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The Impact of COVID-19 on Japanese Firms: Mobility and Resilience via Remote Work*

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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 crisis environment by increasing the number of employees working from home is also found to moderately reduce the negative impact on sales and work hours.

Keywords: COVID-19, Work from Home (WfH), Remote work, Firm sales, Employment, Hours worked, Japanese economy.

JEL classification: J5, J6.

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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. 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 samples, sales declined by an average of 2.8% in response to a 10% drop in peoples' mobility compared to the same month of the previous year. The decline, however, was much lower among firms that had previously implemented some remote work prior to the crisis and the negative impact on sales was also mitigated by 55%. We also find that firms which increased the number of employees working from home after the crisis were able to reduce the negative impact, though quantitative effect was moderate.

Similar differences were found in the effect on employment at the intensive margin, while there was little impact at the extensive margin. On average, work hours declined by 2.1% in response to a 10% decline in mobility and the effect was reduced by 35% if firms had adopted WfH arrangements prior to onset of the crisis. 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. We also find that the mitigation effect of WfH was prevalent among firms in low-contact sectors, where the degree of social interaction with customers or employees is relatively low.

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, Section 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. (2020). 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 (Bloom et al. (2021); Bartik et al. (2020a); 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 (Bloom et al. (2021); Fairlie (2021); Alekseev et al. (2020)). 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 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 and Kalemli-Ozcan (2020)), short-time work schemes (Giupponi and Landais (2020)), unemployment insurance (Ganong et al. (2020)), and fiscal stimulus (Auerbach et al. (2020)). With lockdown restrictions, broad-based demand stimulus is much less effective in increasing aggregate demand unlike ordinary recessions (Baqaee and Farhi (2020); Guerrieri et al. (2020)).

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 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. (2020); Bartik et al. (2020b)).

In Japan, Morikawa (2021) 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 adopted to WfH arrangements after 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 (2020) 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* COVID-19 has mitigated the scarring effect on firms' sales, employment, and work hours.

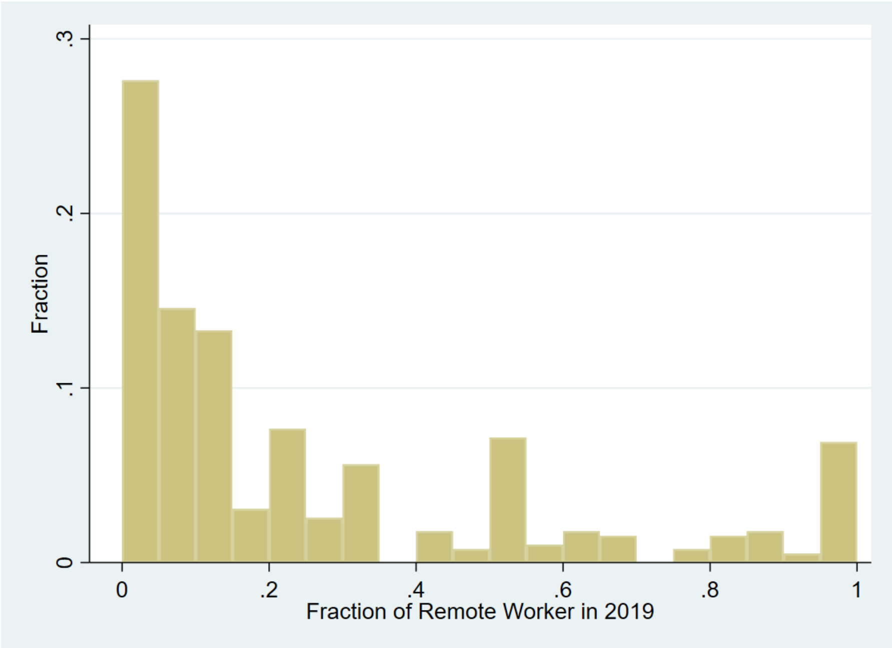
3 Data

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 received responses from 5,695 firms. Of these, 4,093 firms are matched to the TSR credit file. Dropping those with missing values that are necessary for the analysis reduces the number of firms to 3,632 firms. The credit file includes more detailed information on firms, including year of establishment, head quarter 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.[1] Figure 1 illustrates the distribution of the fraction of workers who worked remotely among the firms that had already adopted remote work environment prior to the pandemic.

[1]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.

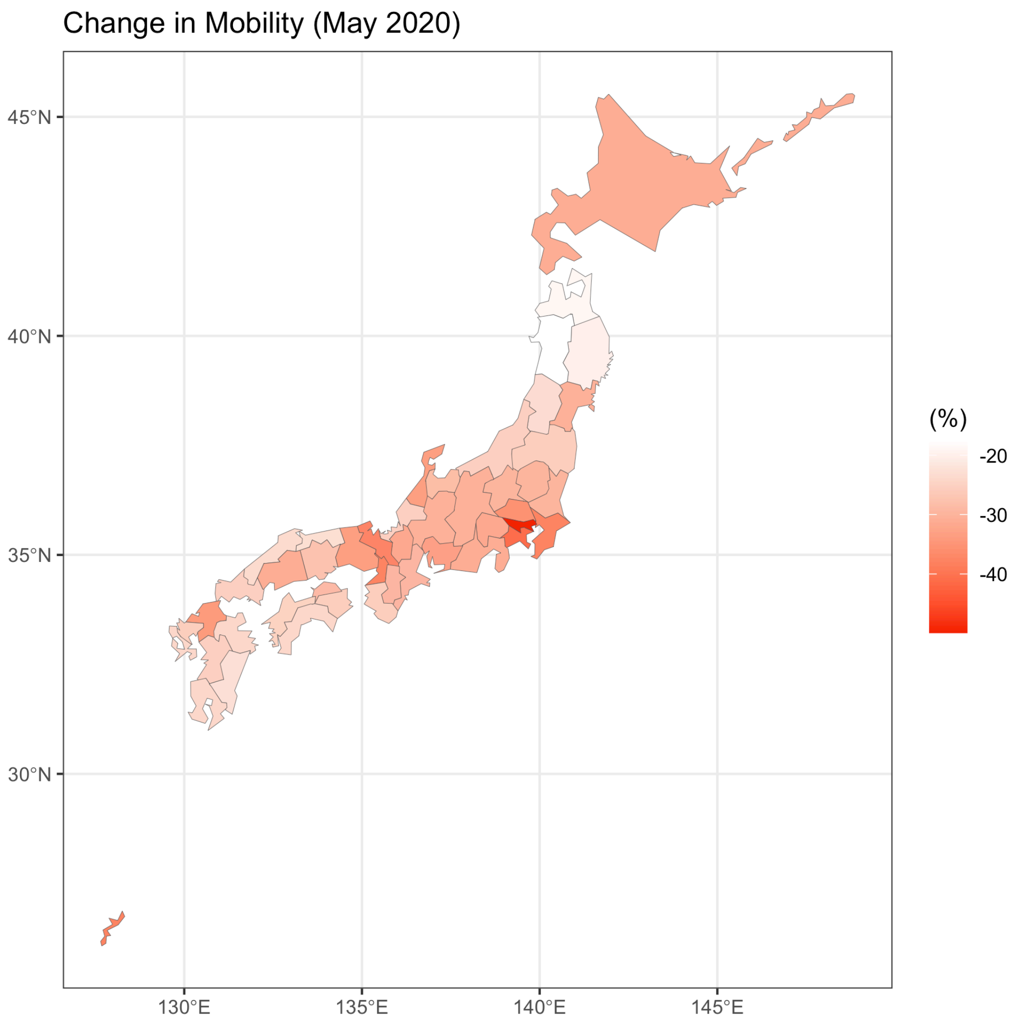
Figure 1: Fraction of Remote Workers among Adoptors in 2019



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.

As a proxy of the COVID-19 shock, we use people 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, Figure 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 in urban prefectures such as Tokyo (40-50%) and Osaka prefectures (20-30%), demonstrating that the pandemic was an urban phenomena.

Figure 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.

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.

Table 1: Descriptive Statistics for Introduction of Remote Work in 2019

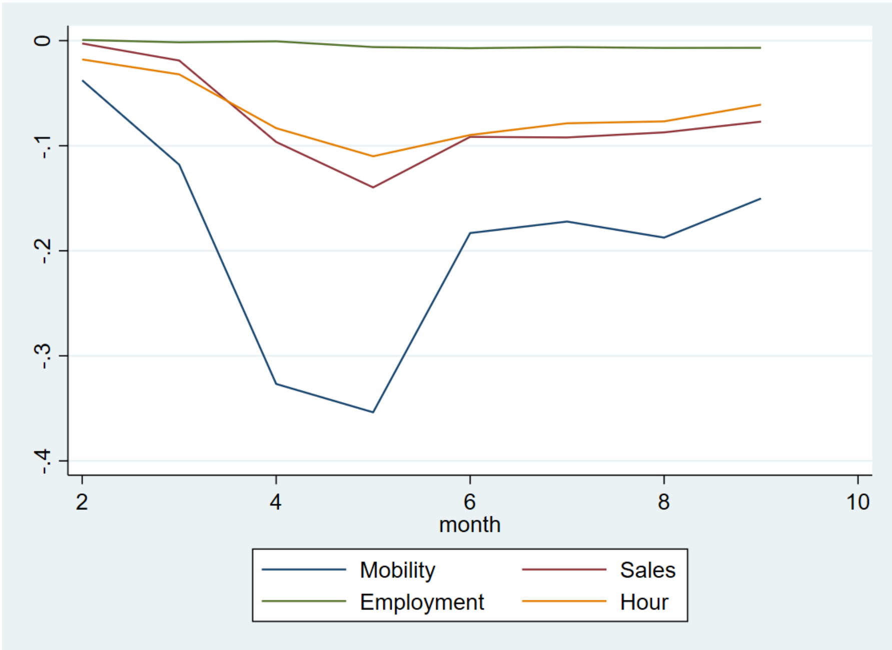
WfH 2019	No	Yes	Total
Mobility	-0.187	-0.224	-0.191
	(0.118)	(0.130)	(0.120)
Sales growth	-0.075	-0.078	-0.076
	(0.314)	(0.332)	(0.316)
Emp growth	-0.004	-0.005	-0.004
	(0.103)	(0.118)	(0.105)
Hour growth	-0.069	-0.067	-0.069
	(0.187)	(0.190)	(0.187)
Firm age	44.16	36.64	43.35
	(20.41)	(22.92)	(20.82)
Lagged sales growth	0.111	0.103	0.110
	(2.497)	(0.599)	(2.367)
N	25928	3128	29056

Source: Google Community Mobility Report and TSR-CREPE survey
Note: Standard deviations are reported in parentheses.

Time series of mobility, YoY sales, hours and employment growth between February and September of 2020 are reported in Figure 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, Figure 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, Figure 5 show 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 Figure 6 show a positive correlation, implying that reduction in peoples' mobility results in a reduction in hours worked. The contrast between employment adjustment and hours adjustment is consistent with the consensus that Japanese firms tend to adjust hours worked and avoid firing existing workers.

Figure 3: Mobility, YoY Growth of Sales, Employment and Hours Worked



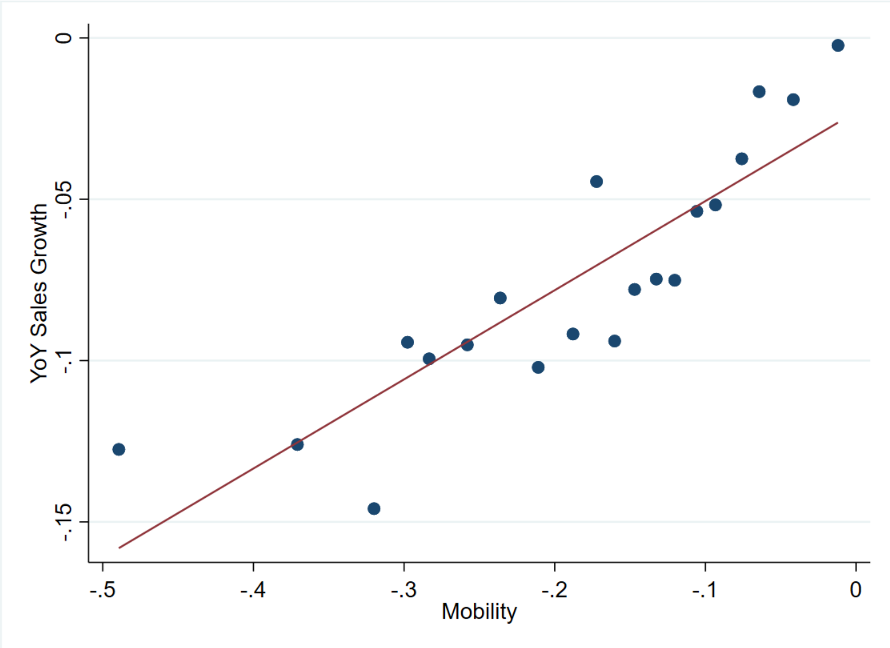
Source: Google Community Mobility Report and TSR-CREPE survey
Note: Mobility is the average of mobility to retail and recreation, public transportation, and work place relative to January 2020. Sales, employment, and hours worked are year-to-year growth relative to the same month of 2019.

4 Effects of People Mobility on Firms' Performance

4.1 Overall Impact

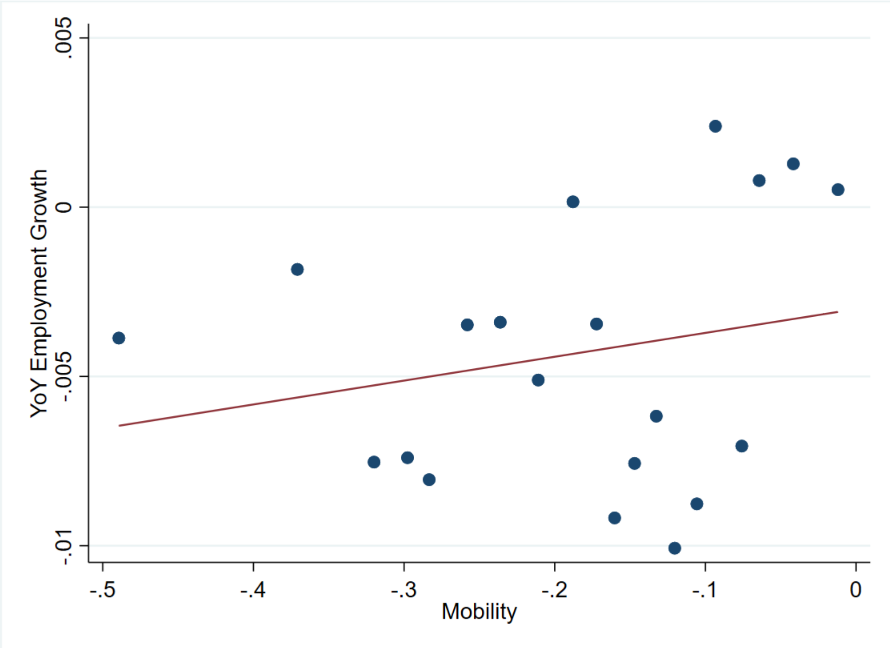
The scatter diagrams in Figures 4, 5 and 6 indicate that mobility and YoY sales or hours worked are positively correlated, suggesting that a decrease in mobility results in a decrease in sales or hours worked per employee. However, one may be concerned that the effect of COVID-19 is heterogeneous across 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.

Figure 4: Mobility and YoY Sales Growth



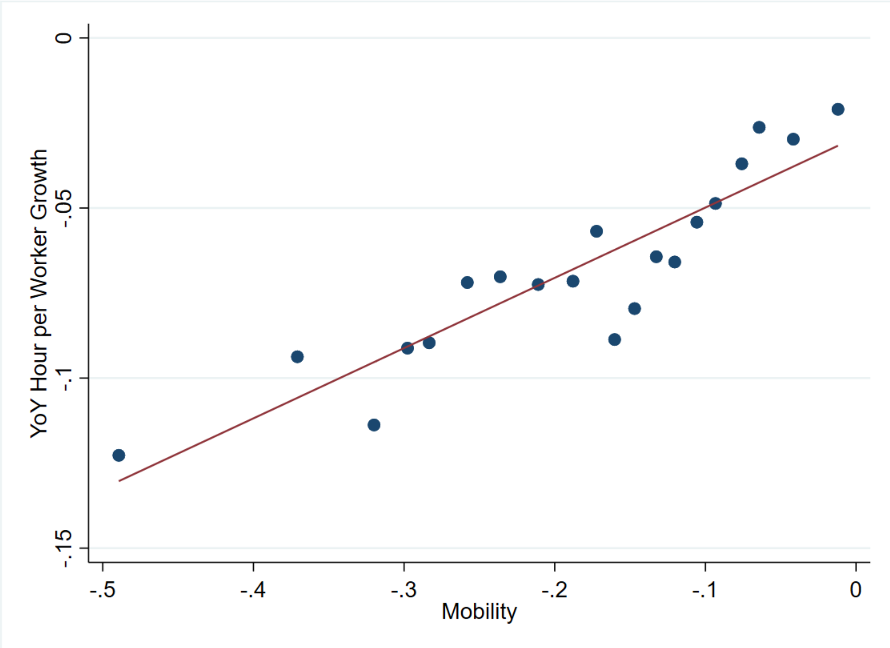
Source: Google Community Mobility Report and TSR-CREPE survey
Note: Each dot corresponds to the binned average of YoY sales growth relative to the same month of 2019. The bins are created by dividing the mobility measure into 20 equal intervals for firms adopting remote work and those that do not. Mobility is the average of mobility to retail and recreation, public transportation, and work place relative to January 2020.

Figure 5: Mobility and YoY Employment Growth



Source: Google Community Mobility Report and TSR-CREPE survey
Note: Each dot corresponds to the binned average of YoY employment growth relative to the same month of 2019. The bins are created by dividing the mobility measure into 20 equal intervals for firms adopting remote work and those that do not. Mobility is the average of mobility to retail and recreation, public transportation, and work place relative to January 2020.

Figure 6: Mobility and YoY Hours Worked Growth



Source: 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 by dividing the mobility measure into 20 equal intervals for firms adopting remote work and those that do not. Mobility is the average of mobility to retail and recreation, public transportation, and work place relative to January 2020.

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 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:

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

where i is the index for a firm, j is the index for a prefecture, 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, $\ln FirmAge_{it-1}$ is the natural logarithm of firm age, $\Delta \ln(Sales)_{it-1}$ is lagged sales growth in the previous accounting period, and Ind_i is the 2-digit or 3-digit industry fixed effects. 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.

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 size variables or industry fixed effects. The estimated coefficient for mobility at 0.276 implies that a 10 percent reduction in mobility results in a 2.8% decrease ine 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 size 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 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%.

Table 2: Effect of Mobility on YoY Sales Growth

	(1)	(2)	(3)	(4)	(5)
Mobility	0.276***	0.276***	0.274***	0.274***	0.276***
	(0.023)	(0.022)	(0.021)	(0.021)	(0.021)
ln(Firm age)		-0.000	0.002	0.005	-0.001
		(0.007)	(0.007)	(0.008)	(0.008)
Lagged sales growth		0.001**	0.001**	0.001***	0.001***
		(0.000)	(0.000)	(0.001)	(0.000)
Industry FE	No	No	2-digit	3-digit	3-digit
Est Size FE	No	No	No	No	Yes
R2	0.01	0.01	0.07	0.12	0.12
N	29,056	29,056	29,056	29,056	29,056

Source: 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 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 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.

Table 3: Effect of Mobility on YoY Employment Growth

	(1)	(2)	(3)	(4)	(5)
Mobility	0.007	0.006	0.012	0.011	0.013*
	(0.008)	(0.008)	(0.008)	(0.007)	(0.007)
ln(Firm age)		0.003	0.004	0.005*	0.002
		(0.003)	(0.003)	(0.003)	(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
Est Size FE	No	No	No	No	Yes
R2	0.00	0.00	0.05	0.12	0.13
N	29,056	29,056	29,056	29,056	29,056

Source: 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 and 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.

Table 4: Effect of Mobility on YoY Hours Worked Growth

	(1)	(2)	(3)	(4)	(5)
Mobility	0.207***	0.206***	0.215***	0.210***	0.211***
	(0.015)	(0.014)	(0.013)	(0.013)	(0.013)
ln(Firm age)		0.003	0.007	0.008*	0.006
		(0.005)	(0.005)	(0.005)	(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
Est Size FE	No	No	No	No	Yes
R2	0.02	0.02	0.08	0.13	0.13
N	29,056	29,056	29,056	29,056	29,056

Source: Google Community Mobility Report and TSR-CREPE survey
Note: Standard errors robust against prefecture-level clustering are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

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) reports 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.[2] Perhaps for the same reasons, many public programs for supporting businesses in Japan are targeted toward small- and medium-size 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 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.

[2]See, for example, Fairlie (2021), Alekseev et al. (2020), Bartik et al. (2020a), Buffington et al. (2020) and Kawaguchi et al. (2021).

Table 5: Heterogeneous Impact of Mobility by Firm Size

	(1) All	(2) Small	(3) Large
Panel A			
Sales Growth	0.276***	0.354***	0.265***
	(0.021)	(0.063)	(0.022)
R2	0.12	0.18	0.11
Panel B			
Employment Growth	0.013*	0.007	0.014*
	(0.007)	(0.024)	(0.008)
R2	0.13	0.13	0.14
Panel C			
Hours Growth	0.211***	0.286***	0.201***
	(0.013)	(0.041)	(0.014)
R2	0.13	0.20	0.12
Industry FE	3-digit	3-digit	3-digit
Est Size FE	Yes	Yes	Yes
N	29,056	4,296	24,760

Source: 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 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.[3] 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).

[3]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 by Industry

	(1) All	(2) Low-contact	(3) High-contact
Panel A			
Sales Growth	0.276***	0.252***	0.318***
	(0.021)	(0.025)	(0.036)
R2	0.12	0.09	0.17
Panel B			
Employment Growth	0.013*	0.014*	0.010
	(0.007)	(0.008)	(0.014)
R2	0.13	0.11	0.16
Panel C			
Hours Growth	0.211***	0.205***	0.222***
	(0.013)	(0.017)	(0.020)
R2	0.13	0.11	0.18
Industry FE	3-digit	3-digit	3-digit
Est Size FE	Yes	Yes	Yes
N	29,056	19,264	9,792

Source: 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. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

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-contract industry includes 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 Figure 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 Officet 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.[4] 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. 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:

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

where Y is sales, employment, or average hours worked, M is mobility, R is some measure of adoption of remote work arrangements, $FirmAge$ is years since firm establishment, and $\Delta Sales_{it-1}$ is lagged sales growth. As before, the impact of mobility on outcomes is captured by β_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 β_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

[4] https://www5.cao.go.jp/keizai2/manzoku/pdf/result2_covid.pdf (in Japanese)

biases OLS estimators, both $\hat{\beta}_2$ and $\hat{\beta}_3$, upward. 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}.

Table 7: Heterogeneous Impact by Adoption of Remote Work as of 2019

	(1) All	(2) Low-contact	(3) High-contact
Panel A: Sales Growth			
Mobility	0.276***	0.256***	0.313***
	(0.021)	(0.025)	(0.036)
Mobility × Remote 2019	-0.153**	-0.194***	-0.027
	(0.061)	(0.072)	(0.113)
Remote 2019	-0.011	-0.008	-0.019
	(0.013)	(0.016)	(0.023)
R2	0.12	0.09	0.17
Panel B: Employment Growth			
Mobility	0.011	0.011	0.009
	(0.007)	(0.008)	(0.014)
Mobility × Remote 2019	0.004	0.008	-0.010
	(0.023)	(0.029)	(0.034)
Remote 2019	-0.006	-0.009	0.002
	(0.005)	(0.007)	(0.006)
R2	0.13	0.11	0.16
Panel C: Hours Growth			
Mobility	0.211***	0.206***	0.220***
	(0.013)	(0.017)	(0.020)
Mobility × Remote 2019	-0.073*	-0.079	-0.049
	(0.038)	(0.048)	(0.054)
Remote 2019	-0.002	-0.002	-0.002
	(0.008)	(0.010)	(0.012)
R2	0.13	0.11	0.18
Industry FE	Yes	Yes	Yes
Est Size FE	Yes	Yes	Yes
N	29,056	19,264	9,792

Source: 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 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 2.76% among non-adoptors of remote work, whereas the impact is mitigated to 1.53% among adoptors. 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 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.

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.

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 setting 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-size-region because the technical feasibility of adopting remote work differs substantially by industry, firm size, and the spread of COVID-19 in a region. In particular, we estimate the following equation:

$$\Delta \ln Y_{it} = \beta_1 \Delta \ln M_{jt} + \beta_2 \Delta \ln M_{jt} \times \Delta R_{it} + \beta_3 \Delta R_{it} \\ + \beta_4 R_{it-1} + + \beta_5 \ln(FirmAge)_{it} + \beta_6 \Delta \ln(Sales)_{it-1} + Ind_i + Size_i + u_{it}, \quad (3)$$

where Y_{it} is sales, employment or average hours worked, M_{it} is mobility, R_{it} is degree of remote work adoption, $FirmAge$ is years since firm establishment, and $\Delta Sales_{it-1}$ 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 ΔR_{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, ΔR_{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:

$$Z_{jt}^{Bartik} = \Delta M_{jt}^{W} \cdot S_{it-1}, \quad (4)$$

where ΔM_{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 an alternative instrument variable that is:

$$Z_{jt}^{Share} = \sum_{p=1}^{J} \gamma_p \mathbb{1}(p = j) \cdot S_{it-1}, \tag{5}$$

where p is the index for prefecture, $\mathbb{1}$ is the indicator function that takes one if the argument is true. This approach frees up the shift variable (i.e. ΔM_{jt}^{W}) as the estimated parameters γ_p, $p = \{1, 2, ..., J\}$ and relaxes the assumption on exogeneity of the shift variable.

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. 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 ($\Delta Frac$) 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.

Table 8: Heterogeneous Impact by Adoption of Remote Work between December 2019 and May 2020

	(1) OLS	(2) IV(Bartik)	(3) IV(Share)
Panel A: Sales Growth			
Mobility	0.184***	0.467***	0.442***
	(0.055)	(0.064)	(0.052)
Mov $\times \Delta$ Frac	0.268***	-0.553**	-0.477**
	(0.083)	(0.214)	(0.188)
Δ Frac	-0.017	0.038	0.037
	(0.027)	(0.116)	(0.074)
Fraction Remote 2019	-0.061**	0.105	0.091
	(0.029)	(0.093)	(0.071)
Panel B: Employment Growth			
Mobility	0.001	-0.033	-0.007
	(0.005)	(0.052)	(0.025)
Mov $\times \Delta$ Frac	0.027**	0.061	0.043
	(0.013)	(0.144)	(0.076)
Δ Frac	-0.009	-0.080***	-0.018
	(0.007)	(0.029)	(0.019)
Fraction Remote 2019	-0.013	-0.064	-0.021
	(0.008)	(0.045)	(0.022)
Panel C: Hours Growth			
Mobility	0.136***	0.279***	0.251***
	(0.013)	(0.043)	(0.031)
Mov $\times \Delta$ Frac	0.216***	-0.132	-0.091
	(0.024)	(0.134)	(0.125)
Δ Frac	-0.018	0.075	0.031
	(0.014)	(0.060)	(0.041)
Fraction Remote 2019	-0.040**	0.074*	0.039
	(0.015)	(0.042)	(0.032)
Industry FE	3-digit	3-digit	3-digit
Est Size FE	Yes	Yes	Yes
N	29,056	29,056	29,056

Source: Google Community Mobility Report and TSR-CREPE survey

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

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 at the intensive margin, which is consistent with the finding at the extensive margin. The effects on employment and hours worked are consistently insignificant.

Table 9: Heterogeneous Impact of Adoption by Industry

	(1) Low-contact	(2) High-contact
Panel A: Sales Growth		
Mobility	0.379***	0.461***
	(0.054)	(0.106)
Mov $\times\Delta$ Frac	-0.419**	-0.328
	(0.200)	(0.363)
Δ Frac	0.000	0.071
	(0.080)	(0.145)
Fraction Remote 2019	0.068	0.075
	(0.069)	(0.101)
Panel B: Employment Growth		
Mobility	-0.004	0.028
	(0.018)	(0.029)
Mov $\times\Delta$ Frac	0.033	-0.090
	(0.066)	(0.097)
Δ Frac	-0.026	-0.040
	(0.025)	(0.030)
Fraction Remote 2019	-0.023	-0.015
	(0.019)	(0.028)
Panel C: Hours Growth		
Mobility	0.237***	0.242***
	(0.041)	(0.067)
Mov $\times\Delta$ Frac	-0.096	0.023
	(0.194)	(0.220)
Δ Frac	0.007	0.076
	(0.053)	(0.066)
Fraction Remote 2019	0.029	0.048
	(0.038)	(0.047)
Industry FE	3-digit	3-digit
Est Size FE	Yes	Yes
N	19,264	9,792

Source: 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 firm-level clustering are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

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.

6 Conclusion

The COVID-19 crisis caused sudden and massive disruption of normal operations because physical interaction and people's mobility was 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 helps 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 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 percent 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%.

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.

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