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Productivity of Working from Home during the COVID-19 Pandemic: Panel Data Analysis

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Abstract

Using panel data from original surveys conducted in June 2020 and July 2021, this study analyzes the changes in adoption and productivity of working from home (WFH) during the COVID-19 pandemic. First, the results indicate that the mean WFH productivity has improved by more than ten percentage points in the past year, although it is still approximately 20% lower compared to when working in the office. 1) "Selection effect" arising from the exit of workers with relatively low WFH productivity from the WFH practice and 2) the improvement in WFH productivity through the "learning effect" contributed almost equally to the productivity growth of WFH. Second, additional working hours extracted from reduced commuting are approximately 3.0% and 0.7% of the total labor input of WFH workers and all workers, respectively. Even after adjusting for additional working hours from reduced commuting, the conclusion of relatively low productivity at home remains essentially unchanged. Third, the percentage of employees who want to continue frequent WFH after the end of the pandemic has increased substantially, suggesting that WFH may become a popular workstyle.

Keywords: COVID-19, work from home, productivity, commuting

JEL Classification: I12, J22, J24, R41

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1. Introduction

Following the spread of the COVID-19 pandemic, employees engaged in working from home (WFH) increased rapidly. WFH may become a standard workstyle through the hysteresis effect even after the COVID-19 pandemic is contained. However, it will depend on both the productivity and non-pecuniary benefits of WFH. Under the rapid diffusion of WFH induced by the pandemic, studies on WFH have been increasing. They have unraveled the individual characteristics who can work from home (e.g., Adams *et al*., 2020; Dingel and Neiman, 2020; Boeri *et al*., 2020; Brussevich *et al*., 2020; Kikuchi *et al*., 2021; Kawaguchi and Motegi, 2021) and those who have adopted the WFH practice (e.g., Bick *et al*., 2020; Brynjolfsson *et al*., 2020; Morikawa, 2020; Okubo, 2020). These studies generally indicate that high-skill and high-wage, white-collar workers tend to undertake WFH and that, consequently, the diffusion of WFH after the COVID-19 pandemic has increased inequality in the labor market.

In contrast, formal studies on WFH productivity are limited. Studies based on surveys of individual workers include Etheridge *et al*. (2020), Morikawa (2020), and Barrero *et al*. (2021). [1] Since it is extremely challenging to measure the productivity of white-collar workers who perform a large variety of tasks, all of these studies depend on workers' self-assessment of WFH productivity. Etheridge *et al*. (2020), using survey data from the United Kingdom, indicate that, on average, workers adopting WFH report little difference in productivity relative to the productivity before the pandemic, but that the WFH productivity is quite heterogeneous by worker characteristics. Morikawa (2020), based on a survey of workers in Japan, documents that the mean WFH productivity relative to working at the usual workplace was approximately 60% to 70% and that it was lower for employees who started WFH practices only after the spread of the COVID-19 pandemic. Barrero *et al*. (2021), based on a survey in the United States, indicate that most respondents who have adopted WFH practice report equal to or higher WFH productivity than

[1] Dutcher (2012), Bloom *et al*. (2015), and Battiston *et al*. (2021) are representative studies related to the productivity of WFH before the COVID-19 pandemic.

productivity on business premises. [2] To summarize, studies on the productivity of WFH have been limited, and have varied results.

Morikawa's study (2020), mentioned above, is based on a cross-sectional survey conducted in June 2020 (from now on, "2020 survey"). This study extends Morikawa's (2020) analysis using panel data constructed from the 2020 survey, and the new survey conducted in July 2021 (from now on, "2021 survey"), and documents changes in the prevalence, frequency, and productivity of WFH during the past year. Additionally, this study presents new findings regarding the use of saved commuting hours. The main contributions of this study are 1) to identify the impacts of selection and learning effects on the improvement in WFH productivity, and 2) to clarify the impact of additional working hours extracted from saved commuting on the measurement of WFH productivity.

The remainder of this paper is organized as follows. Section 2 describes the survey design. Section 3 reports the results on the prevalence, frequency, and productivity of WFH, use of saved commuting hours, and the workers' intention to continue WFH after the end of the COVID-19 pandemic. Section 4 summarizes the conclusions and implications of this study.

2. Outline of the Survey

The survey data used in this study 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 Rakuten Insight, Inc. in late June 2020 and early July 2021. The 2020 survey questionnaire was sent via e-mail to 10,041 individuals who responded to a survey conducted in 2017, and 5,105 individuals responded.[3] The 2021 survey questionnaire was sent to those who responded to the 2020 survey, resulting in 4,479 responses. Simultaneously, the same 2021 survey questionnaire was sent to additional registered monitors stratified by gender and age in proportion to the latest composition of the Japanese population. The number of additional respondents is

[2] Studies on WFH productivity using firm surveys include Bartik *et al*. (2020) and Morikawa (2021).

[3] In the 2017 survey, the sample individuals were randomly chosen from about 2.3 million registered monitors of Rakuten Insight, Inc., stratified by gender, age, and region, in proportion to the population composition of the 2015 Population Census (Statistics Bureau, Ministry of Internal Affairs and Communications).

4,430. Consequently, the total number of observations in the 2021 survey is 8,909.

This study mainly uses a sample of 4,697 employed individuals at the time of the 2021 survey. As the survey asked about the type of employment, we exclude self-employed individuals and family workers, whose workplace is likely to be at home, to focus on the WFH of ordinary employees. Among the employee sample, 2,267 people responded to both 2020 and 2021 surveys (from now on, "panel employee"), and 2,430 people are the additional respondents in the 2021 survey. The compositions of respondents and the subsample of employees by gender and age categories are reported in **Table 1**. When comparing the two surveys, we further restrict the sample to those who are working as employees in both surveys (2,117 people, from now on "panel employees) when necessary.

Among the survey questions related to WFH in the 2021 survey, adoption, frequency, and subjective productivity of WFH and intention to continue WFH after the COVID-19 pandemic, are the same as the 2020 survey. The new questions in the 2021 survey include the use of saved commuting hours and the colleague's assessment of the productivity of WFH workers. Additionally, the survey collects information about individual characteristics such as gender, age, education, prefecture of residence, and annual household income (16 categories). For those who are working, type of employment (nine categories), industry (14 categories), occupation (13 categories), firm size (12 categories), annual earnings from work (18 categories), weekly working hours (12 categories), and commuting hours between home and workplace (round trip, ten categories). [4] These items are in the form of multiple-choice questions and are designed to be consistent with those in the Employment Status Survey (Ministry of Internal Affairs and Communications).

When conducting regressions, household income, earnings from work, working hours, and commuting hours are converted into continuous logarithmic variables using the central values of each category. In this calculation, the maximum categories (household income of "30 million yen or more," annual earnings of "20 million yen or more," working hours of "75 hours or more," and commuting hours of "4 hours or longer") are treated as 32.5 million yen, 21.25 million yen, 80.5 hours, and 4.25 hours, respectively. The figures applied to the highest categories are based on the

[4] In the analysis presented later, some categories are integrated into a smaller number of classifications. For example, junior and senior high school graduates are combined into high school graduates. The types of employment are integrated into two types: regular (permanent full-time) and non-regular (part-time, contractual, and temporary) employees.

difference between the central value of the second-highest category and the lower bound of the highest category. [5]

3. Results

3-1. Prevalence and Frequency of WFH

Table 2 shows the tabulation results of the prevalence of WFH. The percentage of employees engaged in WFH has dropped from 32.2% in 2020 to 21.5% in 2021 (column (1)). When the sample is limited to those whose working type are employees in both surveys, the reduction is larger, from 37.1% to 21.1% (column (2)). **Table 3** presents the transition matrix for the subsample of panel employees. Those who started WFH during the past year are 3.2% and those who exited from WFH are 41.7%, indicating that many employees engaged in WFH just after the pandemic's onset returned to the workplace. The 2020 survey asked whether he/she adopted WFH before the COVID-19 pandemic (from now on "early WFH adopters") or after the onset of the pandemic (from now on "new WFH adopters"). According to this distinction, the exit rate of early WFH adopters is 17.5%, and that of new WFH adopters is 44.8%. Additionally, those who engaged in WFH less frequently and those who expressed low self-assessed WFH productivity in the 2020 survey are more likely to exit from WFH. [6] This result indicates a natural selection mechanism based on productivity at home.

Table 4 presents simple probit estimation results by observable individual characteristics to explain the engagement in WFH. The reference categories for the dummy variables are male, age 40–49, high school education, those living outside the Tokyo area, regular employee, manufacturing industry, clerical job, and firm size of 100–299 employees. As the table shows marginal effects, the figures indicate WFH probability relative to the reference categories.

The coefficients for younger (age categories of 20–29 and 30–39 years) and older (age 70 or older) employees, higher education, annual earnings, Tokyo area, information and communications industry, administrative occupation, and large firms (500 or more employees)

[5] For example, the second-highest earnings category in the survey is 17.5–20 million yen.
[6] High education, high-wage, Tokyo area, and information and communication industry are associated with a low probability of exit from WFH.

are positive and significant, meaning that these characteristics are associated with a higher probability of participating in WFH practice after controlling for other individual characteristics. In the case of annual earnings, doubling annual earnings is associated with an approximately 3% higher probability of adopting WFH. While not reported in the table, when the dummy for the Tokyo area is replaced by commuting hours (expressed in logs), the coefficient is positive and statistically significant at the 1% level. Quantitatively, doubling commuting hours is associated with an approximately 4% higher probability of using WFH.

Conversely, the coefficients for transportation, wholesale and retail, healthcare and welfare industries, sales, service, and production occupations are negative and statistically significant. Interestingly, the coefficients for female and non-regular employment are insignificant. According to a simple tabulation of the 2021 survey, there are large differences in WFH participation rate by gender and employment type: males 26.1%, females 27.9%, regular employees 27.9%, and non-regular employees 10.7%. However, the coefficients for female and non-regular employees are insignificant after controlling for the other individual characteristics, indicating that the compositions of other attributes such as industry and occupation are very different by gender and employment type. In comparison with the result for the 2020 survey (column (2)), the patterns are generally the same, but the coefficient for the education industry turns negative, and the coefficients for the wholesale, retail, and administrative occupations become significant.

Regarding the weekly frequency of WFH, the mean and median are 2.75 days and two days, respectively, in the 2021 survey. However, the frequency of WFH is highly dispersed, even among employees engaged in WFH. According to the 2021 survey, weekly frequencies of WFH at the 25 and 75 percentiles are one and four days, respectively. The 2021 survey asked about WFH days per week, but the 2020 survey asked about the percentage of WFH on weekly working days. Therefore, WFH days in the 2021 survey is converted into percentage term to enable comparison (**Table 5**). The mean share of WFH days, WFH days divided by the weekly working days, is almost unchanged during the past year: 55.7% in the 2020 survey and 56.6% in the 2021 survey. Even for the subsample of those who responded to both surveys, the frequencies of WFH are almost unchanged (55.9% in 2020 and 54.3% in 2021), provided that they continue to use WFH (column (2)). As reported before, the change in the extensive margin (the percentage of employees engaged in WFH) is relatively large, but, in contrast, the change in the intensive margin is negligible.

3-2. Productivity of WFH

The survey asked for self-assessed WFH productivity relative to one's productivity in the usual workplace. The specific question is, "Suppose your productivity at the usual workplace is 100; how do you evaluate your work productivity at home? Please answer this question by considering all your tasks." It was noted that "If your productivity at home is higher than that at the usual workplace, please answer with a figure higher than 100." The distributions of WFH productivity in 2020 and 2021 are shown in **Figure 1**. The figure indicates that 1) the overall distribution has shifted slightly right, and 2) the lower end of the distribution has shrunk substantially. The mean WFH productivity has improved from 60.6 in 2020 to 77.5 in 2021 (the median has increased from 70 to 80). The subsample of panel employees shows a similar pattern: the mean productivity has improved from 61.4 to 76.6 (the median has increased from 70 to 80).

Table 6 shows the transition matrix for the sample of panel employees. The WFH productivity of those who engaged in WFH has improved from 70.4 in 2020 to 78.2 in 2021, indicating that productivity of WFH has improved through learning effects and investment in WFH infrastructure at home. However, the median WFH productivity is 80 in both surveys, suggesting that those with relatively low WFH productivity disproportionally contribute to increased mean productivity. This is confirmed by simple regression. When the WFH productivity level in 2020 is included as an additional variable into the equation to explain WFH productivity in 2021, the coefficient for this variable is negative and significant, indicating a convergence of WFH productivity.

Although the number of those who started WFH after the 2020 survey is small, the mean WFH productivity is 62.4, which is lower than the productivity of WFH continuers. While not reported in the table, the mean WFH productivity of the early WFH adopters (those who adopted WFH before COVID-19) in 2021 is 90.5 (+4.8 points), and that of new WFH adopters (those who started WFH after the onset of the COVID-19 pandemic) in 2021 is 75.8 (+8.4 points), suggesting a catch-up of WFH productivity through the learning effect.

The mean WFH productivity in the 2020 survey of those who exit from WFH was 48.7, far lower than that of WFH continuers. **Figure 2** depicts productivity distributions in the 2020 survey of the panel employees, which confirms that many low-WFH performers have returned to the workplace. This self-selection mechanism contributes to 9.1 points improvement in mean WFH productivity, which is a somewhat larger magnitude than the learning effect.[7]

Table 7 reports OLS estimation result to explain WFH productivity by individual characteristic. The explanatory variables are the same as the participation probability estimation (reported in **Table 4**). The determinants of WFH productivity have changed between 2020 and 2021. In the 2021 survey (column (1)), variables such as education, employment type, and the Tokyo area are statistically insignificant. [8] Our interpretation is that the selective exit of relatively low WFH performers contributes to the shrinkage of differences by the observable characteristics.

The 2021 survey has a question for those who are not engaged in WFH but have colleagues who do, about their assessment of the WFH productivity of their colleagues at home. The specific question is, "How would you rate the productivity of your colleagues when they telecommute if their productivity were to be rated 100 at the regular workplace?" The mean and the median of this question are 53.3 and 50, respectively. **Figure 3** depicts the distributions of the colleagues' assessment and self-assessment, which indicates that the colleagues' assessment distributed far lower than the self-assessment of employees engaged in WFH. Since it is challenging for colleagues to accurately evaluate their colleagues' productivity at home, the result cannot be interpreted as an objective assessment. Our interpretation is that those who are not engaged in WFH are skeptical about the performance of teleworkers at home. This result suggests that labor-management is not easy for workplaces where WFH workers and non-WFH workers coexist.

3-3. How Are Reduced Commuting Hours Used?

The 2021 survey asked about the use of reduced commuting hours produced by adopting WFH. The specific question is, "How do you use the time saved by telecommuting?" The three choices are 1) "mainly for work," 2) "half for work and a half for daily activities/leisure," and 3) "mainly for daily activities/leisure." **Table 8** presents the tabulation results by gender. The responses of all respondents are as follows: mainly for work 20.0%, half and half 38.2%, and 41.8% for daily

[7] As stated in subsection 3-1, a small number of employees (45 people) have started WFH between 2020 and 2021. Since the mean productivity of these new WFH employees (62.4) is lower than the WFH continuers (78.2), these new WFH employees reduce mean WFH productivity in 2021 by about 1.6 points.
[8] When the dummy for the Tokyo area is replaced by commuting hours (expressed in logs), the coefficient is positive and statistically significant at the 10% level in 2020 and 5% level in 2021.

activities/leisure. Male employees tend to use the saved commuting hours for work. When roughly calculating the share of hours used for work by applying 100%, 50%, and 0% for the three choices, the simple mean is 39.1% for all employees engaged in WFH. The shares of males and females are 41.4% and 33.2%, respectively; the difference by gender is statistically significant at the 1% level.

Based on the responses, it is possible to make a back-of-the-envelope calculation of the additional supply of working hours extracted from saved commuting hours by multiplying 1) the share (100%, 50%, or 0%), 2) round commuting hours between home and office, and 3) WFH days per week. The additional working hours amount to 3.0% of the total working hours for WFH workers and 0.7% for all employees. It is often argued that an increase in labor supply obtained by reduced commuting is a benefit of WFH, but the contribution is quantitatively small, at least on average.[9]

The impact of the substitution from commuting to working hours on the measured WFH productivity depends on whether the respondents interpret the productivity at home as a worker-day or worker-hour basis. In the case of worker-day productivity interpretation, reported WFH productivity overestimates worker-hour productivity. In the case of worker-hour productivity interpretation, the reported WFH productivity underestimates worker-day productivity. However, in any case, as evident from the above calculation, the bias of measured WFH productivity arising from the substitution from commuting to work is quantitatively limited.

Column (1) of **Table 9** shows the OLS estimation results to explain additional working hours obtained from saved commuting by individual characteristics. The explanatory variables are gender, age categories (40-49 is the reference category), annual earnings (expressed in the log), and weekly working hours (expressed in the log). The coefficient for the female is negative and significant at the 1% level. The coefficients for earnings and working hours are both positive and significant at the 1% level.

However, by definition, the saved commuting hours tend to be greater for long-commuters. In this regard, column (2) of the table shows the regression result by including commuting hours (expressed in the log) as an additional variable. In this case, although the coefficient for the female is still negative, the significance level is marginal, and the size of the coefficient becomes smaller.

[9] However, it should be noted that there is a large dispersion. At the individual level, the median, 75th percentile, and 90th percentile is 0.6%, 3.9%, and 9.6%, respectively.

This result reflects the fact that commuting hours are generally short among female employees. Conversely, the coefficients for earnings and working hours are still positive, highly significant, and the size is not much different from the result in column (1). In short, high-wage workers and those who work long hours tend to use saved commuting hours for work.

3-4. WFH after the COVID-19 Pandemic

Both 2020 and 2021 surveys asked the telecommuters' intention to continue WFH after the COVID-19 pandemic. The question is only for those using WFH. The specific question is, "Do you want to continue WFH after the covid-19 pandemic subsides?" The choices are 1) "I want to continue WFH as frequently as I do now," 2) "I want to continue WFH, although less frequently than now," and 3) "I want to work at my workplace instead of WFH."

Table 10 summarizes the tabulation results. The percentage of choosing "I want to telecommute as frequently as I do now" has increased substantially from 38.1% in the 2020 survey to 62.6% in the 2021 survey. These figures include compositional changes caused by the exit of low-WFH performers, but even if the sample is limited to WFH continuers, the percentage has increased from 56.2% to 68.2% (column (3)). We conjecture that the possible reasons behind this increase are 1) the improved WFH productivity through the learning effect and investments in WFH infrastructure at home and 2) improved recognition of the amenity value of WFH. Since the intention to continue frequent WFH in the 2020 survey and the actual implementation of WFH in the 2021 survey have a strong positive correlation, the result suggests that WFH will become a standard workstyle even after the COVID-19 pandemic. As described before, the productivity of WFH is, on average, still lower than that of the usual workplace. The result suggests that WFH has a high amenity value for teleworkers.

Table 11 presents ordered probit estimations to explain the intention to continue WFH after the end of the pandemic. The dependent variable is defined as: "I want to continue WFH as frequently as I do now" =3, "I want to continue WFH, although less frequently than now" =2, and "I want to work at my workplace instead of WFH" =1. The reference categories of dummy variables are male, age 40-49, and high school education. Female and younger (age 20-29 and 30-39) employees and those living in Tokyo have a significantly strong desire to continue frequent WFH in the 2021 survey.[10] Additionally, as expected, higher subjective WFH productivity is associated with a high desire to continue frequent WFH in the 2020 and 2021 surveys. In short, employees, particularly female and young employees, recognize the high amenity value of WFH, even if the productivity at home is lower than at the office.

4. Conclusion

Using panel data from original surveys conducted in June 2020 and July 2021, this study presents evidence of the changes in WFH practice during the COVID-19 pandemic in Japan. The main contributions of this study are 1) to identify the contributions of selection and learning mechanisms on improving WFH productivity and 2) to clarify the impact of additional working hours from saved commuting on WFH productivity. The major findings of this study can be summarized as follows:

First, although the WFH productivity, on average, is still approximately 20% lower than the productivity at the workplace, it has improved by more than ten percentage points during the past year. 1) "Selection effect" arising from the exit of low WFH productivity employees from the WFH practice and 2) the improvement in WFH productivity through "learning effect" contributed almost equally to the improved productivity of WFH. The learning effect is stronger for those at the lower end of the WFH productivity distribution in 2020, indicating convergence of WFH productivity.

Second, approximately 58% of WFH employees use some portion of the saved commuting hours to work. The additional working hours extracted from reduced commuting are approximately 3.0% and 0.7% of the total labor input of WFH workers and all workers, respectively. Even if adjusting for the substitution of commuting hours to additional work, the conclusion of relatively low productivity at home is essentially unchanged.

Third, the percentage of employees who want to continue frequent WFH after the end of the COVID-19 pandemic has increased substantially. This indicates that WFH has a high amenity value for those who conduct WFH-friendly tasks, and WFH may become a popular workstyle

[10] When the dummy for the Tokyo area is replaced by commuting hours (expressed in logs), the coefficient was positive and statistically significant in 2020 but insignificant in 2021.

even after the COVID-19 pandemic.

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Table 1. Composition of the Respondents in the 2021 survey

	(1) Total	(2) Employee	(2-1) Responded to the 2020 survey	(2-2) New respondents
Nobs.	8,909	4,697	2,267	2,430
Male	52.6%	31.0%	31.7%	30.4%
Female	47.4%	21.7%	19.0%	24.4%
Age 20-29	7.8%	5.7%	1.7%	9.7%
30-39	13.2%	9.7%	8.2%	11.3%
40-49	19.3%	14.0%	13.6%	14.4%
50-59	19.5%	12.5%	14.4%	10.7%
60-69	23.1%	8.5%	10.5%	6.5%
70 or older	17.0%	2.2%	2.1%	2.3%

Table 2. Prevalence of WFH

	(1) All employees		(2) Panel employee	
	2021 survey	2020 survey	2021 survey	2020 survey
Not doing WFH	3,685	1,842	1,670	785
Doing WFH	1,012	876	447	1,332
WFH ratio	21.5%	32.2%	21.1%	37.1%

Note: Column (2) shows the figures for those working as employees in both the 2020 and 2021 surveys.

Table 3. Transition Matrix of WFH Adoption

		2021 survey		
		Doing WFH	Not doing WFH	Total
2020 survey	Doing WFH	402	287	689
		58.3%	41.7%	
	Not doing WFH	45	1,383	1,428
		3.2%	96.8%	
	Total	447	1,670	2,117

Note: Column (2) shows the figures for those working as employees in both the 2020 and 2021 surveys. The percentages are the ratio of the total number in the 2020 survey.

Table 4. Probability of WFH Adoption by Employee Characteristics

		(1) 2021 survey			(2) 2020 survey		
		dF/dx	Robust S.E.		dF/dx	Robust S.E.	
Gender	Female	0.014	0.014		-0.018	0.025	
Age	20-29	0.091	0.026	***	0.118	0.050	**
	30-39	0.034	0.018	**	0.058	0.030	**
	50-59	0.007	0.015		0.040	0.028	
	60-69	0.029	0.021		0.069	0.031	**
	70 or older	0.108	0.046	***	0.131	0.065	**
Education	Vocational school	0.048	0.026	**	0.040	0.039	
	Junior (2-year) college	0.083	0.030	***	0.062	0.039	
	4-year university	0.116	0.016	***	0.119	0.026	***
	Graduate school	0.252	0.038	***	0.287	0.051	***
Income	ln Household income	0.039	0.010	***	0.072	0.016	***
Region	Tokyo area	0.136	0.013	***	0.205	0.021	***
Type	Non-standard employee	-0.025	0.017		-0.021	0.029	
Industry	Agriculture	-0.055	0.067		-0.062	0.113	
	Construction	0.004	0.025		0.019	0.045	
	Information & communications	0.231	0.040	***	0.333	0.057	***
	Transport	-0.097	0.017	***	-0.189	0.034	***
	Wholesale & retail	-0.054	0.019	**	-0.045	0.039	
	Finance & insurance	-0.038	0.022		0.071	0.052	
	Real estate	-0.015	0.035		0.006	0.067	
	Accommodations & restaurants	-0.073	0.032	*	-0.115	0.071	
	Health care & welfare	-0.167	0.009	***	-0.250	0.020	***
	Education	-0.079	0.017	***	0.093	0.048	**
	Other services	-0.028	0.018		-0.030	0.034	
	Public services	-0.069	0.021	***	0.045	0.052	
	Other industries	0.044	0.026	*	0.100	0.043	**
Occupation	Administrative & managerial	0.045	0.024	**	0.059	0.040	
	Professional & engineering	0.022	0.018		0.018	0.031	
	Sales	-0.123	0.015	***	-0.151	0.042	***
	Trade-related	0.030	0.024		0.160	0.048	***
	Service	-0.075	0.018	***	-0.078	0.037	**
	Production & other	-0.096	0.014	***	-0.145	0.025	***
Firm size	99 or smaller	-0.013	0.018		-0.028	0.029	
	300-499	0.019	0.027		-0.018	0.044	
	500-999	0.064	0.028	**	0.067	0.043	
	1,000 or larger	0.128	0.023	***	0.085	0.033	***
	Government	0.067	0.043	*	0.015	0.056	
Nobs.		4,695			2,718		
Pseudo R^2		0.2653			0.2465		

Notes: Probit estimation results with marginal effects are presented. ***: p<0.01, **: p<0.05, *: p<0.10.

Table 5. Frequency of WFH (%)

	(1) All employee		(2) Panel employee	
	2021 survey	2020 survey	2021 survey	2020 survey
Mean	56.6	55.7	54.3	55.9
Median	60	50	40	50

Note: In the 2021 survey, those who responded to weekly working days as "irregular" (N=27) are excluded from the calculation.

Table 6. Transition Matrix of WFH Productivity

		2021 survey	
		Doing WFH (**77.5**)	Not doing WFH
2020 survey	Doing WFH (**60.6**)	**70.4 ⇒ 78.2**	**48.7 ⇒ —**
	Not doing WFH	**— ⇒ 62.4**	

Table 7. WFH Productivity by Employee Characteristics

		(1) 2021 survey			(2) 2020 survey		
		Coef.	Robust S.E.		Coef.	Robust S.E.	
Gender	Female	4.163	2.504	*	0.083	3.319	
Age	20-29	0.460	3.600		-0.185	4.849	
	30-39	-4.531	2.658	*	1.900	3.327	
	50-59	-2.298	2.488		4.302	3.223	
	60-69	-2.716	3.334		2.019	4.075	
	70 or older	-0.793	7.633		8.551	8.636	
Education	Vocational school	-5.707	4.559		6.017	5.200	
	Junior (2-year) college	-1.534	4.189		13.644	5.290	**
	4-year university	2.933	3.019		14.000	3.606	***
	Graduate school	5.613	3.485		19.152	4.450	***
Income	ln Household income	2.479	1.934		3.654	2.042	*
Region	Tokyo area	2.254	1.867		6.838	2.375	***
Type	Non-standard employee	2.289	3.421		7.181	4.125	*
Industry	Agriculture	-15.389	13.121		12.329	16.852	
	Construction	-12.668	4.308	***	-5.353	4.647	
	Information & communications	3.418	2.672		4.513	4.227	
	Transport	-10.323	7.319		-23.553	11.722	**
	Wholesale & retail	-6.233	3.763	*	-6.825	4.558	
	Finance & insurance	-7.573	3.770	**	-16.659	4.856	***
	Real estate	1.910	7.069		-17.713	8.640	**
	Accommodations & restaurants	-15.680	9.563		1.725	16.849	
	Health care & welfare	-8.674	7.612		-26.085	8.150	***
	Education	-1.647	4.924		-15.531	4.938	***
	Other services	2.685	3.370		-2.932	4.391	
	Public services	-10.558	8.793		-27.580	6.064	***
	Other industries	-2.940	4.381		2.253	5.030	
Occupation	Administrative & managerial	4.287	3.448		4.808	3.881	
	Professional & engineering	7.257	3.044	**	5.334	3.535	
	Sales	0.199	6.213		-18.637	9.173	**
	Trade-related	-0.836	3.545		-3.503	4.567	
	Service	-6.049	5.085		-4.905	6.071	
	Production & other	-0.907	4.292		-9.059	4.379	**
Firm size	99 or smaller	-4.834	3.371		-0.859	3.814	
	300-499	-5.035	4.573		6.934	5.590	
	500-999	-3.084	4.208		-4.483	4.867	
	1,000 or larger	0.803	3.150		-1.517	3.782	
	Government	-7.600	9.228		-3.357	6.717	
Cons.		60.938	12.900	***	27.031	14.379	*
Nobs.		1,012			876		
Pseudo R^2		0.0953			0.1765		

Notes: OLS estimation results. ***: p<0.01, **: p<0.05, *: p<0.10.

Table 8. Use of Reduced Commuting Hours

	(1) All	(2) Male	(3) Female
1) Mainly for work	20.0%	22.0%	14.9%
2) Half for work and half for daily activities/leisure	38.2%	38.9%	36.7%
3) Mainly for daily activities/leisure	41.8%	39.1%	48.4%
Nobs.	1,012	723	289

Table 9. Additional Working Hours Extracted from Reduced Commuting by Employee Characteristics

	(1)			(2)		
	Coef.	Robust S.E.		Coef.	Robust S.E.	
Fenale	-0.264	0.100	***	-0.155	0.091	*
20-29	0.071	0.161		0.087	0.154	
30-39	0.050	0.143		0.073	0.133	
50-59	0.203	0.169		0.126	0.154	
60-69	-0.148	0.136		-0.240	0.127	*
70 or older	0.106	0.230		0.000	0.208	
ln Household income	0.216	0.053	***	0.182	0.048	***
ln Working hours	0.349	0.096	***	0.285	0.090	***
ln Commuting hours				1.053	0.100	***
Cons.	-1.537	0.430	***	-1.087	0.391	***
Nobs.	1,449			1,449		
R-squared	0.0436			0.1718		

Notes: OLS estimations. ***: p<0.01, *: p<0.10.

Table 10. Intention to Continue WFH after the COVID-19 Pandemic

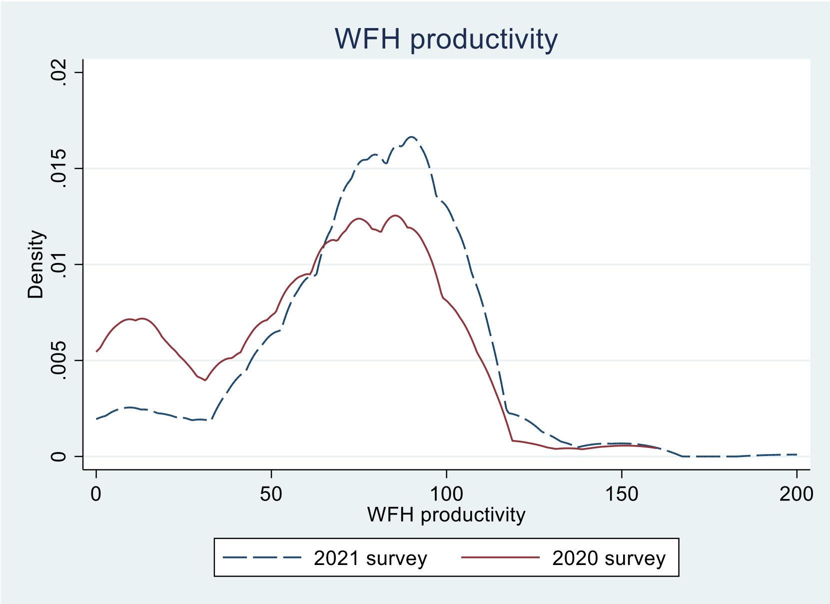
	(1) All WFH employees		(2) Panel WFH employees		(3) Continuing WFH	
	2020	2021	2020	2021	2020	2021
1) I want to do WFH as frequently as I do now.	38.1%	62.6%	36.1%	61.1%	56.2%	68.2%
2) I want to do WFH, although less frequently than now.	36.6%	26.5%	38.3%	27.5%	31.1%	23.1%
3) I want to work at my workplace instead of WFH.	25.2%	10.9%	25.5%	11.4%	12.6%	8.8%
Nobs.	876	1,012	689	447	594	594

Table 11. Intention to Continue WFH by Employee Characteristics

		(1) 2021 survey			(2) 2020 survey		
		Coef.	Robust S.E.		Coef.	Robust S.E.	
Gender	Female	0.215	0.091	**	0.174	0.093	
Age	20-29	0.315	0.137	**	-0.044	0.169	
	30-39	0.385	0.117	***	-0.026	0.117	
	50-59	0.093	0.107		-0.183	0.105	*
	60-69	0.116	0.135		-0.369	0.122	***
	70 or older	0.176	0.241		0.128	0.258	
Education	Vocational school	-0.236	0.192		0.240	0.183	
	Junior (2-year) col	-0.231	0.193		-0.070	0.177	
	4-year university	-0.102	0.129		0.102	0.123	
	Graduate school	-0.186	0.154		-0.020	0.149	
Region	Tokyo area	0.188	0.079	**	0.150	0.079	*
WFH productivity		0.014	0.002	***	0.013	0.001	***
Nobs.		1,012			876		
Pseudo R^2		0.0756			0.0851		

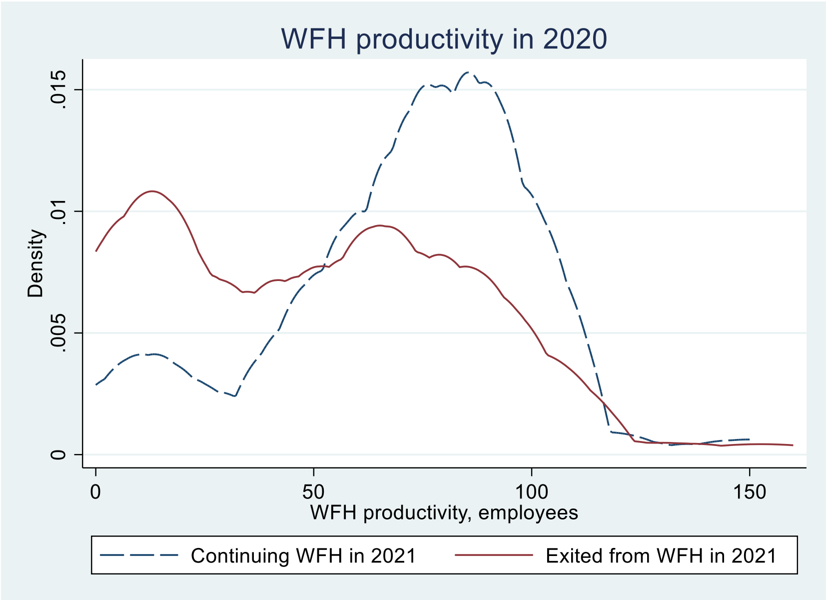
Notes: Ordered probit estimations ***: p<0.01, **: p<0.05, *: p<0.10. The dependent variable is defined as “I want to continue WFH as frequently as I do now,” =3, “I want to continue WFH, although less frequently than now,” =2, and “I want to work at my workplace instead of WFH” =1.

Figure 1. Change in WFH Productivity Distribution



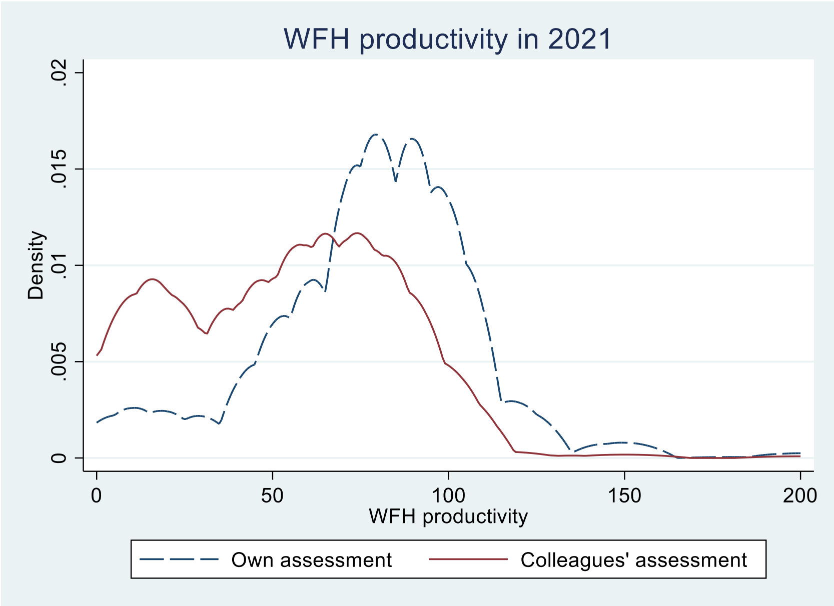
Notes: The figure depicts the distribution of WFH productivity for those working as employees in the 2020 and 2021 surveys.

Figure 2. WFH Productivity Distributions in 2020 by WFH Status in 2021



Notes: The figure depicts the distribution of WFH productivity in 2021 for those working as employees in the 2020 and 2021 surveys.

Figure 3. WFH Productivity Distribution: Employee's Evaluation and Colleague's Evaluation



Note: The figure depicts WFH productivity distributions of colleagues' assessment and self-assessment from the 2021 survey.