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Work-from-Home Productivity during the COVID-19 Pandemic: Evidence from Surveys of Employees and Employers

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Abstract

Using data from original surveys of employees and employers, this study examines the prevalence, intensity, and productivity of working from home (WFH) practices during the coronavirus disease 2019 (COVID-19) pandemic in Japan. The results reveal that the mean WFH productivity relative to working at the usual workplace was about 60–70 percent, and it was lower for employees and firms that started WFH practice only after the spread of the COVID-19 pandemic. However, there is a large dispersion of WFH productivity, both by individual and firm characteristics. Highly educated and high-wage employees tended to exhibit a relatively small reduction in WFH productivity. The results obtained from the employee and employer surveys were generally consistent with each other.

Keywords: COVID-19, productivity, social distancing, working from home
JEL Classification: D24, I12, J22, J24, M12, M54, R41

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Work-from-Home Productivity during the COVID-19 Pandemic:
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1. Introduction

Following the spread of the coronavirus disease 2019 (COVID-19) pandemic, the practice of working from home (WFH) has been increasingly adopted in major advanced countries. During normal times, the percentage of workers participating in WFH practice was approximately 10 percent or less in major advanced countries, but the number of workers who frequently or occasionally conduct their jobs at home has increased suddenly since 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 percent in 2017 (Morikawa, 2018). However, many firms introduced WFH practices to prevent COVID-19 infection. In particular, the number of workers engaged in WFH increased further following the first declaration of a state of emergency by the Japanese government in April 2020.

Since the onset of the COVID-19 pandemic, epidemiological models that augment economic behavior have been developed, and simulation analyses of the effects of social distancing measures, such as a shelter-in-place order and mandatory shutdown of service industries and schools 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 of the pandemic (i.e., "flattening the curve"), but they have large negative effects on economic activity, that is, there is a trade-off, at least in the short run, between public health and the severity of the recession. Some of the simulation models explicitly consider WFH practices (e.g., Akbarpour *et al*., 2020; Aum *et al*., 2020;

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

Bodenstein *et al*., 2020; Brotherhood *et al*., 2020; Jones *et al*., 2020; Fujii and Nakata, 2021) because the feasibility of WFH practice can mitigate the trade-off between health and economic activity arising from social distancing policies.[2]

Along with the accumulation of actual data on the number of COVID-19 infections and deaths, empirical evaluations of the effects of WFH have also 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 suppresses the spread of the pandemic and/or lessens the negative effect of the pandemic on production and employment.

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

Our analysis of the survey results revealed that, for a large majority of employees and firms 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 60–70 percent, and it was lower for employees who started WFH 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 practice. The major reasons for the reduced productivity were the loss of quick

[2] Behrens *et al*. (2021) develop a general equilibrium model to study the WFH intensity on the efficiency of firms and its effect on the whole economy. They indicate that the relationship between WFH and productivity or GDP is ∩-shaped and the share of WFH that maximizes GDP is between 20 and 40 percent (one or two working days per five-day week).

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 figures obtained from the employee and firm surveys are generally consistent with each other.

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 design of employee survey and reports on the prevalence, intensity, and productivity of WFH practice during the COVID-19 pandemic, with a focus on the differences in individual characteristics. Section 4 explains the design and results of the firm survey on WFH and how it relates to firm characteristics. Section 5 provides the conclusions and discusses policy implications.

2. Literature Review

Following the spread of the COVID-19 pandemic, 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), in an early representative study, estimated that 34 percent of U.S. jobs can plausibly be performed at home. Boeri *et al*. (2020) indicate that between 23 and 32 percent 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 UK, document the percentage of *tasks* (on a scale of 0–100 percent) 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 percent in both countries. The results suggest 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 percentage 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 percent of workers engage in WFH in the United States and some major European countries. Certain studies report results from firm surveys that about half of the firms introduced WFH practice in April 2020 (e.g., Bartik *et al*., 2020; Buchheim *et al*., 2020).

Overall, quantitative evidence on the potential and actual percentages of WFH practices has been accumulating rapidly. In 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) note 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 against working at the usual workplace.

At a normal time before the COVID-19 pandemic, Bloom *et al*. (2015) present evidence from a field experiment with call center employees in China. They show that WFH practices enhanced the total factor productivity (TFP) of the organization. The positive effect on productivity arises from both improvements in individual workers' performance and from reductions in office space. In contrast, Battiston *et al*. (forthcoming), exploiting a natural experiment with a public sector organization in the UK in charge of answering emergency calls, find that productivity is higher when teammates are in the same room, and that the effect is stronger for urgent and complex tasks. They suggested 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 effect on employee productivity for creative tasks but a negative impact on dull tasks.[3]

These studies indicate that employee productivity under WFH practices depends on the characteristics of the occupations and the specific tasks undertaken. The recent increase in WFH practices has been widespread, involving a variety of white-collar workers, but

[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.

causal evidence of the productivity of ordinary office workers under WFH has been scant. As the recent surge in WFH practices brought about by the COVID-19 pandemic can be considered a natural experiment, we can observe causal evidence of employee productivity under WFH practices through appropriately designed surveys.

After the onset of the COVID-19 pandemic, a small number of studies have presented evidence on WFH productivity based on individual or firm surveys. Etheridge *et al.* (2020), whose study is based on a survey of individuals in the UK, show that, on average, WFH productivity is not significantly different from that of workplace productivity, but it varies depending on individuals' socio-economic status, industry, and occupation. Barrero *et al.* (2020), based on a survey of individuals in the United States, indicate that the majority of respondents who have adopted WFH practice report higher WFH productivity than their expectations before the start of the pandemic. Empirical studies investigating the productivity of WFH under COVID-19 from the employer side have been rare. An exception is Bartik *et al.* (2020), who use data from a survey of small- and medium-sized firms in the United States from March to April 2020, reported a decrease in productivity of about 20 percent on average. However, as the authors stated, the results reflect the self-selection of workers into WFH.

To supplement the paucity of studies on WFH productivity, based on an originally designed survey for individuals conducted in June 2020, as well as a firm survey from August to September 2020, this study presents novel observations about the prevalence, intensity, and productivity of the WFH practice 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 on the economy. Importantly, this study presents complementary evidence from both the employee and employer sides. However, it is challenging to measure the productivity of individual workers, particularly 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 at home 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. Employee Survey

A. Survey Design

The employee survey data are retrieved from the "Follow-up Survey of Life and Consumption under the Changing Economic Structure" designed by the author of this paper and conducted 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 a survey conducted in 2017. In the 2017 survey, the sample individuals were randomly chosen from the 2.3 million registered monitors of 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 percent response rate) to the 2020 survey.

The distribution of these respondents by gender and age is presented in **Appendix Table A1**.[6] 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

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[4] The survey was contracted out to Rakuten Insight, Inc., a subsidiary of Rakuten, Inc., which is a large online retailer in Japan.

[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 considering 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] 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.

when necessary. For example, the educational attainment of individuals was taken from the 2017 survey.

The major questions regarding WFH included (1) whether an employee participated in WFH practice and the timing when the WFH 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). [7]

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 since 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 workdays did you spend WFH when the frequency of your WFH days was the highest?" This question requires a specific share of the WFH. 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 by considering all of your tasks." For this question, it was noted that "If your productivity at home is higher than that in the

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

workplace, please answer with a figure higher than 100."[8] In fact, some respondents reported figures higher than 100. Because this productivity measure is subjective, some measurement errors of true productivity were unavoidable. However, it should be stressed that an employee's productivity under WFH conditions was asked as a relative measure 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, we present the cross-tabulation and simple regression results of the answers to the questions explained above.

B. Prevalence and Frequency of WFH

Among the 5,105 survey respondents, 3,324 were working at the time of the survey.[9] This subsection describes the prevalence and frequency of WFH practices in this sample.

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

[9] The number of those who lost their jobs owing to the COVID-19 pandemic is 103 (2.0 percent), and the number of employees who moved to other firms is 48 (0.9 percent). Most workers in our sample continued working with the same firms at the time of the survey.

Table 1 shows the tabulated results on the prevalence of WFH during the COVID-19 pandemic. About 35.9 percent (column (1)) of all workers participated in the WFH arrangement, of which 10.6 percent had been under such an arrangement before the COVID-19 pandemic (hereinafter “early WFH adopters”), and 25.3 percent started the practice after the onset of the COVID-19 pandemic (hereinafter “new WFH adopters”). However, these figures include self-employed and family workers who usually conduct businesses at home. When limiting the sample to employees (2,718 people), the corresponding percentages are 32.2 percent, 4.3 percent, and 27.9 percent, respectively (column (2)). It is obvious that a 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 major European countries, as referred to in the previous section.

Cross-tabulated results on the prevalence of WFH practices by employee characteristics are presented in **Appendix Table A2**. The percentages of males, those aged 20–29 years, and those who are highly educated are higher than the mean. Differences by education are particularly clear: 41.4 percent and 64.2 percent of workers with university and postgraduate education, respectively, used the WFH arrangement. By employment type, the share of WFH adopters is 39.9 percent for standard employees, which is more than two times higher than the share of non-standard employees (19.7 percent).[10] By industry, information and communication (75.2 percent) and finance and insurance (58.3 percent) show higher shares of WFH adopters. By contrast, the shares of WFH adopters are very low in healthcare and welfare (7.2 percent), accommodations and restaurants (9.4 percent), and transport (10.4 percent) industries. By occupation, trade-related (59.3 percent), administrative and managerial (55.5 percent), and professional and engineering jobs have high proportions of WFH adopters. In contrast, production-related (16.0 percent) and service (16.9 percent) occupations show very low shares of WFH adopters. In short, the prevalence of WFH adoption is heterogeneous across industries and different types of occupations.

The difference by firm size is evident in the results. The share of WFH adopters is 46.8

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

percent in firms with 1,000 or more employees, but the share is less than 30 percent in firms with less than 500 employees. Annual earnings are also strongly associated with the adoption of WFH; approximately two-thirds of the workers earning nine million yen or higher participate in the WFH arrangement. By region, 61.6 percent 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 arrangement.

Overall, highly educated, high-wage, white-collar employees who work in large firms located in metropolitan areas tend to participate in WFH practices more 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 binary 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.[11] 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 2**, where 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

[11] 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.

observable characteristics. Meanwhile, the coefficients for the 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 differs from the observations through cross-tabulation. The results suggest that female and non-standard employees tend to work in industries and occupations where WFH is difficult.

Table 3 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 weekly workdays when the WFH frequency was the highest. Approximately 20.4 percent of these employees did their jobs completely at home. The mean and median frequency of WFH were 0.557 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.

While not reported in the table, the difference in the timing of WFH initiation is small. The mean frequency of WFH for those who engaged in WFH practice before the COVID-19 pandemic (i.e., early WFH adopters) was 0.592, and that for those who started WFH after the onset of COVID-19 (new WFH adopters) was 0.551 (median figures are 0.55, 0.5, respectively). According to a survey conducted in 2017, the majority of teleworkers spend only one day or less per week (Morikawa, 2018), meaning that the frequency of WFH increased substantially after the COVID-19 pandemic, even for early WFH adopters.[12]

The mean frequency of WFH according to individual characteristics is presented in **Appendix Table A3**. The differences by gender, age, education, and employment type are small, but the differences by industry are large. The frequency of WFH is high for the information and communications industry, and the prevalence of WFH in this industry is also high. In 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

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

by multiplying the usual weekly working hours by the frequency of WFH. The aggregated share of WFH hours ("WFH intensity") 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 percent, which is slightly less than one-fifth of work conducted at home by the employees in our sample. The remaining 80.6 percent of the work is conducted in 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.[13]

It is expected that WFH will contribute to mitigating the congestion of public transport. Using data on commuting hours, we can also calculate the reduction in aggregate commuting hours attributable to WFH, which is estimated to be 24.5 percent. Because both the probability and frequency of WFH are 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 has a positive effect on reducing the risk of infection arising from physical contact among commuters.

C. Productivity of WFH

The distribution of WFH adopters' subjective productivity at home relative to their usual workplace (= 100 percent) is summarized in **Table 4**. The mean and median of this measure of WFH productivity were 60.6 percent and 70 percent, respectively. However, this WFH productivity measure is very heterogeneous; the standard deviation is 35.1 percent and the gap between the 75th and 25th percentiles is 56.5 percent. 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 percent, 14.2 percent, and 82.0 percent, respectively. For a large majority of employees, productivity at home is lower than productivity in the

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

office.

The distributions of WFH productivity for the subsamples of early and new adopters are shown in **Appendix Figure A1**. 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 percent, which is 18.7 percentage points higher than that of new adopters (58.1 percent), and the difference is statistically significant at the 1 percent level.

The higher WFH productivity of early adopters reflects both the selection mechanism and the learning effect. It is conceivable that early WFH adopters 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 may have improved 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 converge to about 70–80 percent of their productivity at the workplace.

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

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

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

As the dispersion of WFH productivity is very large, the natural question that comes to mind concerns the differences between individual characteristics. The mean WFH productivity based on individual characteristics is reported in **Appendix Table A4**.

Although the differences by gender, age, and employment type are small, the differences by education, industry, occupation, firm size, and annual earnings are remarkable. Mean WFH productivity stands out in the information and communications industry (73.5 percent). By occupation, professional and engineering (69.2 percent) and administrative and managerial (67.5 percent) occupations showed 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 WFH productivity depends heavily on the nature of the jobs. In addition, the relative WFH productivity is higher for those who have postgraduate education (72.0 percent), those with annual earnings of 10 million yen or higher (73.7 percent), and workers who commute more than three hours a day between home and the workplace (69.9 percent).

Table 5 reports simple ordinary least square (OLS) regression results regarding WFH productivity. The explanatory variables are the same as those in the probit estimation (whose results are reported in **Table 2)**: gender, age, education, annual earnings (expressed in logarithm), commuting hours (expressed in logarithm), employment type, industry, occupation, and firm size.

According to the baseline regression (column (1)), the coefficients for high education, annual earnings, and commuting hours are positive and significant, confirming the observation from the simple tabulation. Unexpectedly, the coefficient for non-standard employees is positive and significant at the 5 percent 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 approximately eight percent higher than that of standard employees. Our interpretation is that the job descriptions 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 of the firm-size classes are insignificant. Although employees of large firms are likely to practice WFH during the pandemic (see **Table 2**), their relative productivity at home is similar to that of employees working with small firms.

Column (2) of **Table 5** shows the results 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 percent lower than that of early adopters, although the gap is smaller than the raw comparison (18.7 percent). Column (3) of the table shows the estimation results when the frequency of WFH is added as an explanatory variable. The estimated coefficient for this variable is positive and highly significant. Quantitatively, the relative WFH productivity of employees with one more day of WFH per week is approximately 3.5 percentage points higher. This result implies that employees with relatively high WFH productivity tend to practice WFH frequently.

The survey asked about factors that affect WFH productivity. There were eight choices for the survey. The results are summarized in **Table 6**. 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 (chosen by 38.5 percent of the respondents), (2) poor telecommunication environment at home relative to the workplace (34.9 percent), (3) rules and regulations that require some tasks to be conducted in the office (33.1 percent); and (4) some tasks cannot be conducted at home, even though these are not required by rules and regulations (32.4 percent).

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 effect of COVID-19, making investments and efforts to reform work practices that are unsuitable for WFH practice 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 the 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.

4. Firm Survey

A. Survey Design

The firm survey data are retrieved from the "Survey of Corporate Management and

Economic Policy" (SCMEP), which was designed by the author of this paper and conducted by the RIETI from August to September 2020. The survey questionnaire was sent to 2,498 Japanese firms that responded to the previous SCMEP in early 2019. The number of firms that responded to the current SCMEP was 1,579 (a response rate of approximately 63 percent).[14] The SCMEP in 2019 was sent to 15,000 firms that operate in the manufacturing and service industries, which were randomly selected from the registered list of the Basic Survey of Japanese Business Structure and Activities (BSJBSA), an annual statistical survey conducted by the Ministry of Economy, Trade and Industry (METI). The firms registered in the BSJBSA have at least 50 employees and capital of at least 30 million yen among firms with business establishments that belong to the manufacturing, wholesale, retail, and service industries. In other words, the SCMEP does not include small firms with fewer than 50 employees or capital of less than 30 million yen.

The distribution of the firms that responded to this survey by industry is as follows: manufacturing (53.5 percent), information and communications (5.3 percent), wholesale (17.8 percent), retail (10.2 percent), service (9.0 percent), and others (4.2 percent).[15] In terms of firm size (classified by capital over 100 million yen or less), 34.8 percent are large firms, whereas 65.2 percent are small- and medium-sized firms.[16]

The following are the main aspects regarding WFH: (1) whether the WFH practice has been implemented, (2) the percentage of employees who have used this workstyle (at the maximum time); (3) the mean WFH frequency of teleworkers (at the maximum time); (4) the mean productivity of WFH relative to the workplace; (5) factors that affect the adoption of the WFH system and productivity of employees adopting this workstyle; and (6) specific regulations or rules restricting the adoption of the WFH system and productivity of this workstyle. The specific wording of the questions and choices, as well as the results, are explained in the following subsections. Further, the SCMEP also asked about the industries (six categories) of the firm's main business, number of standard and

[14] The respondents to the SCMEP were the managers themselves or departments that can write their opinions on their behalf.

[15] "Other industries" include firms with unknown classification.

[16] The capital of the firm uses the BSJBSA data for the fiscal year 2018.

non-standard employees, and number of employees by gender.

As mentioned previously, given that the current survey targets firms that responded to the 2019 SCMEP, information on the firm characteristics collected in the 2019 survey is available. In this study, we use the percentage of employees who have a university degree or higher in the analysis. By linking with BSJBSA's data for the fiscal year 2018, information available in the BSJBSA can be used as well. This study uses capital, mean wages (total cash salary divided by the number of employees), and location of firm headquarters (prefectures) from the BSJBSA. The major variables and summary statistics are presented in **Appendix Table A5**.

B. Adoption and Intensity of WFH

The question regarding whether the WFH practice has been adopted is as follows: "Did your firm implement the WFH practice during the spread of the COVID-19?" The three options are as follows: "1) The WFH practice has been adopted before the onset of the COVID-19 pandemic," "2) The WFH practice were introduced after the spread of the COVID-19," and "3) The WFH practice has not been adopted."

Table 7 presents the tabulation results. The percentage of firms that adopted the WFH system prior to the onset of the COVID-19 pandemic ("early WFH adopters") was 4.1 percent, 45.5 percent introduced it after the pandemic ("new WFH adopters"), and 50.4 percent did not. The WFH adoption rate is high in large firms. By industry, the information and communications industry is the highest. The table shows the results of separately tabulating Tokyo and other prefectures. A significant difference is observed between firms headquartered in Tokyo and other prefectures.

Table 8 compares the firm characteristics between WFH adopters and non-adopters, focusing on the composition of employees. Firms adopting the WFH system have low ratios of female and non-standard employees, although the quantitative differences are small: the difference in the female ratio is 2.1 percentage points, and the non-standard ratio is 5.6 percentage points. The major difference is found in the educational background of employees: the mean ratio of university graduates or higher is 41.9 percent for firms that adopt the WFH system, and 21.6 percent for those that do not. This indicates that employees using this workstyle were concentrated in highly educated white-collar workers. In addition, firms adopting the WFH system are mostly large and pay high wages. When converted to percentages, the difference in mean wages is at least 20 percent. In summary, the results obtained from the firm-level survey are generally consistent with those from the employee survey.

Table 9 shows the results of the probit estimation with WFH adoption used as the binary dependent variable. The larger the firm size (the logarithm of the number of regular employees), the higher is its probability of adopting the WFH system. By industry, firms in the information and communications industry have a high probability, whereas those in the retail industry have a low probability of adopting the WFH system. Firms headquartered in Tokyo, those with a large share of female and highly educated employees, and those paying higher wages have a higher probability of adopting the WFH system (column (1)). The coefficient for the female employee ratio is positive and significant, which is different from the simple tabulation result. In other words, after controlling for other firm characteristics, firms with a high proportion of female employees tend to implement WFH practices. When the population density of the head office location is used as the explanatory variable, rather than the Tokyo dummy, the coefficient of population density is positive and significant at the 1 percent level (column (2)). Quantitatively, doubling the population density, the probability of adopting the WFH system is approximately seven percent higher. In this specification, no essential difference is observed in the coefficients of the other explanatory variables.

Even for firms that have adopted the WFH system, not all employees used this workstyle. The share of employees covered by the WFH system may differ by firm. In this regard, the survey asks, "What percentage of your employees used the WFH practice after the spread of COVID-19?" The tabulation results are presented in column (1) of **Table 10**. The mean percentage of WFH-adopting firms was 30.7 percent. The percentages are 49.1 percent for early WFH adopters and 29.0 percent for new WFH adopters. This result shows that firms that are relatively easy to introduce the WFH practice owing to the nature of their businesses adopted it earlier, and a large percentage of employees tend to telework during the COVID-19 pandemic. By industry, the information and communications industry (59.6 percent) is the highest, and the manufacturing industry (18.8 percent) is the lowest. Large firms have higher percentages than small firms, and firms headquartered in Tokyo have a high share of teleworkers.

Even for employees who adopted this workstyle, they were not necessarily full-time teleworkers (i.e., working at home on all working days) as many of them went to the workplace several days per week. Thus, the survey asks, “What was the average number of WFH days per week for employees who implemented the WFH practice?” The tabulation results are summarized in column (2) of **Table 10**. The mean frequency of WFH implementation was 3.67 days per week. Assuming that the normal working week is five days, teleworkers spend more than 70 percent of their work hours at home.

Similar to the share of teleworkers, employees of firms that have adopted the WFH system prior to the COVID-19 pandemic implemented this workstyle frequently, with an average of 4.54 days. Conversely, the average number of firms that introduced it after COVID-19 was 3.59 days. Specifically, teleworkers of early WFH adopters performed about 90 percent of their work at home during the peak when the “state of emergency” was declared. However, no significant difference was observed by firm size. By industry, the information and communications industry (4.28 days) is the highest, whereas the retail industry (3.39 days) has the lowest frequency. The WFH practice was somewhat more frequently conducted in firms headquartered in Tokyo, but the quantitative difference with firms in other prefectures is small.

Next, we calculate the WFH intensity at the firm level as the ratio of WFH employees multiplied by the frequency of WFH per week (converted into percentage), which indicates the contribution of WFH hours to the total labor input.[17] As we do not have information on the working hours of individual employees, this calculation assumes that the working hours of all employees are equal. In addition, even on the WFH day, it is possible that he or she may go to the workplace for several hours. Therefore, we should emphasize that the WFH intensity calculated here is only an approximation.

The results are presented in column (3) of **Table 10**. The mean WFH intensity of firms adopting the WFH system was 23.3 percent. Even if a firm adopts this workstyle, many

[17] The frequency of working from home is converted into percentage terms, assuming the standard working days of five days per week. Among the responding firms, 11 firms answered that the number of WFH days per week exceeded 5. Hence, the WFH frequency of these firms was considered 100 percent.

employees did not exploit it, and even those who used this work arrangement did not necessarily work at home throughout the week; hence, the mean contribution of the WFH system to labor input was less than a quarter. Firms that have adopted the WFH system before the COVID-19 pandemic, large firms, and those headquartered in Tokyo show high WFH intensity. By industry, the information and communications industry is the largest at 51.1 percent. This indicates that at the time when the WFH intensity was at its peak, about half of the total labor input was performed at home. Conversely, the manufacturing industry is the smallest at 13.6 percent, reflecting the difficulty of implementing the WFH system at factory production sites.

The weighted average of the WFH intensity (column (4) of **Table 10**) is calculated using the number of employees as weight and including the WFH non-adopters, whose WFH intensity is regarded as zero. In other words, it shows the contribution of the WFH system to the total labor input of the industry. The weighted average is 10.9 percent for all industries: the contribution of WFH to labor input is surprisingly small, even during the period when WFH peaks. By industry, the information and communications industry is the highest at 44.6 percent, whereas the retail industry is extremely small at 3.9 percent. This is an unsurprising result, as more than 70 percent of firms in the retail industry did not implement the WFH system (**Table 7**).

Table 11 shows the results of the OLS estimations that explain the WFH intensity based on various firm characteristics. In columns (1) and (2), only firms that adopted the WFH system during the COVID-19 pandemic are used as samples. Information from the 2019 SCMEP is used to calculate the ratio of university graduates or higher, and that from the BSJBSA for the fiscal year 2018 was used to calculate the mean wages. Considering that the reference category of the industry dummy is manufacturing, the coefficient of each industry indicates a difference from manufacturing.

The estimation results show that the information and communications, and service industries have high WFH intensity. The coefficient for Tokyo has a relatively large positive value: the WFH intensity is about 15 percent higher than that of firms headquartered in other prefectures. The coefficient of the female ratio is positive despite the low significance level, and the coefficient of non-standard ratio is negative and significant at the 5 percent level. The coefficient of the ratio of employees with university degrees or higher is positive and significant at the 1 percent level. These results indicate that firms with high female, standard, and educated employees have high WFH intensity after accounting for other firm characteristics. Despite the low significance level, the coefficient of mean wages is positive, suggesting that firms paying higher wages tend to have higher WFH intensity. When the prefectural population density is used instead of the Tokyo dummy, the result is presented in column (2). The WFH intensity is higher for firms headquartered in densely populated prefectures. Even in this specification, the coefficients of the other variables are generally the same as the result in column (1), except that the coefficient of the wholesale industry becomes positive and significant.

In these estimations, firms that did not adopt the WFH system were excluded from the sample. The results of the same specification, including firms that did not adopt WFH, of which the WFH intensity is regarded as zero, are shown in columns (3) and (4) of the table. In this case, the results are essentially the same as those in columns (1) and (2).

C. Productivity of WFH

The question about WFH productivity evaluated from the employer's viewpoint, which is the main interest of this study, is "Suppose that employees' productivity at the workplace is 100, how do you evaluate their productivity at home? Please answer the mean productivity by considering all tasks covered by the WFH system." The questionnaire noted that "if WFH is more productive than the workplace, please answer with a figure over 100." Thus, respondents can answer the possibility that WFH is more productive than workplace.[18]

Table 12 presents the tabulation results. The simple average of firms adopting WFH was 68.3 percent.[19] According to a survey of employees, the mean subjective productivity of WFH was 60.6 percent, as reported in the previous section. As the firms surveyed in this study are those with at least 50 employees, we should be careful in simply

[18] In fact, 9 firms answered that the productivity of WFH exceeds 100 (the maximum was 120), and 50 firms answered exactly 100.

[19] The aggregate loss arising from the lower WFH productivity, calculated from the WFH intensity and the WFH productivity weighted by the number of employees, is about 3.2%.

comparing the figures, but the figures are similar to the subjective productivity of employees.

The WFH productivity was 81.8 percent and 67.0 percent for the early and new WFH adopters, respectively. The 14.7 percentage points difference is statistically significant at the 1 percent level. **Appendix Figure A2** shows the productivity distribution of these firms. Noticeably, the productivity distribution of the early WFH adopters is located on the right side, despite the large dispersion. In the employee survey, a large difference (18.7 percentage points) in productivity was observed between those who had adopted the WFH system before the COVID-19 pandemic and those who adopted it after the spread of COVID-19. The results of the firm survey are consistent with those of the employee survey. However, even firms that have adopted the WFH system before COVID-19 might expand their coverage to employees who had not used this workstyle until the spread of the COVID-19 infection. Therefore, it should be noted that teleworkers in the firm survey did not necessarily experience WFH prior to the onset of the COVID-19 pandemic.

Almost no difference was found by firm size. By industry, the mean WFH productivity of the information and communications industry is the highest at 80.3 percent, and the figures for the rest of the industries are between 62.6 percent and 69.5 percent. The mean figure of firms headquartered in Tokyo is 72 percent and that in other prefectures is 66.8 percent, a difference of 5.2 percentage points. As this is only a simple comparison wherein other factors were not controlled for, differences in the composition of industries and employees were reflected. However, as will be described later, even if a regression analysis is conducted, the coefficient of Tokyo is positive and statistically significant. This result is similar to that of the employee survey. We conjecture that, as a large number of employees working with firms located in Tokyo commute for a long distance, it may be related to the reduction in fatigue caused by long commuting hours.

Table 13 shows the OLS estimation results to explain WFH productivity using the same explanatory variables as in the previous regressions. The coefficient of firm size is insignificant, confirming the simple tabulation results reported in **Table 12**. By industry, the coefficient for the information and communications industry is positive and that for retail is negative, and they are both highly significant, reflecting the nature of businesses. The coefficient of Tokyo is positive and significant at the 5 percent level, and the interpretation is the same as stated above. The coefficient of the female ratio is positive and significant at the 5 percent level. This indicates that firms' evaluation of WFH productivity is higher in firms with a large share of female employees after accounting for the other firm characteristics. The coefficient of the non-standard ratio was insignificant. Although firms with a large share of non-standard workers have low WFH intensity, as mentioned previously, no significant difference is observed in terms of productivity. The coefficient for the share of university graduates or higher is statistically insignificant, but the sign is positive. The coefficient of mean wages is positive and significant at the 5 percent level, indicating that firms paying lower wages tend to be less productive in the WFH system. This is similar to the results of the employee survey.

In summary, the WFH productivity pattern based on the firm survey is generally consistent with the results of the employee survey presented in the previous section. A few exceptions are that the coefficients of higher education and non-regular employment are statistically insignificant in the firm survey.

D. Factors Affecting the Adoption and Productivity of WFH

The firm survey asked multiple-choice questions about factors that negatively affect the adoption and productivity of WFH. The specific question is, "Were there any obstacles or limitations in adopting or expanding the WFH practice or matters that negatively affected WFH productivity?" There are nine choices for this question: (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 although these are not required by the rules and regulations," (4) "At the employees' home, it is difficult to concentrate on working owing to the presence of family members," (5) "Some employees do not have their private room suitable for teleworking," (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," (8) "Much of the work requires direct interaction with customers," and (9) "Other reasons." These choices are basically the same as the survey for employees, but choice (8) is added to the firm survey.

Table 14 presents the tabulation results. A large number of firms chose, in descending order, “Some tasks cannot be conducted at home although these are not required by the rules and regulations” (76.1 percent), “Poor telecommunication environment at home relative to the workplace” (60.8 percent), “Rules and regulations that require some tasks to be conducted in the office” (57.7 percent), and “Loss of immediate communication that is only possible through face-to-face interactions with colleagues at the workplace” (46 percent). Although the percentages are different, these four reasons occupy the top positions in both the employee and firm surveys.

In addition to the question above, the survey asked, “Were any of the following regulations or rules restrict your firm’s adoption of WFH?”. The choices are (1) “Permission or licenses on businesses,” (2) “Labor regulations,” (3) “Environmental regulations,” (4) “Land use/building regulations,” (5) “Regulations on protecting consumers/personal information,” (6) “Corporate law,” (7) “Occupational licensing system,” (8) “Tax system,” (9) “Social security system,” and (10) “Guidance of government/municipality not based on the law.” The tabulation results are presented in **Appendix Table A6**. A relatively large number of firms chose “Labor regulations” (26.9 percent) and “Regulations on protecting consumers/personal information” (25.9 percent).

In summary, the results suggest that the feasibility of the WFH system can be improved, and WFH productivity can be enhanced by improving the information and communication environment at home for teleworkers and by revising existing laws and regulations, as well as internal rules inhibiting work at home. However, in reality, the tasks that must be performed at the workplace and the difficulty of efficient face-to-face communication at home are likely to continue as restrictions to the diffusion of the WFH practice.

5. Conclusion

This study, using unique data from original surveys of employees and employers, presents evidence on the prevalence, intensity, and productivity of WFH practices during the COVID-19 pandemic in Japan. The findings from the employee and employer surveys are generally consistent with each other. The main results for the period covered in the survey are summarized below.

First, the percentage of employees who practiced WFH was approximately 32 percent. The WFH intensity (i.e., the contribution of WFH to total labor input) was about 19 percent in the employee survey and approximately 11 percent in the firm survey.

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

Third, the mean WFH productivity was approximately 60–70 percent of the productivity at workplace. Although the WFH practice is attracting attention owing to COVID-19, employees' productivity was lower than that in the workplace, at least on average. WFH productivity was particularly lower for employees and firms 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, highly educated, high-wage employees, long-distance commuters, and those who work in the information and communications industry tended to exhibit a relatively small reduction in productivity. Those who worked at home before COVID-19 tended to practice WFH frequently, suggesting a natural selection of work location based on productivity.

Fifth, the lack of face-to-face interactions, poor telecommunication environment at home, and the existence of tasks that must be conducted in the office owing to rules, regulations, and other reasons were the major impediments to improving productivity at home. Because some important information that is hard to digitalize will continue to be exchanged through face-to-face interaction, it is difficult for WFH productivity to reach the same level as that at the workplace, at least on average.

Considering the possibility that the WFH system becomes a new workstyle even after this pandemic is over, further development of information and communications infrastructure and revisions of rules and regulations hindering WFH is required. However, even firms that have adopted the WFH system do not necessarily enforce it on all their employees, and employees engaged in full-time WFH are rare. Thus, human resource management plays an important role in the selective application of WFH practice to employees who are engaged in tasks suitable for this workstyle. In addition, using new communication tools, such as teleconference systems, should be considered, depending on their advantages and disadvantages relative to face-to-face communications. 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 accurately measure the productivity of individual workers, particularly that of white-collar workers. Because 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 the teleworkers' productivity in 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 practice among a wide range of white-collar workers, we cannot 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, and hairdressers, the productivity of teleworking is prohibitively low.

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Table 1. Prevalence of WFH practice.

	(1) All workers	(2) Employees
Doing WFH	35.8%	32.2%
Early WFH adopters	10.6%	4.3%
New WFH adopters	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. Probability of participating in WFH practice: Estimation results.

Variables	dF/dx	Std. Err.		Variables (continued)	dF/dx	Std. Err.	
Female	-0.014	(0.025)		Real estate	0.051	(0.074)	
20-29	0.146	(0.051)	***	Accommodations & restaurants	-0.103	(0.072)	
30-39	0.076	(0.030)	***	Health care & welfare	-0.224	(0.021)	***
50-59	0.039	(0.027)		Education	0.093	(0.048)	**
60-69	0.045	(0.030)		Other services	-0.009	(0.034)	
70-79	0.128	(0.068)	**	Public services	0.065	(0.054)	
Junior high school	-0.153	(0.081)		Other industries	0.116	(0.043)	***
Vocational school	0.028	(0.039)		Administrative & managerial	0.051	(0.038)	
Junior (2-year) college	0.050	(0.040)		Professional & engineering	-0.004	(0.030)	
4-year university	0.101	(0.026)	***	Sales	-0.143	(0.039)	***
Graduate school	0.246	(0.052)	***	Trade-related	0.125	(0.046)	***
Ln earnings	0.090	(0.017)	***	Service	-0.067	(0.035)	*
Ln commuting hours	0.111	(0.012)	***	Production & other	-0.147	(0.024)	***
Non-standard employee	0.015	(0.029)		99 or smaller	-0.018	(0.029)	
Agriculture	-0.065	(0.118)		300-499	-0.016	(0.043)	
Construction	0.032	(0.044)		500-999	0.068	(0.043)	*
Information & communications	0.298	(0.059)	***	1,000 or larger	0.095	(0.033)	***
Transport	-0.163	(0.035)	***	Government	-0.018	(0.052)	
Wholesale & retail	-0.036	(0.038)		Observations	2,656		
Finance & insurance	0.061	(0.051)		Pseudo R^2	0.2599		

Notes: Probit estimations with robust standard errors are in parentheses. ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$. The categories used as references were male, age 40–49, senior high school, standard employee, manufacturing, clerical, and firm size of 100–299 employees.

Table 3. Distribution of the frequency of WFH.

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 4. WFH 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%

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

Table 5. WFH productivity: Estimation results.

Variables	(1) Coef.	Std. Err.		(2) Coef.	Std. Err.		(3) 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)	*
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)	
Industry dummies	yes			yes			yes		
Occupation dummies	yes			yes			yes		
Observations	828			828			828		
R-squared	0.1840			0.1975			0.2054		

Notes: OLS estimations with robust standard errors are in parentheses. ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$. The categories used as references were male, age 40–49, senior high school, standard employee, manufacturing, clerical, and firm size of 100–299 employees.

Table 6. Factors affecting WFH 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%

Note: Multiple answers were allowed for this question.

Table 7. Adoption of the WFH.

	(1) Early WFH adopters	(2) New WFH adopters	(3) Non-adopters
Total	4.1%	45.5%	50.4%
Large firms	5.3%	57.8%	36.9%
Small & medium firms	3.5%	38.9%	57.5%
Manufacturing	3.0%	42.6%	54.4%
Information & communications	20.5%	75.9%	3.6%
Wholesale	2.1%	57.1%	40.7%
Retail	1.2%	28.6%	70.2%
Services	5.6%	38.0%	56.3%
Other industries	10.6%	51.5%	37.9%
Tokyo	11.1%	73.7%	15.3%
Other prefectures	2.7%	39.9%	57.4%

Notes: "Early WFH adopters" are firms adopting the WFH system before the COVID-19 pandemic. "New WFH adopters" are the firms adopted the WFH system after the COVID-19 pandemic (N = 1,574).

Table 8. Comparison of WFH adopter and non-adopter.

	Adopters	Non-adopters	Diff.		Early adopters	New adopters	Diff.	
Female ratio	0.321	0.301	0.021	**	0.303	0.281	0.022	
Non-standard ratio	0.262	0.205	0.056	***	0.207	0.190	0.017	
Ratio of university or higher	0.216	0.419	-0.203	***	0.412	0.496	-0.084	**
ln employees	4.881	5.113	-0.233	***	5.088	5.409	-0.320	***
ln mean wages	1.297	1.527	-0.230	***	1.523	1.566	-0.042	

Notes: ***: $p < 0.01$ and **: $p < 0.05$ by t-test. The ratio of employees with university or higher education was taken from a survey conducted in 2019. The number of employees and mean wages were calculated from the BSJBSA for the fiscal year 2018.

Table 9. Determinants of WFH adoption.

	(1)			(2)		
	dF/dx	Std. Err.		dF/dx	Std. Err.	
Number of employees (log)	0.135	(0.025)	***	0.143	(0.024)	***
Information & communications	0.360	(0.100)	**	0.401	(0.082)	***
Wholesale	-0.050	(0.047)		-0.018	(0.048)	
Retail	-0.260	(0.052)	***	-0.233	(0.054)	***
Services	-0.053	(0.059)		-0.057	(0.058)	
Other industries	0.022	(0.083)		0.032	(0.081)	
Tokyo	0.338	(0.038)	***			
Population density (log)				0.095	(0.011)	***
Female ratio	0.267	(0.107)	**	0.293	(0.108)	***
Non-standard ratio	-0.073	(0.085)		-0.137	(0.085)	
University or higher	0.692	(0.085)	***	0.594	(0.087)	***
Mean wages (log)	0.293	(0.059)	***	0.273	(0.059)	***
Nobs.	1292			1292		
Pseudo R^2	0.2307			0.2356		

Notes: Probit estimations with robust standard errors are in parentheses. ***: $p < 0.01$, **: $p < 0.05$. Manufacturing is the reference category for industries.

Table 10. Share, frequency, and intensity of WFH.

	(1) Share of employees using WFH	(2) Frequency of WFH per week	(3) WFH intensity (unweighted)	(4) WFH intensity (weighted)
Total	30.7%	3.67	23.3%	10.9%
Early WFH adopters	49.1%	4.54	41.4%	37.6%
New WFH adopters	29.0%	3.59	21.7%	20.7%
Large firms	34.6%	3.61	25.5%	14.4%
Small & medium firms	27.7%	3.71	21.7%	9.1%
Manufacturing	18.8%	3.64	13.6%	6.0%
Information & communications	59.6%	4.28	51.3%	44.6%
Wholesale	38.2%	3.41	27.4%	15.3%
Retail	21.8%	3.39	15.2%	3.9%
Services	41.8%	3.77	32.1%	13.3%
Other industries	49.6%	3.93	42.1%	24.2%
Tokyo	48.4%	3.82	38.2%	30.5%
Other prefectures	23.7%	3.61	17.3%	7.0%
Nobs.	778	771	741	1,579

Notes: WFH intensity—contribution of WFH hours to total hours—is calculated as the ratio of WFH employees multiplied by the frequency of WFH per week (expressed as a percentage).

Table 11. Determinants of WFH intensity.

	(1)			(2)			(3)			(4)		
	Coef.	Std. Err.		Coef.	Std. Err.		Coef.	Std. Err.		Coef.	Std. Err.	
Number of employees (log)	0.000	(0.010)		0.005	(0.010)		0.009	(0.007)		0.013	(0.007)	*
Information & communications	0.243	(0.042)	***	0.278	(0.040)	***	0.262	(0.040)	***	0.295	(0.039)	***
Wholesale	0.034	(0.022)		0.048	(0.022)	**	0.010	(0.013)		0.024	(0.014)	*
Retail	-0.024	(0.035)		-0.027	(0.034)		-0.025	(0.012)	**	-0.013	(0.012)	
Services	0.159	(0.039)	***	0.162	(0.037)	***	0.073	(0.022)	***	0.075	(0.021)	***
Other industries	0.194	(0.044)	***	0.206	(0.046)	***	0.133	(0.034)	***	0.144	(0.036)	***
Tokyo	0.150	(0.021)	***				0.164	(0.018)	***			
Density (log)				0.043	(0.006)	***				0.036	(0.004)	***
Female ratio	0.117	(0.060)	*	0.151	(0.059)	**	0.120	(0.032)	***	0.129	(0.032)	***
Non-standard ratio	-0.114	(0.045)	**	-0.145	(0.044)	***	-0.062	(0.025)	**	-0.086	(0.024)	***
University or higher	0.249	(0.042)	***	0.206	(0.043)	***	0.234	(0.029)	***	0.207	(0.029)	***
Mean wages (log)	0.061	(0.034)	*	0.059	(0.034)	*	0.072	(0.020)	***	0.068	(0.020)	***
Cons.	-0.072	(0.074)		-0.355	(0.080)	***	-0.182	(0.043)	***	-0.395	(0.045)	***
Nobs.	623			623			1292			1292		
R-squared	0.4300			0.4232			0.4577			0.4357		

Notes: OLS estimations with robust standard errors are in parentheses. ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$. Columns (3) and (4) include firms that did not adopt WFH, of which the WFH intensity was regarded as zero.

Table 12. Mean productivity of WFH relative to the productivity at the workplace.

	Productivity
Total	68.3
Early WFH adopters	81.8
New WFH adopters	67.0
Large firms	69.4
Small & medium firms	67.4
Manufacturing	68.0
Information & communications	80.3
Wholesale	65.0
Retail	62.6
Services	66.5
Other industries	69.5
Tokyo	72.0
Other prefectures	66.8
Nobs.	762

Note: Productivity of WFH is relative to productivity at the workplace (= 100).

Table 13. Determinants of WFH productivity.

	(1)			(2)		
	Coef.	Std. Err.		Coef.	Std. Err.	
Number of employees (log)	1.162	(0.949)		1.314	(0.940)	
Information & communications	9.936	(3.490)	***	10.951	(3.437)	***
Wholesale	-5.299	(2.874)	*	-4.949	(2.857)	*
Retail	-14.640	(5.083)	***	-14.843	(5.107)	***
Services	-4.909	(3.617)		-4.994	(3.620)	
Other industries	-0.729	(3.880)		-0.503	(3.959)	
Tokyo	4.217	(1.876)	**			
Density (log)				1.458	(0.626)	**
Female ratio	14.298	(6.518)	**	15.274	(6.491)	**
Non-standard ratio	1.153	(5.369)		0.397	(5.358)	
University or higher	2.107	(4.298)		0.598	(4.356)	
Mean wages (log)	7.948	(3.244)	**	7.810	(3.230)	**
Cons.	44.203	(7.764)	***	34.829	(8.517)	***
Nobs.	615			615		
R-squared	0.0714			0.0732		

Notes: OLS estimations with robust standard errors are in parentheses. ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$.

Table 14. Factors affecting adoption and productivity of WFH.

Factors	
Poor telecommunication environment at home relative to the workplace	60.8%
The requirements by rules and regulations that some tasks must be conducted in the office	57.7%
Some tasks cannot be conducted at home even though these are not required by rules and regulations	76.1%
It is difficult to concentrate on job because of the presence of family members	33.0%
Lack of a private room specifically designed for work	36.9%
Loss of quick communication that is only possible through face-to-face interactions with their colleagues at the workplace	46.0%
Lack of pressure from the boss, colleagues, and subordinates	36.4%
Much of the work requires direct interaction with customers	34.3%
Other reasons	4.1%

Note: Multiple answers were allowed for this question.

Appendix

Appendix Table A1. Composition of survey respondents.

	Respondents	2015 Census
Male	54.3%	49.4%
Female	45.7%	50.6%
20-29	3.8%	13.2%
30-39	12.8%	16.6%
40-49	20.0%	19.6%
50-59	20.2%	16.4%
60-69	29.5%	19.3%
70-79	13.7%	14.9%

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

Table A2. Prevalence of WFH 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 participated in the WFH arrangement. 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 A3. Mean frequency of WFH 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 versions of the original choices in the survey questions.

Table A4. WFH 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 A5. Summary statistics.

	Nobs.	Mean	Std. Dev.
WFH adoption	1,579	0.495	0.500
WFH intensity	741	0.299	0.286
WFH intensity (adjusted)	1,579	0.140	0.246
WFH productivity	762	68.281	23.440
WFH productivity (adjusted)	1,579	32.951	37.814
Number of employees	1,561	4.973	0.879
Tokyo	1,579	0.168	0.374
Population density (log)	1,579	6.573	1.497
Female ratio	1,561	0.311	0.196
Non-standard ratio	1,552	0.234	0.240
Ratio of university or higher	1,364	0.315	0.246
Mean wages (log)	1,514	1.411	0.394

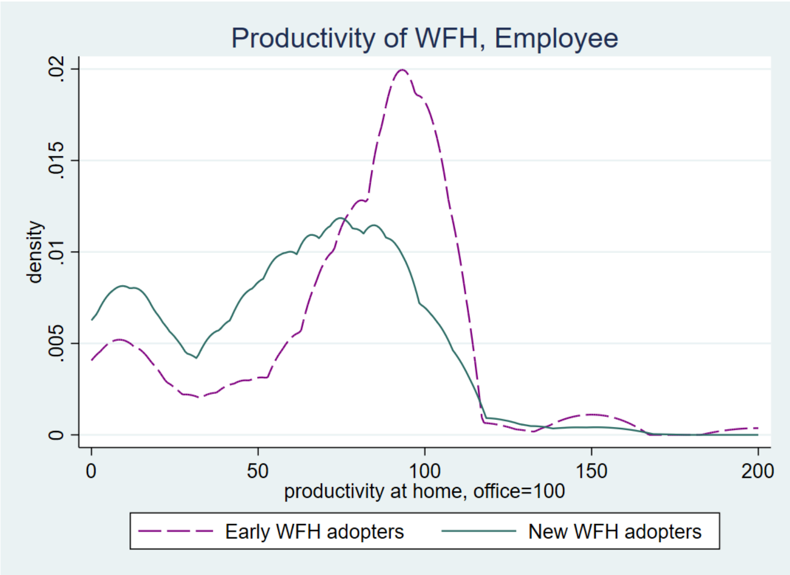
Notes: WFH intensity is calculated as the ratio of WFH employees multiplied by WFH frequency per week (expressed as a percentage). "Adjusted" figures are calculated by including WFH non-adopters, whose WFH intensity and productivity are zero.

Table A6. Regulations or rules restrictive to the adoption and productivity of WFH.

Regulations or rules	Percentage
Permission or licenses on businesses	6.0%
Labor regulations	26.9%
Environmental regulations	6.9%
Land use/building regulations	0.3%
Regulations on protecting consumers/personal information	25.9%
Corporation law	10.0%
Occupational licensing system	1.5%
Tax system	2.7%
Social security system	5.2%
Guidance of government/municipality not based on the law	2.4%

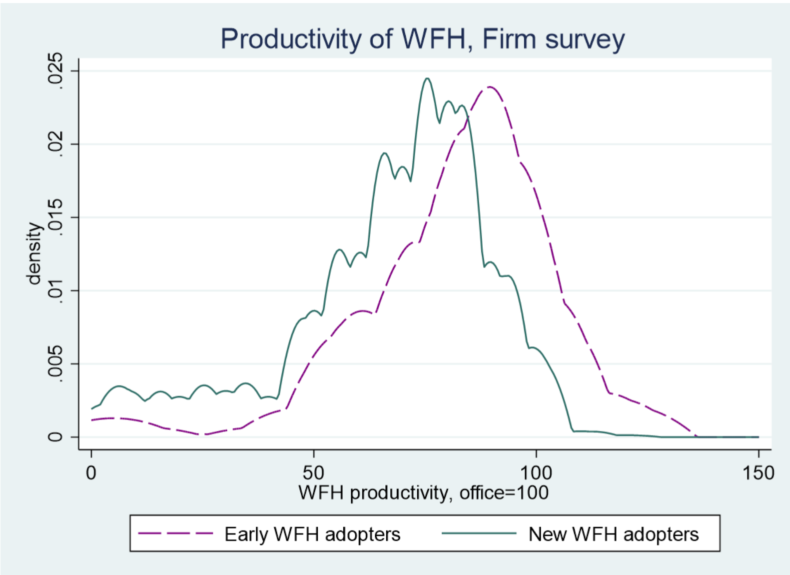
Note: Multiple answers were allowed for this question.

Figure A1. Distribution of WFH productivity by the timing of adoption.



Note: The label "Early 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.

Figure A2. Distribution of WFH productivity by the timing of adoption.



Notes: "Early WFH adopters" are firms adopting the WFH arrangement before the COVID-19 pandemic. "New WFH adopters" are the firms adopted the WFH arrangement after the COVID-19 pandemic.