



# The impact of COVID-19 on Japanese firms: mobility and resilience via remote work

Daiji Kawaguchi<sup>2</sup> · Sagiri Kitao<sup>3</sup> · Manabu Nose<sup>1</sup>

Accepted: 13 July 2022 / Published online: 3 September 2022

© The Author(s), under exclusive licence to Springer Science+Business Media, LLC, part of Springer Nature 2022

## Abstract

Drawing on the original survey of Japanese firms during the COVID-19 pandemic, we estimate the impact of the crisis on firms' sales, employment and hours worked per employee and roles of work-from-home (WfH) arrangements in mitigating negative effects. We find that the lowered mobility, induced by the state of emergency declared by the government and fear of infection, significantly contracted firms' activities. On average, a 10% reduction in mobility reduced sales by 2.8% and hours worked by 2.1%, but did not affect employment. This muted employment response is consistent with limited changes in aggregate employment at the extensive margin during COVID-19 in Japan. We find that the adoption of WfH before COVID-19 mitigated the negative impact by 55% in terms of sales and by 35% in terms of hours worked. Adapting to the pandemic by increasing the number of remote work employees also helped firms moderately mitigate the negative impact on sales and work hours and reduce the probability of filing for the short-time work subsidy.

**Keywords** COVID-19 · Work-from-home (WfH) · Firm sales · Employment · Hours worked · Short-time work · Japanese economy

**JEL Classification** J5 · J6 · H5

---

✉ Manabu Nose  
manabu.nose@gmail.com

Daiji Kawaguchi  
kawaguchi@e.u-tokyo.ac.jp

Sagiri Kitao  
sagiri.kitao@gmail.com

<sup>1</sup> The International Monetary Fund and the University of Tokyo, Washington, DC, USA

<sup>2</sup> The University of Tokyo, Research Institute of Economy, Trade and Industry, and IZA, Tokyo, Japan

<sup>3</sup> The University of Tokyo and Research Institute of Economy, Trade and Industry, Tokyo, Japan

## 1 Introduction

The COVID-19 pandemic has caused significant economic damage across the world and Japan is no exception. The Japanese government quickly responded to the crisis by declaring a state of emergency in major metropolitan areas in early April 2020 and expanding the declaration to cover the entire country from mid-April until mid-May. Because of the emergency situation and out of the fear of infection risk, people's mobility level plunged and physical economic activities came to a halt. Firms did not have ample time to adjust to the new operating environment. Some businesses that involve much social and physical interaction had no choice but to curtail, if not entirely suspend, normal operations. Even other businesses that do not necessarily involve much human interaction also had to contract, not only because shocks negatively affected demand for their products but also because employees were unable to commute to the workplace, especially in metropolitan areas where public transportation is essentially the only commuting option for many employees.

This paper investigates how the sudden and massive reduction in people's mobility affected firms' activities during the COVID-19 crisis and whether firms' adoption of work-from-home (WfH) arrangements helped them mitigate the negative impact on performance. The existing studies demonstrated the negative impact of COVID-19 on firms' performance and how the feasibility of WfH mitigated the negative impacts (Bai et al., 2021; Zhang et al., 2021; Alipour et al., 2021), but the individual firms' behavior on the adoption of WfH during the pandemic and its effect on firms' outcomes is largely unknown perhaps due to the lack of data that records the firms' behavior and outcomes after the onset of COVID-19. To overcome the limitation, we use the original survey of several thousand Japanese firms conducted by the Tokyo Shoko Research (TSR) and Center for Research and Education in Program Evaluation (CREPE) of the University of Tokyo. The survey asks firms whether their employees worked from home before onset of the COVID-19 crisis in December 2019 and whether they adjusted the ratio of employees working from home during the crisis. The survey also collects information about firms' activities, including sales, employment, and work hours during each month between February and September 2020.

We find that a decline in mobility significantly reduced firms' sales. Among our sample firms, sales declined by an average of 2.8% in response to a 10% drop in people's mobility compared to the same month of the previous year. The negative impact of the pandemic on the sales does not propagate to the employment; a drop in the mobility does not reduce the employment in statistically significant ways. In contrast, a drop in mobility reduces the hours worked by an employee; a 10% drop in the mobility reduces the average hours worked by 2.1%. Ambiguous effects on employment at the extensive margin are consistent with a small change in unemployment observed during the COVID-19 crisis in Japan. They are likely to be attributable to government policies implemented during the crisis, including the employment adjustment subsidy and leave compensation, which encouraged firms to retain employees, as well as to Japan's less flexible hiring and layoff practices than those of countries such as the U.S. In sum, the limited adjustment

of employment at the extensive margin and moderate adjustment at the intensive margin is consistent with what has been found on the Japanese Economy in the literature.

We also look at the heterogeneity of impacts of the pandemic across firm sizes and industries. The negative impacts were more significant among SMEs than among larger firms. Similarly, the impacts were more significant among firms in the industry that requires face-to-face contacts than the industries that do not require them. These heterogeneous impacts, however, are not precisely estimated.

The adoption of WfH arrangement substantially mitigates the impact of the pandemic on sales. In the estimation of the mitigation effect of WfH, the challenge is to address the endogeneity of the WfH adoption. We are in particular concerned about the reverse causality that the firms severely hit by the pandemic, such as firms located in the urban center, are more likely to adopt the WfH setting. If this selection occurs based on the unobserved shock, the adoption of WfH seemingly amplifies the negative shock instead of mitigating it. To address this endogeneity problem, we employ two identification strategies. First, we use the adoption of WfH before the pandemic, namely as of December 2019. Second, we use the average adoption rate of WfH before the pandemic by industry–firm size as the instrumental variable to approximate the technical “remote workability” that presumably differs by industry and firm size. Among the firms that had previously implemented some remote work prior to the crisis, the negative impact of lower mobility on sales was mitigated by 55%. Similarly, the negative impact on hours worked was mitigated by 35%. We also find that firms which increased the number of employees working from home after the crisis were able to reduce the negative impact on sales, though quantitative effect was moderate. Overall, we find robust evidence that the adoption of WfH arrangement mitigated the negative impact of COVID-19 on firms’ sales.

The adoption of WfH lessens the fiscal burden of the government through the reduction of the receipt of Employment Adjustment Subsidy, the short-time work subsidy scheme of Japan. Similar to some European countries, Japanese government has provided massive subsidies so that firms can hoard their employment; 68% of all the firms applied for the program by August 2021 and 4.2 trillion Japanese Yen, which is 0.8% of the Japan’s GDP, has been paid out from April 2020 to August 2021. Exploiting data on firms’ receipts of the Employment Adjustment Subsidy, we demonstrate that the reduction of the mobility increases the probability of applying for the subsidy. We find, however, that the adoption of WfH reduces the number of applications and mitigates the fiscal burden. We then quantify how much the adoption of WfH would reduce the government expenditures based on the estimated mitigation effect. Our conservative estimate shows that the fiscal burden would have been reduced by 2.5% if all the firms were to adopt a decent degree of the WfH arrangement (allowing 16% of all workers to work remotely). This simulation result suggests that subsidizing WfH and encouraging firms to offer flexible work arrangements could be beneficial from the public finance perspective.

The rest of this paper is organized as follows. Section 2 reviews related literature. Section 3 describes the survey data used in our analysis. Section 4 presents our estimated impact of COVID-19 on firms’ outcome, Sect. 5 presents the mitigation effect of remote work settings. Section 6 concludes.

## 2 Literature

This paper draws on two strands of literature: (a) the economic impact of the pandemic on firms' activities and (b) the role of WfH in mitigating the scarring effect.

There has been a rapidly growing body of literature on the economic impact of COVID-19, much of which is reviewed in Brodeur et al. (2021). Lockdowns due to COVID-19 have created pronounced losses in households' income, wealth, and expenditures (Coibion et al., 2020). The demand shock has triggered sudden and deep damage on firms' revenues and profits across the globe (Bartik et al., 2020; Bachas et al., 2020), which has increased the bankruptcy rate among small-and-medium enterprises (Gourinchas et al., 2020; Miyakawa et al., 2020). COVID-19 also created large supply shocks on labor productivity and TFP (Bloom et al., 2020) with non-negligible intersectoral spillovers.

COVID-19 has had divergent effects across countries and industries. The adverse impact has been concentrated in high-contact sectors, while employment loss has been severe among lower-skilled workers. Based on business surveys of small firms, several papers look at the heterogeneous effect of the pandemic on firms' sales, employment, and finance by firm size, industry, and owners' characteristics.<sup>1</sup> Bloom et al. (2021), for example, used a survey of businesses in the U.S. and found that large "online" firms that generate the majority of their sales online have experienced much smaller sales losses than small "offline" firms. Using monthly panel data from a post-COVID-19 survey, we gauge the short-term scarring effect on Japanese firms' revenues and employments over 8 months, shedding light on its asymmetric impact across sectors and according to firm size.

Governments' effective policy supports are essential for minimizing the severity of the short-term economic costs of COVID-19. Given a unique policy trade-off in stimulating the economy while containing the spread of infections, the design of policies for mitigating the impact of the pandemic is complex, involving economic policies as well as non-economic and non-pharmaceutical interventions (NPIs, such as masks and social distancing). Recent papers showed that aggressive anti-contagion policies need to be deployed early to restrict people's mobility, physical contact, and virus transmission rate (Hsiang et al., 2020; Chernozhukov et al., 2020). Another line of literature has evaluated various economic policies including targeted liquidity supports (Gourinchas et al., 2020; Landais et al., 2020), a negative lump-sum tax on small- and medium-size enterprises (Drechsel & Kalemli-Ozcan, 2020), short-time work schemes (Giupponi & Landais, 2020a), unemployment insurance (Ganong et al., 2020), and fiscal stimulus (Auerbach et al., 2022). With lockdown restrictions, broad-based demand stimulus is much less effective in increasing aggregate demand unlike ordinary recessions (Baqae & Farhi, 2022; Guerrieri et al., 2022).

The most symbolic phenomenon unique to COVID-19 is the rapid shift toward remote work to build firms' resilience to the pandemic. Large-scale shocks have often necessitated a reorganization of production processes. For example, natural

<sup>1</sup> See, for example, Fairlie (2020), Looze and Desai (2020), Kim et al. (2020), Alekseev et al. (2020), Fairlie and Fossen (2022), and Bloom et al. (2021).

disasters have prompted diversification of input–output production networks to avoid amplification of any supply shock, as found during a destructive earthquake (Carvalho et al., 2021). In contrast, the COVID-19 shock has promoted diversification of labor inputs from work-from-office (WfO) to WfH.

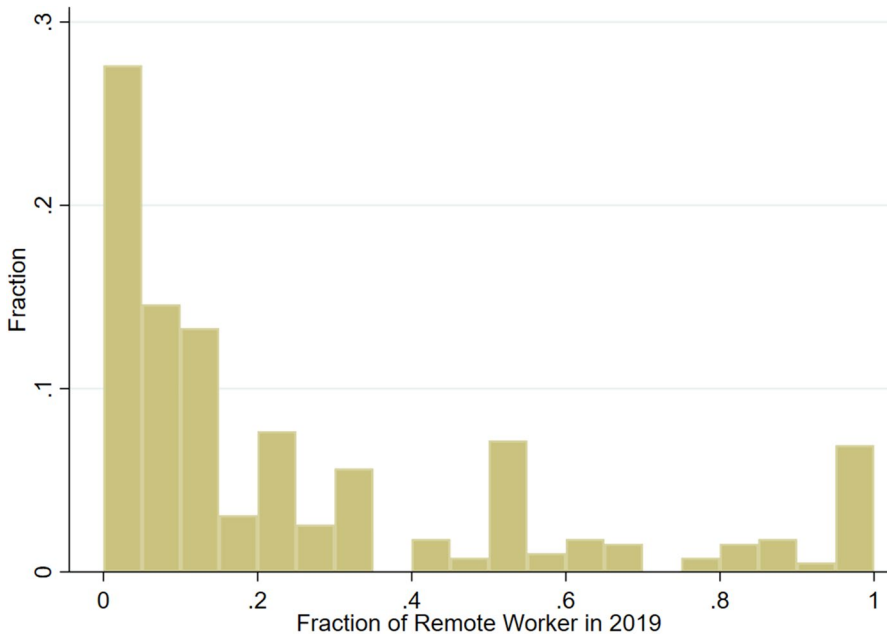
Theoretically speaking, the impact of household's adoption of WfH on work locations and income distribution depends on the elasticity of substitution between WfH and WfO which varies across industries and occupations (Davis et al., 2021; Kaplan et al., 2020). The change to WfH in the labor market has been rapid and persistent in the U.S., which has generally had a positive impact on productivity although with considerable variation across industries (Barrero et al., 2021).

In Japan, Morikawa (2022) uses an original survey of firms and finds that the average WfH productivity to be lower than WfO productivity by approximately 30%, although WfH intensity and productivity differ significantly across firms. Okubo (2020) also finds that the effect of WfH on productivity is negative on average but varies across industries and occupations. The effect has been more negative for occupations that require face-to-face interaction and for workers who utilized WfH arrangements the least during the pandemic.

There has been a small number of empirical studies on how WfH mitigates the COVID-19 shock on firms' performance. Perhaps closest to our study is Bai et al. (2021), which studies the effect of firms' resilience against the pandemic via WfH in the U.S. They construct an index that represents a firm's WfH feasibility and show that those with a high WfH index have had higher sales, net incomes and stock returns than those with a low index. Zhang et al. (2021) compare effects of COVID-19 on firms' performance across different states and show that firms in states with high WfH rates have experienced a smaller decline in revenue, cash flow, and supply chain disruption. Papanikolaou and Schmidt (2022) use the American Time Use Survey (ATUS) to assess the ability of workers to work from home across industries and find that industries with more flexibility experienced less severe effects from COVID-19 on employment, expected revenue growth, stock performance, and default probability. For lack of real-time data, their analysis is based on analysts' forecast of revenue growth. Our study sheds new light on the literature by analyzing how the benefits of remote work vary across firms and by estimating how much the adoption of WfH *before* and *after* onset of COVID-19 has mitigated the scarring effect on firms' sales, employment, and work hours.

### 3 Data

The dataset used in this study is the online firm survey on the effect of COVID-19 implemented by Tokyo Shoko Research (TSR) and Center for Research and Education in Program Evaluation (CREPE) of The University of Tokyo. We extended invitations to the TSR e-mail magazine subscribers to participate in the survey between October 26th and November 6th in 2020. We distributed the invitation to 158,264 firms and received responses from 5695 firms, which implies that the response rate is 3.6%. Of these, 4093 firms are matched to the TSR credit file. Online appendix B of Hoshi et al. (2022) reports the characteristics of respondents and non-respondents

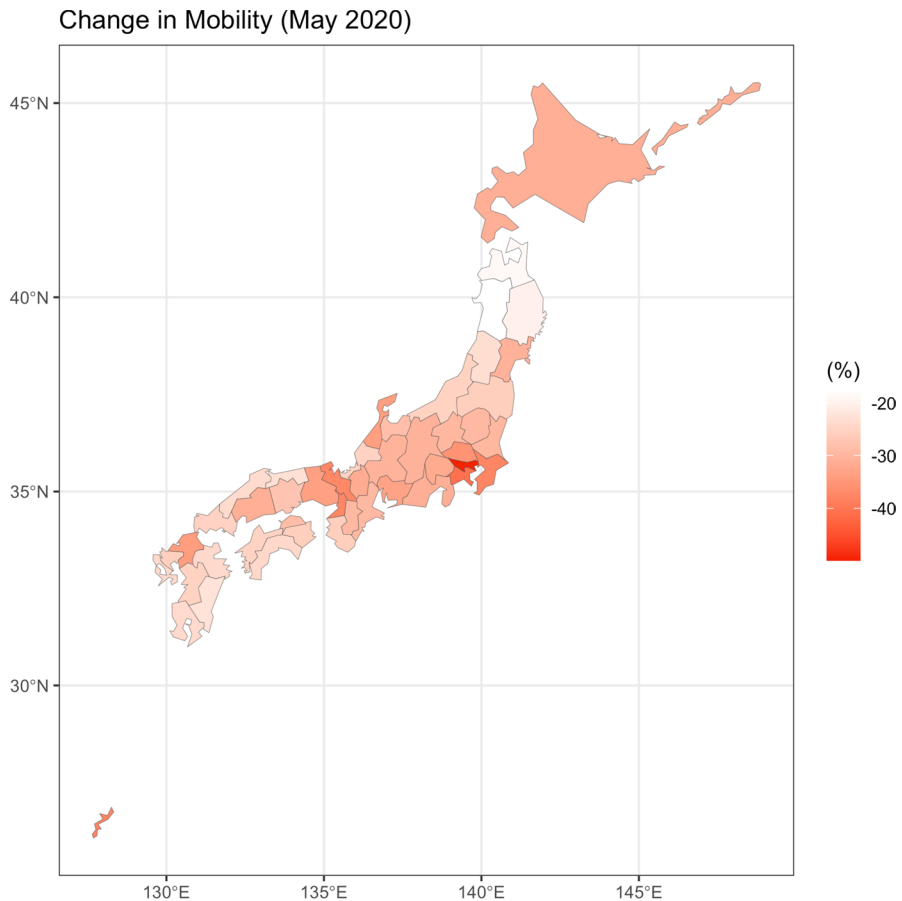


**Fig. 1** Fraction of remote workers among adopters in 2019. *Source* TSR-CREPE survey. *Note* As of December 2019, 11% of firms adopted a remote work setting. The histogram shows the distribution of the fraction of workers engaging in remote work among the adopting firms

based of TSR firm database as of December 2019. The comparison reveals that respondent firms have higher credit score, higher profit per worker, and larger in terms of the number of employees than non-respondent firms. Dropping those with missing values that are necessary for the analysis reduces the number of firms to 3632. The credit file includes more detailed information on firms, including year of establishment, headquarter location, industry defined based on major product or service, sales, number of employees, profit, and CEO profile.

The online survey asks the growth rate of sales in each month between February and September in 2020, relative to the same month in 2019. Similarly, the survey asks year-over-year (YoY) employment growth and hours worked growth in each month. These YoY changes are used as outcome variables representing firms' performance during the pandemic. The online survey also asks firms whether they had introduced remote work as of December 2019. For respondents that answer yes to this question, we further ask what fraction of workers worked remotely. In the analysis sample, 11% of firms had introduced some type of remote work.<sup>2</sup> Figure 1 illustrates the distribution of the fraction of workers who

<sup>2</sup> Note that this number is calculated based on the number of firms. This number does not coincide with the fraction of observations of remote work firms reported in Table 1 because the table tabulates the number of observations according to firm-month units.



**Fig. 2** Changes in mobility in May 2020 relative to January 2020. *Source* Google Community Mobility Report. *Note* The average of changes in mobility for retail stores and recreational venues, workplaces, and public transportation

worked remotely among the firms that had already adopted remote work environment prior to the pandemic.

As a proxy of the COVID-19 shock, we use people's mobility. To measure mobility, we use the Google community mobility report that records mobility at specific places on a daily basis relative to the baseline period, which is January 2020. The geographic unit of the data is 47 prefectures. As a mobility measure, we take the average of three mobility scores measured at "retail and recreation," "transit stations," and "workplaces." To match the frequency of TSR-CREPE survey, we take the mobility average at prefecture-month level. As an illustration, Fig. 2 illustrates the change in mobility in retail and recreation places in May 2020, when the first state of emergency was issued, compared with mobility in January 2020. The figure clearly shows that drops in mobility were concentrated

**Table 1** Descriptive statistics

Adoption of WfH in 2019	No	Yes	Total
Change in mobility from January 2020	- 0.187 (0.118)	- 0.224 (0.130)	- 0.191 (0.120)
Year on year sales growth	- 0.075 (0.314)	- 0.078 (0.332)	- 0.076 (0.316)
Year on year employment growth	- 0.004 (0.103)	- 0.005 (0.118)	- 0.004 (0.105)
Year on year hour growth	- 0.069 (0.187)	- 0.067 (0.190)	- 0.069 (0.187)
Firm age	44.16 (20.41)	36.64 (22.92)	43.35 (20.82)
Lagged sales growth	0.111 (2.497)	0.103 (0.599)	0.110 (2.367)
<i>N</i>	25,928	3128	29,056

*Sources* Google Community Mobility Report and TSR-CREPE survey

*Note* Mean values are reported. Standard deviations are reported in parentheses

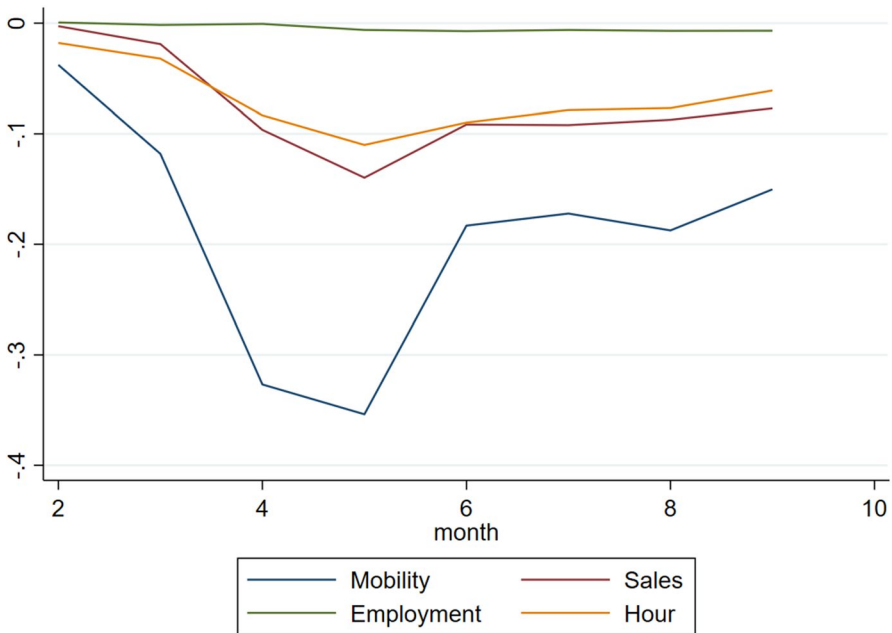
in urban prefectures such as Tokyo (40–50%) and Osaka prefectures (20–30%), demonstrating that the pandemic was an urban phenomenon.

Table 1 reports descriptive statistics of the analysis sample. Average firms experience a 19% reduction in mobility between February and September relative to January 2020. In terms of firms' performance, average firms experience a 7.6% decline in year-to-year sales and a 6.9% reduction in work hours between February and September. By contrast, employment fell by only 0.4%, which is negligible. The average number of employees is 150. Comparison of non-remote and remote firms reveals that remote firms experience greater negative mobility change and change in sales as well.

Time series of mobility, YoY sales, hours, and employment growth between February and September of 2020 are reported in Fig. 3. A significant drop in mobility coincides with the timing of the declaration of a state of emergency covering all regions of Japan, which extended from April 16th to May 14th. YoY sales and hours series co-move with mobility.

To further articulate the relationship between mobility and sales growth, Fig. 4 plots the bin average of YoY sales growth by changes in mobility. The figure shows that changes in mobility and sales growth are positively correlated, implying that the decrease in mobility due to COVID-19 reduces sales relative to the same month of the previous year. Similarly, Fig. 5 shows the relationships between mobility and employment growth. The figure shows no apparent relationship. This is consistent with findings that the adverse effect of COVID-19 on unemployment rate has been limited in Japan. On the other hand, the mobility and growth rate of hours worked reported in Fig. 6 show a positive correlation, implying that reduction in peoples' mobility results in a reduction in hours worked. The contrast between employment





**Fig. 3** Mobility, YoY growth of sales, employment and hours worked. *Sources* Google Community Mobility Report and TSR-CREPE survey. *Note* Mobility is the average of mobility to retail and recreation, public transportation, and workplace relative to January 2020. Sales, employment, and hours worked are year-to-year growth relative to the same month of 2019

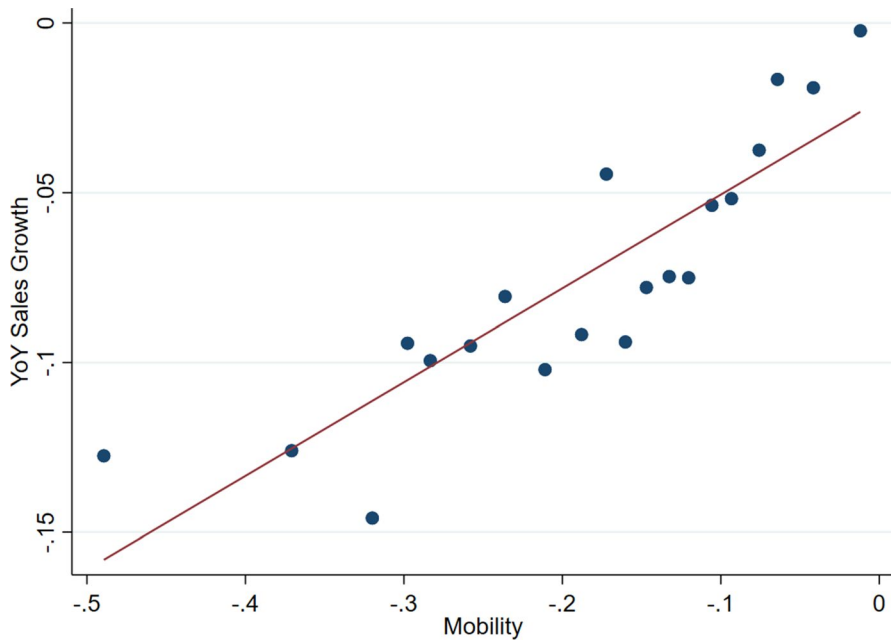
adjustment and hours adjustment is consistent with the consensus that Japanese firms tend to adjust hours worked and avoid firing existing workers (Hamada & Kurosaka, 1984; Lee, 2000; Ohanian & Raffo, 2012; Hijzen & Martin, 2013; Zanin, 2014).

## 4 Effects of people's mobility on firms' performance

### 4.1 Overall impact

The scatter diagrams in Figs. 4, 5, and 6 indicate that mobility and YoY sales or hours worked are positively correlated, suggesting that a decrease in mobility results in a decrease in sales or hours worked per employee. However, one may be concerned that the effect of COVID-19 is heterogeneous across firm sizes or industry, and the heterogeneity is systematically correlated with peoples' mobility. For example, if an industry, which operates face-to-face with customers and has been seriously disrupted by the current pandemic, is concentrated in an urban area where we observe a decrease in mobility, then mobility and YoY sales growth become spuriously correlated.

To establish causal impact of mobility on sales growth, we estimate the impact of mobility on firms' performance conditional on firm size as measured by the number



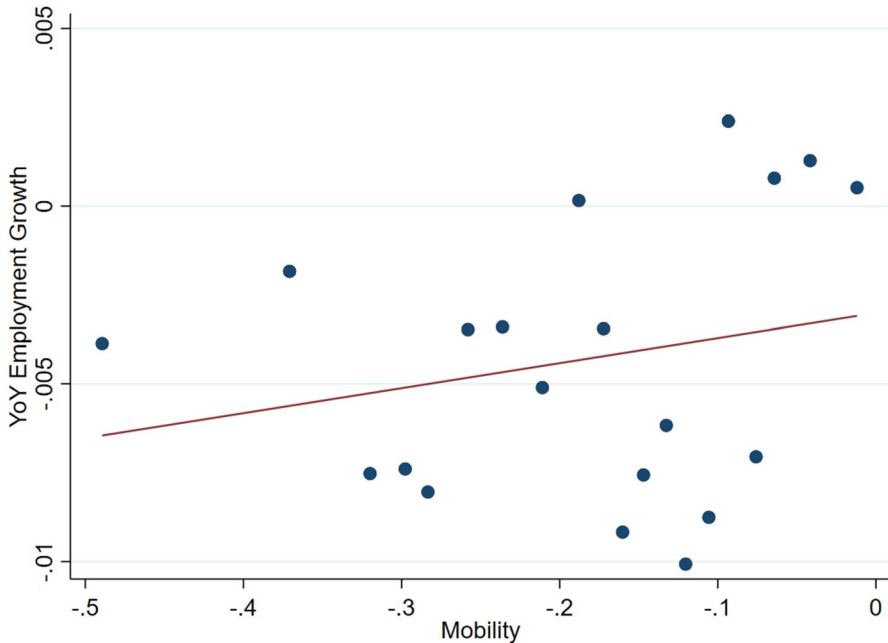
**Fig. 4** Mobility and YoY sales growth. *Sources* Google Community Mobility Report and TSR-CREPE survey. *Note* Each dot corresponds to the binned average of YoY sales growth relative to the same month of 2019. The bins are created such that each bin includes an equal number of observations. Mobility is the average of mobility to retail and recreation, public transportation, and workplace relative to January 2020

of employees and sales in the previous year. We also estimate a model that allows for industry and firm-size fixed effects. Specifically, we estimate the following model:

$$\Delta \ln Y_{it} = \beta_1 \Delta \ln M_{jt} + \beta_2 \ln(\text{FirmAge})_{it} + \beta_3 \Delta \ln(\text{Sales})_{it-1} + \text{Ind}_i + \text{Size}_i + u_{it}, \quad (1)$$

where  $i$  is the index for a firm,  $j$  is the index for a prefecture, and  $t$  is the index for a month from February to September 2020.  $\Delta \ln Y_{it}$  is year-to-year growth of sales, employment, and hours worked per employee,  $\Delta \ln M_{jt}$  is the change in mobility relative to January 2020,  $\ln(\text{FirmAge})_{it}$  is the natural logarithm of firm age,  $\Delta \ln(\text{Sales})_{it-1}$  is lagged sales growth in the previous accounting period,  $\text{Ind}_i$  is the 2-digit or 3-digit industry fixed effects, and  $\text{Size}_i$  is the establishment size fixed effect. The mobility measure defined by the prefecture  $\times$  month is matched to the individual firm  $\times$  month level observation. Since the main explanatory variable is measure at the prefecture level, we estimate standard errors that are robust against prefecture-level clustering.

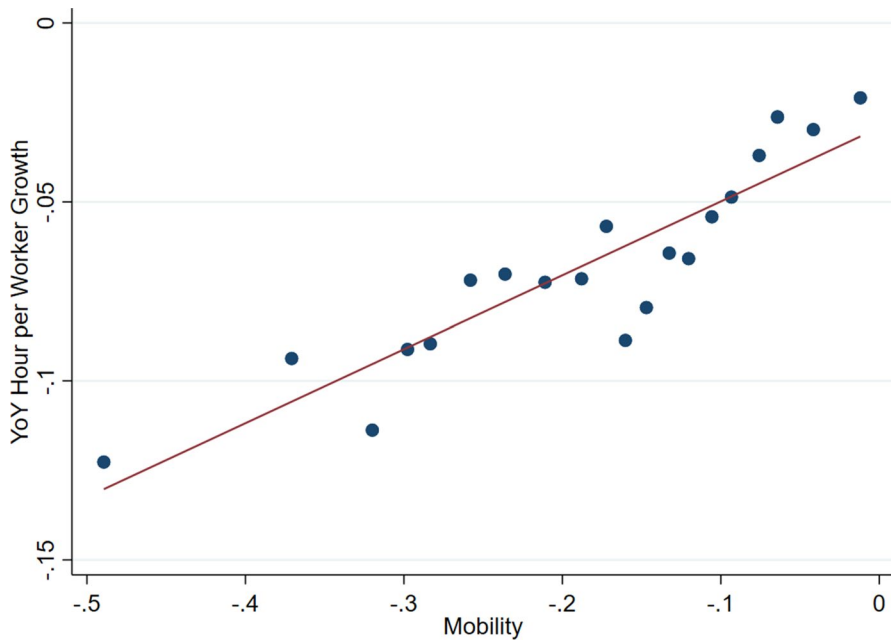
In this estimation, we investigate how a decline in mobility affects firms' performance and how it is mitigated by the WfH arrangements. We acknowledge that the variation in the change in mobility across prefectures is likely to come from the difference in the prevalence of the COVID-19 pandemic, roughly approximated by the new infection cases. In this framework, we take stance that the policy intervention



**Fig. 5** Mobility and YoY employment growth. *Source* Google Community Mobility Report and TSCREPE survey. *Note* Each dot corresponds to the binned average of YoY employment growth relative to the same month of 2019. The bins are created such that each bin includes an equal number of observations. Mobility is the average of mobility to retail and recreation, public transportation, and workplace relative to January 2020

such as the regional state of emergency affects the outcomes through the decrease in mobility, and the parameter  $\beta_1$  is consistently estimated. As a caveat, we acknowledge possibilities that policy intervention directly deteriorates firms' outcome. For example, the issue of state of emergency or the increase in new cases might affect consumers' minds and reduce sales. In such a case, the coefficient for mobility could overestimate the impact of mobility, although we think the quantitative impact of this omitted variable bias is limited, because the effect through the reduction of mobility is a primary pathway how policy interventions affect firms' outcomes.

Table 2 reports the regression result of sales growth relative to the same month of the previous year. Column 1 reports the estimates without including control variables or industry and establishment size fixed effects. The estimated coefficient for mobility at 0.276 implies that a 10% reduction in mobility results in a 2.8% decrease in sales. Column 2 reports the estimated coefficients for the specification that includes the natural logarithm of age of firms and lagged sales growth. Controlling for firm characteristics does not change the estimated coefficient for mobility. Columns 3 and 4 report the estimated coefficients in the specifications that include 2-digit and 3-digit industry dummy variables. Controlling for 2-digit and 3-digit industry fixed effects renders almost identical results, suggesting that the 2-digit industry code sufficiently captures industry heterogeneity relevant for the effect of mobility decline. Given the stable results, we take the specification with 3-digit industry code as our



**Fig. 6** Mobility and YoY hours worked growth. *Sources* Google Community Mobility Report and TSR-CREPE survey. *Note* Each dot corresponds to the binned average of YoY growth of hours worked per an employee relative to the same month of 2019. The bins are created such that each bin includes an equal number of observations. Mobility is the average of mobility to retail and recreation, public transportation, and workplace relative to January 2020

**Table 2** Effect of change in mobility on YoY sales growth

	(1)	(2)	(3)	(4)	(5)
Change in mobility	0.276*** (0.023)	0.276*** (0.022)	0.274*** (0.021)	0.274*** (0.021)	0.276*** (0.021)
ln(Firm Age)		-0.000 (0.007)	0.002 (0.007)	0.005 (0.008)	-0.001 (0.008)
Lagged sales growth		0.001** (0.000)	0.001** (0.000)	0.001*** (0.001)	0.001*** (0.000)
Industry FE	No	No	2-digit	3-digit	3-digit
Establishment size FE	No	No	No	No	Yes
$R^2$	0.01	0.01	0.07	0.12	0.12
$N$	29,056	29,056	29,056	29,056	29,056

*Sources* Google Community Mobility Report and TSR-CREPE survey

*Note* Standard errors robust against prefecture-level clustering are reported in parentheses. \* $p < 0.1$ , \*\* $p < 0.05$ , \*\*\* $p < 0.01$

**Table 3** Effect of change in mobility on YoY employment growth

	(1)	(2)	(3)	(4)	(5)
Change in mobility	0.007 (0.008)	0.006 (0.008)	0.012 (0.008)	0.011 (0.007)	0.013* (0.007)
ln(Firm Age)		0.003 (0.003)	0.004 (0.003)	0.005* (0.003)	0.002 (0.003)
Lagged sales growth		-0.000 (0.000)	-0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
Industry FE	No	No	2-digit	3-digit	3-digit
Establishment size FE	No	No	No	No	Yes
R <sup>2</sup>	0.00	0.00	0.05	0.12	0.13
N	29,056	29,056	29,056	29,056	29,056

Sources Google Community Mobility Report and TSR-CREPE survey

Note Standard errors robust against prefecture-level clustering are reported in parentheses. \* $p < 0.1$ , \*\* $p < 0.05$ , \*\*\* $p < 0.01$

preferred specification. Adding the establishment size dummy does not affect the coefficient for mobility, as shown in Column 5. In sum, a 10% reduction in mobility reduces sales of non-remote firms by 2.8%.<sup>3</sup>

Table 3 reports the regression results of YoY employment growth. The estimated coefficients on mobility are close to zero and not statistically significant across all specifications. Given significant negative impact of mobility on sales, no impact on employment implies that firms did not adjust employment regardless of a drop in sales. There are two potential reasons for this inaction regarding employment. First, the government generously provides firms with subsidies for wage payments to furloughed workers. Starting on April 1st of 2020 up to the present (as of July 2021), the government has subsidized 66% to 100% of wages of furloughed workers using the unemployment insurance account. Second, Japanese employment tends not to react to the business cycle as exemplified in low employment-to-output elasticity (Görg et al., 2018). Policy intervention in conjunction with the nature of Japanese labor market leads to sluggish adjustment of employment.<sup>4</sup>

<sup>3</sup> We examine which prefecture provides the identifying variation of the change in mobility by dropping one prefecture from the analysis sample. Examination of the regression coefficients of Column 5 of Table 2 reveals that the estimated coefficients are stable except for the case when Tokyo prefecture is dropped. This result suggests that the variation of the mobility in Tokyo plays a key role to estimate the impact of mobility on firms' outcomes. This result is not surprising given the decrease in mobility was substantial in Tokyo after onset of the pandemic and a large number of firms in the sample are located in Tokyo. However, note that this exercise is not a simple comparison between firms in Tokyo and other prefectures. Rather, this is virtually a triple difference exercise exploiting the time dimension (before and after onset of the pandemic), cross-sectional dimension (Tokyo vs. other prefectures), and the treatment intensity (WfH firms vs. non-WfH firms).

<sup>4</sup> Lee (2000) estimates the Okun's coefficients among OECD countries. The Okun's coefficient is the regression coefficient of the change in output on the change in unemployment rate, and thus it is the inverse of the sensitivity of unemployment rate to the output. Lee (2000) tries several estimation methods and reports consistently high Okun's coefficient of Japan among OECD countries.

**Table 4** Effect of change in mobility on YoY hours worked growth

	(1)	(2)	(3)	(4)	(5)
Change in mobility	0.207*** (0.015)	0.206*** (0.014)	0.215*** (0.013)	0.210*** (0.013)	0.211*** (0.013)
ln(Firm Age)		0.003 (0.005)	0.007 (0.005)	0.008* (0.005)	0.006 (0.005)
Lagged sales growth		0.001** (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
Industry FE	No	No	2-digit	3-digit	3-digit
Establishment size FE	No	No	No	No	Yes
$R^2$	0.02	0.02	0.08	0.13	0.13
$N$	29,056	29,056	29,056	29,056	29,056

Sources Google Community Mobility Report and TSR-CREPE survey

Note Standard errors robust against prefecture-level clustering are reported in parentheses. \* $p < 0.1$ , \*\* $p < 0.05$ , \*\*\* $p < 0.01$

Table 4 reports the regression results for hours worked per employee. Differently from the results for employment, the decrease in mobility reduces the hours worked per employee. The estimated coefficient implies that a 10% reduction in mobility results in a 2.1% reduction in hours worked. The combination of the inaction of employment and a significant adjustment in hours worked per employee is consistent with what was observed in Japan after the Great Financial Crisis (Hijzen & Martin, 2013). Overall, Japanese firms tend to adjust hours instead of employment to absorb shocks, and we observed this typical reaction to the shock caused by COVID-19.

## 4.2 Heterogeneous effects by firm size and industry

We examine the heterogeneity of the COVID-19 impact on business activities in this subsection. Some previous studies report that the adverse impact of COVID-19 was more concentrated among smaller-scale firms. For instance, Bloom et al. (2021) report a “polarization” of impact; small offline firms experienced a 40% drop in sales whereas the decline was only 10% for large online firms. Based on the presumption that the impact has been concentrated among smaller firms or such firms faced more severe liquidity constraints, several studies have targeted smaller firms in their original surveys.<sup>5</sup> Perhaps for the same reasons, many public programs for supporting businesses in Japan are targeted toward small- and medium-sized enterprises (SMEs). For example, the Japan Finance Corporation’s concessional loan program, the largest program of its kind providing an interest rate subsidy and government

<sup>5</sup> See, for example, Fairlie (2020), Alekseev et al. (2020), Bartik et al. (2020), Buffington et al. (2020), and Kawaguchi et al. (2021).

**Table 5** Heterogeneous impact of mobility by firm size

	(1)	(2)	(3)
	All	Small	Large
<i>Panel A: YoY Sales growth</i>			
Change in mobility	0.276*** (0.021)	0.354*** (0.063)	0.265*** (0.022)
R <sup>2</sup>	0.12	0.18	0.11
<i>Panel B: YoY Employment growth</i>			
Change in mobility	0.013* (0.007)	0.007 (0.024)	0.014* (0.008)
R <sup>2</sup>	0.13	0.13	0.14
<i>Panel C: YoY Hours growth</i>			
Change in mobility	0.211*** (0.013)	0.286*** (0.041)	0.201*** (0.014)
R <sup>2</sup>	0.13	0.20	0.12
Industry FE	3-digit	3-digit	3-digit
Establishment size FE	Yes	Yes	Yes
N	29,056	4296	24,760

Sources Google Community Mobility Report and TSR-CREPE survey

Note Standard errors robust against prefecture-level clustering are reported in parentheses. \* $p < 0.1$ , \*\* $p < 0.05$ , \*\*\* $p < 0.01$

guarantee, is only available for SMEs. In light of the research and policy focus on SMEs, examining heterogeneous impact according to firm size is warranted.

Table 5 reports the effect of mobility change on YoY sales change (Panel A), YoY employment change (Panel B), and YoY average hours change (Panel C). We divide the sample into small and large firms pursuant to the definition in Japan's SME Basic Act.<sup>6</sup> Panel A shows that the impact of mobility change on sales growth does not change substantially with firm size. For instance, a 10% reduction in mobility reduces the sales of small and large firms by 3.5% and 2.7%, respectively; nor do we find any significant variations in the impact of mobility on employment change or average hour change according to firm size. The impact of mobility on employment and average hours worked is not significantly different, except that large firms faced a slightly larger employment drop (although only marginally significant).

Adverse COVID-19 impact may well differ across industries. As a way of examining heterogeneous impact, we divide industries into two categories: industries that require low contact with customers or among employees and those that require high contact. Following Kaplan et al. (2020)'s classification, low-contact industries include construction, manufacturing, wholesale trade, information, finance & insurance, public utilities, and miscellaneous industries; high-contact industry includes

<sup>6</sup> The official cutoff for SME size varies by industry: 50 employees for retail, 100 for wholesale and service industries, and 300 for manufacturing, construction, and other industries.

**Table 6** Heterogeneous impact of mobility by industry

	(1)	(2)	(3)
	All	Low-contact	High-contact
<i>Panel A: YoY sales growth</i>			
Change in mobility	0.276*** (0.021)	0.252*** (0.025)	0.318*** (0.036)
$R^2$	0.12	0.09	0.17
<i>Panel B: YoY employment growth</i>			
Change in mobility	0.013* (0.007)	0.014* (0.008)	0.010 (0.014)
$R^2$	0.13	0.11	0.16
<i>Panel C: YoY hours growth</i>			
Change in mobility	0.211*** (0.013)	0.205*** (0.017)	0.222*** (0.020)
$R^2$	0.13	0.11	0.18
Industry FE	3-digit	3-digit	3-digit
Establishment size FE	Yes	Yes	Yes
$N$	29,056	19,264	9792

*Sources* Google Community Mobility Report and TSR-CREPE survey

*Note* Low-contract industries include construction, manufacturing, wholesale trade, information, finance & insurance, public utilities, and miscellaneous industries; high-contract industry includes transportation, retail trade, accommodation & food services, real estate, and other service industries. Standard errors robust against prefecture-level clustering are reported in parentheses. \* $p < 0.1$ , \*\* $p < 0.05$ , \*\*\* $p < 0.01$

transportation, retail trade, accommodation & food services, real estate, and other service industries.

In Table 6, Panel A reports the impact of mobility on YoY sales growth, Panel B reports the impact on YoY employment growth and Panel C reports the impact on YoY hour growth. Perhaps surprisingly, the impact of mobility on sales, employment, and hours worked do not differ substantially between low- and high-contract industries. Given the magnitude of sizes of estimated standard errors, the estimated coefficients on mobility are not statistically different between the two industry groups.

The analysis in this section documents that the impact of lower human mobility on firms' sales is quite homogeneous across firm size and industry type. As we confirmed in Fig. 2, the decline in mobility was heavily concentrated in urban areas, where infection rates have been higher than in other areas. Therefore the impact of COVID-19 is heterogeneous across regions. Once, however, the regional difference in the mobility is conditioned on, firms uniformly suffer from a decrease in mobility regardless of firm size or industry.



## 5 Does WfH mitigate the negative impact of COVID-19?

The COVID-19 outbreak prompted a swift adoption of WfH arrangements among firms. According to a Cabinet Office survey conducted in the middle of the first declaration of the state of emergency in May 2020, 27.7% of workers worked from home whereas only 10.3% did so in December 2019.<sup>7</sup> The adoption of WfH presumably helped firms to maintain business continuity and cope with the pandemic's adverse impact on sales and employment better than if they had not adopted WfH arrangements. As an important pathway, the adoption of WfH enables firms to procure labor services even when the surge of new cases scares workers off from commuting, or the declaration of the state of emergency disables workers to commute. The adoption of WfH entails a certain digitization of workflow such as abolishing of stamping documents, which is widely used instead of signature in Japanese business. In contrast, without WfH, the decline in mobility to workplace directly decreases the labor supply to the firms, which in turn are forced to contract their operations. The analysis of this subsection aims to quantify the extent to which adoption of WfH arrangements mitigated the pandemic's impact on sales, employment and average hours worked.

We attempt to estimate the following model to quantify how much remote work adoption mitigates the impact of reduced mobility:

$$\Delta \ln Y_{it} = \beta_1 \Delta \ln M_{jt} + \beta_2 \Delta \ln M_{jt} \times R_{it} + \beta_3 R_{it} + \beta_4 \ln(\text{FirmAge})_{it} + \beta_5 \Delta \ln(\text{Sales})_{it-1} + \text{Ind}_i + \text{Size}_i + u_{it}, \quad (2)$$

where  $Y_{it}$  is sales, employment, or average hours worked of the firm  $i$  in month  $t$ ,  $M_{jt}$  is mobility of prefecture  $j$  in month  $t$ ,  $R_{it}$  is some measure of adoption of remote work arrangements of the firm  $i$  in month  $t$ ,  $\text{FirmAge}_{it}$  is years since firm establishment, and  $\Delta \text{Sales}_{it-1}$  is lagged sales growth. As before, the impact of mobility on outcomes is captured by  $\beta_1$ , which is predicted to be positive because the decreased mobility induced by COVID-19 reduces sales, employment, and hours worked. The adoption of a remote work setting is expected to mitigate the impact, thus  $\beta_2$  is expected to be negative. We also include the linear term of  $R_{it}$  to capture the underlying difference in growth between firms that adopt remote work and those that do not.

The challenge in estimating *causal* mitigation effect is the endogenous adoption of remote work. The principal motivation for a firm to adopt a remote work setting is to reduce its workers' risk of infection, therefore the severe infection situation affects remote work setting adoption,  $R_{it}$ . The severe infection situation may well negatively affect firms' sales, even conditioned on mobility, thus it is likely to be included in the idiosyncratic error term  $u_{it}$ . Since this endogenous adoption of a remote work setting is substantial, we would suspect a strong negative correlation between  $R_{it}$  and  $u_{it}$ . This endogeneity biases OLS estimators,  $\hat{\beta}_3$ , downward. Furthermore, the

<sup>7</sup> <https://www5.cao.go.jp/keizai2/wellbeing/covid/index.html> (in Japanese).

endogeneity bias strengthens the co-movement of mobility and sales, thus  $\hat{\beta}_2$  is upward biased. Consequently, standard OLS estimation of the above equation fails to capture the mitigation effect of remote work adoption (i.e.,  $\beta_2 < 0$ ).

We propose two distinct ways to handle the endogeneity of remote work setting adoption. The first is a simple strategy of using the firms' adoption of remote work before the pandemic as a measure of the adoption of remote work under the state of emergency. The second strategy is to exploit heterogeneity in the technical possibility for adopting a WfH setting by industry and firm size.

### 5.1 Heterogeneity by remote work status as of 2019

We first introduce an empirical strategy to exploit variation in the adoption of a WfH setting as of December 2019. A survey question asks whether the firm adopted a remote work arrangement as of December 2019. Since the adoption of remote work arrangements is predetermined before onset of the pandemic, the endogenous adoption of remote work arrangements as a response to rising infection risks is not a concern. As a measure of remote work adoption before onset of the pandemic, we use the responses to a survey question asking if the firm allowed its employees to work from home as of December 2019. As mentioned in the data section, approximately 10% of respondent firms allowed employees to work from home. We estimate (2) using the dummy variable indicating whether the firm adopted WfH as of December 2019 as a proxy for  $R_{it}$ .<sup>8</sup>

Table 7 tabulates the regression results for all industries (Column 1), low-contact industries (Column 2), and high-contact industries (Column 3). In the analysis sample, 13% of firms in low-contact industries and 8% of firms in high-contact industries adopted remote work as of December 2019. Panel A reports the regression results of YoY sales growth. Using all industries as the analysis sample, the results indicate that a 10% reduction in mobility reduces sales by 2.77% among non-adopters of remote work, whereas the impact is mitigated to 1.53% among adopters. Thus, the adoption of remote work before the pandemic mitigates the negative impact by more than half. Notwithstanding the striking mitigation impact, the impact is concentrated only among low-contact industries (Column 2) and we observe no mitigation effect in high-contact industries (Column 3). The finding that the benefit of remote work was concentrated among low-contact industries is sensible because in low-contact industries many jobs can be more easily done from home than in high-contact industries. Firms' experience of adopting remote work before the pandemic helped them to increase the number of workers who work from home and mitigate the negative impact due to the difficulty of working at the office. By contrast, in high-contact

<sup>8</sup> We characterize the source of identification by examining the variation of the dummy variable indicating for the adoption of WfH as of December 2019. Appendix Section 1.1 summarized the analysis. In terms of regions, firms located in urban area are more likely to have adopted WfH than those in rural area. There is substantial difference in the adoption of WfH before the pandemic by industry and firm sizes. To capture the heterogeneity, the model (2) incorporates the industry and firm-size dummy variables.

**Table 7** Heterogeneous impact of mobility by adoption of remote work as of 2019

	(1)	(2)	(3)
	All	Low contact	High contact
<i>Panel A: Sales growth</i>			
Change in mobility	0.277*** (0.021)	0.258*** (0.024)	0.316*** (0.030)
Change in mobility × Remote 2019	- 0.153*** (0.041)	- 0.194*** (0.047)	- 0.024 (0.063)
Remote 2019	- 0.015 (0.012)	- 0.011 (0.013)	- 0.023 (0.020)
$R^2$	0.12	0.09	0.17
<i>Panel B: Employment growth</i>			
Change in mobility	0.012** (0.005)	0.012* (0.006)	0.010* (0.006)
Change in mobility × Remote 2019	0.004 (0.013)	0.008 (0.020)	- 0.010 (0.020)
Remote 2019	- 0.008** (0.004)	- 0.011*** (0.004)	- 0.001 (0.007)
$R^2$	0.13	0.11	0.16
<i>Panel C: Hours growth</i>			
Change in mobility	0.212*** (0.009)	0.207*** (0.013)	0.221*** (0.011)
Change in mobility × remote 2019	- 0.073*** (0.027)	- 0.079*** (0.030)	- 0.046 (0.036)
Remote 2019	- 0.004 (0.007)	- 0.004 (0.010)	- 0.004 (0.011)
$R^2$	0.13	0.11	0.18
Industry FE	3-digit	3-digit	3-digit
Establishment size FE	YES	YES	YES
$N$	29,056	19,264	9792

*Sources* Google Community Mobility Report and TSR-CREPE survey

*Note* Standard errors robust against prefecture-level clustering are reported in parentheses. \* $p < 0.1$ , \*\* $p < 0.05$ , \*\*\* $p < 0.01$

industries, any increase in the list of jobs that can be done from home is presumably limited because a high fraction of jobs require contact with customers or colleagues due to the nature of the industry. Furthermore, in high-contact industries, WfH might have helped to procure labor service but it is less likely to mitigate the negative impact on demand.

Panels B and C of Table 7 report the regression results of YoY changes in employment and YoY changes in average hours worked. Regarding the employment and hours adjustment reported in Panels B and C, the estimated results do not change substantially from the regression results without the remote work adoption reported in Table 6.

In sum, the analysis in this subsection demonstrates that firms that adopted WfH arrangements suffer less from a decrease in mobility. This finding suggests that the adoption of remote work mitigated the negative shock from COVID-19. However, the mitigation effect on sales was found only among firms belonging to industries that require low human contact.

Before proceeding to the next analysis, we address two concerns that could confound our analysis. The first concern is that the firm that adopted WfH before the pandemic is a firm that is cautious about future shocks and resilient to the shocks in general. If this is the case, WfH per se may not be mitigating shocks, but the firm's attitude toward risk may be. To address this plausible concern, we add a dummy variable that indicates the firm had Business Continuation Plan (BCP) before the pandemic, exploiting the survey question asking whether the firm had BCP. The estimation results reported in Appendix Section 2.1 show that having BCP does not affect the outcomes. Reflecting this, the estimated coefficients for the change in mobility and its interaction term with the adoption of WfH in 2019 do not change almost at all. This result suggests that WfH per se is a shock mitigating factor.

The second concern is a possible correlation of the adoption of WfH and the adoption of e-commerce. If the firm that adopted WfH before the pandemic is inclined to adopt e-commerce, the estimated mitigation effect of WfH may have picked up the mitigation effect of relying on e-commerce during the pandemic. Since our survey does not ask the adoption of e-commerce, we address this concern by examining the sensitivity of the estimation results by excluding wholesale and retail sectors that are presumably most intensively dependent on e-commerce. The estimation results reported in Appendix Section 2.2 show that the estimated coefficients do not change in substantive way when low-contact and high-contact industries are pooled. From this result, we argue that the shock mitigating effect of WfH is not driven by the correlation of the adoption of WfH and the adoption of e-commerce.

## 5.2 Adoption of remote work and mitigation of COVID-19 shock

We have demonstrated that adoption of WfH arrangements *before* the pandemic mitigated the negative shock on sales. Did the adoption of WfH arrangements *after* onset of the pandemic mitigate the negative shock too? To answer this question, we move on to the second identification strategy. Answering this question is not trivial because WfH expansion in response to an increase in new infection cases may be premature and not effective. Also, the expansion of WfH arrangements in response to the pandemic causes endogeneity in WfH adoption because the negative shock of COVID-19, not captured by the decline in the mobility, may reduce sales on the one hand, and may encourage adoption of WfH on the other hand.

To address endogeneity in WfH adoption, we exploit WfH penetration variation by industry and firm size because the technical feasibility of adopting remote work differs substantially by industry and firm size. In particular, we estimate the following equation:

$$\begin{aligned} \Delta \ln Y_{it} = & \beta_1 \Delta \ln M_{jt} + \beta_2 \Delta \ln M_{jt} \times \Delta R_{it} + \beta_3 \Delta R_{it} \\ & + \beta_4 R_{it-1} + \beta_5 \ln(\text{FirmAge})_{it} + \beta_6 \Delta \ln(\text{Sales})_{it-1} + \text{Ind}_i + \text{Size}_i + u_{it}, \end{aligned} \tag{3}$$

where  $Y_{it}$  is sales, employment or average hours worked,  $M_{it}$  is mobility,  $R_{it}$  is degree of remote work adoption,  $\text{FirmAge}_{it}$  is years since firm establishment, and  $\Delta \text{Sales}_{it-1}$  is lagged sales growth. In this estimation, we use the fraction of employees engaging in remote work as the measure of  $R_{it}$ . Our survey asks the fractions in December 2019 and May 2020, thus we construct  $\Delta R_{it}$  as the increase in the fraction of employees engaging in remote work. This specification controls for the initial level of remote work by  $R_{it-1}$  to capture preexisting heterogeneity.

To address the endogenous adoption of remote work,  $\Delta R_{it}$ , we construct the Bartik instrumental variable. The Bartik instrumental variable consists of a “shift” part that captures the aggregate level change and a “share” part that captures the difference in exposure to aggregate change. As aggregate change (Shift), we use the change in mobility to the workplace in the prefecture available in the Google community mobility report. The mobility report provides daily mobility change relative to mobility in January 2020, and we calculate the monthly mean for changes in mobility to the workplace in May. The decrease in mobility to the workplace differs substantially across prefectures reflecting the situation of new cases, which is more severe in urban prefectures than in rural prefectures. As the degree of exposure (Share), we use the average remote work adoption rate by industry and firm-size category as of December 2019. The average adoption rate differs substantially across industry and firm size: high at large firms in the information/telecommunication industry, low at small firms in the service industry. The idea of Bartik instrument is to capture the impact of aggregate change felt differently by industry and firm size. Specifically, the Bartik instrumental variable is constructed as:

$$Z_{jt}^{\text{Bartik}} = \Delta M_{jt}^W \cdot S_{it-1}, \tag{4}$$

where  $\Delta M_{jt}^W$  is the change in mobility to the workplace in prefecture  $j$  between January and May, and  $S_{it-1}$  is the mean of the dummy variable if firms adopted WfH arrangements in December 2019 by industry and firm-size group. The identifying assumptions are that the change in mobility to the workplace does not directly affect firms’ sales, employment, or average hours worked (i.e., not correlated with  $u_{it}$  of (2)).

The fundamental source of variation exploited by the Bartik (shift-share) instrumental variable is the variation in initial share (Goldsmith-Pinkham et al., 2020). In our context, if the difference in technical difficulty to adopt remote work setting by industry and firm size is exogenous from the shock induced by COVID-19, we can estimate the causal impact even if the reaction to the shock (overall adoption of remote work setting) is endogenous. Drawing on this idea, we also propose using the mean of the dummy variable if firms adopted WfH arrangements in December 2019 by industry and firm-size group,  $S_{it-1}$ , as an alternative instrumental variable. This approach frees up the shift variable (i.e.,  $\Delta M_{jt}^W$ ) as the estimated parameters and relaxes the assumption on exogeneity of the shift variable.

**Table 8** Heterogeneous impact of mobility by adoption of remote work between December 2019 and May 2020

	(1)	(2)	(3)
	OLS	IV(Bartik)	IV(Share)
<i>Panel A: YoY sales growth</i>			
Change in mobility	0.184*** (0.055)	0.467*** (0.064)	0.442*** (0.052)
Change in mobility × Change in WfH	0.268*** (0.083)	− 0.553** (0.214)	− 0.477** (0.188)
Change in WfH	− 0.017 (0.027)	0.038 (0.116)	0.037 (0.074)
Fraction WfH 2019	− 0.061** (0.029)	0.105 (0.093)	0.091 (0.071)
<i>Panel B: YoY employment growth</i>			
Change in mobility	0.001 (0.005)	− 0.033 (0.052)	− 0.007 (0.025)
Change in mobility × Change in WfH	0.027** (0.013)	0.061 (0.144)	0.043 (0.076)
Change in WfH	− 0.009 (0.007)	− 0.080*** (0.029)	− 0.018 (0.019)
Fraction WfH 2019	− 0.013 (0.008)	− 0.064 (0.045)	− 0.021 (0.022)
<i>Panel C: YoY hours growth</i>			
Change in mobility	0.136*** (0.013)	0.279*** (0.043)	0.251*** (0.031)
Change in mobility × Change in WfH	0.216*** (0.024)	− 0.132 (0.134)	− 0.091 (0.125)
Change in WfH	− 0.018 (0.014)	0.075 (0.060)	0.031 (0.041)
Fraction WfH 2019	− 0.040** (0.015)	0.074* (0.042)	0.039 (0.032)
Industry FE	3-digit	3-digit	3-digit
Establishment size FE	Yes	Yes	Yes
<i>N</i>	29,056	29,056	29,056
Kleibergen–Paap <i>F</i> statistic		31.480	

Sources Google Community Mobility Report and TSR-CREPE survey

Note Standard errors robust against prefecture-level clustering are reported in parentheses. \* $p < 0.1$ , \*\* $p < 0.05$ , \*\*\* $p < 0.01$

Table 8 reports the regression results of YoY sales growth (Panel A), YoY employment growth (Panel B), and YoY average hours growth (Panel C). Column 1 reports OLS estimates, Column 2 reports Bartik IV estimates, and Column 3 reports Share IV estimates. The first stage Kleibergen–Paap *F* statistics reported in Column 2 indicate that the instrumental variables are strongly correlated with

the endogenous variables.<sup>9</sup> Regarding sales growth, the OLS estimate shows that a decrease in mobility decreases sales, and an increase in the fraction of employees engaging in remote work ( $\Delta\text{Frac}$ ) even *amplifies* the negative impact as implied by the positive coefficient for the interaction term. However, we suspect this amplifying effect is due to endogeneity because firms located in an area where the infection is severe are more likely to adopt a remote work setting. The IV estimation results reported in Columns 2 and 3 address this endogeneity concern. These results indicate that a decrease in mobility substantially decreases sales, but an increase in the fraction of employees engaging in remote work helps mitigate the negative impact. More specifically, according to the Bartik IV estimate reported in Column 2, a 10% reduction in mobility decreases sales by 4.7% and this impact is mitigated by 0.6 percentage points (or by 13%) when the firm increases the fraction of employees engaging in remote work by 10 percentage points. For reference, the mean fraction of employees engaging in remote work was 3% in December 2019 and 24% in May 2020. The mitigation effect does not change in a statistically significant way when share IV is used as reported in Column 3. Overall, after correcting for endogeneity bias, we find the adoption of remote work setting mitigates the negative impact of COVID-19 in terms of sales.

Panel B of Table 8 reports the regression results of YoY employment growth and Panel C reports the regression results of YoY average hours growth. As we found previously, we do not find any significant impact of mobility on employment growth as reported in Panel B. The regression result of the growth of average hours worked, reported in Panel C, shows that a reduction in mobility reduces average hours worked as found previously. According to the IV estimates reported in Columns 2 and 3, an increase in the fraction of employees engaging in remote work mitigates the negative impact but the mitigation effect is not precisely estimated and not significantly different from zero.

Similar to Table 7, Table 9 estimates the intensive margin results by industry type for sales growth (Panel A), employment growth (Panel B), and average hours growth (Panel C). As our preferred specification, the Share IV estimates are reported separately for low- or high-contact industries. The result in Panel A shows significantly larger mitigation effect on sales growth by adopting remote work only among low-contact industries, which is consistent with the finding in the previous analysis based on the adoption of WfH in December 2019. The effects on employment and hours worked are consistently insignificant.

To summarize the results of this subsection, we found that adoption of WfH in the middle of the COVID-19 pandemic indeed was useful in mitigating the negative impact of reduced mobility on sales. The estimated mitigation effect is moderate and increasing the ratio of employees engaging in WfH by 10 percentage points mitigates the negative impact by about 13%. This mitigation effect does not propagate to employment or hours worked, at least in statistically significant ways.

<sup>9</sup> The result of the first stage is reported in Appendix 3. All the estimated coefficients are signed as we expected.

**Table 9** Heterogeneous impact of adoption by industry

	(1)	(2)
	Low contact	High contact
<i>Panel A: YoY sales growth</i>		
Change in mobility	0.379*** (0.054)	0.461*** (0.106)
Change in mobility × Change in WfH	- 0.419** (0.200)	- 0.328 (0.363)
Change in WfH	0.000 (0.080)	0.071 (0.145)
Fraction WfH 2019	0.068 (0.069)	0.075 (0.101)
<i>Panel B: YoY employment growth</i>		
Change in mobility	- 0.004 (0.018)	0.028 (0.029)
Change in mobility × Change in WfH	0.033 (0.066)	- 0.090 (0.097)
Change in WfH	- 0.026 (0.025)	- 0.040 (0.030)
Fraction WfH 2019	- 0.023 (0.019)	- 0.015 (0.028)
<i>Panel C: YoY hours growth</i>		
Change in mobility	0.237*** (0.041)	0.242*** (0.067)
Change in mobility × Change in WfH	- 0.096 (0.194)	0.023 (0.220)
Change in WfH	0.007 (0.053)	0.076 (0.066)
Fraction WfH 2019	0.029 (0.038)	0.048 (0.047)
Industry FE	3-digit	3-digit
Establishment size FE	Yes	Yes
<i>N</i>	19,264	9,792

*Sources* Google Community Mobility Report and TSR-CREPE survey

*Note* The Share IV estimates are reported separately for high- and low-contact industries. Standard errors robust against prefecture-level clustering are reported in parentheses. \* $p < 0.1$ , \*\* $p < 0.05$ , \*\*\* $p < 0.01$

### 5.3 Implications for public policies

Finally, this subsection discusses what our results imply for Japan's public finance. As in other countries, Japanese government provides the subsidy for the short-time work (STW), known as the Employment Adjustment Subsidy, to support firms'



efforts to maintain employment under Japan's employment insurance system.<sup>10</sup> The STW allows employers that experience temporary drops in demand to reduce their employees' work hours instead of laying them off. During recessions, hoarding labor allows firms to retain workers with specific skills and avoid costly job separation.

Given an unprecedented scale of the COVID-19 crisis, we have observed a spike in the STW applications. We similarly experienced a significant increase in the STW applications after the 2007–2008 Global Financial Crisis (Kambayashi, 2012), although the number of STW applications has been even larger during the current pandemic. Data from the Ministry of Health, Labour, and Welfare record that the number of total applications has reached about 4.5 million since the outbreak of the pandemic (at the end August 2021), implying that about 68% of firms (6.4 million total establishments based on 2019 Economic Census) applied for the STW program.<sup>11</sup>

The STW program is also at the center of countercyclical fiscal policy actions to the COVID-19 around the globe. European countries with well-established STW schemes, such as France, Italy, Germany, and Belgium, have similarly faced a massive increase in the take-up of the STW subsidy (Giupponi & Landais, 2020a, b). The STW had large positive effects on preserving employment as expected, although the government faced a large fiscal burden. In Germany, the number of employees receiving its STW scheme (*Kurzarbeit*) significantly increased compared with the peak of the Great Recession, which created large pressure on the government budget. Alipour et al. (2021) found that probability that a firm applies for the STW significantly differs by the adoption of telework. In Germany's context, firms with higher WfH potential filed much fewer applications for STW: 1 p.p. increase in the share of teleworkable jobs reduces STW applications by 0.8–2.6 p.p.

In Table 10, we examine whether Japanese firms' adoption of WfH affected the STW application decision in response to the mobility shock due to the pandemic. The CREPE-TSR survey asks whether firms applied for the STW. If they did, it records the month of the STW application and total amount they received from the government.

Columns (1)–(2) estimate the effect of the adoption of WfH in December 2019 on the application decision, while Columns (3)–(6) look at the effect of an increase in the fraction of workers engaging in WfH in May 2020. The models that include an increase in the fraction of workers engaging in WfH (i.e.,  $\Delta$  WfH Fraction) are estimated by IV method using the fraction of establishments that adopted WfH in December 2019 by industry and firm size as the IV. As our preferred specification for the policy simulation, we account for the nonlinearity of the effect of remote works. The cutoff (15%) in Columns (2) and (4) is the median value of the fraction of remote workers before the pandemic. In Columns (5) and (6), we examine how the effect changes when the sample average and the 75 percentiles of the increase in remote workers (20% and 40%, respectively) are used as the cutoff value. All regressions include firm-level fixed effect.

<sup>10</sup> See the institutional details at <https://www.mhlw.go.jp/english/wp/wp-hw7/dl/05e.pdf>.

<sup>11</sup> Source: [https://www.mhlw.go.jp/stf/covid-19/kurashiyashigoto\\_00006.html](https://www.mhlw.go.jp/stf/covid-19/kurashiyashigoto_00006.html).

**Table 10** The application of the subsidy for short-time work (STW)

	(1)	(2)	(3)	(4)	(5)	(6)
	Apply for the Short-time Work (=1)					
Change in mobility	-0.158*** (0.028)	-0.162*** (0.028)	-0.256*** (0.032)	-0.256*** (0.034)	-0.260*** (0.034)	-0.252*** (0.027)
Change in mobility × Fraction WFH 2019	0.180*** (0.039)					
Change in mobility × I[1% ≤ Fraction WFH 2019 ≤ 15%]		0.001 (0.053)				
Change in mobility × I[Fraction WFH 2019 ≥ 16%]		0.086** (0.032)				
Change in mobility × Δ WFH Fraction			0.383*** (0.096)			
Change in mobility × I[Δ WFH Fraction ≥ 16%]				0.208*** (0.063)		
Change in mobility × I[Δ WFH Fraction ≥ 20%]					0.219*** (0.061)	
Change in mobility × I[Δ WFH Fraction ≥ 40%]						0.291*** (0.050)
Specification	OLS	OLS	IV(Share)	IV(Share)	IV(Share)	IV(Share)
Firm FE	YES	YES	YES	YES	YES	YES
N	29,056	29,056	29,056	29,056	29,056	29,056

Sources Google Community Mobility Report and TSR-CREPE survey

Note Standard errors robust against prefecture-level clustering are reported in parentheses. \* $p < 0.1$ , \*\* $p < 0.05$ , \*\*\* $p < 0.01$

In Column (2), we found that Japanese firms with more than 16% of employees working from home are much less likely to file STW applications, and the probability declines by 8.6 p.p., as similarly found by Alipour et al. (2021). Columns (4)–(6) show that firms that increased the fraction of remote workers by more than 16, 20, or 40% after the pandemic tended to file significantly fewer STW applications by 20.8, 21.9, and 29.1 p.p, respectively.

As in many European countries, a surge in STW payments created massive fiscal pressure in Japan. During the Great Recession and in the aftermath of the 2011 Great East Japan Earthquake, Japanese government paid about 1.2 trillion Japanese Yen during the period of 2009–11 from the Employment Insurance Account. For the COVID-19, the government has already paid 4.2 trillion Japanese Yen over a period of one year and five months, from April 2020 to August 2021, and it is much larger than the total subsidies paid during the previous recession. Employees can work regular hours remotely, thereby do not need to work short-time. By adopting WfH, the probability of STW filing is expected to decrease. This implies that the WfH will not only mitigate the negative shock on firms' performance as we found above, but could also decrease the fiscal burden to finance the STW program.

To illustrate the magnitude of the possible fiscal saving, we offer a simple back-of-the-envelope calculation using the estimates in Table 10. The first policy counterfactual is the situation where we assume that all firms adopted WfH prior to the pandemic, and were prepared to cope with the shock ex-ante. Using the estimate in Column (2), we calculate the expected economy-wide fiscal saving based on the following formula:

$$\sum_p \beta \Delta M_p S\bar{T}W_p N_p \quad (5)$$

where  $\beta$  is the estimated mitigation effect of WfH,  $\Delta M_p$  is the largest mobility shock for each prefecture  $p$  during the sample period.  $S\bar{T}W_p$  is the prefecture  $p$ 's median amount of STW subsidy that firms located in the prefecture received by the end of September 2020.  $N_p$  is the number of establishments that did not adopt remote works or ones that adopted but only in a minor scale (i.e., the fraction of remote workers among adopters was less than the median value of 15%) prior to the COVID-19.<sup>12</sup>  $\beta$  is equal to 0.086 from Column (2) to simulate the expected fiscal saving in case all firms adopted WfH for more than 16% of workers before the pandemic. The calculation yields an expected fiscal saving of 2.5% of 1.6 trillion Yen, actual STW subsidies paid to firms that applied for the STW program by the end of September 2020. The saving is even larger at 8.4% if the prefecture average amount, rather than the median, of STW subsidy is used as  $S\bar{T}W_p$  in equation (6). The difference indicates large heterogeneity of STW payments to firms, in particular, a small number of firms receiving a large amount of subsidies.

<sup>12</sup> The number of establishments for each prefecture is from the 2019 Economic Census. We calculate the non-remote working firms based on the fraction of firms adopting WfH in our survey.

The second policy counterfactual is that all firms increased the adoption of WfH in response to the COVID-19 by more than a critical level. We consider three thresholds: 16% (baseline, Column 4), 20% (the sample average of the increase in remote workers, Column 5), and 40% (the 75 percentiles of the increase in remote workers, Column 6).  $\beta$  of each column is used for the calculation in equation (6).  $N_p$  is the number of all establishments located in each prefecture. The calculation yields an expected fiscal saving, ranging from 6.4 to 8.9% of actual STW payments. The fiscal saving is significantly larger, ranging from 21.6 to 30.3%, if we use the prefecture average amount of STW subsidy.

The counterfactual analysis indicates significant saving on the STW payments by mainstreaming WfH in response to the COVID-19. This gives another evidence to support the provision of subsidies for the introduction of WfH.

## 6 Conclusion

The COVID-19 crisis caused sudden and massive disruption of normal operations because physical interaction and people's mobility were significantly curtailed. The state of emergency declared by the government in April through May in 2020, coupled with fear of infection, decreased people's mobility and prevented many workers from commuting to the workplace.

This paper investigates the effect of a decline in people's mobility on firms' activities during the COVID-19 crisis and studies whether adoption of work-from-home (WfH) arrangements by firms helped them accommodate to the shock better than others. We use the original survey conducted from February to September 2020 of several thousand firms on their sales, employment and work hours. We also use information about the implementation of WfH arrangements before and after the onset of the COVID-19 crisis, and quantify the effects of their preparedness for the new work environment by having already employed WfH options, as well as of their adaptation to the crisis by increasing the number of employees working from home.

We find that a decline in mobility during the crisis caused a major fall in firms' sales, but the negative effect was significantly mitigated for firms that had implemented remote work prior to the crisis. More precisely, a 10% reduction in mobility caused a 2.8% drop in sales among firms that had not adopted remote work, but the decline was limited to 1.2% among firms that had implemented such arrangements before the crisis. We also find a major difference in work hours between firms that had and had not previously allowed employees to work remotely, but the effect on employment at the extensive margin was not significant.

Adapting to the crisis environment by increasing the number of remote work employees also helped firms mitigate the negative effect on sales and work hours. To address concerns about endogeneity in OLS estimates, we construct Bartik instrumental variables utilizing data on aggregate changes in mobility across prefectures and average adoption rates of remote work by industry and firm size prior to the crisis. We demonstrate that a 10% decline in mobility decreases sales by 4.7% and this impact is mitigated by 13% when the firm increases the share of employees engaging in remote work by 10%. The mitigation effect of WfH also reduces the

fiscal burden through reducing the probability to apply for Employment Adjustment Subsidy (short-time work subsidy). Our conservative calculation suggests that the government expenditures for the program would have been reduced by 2.5% had all firms adopted a moderate degree of WfH.

Our results reveal large negative effects on sales and work hours of employees triggered by a decline in mobility during the COVID-19 crisis. Our analysis suggests that adopting flexible work arrangements helps mitigate negative effects from such a crisis and that investing in such arrangements regularly would pay off when a sizeable shock like the COVID-19 crisis unexpectedly hits the economy. Furthermore, the benefit of adopting WfH goes beyond the private benefit and reaches to the public benefit by lessening the fiscal burden due to the subsidy for the labor hoarding.

**Supplementary Information** The online version contains supplementary material available at <https://doi.org/10.1007/s10797-022-09749-7>.

**Acknowledgements** The authors thank Nobuko Nagase, Mathias Dolls, the editor and two anonymous referees, participants at the WEAI and the IIPF annual conferences, and IMF colleagues for their useful comments. This research has been conducted under a joint research agreement between the Center for Research and Education in Program Evaluation (CREPE) at The University of Tokyo and Tokyo Shoko Research, LTD (TSR) and it is part of research undertaken at the Research Institute of Economy, Trade and Industry (RIETI). The Japan Science and Technology Agency provided financial support for this research (JPMJRX18H3). The views expressed in this paper are those of the authors and do not reflect the views of the IMF, its Executive Board, or the management.

## References

- Alekseev, G., Amer, S., Gopal, M., Kuchler, T., Schneider, J., Stroebel, J., & Wernerfelt, N. (2020). The effects of COVID-19 on U.S. small businesses: Evidence from owners, managers, and employees. NBER Working Paper No. 27833.
- Alipour, J.-V., Fadinger, H., & Schymik, J. (2021). My home is my castle—The benefits of working from home during a pandemic crisis. *Journal of Public Economics*, 196, 104373.
- Auerbach, A. J., Gorodnichenko, Y., McCrory, P. B., & Murphy, D. (2022). Fiscal multipliers in the COVID19 recession. *Journal of International Money and Finance*, 126, 102669.
- Bachas, P., Brockmeyer, A., & Semelet, C. (2020). *The impact of COVID-19 on formal firms: micro tax data simulations across countries*. Policy Research Working Paper No. 9437, World Bank.
- Bai, J. J., Brynjolfsson, E., Jin, W., Steffen, S., & Wan, C. (2021). *Digital resilience: How work-from-home feasibility affects firm performance*. NBER Working Paper No. 28588.
- Baqee, D., & Farhi, E. (2022). Supply and demand in disaggregated Keynesian economies with an application to the Covid-19 crisis. *American Economic Review*, 112(5), 1397–1436.
- Barrero, J. M., Bloom, N., & Davis, S. J. (2021). *Why working from home will stick*. NBER Working Paper No. 28731.
- Bartik, A. W., Bertrand, M., Cullen, Z., Glaeser, E. L., Luca, M., & Stanton, C. (2020). The impact of COVID-19 on small business outcomes and expectations. *Proceedings of the National Academy of Sciences*, 117(30), 17656–17666.
- Bloom, N., Bunn, P., Mizen, P., Smietanka, P., & Thwaites, G. (2020). *The impact of Covid-19 on productivity*. NBER Working Paper No. 28233.
- Bloom, N., Fletcher, R. S., & Yeh, E. (2021). *The impact of Covid-19 on US firms*. NBER Working Paper No. 28314.
- Brodeur, A., Gray, D., Islam, A., & Bhuiyan, S. (2021). A literature review of the economics of COVID-19. *Journal of Economic Surveys*, 35(4), 1007–1044.

- Buffington, C., Dennis, C., Dinlersoz, E., Foster, L., & Klimek, S. (2020). *Measuring the effect of Covid-19 on US small businesses: The small business pulse survey*. Working Papers 20–16, Center for Economic Studies, U.S. Census Bureau.
- Carvalho, V. M., Nirei, M., Saito, Y. U., & Tahbaz-Salehi, A. (2021). Supply chain disruptions: Evidence from the Great East Japan Earthquake. *Quarterly Journal of Economics*, 136(2), 1255–1321.
- Chernozhukov, V., Kasahara, H., & Schrimpf, P. (2020). Causal impact of masks, policies, behavior on early Covid-19 pandemic in the US. *Journal of Econometrics*, 220(1), 23–62.
- Coibion, O., Gorodnichenko, Y., & Weber, M. (2020). *The cost of the Covid-19 crisis: Lockdowns, macroeconomic expectations, and consumer spending*. NBER Working Paper No. 27141.
- Davis, M. A., Ghent, A. C., & Gregory, J. M. (2021). *The work-from-home technology boon and its consequences*. NBER Working Paper No. 28461.
- Drechsel, T., & Kalemli-Ozcan, S. (2020). *Are standard macro and credit policies enough to deal with the economic fallout from a global pandemic? a proposal for a negative SME tax* (p. 23). The University of Maryland.
- Fairlie, R. (2020). The impact of COVID-19 on small business owners: Evidence from the first three-months after widespread social-distancing restrictions. *Journal of Economics & Management Strategy*, 29(4), 727–740.
- Fairlie, R., & Fossen, F. M. (2022). The early impacts of the Covid-19 pandemic on business sales. *Small Business Economics*, 58, 1853–1864.
- Ganong, P., Noel, P., & Vavra, J. (2020). US unemployment insurance replacement rates during the pandemic. *Journal of Public Economics*, 191, 104273.
- Giupponi, G., & Landais, C. (2020a). Building effective short-time work schemes for the COVID-19 crisis. In *VoxEU*.
- Giupponi, G., & Landais, C. (2020b). *Subsidizing labor hoarding in recessions: The employment and welfare effects of short time work*. London School of Economics.
- Goldsmith-Pinkham, P., Sorkin, I., & Swift, H. (2020). Bartik instruments: What, when, why, and how. *American Economic Review*, 110(8), 2586–2624.
- Görg, H., Hornok, C., Montagna, C., & Onwordi, G. (2018). *Employment to output elasticities & reforms towards flexicurity: Evidence from OECD countries*. IZA Discussion Paper No. 12004.
- Gourinchas, P.-O., Kalemli-Ozcan, S., Penciakova, V., & Sander, N. (2020). *Covid-19 and SME failures*. NBER Working Paper No. 27877.
- Guerrieri, V., Lorenzoni, G., Straub, L., & Werning, I. (2022). Macroeconomic implications of COVID-19: Can negative supply shocks cause demand shortages? *American Economic Review*, 112(5), 1437–1474.
- Hamada, K., & Kurosaka, Y. (1984). The relationship between production and unemployment in Japan: Okun's law in comparative perspective. *European Economic Review*, 25(1), 71–94.
- Hijzen, A., & Martin, S. (2013). The role of short-time work schemes during the global financial crisis and early recovery: A cross-country analysis. *IZA Journal of Labor Policy*, 2(1), 1–31.
- Hoshi, T., Kawaguchi, D., & Ueda, K. (2022). Zombies, again? The Covid-19 business support programs in Japan. *Journal of Banking & Finance* 106421.
- Hsiang, S., Allen, D., Annan-Phan, S., Bell, K., Bolliger, I., Chong, T., Druckenmiller, H., Huang, L. Y., Hultgren, A., & Krasovich, E. (2020). The effect of large-scale anti-contagion policies on the COVID-19 pandemic. *Nature*, 584(7820), 262–267.
- Kambayashi, R. (2012). *Mismatch and labor market institution: The role of short-time work subsidy during the recent crisis (in Japanese)*. <https://www.jil.go.jp/institute/zasshi/backnumber/2012/09/pdf/034-049.pdf>.
- Kaplan, G., Moll, B., & Violante, G. L. (2020). *The great lockdown and the big stimulus: Tracing the pandemic possibility frontier for the U.S.* NBER Working Paper No. 27794.
- Kawaguchi, K., Kodama, N., & Tanaka, M. (2021). Small business under the COVID-19 crisis: Expected short- and medium-run effects of anti-contagion and economic policies. *Journal of the Japanese and International Economies*, 61, 101138.
- Kim, O. S., Parker, J. A., & Schoar, A. (2020). *Revenue collapses and the consumption of small business owners in the early stages of the Covid-19 pandemic*. NBER Working Paper No. 28151.
- Landais, C., Saez, E., & Zucman, G. (2020). A progressive European wealth tax to fund the European COVID response. In *VoxEU*.
- Lee, J. (2000). The robustness of Okun's law: Evidence from OECD countries. *Journal of Macroeconomics*, 22(2), 331–356.

- Looze, J., & Desai, S. (2020). *How has COVID-19 changed challenges for entrepreneurs: Implications for entrepreneurship support*. Available at SSRN: <https://ssrn.com/abstract=3778849>.
- Miyakawa, D., Oikawa, K., & Ueda, K. (2020). Firm exit during the Covid-19 pandemic: Evidence from Japan. *Journal of the Japanese and International Economies*, 59, 101118.
- Morikawa, M. (2022). Work-from-home productivity during the COVID-19 pandemic: Evidence from Japan. *Economic Inquiry*, 60(2), 508–527.
- Ohanian, L. E., & Raffo, A. (2012). Aggregate hours worked in OECD countries: New measurement and implications for business cycles. *Journal of Monetary Economics*, 59(1), 40–56.
- Okubo, T. (2020). Spread of COVID-19 and telework: Evidence from Japan. *Covid Economics*, 32, 1–25.
- Papanikolaou, D., & Schmidt, L. D. (2022). Working remotely and the supply-side impact of Covid-19. *The Review of Asset Pricing Studies*, 12(1), 53–111.
- Zanin, L. (2014). On Okun's law in OECD countries: An analysis by age cohorts. *Economics Letters*, 125(2), 243–248.
- Zhang, T., Gerlowski, D., & Acs, Z. (2021). Working from home: Small business performance and the COVID-19 pandemic. *Small Business Economics*, 58, 1–26.

**Publisher's Note** Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

Springer Nature or its licensor holds exclusive rights to this article under a publishing agreement with the author(s) or other rightsholder(s); author self-archiving of the accepted manuscript version of this article is solely governed by the terms of such publishing agreement and applicable law.