Since January 2020 Elsevier has created a COVID-19 resource centre with free information in English and Mandarin on the novel coronavirus COVID-19. The COVID-19 resource centre is hosted on Elsevier Connect, the company's public news and information website.

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Long-term care at home and female work during the COVID-19 pandemic

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ABSTRACT

This study analyzes the impacts of COVID-19 on two elements: long-term care at home, which is available for care recipients who live in their own home, and working status in Japan. A regression analysis of municipality data reveals that the number of users of adult daycare is negatively correlated to COVID-19, both nationally and regionally. This finding is intuitive because people avoid daycare due to the increased risk of exposure to infection. However, the number of users of home care is positively correlated to users of daycare, which implies that home care has not functioned as a replacement for daycare, despite government encouragement. Furthermore, a regression analysis using prefecture data shows that working hours for both females and males were negatively correlated to the national status of the pandemic, while the regional status of the pandemic was negatively correlated only to female working hours. This implies that female labor status is more vulnerable to such outbreaks in Japan. Also, we find consistent results with a situation in which informal care compensated for the decline in daycare use; and this care has been provided primarily by especially females who have reduced their working hours by COVID-19.

1. Introduction

It has been widely reported that the elderly, who are the main recipients of long-term care, are especially vulnerable to COVID-19 [1]. Thus, researchers have actively studied the impacts of the COVID-19 outbreak on nursing homes [2,3] and hospitals [4]. However, there has been limited research on the impacts of the pandemic on formal long-term care at home, which is available for care recipients who live in their own home.

To address this research gap, we analyze data from Japan, which established a mandatory social program for Long-term Care Insurance (LTCI) in 2000 [5-6]. The Japanese LTCI covers various formal care services at home, not only to support care recipients, but also their family members. Researchers have reported that the LTCI has had encouraging effects on the labor participation of female family members [7]. Therefore, we analyze not only the direct effects of COVID-19, but also the indirect effects of the pandemic, via long-term care use, on working status. We concentrate on home care and daycare, which occupy the largest shares among formal long-term care services at home.

Several studies have shown that people are avoiding or reducing adult daycare use due to the danger of exposure to COVID-19. Dawson et al. [8] reported that this reduction in daycare has led to an increase in home care in several countries, and Rodrigues et al. [9] showed that in Austria, daycare has been replaced by informal family care. However, while many studies have analyzed the impacts of COVID-19 on the working status of females caring for children [10-13], the impact on work for long-term caregivers has not been well studied.

2. Study data and methods

2.1. Study design

We employ empirical analyses using regional monthly panel data, where monthly observations are pooled. We conduct three analyses: Analysis 1 concerns the relationship between the pandemic and long-term care use. Analyses 2 and 3 examine the relationship between the pandemic, long-term care use, and working status. Analysis 2 adopts working status as our outcome variable, while Analysis 3 adopts long-term care use. Each analysis consists of two estimation methods: ordinary least squares (OLS) and instrumental variable (IV) estimation.

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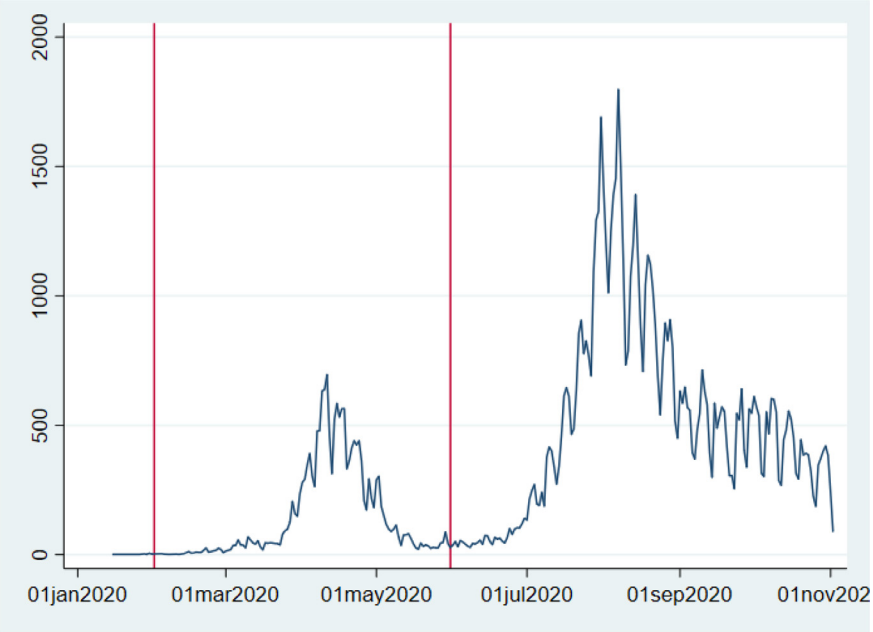

Fig. A1. Daily positive PCR tests.

In OLS estimation, for region i at time t,

$$y_{it} = w_{it}\alpha + \mathbf{x}_{it}'\boldsymbol{\beta} + \delta_t + \lambda_{it} + \epsilon_{it}, \tag{0.1}$$

where y_{it} is an outcome variable; w_{it} is our main explanatory variable, which measures the COVID-19 outbreak in region i at time t; and $\mathbf{x}_{it}$ is a vector of the other explanatory variables. δ_t is a coefficient for a month dummy for t, and λ_{it} is a coefficient for an additional month dummy for regions with a longer emergency policy. Finally, ϵ_{it} is the error term.

In IV estimation, for region i at time t,

$$y_{it} = w_{it}\alpha + r_{it}\gamma + \mathbf{x}_{it'}\boldsymbol{\beta} + \delta_t + \lambda_{it} + \epsilon_{it}, \tag{0.2}$$

where y_{it} is an outcome variable, r_{it} is an endogenous variable, and the remaining variables follow the definitions given for equation (1.1).

In Analysis 1, we use municipality-level data and estimate cluster standard errors on prefecture. In OLS estimation, we adopt two outcome variables, daycare and home care use. In IV estimation, the outcome and endogenous variables are home care use and daycare use, respectively. Because consumers may decide to use these services simultaneously, we need to control endogeneity.

Analyses 2 and 3 use prefecture-level data. In Analysis 2, our outcome variable is working status. In IV estimation, the endogenous variable is again daycare use, where working status and daycare use might be simultaneously chosen by individuals. In Analysis 3, our outcome variable is daycare use. In IV estimation, the endogenous variable is working status. Analyses 2 and 3 are separately employed in order to find a causal relationship, not just a correlation, between daycare use and working status.

2.2. Research period and data sources

Our data were collected between February 1, 2020 and May 31, 2020, considered the "first wave" of the COVID-19 pandemic in Japan. The first positive case appeared on January 15, 2020, and a rapid increase occurred in March and April. The outbreak then settled down at the end of May. Fig. A1 in the Appendix illustrates the daily numbers of positive polymerase chain reaction (PCR) tests of COVID-19 in Japan.

During the first wave, the national government announced a state of emergency from April to May. During this emergency period, the government requested that people stay home, but no actual restriction was assigned. Furthermore, elementary and secondary schools were closed from March second to June first [14].

Our data were obtained through several channels, details of which are provided in Appendix A. For long-term care use, we take insurer-level data from the Monthly Report on Long-Term Care Insurance by the Ministry of Health, Labor and Welfare. These insurers are individual municipalities or unions of multiple municipalities. In Analysis 1, for municipality data, we exclude unions of multiple municipalities. This is because our main explanatory variable, which measures the COVID-19 outbreak in the region, could include information from other municipalities if we included these unions in our sample. We expect the impact of this exclusion to be small because these unions account for only 40 of the 1571 insurers. However, these unions are included in the prefecture-level data for Analyses 2 and 3 because none include municipalities in different prefectures.

For working status, we adopt working hours as our main variable using prefecture data from the Monthly Labor Survey by the Japanese Ministry of Health, Labor and Welfare.

For the variables related to COVID-19, we employ microdata for PCR positives provided by J.A.G JAPAN (https://gis.jag-japan.com/covid19jp/). Because the government of Tokyo did not provide information on the municipality of residence for those who tested positive, we exclude Tokyo from our sample in the municipality-level analysis. However, we include Tokyo in the prefecture-level research. As discussed in Appendix A.5, the key variables for Tokyo follow a similar tendency as the other regions, so we do not expect a serious selection problem.

Appendix A.2 provides more information on the other explanatory variables, $\boldsymbol{x}$. For most components of $\boldsymbol{x}$, we do not obtain monthly values but values from before our research period; hence, they are treated as time-invariant variables in our regression analysis.

2.3. Outcome variables

In several analyses, we adopt the number of daycare and home-care users as our respective outcome variables. In these variables, we include all beneficiaries, both elderly (65 years old or more) and non-elderly individuals with aging-related diseases (40 to 64 years old). Daycare contains both ordinary daycare and community daycare. For number of users, a person is counted only once, even if he or she purchases services multiple times a month.

In the analysis of long-term care use, we focus on the demand-side shock of COVID-19. As discussed in Appendix A.4, the supply-side shock seems to be minor in comparison.

In Analysis 2, the choice of an appropriate variable for working status that can reflect the impact of the pandemic is not straightforward. In the Labor Force Survey conducted by the Ministry of Internal Affairs and Communications, it is revealed that neither the unemployment rate nor wages showed a large change during the first wave. Instead, as shown in the Monthly Labor Survey, working hours showed a large decline, even in the first wave.

Thus, we use working hours as our main outcome variable. From the Monthly Labor Survey, we take average working hours for full-time workers at firms with five or more employees. To see the gender difference, we analyze both females and males.

Additionally, we also considered cost per user for long-term care services and worker rates as candidate outcome variables—as intensive margins for long-term care use and extensive margins for work, respectively. However, averages of these values did not decrease during the first wave, so the influence of the pandemic is not intuitive. We provide analyses for these variables in Appendix B.

For all outcome variables, we take the difference from the value in the same month in the previous year to show the change during our research period.

2.4. Primary explanatory variables

In all analyses, to capture the impacts of the pandemic, we include two categories of explanatory variables. First are variables that represent the nation-level impact. Here, we include month dummies, March, April, and May, where February is a reference option, and their coefficients are measured by δ_t. We expect these coefficients to capture the effects of the state of emergency.

Furthermore, we adopt additional month dummies regions with longer states of emergency, the effects of which are measured by λ_{it}. Specifically, we adopt three variables: long emergency in April, long emergency in May, and very long emergency in May, as described in Appendix A.3.

The month dummies also play an important role in Analysis 2. Since 2019, the Labor Standards Act was amended to regulate overtime work in Japan. The regulation went into effect in April 2019 for large firms and April 2020 for small firms. Thus, month dummies after April can capture the impact of this amendment in Analysis 2.

Another category of COVID-19 is constructed using the number of PCR positives in each region, w_{it}, the coefficient of which is represented by α. For Analysis 1 using municipality data, we adopt the monthly number of PCR positives. For Analyses 2 and 3 using prefecture data, we utilize the number of PCR positives per 10,000 people to obtain stable coefficient estimates.

Because δ_t is common for all regions, it represents the national-level impact of the pandemic, while α represents the regional impact of the COVID-19 outbreak. It is important to note that the number of PCR positives heavily depends on the regional medical systems, which were not equal during the first wave. In other words, the regional number of PCR positives did not always correspond to the actual number of COVID-19 infections. Rather, it is more natural to interpret α as the response of people to broadcast information on peer status.

2.5. Instrumental variables

In IV estimation for Analyses 1 and 2, we include daycare provision as endogenous variable r_{it}. We adopt the number of users as this variable, taking the difference from last year. To control the endogeneity between r_{it} and y_{it}, the number of home care users and working hours, we utilize two instruments.

The first is $r_{i,t-1}$, the lagged value of daycare users. Because long-term care services are repeatedly provided for many months, it is common to use similar amounts of services as the previous month; hence, this instrument is likely to be correlated to the endogenous variable. There is a possibility that daycare use in the previous month affects the dependent variable at the previous month, and the dependent variable has autocorrelation. To exclude this causal path, we also add $y_{i,t-1}$, the lagged value of the dependent variable. Then, we expect the one-month lag of daycare use has no other routes to affect the outcome variable than the path through current daycare use.

The second instrument is the regional capacity of daycare per 1000 persons, which is defined as the ratio of the capacities for all daycare providers in the region over the regional population times 1000. Because the regional capacity affects availability of services, the number of users is intuitively correlated to this instrument. However, given the number of daycare users, supply-side daycare information does not have an intuitive direct relationship to home care or working hours.

Capacity information is taken from the Survey of Institutions and Establishments for Long-term Care conducted by the Ministry of Health, Labor and Welfare. Because this is an annual survey, we do not observe monthly statistics, so we use information from September 2019. Additionally, only prefecture-level data is available.

In Analysis 3, we include working hours as an endogenous variable, where the outcome variable is daycare use. For the instruments, in the manner similar to the first instrument above, we adopt working hours with one- and two-month lags and include the lagged value of the dependent variable into explanatory variables to control the possible causal path from the instrument to outcome.

2.6. Other explanatory variables

For all analyses, we include two categories of explanatory variables, demographic and economic. For demographic, we include population density, share of elderly people in the population, and share of single households with at least one elder. For economic, we include the unemployment rate; share of primary industry workers, namely agriculture and forestry and fishery; share of secondary industry workers, namely manufacturing, construction, electric power and gas, and mining; and the female employment rate.

For Analysis 1 using municipality data, we adopt additional variables to control more elements. For demographic variables, we add log population, squared log population, and livable areas, while for economic variables, we add individual local tax per capita, firm local tax per capita, and asset tax per capita. Additionally, as an alternative to long-term care services, we control the number of hospitals per capita. Furthermore, we include prefecture dummies.

Table 1
Descriptive statistics for the main variables. Variables of daycare, home care, and working hours take the difference from the value of the same month the previous year. Descriptive statistics for female and male working hours are calculated with 147 observations because data for May in Niigata is missing.

		Variable	Mean	S.D.		
Analysis 1,2	y	#Users of daycare	−31.70	210.71		
(Municipality)		#Users of home care	−1.31	44.72		
	w	#COVID-19 Positives	1.65	14.08		
Observations		#Regions	1451			
		#Months	4			
		#Regions x #Month	5804			
Analysis 3,4	y	Female working hours	−5.10	4.61		
(Prefecture)		Male working hours	−4.94	5.59		
	w	#Positives per 10,000 population	0.22	0.40		
	r	#Users of daycare	−1539.50	4007.94		
Observations		#Regions	37			
		#Months	4			
		#Regions x #Month	148			
Monthly means			Feb	Mar	Apr	May
		#COVID-19 Positives	0.08	0.85	4.79	0.86
		#Users of daycare	24.36	−13.91	−50.86	−86.40
		#Users of home care	4.49	2.24	−2.67	−9.30
		Female working hours	−1.93	−2.29	−5.73	−10.58
		Male working hours	−1.91	−1.32	−4.70	−12.01

3. Study results

3.1. Descriptive statistics

Table 1 shows the descriptive statistics for our main variables. The variables of daycare, home care, and working status are the difference from the same month in the previous year. The numbers of daycare and home care users have negative means, while the magnitude is much larger for daycare. For working hours, both females and males have negative means, and the magnitude is slightly larger for females.

To illustrate the time-series properties in more detail, the lower part of Table 1 shows monthly sample means. The peak of the COVID-19 pandemic appeared in April, while the reductions in daycare and home care users increased throughout the study period, even in May. The number of home care users had a positive mean, even in March, when the COVID-19 outbreak had already started. This implies that the demand for home care is less sensitive to the pandemic than the demand for daycare.

For working hours, both males and females have similar patterns of monotone decreasing, while the magnitude of decrease is slightly larger for females, except in May. Interestingly, the means were negative, even in February. This might correspond to the amendment of the Basic Labor Act, which has been in effect for large firms since April 2019.

3.2. Analysis 1

Table 2 shows the empirical results for Analysis 1 on the relationship between the pandemic and use of formal care services at home. Columns (1) and (2) report the OLS results, where the dependent variables are daycare and home care users. For month effects δ_t, we have significantly negative coefficients for March, April, and May for both analyses. Because February—with its limited number of PCR positives—is the reference alternative, these negative month effects imply that utilization of daycare decreased as the national-level pandemic proceeded. Moreover, as in the descriptive statistics, although the pandemic was subsiding, the negative month effects have larger magnitudes in May. Together with the large coefficient for the long-emergency dummy variable in May, the national-level effects are likely to capture the response of people to the national emergency policy, which continued until May, instead of the actual status of the pandemic.

For the coefficients of the regional outbreak of COVID-19, α, the number of PCR positives is significantly negative. This implies that if there were more PCR positives in a region, more people refrained from using daycare. Using these coefficient estimates, Appendix B.3 provides further quantitative analysis.

Our analysis of costs per user shows that both daycare and home care costs were negatively impacted by the COVID-19 pandemic (Appendix B.1).

Column (3) of Table 2 shows the results of the IV estimation of home care, controlling the number of daycare users. From the IV estimation, we have a significantly positive coefficient γ for the number of daycare users. This implies that, even controlling endogeneity, the decrease in daycare users corresponded to the decrease in home care users. The first-stage F-statistic is 64.503, which exceeds 10, a standard weak instrument cutoff. The overidentification test statistic is 0.73 and p-values are 0.39, which shows that the exclusion restriction holds for our instruments.

For month effects δ_t, the estimates are significantly negative. As with the OLS results, the coefficients are monotone decreasing with the month, while the values are much smaller than those for daycare. This implies that the number of users for home care was also influenced by the pandemic at the national level, but the magnitudes were much smaller than those of daycare.

For the coefficients of regional outbreak of COVID-19, α, the number of PCR positives has an insignificant coefficient for the number of home care users. Thus, controlling the national-level impacts indicates the regional impacts are not substantial.

3.3. Analysis 2

Table 3 shows the empirical results for Analysis 2, where working hours are the outcome variables. In this analysis, we include observations only for February, March, and April. If we include May, we do not obtain significant α. In this case, we conclude that firms followed a national-level policy in May; hence, the regional impacts become minor.

Columns (1) and (2) of Table 3 show the OLS results on female and male working hours, respectively. For month effects δ_t, both female and male working hours have significantly negative coefficients for April. Thus, the national impacts, probably due to the national emergency, affected the working hours of both females and males. However, the dummy variable for long emergency in April has insignificant coefficients. This might imply that the April

Table 2
Estimation results for Analysis 1 on the number of care users. Cluster standard errors are in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

		(1)	(2)	(3)			
Equation	(1.1)	(1.2)					
y	#Users	daycare	home care	home care			
Method		OLS	IV				
		Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
α	#Positives	−7.42***	(1.386)	−0.66	(0.589)	0.06	(0.302)
γ	#Users of daycare					0.07***	(0.020)
δ	March	−32.50***	(5.042)	−1.74**	(0.737)	−0.07	(1.358)
	April	−37.17***	(5.388)	−3.86***	(1.159)	−0.27	(0.788)
	May	−80.37***	(13.314)	−9.73***	(1.841)	0.43	(1.562)
λ	April x Long Emergency	−17.40	(23.655)	−1.01	(6.146)	−3.60	(2.660)
	May x Long Emergency	−238.08***	(72.851)	−34.98***	(6.694)	−10.81**	(4.471)
	May x Very Long Emergency	−38.50	(45.270)	−5.27	(5.988)	−2.46	(1.744)
Observations	5804	5804	5804				

Table 3
Estimation results for Analysis 2 on work hours. Robust standard errors are in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

		(1)	(2)	(3)			
Equation	(1.1)	(1.2)					
y	Working hours	Female	Male	Female			
Method		OLS	IV				
		Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
α	#Positive per 10,000 population	−1.87**	(0.792)	−1.13	(1.026)	−1.72**	(0.839)
γ	#Users of daycare					−0.00	(0.000)
δ	March	−0.19	(0.576)	0.69	(0.717)	0.78	(0.588)
	April	−2.50***	(0.774)	−1.71*	(1.007)	−1.47**	(0.632)
λ	April x Long Emergency	−0.48	(1.034)	−1.88	(1.184)	−2.36*	(1.424)
Observations	111	111	111				

dummy also captures the impacts of the amendment to the Basic Labor Act.

In Column (1), the regional number of COVID-19 positives has a significantly negative coefficient, α, for female working hours. However, in Column (2), male working hours have insignificant coefficients with the regional COVID-19 outbreak. These results imply the pandemic had unequal effects on genders in Japan.

In Appendix B.2, we show the regression results on the extensive margins of work, where both month dummies and the coefficient for regional COVID-19 positives are not significant. This result implies that extensive margins of working status were not substantially affected by the pandemic.

For regional impacts, Column (3) of Table 3 shows the results of the IV estimation where we control daycare use. We abbreviate to show the result for male working hours, because the coefficient for regional COVID-19 positives is already insignificant in the OLS results for males.

From the IV estimation, we obtain an insignificant coefficient γ for the number of daycare users. The first-stage F-statistic is 10.339, and the overidentification test statistic is 1.139 with 0.29 p-value, which show the validity of our instruments.

The coefficient for regional COVID-19 positives, α, is still significantly negative at the 5% level. We also obtain similar coefficients for month effects δ_t for March and April, while we obtain a negative coefficient at the 5% level for the dummy variable for long emergency in April, which is not significant in OLS.

3.4. Analysis 3

Table 4 shows the empirical results for Analysis 3, where the prefecture-level number of daycare users is the outcome variable. Based on the results of Analysis 2, we mainly consider effects of female working hours and males are analyzed in Appendix B.4. Columns (1) and (2) report the results of the OLS and IV estimations without and with controlling female working hours, respectively. We use a sample up to April, without February, because female working hours are available only from January, and its second lag is one of our instruments. For IV estimation, the first-stage F-statistic is 28.91, and the overidentification test statistic is 2.8 with 0.6 p-value, which shows the validity of our instruments.

For impacts of COVID-19, the coefficients for regional COVID-19 positives and for the dummy variable for long emergency in April are all significantly negative in Columns (1) and (2). Comparing these columns, magnitudes for both regional and national impacts are smaller in the IV estimation controlling working hours. However, the coefficient of working hours is not significant.

Because the sample size in Columns (1) and (2) is small, there is a possibility of the type I error. Thus, Columns (3) and (4) analyze a larger sample from February to March. Further, to avoid a reduction of observations due to two-month lag variables, we adopt the lagged variable of female working hours as the explanatory variable, which should be free from a simultaneity bias.

The results in Columns (3) and (4) show a reduction in the negative impacts of COVID-19, from both regional and national perspectives, by controlling the working hours. Additionally, we have a significantly positive coefficient for working hours.

As shown in Appendix B.4, for males, we have similar results that impacts of COVID-19 are smaller if we control working hours. On the other hand, a coefficient for male working hours is not significant in any setting.

4. Discussion

As is clearly shown in Analysis 1, people refrained from using daycare due to the COVID-19 outbreak. As the pandemic continued, the Japanese government announced short-run policies to encourage replacing daycare with home care (https://www.mhlw.go.jp/stf/seisakunitsuite/bunya/0000045312/matome.html). The policies included flexible operations with minimal staff requirements and simplified monitoring procedures. However, home care did not function as a substitute for daycare in the first wave of the pandemic.

Table 4
Estimation results for Analysis 3 on daycare use. Robust standard errors are in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

		(1)	(2)	(3)	(4)				
Equation		(1.1)	(1.2)	(1.1)	(1.1)				
y	$Users of daycare								
Method		OLS	IV	OLS	OLS				
		Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
α	#Positives	−2079.93***	(677.698)	−1151.22**	(515.541)	−2795.08***	(1034.042)	−2587.09***	(948.915)
γ	Female working hours			18.82	(49.638)				
δ	March					−1419.40***	(438.973)	−1011.78**	(431.995)
	April	126.34	(306.390)	430.01	(293.002)	−1066.20**	(426.200)	−652.26	(451.105)
	May					−3564.84***	(691.021)	−2413.83***	(559.551)
λ	April x Long Emergency	−3754.33***	(868.808)	−2902.37***	(612.829)	−2870.69**	(1424.721)	−3118.69**	(1331.883)
	May x Long Emergency					−7466.72**	(2861.016)	−7144.37**	(2744.994)
	May x Very Long Emergency					−5878.21***	(1278.331)	−5856.98***	(1215.557)
β	Female working hours, previous month							202.81***	(67.660)
Observations	74	74	148	148					

In sum, our finding indicates that daycare was not replaced by home care. There are reasons why it is difficult to replace daycare with home care. Many households do not want to receive a caregiver from outside the family who is at risk of bringing the virus or being exposed to it.

In Analysis 2, we show that female working hours were reduced in areas seriously impacted by the pandemic, while male working hours did not show such regional responses. This result might correspond to the analysis of Kikuchi et al. [15], who note that Japanese females are likely to work in fields vulnerable to outbreak, and Yamamura and Tsutsui [13] showed that, in Japan, the childcare burden has been shouldered by women during the pandemic.

However, the decline in daycare use did not have a direct effect on female working hours, and the effects of COVID-19 on working hours is not much different, even if we control daycare use in Analysis 2. An intuitive explanation for these results is that the number of females who need daycare is not so large as to have significant impacts on regional averages of working hours.

To explore the relationship between daycare and female working hours under COVID-19, in Analysis 3, the direction of causality is the opposite. In this analysis, it is implied that daycare use is reduced less by COVID-19 if we control female or male working hours. Furthermore, an estimation result is consistent with a direct effect from past reduction in female working hours on daycare use. These results are compatible to a situation where daycare is replaced with informal care especially by females who reduced their working hours by COVID-19.

When home care does not work as a substitute for daycare, informal care is a realistic solution under a national emergency because many firms introduced flexible work options. As a policy implication, governmental support for flexible work, including more flexible paid leave, is recommended.

However, it is possible our results are distorted by spurious correlations because we only have access to regional aggregate data; hence, many elements, such as childcare burden or household income, are not controlled. When microdata on individual workers becomes available, further studies could reveal a more detailed relationship between care, work, and the pandemic.

5. Conclusion

This study analyzes the effects of the first wave of the COVID-19 pandemic on long-term care at home, and its impacts on working hours in Japan. From the regression results using regional data, we clearly find a reduction in daycare use during the pandemic. Further, our results indicate that daycare was not replaced by home care, which was encouraged by the government. We also show that female labor status was more vulnerable to the pandemic. Our results are consistent with a situation where informal care, provided especially by females who reduced their working hours due to COVID-19, compensated for the reduction in daycare use.

Our research has several limitations due to data availability. First, as we discussed in Section 4, we obtain only regional aggregate data. When microdata becomes available, further analyses should be conducted. Second, for Analysis 3, we obtain data only on full-time workers. However, part-time workers are more likely to change their working hours in response to the care needs of family members [16]. Thus, our estimation result may underestimate the impact of COVID-19.

Further, our research is concerned only with the first wave of the pandemic, not the second and third waves. The pandemic continues in Japan, and as it goes on, its impacts may occur in multiple directions. For example, the first wave mainly affected working hours, while the longer pandemic might affect the unemployment rate. If the reduction in demand continues, daycare services may

close. Thus, further research on the impacts of the whole pandemic is required in the near future.

Declaration of Competing Interest

The authors have no conflicts of interest to declare.

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Appendix

A. Details of data

A.1 Detailed data sources for working hours

The working hours are taken from the following web addresses, which were accessed in October 2020.

- Hokkaido http://www.pref.hokkaido.lg.jp/ss/tuk/007mls/index.htm
- Aomori Missing observation
- Iwate http://www3.pref.iwate.jp/webdb/view/outside/s14Tokei/tyosaBtKekka.html;jsessionid=08DA6C07373D900CFD62F34C459AB0F1?searchJoken=I034
- Miyagi https://www.pref.miyagi.jp/soshiki/toukei/koyoutochingin2008.html
- Akita
  - https://www.pref.akita.lg.jp/pages/archive/10653
- Yamagata https://www.pref.yamagata.jp/020052/kensei/shoukai/toukeijouhou/kinroutoukei/maikm.html
- Fukushima https://www.pref.fukushima.lg.jp/sec/11045b/15871.html
- Ibaraki https://www.pref.ibaraki.jp/kikaku/tokei/fukyu/tokei/betsu/rodo/maikin/index.html
- Tochigi http://www.pref.tochigi.lg.jp/c04/pref/toukei/toukei/maikin3.html
- Gumma
  - https://toukei.pref.gunma.jp/maikin/month-old.html
- Saitama https://www.pref.saitama.lg.jp/a0206/a031/2018geppou-ikkatu.html
- Chiba https://www.pref.chiba.lg.jp/toukei/toukeidata/kinrou-chihou/index.html
- Tokyo
  - https://www.toukei.metro.tokyo.lg.jp/maikin/mk-kako.htm(Not used, because of missing PCR information)
- Kanagawa https://www.pref.kanagawa.jp/docs/x6z/tc30/maikin/maitsukikinrou.html
- Niigata (Information for May 2019 is missing) https://www.pref.niigata.lg.jp/sec/tokei/1201021235308.html
- Toyama Missing observation
- Ishikawa http://toukei.pref.ishikawa.jp/search/min.asp?sc_id=12
- Fukui
  - https://www.pref.fukui.lg.jp/doc/toukei-jouhou/maikin/maikin.html
- Yamanashi https://www.pref.yamanashi.jp/toukei_2/DB/EDC/dbce02500_R02.html
- Nagano https://tokei.pref.nagano.lg.jp/statist_list/603.html
- Gifu
  - https://www.pref.gifu.lg.jp/page/5230.html
- Shizuoka https://toukei.pref.shizuoka.jp/search?class=12&invest=12040
- Aichi https://www.pref.aichi.jp/toukei/jyoho/history/history.html
- Mie Missing observation
- Shiga Missing observation
- Kyoto https://www.pref.kyoto.jp/tokei/monthly/maikin/maikintop.html
- Osaka http://www.pref.osaka.lg.jp/toukei/maikin/maikin-kako.html
- Hyogo https://web.pref.hyogo.lg.jp/kk11/ac08_4_000000036.html
- Nara
  - http://www.pref.nara.jp/6206.htm
- Wakayama Missing observation
- Tottori
  - https://www.pref.tottori.lg.jp/toukei/maikin/
- Shimane
  - http://pref.shimane-toukei.jp/index.php?view=20814
- Okayama Missing observation
- Hiroshima https://www.pref.hiroshima.lg.jp/soshiki/21/maikinback.html
- Yamaguchi https://www.pref.yamaguchi.lg.jp/cms/a12500/tingin/maikin_bknumber.html
- Tokushima Missing observation
- Kagawa Missing observation
- Ehime https://www.pref.ehime.jp/toukeibox/datapage/maikin/m/maikin-mgaiyou.html
- Kochi Missing observation
- Fukuoka
  - https://www.open-governmentdata.org/fukuoka-pref/search/keyword:%E6%AF%8E%E6%9C%88%E5%8B%A4%E5%8A%B4%E7%B5%B1%E8%A8%88/sort:score%20desc%2C%20metadata_modified%20desc/search_clear:#result_area
- Saga
  - https://www.pref.saga.lg.jp/toukei/list01602.html
- Nagasaki https://www.pref.nagasaki.jp/bunrui/kenseijoho/toukeijoho/maikin/
- Kumamoto https://www.pref.kumamoto.jp/hpkiji/pub/List.aspx?c_id=3&class_set_id=1&class_id=5138
- Oita https://www.pref.oita.jp/site/toukei/index-mls.html
- Miyazaki https://www.pref.miyazaki.lg.jp/tokeichosa/kense/toke/maikin-geppou/20201023163953.html
- Kagoshima http://www.pref.kagoshima.jp/ac09/tokei/bunya/chingin/kinrotokei/maikin-gepou.html
- Okinawa https://www.pref.okinawa.jp/toukeika/mls/mldata.html

A.2 Data sources of the Other explanatory variables

We take population, share of elderly, share of single elder households, unemployment rate, share of workers in the primary sector of industry, share of workers in the secondary sector of industry, and female employment rate from the 2015 Census. Livable areas are taken from the Annual Reports of the Land Survey of Prefectures Shi, Ku, Machi, and Mura by Geospatial Information Authority of Japan. Individual local tax per capita, firm local tax per capita, and asset tax per capita are taken from the 2018 Annual Statistics on Municipal Tax by the Japan Ministry of Internal Affairs and Communications. The number of hospitals is taken from the 2016 Survey of Medical Institutions by the Ministry of Health, Labor and Welfare.

A.3 Longer emergency dummies

Seven prefectures, Tokyo, Kanagawa, Saitama, Chiba, Osaka, Hyogo, and Fukuoka, began a state of emergency earlier, from April seventh, while the other prefectures started it on April 16th.

Table A1
Selected variables of Tokyo.

	Feb	Mar	Apr	May
#COVID-19 Positives	34	489	3750	961
#Users of daycare	2764	−6514	−19,407	−25,986
#Users of home care	436	−362	−3020	−4976

Table A2
Descriptive statistics for the main variables adopted in the appendix. Variables take the difference from the value in the same month the previous year. Tokyo is eliminated from prefecture-level analyses.

		Variable	Mean	S.D.
Analysis 1	y	Costs per a user, daycare	1.35	7.59
(Municipality)		Costs per a user, home care	3.73	10.29
Observations		#Regions	1451	
		#Months	4	
		#Regions x #Month	5804	
Analysis 2,3	y	Female working rate	2.16	6.46
(Prefecture)				
Observations		#Regions	46	
		#Months	3	
		#Regions x #Month	138	

Thus, we construct a dummy variable for the long emergency in April, which takes unity for the seven prefectures. For the end of the national emergency, 39 prefectures ended on May 14th. Osaka, Kyoto, and Hyogo ended on May 21st, while Tokyo, Kanagawa, Saitama, Chiba, and Hokkaido end on May 25th. We construct a dummy variable for the long emergency in May, which takes unity for Osaka, Kyoto, and Hyogo, and a dummy variable for the very long emergency in May, which takes unity for Tokyo, Kanagawa, Saitama, Chiba, and Hokkaido.

A.4 Supply and demand side influences of pandemic

In the analysis of long-term care use, our research mainly focuses on the demand-side shock of COVID-19. However, there is a possibility that this is caused by a supply-side shock. To see this, a new story by NHK, a major broadcaster in Japan, on April 21st, 2020(https://www3.nhk.or.jp/news/html/20200421/k10012399411000.html) reported the existence of a supply shock caused by the shutdown of long-term care service providers, including both daycare and homecare, due to the pandemic. Using figures from NHK news, 121 providers of daycare, outpatient rehabilitation, and short-stay services were suspended in Tokyo on April 20th. According to the Survey of Institutions and Establishments for Long-term Care, the total number of service providers in Tokyo was 4799 (excluding preventive services) in September 2019, so the share of suspended providers was approximately 2.5%. However, the rate of reduction for daycare users was approximately 13.5% in Tokyo. Thus, the reduction in demand appears to be much larger than that of supply. That is, the supply-side shock seems to be minor in comparison to the demand-side shock.

A.5 Elimination of Tokyo

Table A1 shows the values of the key variables for Tokyo. In comparison with the lower part of Table 1 , the key variables have a similar tendency as those for Japan as a whole, described in SubSection 3.1. Specifically, the COVID-19 pandemic was most serious in April, while the reductions in daycare and home care users continued in May. The magnitudes of reduction were much larger for daycare than home care. These figures indicate that Tokyo shared the general tendency of the rest of Japan.

B Additional analysis

B.1 Analysis of long-term care costs per user

In Analysis 1, we also adopt outcome variables that reflect the intensive margins of formal care services at home. Specifically, we analyze the costs per user for daycare and home care services. The variables are constructed from the Monthly Report on Long-Term Care Insurance in a similar manner to the number of users.

We do not employ the IV estimation that includes daycare use in the explanatory variable for the intensive margins. Extensive margins are associated with consumer decisions regarding whether to purchase a service. Thus, it is natural to consider the impacts of simultaneous purchase decisions on daycare and home care services. However, intensive margins are associated with decision on purchase amounts, given decisions to purchase. Thus, purchase of daycare affects the purchase of home care should a consumer purchase both services. If we have microdata on individual consumers, we can control such cases of simultaneous purchase. However, because regional aggregate data may contain different cases, we cannot obtain an intuitive interpretation of the analysis results using regional aggregate data.

Table A2 provides descriptive statistics for the variables used in the additional analysis in this appendix. We have positive means for costs per user for both daycare and home care, unlike the number of users.

Columns (1) and (2) of Table A3 report the results, where dependent variables are costs per user for daycare and home care, respectively. For month effects δ_t, only for daycare costs, we have similar results as those for the number of users, that is, significantly negative coefficients for March, April, and May, and the magnitudes of the negative coefficients increases over time. For home care costs, the coefficients for March and April are not significant, and the coefficient for May is even significantly positive. However, for the regional outbreak of COVID-19, home care costs have a significantly negative coefficients, as in the extensive margins, while daycare costs have an insignificant coefficient.

The interpretation of these results is not straight-forward because they are likely to be a complement to extensive margins. The insignificant coefficient for regional outbreak for daycare costs can

Table A3
Estimation results for Analysis 1 of the costs per user. Cluster standard errors are in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

		(1)	(2)		
Equation	(1.1)				
y		Costs per user daycare	home care		
		Coef.	S.E.	Coef.	S.E.
α	#Positives	−0.01	(0.010)	−0.02*	(0.008)
δ	March	−1.44***	(0.213)	−0.27	(0.263)
	April	−2.50***	(0.363)	0.18	(0.239)
	May	−3.00***	(0.324)	0.76***	(0.247)
λ	April x Long Emergency	−1.63**	(0.757)	0.49	(0.590)
	May x Long Emergency	0.41	(0.399)	1.07	(0.807)
	May x Very Long Emergency	−0.65*	(0.353)	−1.28	(0.882)
Observations		5804		5804	

Table A4
Estimation results for Analysis 2 of female working rates. Robust standard errors are in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

		(1)	
Equation		(1.1)	
y	Female working rate		
Method		OLS	
		Coef.	S.E.
α	#Positive per 10,000 population	2.43	(1.871)
γ	#Users of daycare		
δ	March	−0.40	(1.288)
	April	−1.66	(1.488)
λ	April x Long Emergency	0.59	(2.917)
Observations		138	

be interpreted as meaning the regional situation was controlled in extensive margins for daycare use. Yet, for home care, once a consumer decides to purchase the service, the amount of purchase is not affected by the national status of the pandemic, while the regional status of the pandemic still matters. The difference for daycare and home care costs might correspond to different risks of infection, where daycare users are exposed to more people than home care users.

B.2 Analysis of female working rates

In this appendix, we analyze extensive margins of work. In Japan, there are no monthly statistics on regional unemployment rates or similar variables. Thus, we analyze the rates of female spouses of household heads who work in the capital city of each prefectures, which we call female working rates. The rates are taken from the Family Income and Expenditure Survey by the Ministry of Internal Affairs and Communications. In the survey, the rates are calculated from less than 100 households consisting of two or more members. Because Tokyo prefecture has no capital city, Tokyo is eliminated from this analysis.

In Table A2 , we have positive means for the female working rates, unlike working hours.

Table A4 shows the regression results for the third analysis of female working rates. Both month dummies and the coefficient for the regional number of COVID-19 positives are not significant. This result implies that extensive margins for the working status of females were not very affected by the pandemic.

B.3 Quantitative analysis based on estimates from Analysis 1

From the estimation results of Analysis 1, we can obtain more quantitative results using the estimates in Column (1) of Table 2. For April, $\delta_t/\alpha = 37.17/7.42 \approx 5$ when we use the coefficient for the number of PCR positives as α. This means that if there were five or more PCR positives, the regional reduction of daycare use became greater than the national-level reduction. As seen in Table 1, the mean of PCR positives in April was 4.79. Thus, these quantitative results show that if there were more PCR positives than average, the regional impact was larger than the national impact in April. However, the relation does not hold in May, where the national impact was much larger than the regional impact.

B.4 Results using male working hours for Analysis 3

In this appendix, we provide empirical results for Analysis 3 using male working hours. Table A5 reports the results, where Columns (1) and (3) are equivalent to them for Table 4. For IV estimation, the first-stage F-statistic is 16.224, and the overidentification test statistic is 0.002 with 0.97 p-value, which shows the validity of our instruments.

Comparing Columns (1) and (2), magnitudes for both regional and national impacts are smaller in the IV estimation controlling working hours. However, the coefficient of working hours is not significant. These results are similar to them for females. On the other hand, in Column (4), working hours in the previous month do not have a significant coefficient.

Table A5
Estimation results for Analysis 3 of male working hours. Robust standard errors are in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

		(1)	(2)	(3)	(4)				
Equation		(1.1)	(1.2)	(1.1)	(1.1)				
y	$Users of daycare								
Method		OLS	IV	OLS	OLS				
		Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
α	#Positives	−2079.93***	(677.698)	−1154.36**	(512.207)	−2795.08***	(1034.042)	−2683.82***	(979.142)
γ	Male working hours			25.35	(41.535)				
δ	March					−1419.40***	(438.973)	−1194.29***	(421.623)
	April	126.34	(306.390)	453.37	(294.467)	−1066.20**	(426.200)	−968.81**	(422.773)
	May					−3564.84***	(691.021)	−3138.59***	(556.867)
λ	April x Long Emergency	−3754.33***	(868.808)	−2846.78***	(610.513)	−2870.69**	(1424.721)	−2785.80*	(1421.753)
	May x Long Emergency					−7466.72**	(2861.016)	−7251.16**	(2937.625)
	May x Very Long Emergency					−5878.21***	(1278.331)	−5608.67***	(1339.063)
β	Female working hours, previous month							85.86	(53.763)
Observations		74	148	148					

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