workers in the previous year. The impact was particularly considerable for those aged 60 and 65, thus suggesting that they lost their re-employment opportunity due to COVID-19. Fourth, all these adverse effects were greater for people working in service and sales occupations. Fifth, a counterfactual experiment of more stringent policies indicates that while an average worker would lose JPY 3,857 in weekly earnings by shortening their work hours, the weekly loss for those aged 31 to 45 years and working in service and sales occupations would be about JPY 13,842.

Keywords: COVID-19, Inequality, Short-time work, Working from home, Behavior

JEL classification: E24, J31, J23, J26, J63

*This study is conducted as a part of the research at the Research Institute of Economy, Trade and Industry (RIETI). This study utilizes the micro data of the questionnaire information based on "the Labor Force Survey" which is conducted by the Ministry of Internal Affairs and Communications (MIAC).

† Vancouver School of Economics, UBC

‡ Vancouver School of Economics, UBC

§ Research Institute of Economy, Trade and Industry (RIETI)

** Economic and Social Research Institute (ESRI), Cabinet Office and Tohoku University

†† School of Economics, University of Queensland

1 Introduction

The declaration of a state of emergency and the accompanying policies such as requesting restaurants to shorten their business hours and restricting people from going out can reduce the spread of infection by discouraging people from going out or moving around unnecessarily. On the other hand, the declaration of a state of emergency may cause economic damage, such as bankruptcy and unemployment, especially in the restaurant, retail, and tourism industries. Non-pharmaceutical COVID-19 interventions encounter such a trade-off between economic activities and epidemic prevention through affecting people's behavior. While recent economics literature analyzes such a trade-off using a Susceptible, Infected and Recovered (SIR) model (Eichenbaum et al. 2020; Acemoglu et al. 2020; Kaplan et al. 2020), empirically analyzing the impact of non-pharmaceutical interventions on economic activities by using microeconomic data is critical for giving realistic policy recommendations.

This paper empirically investigates the heterogeneous effect of a policy-induced change in people's mobility on various labor market outcomes: unemployment, absence from work, and work hours. To analyze it, we combine individual-level microdata on labor with the people's mobility data from Google Mobility Reports, and the measures on COVID-19 related non-pharmaceutical interventions. The mobility measure is critical for capturing the keystone of the trade-off. We utilize the two-stage least square (2SLS) estimation where people's mobility is instrumented with a cross-prefecture difference in the policy stringency. The policy index allows us to examine the effect of the changes in mobility induced by policy changes on labor market outcomes.

Our findings are summarized as follows:

1. While the number of people absent from work increased dramatically for all groups of individuals due to a decline in people's mobility, the magnitude was especially large for workers with non-regular employment status, low-educated people, females, and those aged 31 to 45 years.

2. While work hours also decreased for almost all groups, the magnitude was significantly greater for executives, owners, family workers, and those aged 31 to 45 years.

3. While the effect of decreasing mobility on unemployment was not significant overall, it was significantly greater for people aged 61 and above. Among older adults, the impact on unemployment was substantial for older males aged 60 and 65 who worked as regular workers in the previous year, thus suggesting a possibility that they lost the re-employment opportunity after their retirement due to COVID-19.

4. The adverse effects on absence from work, work hours, and unemployment were especially greater for people in service and sales occupations than other occupations.

5. Our counterfactual analysis indicates that if the policy stringency were to increase from the level in Yamanashi to that in Tokyo in April, the weekly earnings for an average worker would reduce by JPY 3,857, while for those aged 31 to 45 years working in service and sales occupations, the weekly loss would be JPY 13,842.

This paper is related to increasingly large empirical literature that use individual-level microdata to analyze the effect of COVID-19 on labor markets. For example, using the Current Population

Survey in the US, several papers show that the negative effect of COVID-19 on employment is large for people who could not work from home, those in high-physical-proximity jobs, Hispanic, younger workers, those with high school degrees and some college, females, and workers in "non-essential" industries (Gupta et al. 2020; Mongey et al. 2020; Montenovo et al. 2020; Albanesi and Kim 2021; Lee et al. 2021). Similar patterns are observed in different countries, such as Guven et al. (2020) for Australia and Casarico and Lattanzio (2020) for Italy. Other papers compare the impact of COVID-19 and its heterogeneity across different countries (Adam-Prassl et al. 2020 for the US, the UK, and Germany; Alon et al. 2021 for the US, Canada, Germany, the Netherlands, Spain, and the UK) using microdata from multiple national surveys or real-time surveys. Our paper contributes to this literature by providing evidence using Japanese individual-level microdata. Furthermore, our work offers estimation results using a measure of people's mobility with policy instruments as sources of variations. We may causally interpret the estimated effect of people's mobility on labor market outcomes to the extent that a variation across the timing and the size of policy changes is exogenous.

Our paper is also related to the studies on the effect of COVID-19 on the labor market in Japan.[1] For example, Kikuchi et al. (2021), Kawata (2020), and Hoshi et al. (2021) analyze the effect of COVID-19 on the labor market using publicly available, aggregate data. Compared to them, our paper uses individual-level microdata and finds considerable heterogeneity in the negative impact of COVID-19 on labor market outcomes. A recent article by Fukai et al. (2021) uses the same individual-level microdata as ours and observes the heterogeneous effects of the COVID-19 pandemic on the labor market in Japan. Our paper is different from Fukai et al. (2021) in that we use people's mobility measure as the primary explanatory variable and analyze the effect of a policy-induced mobility change on unemployment, absence from work, and work hours. Using the mobility measure improves our identification of the impact of COVID-19, and allows us to conduct counterfactual policy analysis. As people's mobility are the driving force of the spread of COVID-19, our use of mobility measures also provides some insight into the trade-offs between economic activities and epidemic prevention due to non-pharmaceutical COVID-19 interventions.

The remainder of this paper is organized as follows. Section 2 explains the background of COVID-19 in Japan and provides a data summary. After the introduction of an econometric framework in Section 3, Section 4 presents the estimation results. Section 5 provides the results from counterfactual exercises. Finally, Section 6 offers some concluding thoughts.

2 Background and Data

2.1 Background

In Japan, the first case of COVID-19 was reported on January 16, 2020. Throughout February and March, the virus spread gradually, prompting the central and local governments to begin to respond in several ways. The central government requested a nationwide school closure for elementary and middle schools on February 27. On February 28, Hokkaido prefecture declared a state of emergency and ordered a voluntary ban on leaving home during the weekends.

[1]Other papers analyze the impact of COVID-19 on consumption and prices in Japan (Watanabe 2020), on Japanese firms (Kawaguchi et al. 2020), and on telework utilization in Japan (Okubo 2020).

On April 7, the central government declared a state of emergency until May 6 for seven prefectures: Tokyo, Chiba, Saitama, Kanagawa, Osaka, Hyogo, and Fukuoka. The state of emergency was extended to all prefectures on April 16. Based on the state of emergency, local governments asked (1) people to work remotely and refrain from going out, (2) some types of businesses (e.g., movie theaters, department stores, and nightclubs) to close, and (3) services classified as essential (e.g., hospitals, public transportation, and banks) to remain open.[2] After an extension of the term, the state of emergency was finally lifted on May 14 for 39 prefectures, on May 21 for Osaka, Kyoto, and Hyogo, and on May 25 for Tokyo, Saitama, Chiba, Kanagawa, and Hokkaido.

In addition to the state of emergency, the central and local governments used subsidy programs to mitigate the adverse impact of COVID-19 on firms and labor, such as the business suspension subsidy (*Kyugyo Shienkin* in Japanese) and the business continuation subsidy (*Jizokuka Kyufukin* in Japanese).

The short-time work compensation (or Employment Adjustment Subsidy) is one of the most relevant subsidies for labor markets. The objective of this program is for firms to maintain their employment without laying employees off during times of recession. According to Ando et al. (2020), the Japanese government used this subsidy program for maintaining employment during the initial several months of COVID-19, without modifying the unemployment compensation system until the middle of June. Therefore, the Japanese labor market witnessed a sharp increase in absence from work during the initial periods while maintaining only a modest increase in unemployment.

While that compensation system had existed since 1975, it relaxed its criteria in April 2020 in response to the COVID-19 pandemic; furthermore, the upper limit for the reimbursement of leave allowance increased from JPY 8,330 to JPY 15,000 per day per employee in June 2020. Consequently, 360,000 business owners applied for the program, and 232,000 of applicants (about JPY 181 billion in total) were accepted by the end of June 2020.[3]

Because Japan responded to the COVID-19 pandemic with relatively moderate policy measures, the early impact of COVID-19 on aggregate product and labor market statistics was not catastrophic. According to the International Labour Organization (2020), Japan had the weakest policy stringency in lockdown and other measures among G20 countries, while Japan's industrial production, employment, work hours, unemployment rate, and labor force participation rate were the least affected by the pandemic in comparison with other G20 countries. However, these aggregate numbers could mask the heterogeneous impacts across different individuals depending on their gender, age, education, industry, occupation, location, and employment status. These hidden heterogeneous effects, which we cannot identify from the aggregate statistics, motivate us to use individual-level microdata.

2.2 Data

We use the Labour Force Survey (LFS), provided by the Statistics Bureau of the Ministry of Internal Affairs and Communications (MIC). The survey is conducted every month on about 40,000 households aged 15 and above residing in Japan. There are two surveys within the LFS. The first is the basic survey with a rotating panel design, similar to the Current Population Survey in the US, where

[2] See https://corona.go.jp/en/ and https://www3.nhk.or.jp/news/special/coronavirus/emergency/.

[3] See https://www.mhlw.go.jp/stf/seisakunitsuite/bunya/koyou_roudou/koyou/kyufukin/pageL07.html (in Japanese).

each household member is interviewed for two consecutive months in a year, not surveyed for the subsequent ten months, and then asked again for two consecutive months. The last interview also asks about their yearly income, education, and detailed information on their previous jobs, etc., which is recorded in the supplemental survey. We combine the basic and supplemental surveys.

Our primary outcome variables are absence from work, work hours, and unemployment. First, the LFS asks for working status in the final week of a survey month (i.e., mainly working, working and schooling, working and doing housework, absence from work, looking for jobs, schooling, doing housework, and others), which we use for constructing a dummy variable for absence from work. Second, our measure of working hours is constructed from the question on work hours obtained in the final week of a survey month from the LFS. Third, a dummy variable for being unemployed is constructed by the information on the work status. Finally, we constructed a dummy variable for being unemployed due to employer's reasons from a survey question on the reason for being unemployed (i.e., layoffs, retirement, family reason, graduation, the need for income, and other reasons).

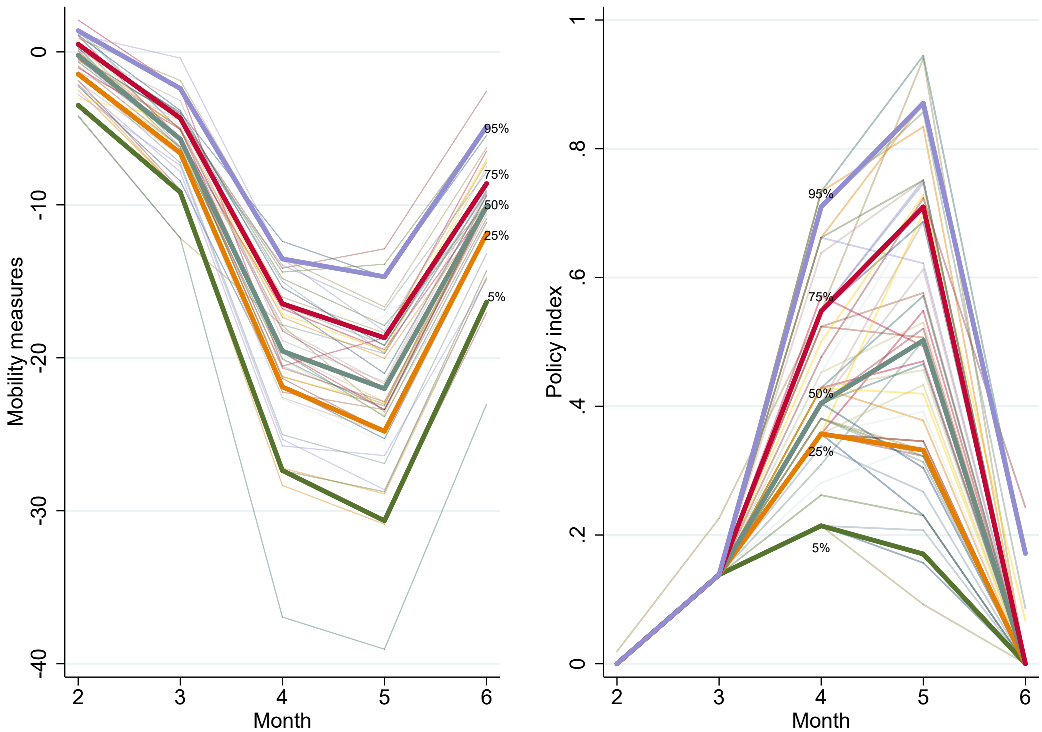
Other variables for our regression analysis include the Google mobility measure, the policy index, the occupation-level Dingel-Neiman telework index, and the occupation-industry-level essential job index. First, the Google mobility measure is from the Google COVID-19 Community Mobility Reports (Google LLC 2020). The reports provide six measures of movement trends: "Grocery & pharmacy", "Parks", "Transit stations", "Retail & recreation", "Residential", and "Workplaces". Each of them is a percentage change in the number of visits and the length of stay at different places relative to the baseline value computed from January 3 to February 6, 2020. The daily measures at different places are aggregated into the prefecture-month level. Our mobility measure for prefecture p in month t is defined by a simple average of four Google mobility measures,

$$\text{Mobility}_{pt} = \frac{\text{Workplaces}_{pt} + \text{Retail \& recreation}_{pt} + \text{Grocery \& pharmacy}_{pt} + \text{Transit stations}_{pt}}{4}. \tag{1}$$

The left panel of Figure 1 shows the computed mobility measure for each prefecture, where thick lines express the 5th, 25th, 50th, 75th, and 95th percentile values. Coinciding with the timing of the state of emergency, the mobility measure declined in April and then recovered in June. We also noticed that urban prefectures such as Tokyo, Kanagawa, and Osaka had experienced larger declines in mobility than rural prefectures such as Iwate and Tottori. For example, Tokyo declined its average mobility by 36.9% in April, but Iwate declined only by 12.4% in the same month. In our regression analysis, we utilize a cross-prefecture and over-month variation to identify the effect of a mobility decline on outcomes.

The mobility measure is critical for analyzing the effect of COVID-19 on labor markets. First, the governments use policies and appeal to people's voluntary actions to affect people's mobility through which COVID-19 typically spreads. The Google mobility measure partly quantifies such mobility. Second, people's mobility is, in turn, a central element of the economic activities in industries and occupations, such as restaurants, hotels, education sectors, and service and sales occupations. Therefore, governmental non-pharmaceutical interventions affect both labor supply and demand through people's mobility. In that sense, estimating the effect of mobility on labor market outcomes provides us a building block for the trade-off between economic activities and the spread

Figure 1. Mobility measure and policy index for each prefecture



Note: The left figure plots the mobility measure for each prefecture defined in equation (1). The 5th, 25th, 50th, 75th, and 95th percentiles are plotted with thick lines. The right figure plots the policy index for each prefecture defined in equation (2). The 5th, 25th, 50th, 75th, and 95th percentiles are plotted with thick lines.

of COVID-19, which may be heterogeneous across different types of individuals.

The policy index is defined by a simple average of seven policy measures,

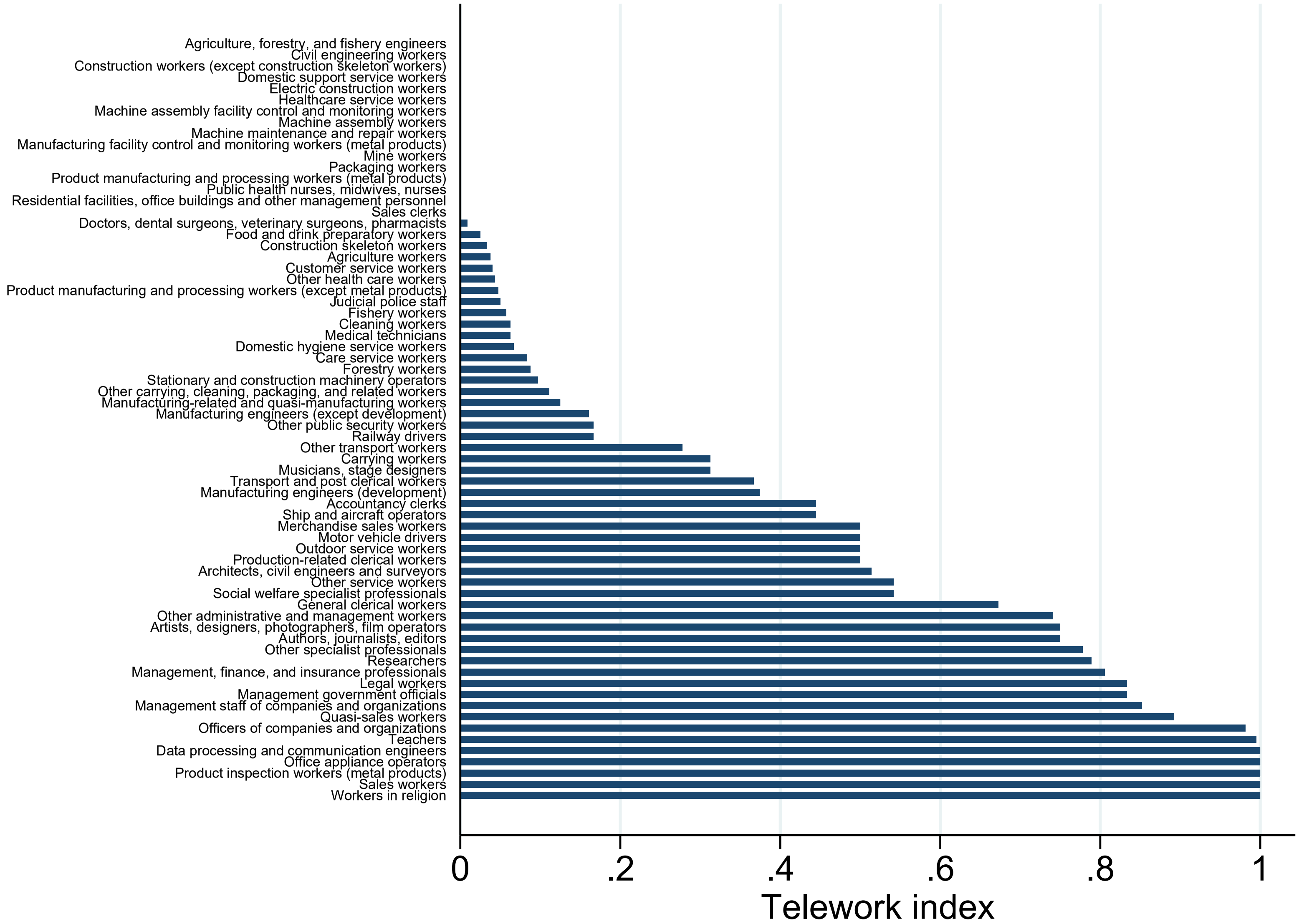
$$\text{Policy}_{pt} = \frac{\text{Emergency}_{pt} + \text{Museum}_{pt} + \text{School}_{pt} + \text{Commercial}_{pt} + \text{Bar}_{pt} + \text{NightClub}_{pt} + \text{Movie}_{pt}}{7}, \tag{2}$$

where each of the right-hand-side variables represents the monthly average of a corresponding daily indicator on whether a prefecture used a policy instrument. The original daily information on whether a prefecture held a specific regulation is from the website of the office of the Prime Minister.[4] For instance, if $Museum_{Tokyo,April} = 0.5$, it means that Tokyo had restrictions on museums for half a month during April. The right panel of Figure 1 presents the evolution of the policy index for each prefecture. The policy index increased in April and May across prefectures and then sharply decreased in June. There also exists a considerable variation across prefectures within a month. For example, in April the policy index in Tokyo was 0.77, while in Tokushima the index was 0.21.

The telework and essential job indices are constructed following Dingel and Neiman (2020) for each two-digit occupation of the Japan Standard Occupational Classification (JSOC) and following Blau et al. (2021) for each occupation-industry category, respectively. The details of the constructions of the two indices are presented in Appendix A1. We use these two indices as controls in our regression analysis. Figure 2 presents the Dingel-Neiman telework index for each occupation.

[4] https://www.kantei.go.jp/jp/pages/corona_news.html. We make our policy instrument data set publicly available at https://docs.google.com/spreadsheets/d/1wrWQ0iuKhaNnwUZfi0lBuWEm6mEg3ztNqi6PEvHz7wM/edit?usp=sharing.

Figure 2. Telework index in each occupation



Note: The bar figure presents the telework index calculated following Dingel and Neiman (2020) for each Japan Standard Occupational Classification (JSOC) two-digit occupation. Occupations are sorted in ascending order.

Occupations such as “Healthcare service workers” and ‘Public health nurses, midwives, nurses” have a zero telework index, suggesting they are difficult to be worked at home. On the other hand, occupations such as “Data processing and communication engineers” and “Office appliance operators” have their index as one and thus find it easy to be worked at home. We analyze how the effect of a policy-driven mobility decline on outcomes depends on the degree of teleworkability measured by these telework indices.

Our sample period covers from February to June 2020.[5] In addition, we focus on individuals that report all four surveys in order to use their first and second rounds of the surveys conducted in 2019. Table 1 presents the summary statistics of our final sample.

Table 1: Summary Statistics

	2020			2019			Difference (2020 - 2019)		
Month	Hours	Leave	Unemployed	Hours	Leave	Unemployed	Hours	Leave	Unemployed
Feb	7.51	0.016	0.010	7.59	0.014	0.012	-0.08**	0.002	-0.001
Mar	7.48	0.022	0.011	7.62	0.017	0.012	-0.14***	0.005***	-0.001
Apr	7.41	0.047	0.014	7.63	0.015	0.013	-0.22***	0.032***	-0.000
May	7.34	0.031	0.014	7.57	0.012	0.013	-0.23***	0.019***	0.001
Jun	7.35	0.020	0.015	7.51	0.013	0.013	-0.16***	0.007***	0.002

Note: “Hours” is the average of work hours per day. “Leave” is the percentage of people absent from work. “Unemployed” is the percentage of unemployed people. Sampling weights provided by the Statistics Bureau of the MIC are used for deriving the results. *** p<0.01, ** p<0.05, * p<0.1

2.3 Data summary: absence from work

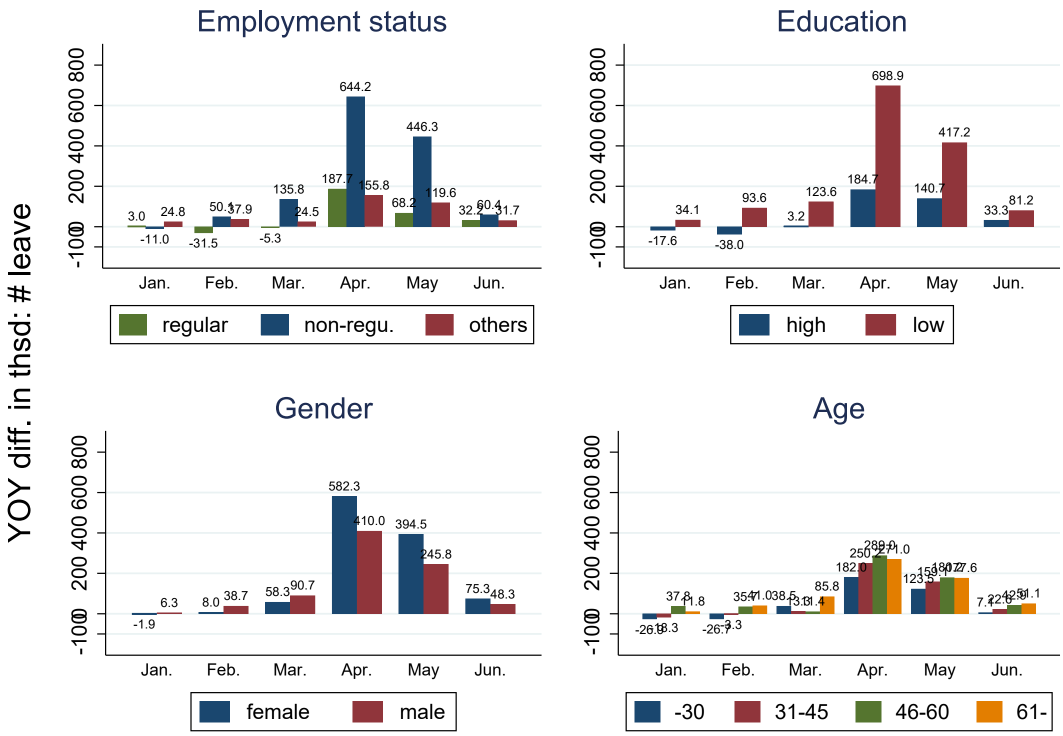
The remaining subsections provide the data summary visually, highlighting heterogeneity across different groups of individuals, such as regular vs. non-regular jobs, education, gender, and ages. Observations are weighted by sampling weights provided by the Statistics Bureau of the MIC to make the results representative.

The first outcome variable is absence from work. Figure 3 shows a year-over-year (YOY) difference in the number of people absent from work for each subgroup. First, the number of people absent from work increased sharply in April and May. It then became negligible in June, consistent with the timing of the policy index and the mobility measure. Second, the number of people absent from work is larger for workers with non-regular employment status, low-educated people, and females. Figure 4 indicates that the number of people absent from work is high in April and May for the restaurant-hotel, retail, service, and education sectors, requiring face-to-face communication to conduct their jobs. Figure 5 shows a large number of absences from work in sales, service, and professional-engineering occupations. The professional-engineering occupation includes researchers, artists, manufacturing engineers, and school teachers. The rise in absence from work for professional-engineering occupations in April and May is consistent with a nationwide school closure by the Japanese government.

Figure 6 shows a scatter plot and its fitted line for the relationship between the YOY difference in the number of people absent from work and the mobility measure constructed in equation (1). There is a negative relationship between the mobility measure and the YOY difference in the number of people absent from work. The result indicates that a decrease in the mobility measure by

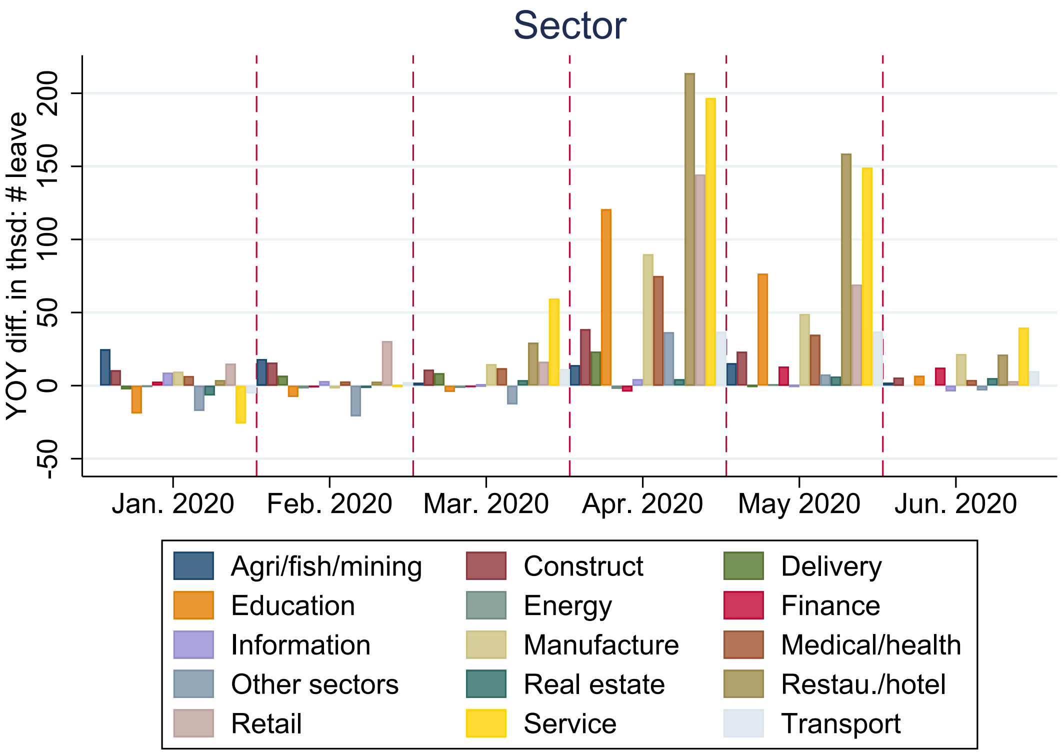
[5] This is because the Google mobility measure and the policy index start from February 2020.

Figure 3. Number of people absent from work (leave) across individual characteristics



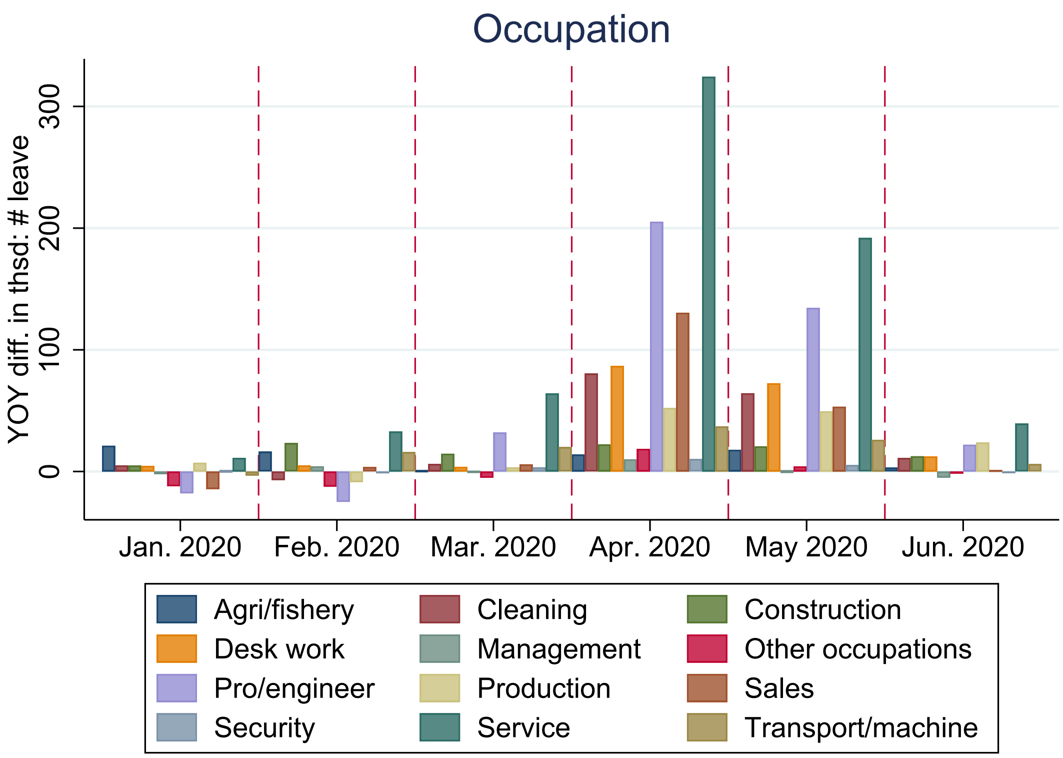
Note: Each figure indicates the year-over-year (YOY) difference in the number of people absent from work. An individual is defined as absent from work if they report their working status in the final week of a month as "absent from work". The top-left panel shows the YOY difference for different employment statuses in the current period. Non-regular worker status includes those who are called in their workplace as part-timers (part-time or *arubaito* in Japanese), contingent workers, contract employees, non-regular staff, and other non-regular workers. Other status includes those who are called in their workplace as executives, self-employed with or without other employees, family workers, and working on the side. The top-right panel shows the YOY difference for different educational levels. High education includes people whose final education is university or post-graduate level. Low education includes those whose final education is elementary, middle, or high school, two-year or technical college, or not-in-any-school. The bottom-left panel shows the YOY difference for males and females. The bottom-right panel shows the YOY difference for each age category. Sampling weights provided by the Statistics Bureau of the MIC are used for deriving the results.

Figure 4. Number of people absent from work (leave) by sector



Note: The figure shows the year-over-year (YOY) difference in the number of people absent from work for each aggregated industry in each month. The aggregated industry roughly corresponds to a 1-digit Japan Standard Industry Classification (JSIC). Sampling weights provided by the Statistics Bureau of the MIC are used for deriving the results.

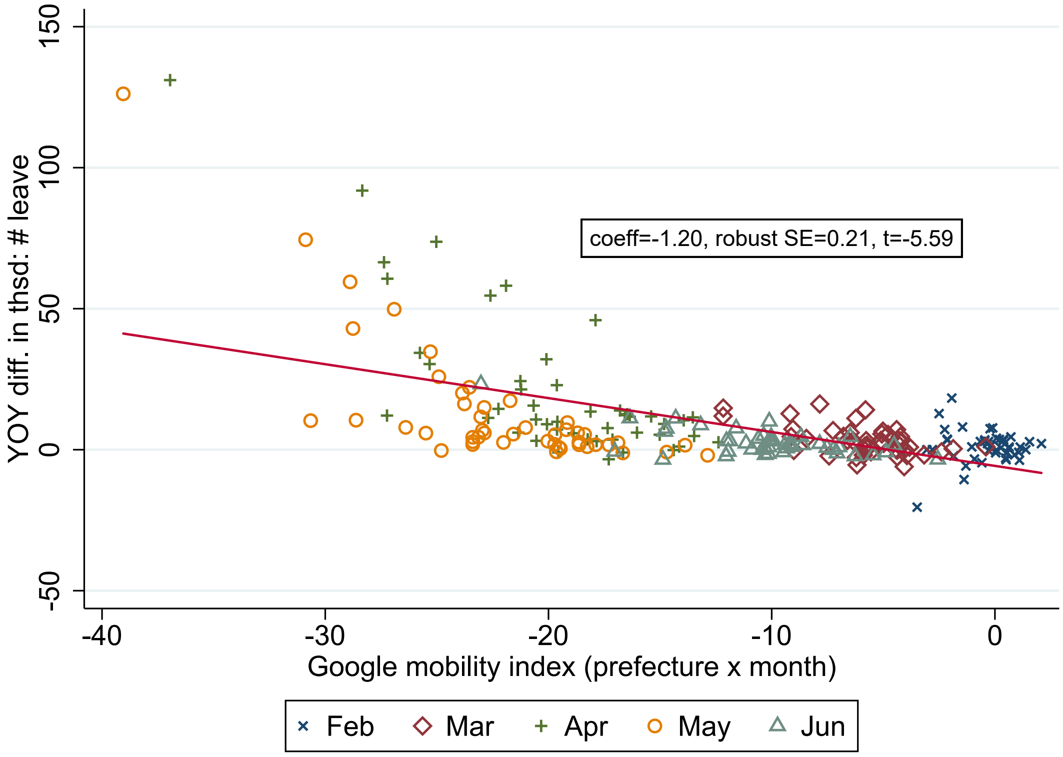
Figure 5. Number of people absent from work (leave) by occupation



Note: The figure shows the year-over-year (YOY) difference in the number of people absent from work for each aggregated occupation in each month. The aggregated occupation roughly corresponds to a one-digit Japan Standard Occupational Classification (JSOC). Sampling weights provided by the Statistics Bureau of the MIC are used for deriving the results.

one standard deviation is associated with an increase in the number of people absent from work by 10.8 thousand. The magnitude is large compared to the average YOY difference (6,937) suggesting that the adjustment through absence from work was a significant channel through which firms responded to government regulations and demand shocks during the first several months of COVID-19 in Japan.

Figure 6. Relation between number of people absent from work (leave) and mobility measures



Note: The figure shows a scatter plot and its fitted line for the relationship between the YOY difference in the number of people absent from work and our mobility measure. Each dot corresponds to the value in a prefecture-month. The points for different months are symbolized by different shapes. The slope coefficient, standard error, and t-statistics of the fitted line are reported within the box. Sampling weights provided by the Statistics Bureau of the MIC are used for deriving the results.

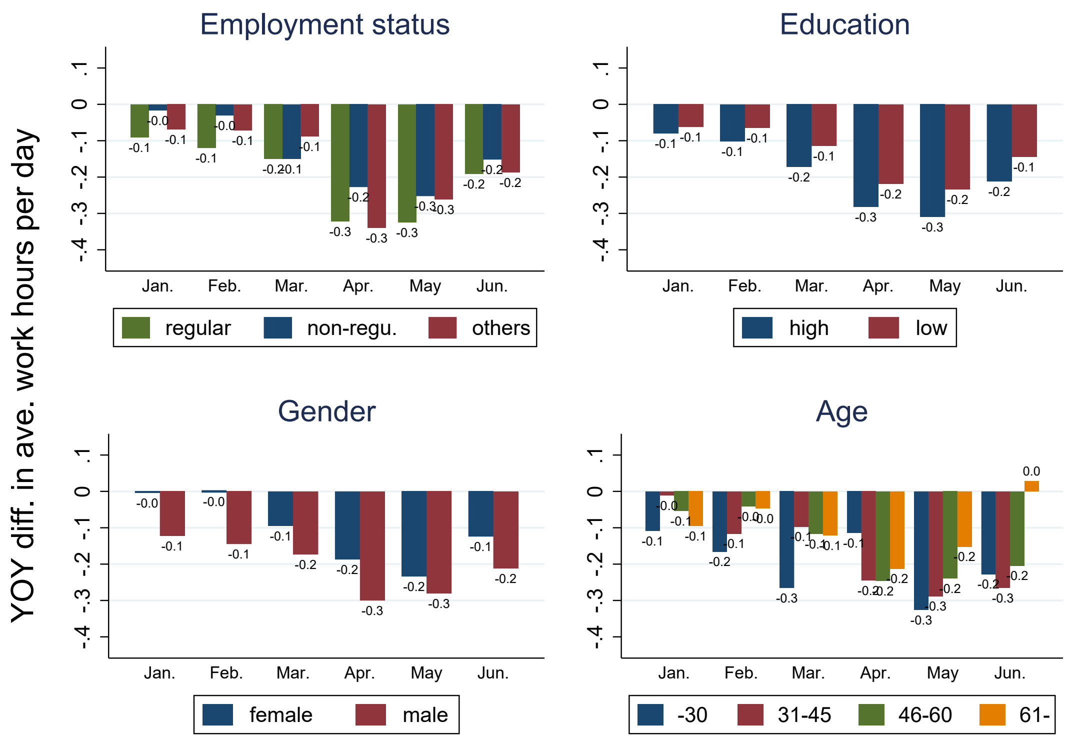
2.4 Data summary: average work hours

The second outcome variable is work hours obtained from the information in the final week of a survey month. The number of holidays in the final week of a month differs between 2019 and 2020.[6] To compare average work hours across years without contamination by such differences, we use work hours per day rather than work hours in this data summary. We account for such differences by including monthly fixed effects in our regression analysis.

Figures 7 to 9 provide a YOY difference in average work hours per day for each subgroup. There are two points to notice from Figure 7. First, the YOY difference in work hours per day is negative in general, grows significantly in April and May, and then decreases a little in June. The timing of this

[6]There was a national holiday, the emperor's birthday, in the final week of February 2020, while there was nothing in the corresponding week in 2019. There were also two national holidays, Showa Day and its makeup holiday, in the final week of April 2019, while there was only Showa Day without any compensating holidays in the corresponding week in 2020.

Figure 7. Average work hours per day across individual characteristics

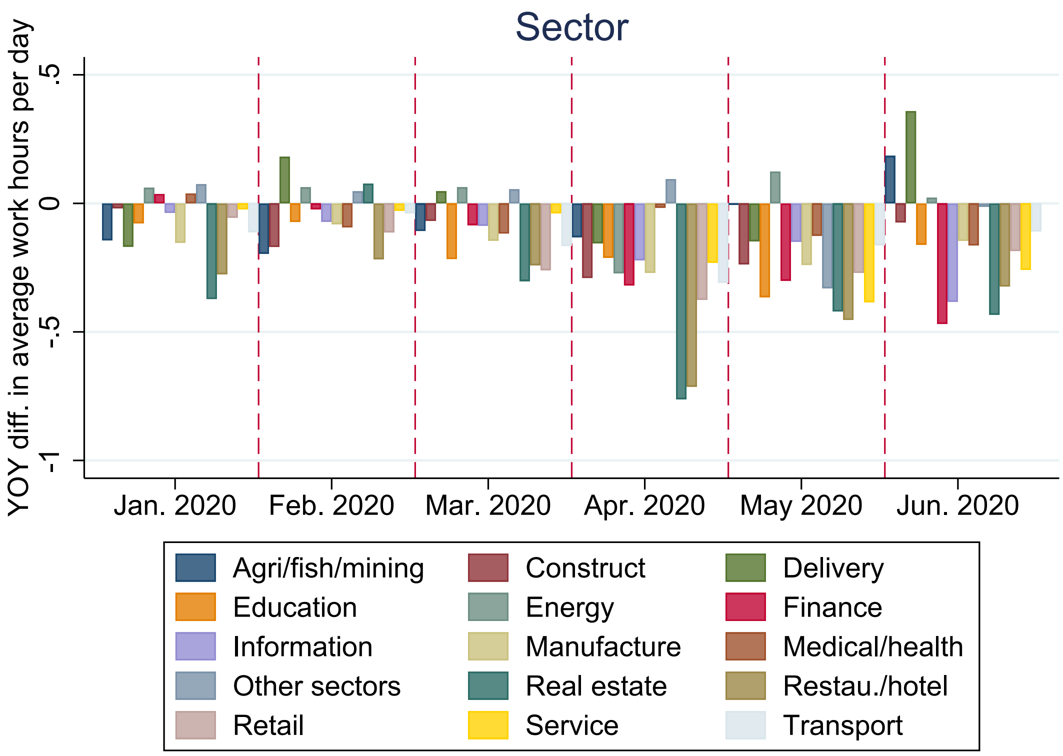


Note: Each figure shows the year-over-year (YOY) difference in the average work hours per day. Non-regular worker status includes those who, in their workplace, are called part-timers (part-time or *arubaito* in Japanese), contingent workers, contract employees, non-regular staff, and other non-regular workers. Other status includes those who are called executives, self-employed with or without other employees, family workers, and working on the side. The top-left panel shows the YOY difference for different employment statuses in the current period. The top-right panel shows the YOY difference for different educational levels. High education includes people whose final education is university or post-graduate level. Low education includes those whose final education is elementary, middle, or high school, two-year or technical college, or not-in-any-schools. The bottom-left panel shows the YOY difference for males and females. The bottom-right panel shows the YOY difference for each age category. Sampling weights provided by the Statistics Bureau of the MIC are used for deriving the results.

up and down again corresponds to a surge in COVID-19 related policies and a decline in mobility. Second, the drop in work hours is substantial for the subgroups of people classified as “others” (i.e., executives, owners, and family workers), people with regular employment status, high-educated people, males, and those less than 45 years old.

Figures 8 and 9 show the YOY difference in work hours per day by occupations and sectors. Workers in real estate, restaurant-hotel and service sectors, those in other sectors (i.e., unclassifiable categories), and sales and service occupations experienced a significant decline in work hours in April and May. Some sectors such as agriculture-fishery-mining and delivery, and occupations like agriculture-forestry-fishery and transport-machine operation saw an increase in work hours in May and June, indicating that these sectors and occupations had essential or booming tasks in the emerging COVID-19 situation. This finding thus motivates us to control for essential sectors and occupations later in the econometric analysis.

Figure 8. Average work hours per day by sector

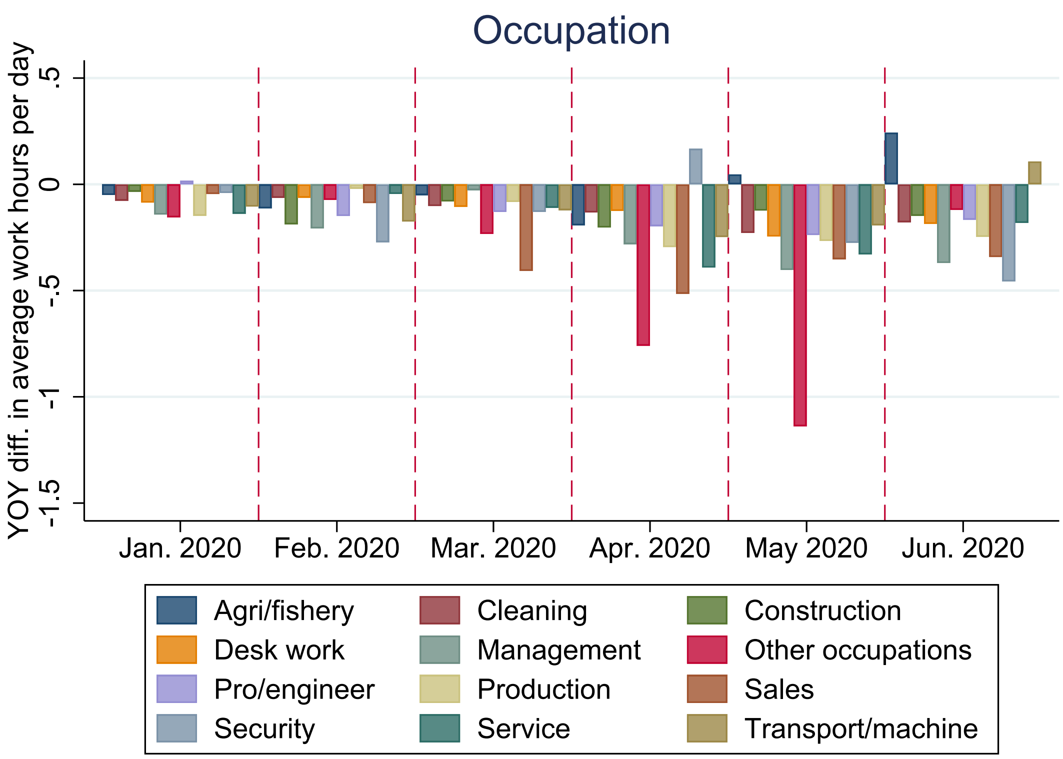


Note: The figure shows the year-over-year (YOY) difference in the average work hours per day for each aggregated industry in each month. The aggregated industry roughly corresponds to a one-digit Japan Standard Industry Classification (JSIC). Sampling weights provided by the Statistics Bureau of the MIC are used for deriving the results.

Figure 10 shows a scatter plot and its fitted line for the relationship between the YOY difference in work hours per day and the mobility measure across prefecture-months. There is a negative correlation between the mobility measure and the YOY difference in work hours per day. The estimate implies that a decrease in the mobility measure by one standard deviation is associated with a decrease in the YOY work hours difference by 0.0538.[7]

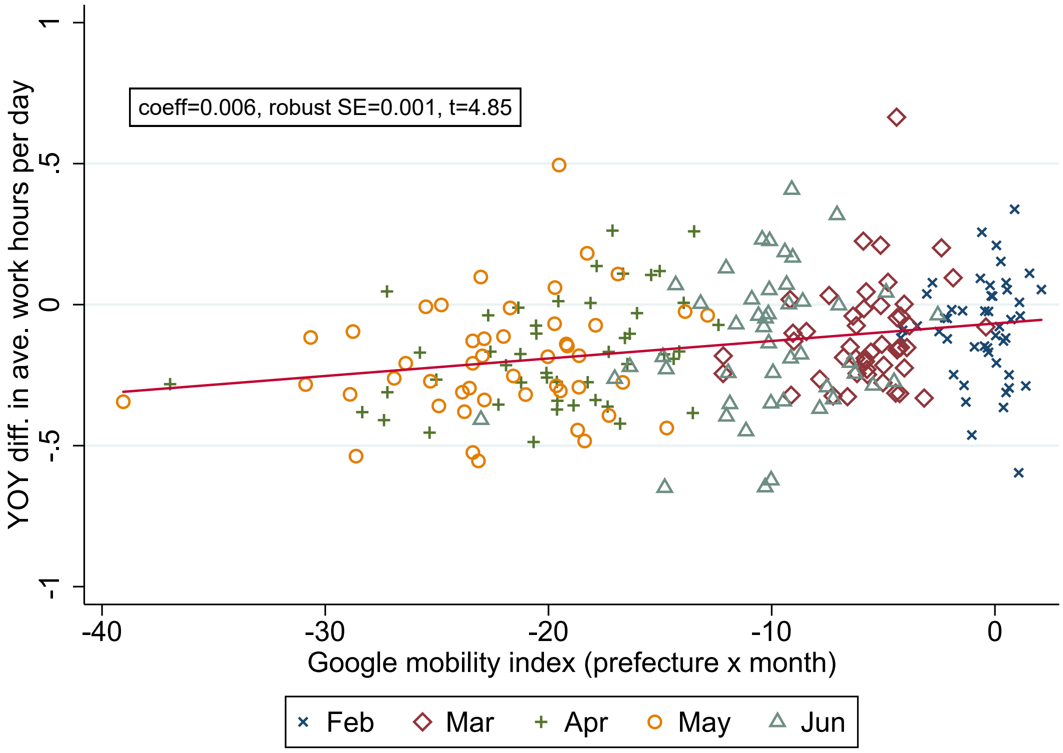
[7]One standard deviation of mobility is 8.972, and the mean of the YOY difference in work hours per day is -0.133.

Figure 9. Average work hours per day by occupation



Note: The figure shows the year-over-year (YOY) difference in the average work hours per day for each aggregated occupation in each month. The aggregated occupation roughly corresponds to a one-digit Japan Standard Occupational Classification (JSOC). Sampling weights provided by the Statistics Bureau of the MIC are used for deriving the results.

Figure 10. Relation between average work hours per day and mobility measures

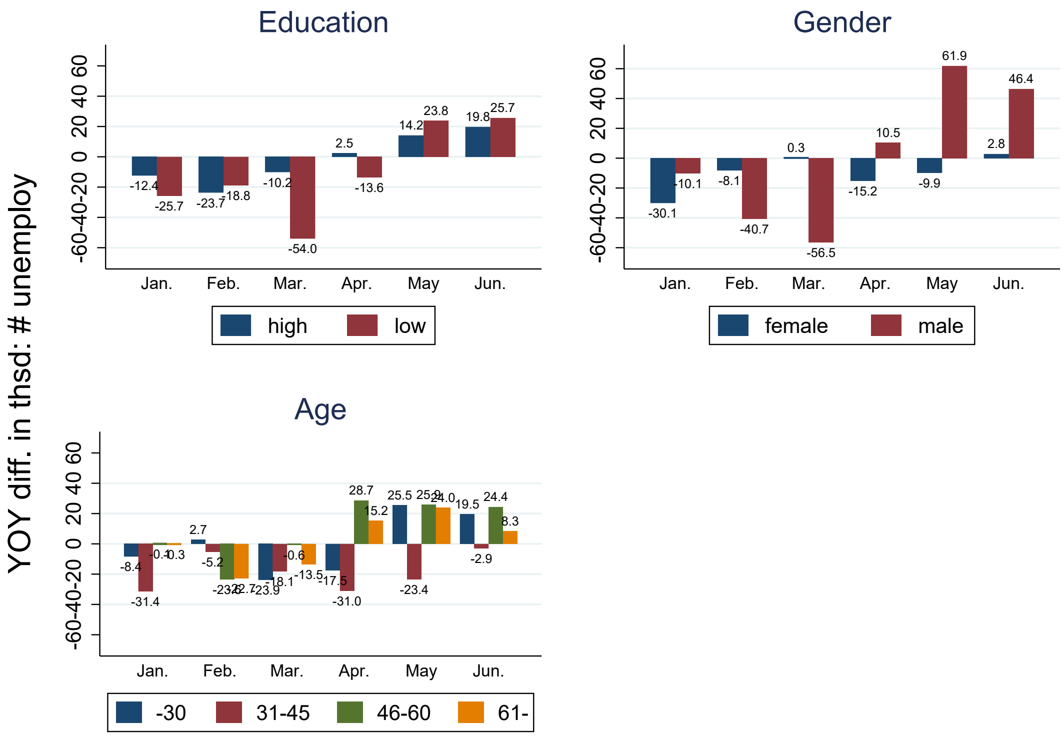


Note: The figure shows a scatter plot and its fitted line for the relationship between the YOY difference in work hours per day and our mobility measure. Each dot corresponds to the value in a prefecture-month. The points for different months are symbolized by different shapes. The slope coefficient, standard error, and t-statistics of the fitted line are reported within the box. Sampling weights provided by the Statistics Bureau of the MIC are used for deriving the results.

2.5 Data summary: unemployment

The third outcome variable is unemployment. Figure 11 shows a YOY difference in the number of unemployed people for each subgroup.[8] First, the YOY difference in the number of unemployed people is negative in general until April and then becomes mostly positive in May and June. This observation suggests that people responded to COVID-19 initially by reducing work hours and being absent from work (Figures 3-10), and then gradually became unemployed from May and June. Second, the YOY difference tends to be larger for low-educated people, males, and people aged 46 to 60 years than for other groups.

Figure 11. Number of unemployed across individual characteristics

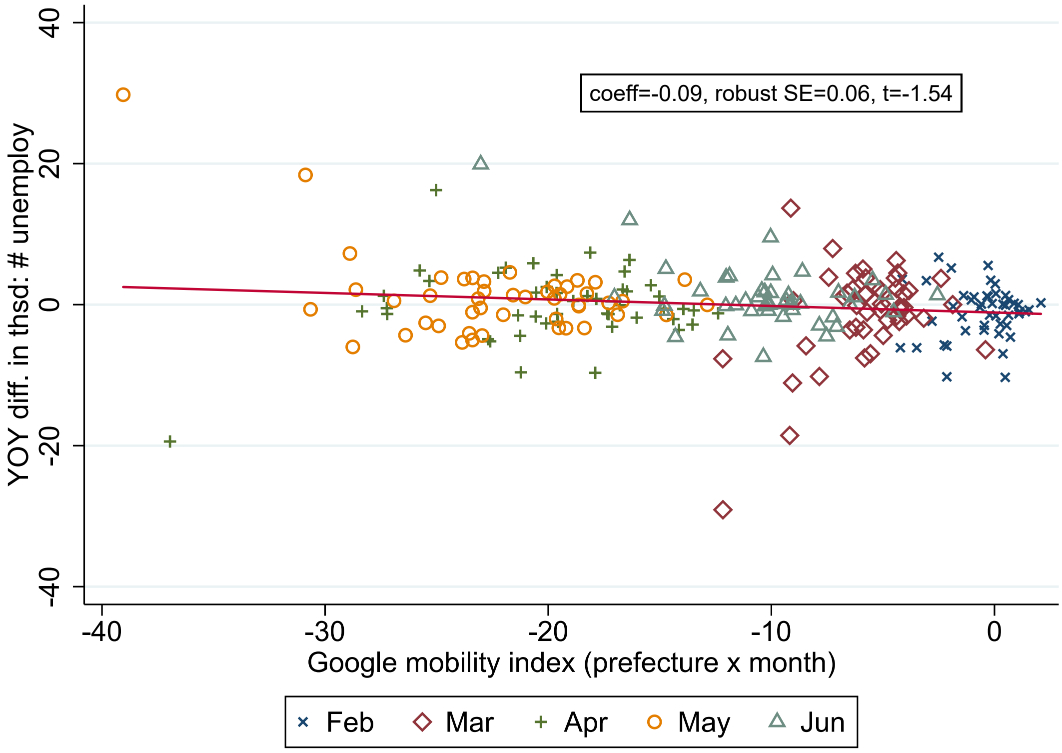


Note: Each figure shows a year-over-year (YOY) difference in the number of unemployed people. An individual is defined as unemployed if they report their working status in the final week of a month as "looking for a job". The top-left panel shows the YOY difference for different educational levels. High education includes people whose final education is university or post-graduate level. Low education includes those whose final education is elementary, middle, or high school, two-year or technical college, or not-in-any-school. The top-right panel shows the YOY difference for males and females. The bottom panel shows the YOY difference for each age category. Sampling weights provided by the Statistics Bureau of the MIC are used for deriving the results.

Figure 12 shows a correlation between the YOY difference in the number of unemployed and our mobility measure across prefecture-months. Although a negative relationship exists, the slope is not significantly different from zero, suggesting that unemployment might not come out as quickly in response to the declining mobility, at least in the first several months of COVID-19.

[8]Note that we cannot calculate the number of unemployed for the subgroup of each working status, sector, and occupation, because unemployed people in a month do not engage simultaneously in any working status, sector, and occupation.

Figure 12. Relation between number of unemployed and mobility measures

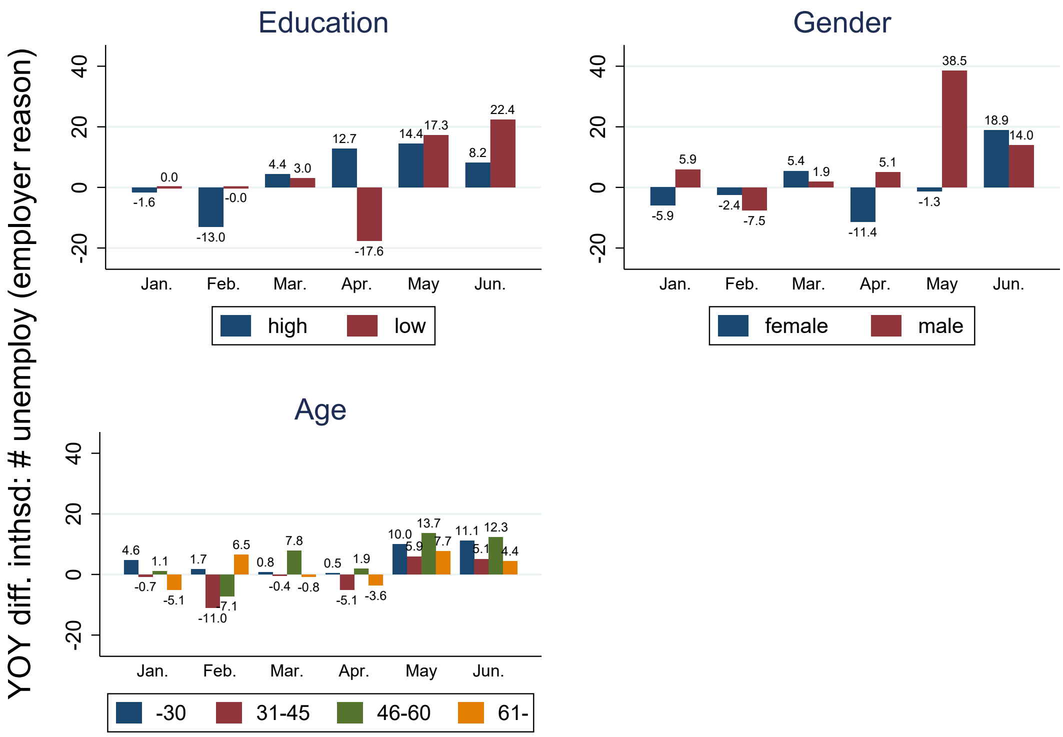


Note: The figure shows a scatter plot and its fitted line for the relationship between the YOY difference in the number of unemployed people and our mobility measure. Each dot corresponds to the value in a prefecture-month. The points for different months are symbolized by different shapes. The slope coefficient, standard error, and t-statistics of the fitted line are reported within the box. Sampling weights provided by the Statistics Bureau of the MIC are used for deriving the results.

2.6 Data summary: unemployed due to employer reason

We now present present an additional finding for the above, based on a strong negative relationship between mobility and unemployment due to employer's reasons in our companion paper (Hoshi et al. 2021). Figure 13 shows a YOY difference in the number of unemployed people due to the employer's reason for each subgroup. It gives us similar patterns to the result using the entire unemployment provided in Figure 11. Figure 14 also provides a similar, albeit, small negative relationship between the YOY difference in the number of employer-reason unemployment and our mobility measure.

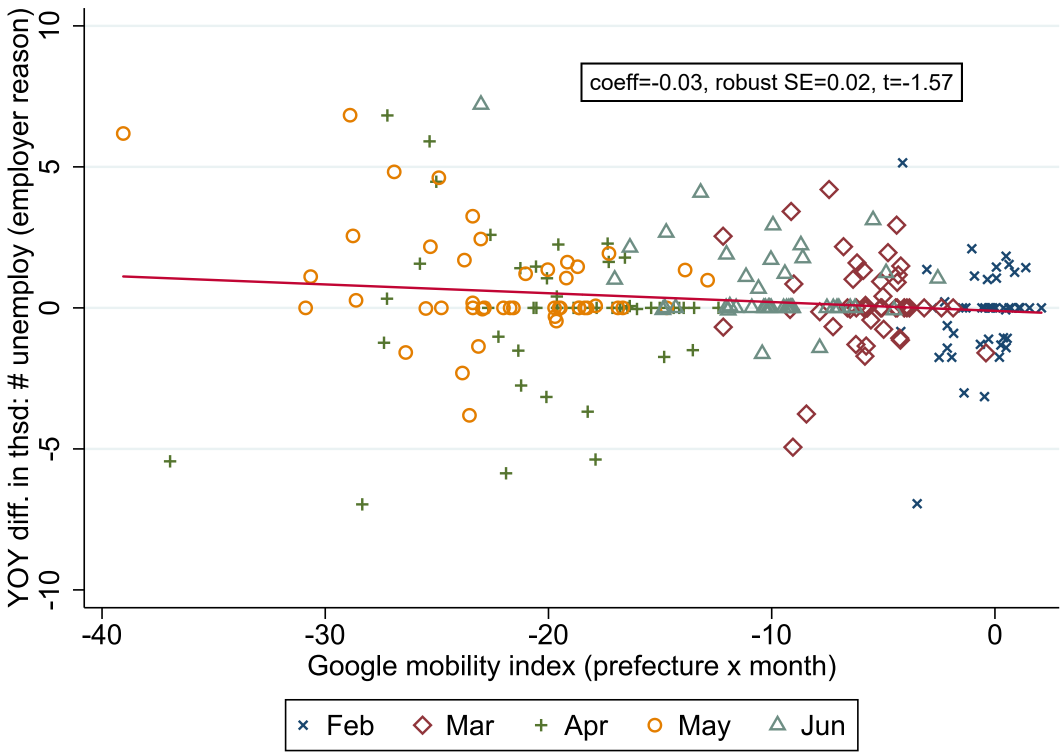
Figure 13. Number of unemployed due to employer's reason across individual characteristics



Note: Each figure shows a year-over-year (YOY) difference in the number of people unemployed due to employer's reason. An individual is defined as being unemployed due to employer's reason if they report both (a) the working status in the final week of a month as "looking for a job" and (b) a reason of seeking a job as "separating from the last job due to employer's reasons". The top-left panel shows the YOY difference for different educational levels. High education includes people whose final education is university or post-graduate level. Low education includes those whose final education is elementary, middle, or high school, two-year or technical college, or not-in-any-school. The top-right panel shows the YOY difference for males and females. The bottom panel shows the YOY difference for each age category. Sampling weights provided by the Statistics Bureau of the MIC are used for deriving the results.

In sum, the descriptive data analysis shows the heterogeneous effects of COVID-19 on absence from work, work hours, and unemployment. We find that the negative impact of COVID-19 is substantial for low-educated and female people and those in service sectors. In addition, the effects are associated with people's behavior represented by the mobility measure. The change in the mobility measure coincides with the policy changes. To examine the heterogeneous COVID-19 effects across individuals more formally, we conduct a regression analysis in the next section.

Figure 14. Relation between number of unemployed due to employer's reason and mobility measures



Note: The figure shows a scatter plot and its fitted line for the relationship between the YOY difference in the number of people unemployed due to employer's reason and our mobility measure. Each dot corresponds to the value in a prefecture-month. Different shapes symbolize dots in different months. The slope coefficient, standard error, and t-statistics of the fitted line are reported within the box. Sampling weights provided by the Statistics Bureau of the MIC are used for deriving the results.

3 Econometric Framework

3.1 Specification

We now conduct a regression analysis using individual-level microdata. Our companion paper (Hoshi et al. 2021) provides the average effect of COVID-19 on unemployment due to employer's reason using the prefecture-level data. However, the average result can hide heterogeneous effects across individuals. For example, Kikuchi et al. (2020) point out, using Japanese data, that the negative impact of COVID-19 reduces expenditure more in the service sector than in the manufacturing sector, thus suggesting heterogeneous effects in the labor market.

Our specification examines how the policy-driven change in people's mobility heterogeneously affects individual labor market outcomes (absence from work, work hours, and unemployment), depending on the teleworkability and essentialness of their industries and occupations as follows:

$$\begin{aligned}\Delta Y_{it} = &\beta_1 mobility_{it} + \beta_2 telework_{it-12} + \beta_3 essential_{it-12} + \beta_4 mobility_{it} \times telework_{it-12} \\ &+ \beta_5 mobility_{it} \times essential_{it-12} + \beta_6 telework_{it-12} \times essential_{it-12} + \mathbf{X}_{it}^{'}\beta_7 + \epsilon_{it},\end{aligned} \tag{3}$$

where ΔY_{it} denotes a 12-month difference in an outcome variable for individual i in month t. Taking the 12-month difference allows us to cancel out time-invariant additive individual characteristics and to control for seasonality. $mobility_{it}$ is a Google mobility measure in the prefecture at month t where individual i resides, $telework_{it-12}$ is the Dingel-Neiman telework index for the occupation in which individual i engages in the previous year, and $essential_{it-12}$ is a dummy variable for workers in essential jobs in the previous year. This *essential* variable controls for job-specific demand shocks, which can be a confounder for identifying the role of teleworkability in determining the effect of the COVID-19 pandemic. X_{it} includes variables such as prefecture, gender, low-education, and age-category fixed effects. It also includes month-lag industry fixed effects to absorb both industry-specific demand-side effects related to the COVID-19 pandemic and other contemporaneous policy changes.[9] [10] Finally, observations in each regression are weighted by sampling weights to make the regression results representative.

We focus on the coefficient of mobility measure and its interactions with the telework index and the essentialness index. In particular, β_1, β_4, and β_5 represent the effect of declining mobility on outcome variables for people not in teleworkable occupations nor essential jobs, that for people in teleworkable occupations in the previous year, and that for those engaged in essential jobs in the previous year, respectively.

Taking working hours as an outcome variable, we expect that the coefficient β_1 is positive because declining mobility is associated with a negative labor demand due to slower economic activities. In addition, when staying at home is required under the state of emergency, it is impossible to continue working if the job requires social interactions (e.g., serving at restaurants), decreasing working hours. We also expect that the coefficient β_4 is negative because teleworkable jobs suffer less from declining mobility as work from home is possible without social interactions. Furthermore, highly teleworkable occupations, such as programmers and system designers in "Data pro-

[9] The LFS includes 82 industry classifications, approximately equivalent to a 2-digit Japan Standard Industry Classification (JSIC).

[10] For example, the revised Japanese labor law was enforced on April 1st, 2020, which limited overtime work to 45 hours per month with a maximum of 360 hours in a year for workers in small and medium-sized firms.

cessing and communication engineers," may experience an increase in their labor demand when more people stay at home and work from home. The coefficient β_5 is also expected to be negative because essential jobs are less vulnerable to negative economic shocks associated with declining mobility or may even experience an increase in demand under the state of emergency (e.g., medical and logistics service).

3.2 Instruments

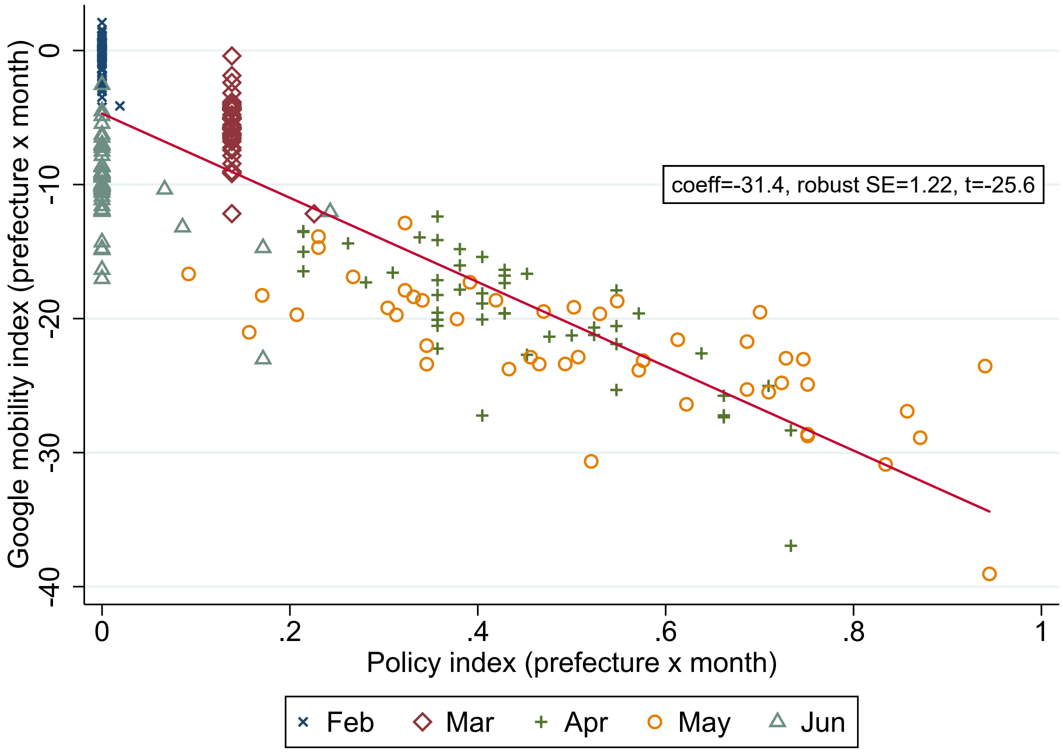
A potential concern in estimating these coefficients is the endogeneity of the mobility measure. For instance, declining individual work hours can reduce the prefecture-level mobility index through a decrease in Workplaces_{pt} in equation (1), thus leading to a correlation between the mobility term and the error term and causing biased estimates. To address this endogeneity concern, we use the policy index as our instrumental variable. The identification assumption is that COVID-19 policies affect outcome variables only through the change in mobility, after controlling for explanatory variables.

Figure 15 shows the substantial predictive power of the policy instrument for a difference in the Google mobility measure. An increase in the policy index by one standard deviation in all sample periods (i.e., 0.25, which is similar to a difference in the policy index in April between Tokyo and Yamanashi) corresponds to a decrease in the Google mobility measure by 7.9. We will test the strength of predicted power when we report the regression results below.

While we cannot formally test with our just-identified setting, the policy instrument is likely to satisfy the exclusion restriction given our rich set of controls. In particular, the error terms are residualized by month-lag industry, age category, gender, low-education, and prefecture fixed effects. It also excludes time-invariant additive individual-specific factors because we take the year-over-year difference in the outcome variables. We thus expect that these factors control for standard determinants of an individual's work hours, absence from work, and being unemployed.

In Appendix A4, we also present the reduced-form regression in which labor market outcome variables are regressed on the policy index and its interactions with indices for teleworkability and essentialness of occupations together with other controls. The reduced-form results provide similar implications to the 2SLS results.

Figure 15. Plot on the first-stage regression



Note: The figure shows a scatter plot and its fitted line for the relationship between the Google mobility measure and the policy index. Each point corresponds to the value in a prefecture-month. The points for different months are symbolized by different shapes. The slope coefficient, standard error, and t-statistics of the fitted line are reported within the box. Sampling weights provided by the Statistics Bureau of the MIC are used for deriving the results.

4 Results

4.1 Results on absence from work

Table 2 shows the impact of a policy-driven decline in mobility on absence from work for each subgroup defined by regular vs. non-regular jobs, education, gender, and age categories. Here, equation (1) is applied separately for each subgroup, and the result is reported in each column. There are three things to notice. First, the negative estimated coefficient of mobility indicates that a decline in mobility due to COVID-19 policies increases absence from work on an average (column 1), and especially for non-regular workers (column 3), low-educated people (column 5), females (column 8) and people aged 31 to 45 years (column 10). Specifically, when comparing column 3 with column 2, people who worked as non-regular workers in the previous period are more likely to be absent from work in this period than those who worked as a regular worker in the previous period. Second, the coefficient on the interaction term between mobility and essential jobs tends to be positive and statistically significant for the sub-sample of people aged 31 to 45 years. The positive interaction suggests that the effect of COVID-19 raises the demand for workers in some essential industries and occupations, and thus they are less likely to be absent from work. Finally, our instrumental variable is relevant, as Sanderson and Windmeijer's (2016) conditional first-stage F-statistics are large enough, as reported at the bottom of the table.

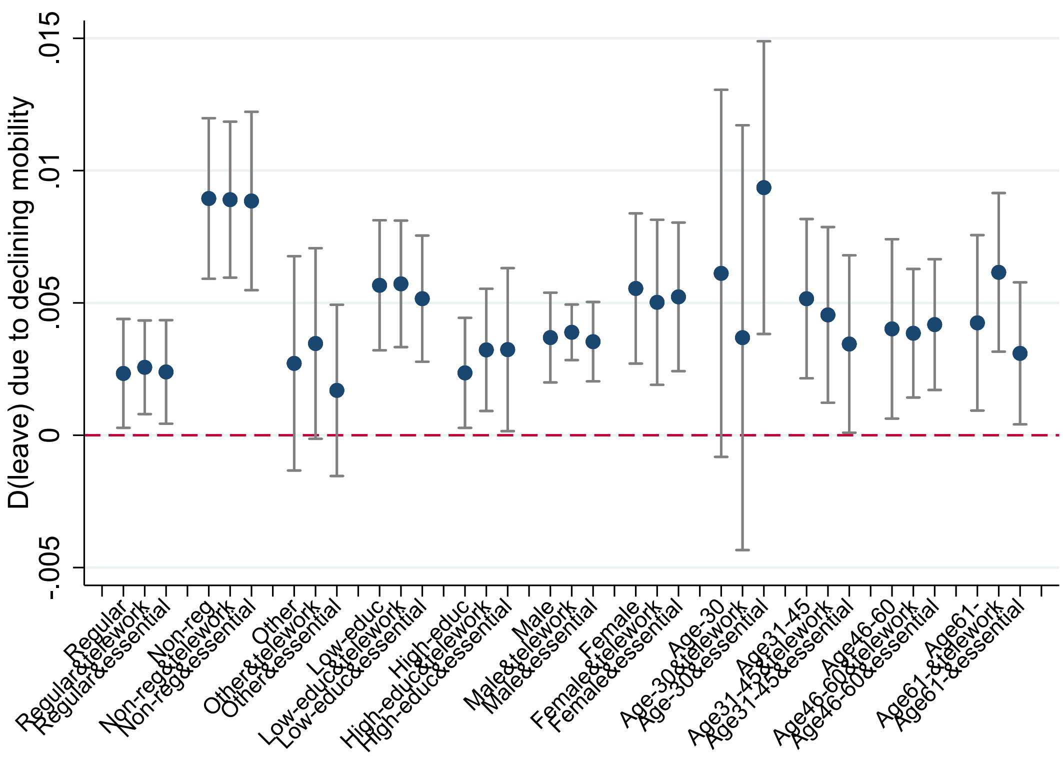
Table 2: Effect of a policy-driven decline on absence from work (leave)

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Δ **absence from work**											
mobility	-0.0045***	-0.0023**	-0.0089***	-0.0027	-0.0057***	-0.0024**	-0.0037***	-0.0055***	-0.0061*	-0.0052***	-0.0040**	-0.0042**
	(0.0010)	(0.0010)	(0.0015)	(0.0021)	(0.0013)	(0.0011)	(0.0009)	(0.0014)	(0.0035)	(0.0015)	(0.0017)	(0.0017)
telework_{t-12}	-0.0060	0.0033	-0.0079	-0.0286*	-0.0107	-0.0078	-0.0065	-0.0022	0.0293	0.0008	-0.0001	-0.0369***
	(0.0054)	(0.0067)	(0.0127)	(0.0153)	(0.0077)	(0.0099)	(0.0091)	(0.0108)	(0.0231)	(0.0090)	(0.0082)	(0.0109)
essential_{t-12}	-0.0038	0.0103	-0.0165	0.0123	0.0032	-0.0187	0.0216**	-0.0131	-0.0293	-0.0101	0.0037	0.0266
	(0.0100)	(0.0127)	(0.0156)	(0.0246)	(0.0098)	(0.0199)	(0.0085)	(0.0132)	(0.0516)	(0.0168)	(0.0093)	(0.0191)
$\text{telework}_{t-12}\#\text{essential}_{t-12}$	0.0401**	0.0044	0.0654**	0.0783*	0.0353*	0.0353	-0.0267	0.0747***	0.0199	0.0624***	0.0090	0.0334
	(0.0164)	(0.0239)	(0.0280)	(0.0412)	(0.0205)	(0.0380)	(0.0231)	(0.0276)	(0.0698)	(0.0238)	(0.0227)	(0.0281)
$\text{mobility}\#\text{telework}_{t-12}$	0.0000	-0.0002	0.0000	-0.0007	-0.0001	-0.0009	-0.0002	0.0005	0.0024	0.0006	0.0002	-0.0019***
	(0.0005)	(0.0005)	(0.0008)	(0.0010)	(0.0006)	(0.0008)	(0.0007)	(0.0006)	(0.0016)	(0.0007)	(0.0007)	(0.0005)
$\text{mobility}\#\text{essential}_{t-12}$	0.0002	-0.0001	0.0001	0.0010	0.0005	-0.0009	0.0002	0.0003	-0.0032	0.0017*	-0.0002	0.0012
	(0.0006)	(0.0007)	(0.0007)	(0.0014)	(0.0005)	(0.0010)	(0.0007)	(0.0006)	(0.0025)	(0.0009)	(0.0008)	(0.0012)
Observations	52,692	26,609	16,419	9,648	37,843	14,849	29,573	23,119	4,556	14,947	19,071	14,118
R-squared	0.039	0.036	0.079	0.075	0.049	0.054	0.044	0.052	0.116	0.057	0.068	0.069
Sub_sample	all	regular	non-reg	other	low-educ	high-educ	male	female	-30	31-45	46-60	61-
Month-sector FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age category FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No	No	No
Gender FE	Yes	Yes	Yes	Yes	Yes	Yes	No	No	Yes	Yes	Yes	Yes
Low educ FE	Yes	Yes	Yes	Yes	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Prefecture FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SW F-stat: mob	619.24	708.53	577.03	572.22	503.36	728.79	588.80	673.30	737.23	684.24	572.78	506.39
SW F-stat: mob#tele	941.77	1021.38	680.55	337.67	437.89	961.69	993.59	878.62	1082.11	1004.23	756.88	810.18
SW F-stat: mob#ess	548.73	499.61	274.14	1196.57	461.03	526.88	1079.5	470.58	346.14	455.68	825.12	1189.17

Note: The table reports the 2SLS estimation of equation (3) on a year-over-year (YOY) difference in a leave status. The dependent variable is a YOY difference in a dummy variable of individual i in a leave of absence in month t. The main explanatory variables are a prefecture-level mobility measure where individual i resides, the telework index in the occupation that individual i engaged 12 months ago, a dummy variable for individual i engaging in essential jobs 12 months ago, and their interactions. The regressions also include a set of fixed effects, such as month-lag sector, age category, gender, low-education, and prefecture. The bottom three rows report Sanderson and Windmeijer's (2016) conditional first-stage F-statistics for the validity of instruments. Each column in columns 1 to 12 shows a result for a different subgroup: full sample, people who worked as a regular worker 12 months ago, those who worked as a non-regular worker 12 months ago, those with other employment statuses (i.e., executives, owners, and family workers), low-educated people, high-educated people, males, females, people aged 30 and younger, those aged 31 to 45 years, those aged 46 to 60 years, and those aged 61 and above. Clustered robust standard errors at the prefecture-level are in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Figure 16 visually plots the results of Table 2. The coefficient on the mobility term is labeled as "*subgroup name*" on the x-axis. The sum of the coefficient on the mobility term and that on the interaction term between mobility and the telework index (essential jobs dummy variable) is labeled as "*subgroup name* & telework" (as "*subgroup name* & essential"). Comparing the size of the coefficients nearby within a subgroup reveals the extent to which remote-work technology and job essentiality mitigate the negative effect of COVID-19. Their standard errors are calculated by the delta method. Figure 16 shows that absence from work increases for all subgroups due to the policy-driven decrease in mobility, where the magnitude is considerable for non-regular workers, low-educated people, and females.

Figure 16. Effect on absence from work (leave) for each group



Note: The figure plots the estimated coefficients on the effect of a policy-driven mobility decline on a leave of absence for each subgroup. Three nearby coefficients in a bundle are obtained from the same 2SLS estimation for a subgroup. The left out of three points corresponds to the coefficient on the mobility term in the regression. The middle point is from the coefficient on the mobility term, plus that on the interaction of mobility and the Dingel-Neiman telework index. The right point corresponds to the coefficient on the mobility term, plus that on the interaction of mobility and essential jobs. Sampling weights provided by the Statistics Bureau of the MIC are used for deriving the results.

4.2 Results on work hours

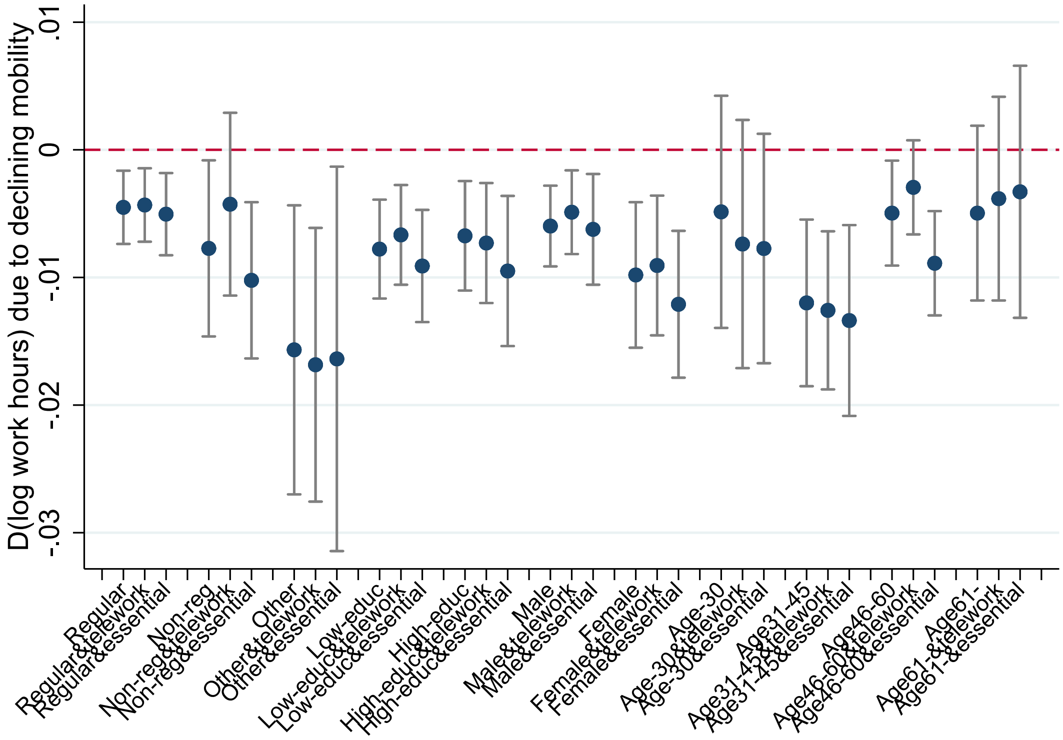
From here on, we will report all the regression results in figures, while the corresponding tables are included in Appendix A3.

Figure 17 reports the effect on work hours across different subgroups, where the outcome variable is a change in log work hours from the previous to this year.[11] The results indicate that policy-

[11]The sample of this analysis is restricted to individuals who work continuously during both years.

driven mobility decline reduces work hours for all subgroups, but the effect is especially large for executives and owners, female workers, and people aged 31 to 45 years.

Figure 17. Effect on log work hours for each group



Note: The figure plots the estimated coefficients on the effect of a policy-driven mobility decline on log work hours for each subgroup. Three nearby coefficients in a bundle are obtained from the same 2SLS estimation for a subgroup. The left out of three points corresponds to the coefficient on the mobility term in the regression. The middle point is from the coefficient on the mobility term, plus that on the interaction of mobility and the Dingel-Neiman telework index. The right point corresponds to the coefficient on the mobility term, plus that on the interaction of mobility and essential jobs. The sample of this analysis is restricted to individuals who continuously worked during both years. Sampling weights provided by the Statistics Bureau of the MIC are used for deriving the results. Table A1 of the Appendix reports the corresponding results.

Why does a decline in work hours come out for executives and owners? To investigate this question further, we disaggregate the group into sub-categories: executives, owners with employees, owners without employees, and support for family businesses. It turns out that the negative impact on work hours among executives and owners comes mostly from owners without employees, that is, self-employed workers (Figure A1). One possible explanation is that 26.3% of owners without employees worked in the service sectors in the previous period, which was the highest percentage among all sub-categories of executives and owners. The result also suggests that owners without employees may not have been fully covered by governmental support during the initial period of COVID-19.

Similarly, why have people aged 31 to 45 years experienced a larger decline in work hours than other groups? There could be at least two possible explanations. First, they had worked longer hours than other groups before the COVID-19 pandemic and therefore found it easier to reduce their work hours under the state of emergency. Second, people aged 31 to 45 years are more likely to have school-aged children. Given the temporary closure of schools from early March to May, they may have shortened their work hours to take care of children at home, especially for females (Albanesi and Kim 2020; Alon et al. 2021).

To investigate the plausibility of these explanations, we augment our baseline regression by including the lag work hours and their interaction and implementing the regression for each gender. Unfortunately, our LFS does not include the number of children in each household and thus, we are unable to directly control it.[12]

The result in Table A2 in the Appendix suggests that workers who worked long hours in 2019 were inclined toward reducing their work hours in 2020, irrespective of whether a prefecture had a considerable change in mobility due to COVID-19 related policy changes. Therefore, we do not find any conclusive evidence that COVID-19 reduces work hours more for those working longer hours before the pandemic. Females aged 31 to 45 years had a large estimate on mobility even after controlling for lag work hours, but the estimate is insignificant, providing inconclusive evidence for the hypothesis that females aged 31 to 45 years had reduced work hours.

4.3 Results on unemployment

Figure 18 shows that the effect on unemployment is mostly statistically insignificant. This could be because the Japanese government expanded assistance to people absent from work during the initial periods of COVID-19 without changing the system of unemployment benefits until the end of June. Therefore, an increase in the number of unemployed people could come out later.[13] However, the following three observations are worth noting. First, some groups such as males and people aged 61 and above are likely to be unemployed due to the policy-driven mobility decline. Second, if a job can be performed remotely at home or is an essential one, then the effect of decreasing mobility is mitigated. For example, the coefficient on the interaction term between mobility and the telework index is positive and statistically significant for the sub-sample of high-educated people (column 6 in Table A3). This implies, as shown in Hoshi et al. (2021), that the negative effect of a policy-driven decline in mobility is partly mitigated by the availability of remote-work technologies in the occupation. Third, the coefficient on the interaction term between mobility and essential jobs is positive and statistically significant for the same group, suggesting a rise in demand for such jobs under the state of emergency.

There is another question that arises from the results. Why are people aged 61 and above more likely to be unemployed? To gain an insight into this question, we focus on the sample of people aged 55 to 70 years and implement the same 2SLS estimation, including a dummy variable for each age and its interaction with the mobility term.

Figure 19 shows the results for workers neither in teleworkable nor in essential jobs. A policy-driven decline in mobility raises the probability of unemployment for those aged 60 and 65—typical retirement ages—but not for people of other ages.[14]

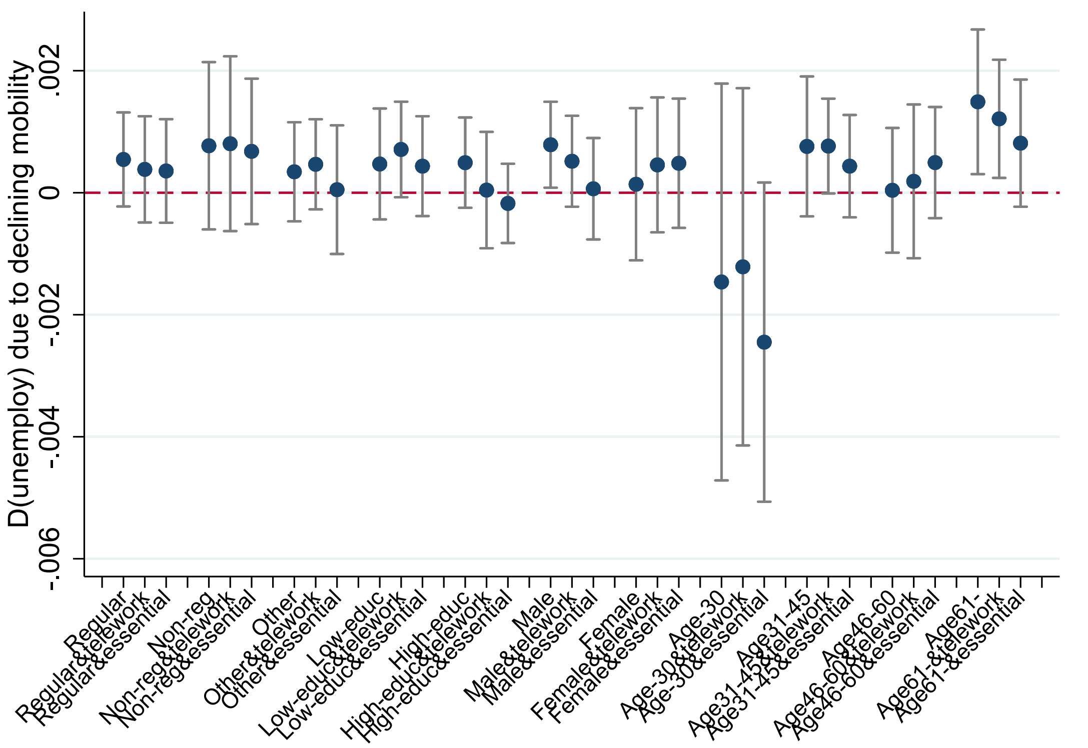
[12]We are currently in the process of applying to access the data for the number of children, but the application process takes several months.

[13]The publicly available aggregate LFS shows that the unemployment rate continued to rise for both genders from June to August and then continued to increase especially for males from September to December.

[14]An Act on Stabilization of Employment on Elderly Persons was established in 1971 to keep employment for older people stable and promote their re-employment. It was then amended in 2012 and started (a) prohibiting firms from setting their retirement age below 60, and (b) requiring them to raise their retirement age to 65 by April 2025. Therefore, most firms have their retirement age at 60 or 65. In fact, according to the General Survey on Working Conditions by the Ministry of Health, Labour and Welfare, 79.3% of firms that have their retirement age set at age 60, 16.4% set it at age

Table A4 in the Appendix reports the estimates using people aged 55 to 70 years (column 1), those using older people who worked as regular workers in the previous year (column 2), and those using the older people who worked as non-regular workers in the previous year (column 3). The significant negative estimates around the retirement age (60 and 65) are observed only for regular workers but not for non-regular workers. One explanation is that people who retired at 60 or 65 were hired continuously by the same firms under the post-retirement re-employment system prior to COVID-19, but the pandemic prevented them from being re-hired after their retirement and, consequently, they became unemployed.[15] [16]

Figure 18. Effect on unemployment for each group



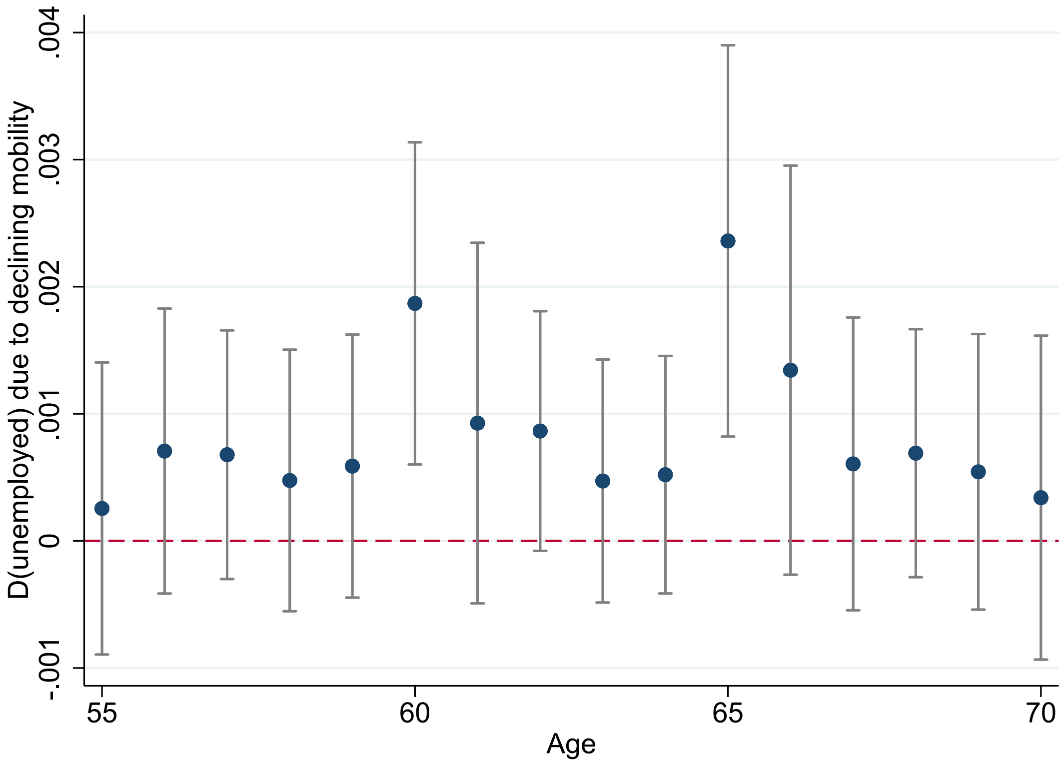
Note: The figure plots the estimated coefficients on the effect of a policy-driven mobility decline on being unemployed for each subgroup. Three nearby coefficients in a bundle are obtained from the same 2SLS estimation for a subgroup. The left out of three points corresponds to the coefficient on the mobility term in the regression. The middle point is from the coefficient on the mobility term, plus that on the interaction of mobility and the Dingel-Neiman telework index. The right point corresponds to the coefficient on the mobility term, plus that on the interaction of mobility and essential jobs. Sampling weights provided by the Statistics Bureau of the MIC are used for deriving the results. Table A3 of the Appendix reports the corresponding results.

65, and the remaining at other ages in 2017. See https://www.mhlw.go.jp/toukei/itiran/roudou/jikan/syurou/17/dl/gaiyou02.pdf (in Japanese).

[15] This pattern is consistent with a finding by Coibion et al. (2020), which, using the Nielsen Homescan panel data in the US, observe a large increase in people out of the labor force due to earlier than planned retirements during the onset of COVID-19. Bui et al. (2020) also observe that the effect of COVID-19 on unemployment is larger for people in near retirement ages than younger people.

[16] See, for example, https://business.nikkei.com/atcl/gen/19/00223/121500001/ (in Japanese), a newspaper article on retired workers looking for jobs and firms that are reluctant to hire them.

Figure 19. Effect on unemployment for people aged 55-70



Note: The figure plots the estimated coefficients on the effect of a policy-driven mobility decline on being unemployed for people aged 55 to 70 years. Each point corresponds to the coefficient on the interaction of an age dummy and the mobility term. Sampling weights provided by the Statistics Bureau of the MIC are used for deriving the results. Table A4 (column 1) of the Appendix reports the corresponding results.

Similarly, we investigate why males are more likely to be unemployed by implementing the same regression for each gender and age category. Table A5 indicates that males aged 61 and above are more likely to be unemployed due to a policy-driven mobility decline (column 7). In contrast, males in other age categories do not respond to mobility changes (columns 1, 3, and 5). These results suggest that older males engaged in regular work prior to the pandemic are more likely to be impacted by the COVID-19 pandemic than other groups.

While our 2SLS estimates reported so far represent the effect of changes in mobility induced by policy changes, we also implement a reduced-form estimation on the effect of policy changes on the labor market outcomes. Appendix A4 reports the results. The reduced-form results are comparable to 2SLS estimates not only qualitatively but also quantitatively. For instance, while a one standard deviation increase in the policy index, 0.25, causes an increase in a 12-month difference in the absence from work by 0.0311 for non-regular workers, a one standard deviation decrease in mobility, 8.972, leads to an increase in the outcome by 0.0798 for the same group. This suggests that the effect of policy changes is mostly through the change in mobility.

4.4 Results in service and sales occupations

It is known that female and low-skilled workers are hit harder by the negative effect of the pandemic than male and high-skilled workers (e.g., Alon et al. 2021). This is partly because they are more likely to work in industries and occupations requiring face-to-face communication and on-site work. Figure 20 shows the number of individuals in gender-education groups for each occupation. In comparison to other occupations, service and sales occupations employ the largest number of low-educated females.

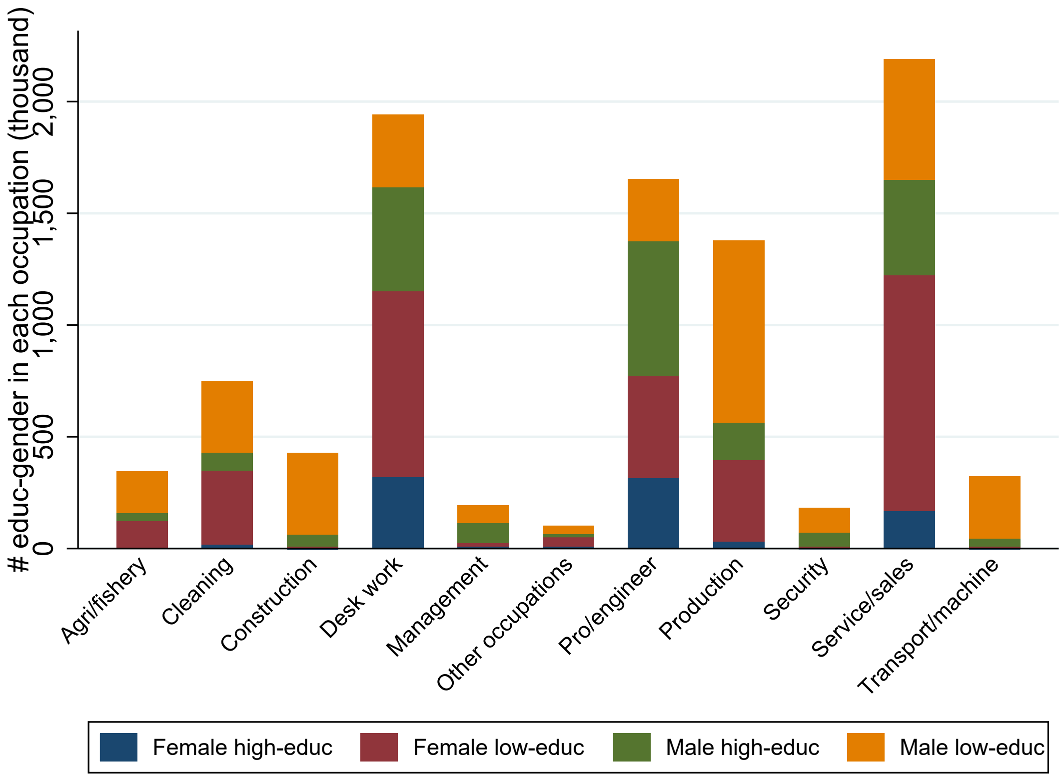
To investigate the heterogeneous effect of the pandemic in Japan's service and sales occupations, we analyze the sample of individuals who worked in service or sales occupations in the previous year.

The effect on absence from work is reported in Figure 21. Absence from work increased in most subgroups within the service and sales occupations. However, the magnitude was larger for the low-educated, females, and those aged 31 to 45 years. In addition, these estimates for this subsample of service and sales occupations tend to be larger than those for the entire sample reported in Figure 16. For example, the estimated coefficient for the subgroup of non-regular workers in service and sales occupations is -0.015 (statistically significant, reported in Table A6 of the Appendix), but it is -0.009 for the full sample. Therefore, consistent with the other existing studies on COVID-19, the negative effect on absence from work is estimated to be larger for the service and sales occupations than other occupations.

Figure 22 shows the effect on work hours in the service and sales occupations. Working hours decrease when mobility declines in most subgroups of individuals in the service and sale occupations. These effects, however, seem to be greater for female workers and those aged 31 to 45 years. This is in line with the results using the entire sample.

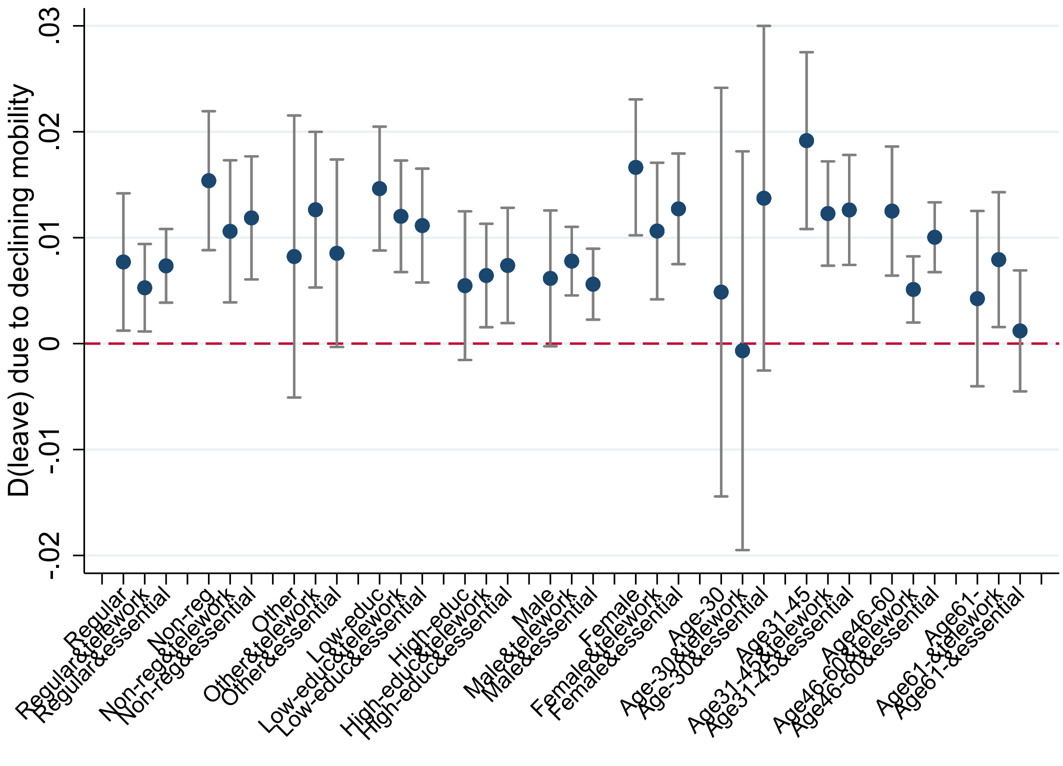
Finally, the effect on unemployment in service and sales occupations is reported in Figure 23. Here, we report the effect on unemployment due to employer's reason because involuntary unemployment is of particular interest. There are three things to notice. First, people in most subgroups are more likely to be unemployed due to employer's reason as a result of the policy-driven mobility

Figure 20. Number of individuals in each occupation



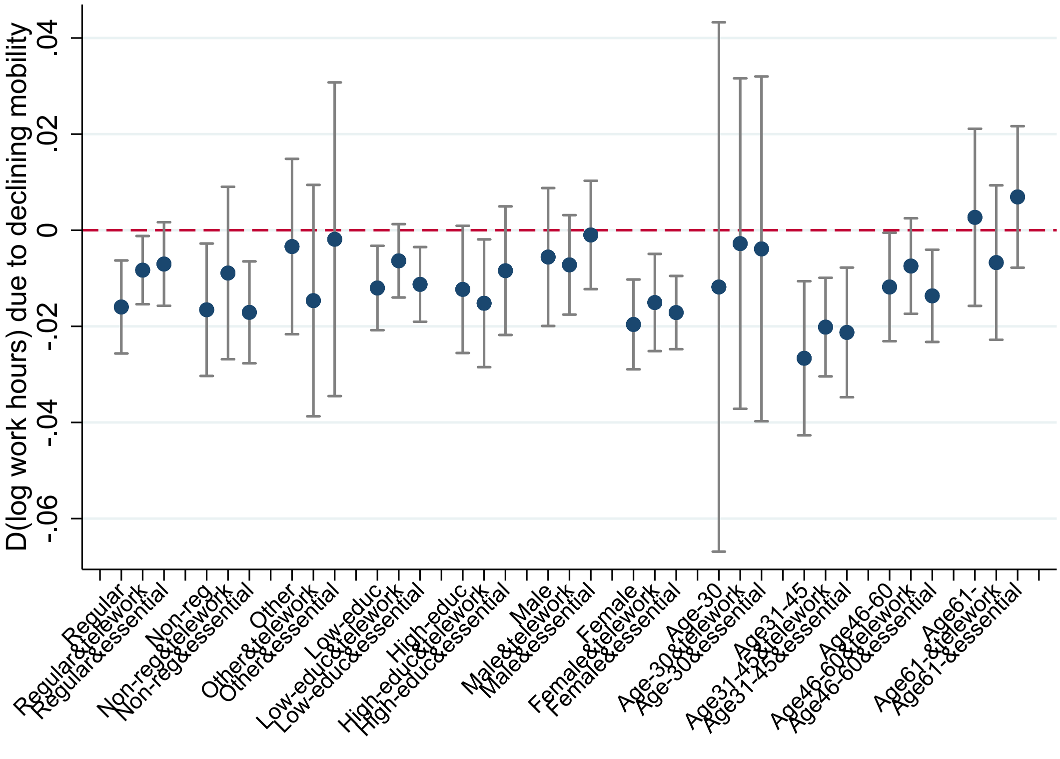
Note: The figure shows the number of high-educated males, low-educated males, high-educated females, and low-educated females in each occupation in 2019. Service and sales occupations are combined into one category (Service/sales). Sampling weights provided by the Statistics Bureau of the MIC are used for deriving the results.

Figure 21. Effect on absence from work (leave) for service and sales occupations



Note: The figure plots the estimated coefficients on the effect of a policy-driven mobility decline on a leave of absence for each subgroup, focusing on workers in service and sales occupations in the last period. Three nearby coefficients in a bundle are obtained from the same 2SLS estimation for a subgroup. The left out of three points corresponds to the coefficient on the mobility term in the regression. The middle point is from the coefficient on the mobility term, plus that on the interaction of mobility and the Dingel-Neiman telework index. The right point corresponds to the coefficient on the mobility term, plus that on the interaction of mobility and essential jobs. Sampling weights provided by the Statistics Bureau of the MIC are used for deriving the results. Table A6 of the Appendix reports the corresponding results.

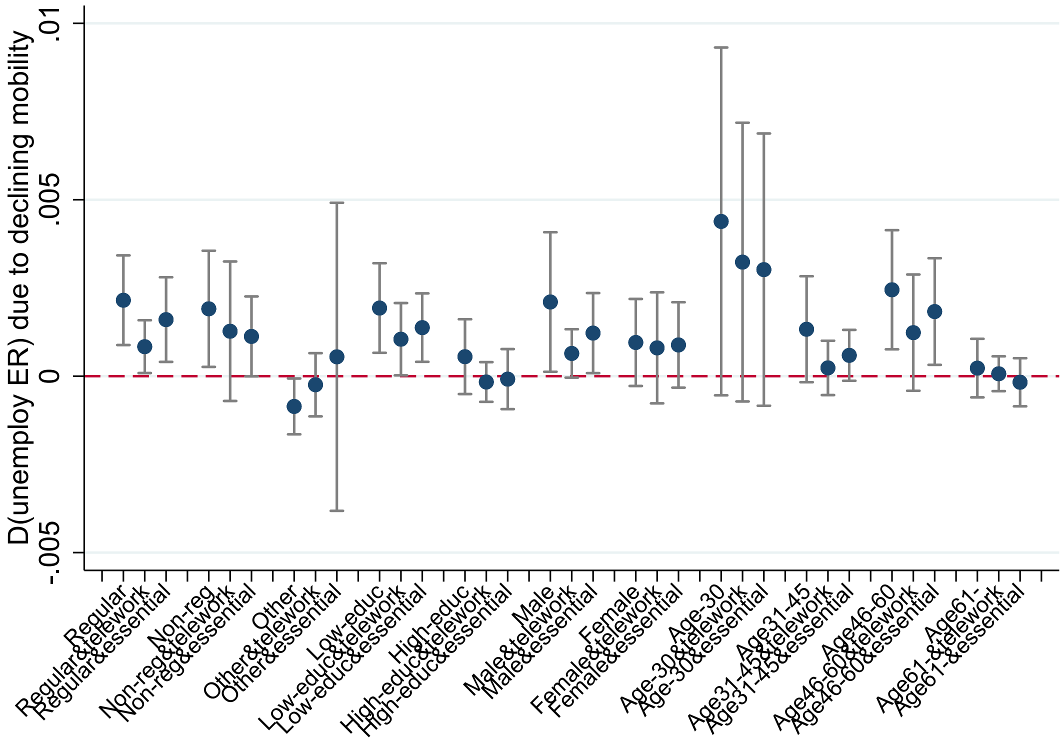
Figure 22. Effect on log work hours for service and sales occupation



Note: The figure plots the estimated coefficients on the effect of a policy-driven mobility decline on log work hours for each subgroup, focusing on workers in service and sales occupations in the last period. Three nearby coefficients in a bundle are obtained from the same 2SLS estimation for a subgroup. The left out of three points corresponds to the coefficient on the mobility term in the regression. The middle point is from the coefficient on the mobility term, plus that on the interaction of mobility and the Dingel-Neiman telework index. The right point corresponds to the coefficient on the mobility term, plus that on the interaction of mobility and essential jobs. Sampling weights provided by the Statistics Bureau of the MIC are used for deriving the results. Table A7 of the Appendix reports the corresponding results.

decline. Second, the magnitude of these coefficients is also larger in service and sales occupations than in the entire sample reported in Figure 18. Third, the effect seems to be especially greater for male workers and those aged 30 and less. The first and the second observations are in line with the results of the entire sample. The third could be because workers employed in service and sales occupations in the previous year tend to be those who worked while attending colleges and universities (or, the *arubaito*) in the previous year (i.e., 36.9% of this subgroup).[17] These college students who work as part-time workers were laid-off due to the COVID-19 pandemic and could not find a new job, possibly suggesting that some college students may be financially in trouble.

Figure 23. Effect on employer-reason unemployment for service and sales occupations



Note: The figure plots the estimated coefficients on the effect of a policy-driven mobility decline on being unemployed due to employer's reason for each subgroup, focusing on workers in service and sales occupations in the last period. Three nearby coefficients in a bundle are obtained from the same 2SLS estimation for a subgroup. The left out of three points corresponds to the coefficient on the mobility term in the regression. The middle point is from the coefficient on the mobility term, plus that on the interaction of mobility and the Dingel-Neiman telework index. The right point corresponds to the coefficient on the mobility term, plus that on the interaction of mobility and essential jobs. Sampling weights provided by the Statistics Bureau of the MIC are used for deriving the results. Table A8 of the Appendix reports the corresponding results.

5 Counterfactual Experiments

Using the regression estimates, we may quantify the heterogeneous impact of declining mobility by conducting counterfactual experiments.[18] Suppose that Yamanashi had a more stringent policy in

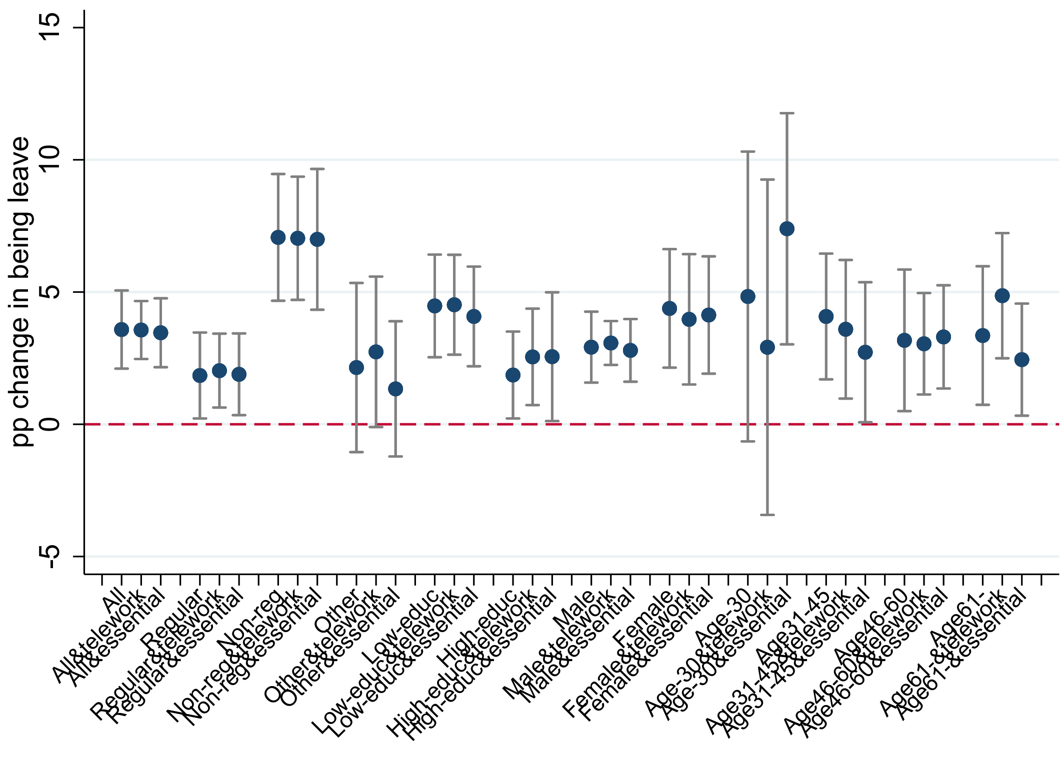
[17] About 75% of people in this category are aged 19 to 22 years.

[18] The purpose of these experiments is to provide an intuition about the magnitude of estimates and their variation across subgroups of individuals, and thus we do not consider any effects from subsidy programs responded to COVID-19.

April than their actual policy. Specifically, we consider a counterfactual scenario where the policy index for Yamanashi in April is 0.73, the same as Tokyo, instead of their actual 0.48.[19] Then, the estimate on the relationship between the policy index and the mobility measure in Figure 15 implies that their mobility measure would have declined additionally by 7.9 percentage-points (pp).[20] If this had been the case, what would have happened to absence from work, work hours, and unemployment in Yamanashi?

First, the decline in mobility by 7.9 pp would have led to a 3.58 pp increase on average in absence from work, as shown in Figure 24. Furthermore, the effect is heterogeneous across subgroups, where the increase is large for non-regular workers (7.07 pp), low-educated people (4.48 pp), and females (4.38 pp), while it is small for regular workers (1.85 pp) and high-educated people (1.86 pp).

Figure 24. Effect of a stricter policy on absence from work (leave)



Note: The figure plots the effect of a counterfactual stricter policy and its effect through changing mobility on a leave of absence for each subgroup. The counterfactual policy change is a change in the policy index by 0.25, the same level as a difference in the index between Yamanashi and Tokyo in April. The counterfactual policy change then results in an additional decline in the mobility measure by 7.9, using the coefficient obtained in Figure 15. The confidence intervals are calculated from standard errors with the delta method, while ignoring standard errors in the imputed decline in the mobility measure. The format of the figure is the same as that in the result section.

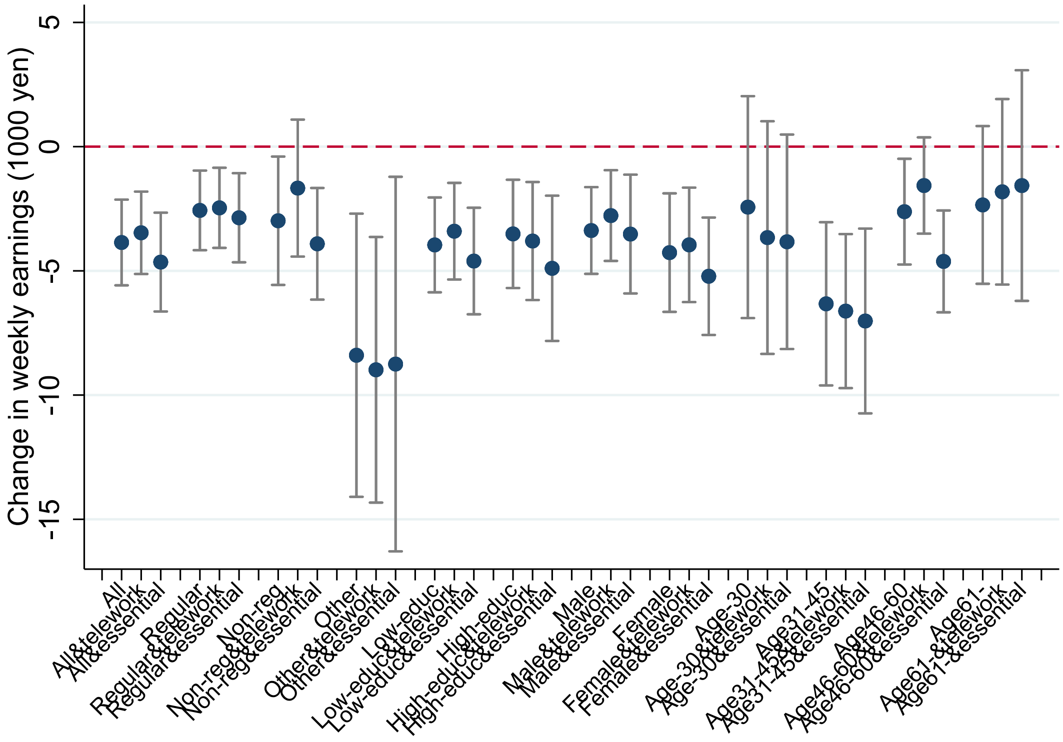
Second, this 7.9 pp decline in mobility would have led to a 5.8 percent decrease in work hours for workers whose job is neither teleworkable nor essential. This decrease in work hours is large for those aged 31 to 45 (9.0 percent) and executives and owners (11.6 percent), while it is only 3.5 percent for regular workers and 3.8 percent for those aged 46 to 60 years.

[19] We choose Yamanashi here because a difference in their policy index in April from that in Tokyo is almost equivalent to one standard deviation of the variable within all sample periods.

[20] Thus, it would have ended up as -29.25 percent in April.

As the average weekly work hours in our sample were 34.5 hours in April 2019, the average 5.8-percent decrease in work hours reduces work hours by 2 hours a week, leading to a loss of weekly earnings by about JPY 3,857.[21] The results on loss of weekly earnings are reported in Figure 25 for each subgroup.[22] The amount of earning losses is large for executives, owners, and family workers, which is about JPY 8,396, and for those aged 31 to 45 years, the loss is about JPY 6,326. In contrast, the losses are small for regular workers (JPY 2,566) and those aged 46 to 60 years (JPY 2,617).

Figure 25. Effect of a stricter policy on weekly earnings through declining work hours



Note: The figure plots the effect of a counterfactual stricter policy and its effect through changing mobility and work hours on weekly earnings for each subgroup. The counterfactual policy change is a change in the policy index by 0.25, the same level as a difference in the index between Yamanashi and Tokyo in April. The counterfactual policy change then results in an additional decline in the mobility measure by 7.9, using the coefficient obtained in Figure 15. The imputed change in weekly work hours is simply multiplied by the average hourly wages (i.e., the average monthly total cash earnings, JPY 276,551, divided by the average hours worked, 143.4 hours, in April 2019) calculated from the Monthly Labour Survey by the Ministry of Health, Labour and Welfare (MHLW). The confidence intervals are calculated from standard errors using the delta method while ignoring the standard errors in the imputed decline in the mobility measure. The format of the figure is the same as that in the result section.

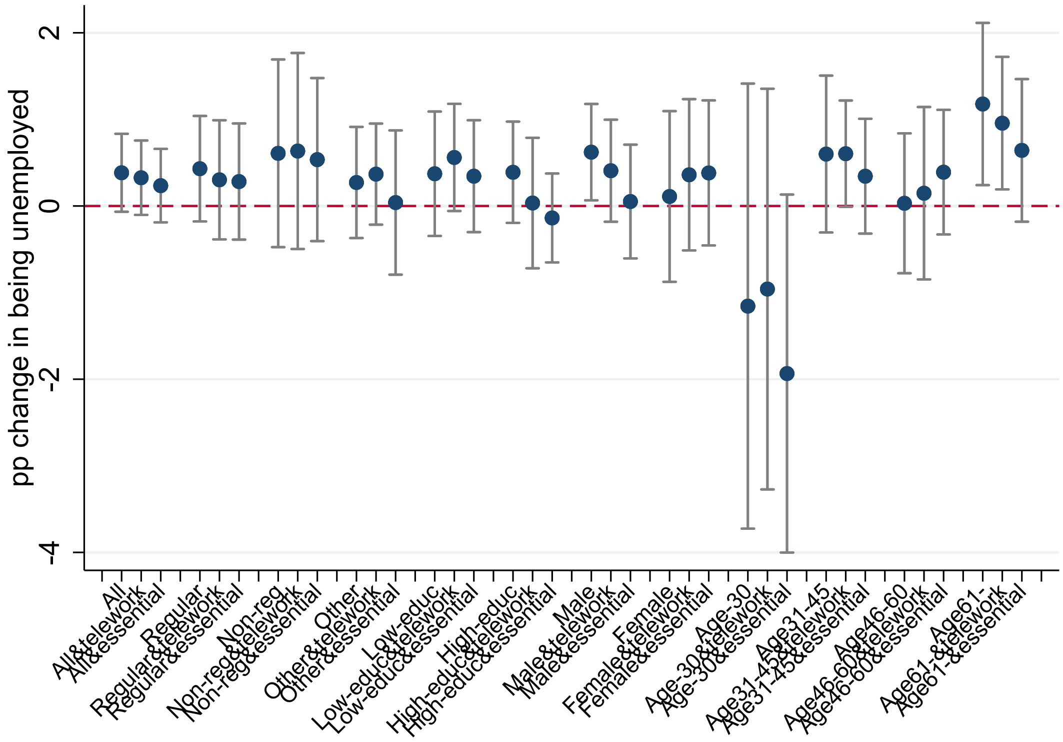
Third, the same decline in mobility by 7.9 pp would have led to a 0.38 pp increase in the percentage of unemployed people in the population aged 15 and above. Figure 26 reports the result. For an individual in a teleworkable occupation, the percentage of being unemployed would have been increased only by 0.33 pp. Similarly, if an individual were in an essential job, then the percentage of being unemployed would have increased only by 0.24 pp. The effect of this counterfactual policy is

[21] The value is calculated by first deriving the average hourly cash earnings from the average monthly total cash earnings (JPY 276,551) divided by the average hours worked (143.4 hours), from the Monthly Labour Survey by the Ministry of Health, Labour and Welfare (MHLW). Second, the average hourly cash earnings are multiplied by a weekly reduction in work hours, 2.00.

[22] The average weekly work hours are calculated differently for each subgroup.

heterogeneous across subgroups, where the effect is non-negligible for males (0.62 pp) and people aged 61 and above (1.18 pp); it is small for females (0.11 pp) and people aged 46 to 60 years (0.03 pp).

Figure 26. Effect of a stricter policy on unemployment



Note: The figure plots the effect of a counterfactual stricter policy and its effect through changing mobility on being unemployed for each subgroup. The counterfactual policy change is a change in the policy index by 0.25, the same level as a difference in the index between Yamanashi and Tokyo in April. The counterfactual policy change then results in an additional decline in the mobility measure by 7.9, using the coefficient obtained in Figure 15. The confidence intervals are calculated from standard errors with the delta method, while ignoring standard errors in the imputed decline in the mobility measure. The format of the figure is the same as that in the result section.

The effect of the counterfactual policy change for workers in service and sales occupations is reported in Figures A2-A4 in the Appendix. As you can expect from the estimation results, the effect is much larger in service and sales occupations than others and heterogeneous across subgroups. For example, an average person aged 31 to 45 in service and sales occupations would have lost JPY 13,842 in a week due to declining work hours. Similarly, an average female in service and sales occupations would have lost JPY 8,479; in contrast, an average male would have lost only JPY 3,338 (statistically insignificant). An average person in service and sales occupations would have experienced an increase in the percentage of being unemployed due to employer's reason by 1.26 pp. These results suggest that the negative effect of a more stringent policy would have been greater on people in service and sales occupations.

6 Conclusion

This paper analyzes the heterogeneous effect of the COVID-19 pandemic on absence from work, work hours, and unemployment, using individual-level microdata in Japan. A unique feature of our analysis is to use a direct mobility measure of people's behavior from Google Mobility Reports and its variation arising from a change in policies. The results indicate, first, that the number of people absent from work increased for all groups of individuals, but the impact was especially large for non-regular workers, low-educated people, females, and those aged 31 to 45 years. Second, while work hours also decreased for most individuals, the magnitude was greater for executives, owners, family workers, and people aged 31 to 45 years. Third, although the effect on unemployment was not significant overall, it was significantly large for those aged 61 and above, suggesting a temporal malfunction of the post-retirement re-employment system. Fourth, the negative effects on labor were considerable for people in service and sales occupations. Finally, our counterfactual analysis suggests that a more stringent policy, a change in the policy index from the level in Yamanashi to that in Tokyo in April, could result in the loss of weekly earnings by JPY 3,857 on average, and by JPY 6,326 for those aged 31 to 45 years. These results suggest that the effect of COVID-19 on labor is highly heterogeneous, and, therefore, policies must take such heterogeneity into account.

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A1 Appendix: Telework and Essential-Job Indices

Telework Index

The telework index is calculated following Dingel and Neiman (2020) for each two-digit occupation of the Japan Standard Occupational Classification (JSOC). Dingel and Neiman classify the feasibility of working at home for all occupations using the O*NET database, created by the US Department of Labor.

They use two sets of surveys from O*NET. One is called the Work Context Questionnaire, which asks questions aiming to capture the physical and social factors that influence the nature of work such as interpersonal relationships, physical work conditions, and structural job characteristics. The second is called the Generalized Work Activities Questionnaire, which includes questions aiming to capture the general types of job behaviors occurring on multiple jobs such as the input of information, interaction with others, mental processes, and work output. With these surveys, they determine whether occupational tasks can be performed at home, by considering, for example, frequency in the usage of emails, requirement for physical activities, etc.

We map Dingel and Neiman's measure defined in the O*NET Standard Occupational Classification (O*NET-SOC) to the JSOC in the following steps. First, we map O*NET-SOC to the Standard Occupational Classification (SOC). Then, we map the SOC to the International Standard Classification of Occupation (ISCO). Finally, we map the ISCO to JSOC. Following which, we aggregate a three-digit level occupational classifications in the JSOC to a two-digit level, as occupations are only available at two-digit level in the LFS.

Essential-Job Index

The essential-job index is constructed similarly to Blau et al. (2021) for each occupation-industry category. First, we select industries and occupations listed as "business required for continuing" in the basic guideline for COVID-19 issued by the COVID-19 task force in the Cabinet of Japan on March 28, 2020.[23]

Second, we further restrict the industries and occupations category that seem to face an increase in demand, such as food processing, medical, and logistics industries and occupations. The industries categorized as "essential" are: agriculture, fisheries, aquaculture, food manufacturing, road freight transportation, service incidental to transport, postal activities, wholesale trade, retail trade (general merchandise), retail trade (food and beverage), food take out and delivery services, medical and other health services, public health and hygiene, and social insurance and social welfare. The occupations that are categorized as "essential" include: health care workers, social welfare profession, transport and postal clerical workers, product sales workers, nursing-care service workers, health-care service workers, farmers, fishery workers, truck drivers, and carrying related workers.

Finally, $essential_i$ is defined as one if individual i belongs to both essential industries and occupations in the previous year and otherwise zero.

[23] https://www.mhlw.go.jp/content/10900000/000634753.pdf.

A2 Appendix: Variables constructed using LFS

Definitions

Work hours:
Work hours are constructed using work hours from the last seven days of a month reported in the LFS basic survey.

Absence from work:
A dummy variable on absence from work is one if an individual reports their working status as "absent from work" in the final week of a month in the LFS basic survey, and zero otherwise.

Unemployed:
A dummy variable on being unemployed is one if an individual reports their working status as "looking for a job" in the final week of a month in the LFS basic survey, and zero otherwise.

Unemployed due to employer's reason:
A dummy variable on being unemployed due to employer's reason is one if an individual reports both their working status as "looking for a job" and the reason for seeking a job as "separating from the last job due to employer's reason" in the LFS basic survey, zero otherwise.

Labor force status:
The labor force status for an individual is defined as *regular* if their title in the job is "regular officer/employee"; as *non-regular* if their title in the job is "part-time," "*arubaito* (temporary worker)," "dispatched worker from temporary labor agency," "contract employee," "entrusted employee," or "other employee"; as *other* if their title in the job is "executives", "self-employed with employees," "self-employed without employees," "family workers," or "working on the side".

Education:
The education level for an individual is defined as *low* if their final education is elementary, middle, or high school, two-year or technical college, or not-in-any-school, reported in the LFS supplementary survey; and *high* if their final education is university or post-graduate level.

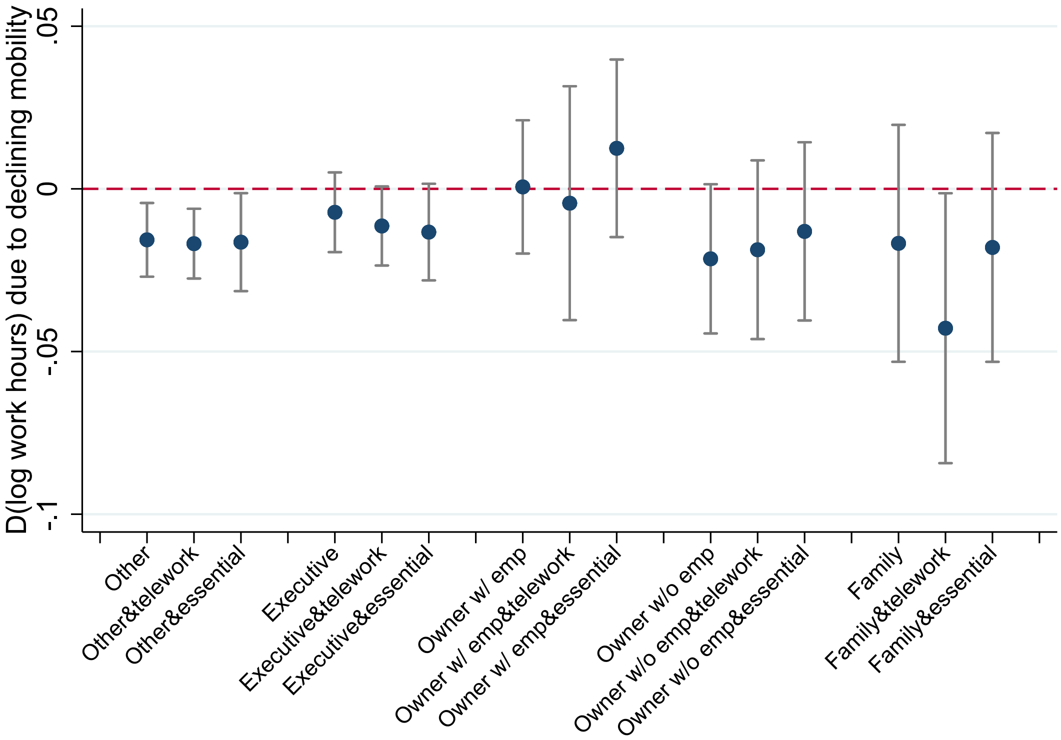
A3 Appendix: Additional Tables and Figures

Table A1: Effect of a policy-driven mobility decline on work hours

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
VARIABLES						**log(work hours)**						
mobility	0.0076***	0.0045***	0.0077**	0.0157***	0.0078***	0.0067***	0.0060***	0.0098***	0.0049	0.0120***	0.0050**	0.0050
	(0.0018)	(0.0015)	(0.0035)	(0.0058)	(0.0020)	(0.0022)	(0.0016)	(0.0029)	(0.0046)	(0.0033)	(0.0021)	(0.0035)
telework$_{t-12}$	-0.0259*	-0.0119	-0.0695***	0.0183	-0.0305**	0.0021	-0.0360**	-0.0148	-0.0088	-0.0238	-0.0284*	-0.0421
	(0.0136)	(0.0118)	(0.0210)	(0.0495)	(0.0147)	(0.0216)	(0.0160)	(0.0239)	(0.0389)	(0.0242)	(0.0160)	(0.0396)
essential$_{t-12}$	0.0202	-0.0076	0.0273	0.1918**	0.0063	0.0669*	-0.0208	0.0404	0.0097	0.0213	0.0384	-0.0137
	(0.0196)	(0.0192)	(0.0385)	(0.0776)	(0.0243)	(0.0351)	(0.0194)	(0.0271)	(0.0508)	(0.0325)	(0.0274)	(0.0475)
telework$_{t-12}$#essential$_{t-12}$	-0.0416	-0.0446	-0.0024	-0.3688***	-0.0304	-0.0711	0.0060	-0.0532	0.0467	-0.0325	-0.0345	-0.0965
	(0.0325)	(0.0286)	(0.0630)	(0.1421)	(0.0441)	(0.0648)	(0.0391)	(0.0473)	(0.0840)	(0.0596)	(0.0606)	(0.0761)
mobility#telework$_{t-12}$	-0.0008	-0.0002	-0.0035**	0.0012	-0.0011	0.0006	-0.0011	-0.0007	0.0025	0.0006	-0.0020***	-0.0011
	(0.0006)	(0.0007)	(0.0015)	(0.0021)	(0.0007)	(0.0011)	(0.0009)	(0.0015)	(0.0030)	(0.0010)	(0.0007)	(0.0019)
mobility#essential$_{t-12}$	0.0016*	0.0005	0.0025	0.0007	0.0013	0.0028	0.0003	0.0023*	0.0029	0.0014	0.0039***	-0.0017
	(0.0009)	(0.0010)	(0.0018)	(0.0040)	(0.0012)	(0.0019)	(0.0010)	(0.0013)	(0.0021)	(0.0015)	(0.0012)	(0.0026)
Observations	47,067	24,871	13,748	8,439	33,619	13,448	27,235	19,832	4,022	13,583	17,785	11,677
R-squared	0.036	0.066	0.060	0.069	0.038	0.068	0.045	0.049	0.153	0.080	0.051	0.059
Sub_sample	all	regular	non-reg	other	low-educ	high-educ	male	female	-30	31-45	46-60	61-
Month-sector FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age category FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No	No	No
Low educ FE	Yes	Yes	Yes	Yes	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Gender FE	Yes	Yes	Yes	Yes	Yes	Yes	No	No	Yes	Yes	Yes	Yes
Prefecture FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SW F-stat: mob	619.24	708.53	577.03	572.22	503.36	728.79	588.80	673.30	737.23	684.24	572.78	506.39
SW F-stat: mob#tele	941.77	1021.38	680.55	337.67	437.89	961.69	993.59	878.62	1082.11	1004.23	756.88	810.18
SW F-stat: mob#ess	548.73	499.61	274.14	1196.57	461.03	526.88	1079.5	470.58	346.14	455.68	825.12	1189.17

Note: The table reports the 2SLS estimation of equation (3) on a year-over-year difference in log work hours. The dependent variable is a year-over-year difference in log work hours for individual i in month t. The main explanatory variables are a prefecture-level mobility measure where individual i resides, the telework index in the occupation that individual i engaged 12 months ago, a dummy variable for individual i engaging in essential jobs 12 months ago, and their interactions. The regressions also include a set of fixed effects, such as month-lag sector, age category, gender, low-educated, and prefecture. The bottom three rows report Sanderson and Windmeijer's (2016) conditional first-stage F-statistics for the validity of instruments. Each column shows a result for a different subgroup: full sample, people worked as a regular worker 12 months ago, those worked as a non-regular worker 12 months ago, those worked in other working statuses (i.e., executives, owners, and family workers), low-educated people, high-educated people, males, females, people aged 30 and younger, those aged 31 to 45 years, those aged 46 to 60 years, and those aged 61 and above from columns 1 to 12. Clustered robust standard errors at the prefecture level are in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Figure A1. Effect on log work hours for different working status in the last period



Note: The figure plots the estimated coefficients on the effect of a policy-driven mobility decline on log work hours for the subgroup of ”Other” working status in the last period. The first three points in the figure are obtained from a regression with all people in the ”Other” status in the last period. The second three points corresponds to the result from those in ”executive” status in the last period. The third, fourth, and fifth groups of points correspond to the results from those in ”owner with employees”, those in ”owner without employees”, and ”family workers”, respectively. The left within a group of three points corresponds to the coefficient on the mobility term in the regression. The middle point is from the coefficient on the mobility term, plus that on the interaction of mobility and the Dingel-Neiman telework index. The right point corresponds to the coefficient on the mobility term, plus that on the interaction of mobility and essential jobs. Sampling weights provided by the Statistics Bureau of the MIC are used for deriving the results.

Table A2: Effect on work hours: people for aged 31-45 and 46-60

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES				Δ **log(work hours)**				
mobility	0.0083**	0.0181***	0.0019	0.0070	0.0028	0.0075*	0.0121**	0.0075
	(0.0042)	(0.0052)	(0.0104)	(0.0079)	(0.0023)	(0.0044)	(0.0059)	(0.0059)
telework$_{t-12}$	-0.0282	-0.0286	-0.0006	0.0250	-0.0325	-0.0034	-0.0183	0.0169
	(0.0230)	(0.0426)	(0.0208)	(0.0395)	(0.0198)	(0.0383)	(0.0171)	(0.0365)
essential$_{t-12}$	0.0066	0.0174	0.0378	0.0523	-0.0048	0.0639	0.0116	0.1096***
	(0.0433)	(0.0471)	(0.0392)	(0.0372)	(0.0301)	(0.0423)	(0.0244)	(0.0396)
log(work hours$_{t-12}$)			-0.5549***	-0.2922***			-0.5239***	-0.2535***
			(0.0426)	(0.0282)			(0.0337)	(0.0211)
telework$_{t-12}$#essential$_{t-12}$	-0.0320	0.0020	-0.0905	-0.0566	-0.0171	-0.0511	0.0017	-0.0995
	(0.0814)	(0.0715)	(0.0603)	(0.0649)	(0.0507)	(0.0831)	(0.0475)	(0.0754)
mobility#telework$_{t-12}$	0.0007	-0.0005	0.0018*	0.0002	-0.0025**	-0.0010	-0.0034***	-0.0017
	(0.0011)	(0.0029)	(0.0011)	(0.0027)	(0.0010)	(0.0020)	(0.0012)	(0.0020)
mobility#essential$_{t-12}$	0.0008	0.0007	-0.0006	0.0012	0.0010	0.0056***	-0.0002	0.0060***
	(0.0021)	(0.0029)	(0.0016)	(0.0028)	(0.0018)	(0.0019)	(0.0015)	(0.0021)
mobility#log(work hours$_{t-12}$)			0.0010	0.0017			-0.0020	-0.0003
			(0.0030)	(0.0016)			(0.0016)	(0.0013)
Observations	8,021	5,562	8,021	5,562	9,823	7,962	9,823	7,962
R-squared	0.125	0.115	0.310	0.224	0.077	0.082	0.259	0.170
Sub_sample	31-45&male	31-45&female	31-45&male	31-45&female	46-60&male	46-60&female	46-60&male	46-60&female
Month-sector FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Low educ FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Prefecture FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SW-F mob	671.63	721.76	406.44	446.33	568.58	635.24	419.51	455.92
SW-F mob#tele	1051	830.61	553.04	547.32	782.6	718.54	494.44	500.79
SW-F mob#ess	802.86	504.23	498	279.12	1149.78	524.95	552.61	299.37
SW-F mob#hur			244.61	516.8			477.84	501.43

Note: The table reports the 2SLS estimation of equation (3) on a year-over-year difference in log work hours. The dependent variable is a year-over-year difference in log work hours for individual i in month t. The main explanatory variables are a prefecture-level mobility measure where individual i resides, the telework index in the occupation that individual i engaged 12 months ago, a dummy variable for individual i engaging in essential jobs 12 months ago, and their interactions. Columns 3, 4, 7, and 8 additional includes log work hours for individual i 12 months ago. The regressions also include a set of fixed effects, such as month-lag sector, low-educated, and prefecture. The bottom three rows report Sanderson and Windmeijer's (2016) conditional first-stage F-statistics for the validity of instruments. Each column shows a result for a different subgroup: male aged 31 to 45 years (columns 1 and 3), female aged 31 to 45 years (columns 2 and 4), male aged 46 to 60 years (columns 5 and 7), and female aged 46 to 60 years (columns 6 and 8). Clustered robust standard errors at the prefecture level are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A3: Effect of a policy-driven mobility decline on unemployment

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
							Δ unemployed					
mobility	-0.0005*	-0.0005	-0.0008	-0.0003	-0.0005	-0.0005	-0.0008**	-0.0001	0.0015	-0.0008	-0.0000	-0.0015**
	(0.0003)	(0.0004)	(0.0007)	(0.0004)	(0.0005)	(0.0004)	(0.0004)	(0.0006)	(0.0017)	(0.0006)	(0.0005)	(0.0006)
telework$_{t-12}$	0.0019	0.0046	0.0011	0.0009	0.0013	0.0022	0.0017	0.0012	0.0156	-0.0023	-0.0003	-0.0002
	(0.0032)	(0.0032)	(0.0087)	(0.0034)	(0.0037)	(0.0041)	(0.0043)	(0.0040)	(0.0145)	(0.0054)	(0.0050)	(0.0054)
essential$_{t-12}$	0.0015	0.0024	-0.0018	0.0061	-0.0007	0.0109	-0.0015	0.0003	0.0167	0.0079	-0.0002	-0.0160
	(0.0042)	(0.0062)	(0.0081)	(0.0055)	(0.0049)	(0.0104)	(0.0087)	(0.0054)	(0.0225)	(0.0056)	(0.0069)	(0.0122)
telework$_{t-12}$#essential$_{t-12}$	-0.0022	-0.0146	0.0018	0.0246	-0.0045	-0.0051	0.0265*	-0.0140	-0.0821**	0.0060	-0.0238	0.0675**
	(0.0102)	(0.0118)	(0.0144)	(0.0277)	(0.0123)	(0.0184)	(0.0158)	(0.0128)	(0.0349)	(0.0102)	(0.0168)	(0.0273)
mobility#telewrok$_{t-12}$	0.0001	0.0002	-0.0000	-0.0001	-0.0002	0.0004*	0.0003	-0.0003	-0.0002	-0.0000	-0.0001	0.0003
	(0.0002)	(0.0003)	(0.0004)	(0.0001)	(0.0003)	(0.0002)	(0.0002)	(0.0004)	(0.0007)	(0.0004)	(0.0004)	(0.0005)
mobility#essential$_{t-12}$	0.0002	0.0002	0.0001	0.0003	0.0000	0.0007**	0.0007***	-0.0003	0.0010	0.0003	-0.0005	0.0007***
	(0.0001)	(0.0002)	(0.0003)	(0.0003)	(0.0002)	(0.0003)	(0.0002)	(0.0003)	(0.0009)	(0.0003)	(0.0003)	(0.0003)
Observations	52,692	26,609	16,419	9,648	37,843	14,849	29,573	23,119	4,556	14,947	19,071	14,118
R-squared	0.014	0.025	0.042	0.098	0.020	0.040	0.025	0.035	0.110	0.045	0.031	0.062
Sub_sample	all	regular	non-reg	other	low-educ	high-educ	male	female	-30	31-45	46-60	61-
Month-sector FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age category FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No	No	No
Gender FE	Yes	Yes	Yes	Yes	Yes	Yes	No	No	Yes	Yes	Yes	Yes
Low educ FE	Yes	Yes	Yes	Yes	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Prefecture FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SW F-stat: mob	619.24	708.53	577.03	572.22	503.36	728.79	588.80	673.30	737.23	684.24	572.78	506.39
SW F-stat: mob#tele	941.77	1021.38	680.55	337.67	437.89	961.69	993.59	878.62	1082.11	1004.23	756.88	810.18
SW F-stat: mob#ess	548.73	499.61	274.14	1196.57	461.03	526.88	1079.5	470.58	346.14	455.68	825.12	1189.17

Note: The table reports the 2SLS estimation of equation (3) on a year-over-year difference in unemployed status. The dependent variable is a year-over-year difference in a dummy variable of individual i being unemployed in month t. The main explanatory variables are a prefecture-level mobility measure where individual i resides, the telework index in the occupation that individual i engaged 12 months ago, a dummy variable for individual i engaging in essential jobs 12 months ago, and their interactions. The regressions also include a set of fixed effects, such as month-lag sector, age category, gender, low-educated, and prefecture. The bottom three rows report Sanderson and Windmeijer's (2016) conditional first-stage F-statistics for the validity of instruments. Each column shows a result for a different subgroup: full sample, people worked as a regular worker 12 months ago, those worked as a non-regular worker 12 months ago, those worked in other working statuses (i.e., executives, owners, and family workers), low-educated people, high-educated people, males, females, people aged 30 and younger, those aged 31 to 45 years, those aged 46 to 60 years, and those aged 61 and above from columns 1 to 12. Clustered robust standard errors at the prefecture level are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A4: Effect on unemployment for aged 55 to 70

VARIABLES	(1) diff_unemp	(2) diff_unemp	(3) diff_unemp
mobility	-0.0003	-0.0008	-0.0001
	(0.0006)	(0.0013)	(0.0015)
Age56#mobility	-0.0005	-0.0011*	0.0000
	(0.0005)	(0.0007)	(0.0009)
Age57#mobility	-0.0004	-0.0006	-0.0002
	(0.0005)	(0.0006)	(0.0009)
Age58#mobility	-0.0002	-0.0008	0.0006
	(0.0004)	(0.0006)	(0.0014)
Age59#mobility	-0.0003	-0.0008*	0.0003
	(0.0004)	(0.0005)	(0.0010)
Age60#mobility	-0.0016***	-0.0020*	-0.0021
	(0.0006)	(0.0011)	(0.0018)
Age61#mobility	-0.0007	-0.0018	0.0001
	(0.0005)	(0.0013)	(0.0010)
Age62#mobility	-0.0006	-0.0018	0.0003
	(0.0005)	(0.0012)	(0.0012)
Age63#mobility	-0.0002	-0.0005	-0.0000
	(0.0003)	(0.0004)	(0.0009)
Age64#mobility	-0.0003	-0.0010*	0.0004
	(0.0004)	(0.0006)	(0.0008)
Age65#mobility	-0.0021**	-0.0034	-0.0017
	(0.0008)	(0.0026)	(0.0014)
Age66#mobility	-0.0011	-0.0045*	0.0003
	(0.0007)	(0.0023)	(0.0010)
Age67#mobility	-0.0004	0.0002	-0.0002
	(0.0006)	(0.0013)	(0.0010)
Age68#mobility	-0.0004	0.0002	-0.0004
	(0.0003)	(0.0004)	(0.0011)
Age69#mobility	-0.0003	0.0011	-0.0000
	(0.0004)	(0.0016)	(0.0009)
Age70#mobility	-0.0001	-0.0008	0.0006
	(0.0005)	(0.0005)	(0.0013)
Observations	16,860	6,070	6,625
R-squared	0.049	0.128	0.121
Sub_sample	55-70	55-70&regular	55-70&non-reg
Month-sector FE	Yes	Yes	Yes
Age FE	No	No	No
Gender FE	Yes	Yes	Yes
Low educ FE Yes	Yes	Yes	
Prefecture FE	Yes	Yes	Yes
SW-F mob	496.25	749.75	409.73
SW-F mob#tele	778.81	1018.67	565.4
SW-F mob#ess	708.34	574.77	589.55

Note: The table reports the 2SLS estimation of equation (3) on a year-over-year difference in unemployed status, especially for people aged 55 and above. The dependent variable is a year-over-year difference in a dummy variable of individual *i* being unemployed in month *t*. The main explanatory variables are a prefecture-level mobility measure where individual *i* resides and its interaction with age dummies from 56 to 70 years-old respectively. The telework index in the occupation that individual *i* engaged 12 months ago, a dummy variable for individual *i* engaging in essential jobs 12 months ago, and their interactions with the mobility measure are also included. The regressions also include a set of fixed effects, such as month-lag sector, age, gender, low-educated, and prefecture. The bottom three rows report Sanderson and Windmeijer's (2016) conditional first-stage F-statistics for the validity of instruments. Each column shows a result for a different subgroup: all people aged 55 to 70 years, people in the age range that engaged in regular work 12 months ago, and those in the age range that engaged in non-regular work 12 months ago, from columns 1 to 3. Clustered robust standard errors at the prefecture level are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A5: Effect of a policy-driven mobility decline on unemployment for each age category and gender

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES				Δ **unemployed**				
mobility	0.0028**	0.0014	-0.0002	-0.0014*	-0.0001	-0.0001	-0.0027**	0.0001
	(0.0014)	(0.0025)	(0.0007)	(0.0008)	(0.0005)	(0.0010)	(0.0011)	(0.0005)
telework$_{t-12}$	0.0184	-0.0143	-0.0030	-0.0000	-0.0015	-0.0009	-0.0003	-0.0015
	(0.0243)	(0.0235)	(0.0068)	(0.0089)	(0.0070)	(0.0084)	(0.0074)	(0.0051)
essential$_{t-12}$	-0.0056	0.0064	0.0148	0.0086	0.0118	-0.0069	-0.0452	-0.0076
	(0.0237)	(0.0286)	(0.0115)	(0.0061)	(0.0094)	(0.0084)	(0.0283)	(0.0118)
telework$_{t-12}$#essential$_{t-12}$	-0.1032**	-0.0284	0.0079	-0.0036	-0.0112	-0.0258	0.1535**	0.0236
	(0.0431)	(0.0400)	(0.0141)	(0.0121)	(0.0176)	(0.0247)	(0.0613)	(0.0163)
mobility#telework$_{t-12}$	-0.0011	-0.0008	0.0001	-0.0004	-0.0000	-0.0005	0.0006	-0.0003
	(0.0009)	(0.0012)	(0.0004)	(0.0005)	(0.0003)	(0.0011)	(0.0007)	(0.0003)
mobility#essential$_{t-12}$	-0.0000	0.0002	0.0005	0.0001	0.0004	-0.0010*	0.0010**	0.0000
	(0.0010)	(0.0010)	(0.0006)	(0.0002)	(0.0003)	(0.0005)	(0.0005)	(0.0004)
Observations	2,388	2,168	8,325	6,622	10,269	8,802	8,591	5,527
R-squared	0.221	0.183	0.076	0.081	0.049	0.078	0.087	0.081
Sub_sample	-30&male	-30&female	31-45&male	31-45&female	46-60&male	46-60&female	61-&male	61-&female
Month-sector FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Low educ FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Prefecture FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SW F-stat: mob	679.84	780.75	671.63	721.76	568.58	635.24	481.92	597.39
SW F-stat: mob#tele	1132.74	989.74	1051	830.61	782.6	718.54	932.61	709.85
SW F-stat: mob#ess	202.97	508.34	802.86	504.23	1149.78	524.95	1429.85	519.11

Note: The table reports the 2SLS estimation of equation (3) on a year-over-year difference in unemployed status for each gender and age category. The dependent variable is a year-over-year difference in a dummy variable of individual i being unemployed in month t. The main explanatory variables are a prefecture-level mobility measure where individual i resides and its interaction. The telework index in the occupation that individual i engaged 12 months ago, a dummy variable for individual i engaging in essential jobs 12 months ago, and their interactions with the mobility measure are also included. The regressions also include a set of fixed effects, such as month-lag sector, low-educated, and prefecture. The bottom three rows report Sanderson and Windmeijer's (2016) conditional first-stage F-statistics for the validity of instruments. Each column shows a result for a different subgroup: males aged 30 and younger, females aged 30 or younger, males aged from 31 to 45, females aged 31 to 45 years, males aged 46 to 60 years, females aged 46 to 60 years, males aged 61 and above, and females aged 61 and above. Clustered robust standard errors at the prefecture level are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A6: Effect of a policy-driven mobility decline on absence from work (leave) in service and sales occupations

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
VARIABLES						Δ **absence from work**						
mobility	-0.0122***	-0.0077**	-0.0154***	-0.0082	-0.0146***	-0.0055	-0.0062*	-0.0166***	-0.0049	-0.0192***	-0.0125***	-0.0042
	(0.0027)	(0.0033)	(0.0033)	(0.0068)	(0.0030)	(0.0036)	(0.0033)	(0.0033)	(0.0098)	(0.0043)	(0.0031)	(0.0042)
telework$_{t-12}$	0.0144	0.0387	0.0056	-0.0480	0.0132	-0.0414	-0.0110	0.0224	0.0093	0.0338	0.0769**	-0.0437
	(0.0277)	(0.0306)	(0.0470)	(0.0544)	(0.0266)	(0.0425)	(0.0367)	(0.0397)	(0.1166)	(0.0406)	(0.0355)	(0.0408)
essential$_{t-12}$	0.0069	0.0085	0.0225	-0.2261*	0.0245	-0.0357	0.0169	0.0234	-0.2244***	0.0108	0.0135	0.0648**
	(0.0164)	(0.0389)	(0.0247)	(0.1291)	(0.0186)	(0.0463)	(0.0211)	(0.0231)	(0.0818)	(0.0438)	(0.0285)	(0.0313)
telework$_{t-12}$#essential$_{t-12}$	0.0299	-0.0038	-0.0165	0.6130*	0.0332	-0.0063	-0.0114	-0.0549	0.4141***	0.0521	0.0016	0.0178
	(0.0420)	(0.0503)	(0.0640)	(0.3200)	(0.0566)	(0.0709)	(0.0389)	(0.1028)	(0.1461)	(0.0629)	(0.0581)	(0.0783)
mobility#telework$_{t-12}$	0.0033*	0.0024	0.0048	-0.0044	0.0026	-0.0010	-0.0016	0.0060*	0.0055	0.0069**	0.0074**	-0.0037
	(0.0019)	(0.0021)	(0.0035)	(0.0041)	(0.0022)	(0.0024)	(0.0024)	(0.0032)	(0.0062)	(0.0032)	(0.0030)	(0.0023)
mobility#essential$_{t-12}$	0.0019	0.0004	0.0035***	-0.0003	0.0035**	-0.0019	0.0005	0.0039**	-0.0089	0.0065**	0.0025	0.0030
	(0.0013)	(0.0028)	(0.0012)	(0.0038)	(0.0015)	(0.0033)	(0.0022)	(0.0016)	(0.0057)	(0.0029)	(0.0023)	(0.0020)
Observations	12,217	4,930	5,154	2,124	9,203	3,014	5,239	6,978	1,220	3,506	4,295	3,196
R-squared	0.084	0.106	0.127	0.133	0.096	0.138	0.116	0.104	0.194	0.149	0.129	0.124
Sub_sample	all	regular	non-reg	other	low-educ	high-educ	male	female	-30	31-45	46-60	61-
Month-sector FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age category FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No	No	No
Gender FE	Yes	Yes	Yes	Yes	Yes	Yes	No	No	Yes	Yes	Yes	Yes
Low educ FE	Yes	Yes	Yes	Yes	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Prefecture FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SW F-stat: mob	78.97	99.47	98.98	69.38	94.29	137.09	109.59	76.96	113.64	77.99	106.72	70.32
SW F-stat: mob#tele	182.16	279.83	152.33	456.05	131.31	365.51	189.71	145.7	208.53	136.08	151.81	358.23
SW F-stat: mob#ess	234.86	296.8	225.04	446.08	202.05	233.03	327.66	203.44	278.09	369.84	197.74	200.71

Note: The table reports the 2SLS estimation of equation (3) on a year-over-year difference in an absence-from-work status, for the subsample of people engaged in service and sales 12 months ago. The dependent variable is a year-over-year difference in a dummy variable of individual i being absent from work in month t. The main explanatory variables are a prefecture-level mobility measure where individual i resides, the telework index in the occupation that individual i engaged 12 months ago, a dummy variable for individual i engaging in essential jobs 12 months ago, and their interactions. The regressions also include a set of fixed effects, such as month-lag sector, age category, gender, low-educated, and prefecture. The bottom three rows report Sanderson and Windmeijer's (2016) conditional first-stage F-statistics for the validity of instruments. Each column shows a result for a different subgroup: full sample, people worked as a regular worker 12 months ago, those worked as a non-regular worker 12 months ago, those worked in other working statuses (i.e., executives, owners, and family workers), low-educated people, high-educated people, males, females, people aged 30 and younger, those aged 31 to 45 years, those aged 46 to 60 years, and those aged 61 and above from columns 1 to 12. Clustered robust standard errors at the prefecture level are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A7: Effect of a policy-driven mobility decline on work hours in service and sales occupations

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
VARIABLES						**Δ log (work hours)**						
mobility	0.0127***	0.0160***	0.0165**	0.0034	0.0120***	0.0123*	0.0056	0.0196***	0.0118	0.0266***	0.0118**	-0.0027
	(0.0045)	(0.0049)	(0.0070)	(0.0093)	(0.0045)	(0.0068)	(0.0073)	(0.0048)	(0.0281)	(0.0082)	(0.0058)	(0.0094)
telework_{t-12}	-0.0389	-0.0676	-0.1009	0.0659	-0.0853*	0.0206	0.0087	-0.0554	-0.3269*	-0.1009	-0.0149	0.0605
	(0.0391)	(0.0633)	(0.0909)	(0.1280)	(0.0449)	(0.0675)	(0.0755)	(0.0628)	(0.1710)	(0.0759)	(0.0528)	(0.1181)
essential_{t-12}	-0.0121	-0.0599	-0.0036	0.0128	-0.0275	0.1142	0.0403	-0.0346	-0.0381	-0.0913	0.0539	-0.0799
	(0.0357)	(0.0535)	(0.0754)	(0.2195)	(0.0309)	(0.1221)	(0.0679)	(0.0474)	(0.1899)	(0.0584)	(0.0570)	(0.0624)
$\text{telework}_{t-12}\#\text{essential}_{t-12}$	-0.0302	-0.1441	0.0317	-0.0650	0.0228	-0.3476	-0.1794	0.0040	0.1806	0.0041	-0.0017	-0.1292
	(0.0761)	(0.1273)	(0.1285)	(0.3096)	(0.0985)	(0.2332)	(0.1767)	(0.1283)	(0.3233)	(0.1822)	(0.1340)	(0.1507)
$\text{mobility}\#\text{telework}_{t-12}$	-0.0022	-0.0077*	-0.0076	0.0113	-0.0057*	0.0029	0.0016	-0.0046	-0.0090	-0.0065	-0.0044	0.0094
	(0.0024)	(0.0040)	(0.0057)	(0.0086)	(0.0031)	(0.0038)	(0.0044)	(0.0030)	(0.0148)	(0.0055)	(0.0030)	(0.0075)
$\text{mobility}\#\text{essential}_{t-12}$	-0.0014	-0.0089***	0.0005	-0.0015	-0.0008	-0.0039	-0.0046	-0.0025	-0.0079	-0.0054*	0.0018	-0.0043
	(0.0016)	(0.0027)	(0.0039)	(0.0118)	(0.0018)	(0.0044)	(0.0036)	(0.0023)	(0.0115)	(0.0030)	(0.0024)	(0.0047)
Observations	10,698	4,543	4,289	1,862	7,996	2,702	4,829	5,869	1,025	3,099	3,909	2,665
R-squared	0.074	0.186	0.100	0.113	0.075	0.179	0.102	0.088	0.261	0.160	0.101	0.117
Sub_sample	all	regular	non-reg	other	low-educ	high-educ	male	female	-30	31-45	46-60	61-
Month-sector FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age category FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No	No	No
Gender FE	Yes	Yes	Yes	Yes	Yes	Yes	No	No	Yes	Yes	Yes	Yes
Low educ FE	Yes	Yes	Yes	Yes	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Prefecture FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SW F-stat: mob	78.97	99.47	98.98	69.38	94.29	137.09	109.59	76.96	113.64	77.99	106.72	70.32
SW F-stat: mob#tele	182.16	279.83	152.33	456.05	131.31	365.51	189.71	145.7	208.53	136.08	151.81	358.23
SW F-stat: mob#ess	234.86	296.8	225.04	446.08	202.05	233.03	327.66	203.44	278.09	369.84	197.74	200.71

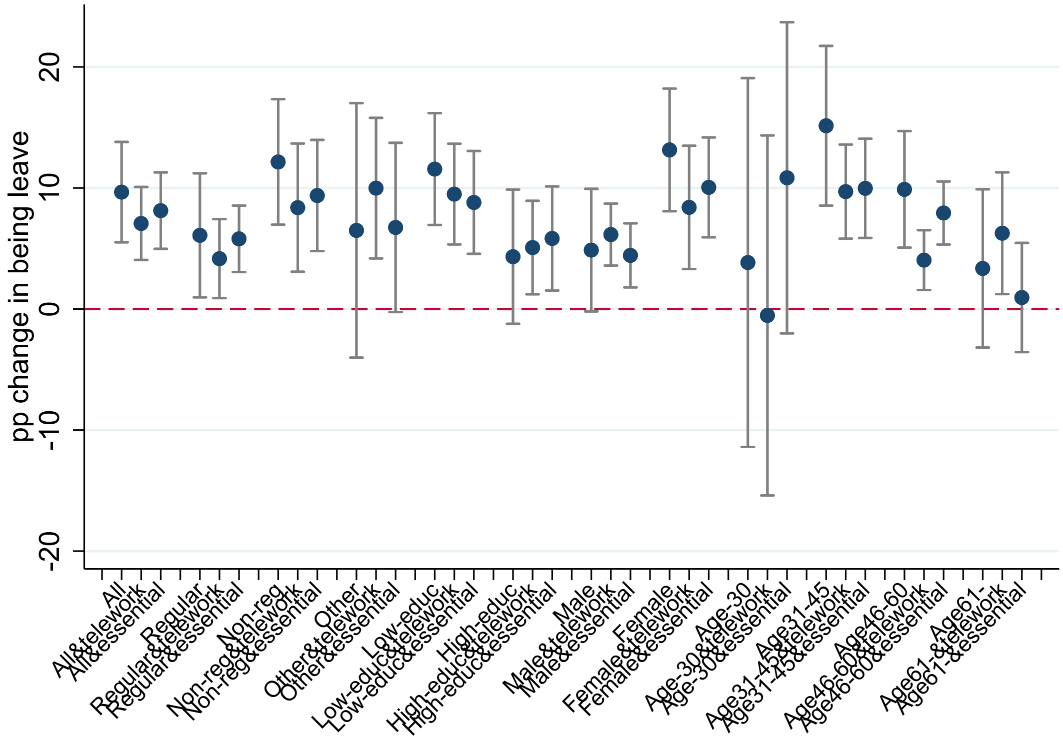
Note: The table reports the 2SLS estimation of equation (3) on a year-over-year difference in log work hours, for the subsample of people engaged in service and sales 12 months ago. The dependent variable is a year-over-year difference in log work hours for individual i in month t. The main explanatory variables are a prefecture-level mobility measure where individual i resides, the telework index in the occupation that individual i engaged 12 months ago, a dummy variable for individual i engaging in essential jobs 12 months ago, and their interactions. The regressions also include a set of fixed effects, such as month-lag sector, age category, gender, low-educated, and prefecture. The bottom three rows report Sanderson and Windmeijer's (2016) conditional first-stage F-statistics for the validity of instruments. Each column shows a result for a different subgroup: full sample, people worked as a regular worker 12 months ago, those worked as a non-regular worker 12 months ago, those worked in other working statuses (i.e., executives, owners, and family workers), low-educated people, high-educated people, males, females, people aged 30 and younger, those aged 31 to 45 years, those aged 46 to 60 years, and those aged 61 and above from columns 1 to 12. Clustered robust standard errors at the prefecture level are in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table A8: Effect of a policy-driven mobility decline on unemployment due to employer's reason in service and sales occupations

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
VARIABLES						**Δ Unemployed due to employer's reason**						
mobility	-0.0016***	-0.0022***	-0.0019**	0.0009**	-0.0019***	-0.0006	-0.0021**	-0.0010	-0.0044*	-0.0013*	-0.0024***	-0.0002
	(0.0005)	(0.0006)	(0.0008)	(0.0004)	(0.0006)	(0.0005)	(0.0010)	(0.0006)	(0.0025)	(0.0008)	(0.0009)	(0.0004)
telework_{t-12}	0.0098*	0.0177*	0.0036	-0.0142	0.0082	0.0063	0.0183	-0.0023	0.0084	0.0107	0.0163	-0.0011
	(0.0055)	(0.0093)	(0.0098)	(0.0099)	(0.0062)	(0.0046)	(0.0127)	(0.0035)	(0.0125)	(0.0098)	(0.0102)	(0.0045)
essential_{t-12}	0.0055	0.0087	0.0102**	-0.0106	0.0045	0.0099*	0.0062	0.0029	0.0168	0.0101	0.0090	-0.0015
	(0.0056)	(0.0073)	(0.0047)	(0.0315)	(0.0066)	(0.0057)	(0.0130)	(0.0030)	(0.0182)	(0.0074)	(0.0077)	(0.0097)
$\text{telework}_{t-12}\#\text{essential}_{t-12}$	0.0266	-0.0025	0.0002	0.0713	0.0346	-0.0021	0.0491	-0.0051	-0.0000	0.0019	-0.0035	0.0805
	(0.0197)	(0.0060)	(0.0096)	(0.0625)	(0.0263)	(0.0105)	(0.0299)	(0.0048)	(0.0264)	(0.0064)	(0.0079)	(0.0508)
$\text{mobility}\#\text{telework}_{t-12}$	0.0009**	0.0013**	0.0006	-0.0006	0.0009*	0.0007**	0.0015*	0.0002	0.0012	0.0011	0.0012	0.0002
	(0.0004)	(0.0006)	(0.0007)	(0.0005)	(0.0005)	(0.0003)	(0.0009)	(0.0002)	(0.0009)	(0.0007)	(0.0008)	(0.0003)
$\text{mobility}\#\text{essential}_{t-12}$	0.0005	0.0005	0.0008**	-0.0014	0.0006	0.0006*	0.0009	0.0001	0.0014*	0.0007	0.0006	0.0004
	(0.0005)	(0.0006)	(0.0004)	(0.0023)	(0.0006)	(0.0004)	(0.0010)	(0.0003)	(0.0008)	(0.0006)	(0.0008)	(0.0007)
Observations	12,217	4,930	5,154	2,124	9,203	3,014	5,239	6,978	1,220	3,506	4,295	3,196
R-squared	0.026	0.068	0.090	0.093	0.037	0.122	0.065	0.033	0.126	0.067	0.077	0.219
Sub_sample	all	regular	non-reg	other	low-educ	high-educ	male	female	-30	31-45	46-60	61-
Month-sector FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age category FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No	No	No
Gender FE	Yes	Yes	Yes	Yes	Yes	Yes	No	No	Yes	Yes	Yes	Yes
Low educ FE	Yes	Yes	Yes	Yes	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Prefecture FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SW F-stat mob	78.97	99.47	98.98	69.38	94.29	137.09	109.59	76.96	113.64	77.99	106.72	70.32
SW F-stat mob#tele	182.16	279.83	152.33	456.05	131.31	365.51	189.71	145.7	208.53	136.08	151.81	358.23
SW F-stat mob#ess	234.86	296.8	225.04	446.08	202.05	233.03	327.66	203.44	278.09	369.84	197.74	200.71

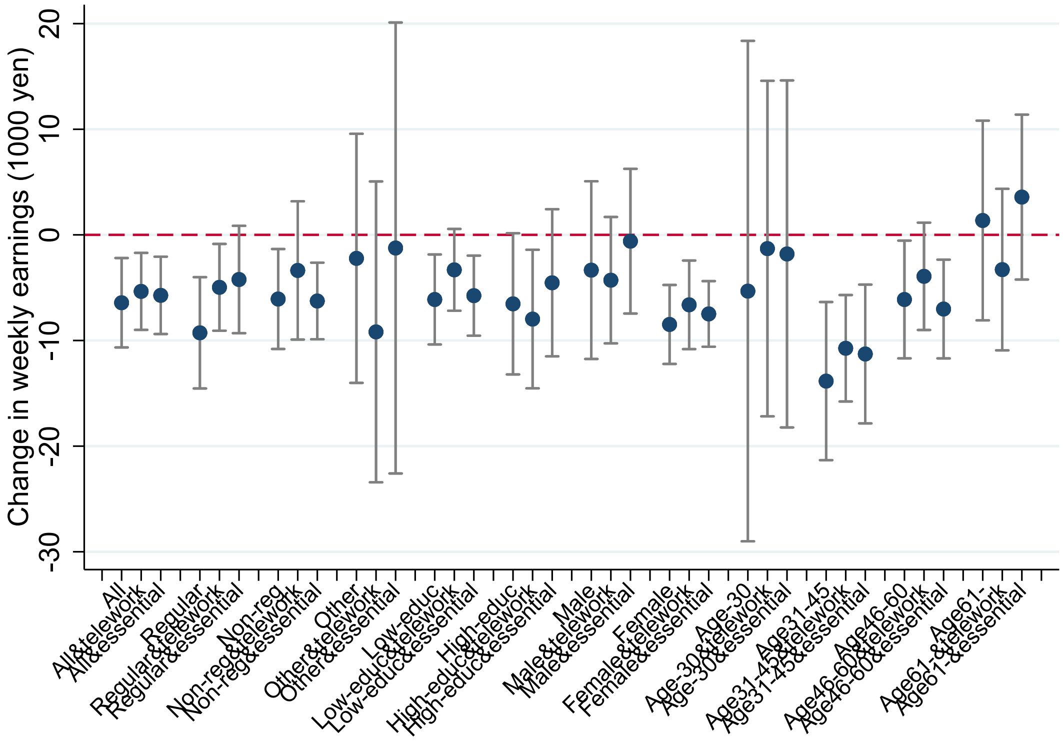
Note: The table reports the 2SLS estimation of equation (3) on a year-over-year difference in being unemployed due to employer's reason, for the subsample of people engaged in service and sales 12 months ago. The dependent variable is a year-over-year difference in a dummy variable of individual i being unemployed due to employer's reason in month t. The main explanatory variables are a prefecture-level mobility measure where individual i resides, the telework index in the occupation that individual i engaged 12 months ago, a dummy variable for individual i engaging in essential jobs 12 months ago, and their interactions. The regressions also include a set of fixed effects, such as month-lag sector, age category, gender, low-educated, and prefecture. The bottom three rows report Sanderson and Windmeijer's (2016) conditional first-stage F-statistics for the validity of instruments. Each column shows a result for a different subgroup: full sample, people worked as a regular worker 12 months ago, those worked as a non-regular worker 12 months ago, those worked in other working statuses (i.e., executives, owners, and family workers), low-educated people, high-educated people, males, females, people aged 30 and younger, those aged 31 to 45 years, those aged 46 to 60 years, and those aged 61 and above from columns 1 to 12. Clustered robust standard errors at the prefecture level are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Figure A2. Effect of stricter policy on absence from work (leave) in service and sales occupations



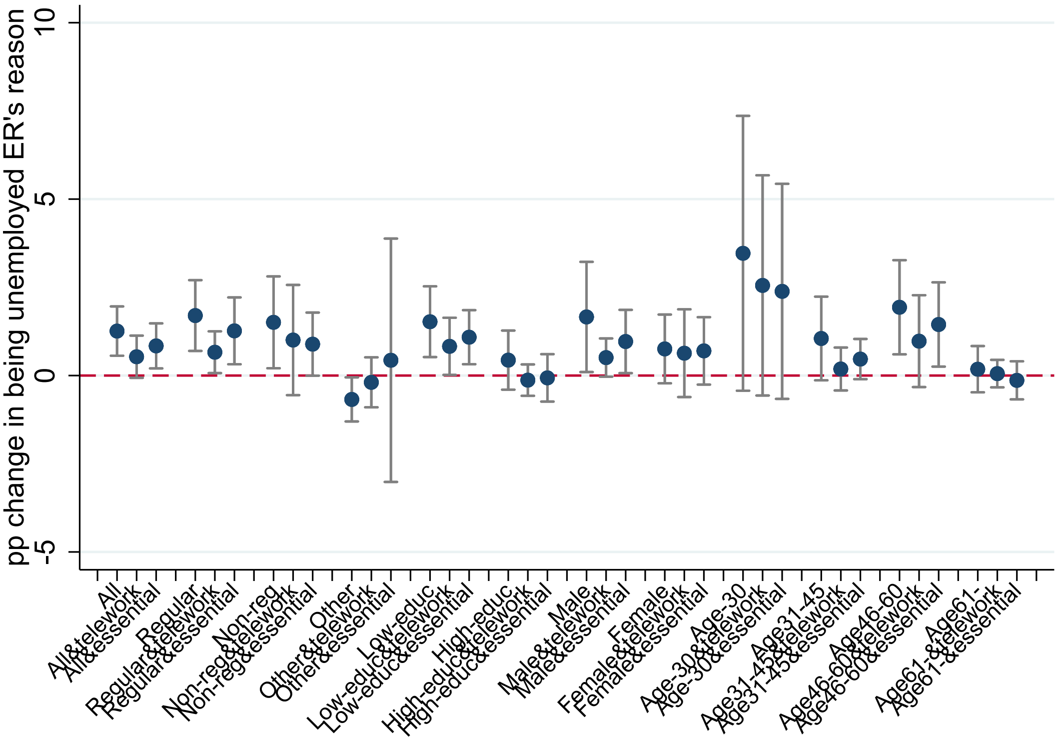
Note: The figure plots the effect of a counterfactual stricter policy and its effect through changing mobility on being absent from work for each subgroup, focusing on workers in service and sales occupations in the last period. The counterfactual policy change is a change in the policy index by 0.25, the same level as a difference in the index between Yamanashi and Tokyo in April. The counterfactual policy change then results in an additional decline in the mobility measure by 7.9, using the coefficient obtained in Figure 15. The confidence intervals are calculated from standard errors with the delta method, while ignoring standard errors in the imputed decline in the mobility measure. The format of the figure is the same as that in the result section.

Figure A3. Effect of stricter policy on work hours in service and sales occupations



Note: The figure plots the effect of a counterfactual stricter policy and its effect through changing mobility and work hours on weekly earnings for each subgroup, focusing on workers in service and sales occupations in the last period. The counterfactual policy change is a change in the policy index by 0.25, the same level as a difference in the index between Yamanashi and Tokyo in April. The counterfactual policy change then results in an additional decline in the mobility measure by 7.9, using the coefficient obtained in Figure 15. The imputed change in weekly work hours is simply multiplied by the average hourly wages (i.e., the average monthly total cash earnings, 276,551 yen, divided by the average hours worked, 143.4 hours in April 2019) calculated from Monthly Labour Survey by the Ministry of Health, Labour and Welfare (MHLW). The confidence intervals are calculated from standard errors with the delta method, while ignoring standard errors in the imputed decline in the mobility measure. The format of the figure is the same as that in the result section.

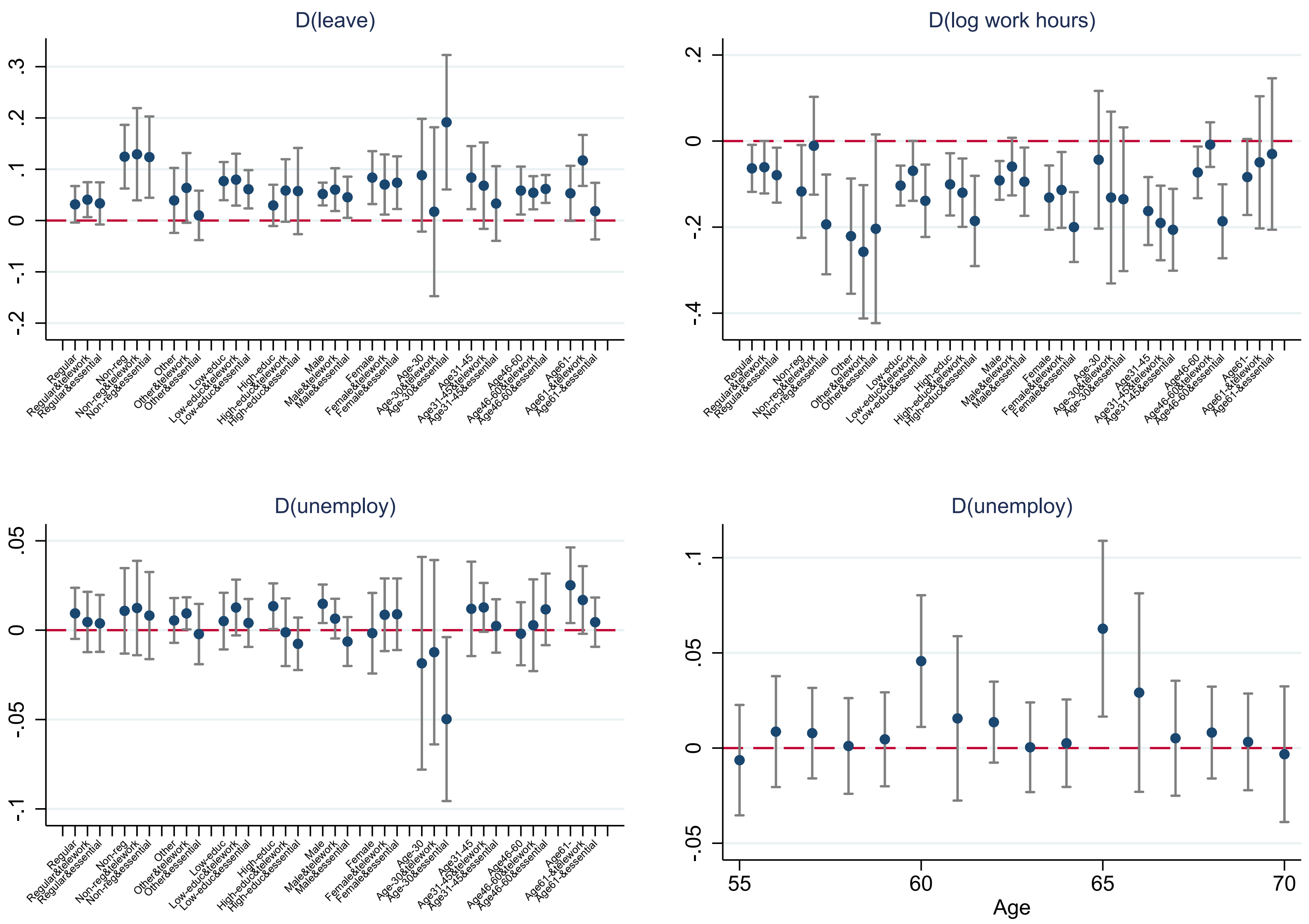
Figure A4. Effect of stricter policy on unemployment in service and sales occupations



Note: The figure plots the effect of a counterfactual stricter policy and its effect through changing mobility on being unemployed due to employer's reason for each subgroup, focusing on workers in service and sales occupations in the last period. The counterfactual policy change is a change in the policy index by 0.25, the same level as a difference in the index between Yamanashi and Tokyo in April. The counterfactual policy change then results in an additional decline in the mobility measure by 7.9, using the coefficient obtained in Figure 15. The confidence intervals are calculated from standard errors with the delta method, while ignoring standard errors in the imputed decline in the mobility measure. The format of the figure is the same as that in the result section.

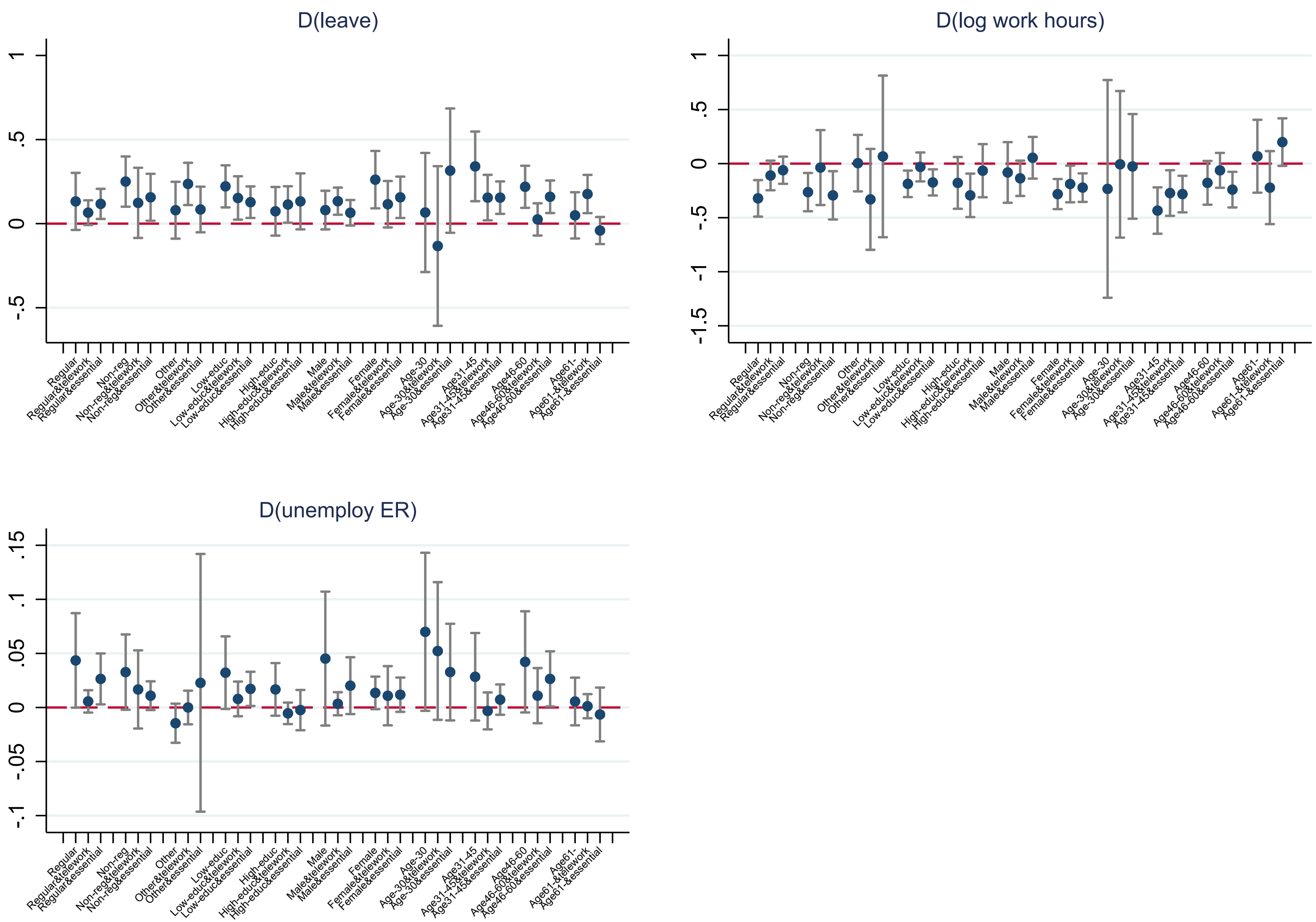
A4 Appendix: Results from reduced-form estimation

Figure A5. Effect of policy changes for each subgroup



Note: The figure plots the estimated coefficients on the effect of policy changes on being a leave of absence (top-left), on log work hours (top-right), on being unemployed (bottom-left) for each subgroup, and on being unemployed for people aged 55 to 70 years (bottom-right). Each panel is a reduced-form estimation of the 2SLS estimation in Figures 16, 17, 18, and 19, respectively. Sampling weights provided by the Statistics Bureau of the MIC are used for deriving the results.

Figure A6. Effect of policy changes for service ans sales occupation



Note: The figure plots the estimated coefficients on the effect of policy changes on being a leave of absence (top-left), on log work hours (top-right), and on being unemployed (bottom-left) for each subgroup, focusing on workers in service and sales occupations in the last period. Each panel is a reduced-form estimation of the 2SLS estimation in Figures 21, 22, and 23, respectively. Sampling weights provided by the Statistics Bureau of the MIC are used for deriving the results.