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MORIKAWA, Masayuki
RIETI

Research Institute of Economy, Trade & Industry, IAA

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Productivity of Working from Home during the COVID-19 Pandemic: Evidence from an Employee Survey*

Masayuki Morikawa (RIETI, Hitotsubashi University)

Abstract

Using data from an original survey conducted in June 2020, this study examines the prevalence, frequency, and productivity of working from home (WFH) practices during the COVID-19 pandemic in Japan. The results reveal that the percentage of employees who practiced WFH was approximately 32%. Labor input attributed to WFH arrangements accounted for approximately 19% of total working hours. Highly educated, high-wage, white-collar employees who work in large firms in metropolitan areas tended to practice WFH. The mean WFH productivity relative to working at the usual workplace was about 60% to 70%, and it was lower for employees who started WFH practices only after the spread of the COVID-19 pandemic. Meanwhile, highly educated, and high-wage employees, as well as long-distance commuters, tended to exhibit a relatively small reduction in WFH productivity.

Keywords: COVID-19, social distancing, working from home, productivity
JEL Classification: I12, J22, J24, R41

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Productivity of Working from Home during the COVID-19 Pandemic: Evidence from an Employee Survey

1. Introduction

Following the spread of the COVID-19 pandemic, the practice of working from home (WFH) has been increasing rapidly. During normal times, the percentage of workers participating in WFH arrangements was approximately 10% or less in major advanced countries, but the number of workers who frequently or occasionally conduct their jobs at home has increased suddenly beginning in March 2020 (e.g., Adams *et al*., 2020; Bartik *et al*., 2020; Bick *et al*., 2020; Brynjolfsson *et al*., 2020; Buchheim *et al*., 2020; Okubo, 2020). In Japan, although teleworking, including WFH, has been promoted by the government as part of the "Work-Style Reform" in recent years, the share of WFH workers was only about 5% in 2017 (Morikawa, 2018). However, a large number of firms introduced WFH practices to prevent COVID-19 infection. Thus, the number of WFH workers increased further following the declaration of a state of emergency by the Japanese government in April.

Epidemiology models extended by augmenting economic behavior have been developed, and simulation analyses on the effects of social distancing measures, such as a shelter-in-place order, mandatory shutdown of service industries, and school closing to suppress COVID-19 infections have been conducted in many countries (e.g., Atkeson, 2020; Eichenbaum *et al*., 2020; Jones *et al*., 2020).[1] These studies generally indicate that stringent social distancing policies are effective in mitigating the spread (i.e., "flattening the curve") of the pandemic, but they have large negative impacts on economic activity, meaning that there is a trade-off, at least in the short-run, between the public's health and the severity of the recession. Some of the simulation models explicitly take into account WFH practices (e.g., Akbarpour *et al*., 2020; Aum *et al*., 2020; Bodenstein *et al*., 2020; Brotherhood *et al*., 2020; Jones *et al*., 2020) because the feasibility of WFH practices can mitigate the trade-off between health and economic activity arising from social distancing policies.

Along with the accumulation of actual data on the number of COVID-19 infections and deaths, empirical evaluations on the effect of WFH have been conducted (e.g., Adams–Prassl *et al*., 2020; Alipour *et al*., 2020; Béland *et al*., 2020a, 2020b; Fadinger and Schymik, 2020; Lin and Meissner, 2020; Mongey *et al*., 2020). These *ex post* analyses generally confirm that WFH arrangements

[1] See Avery *et al*. (2020) and Stock (2020) for the surveys regarding the epidemic models on the spread of COVID-19 such as the SIR (Susceptible, Infected, and Recovered) models.

suppress the spread of the pandemic and/or lessen the negative impact of the pandemic on production and employment.

However, not only the feasibility of WFH, but also its impact on productivity relative to working at the usual workplace, affects the efficacy of WFH in mitigating the negative impact of social distancing policies on the economy. In the simulation studies, the percentage of jobs that can be performed at home is often taken from task-based estimates such as Dingel and Neiman (2020). By contrast, because estimates of WFH productivity have been scarce, simulation studies have assumed arbitrary figures of WFH productivity (e.g., 50% or 70% relative to working at the workplace). To supplement the paucity of studies on the practice of WFH brought about by COVID-19, this study presents quantitative evidence on the prevalence, frequency, and productivity of WFH based on an original survey of employees in Japan during the COVID-19 pandemic.

Our analysis of the survey results revealed that for a large majority of employees in Japan, productivity at home was lower than that at the workplace. The mean WFH productivity relative to working at the usual workplace was about 60% to 70%, and it was lower for employees who started WFH practices only after the spread of the COVID-19 pandemic. Highly educated, high-wage employees, as well as long-distance commuters, tended to exhibit a relatively small reduction in productivity when participating in WFH arrangements. Based on the survey respondents' opinions, the major reasons for the reduced productivity were the loss of quick communication possible only through face-to-face interactions at the workplace, poor telecommunication environment at home relative to that in the office, and the rules (in some cases, for security reasons) and regulations that require some tasks to be conducted in the office.

The remainder of this paper is organized as follows. Section 2 presents a brief review of the related literature and describes the contributions of this study. Section 3 explains the survey data used in this study. Section 4 reports the prevalence and frequency of WFH practices during the COVID-19 pandemic, with focus on the differences in individual characteristics, followed by the results on WFH productivity and how it relates to individual characteristics. Section 5 provides the conclusions and discusses some policy implications.

2. Literature Review

Following the spread of the COVID-19 pandemic, several estimations have been presented on how many jobs can potentially be performed at home (e.g., Adams *et al*., 2020; Dingel and Neiman, 2020; Boeri *et al*., 2020; Brussevich *et al*., 2020). Using data on task contents of occupations taken from the Occupational Information Network (O*NET), Dingel and Neiman

(2020), an early representative study, estimate that 34% of U.S. jobs can plausibly be performed at home. Boeri *et al*. (2020) indicate that between 23% and 32% of jobs can potentially be carried out at home in major European countries. Adams *et al*. (2020), using unique surveys from the United States and the United Kingdom, document the percentage of *tasks* (on a scale of 0% to 100%) that workers can do from home, which differs from estimates on the percentage of *jobs* achievable at home. Although the share of tasks that can be done from home varies considerably across, as well as within, occupations and industries, the mean figures are around 40% in both countries. The result suggests that some tasks must be performed at the workplace, even for workers whose jobs can mostly be conducted at home.

More recently, using individual-level survey data, several studies have reported results on the percentages of workers who engage in WFH practices during the COVID-19 pandemic (e.g., Bick *et al*., 2020; Brynjolfsson *et al*., 2020; Buchheim *et al*., 2020). These studies show that between 35% and 50% of workers actually engage in WFH arrangements in the United States and some major European countries.[2] Certain studies report results from firm surveys that about half of firms introduced WFH practices in April 2020 (e.g., Bartik *et al*., 2020; Buchheim *et al*., 2020).

Overall, quantitative evidence on the potential and actual percentages of WFH arrangements has been accumulating rapidly. By contrast, evidence on the productivity of employees who practice WFH during the COVID-19 pandemic has been limited. In this respect, Dingel and Neiman (2020) caution that it is not straightforward to use the percentage of jobs plausibly performed at home to estimate the share of output that would be produced under stringent social distancing policies because an individual worker's productivity may differ considerably when working at home versus working at the usual workplace. A rare example of a study on WFH productivity is Bartik *et al*. (2020), which indicates that the productivity of remote workers is about 20% lower than that of non-remote workers, based on a survey of small firms in the United States. However, as the authors have stated, the result reflects the self-selection of workers into WFH.[3]

Bloom *et al*. (2015), for example, present evidence from a field experiment with call center employees in China that during normal times WFH practices enhanced the total factor productivity (TFP) of organizations. The positive effect on productivity arises from both improvements in individual workers' performance and from reductions in office space. By

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[2] Okubo (2020), using survey data in Japan, reports that participation in telework increased from 6% in January to 17% in June 2020. In his study, telework is defined as working at a specific place (at home or in a public facility) for a specific number of hours using information and communications technologies.

[3] Morikawa (2018) and Kazekami (2020) indicate that in Japan, there is a positive association between WFH and wages. However, these studies cannot be interpreted as causality running from WFH to wages, because productive workers may self-select into WFH.

contrast, Battiston *et al*. (2017), exploiting a natural experiment with a public sector organization in the United Kingdom, find that productivity is higher when teammates are in the same room, and that the effect is stronger for urgent and complex tasks. They suggest that teleworking is unsuitable for tasks requiring face-to-face communication. Dutcher (2012), based on a laboratory experimental approach, indicates that telecommuting may have a positive impact on employee productivity for creative tasks but a negative impact for dull tasks.

These studies indicate that employee productivity under WFH arrangements depends on the characteristics of occupations and specific tasks undertaken. The recent increase in WFH practices has been widespread, involving a variety of white-collar workers, but causal evidence of the productivity of ordinary office workers under WFH arrangements has been scant. Because the recent surge in WFH practices brought about by the COVID-19 pandemic can be considered as a natural experiment, we can observe causal evidence of employee productivity under WFH arrangements through an appropriately designed survey.

Under these circumstances, based on an originally designed survey for individuals conducted in June 2020, this study presents novel observations about the prevalence, frequency, and productivity of employees engaged in WFH practices in Japan. As the quantitative evidence on WFH productivity has been limited, this study contributes to the literature and policymaking for tackling the negative effects of the COVID-19 pandemic. However, it is challenging to measure the productivity of individual workers, particularly of white-collar workers. For instance, the productivity measure obtained from our survey is subjective in nature, and its accuracy can be debated. However, since productivity in our survey is expressed as a percentage of an employee's productivity under WFH conditions relative to the same employee's productivity at the usual workplace, and not a comparison of his/her productivity against other workers, reporting bias arising from overconfidence, for example, can be avoided.

3. Data and Methodology

The data used in this study were retrieved from the "Follow-up Survey of Life and Consumption under the Changing Economic Structure" designed by the author of this paper, conducted by the Rakuten Insight, Inc., and contracted out by the Research Institute of Economy, Trade, and Industry (RIETI) in late June 2020.[4] The online survey questionnaire was sent via e-mail to 10,041 individuals who responded to the previous survey conducted in 2017. In the 2017 survey, the sample individuals were randomly chosen from the 2.3 million registered monitors of

[4] Rakuten Insight, Inc. is a subsidiary of Rakuten, Inc., which is a large online retailer in Japan.

Rakuten Insight, Inc., stratified by gender, age (from 20 to 79 years), and region (prefecture), in proportion to the population composition of the 2015 Population Census (Statistics Bureau, Ministry of Internal Affairs and Communications).[5]

There were 5,105 respondents (50.8% response rate) to the 2020 survey. The distribution of these respondents by gender, age, and region is presented in **Appendix Table A1**. Compared with the whole population, the survey respondents aged 50 and 60 years were overrepresented, and those aged 20 years was underrepresented. Because this survey was sent to those who responded to the 2017 survey, the aging of respondents in the subsequent three years affected the age distribution. Meanwhile, the distribution by region was comparable to the whole population.

This study mainly used a sample of 3,324 individuals who were working at the time of the survey. The analyses in this study were based on cross-sectional information obtained from the 2020 survey, but data from the 2017 survey were also used when necessary. For example, the educational attainment of individuals was taken from the 2017 survey.

The major questions regarding WFH arrangements included (1) whether an employee participated in WFH practices and the time the WFH practice started, (2) frequency of WFH, (3) subjective productivity under WFH conditions, and (4) factors that affect WFH productivity. In addition, the survey collected information about various individual characteristics, such as gender, age, and prefecture of residence. Those who were working also provided information on the type of employment (nine categories), occupation (13 categories), industry (14 categories), firm size (13 categories), weekly working hours (eight categories), annual earnings (tax inclusive; 18 categories), prefecture of usual workplace, and commuting hours (round trip; 10 categories). These items were in the form of multiple-choice questions and were generally consistent with those in the Employment Status Survey (Statistics Bureau, Ministry of Internal Affairs and Communications).[6]

The specific question regarding WFH practice was “Did you practice WFH after the onset of the COVID-19 pandemic and the stay-at-home request from the government?” The choices were: (1) “I have been practicing WFH before the COVID-19 pandemic,” (2) “I have started practicing WFH after the onset of the COVID-19 pandemic,” and (3) “I have not practiced WFH.” Next, for those who chose (1) or (2), the survey asked the frequency of WFH: “How many work days did

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[5] To be more specific, using a software developed by the Rakuten Research, Inc., the target number of responses was set at the level (i.e., the gender*age*prefecture cell) that was proportional to the Population Census. Then, an invitation e-mail was sent randomly by taking into account the predicted response rate. When the number of responses fell short of the target at the cell level, additional invitation e-mails were sent until the target number was met.

[6] In the analysis presented in Section 4, some categories were integrated into a smaller number of classifications. For example, the type of employment was integrated into standard and non-standard employees.

you spend WFH when the frequency of your WFH days was the highest?" This question required a specific figure. For example, for a worker who spent three days in a week WFH (assuming a five-day-work week), the response is 0.6.

Regarding WFH productivity, which is the focus of this study, the question was "Suppose your productivity in the workplace is 100, how do you evaluate your work productivity at home? Please answer this question considering all your tasks." For this question, it was noted that "If your productivity at home is higher than that in the workplace, please answer with a figure higher than 100." [7] In fact, some respondents reported figures higher than 100. Because this productivity measure is subjective, some measurement error of the true productivity was unavoidable. However, it should be stressed that an employee's productivity under WFH conditions was asked as a relative measurement against his/her own productivity at the usual workplace, not as a comparison with his/her colleagues; thus the figure is unaffected by reporting biases such as the degree of overconfidence or underconfidence.

The question regarding the factors affecting WFH productivity was "What factors negatively affect WFH productivity? Please select the choices relevant to you." The choices were (1) "Poor telecommunication environment at home relative to the workplace," (2) "Rules and regulations that require some tasks to be conducted in the office," (3) "Some tasks cannot be conducted at home even though these are not required by the rules and regulations," (4) "It is difficult to concentrate on the job because of the presence of family members," (5) "Lack of a private room specifically designed for work," (6) "Loss of immediate communication that is only possible through face-to-face interactions with colleagues at the workplace," (7) "Lack of pressure from boss, colleagues, and subordinates," and (8) "Other reasons."

In the following section, we present the cross-tabulation and simple regression results of the answers to the questions explained above.

4. Results and Discussion

4.1 Prevalence and Frequency of Working from Home

Among the survey respondents (5,105 in total), there were 3,324 people who were working at the time of the survey.[8] This subsection describes the prevalence and frequency of WFH practices

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[7] The survey system set the minimum (0) and the maximum (200) values for this question.

[8] The number of those who lost their jobs due to the COVID-19 pandemic is 103 (2.0%), and the number of employees who moved to other firms is 48 (0.9%). Most workers in our sample continued working with the same firms after the COVID-19 pandemic started.

for this sample. **Table 1** shows the tabulated results on the prevalence of WFH practices during the COVID-19 pandemic. About 35.9% (column (1)) of all workers participated in WFH arrangements, of which 10.6% had been under such an arrangement before the COVID-19 pandemic (hereinafter "early WFH adopters"), and 25.3% started the practice after COVID-19 started (hereinafter "new WFH adopters"). However, these figures include self-employed and family workers who usually conduct business at home. When limiting the sample to employees (2,718 people), the corresponding percentages are 32.2%, 4.3%, and 27.9%, respectively (column (2)). It is obvious that the large majority of employees started WFH after the onset of the COVID-19 pandemic. The percentage of WFH adopters is somewhat smaller than the comparable figures for the United States and some European countries, as referred to in Section 2.

Table 2 presents cross-tabulated results on the prevalence of WFH practices by employee characteristics. The percentages of males, those aged 20 and 30 years, and those who are highly-educated are higher than the mean. Difference by education is particularly clear: 41.4% and 64.2% of workers with university and postgraduate education, respectively, participate in WFH arrangements. By employment type, the share of WFH adopters is 39.9% for standard employees, which is more than two times higher than the share of non-standard employees (19.7%).[9] By industry, information and communication (75.2%) and finance and insurance (58.3%) show higher shares of WFH adopters. By contrast, the shares of WFH adopters are very low in the healthcare and welfare (7.2%), accommodations and restaurants (9.4%), and transport (10.4%) industries. By occupation, trade-related (59.3%), administrative and managerial (55.5%), and professional and engineering jobs have high proportions of WFH adopters. By contrast, production-related (16.0%) and service (16.9%) occupations show very low shares of WFH adopters. In short, the prevalence of WFH adoption is quite heterogeneous across industries and different types of occupation.

Differences by firm size are evident from the results. The share of WFH adopters is 46.8% in firms with 1,000 or more employees, but the share is less than 30% in firms with less than 500 employees. Annual earnings are also strongly associated with the adoption of WFH: about two-thirds of workers earning 9 million yen or higher participate in WFH arrangements. By region, 61.6% of those who live in the Tokyo prefecture adopt WFH, which is far higher than those who live in other prefectures. Similarly, the adoption of WFH is associated with the commuting distance: approximately two-thirds of workers who spend two and a half hours or longer for round trips between home and the workplace participate in WFH arrangements.

Overall, highly educated, high-wage, white-collar employees who work in large firms located

[9] Non-standard employees include part-time, hourly-paid, dispatched, contract, and fixed-term employees.

in the metropolitan areas tend to participate in WFH practices during the COVID-19 crisis. However, because these individual characteristics correlate with each other, we conducted a simple probit estimation to investigate the true determinants of WFH adoption. The dependent variable is whether WFH is adopted, and the explanatory variables are gender (female dummy), age category dummies, education dummies, annual earnings (expressed in logarithm), commuting hours (expressed in logarithm), employment type (non-standard dummy), industry dummies, occupation dummies, and firm size dummies.[10] The reference categories for the dummy variables are male, age 40 to 49 years, high school education, standard employee, manufacturing, clerical job, and firm size of 100 to 299 employees.

The results are presented in **Table 3**, where the marginal effects and robust standard errors are reported. The coefficients for the age categories of 20–29 and 30–39 years, university and postgraduate education, annual earnings, commuting hours, information and communications industry, trade-related occupation, and firm size of 1,000 or more are positive and statistically significant, meaning that these characteristics are associated with a higher probability of participating in WFH practice after controlling for other observable characteristics. Meanwhile, the coefficients for transport industry, healthcare and welfare industry, sales occupation, and production-related occupation are negative and significant. Interestingly, the coefficients for female and non-standard employees are insignificant, which differ from the observations through cross-tabulation. The results suggest that female and non-standard employees tend to work in industries and occupations where WFH arrangements are difficult.

Columns (2) and (3) of **Table 3** relate to the separate estimations for the subsamples of new WFH adopters and early WFH adopters. Because a large part of WFH adopters are new adopters, the estimation result in column (2) is similar to that in column (1). Meanwhile, the result for the subsample of early adopters (column (3)) is different: most coefficients are statistically insignificant, mainly because the number of early adopters is very small (118 people). However, the coefficients for higher education and commuting hours are positive and significant, although the absolute size is small.

Table 4 shows the tabulated results of the frequency of WFH among employees who participated in WFH practice (N = 876). The figures in the first column are the ratio of WFH days to total work days when the WFH frequency was the highest. About 20.4% of these employees did their jobs completely at home (1.0). The mean and the median frequency of WFH are 0.557

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[10] The central values of the earnings categories were applied as a logarithmic transformation to construct the variable of annual earnings. In this calculation, "less than 500 thousand yen" and "20 million yen or more" were treated as 250 thousand yen and 21.25 million yen, respectively. A similar logarithmic transformation was applied to the variable of commuting hours. In this calculation, "four hours or longer" was treated as 4.25 hours.

and 0.5, respectively. In other words, in the case of a five-day workweek, typical WFH workers spend two to three days a week at home, but as evident from the table, the frequency of WFH is highly dispersed.

Differences in the timing of WFH initiation are small. The mean frequency of WFH for those who engaged in WFH practices before the COVID-19 pandemic (i.e., early WFH adopters) is 0.592, and that for those who started WFH after the onset of the COVID-19 (new WFH adopters) is 0.551 (median figures are 0.55 and 0.5, respectively). According to a survey conducted in 2017, the majority of teleworkers spend only 1 day or less a week (Morikawa, 2018), meaning that the frequency of WFH increased after the COVID-19 pandemic, even for early WFH adopters.[11]

Table 5 presents the mean of the frequency of WFH by individual characteristics. The differences by gender, age, education, and employment type are small, but the difference by industry is large. The frequency of WFH is high for the information and communication industry, and the prevalence of WFH in this industry is also high. By contrast, the transport, accommodations and restaurants, and healthcare and welfare industries are characterized by both low prevalence and low frequency of WFH. Systematic differences by firm size and annual earnings are not observed, but employees living in Tokyo tend to practice WFH frequently.

Based on the results presented above, we can calculate the individual-level WFH hours by multiplying the usual weekly working hours and the frequency of WFH. The aggregated share of WFH hours can be calculated as the sum of the WFH hours divided by the sum of the weekly working hours of all employees. The resulting aggregate share of WFH is 19.4%: slightly less than one-fifth of work is conducted at home by the employees in our sample. The remaining 80.6% of work is conducted at the usual workplace. Although the number of workers engaged in WFH dramatically increased after the COVID-19 pandemic started, the macroeconomic contribution of WFH labor input was not large because many jobs cannot be done at home and the number of full-time WFH workers is limited. [12]

It is expected that WFH contributes to mitigating congestion of public transport. Using data on commuting hours, we can also calculate the reduction of aggregate commuting hours attributable to WFH, which is estimated to be 24.5%. Since both the probability and frequency of WFH is higher among long commuters, the contribution of WFH to the saving of commuting hours is larger than its share of total working hours. This calculation suggests that WFH had a positive impact on reducing the risk of infection arising from physical contact among commuters.

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[11] In the 2017 survey, the question was about the use of telework, including WFH.

[12] As stated before, the earnings of WFH workers are relatively high. The aggregate contribution of WFH to total earnings is 24.5%, which is higher than the figure for simple working hours.

4.2 Productivity of Working from Home

The distribution of the WFH adopters' subjective productivity at home relative to their usual workplace (= 100) is summarized in **Table 6**. The mean and median of this measure of WFH productivity are 60.6% and 70%, respectively. However, this WFH productivity measure is very heterogeneous: the standard deviation is 35.1% and the gap between the 75th and 25th percentiles is 56.5%. The percentages of WFH adopters whose productivity at home is higher than, equal to, or lower than the productivity at the workplace are 3.9%, 14.2%, and 82.0%, respectively. For a large majority of employees, their productivity at home is lower than their productivity in the office.

Figure 1 depicts the distributions of WFH productivity for the subsamples of early and new adopters. It is clear from the figure that the WFH productivity distribution is very different between these subgroups. The mean of early adopters is 76.8%, which is 18.7% higher than that of new adopters (58.1%), and the difference is statistically significant at the 1% level. The lower rows of **Table 6** show a comparison of the figures for those who engaged in teleworking in the 2017 survey and those who did not. The result is essentially the same as that obtained only from the 2020 survey, confirming that the relative WFH productivity is significantly higher for early adopters.

The higher WFH productivity of early adopters reflects both the selection mechanism and learning effect. It is conceivable that early adopters who practice WFH before the pandemic voluntarily self-selected into a WFH arrangement because their jobs are easy to do at home and their working environment at home is not inferior to the workplace. In addition, the accumulation of WFH experience may have improved their productivity at home. However, it should be noted that even for early adopters, their subjective productivity at home is, on average, lower than their productivity at the workplace. The percentage of those exhibiting higher WFH productivity relative to the workplace is only about a third, even for the subsample of early adopters. The results suggest that the WFH productivity of new adopters improves through the effect of learning-by-experience, but we conjecture that their long-run WFH productivity will be about 70% to 80% of their productivity at the workplace.

As stated before, the share of WFH hours to total labor input is about 19.4%, and the contribution of WFH to total earnings is 24.5%. It is possible to make a rough estimate of the loss of aggregate labor productivity arising from WFH as follows:

$$\text{Loss from WFH (\%)} = [\Sigma(\text{earnings}_i)*(\text{WFH frequency}_i)*(1\text{-WFH productivity}_i)]/\Sigma(\text{earnings}_i).$$

According to this mechanical calculation, the productivity loss is 7.6%. If we assume that the WFH productivity of new adopters converges with those of early adopters through the learning effect, the loss will be reduced by 1.2% to 6.4%.

As the dispersion of WFH productivity is very large, the natural question that comes to mind concerns the differences by individual characteristics. The mean WFH productivity by individual characteristics is reported in **Table 7**. Although the differences by gender, age, and employment type are small, the differences by education, industry, occupation, firm size, and annual earnings are remarkable. The mean WFH productivity stands out in the information and communication industry (73.5%). By occupation, professional and engineering (69.2%) and administrative and managerial (67.5%) occupations show relatively high WFH productivity. As seen in the previous subsection, these industries and occupations are characterized by a high WFH practice rate. These results suggest that efficiency under WFH conditions depends heavily on the nature of the jobs. In addition, the relative WFH productivity is higher for those who have postgraduate education (72.0%), those with annual earnings of 10 million or higher (73.7%), and workers who commute more than three hours a day between home and the workplace (69.9%).

Table 8 reports simple ordinary least square (OLS) regression results regarding WFH productivity. The basic explanatory variables are the same as those in the probit estimation (whose results are reported in **Table 3)**: gender, age, education, annual earnings (expressed in logarithm), commuting hours (expressed in logarithm), employment type, industry, occupation, and firm size. The reference categories for the dummy variables are male, age 40 to 49 years, high school education, standard employee, manufacturing, clerical occupation, and firm size of 100 to 299 employees.

The coefficients for high education, annual earnings, and commuting hours are positive and significant, confirming the observation from the simple tabulation. By industry, the coefficients for transport, finance and insurance, healthcare and welfare, and education are negative and significant. By occupation, the coefficients for sales and production-related occupations are significantly negative. These results are generally unsurprising, with the exception of the significantly low WFH productivity of the finance and insurance industry, where the prevalence of WFH is the second highest. Unexpectedly, the coefficient for non-standard employees is positive and significant at the 5% level. The size of the estimated coefficient (8.489) means that among those who practice WFH, the productivity relative to the workplace of non-standard employees is about 8% higher than that of standard employees. Our interpretation is that the job description of non-standard employees, such as part-time workers, dispatched employees, and contract employees, is clear, and they are less likely to bear the burden of sudden unexpected tasks and coordinating roles in the workplace. The coefficients for the firm size classes are insignificant. Although employees of large firms are likely to practice WFH during the pandemic

(**Table 3**), their relative productivity at home is not different from that of employees working with small firms.

Column (2) of **Table 8** shows the result of using the new WFH adopter dummy as an additional explanatory variable. As expected, the coefficient for this dummy is negative, large, and highly significant. After controlling for the other observable individual characteristics, the WFH productivity of new adopters is 13.7% lower than that of early adopters, although the gap is smaller than the raw comparison (18.7%). Column (3) of the table shows the estimation result when the frequency of WFH as an explanatory variable is added. The estimated coefficient for this variable is positive and highly significant. Quantitatively, the relative WFH productivity of employees with one more day of WFH a week is about 3.5% points higher. This result implies that employees with relatively high WFH productivity tend to practice WFH frequently.

The survey asked for the factors that affect WFH productivity. There are eight choices, as described in Section 3. The results are summarized in **Table 9**. The major reasons for reduced productivity at home are, in descending order, (1) loss of quick communication that is only possible through face-to-face interactions with their colleagues at the workplace (38.5%), (2) poor telecommunication environment at home relative to the workplace (34.9%), (3) rules and regulations that require some tasks to be conducted in the office (33.1%), and (4) some tasks cannot be conducted at home even though these are not required by rules and regulations (32.4%).

Among these obstacles, the telecommunication environment at home can be improved through investments in hardware and software, while inappropriate rules and regulations can be amended to some extent. Considering the possibility of a prolonged impact of the COVID-19, making investments and effort to reform work practices that are unsuitable for WFH practices are important to improve WFH productivity. However, the loss of face-to-face interactions is an inherent constraint on WFH productivity. Although the development of innovative telecommunication technologies and efficient use of such technologies may mitigate this constraint, it will persist in the foreseeable future as a factor that reduces WFH productivity relative to the workplace.

5. Conclusion

This study, using unique data from an original survey conducted in June 2020, presents evidence on the prevalence, frequency, and productivity of WFH during the COVID-19 pandemic in Japan. For the period covered in the survey, the main results are summarized as follows.

First, the percentage of employees who practiced WFH was about 32%, of which 28% started WFH after the onset of the COVID-19 pandemic. The labor input from WFH were about 19% of the weekly working hours.

Second, highly educated, high-wage, white-collar employees who work in large firms in metropolitan areas tended to practice WFH, which suggests that infection risk and social distancing policies may exacerbate economic disparity among employees.

Third, for a large majority of employees (about 82%) their productivity at home was lower than that in their usual workplace. The mean WFH productivity was about 60% to 70% of the productivity at the workplace and lower for employees that started WFH after the onset of the COVID-19 pandemic. The WFH productivity gap between early adopters and new adopters reflects both the selection mechanism and the learning effect.

Fourth, the aggregate loss arising from inferior productivity at home was estimated to be approximately 7%. If new adopters' WFH productivity converges with the productivity of early adopters, the loss will be reduced by about one percentage point.

Fifth, highly educated, high-wage employees, as well as long-distance commuters, tended to exhibit a relatively small reduction in WFH productivity. Those who productively work at home tended to practice WFH frequently, suggesting a natural selection of work location based on productivity.

Sixth, the lack of face-to-face interactions, poor telecommunication environment at home, and the existence of tasks that must be conducted in the office due to rules and regulations and other reasons were the major impediments to improving productivity at home. This result suggests that investments in hardware and software related to WFH and modifications of inappropriate rules and regulations may help improve WFH productivity. However, since some important information that is difficult to digitalize will continue to be exchanged through face-to-face interaction, it is difficult to expect WFH productivity to reach the same level as that at the workplace, at least on average. Even after incorporating the positive effect through learning, the maximum average productivity at home is expected to be about 70% to 80% of productivity at the workplace. To achieve further improvements in WFH productivity, innovation in telecommunication infrastructure and software that enables human interactions in a way that is similar to face-to-face communication is necessary.

It is extremely difficult to measure the productivity of individual workers accurately, particularly that of white-collar workers. Since the productivity measure used in this study depends on subjective reporting, measurement errors are possible. However, WFH productivity is expressed as a relative figure to an employee's own productivity at the usual workplace, not as a comparison with other workers. This way, we can avoid reporting bias, for example, those arising from the overconfidence of the respondents.

Although the COVID-19 pandemic is a natural experiment that exogenously increased the adoption of WFH practices among a wide range of white-collar workers, we cannot completely eliminate the selection effect. In addition, it should be noted that as an extreme case, for many service jobs that require physical contact with customers, such as doctors, nurses, hairdressers, and restaurants, the productivity of teleworking is prohibitively low.

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Table 1. The Prevalence of Working from Home Practice

	(1) All workers	(2) Employees
Doing WFH	35.8%	32.2%
Before the COVID-19	10.6%	4.3%
After the COVID-19	25.3%	27.9%
Not doing WFH	64.2%	67.8%

Note: The percentages in column (2) are calculated after excluding “company executive,” “self-employed,” and “family worker” from all workers.

Table 2. The Prevalence of Working from Home Practice by Individual Characteristics

Categories		WFH	Categories		WFH
Total		32.2%	Occupation	Administrative & managerial	55.5%
Gender	Male	38.7%		Professional & engineering	43.2%
	Female	22.2%		Clerical	36.7%
Age	20-29	39.9%		Sales	11.4%
	30-39	36.0%		Trade	59.3%
	40-49	29.3%		Service	16.9%
	50-59	35.6%		Production & other	16.0%
	60-69	28.0%	Firm size	1-99	22.7%
	70-79	26.2%		100-299	27.3%
Education	Junior high school	5.7%		300-499	29.3%
	Senior high school	17.8%		500-999	40.7%
	Vocational school	21.7%		1,000-	46.8%
	Junior (2-year) college	21.3%		Government	40.9%
	4-year university	41.4%	Earnings	Less than 2 million yen	13.6%
	Graduate school	64.2%		2-2.99	23.2%
Employment type	Standard	39.9%		3-3.99	25.0%
	Non-standard	19.7%		4-4.99	32.9%
Industry	Construction	36.3%		5-5.99	34.6%
	Manufacturing	38.0%		6-6.99	38.8%
	Information & communications	75.2%		7-7.99	43.6%
	Transport	10.4%		8-8.99	55.4%
	Wholesale & retail	24.5%		9-9.99	65.3%
	Finance & insurance	58.3%		10 million yen or more	64.8%
	Real estate	38.8%	Residence	Tokyo	61.6%
	Accommodations & restaurants	9.4%		Aichi & Osaka	34.5%
	Health care & welfare	7.2%		Other	23.0%
	Education	42.6%	Commuting hours (round trip)	Less than 0.5 hour	15.0%
	Other services	26.0%		0.5-0.99	27.6%
	Public services	39.3%		1.0-1.49	45.6%
	Other industries	33.7%		1.5-1.99	48.6%
				2.0-2.49	48.1%
				2.5-2.99	67.6%
				3 hours or longer	66.3%

Notes: This table indicates the percentage of employees who participate in WFH arrangements. Other industries include agriculture, fisheries, and forestry. Some categories for firm size, earnings, residence, and commuting hours integrate the original choices in the survey questions.

Table 3. The Probability of Participating in Work from Home Practices: Estimation Results

	(1) All		(2) New adopters		(3) Early adopters	
	dF/dx	Std. Err.	dF/dx	Std. Err.	dF/dx	Std. Err.
Female	-0.014	(0.025)	-0.014	(0.024)	0.003	(0.007)
20-29	0.146	(0.051) ***	0.133	(0.050) ***	0.019	(0.022)
30-39	0.076	(0.030) ***	0.067	(0.030) **	0.024	(0.013) **
50-59	0.039	(0.027)	0.020	(0.026)	0.033	(0.012) ***
60-69	0.045	(0.030)	0.036	(0.030)	0.022	(0.012) **
70-79	0.128	(0.068) **	0.053	(0.063)	0.101	(0.049) ***
Junior high school	-0.153	(0.081)			0.017	(0.036)
Vocational school	0.028	(0.039)	0.023	(0.038)	0.006	(0.012)
Junior (2-year) college	0.050	(0.040)	0.050	(0.040)	-0.002	(0.010)
4-year university	0.101	(0.026) ***	0.086	(0.025) ***	0.015	(0.007) **
Graduate school	0.246	(0.052) ***	0.221	(0.053) ***	0.036	(0.023) **
Ln earnings	0.090	(0.017) ***	0.088	(0.017) ***	0.007	(0.005)
Ln commuting hours	0.111	(0.012) ***	0.105	(0.011) ***	0.011	(0.003) ***
Non-standard employee	0.015	(0.029)	0.005	(0.028)	0.009	(0.008)
Agriculture	-0.065	(0.118)	-0.042	(0.121)		
Construction	0.032	(0.044)	0.007	(0.041)	0.019	(0.018)
Information & communications	0.298	(0.059) ***	0.300	(0.061) ***	0.004	(0.013)
Transport	-0.163	(0.035) ***	-0.159	(0.031) ***	0.002	(0.017)
Wholesale & retail	-0.036	(0.038)	-0.020	(0.038)	-0.008	(0.010)
Finance & insurance	0.061	(0.051)	0.050	(0.050)	0.017	(0.017)
Real estate	0.051	(0.074)	0.033	(0.068)	0.016	(0.028)
Accommodations & restaurants	-0.103	(0.072)	-0.084	(0.070)		
Health care & welfare	-0.224	(0.021) ***	-0.211	(0.019) ***	-0.012	(0.007)
Education	0.093	(0.048) **	0.091	(0.048) **	0.006	(0.012)
Other services	-0.009	(0.034)	-0.014	(0.033)	0.016	(0.013)
Public services	0.065	(0.054)	0.076	(0.054)	-0.018	(0.005) *
Other industries	0.116	(0.043) ***	0.093	(0.042) **	0.031	(0.018) **
Administrative & managerial	0.051	(0.038)	0.039	(0.037)	0.019	(0.015)
Professional & engineering	-0.004	(0.030)	-0.017	(0.028)	0.021	(0.012) **
Sales	-0.143	(0.039) ***	-0.158	(0.032) ***	0.025	(0.031)
Trade	0.125	(0.046) ***	0.118	(0.046) ***	0.002	(0.011)
Service	-0.067	(0.035) *	-0.060	(0.034) *	-0.007	(0.009)
Production & other	-0.147	(0.024) ***	-0.147	(0.023) ***	0.005	(0.009)
99 or smaller	-0.018	(0.029)	-0.014	(0.029)	-0.004	(0.007)
300-499	-0.016	(0.043)	-0.013	(0.042)	-0.003	(0.010)
500-999	0.068	(0.043) *	0.083	(0.043) **	-0.011	(0.007)
1,000 or larger	0.095	(0.033) ***	0.100	(0.033) ***	0.002	(0.008)
Government	-0.018	(0.052)	-0.008	(0.051)	-0.009	(0.009)
Nobs.	2656		2534		2590	
Pseudo R^2	0.2599		0.2621		0.1268	

Notes: Probit estimations with robust standard errors are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. The categories used as references are male, age 40-49, senior high school, standard employee, manufacturing, clerical, and firm size of 100–299 employees.

Table 4. Distribution of the Frequency of Working from Home

WFH frequency	%
0.1	13.8%
0.2	11.1%
0.3	8.7%
0.4	7.2%
0.5	14.3%
0.6	4.0%
0.7	4.8%
0.8	8.9%
0.9	6.8%
1.0	20.4%

Table 5. The Mean Frequency of Working from Home by Individual Characteristics

Categories		Frequency of WFH (mean)	Categories		Frequency of WFH (mean)
Total		0.557	Occupation	Administrative & managerial	0.531
Gender	Male	0.536		Professional & engineering	0.583
	Female	0.613		Clerical	0.557
Age	20-29	0.586		Sales	0.647
	30-39	0.538		Trade	0.603
	40-49	0.571		Service	0.513
	50-59	0.533		Production & other	0.500
	60-69	0.581	Firm size	1-99	0.541
	70-79	0.570		100-299	0.567
Education	Junior high school	0.450		300-499	0.546
	Senior high school	0.502		500-999	0.549
	Vocational school	0.565		1,000-	0.597
	Junior (2-year) college	0.593		Government	0.416
	4-year university	0.555	Earnings	Less than 2 million yen	0.596
	Graduate school	0.596		2-2.99	0.529
Employment type	Standard	0.545		3-3.99	0.526
	Non-standard	0.596		4-4.99	0.554
Industry	Construction	0.488		5-5.99	0.596
	Manufacturing	0.587		6-6.99	0.548
	Information & communications	0.708		7-7.99	0.481
	Transport	0.282		8-8.99	0.564
	Wholesale & retail	0.587		9-9.99	0.464
	Finance & insurance	0.494		10 million yen or more	0.615
	Real estate	0.421	Residence	Tokyo	0.634
	Accommodations & restaurants	0.400		Aichi & Osaka	0.554
	Health care & welfare	0.429		Other	0.496
	Education	0.565	Commuting hours (round trip)	Less than 0.5 hour	0.423
	Other services	0.605		0.5-0.99	0.539
	Public services	0.368		1.0-1.49	0.549
	Other industries	0.608		1.5-1.99	0.564
				2.0-2.49	0.637
				2.5-2.99	0.565
				3 hours or longer	0.579

Notes: Other industries include agriculture, fisheries, and forestry. Some of the categories above for firm size, earnings, residence, and commuting hours are integrated version of the original choices in the survey questions.

Table 6. Working from Home Productivity

	Mean	Std. Dev.	p25	p50	p75	N	Home<Office
All WFH employees	60.6	35.1	30	70	86.5	876	82.0%
Early WFH adopters	76.8	35.5	70	85	100	118	62.7%
New WFH adopters	58.1	34.4	30	60	80	758	85.0%
Telework in 2017	73.8	34.5	50	80	100	81	71.6%
No telework in 2017	59.3	34.9	30	65	85	795	83.0%

Note: The last column indicates the percentage of employees working from home whose productivity at home is less than 100.

Table 7. Working from Home Productivity by Individual Characteristics

Categories		Mean WFH productivity	Categories		Mean WFH productivity
Total		60.6	Occupation	Administrative & managerial	67.5
Gender	Male	62.2		Professional & engineering	69.2
	Female	56.5		Clerical	58.5
Age	20-29	57.7		Sales	40.1
	30-39	60.1		Trade	57.8
	40-49	59.6		Service	52.3
	50-59	62.9		Production & other	49.1
	60-69	60.3	Firm size	1-99	57.9
	70-79	61.0		100-299	64.3
Education	Junior high school	45.0		300-499	65.6
	Senior high school	48.1		500-999	61.5
	Vocational school	53.7		1,000-	64.5
	Junior (2-year) college	61.1		Government	40.5
	4-year university	61.7	Earnings	Less than 2 million yen	57.2
	Graduate school	72.0		2-2.99	44.2
Employment type	Standard	61.2		3-3.99	55.2
	Non-standard	58.6		4-4.99	51.3
Industry	Construction	62.2		5-5.99	58.5
	Manufacturing	70.1		6-6.99	66.7
	Information & communications	73.5		7-7.99	61.6
	Transport	37.5		8-8.99	65.2
	Wholesale & retail	57.0		9-9.99	62.7
	Finance & insurance	52.4		10 million yen or more	73.7
	Real estate	50.3	Residence	Tokyo	64.9
	Accommodations & restaurants	55.0		Aichi & Osaka	62.1
	Health care & welfare	40.0		Other	56.7
	Education	54.4	Commuting hours (round trip)	Less than 0.5 hour	53.1
	Other services	62.8		0.5-0.99	57.4
	Public services	38.0		1.0-1.49	61.6
	Other industries	67.5		1.5-1.99	61.8
				2.0-2.49	60.9
				2.5-2.99	61.8
				3 hours or longer	69.9

Notes: Other industries include agriculture, fisheries, and forestry. Some categories for firm size, earnings, residence, and commuting hours are integrated versions of the original choices in the survey questions.

Table 8. Work from Home Productivity: Estimation Results

	(1)			(2)			(3)		
	Coef.	Std. Err.		Coef.	Std. Err.		Coef.	Std. Err.	
Female	-2.254	(3.461)		-2.566	(3.456)		-4.070	(3.386)	
20-29	4.261	(4.889)		4.179	(5.055)		3.768	(4.827)	
30-39	3.404	(3.366)		2.854	(3.382)		3.927	(3.323)	
50-59	3.894	(3.266)		2.697	(3.289)		4.612	(3.234)	
60-69	0.793	(4.293)		0.233	(4.228)		0.829	(4.239)	
70-79	11.121	(9.803)		7.987	(9.700)		10.421	(9.454)	
Junior high school	48.482	(11.019)	***	36.363	(12.045)	***	44.029	(11.535)	***
Vocational school	6.382	(5.467)		6.243	(5.383)		5.771	(5.265)	
Junior (2-year) college	14.022	(5.665)	**	14.383	(5.622)	**	13.855	(5.551)	**
4-year university	13.589	(3.729)	***	13.141	(3.695)	***	12.702	(3.626)	***
Graduate school	19.052	(4.627)	***	18.573	(4.644)	***	17.469	(4.554)	***
Ln earnings	5.485	(2.147)	**	5.480	(2.135)	**	5.262	(2.061)	**
Ln commuting hours	3.002	(1.531)	*	2.877	(1.514)	*	1.954	(1.511)	
Non-standard employee	8.489	(4.289)	**	8.087	(4.287)	*	7.610	(4.235)	*
Agriculture	12.294	(16.859)		13.659	(16.316)		10.926	(20.960)	
Construction	-4.562	(4.820)		-5.109	(4.794)		-3.237	(4.950)	
Information & communications	4.884	(4.271)		5.188	(4.283)		2.608	(4.315)	
Transport	-22.990	(11.805)	*	-24.273	(12.276)	**	-18.221	(11.735)	
Wholesale & retail	-8.038	(4.657)	*	-8.004	(4.643)	*	-7.803	(4.575)	*
Finance & insurance	-15.214	(5.035)	***	-15.592	(5.000)	***	-13.020	(4.967)	***
Real estate	-15.342	(8.510)	*	-16.008	(8.275)	*	-12.177	(8.310)	
Accommodations & restaurants	-3.224	(15.537)		-2.819	(15.470)		1.154	(16.470)	
Health care & welfare	-22.333	(8.319)	***	-23.460	(8.173)	***	-20.166	(7.838)	**
Education	-14.392	(5.005)	***	-14.214	(4.938)	***	-13.878	(4.945)	***
Other services	-2.198	(4.452)		-3.254	(4.461)		-2.792	(4.381)	
Public services	-26.143	(6.122)	***	-24.908	(6.121)	***	-23.089	(6.175)	***
Other industries	2.446	(5.397)		1.492	(5.385)		2.128	(5.300)	
Administrative & managerial	4.311	(3.970)		3.700	(3.952)		3.963	(3.884)	
Professional & engineering	4.160	(3.615)		3.132	(3.598)		4.085	(3.572)	
Sales	-22.476	(10.422)	**	-23.757	(10.359)	**	-23.713	(11.083)	**
Trade	-5.021	(4.765)		-4.846	(4.734)		-6.080	(4.809)	
Service	-7.306	(6.004)		-6.958	(6.019)		-6.515	(5.935)	
Production & other	-10.238	(4.653)	**	-11.458	(4.590)	**	-9.563	(4.530)	**
99 or smaller	-1.120	(3.927)		-1.029	(3.942)		-1.043	(3.811)	
300-499	7.466	(5.759)		7.194	(5.795)		7.276	(5.775)	
500-999	-2.693	(4.889)		-1.937	(4.921)		-2.411	(4.833)	
1,000 or larger	-1.519	(3.833)		-1.467	(3.846)		-2.218	(3.733)	
Government	-4.979	(6.779)		-4.992	(6.690)		-5.519	(6.719)	
New WFH adopter				-13.660	(4.375)	***			
WFH frequency							0.173	(0.038)	***
Cons.	18.365	(14.942)		32.259	(15.518)	**	11.533	(14.520)	
Nobs.	828			828			828		
Adjsuted R^2	0.1447			0.1577			0.1661		

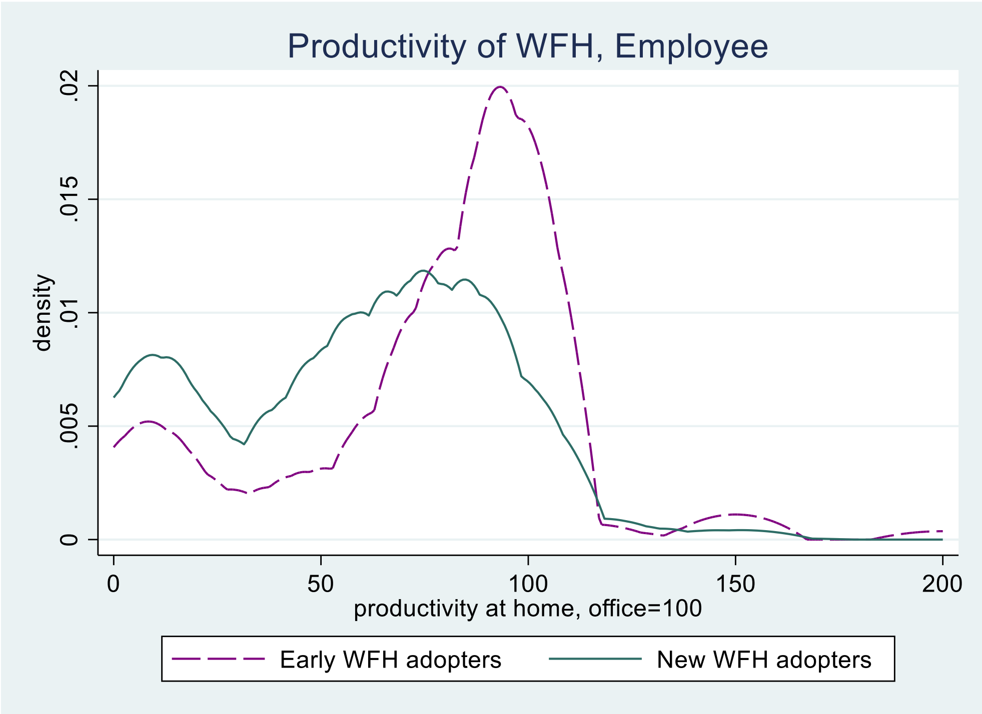
Notes: OLS estimations with robust standard errors are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. The categories used as references are male, age 40–49, senior high school, standard employee, manufacturing, clerical, and firm size of 100–299 employees.

Table 9. The Factors Affecting Work from Home Productivity

	Factors reducing productivity at home	
1	Poor telecommunication environment at home relative to the workplace	34.9%
2	The requirements by rules and regulations that some tasks must be conducted in the office	33.1%
3	Some tasks cannot be conducted at home even though these are not required by rules and regulations	32.5%
4	It is difficult to concentrate on job because of the presence of family members	19.9%
5	Lack of a private room specifically designed for work	15.1%
6	Loss of quick communication that is only possible through face-to-face interactions with their colleagues at the workplace	38.5%
7	Lack of pressure from the boss, colleagues, and subordinates	19.3%
8	Other reasons	10.2%

Notes: Multiple answers were allowed for this question.

Figure 1. Distribution of Work from Home Productivity by the Timing of the Start of Working from Home



Note: The label "Early Work from Home (WFH) adopters" refers to those who practiced WFH before the COVID-19 pandemic while "New WFH adopters" refers to those who started WFH after the start of the COVID-19 pandemic.

Appendix Table A1. Composition of Survey Respondents

	Respondents	2015 Census		Respondents	2015 Census
Male	54.3%	49.4%	Hokkaido	3.9%	4.3%
Female	45.7%	50.6%	Aomori	0.8%	1.0%
20-29	3.8%	13.2%	Iwate	0.9%	1.0%
30-39	12.8%	16.6%	Miyagi	1.9%	1.8%
40-49	20.0%	19.6%	Akita	0.7%	0.8%
50-59	20.2%	16.4%	Yamagata	0.8%	0.9%
60-69	29.5%	19.3%	Fukushima	1.3%	1.5%
70-79	13.7%	14.9%	Ibaraki	2.1%	2.3%
			Tochigi	1.5%	1.6%
			Gumma	1.6%	1.5%
			Saitama	6.0%	5.9%
			Chiba	5.3%	5.0%
			Tokyo	11.8%	11.0%
			Kanagawa	7.7%	7.3%
			Niigata	1.8%	1.8%
			Toyama	0.9%	0.8%
			Ishikawa	0.8%	0.9%
			Fukui	0.5%	0.6%
			Yamanashi	0.7%	0.6%
			Nagano	1.6%	1.6%
			Gifu	1.8%	1.6%
			Shizuoka	3.1%	2.9%
			Aichi	6.2%	5.9%
			Mie	1.3%	1.4%
			Shiga	1.1%	1.1%
			Kyoto	2.1%	2.0%
			Osaka	7.0%	7.0%
			Hyogo	4.4%	4.3%
			Nara	1.1%	1.1%
			Wakayama	0.8%	0.7%
			Tottori	0.5%	0.4%
			Shimane	0.6%	0.5%
			Okayama	1.4%	1.5%
			Hiroshima	2.5%	2.2%
			Yamaguchi	1.1%	1.1%
			Tokushima	0.5%	0.6%
			Kagawa	0.8%	0.7%
			Ehime	1.0%	1.1%
			Kochi	0.4%	0.6%
			Fukuoka	3.3%	4.0%
			Saga	0.6%	0.6%
			Nagasaki	0.9%	1.1%
			Kumamoto	1.2%	1.4%
			Oita	0.7%	0.9%
			Miyazaki	0.7%	0.8%
			Kagoshima	1.1%	1.2%
			Okinawa	0.8%	1.1%

Note: The percentages of the 2015 Population Census data were calculated for people aged 20 to 79 years.