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Work from Home and Human Capital Investment
－ 在宅勤務と人的資本投資 －

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概　　要

本研究では、日本のパネルデータを用いて、在宅勤務（WFH）が成人の人的資本投資（企業が提供する訓練、労働者が自発的に行う訓練、様々な種類の学習を含む）に与える影響を分析した。

WFH の内生性に対処するために、COVID-19 のマクロ・ショックを外生的な変動とし、企業内の WFH 制度から構築される職種間のパンデミック前における WFH 実現可能性の差を操作変数として用いた。

その結果、WFH は自己学習やオンライン学習を促進する一方で、対面学習を減少させることが明らかになった。特に、子どものいる労働者や非正規雇用労働者においてこれらのインパクトが大きいこともわかった。

さらに統計的有意ではないものの、WFH は OJT と OFF-JT を増加させることもわかった。

2000 年以降企業の人的投資が非正規雇用を中心に減少していることが指摘されているが、WFH は減少を防ぐ一助となる可能性がある。

また、昨今リスキリングやリカレント教育など成人の学習が政策的議論になることが多いが、柔軟な働き方とセットで推進すべきである。

Work from Home and Human Capital Investment

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Abstract

Using Japanese panel data, this study analyzes the impact of work from home (WFH) on adult human capital investment, including firm-provided training, worker-initiated training, and various kinds of learning. To address the endogeneity of WFH, we employ a combination of macro shocks from COVID-19 as an exogenous variation and the difference in pre-pandemic feasibility of WFH among occupations constructed from WFH systems within firms as instrumental variables. The findings reveal that WFH enhances self-learning and online learning while reducing in-person learning, particularly among workers with children and non-regular employees. Additionally, WFH appears to increase on-the-job and off-the-job training, although these effects lack statistical significance.

JEL Classification Numbers: J10, J22, J24 and J81
Keywords: Work from home (WFH), Human capital investment, Firm-provided training, On-the-job training (OJT), Off-the-job training (Off-JT), Worker-initiated training, Self-learning, Instrumental variable (IV), Difference-in-Differences (DID)

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1 Introduction

The proliferation of work from home (WFH) arrangements rapidly accelerated with the onset of the COVID-19 outbreak.[1] Initially embraced as a measure to facilitate social distancing during the early stages of the COVID-19 pandemic, WFH garnered considerable scholarly attention. This led to numerous studies examining the characteristics of WFH employees, as evidenced by Dingel and Neiman (2020).[2] Concurrently, researchers have explored the nexus between WFH, productivity, and mental health, driven by the inquiry into whether WFH could maintain pre-existing levels of productivity. Noteworthy contributions include Atkin et al. (2023) and Deole et al. (2023).[3] As the acute phase of the COVID-19 crisis subsided, attention shifted towards WFH's potential as a flexible work paradigm, prompting a surge in research examining its broader societal implications. Notably, investigations have sought to determine whether the time savings afforded by WFH translate into increased engagement in household chores and childcare responsibilities, as seen in studies by Inoue et al. (2023) and Pabilonia and Vernon (2022). Gender dynamics in household labor distribution have also garnered attention due to their relevance to the gender wage gap (Adams-Prassl et al., 2023). For instance, Inoue et al. (2023) observed that WFH led to increased involvement of men in housework. However, scant attention has been paid to exploring how the surplus time gained from WFH impacts individual career trajectories. Notably, the relationship between WFH and human capital investment remains underexplored in the existing literature.

As societies age and the duration of employment extends, investment in human capital beyond the educational phase becomes increasingly crucial. Individuals accrue human capital through experiential learning while on the job, alongside other forms of investment in their

[1] Early exploration into WFH's impact on work performance emerged in management research, with Bloom et al. (2015) as a seminal work. For a comprehensive overview of recent WFH trends, see Barrero et al. (2023).

[2] Additionally, Holgersen et al. (2021), Kawaguchi and Motegi (2021), Brussevich et al. (2022), Alipour et al. (2023), Morikawa (2022), and Morikawa (2023) conducted related analyses.

[3] Previous studies such as Dutcher (2012), Bloom et al. (2015), Kazekami (2020), Kawaguchi and Motegi (2021), Kitagawa et al. (2021), Gibbs et al. (2023), Shen (2023) and Morikawa (2023) have explored similar themes.

own development. Concurrently, firms also play a role in augmenting human capital among their workforce. Previous research, such as Schwerdt et al. (2012), examined the impact of adult education voucher programs, while Hara (2014) explored the effects of training provided by Japanese firms on wages and the transition to regular employment. The implementation of active labor market programs, as studied by Card et al. (2018), serves as another example of post-school human capital investment.[4] However, while many studies have analyzed the outcomes of training, scant attention has been given to the factors that drive participation in training programs. Continual learning and skill enhancement pose common challenges in developed nations and represent significant policy concerns in Japan. Despite this, Japan is internationally recognized for its comparatively low levels of ongoing education. For instance, as of 2012, the Organisation for Economic Co-operation and Development (OECD) average participation rate in recurrent education for individuals aged 25-64 stood at 47%, whereas in Japan, it was 42%, falling below the average. Furthermore, investment in human capital within firms has declined, particularly since the late 2000s, as elucidated by Hara (2014). Thus, although the importance of both WFH and post-entry workforce learning, along with human capital investment, is increasing, little attention has been directed towards examining their relationship. Ideally, workers should autonomously recognize the necessity of investing in human capital within the labor market and take the initiative to do so, without relying solely on government interventions such as subsidies. It is plausible that WFH arrangements could address some of these challenges.

This study uses Japanese panel data to investigate the impact of WFH on individuals' human capital investment, encompassing firm-provided training, on-the-job training (OJT), off-the-job training (Off-JT), self-learning, and various kinds of learning. The theoretical relationship between WFH and human capital investment remains ambiguous. While it is intuitive that individuals may utilize their commuting-free time for study or skill acquisition,

[4] Additional studies include Leuven and Oosterbeek (2008) and Hidalgo et al. (2014). Leuven (2005) surveyed firm-provided training from the perspective of economic theory.

potentially increasing human capital investment, WFH could also diminish opportunities for learning from colleagues or alter work dynamics in a way that reduces the inclination to learn. Moreover, there is the possibility that the extra time gained from WFH is diverted to non-investment activities such as housework, childcare, or caregiving. The net effect of WFH on human capital investment is thus uncertain, necessitating causal inference through microdata analysis.

To address this, our identification strategy combines the instrumental variable (IV) and difference-in-difference (DID) methods. Recognizing the variation in WFH adoption across occupational groups, we leverage pre- and post-COVID-19 outbreak shocks as natural experiments to account for the endogeneity of WFH implementation. We exploit the differing impacts of COVID-19 on various occupations, where those engaged in WFH tend to exhibit stronger work preferences and a propensity for human capital investment and long-term career development. By doing so, we mitigate potential biases stemming from unobserved work preferences. Additionally, we acknowledge the potential for reverse causality; namely, that investments in IT skills among WFH workers may drive the adoption of WFH practices. Consequently, applying standard ordinary least squares (OLS) estimation in this scenario may introduce bias to the estimator.

We utilize a large-sample panel dataset that offers detailed insights into both WFH practices and human capital investment. Notably, such comprehensive panel data, particularly regarding WFH pre-COVID-19, are scarce both nationally and internationally. Our unique dataset encompasses diverse forms of learning, including OJT and Off-JT, providing a nuanced understanding of human capital investment dynamics. Moreover, our WFH data capture a range of WFH system characteristics, including WFH hours, which we introduce in Section IV of this study.

Our analysis reveals that WFH correlates with a 14.1% increase in self-learning and a 15.6% rise in online-based learning. However, it also associates with an 8.9% decrease in in-person learning. While the effects on OJT and Off-JT are not statistically significant, WFH exhibits an increase in both. Despite the intuitive expectation of WFH being incompatible with OJT, no such trend emerged in our findings. Additionally, these effects vary across lifestyles, such as parenthood status and working style, with WFH demonstrating particularly pronounced effects on enhancing human capital among individuals with children.

The contributions of this study are twofold: First, to the best of our knowledge, it represents the initial examination, not only in Japan but internationally, of the intricate relationship between WFH and human capital investment. We carefully address causal inferences using panel data and capitalize on natural experiments to enhance robustness. Second, our analysis explores various determinants of vocational training, diverging from the predominant focus on labor market outcomes such as wages, as exemplified by Hara (2022). While numerous studies explore the impact of vocational training on labor market outcomes, only a limited few analyze its determinants, making our study a valuable addition to the literature.

This study holds significant relevance from a Japanese policy standpoint. The Japanese government has been actively advocating policies aimed at supporting reskilling (relearning) initiatives in light of increasing life expectancies, projected to extend beyond 100 years. For instance, the Ministry of Health, Labor and Welfare (MHLW) substantially augmented subsidies for related programs for 2022, increasing the amount by 12 times over the previous seven years. Furthermore, the MHLW plans to expand the scope of supported courses to over 300 by 2025, a 60% increase from current levels, primarily focusing on digital fields, and intends to elevate subsidy rates. Concurrently, the Japan Federation of Economic Organizations is encouraging companies to afford employees time for reskilling endeavors. Given Japan's status as home to the world's largest aging population, adult learning has assumed heightened importance compared to other nations. If time constraints represent a barrier to learning, the introduction of WFH emerges as a potent avenue for promoting reskilling without necessitating direct government intervention.

The rest of this paper is structured as follows: Section 2 provides an overview of the dataset and delineates variable definitions. Section 3 elucidates our identification strategy and validates underlying assumptions. In Section 4, we present our findings, encompassing robustness checks and heterogeneity analyses. The final subsection of Section 4 discusses the policy implications of our results within the broader literature context. The paper concludes in Section 5.

2 Data

2.1 Basic information

This study utilizes the Japanese Panel Study of Employment Dynamics (JPSED), a nationwide survey representative of individuals aged 15 and above. Conducted by an internet monitor registered to Intage Corporation, JPSED employs a standard set of demographic and labor market variables. Commencing with an initial cohort of 49,131 individuals, the survey evolves over subsequent waves through panel attrition and sample additions, amassing approximately 50,000 observations annually. For our analysis, we leverage data from the 2017-2022 waves (2nd-6th waves), conducted in January.[5]

Of particular significance are the 2019 and 2020 surveys, conducted before and after the onset of COVID-19 (the exogenous shock), respectively. These surveys, conducted in January, predominantly focus on December, aligning with our identification strategy by distinctly demarcating pre- and post-COVID-19 outbreak periods. In January 2020, while the media reported on the COVID-19 outbreak in China, Japan remained relatively unaffected. The first confirmed cases of infection in Japan emerged after February. Subsequently, in April 2020, the government issued an emergency declaration urging WFH adoption and recommending

[5]It is worth noting that the 1st wave of the survey lacks crucial remote work information and employs slightly different questioning methods compared to subsequent waves.

an increase in the number of employees working remotely. Consequently, this period proves suitable for our analysis.

The dataset we utilize offers a rich array of information on WFH both before and after the onset of COVID-19, along with extensive data on human capital investment and learning activities, including OJT, Off-JT, and other learning initiatives. Such comprehensive panel data, encompassing both WFH and human capital investment metrics, are considered rare internationally. With WFH gaining prominence, particularly in the wake of COVID-19, many studies have resorted to retrospective inquiries regarding pre-COVID-19 WFH practices. However, previous research has highlighted the presence of measurement errors in retrospective data, especially when collected after a prolonged period.[6] In contrast, our survey adopts a non-retrospective approach, querying respondents about events occurring within the preceding month or two, thereby providing more reliable information.

To ensure the integrity of our analysis, we confine our sample to individuals who participated in the survey from 2017 (based on their status as of 2016) and maintained consistent employment between 2016 and 2021. We exclude the self-employed from our analysis as our focus lies on evaluating the impact of WFH on human capital investment. Soliciting information on WFH from self-employed individuals would be inappropriate, as their homes often serve as their workplaces. Consequently, eliminating invalid variables further reduces the sample size to 83,431 observations. The core analysis sample comprises employed individuals aged 25-59 years old.

2.2 Explanation of variables

A distinctive aspect of this survey is its inclusion of questions pertaining to engagement in remote work.[7] The first question queries respondents about the number of hours worked

[6] For instance, Sawada et al. (2019) demonstrated that consumption data surveyed in developing countries exhibit measurement errors.

[7] These questions can be found in the appendix.

remotely per week in December of each year. Remote work encompasses working from home, satellite offices, or public venues such as coffee shops or restaurants. Respondents provide a continuous number representing the exact hours worked, including instances where no remote work was undertaken. The second question explores company policies regarding remote work. Respondents select one of the following options: 1) the company established and applies remote work rules to the respondent, 2) the company established rules but they do not apply to the respondent, 3) the company did not set any rules, or 4) I do not know. Additionally, other questions inquire about the extent to which workers are permitted to engage in remote work and the actual location where respondents worked in the preceding December. This array of questions enables us to identify remote workers as treatment effects in the first question and instrumental variables in the second question.

The definition of WFH in this study encompasses workers who engaged in remote work for more than one hour in December each year. Additionally, another criterion considers whether workers are permitted to work remotely for over 40% of their total working hours per week. Currently, a debate exists regarding the optimal ratio of WFH to office work concerning worker satisfaction and productivity. As the COVID-19 situation evolved, many companies encouraged employees to return to office settings, while others advocated for continued teleworking. The WFH-to-office attendance ratio varied among companies during this transitional period, sparking discussions in numerous countries, including the U.S. and Japan. For instance, Apple CEO Tim Cook announced a policy requiring employees to work three days a week in the office starting in September 2021.[8] This study aims to examine how the WFH ratio impacts workers' life from the perspective of human capital investment,

[8]Other examples include Google's directive in April 2022 for employees to attend office settings at least three days a week, Amazon's similar requirement in 2023, and Disney's mandate for at least four days a week (NIKKEIxTREND, 2023). Additionally, X (formerly Twitter) CEO Elon Musk banned WFH entirely in November 2022 (NIKKEI, 2022). French advertising giant Publicis Groupe S.A. garnered attention for its notice to employees warning of potential salary reductions, diminished bonuses, and limited promotion prospects if they fail to attend office settings for fewer than three days a week. Rakuten, a prominent Japanese internet service provider, implemented a policy in 2022 requiring employees to work four days a week with a WFH hybrid workday (TOYOKEIZAI ONLINE, 2022).

offering two definitions. Barrero et al. (2021) also underscored the importance of this aspect. Furthermore, this study employs these definitions in the construction of IVs in Section 3.

Table 1 presents descriptive statistics providing an overview of WFH. First, the WFH implementation rate across the pooled data from 2017-2022 stands at 10%. We assessed whether this percentage aligns with expectations for a WFH study utilizing Japanese data. Notably, 8% of workers engaged in remote work in December 2019, a figure surpassing the 3-4% reported for 2016-2017 by Kazekami (2020) and the 5.2% reported for 2017 by Morikawa (2022), yet closer to the 10% reported for January 2020 by Okubo (2020). Our higher figure compared to Kazekami (2020) and Morikawa (2022) can be attributed to our broader definition of remote workers. Moreover, the WFH rate naturally increased compared to the pre-COVID-19 period, consistent with expectations given the post-COVID-19 outbreak scenario reflected in our statistics. Inoue et al. (2023) also reported WFH rates of 12.5% in 2019 and 28.5% in 2020, slightly exceeding our findings. However, their retrospective survey of individuals working as of December 2020 might bias figures upward due to the impact of COVID-19 on working conditions. Additionally, Morikawa (2023) reported a WFH rate of 18.5% in 2022, contrasting with our 12.6% rate. These discrepancies could be attributed to differences in survey timing, despite both studies being conducted in the same year. Nevertheless, considering these nuances, our overall results appear reasonable. Furthermore, the proportion of individuals able to engage in WFH for 40% of their weekly working hours remains minimal at 3%, indicating that even during and after the COVID-19 outbreak, only a select few could engage in WFH to such a significant extent.

Moving on, we describe the application of the WFH system. The percentage of individuals with WFH implemented as a system, or those with the system in place and actively utilizing it, amounts to 14%. Notably, as highlighted in Kawaguchi and Motegi (2021), some individuals may not engage in WFH despite its institutionalization. Moreover, there are instances where individuals perceive themselves to be engaged in WFH even in the absence of formal institutionalization. In our study, we prioritize actual WFH implementation as the primary variable, emphasizing the importance of discerning whether WFH is actively practiced.

Another notable feature of the JPSED survey is its inquiry into human capital investment.[9] This questionnaire closely resembles the Basic Survey of Human Resources Development utilized by Hara (2017) and others, albeit with greater detail and coverage of a larger cohort of workers.[10] Several variables were derived from this questionnaire, including OJT, Off-JT, self-learning, and kind of learning (KoL). OJT involves mentorship by supervisors or senior staff members to facilitate the acquisition of knowledge and skills by new or temporary employees through on-the-job experiences. A dummy variable is generated, taking a value of 1 if the employee receives training, and 0 otherwise. Off-JT entails the engagement of external instructors to deliver job-relevant skills through classroom instruction. Similarly, a variable is created with a value of 1 indicating receipt of Off-JT and 0 denoting its absence. Self-learning entails proactive learning initiatives undertaken by employees, wherein they set tasks, execute them, evaluate outcomes, and provide feedback for subsequent learning endeavors. These investments represent foundational human capital endeavors.

Furthermore, this study explores more specific types of learning and human capital investment, including "attending school," "participating in one-off courses, seminars, and study groups," "engaging in distance learning," "participating in e-learning," "reading books," "conducting research on the internet," and "consulting with knowledgeable individuals." Each of these seven learning modalities is categorized under KoL. We construct a variable that takes a value of 1 if any of the seven modalities is pursued, and 0 otherwise. Additionally, we aggregate these variables into broader categories. "Attending school" and "consulting with knowledgeable individuals" are designated as "in-person KoL," while "participating in one-off courses, seminars, and study groups," "engaged in distance learning," and "partici-

[9] These questions can be found in the appendix.

[10] The Basic Survey of Human Resources Development focuses solely on companies and establishments with a workforce of 30 or more employees. Given that a majority of establishments in Japan employ fewer than 30 individuals, the survey's suitability for comprehensively understanding the Japanese workforce is limited.

pating in e-learning" are designated as "online KoL."

It is important to note the distinction between OJT and Off-JT from self-learning and KoL in terms of their nature as human capital investments. OJT and Off-JT, also known as firm-provided training, are invested in proactively by the firm, with costs shared between the company and the worker. In contrast, self-learning is initiated independently by the workers themselves, with costs entirely borne by them. Together with WFH, these aspects are considered integral components of human resource management (HRM). Thus, this study investigates the complementarity between WFH and firm-provided training, examining whether the introduction of WFH, as a facet of HRM, enhances firm-provided training, another dimension of HRM. Moreover, it is crucial to assess whether WFH facilitates the utilization of leisure time by mitigating commuting opportunity costs.

Descriptive statistics are provided in Table 1. In terms of OJT, 22% of respondents report its implementation, while 21% indicate the provision of Off-JT. These figures align with those reported in the Basic Survey on Capacity Development. The self-learning rate stands at 33%, indicating a considerable proportion of workers engaging in independent learning initiatives. Notably, 53% of respondents report involvement in KoL, with over half of the employed population actively pursuing learning endeavors. Interestingly, 15% of respondents are practitioners of online learning, while 13% engage in in-person learning, suggesting a slightly higher prevalence of online learning practitioners.

3 Identification strategy

3.1 Estimation equation

This study estimates the impact of WFH on various human capital investments. The estimation equations are as follows:

$$HCI_{it} = \alpha + \beta WFH_{it} + x'_{it}\gamma + \theta_i + \phi_t + u_{it}, \tag{1}$$

where indices i and t represent the individual and time on an annual basis, respectively. The dependent variable HCI_{it} signifies the human capital investment of individual i in year t, encompassing variables such as OJT, Off-JT, and KoL. The variable WFH_{it} is a dummy indicating whether individual i works from home in year t. The vector x_{it} comprises control variables, including age (quadratic function), a dummy indicating partner status, number of children, a dummy indicating the presence of preschoolers, and education category dummies,[11] firm size category dummies,[12] years of tenure (quadratic function), cross-terms for graduation in 2020 and year dummy variables, cross-terms for firm size in 2020 and year dummy variables, and prefecture-year fixed effects.[13] The variables θ_i and ϕ_t represent individual and year fixed effects, respectively. Following Motegi (2022), we consider other macro shocks originating from labor market reforms and incorporate time effects. u_{it} denotes the unobserved error term. In Equation (1), the coefficient of the WFM dummy, β, is the parameter of interest in this study.

[11] These education categories include the following fifteen options: elementary and middle school (graduated), high school (graduated), specialized schools (technical schools) (graduated), junior college (graduated), technical industrial college (graduated), university (graduated), master's program in graduate school (graduated), doctoral program in graduate school (graduated), high school (enrolled), specialized schools (technical schools) (enrolled), junior college (enrolled), technical industrial college (enrolled), university (enrolled), master's program in graduate school (enrolled), and doctoral program in graduate school (enrolled).

[12] The categories of firm size include the following four options: small-sized (less than 100 employees), middle-sized (between 100 and 999 employees), large-sized (1,000 or more employees), and government employees.

[13] We used the prefectures where individuals reside.

The use of OLS presents an endogeneity issue: individuals opting to WFH may have inherent preferences regarding their work style. These individuals naturally lean towards investing in human capital and pursuing long-term careers. Consequently, the unobserved preference for a particular work method introduces bias as an omitted variable. Reverse causality is also plausible; for instance, investments in computer and programming skills might lead to WFH adoption, given its reliance on IT equipment. Here again, OLS estimation suffers from bias. Moreover, the sample period encompassed various macro shocks such as COVID-19 and labor market reforms in Japan, which affected individuals differently. These shocks are incorporated into the unobserved error terms. For example, a 2019 reform mandated firms to reduce working hours, prompting efforts to enhance productivity. Some firms may have turned to WFH to maintain productivity levels, while simultaneously investing in human capital. In such scenarios, the OLS estimator may exhibit upward bias, complicating the direction and magnitude of biases associated with OLS estimation.

In this study, we employ the IV method to address endogeneity arising from time-variant shocks. we use a combination of macro shocks from COVID-19 as an exogenous variable and the implementation of WFH systems within firms as instrumental variables.[14] Initially, we constructed a variable termed WFH feasibility, which we then interacted with macro shocks before and after the COVID-19 outbreak to serve as the IV. Our analysis begins by assessing the presence of a WFH system within a firm. This was determined by examining the pre-COVID-19 data to ascertain the proportion of employees working in companies that had implemented a WFH system, as elaborated in Section 2.[15] These percentages were weighted using 2017 sampling weights and were categorized into 45 medium classifications, closely aligned with the Standard Classification of Occupations in Japan. Utilizing these percentages, we created an occupation category variable, dividing each occupation into two

[14] The idea of this identification strategy is similar to that in Chong and Noguchi (2024).

[15] More specifically, we derived these proportions by considering responses indicating whether 1) the company established WFH rules and they apply to the respondent, or 2) the company established WFH rules, but they do not apply to the respondent.

categories: those with a higher likelihood and those with a lower likelihood of utilizing the WFH system. Figure 1 illustrates this categorization, with 23 occupations identified as having a low likelihood of WFH system usage, and 22 as having a high likelihood. These job category variables were then matched with individual data based on the respondents' job categories at the time of the 2020 survey (as of December 2019), and treatment status was assigned to each individual. In the first stage, the treatment group comprised jobs with a high availability of the WFH system, while the control group comprised those with low availability. From 2019 to 2020, the Japanese labor market experienced the impact of the COVID-19 outbreak, leading to an expansion in WFH availability. However, the extent of this expansion varied between the treatment and control groups. Notably, the treatment group witnessed a more significant increase in WFH availability compared to the control group. Leveraging this disparity in exposure, we utilized it as the IV. Consequently, the coefficient obtained can be interpreted as the local average treatment effect. In essence, this study estimates the impact of WFH within a group that made WFH decisions in response to macro-shocks during COVID-19.

In the first stage of the IV estimation, a DID analysis is conducted for the WFH variable. This is the first-stage estimation equation in the IV method. The following equation (2) is estimated.

$$WFH_{it} = \tilde{\alpha} + \pi T_i \times After_t + x'_{it}\tilde{\gamma} + \tilde{\theta}_i + \tilde{\phi}_t + e_{it}, \tag{2}$$

The variable T_i is a dummy variable indicating whether an individual's occupation as of December 2019 was an occupation with high availability of WFH in the pre-pandemic period. The variable $After_t$ is a dummy that takes the value of 1 after 2021.[16] This equation includes

[16]We take two terms T_i and $After_t$ into consideration by using both fixed effects.

the same control variables as in Equation (1), and the variables $\tilde{\theta}_i$ and $\tilde{\phi}_t$ are the individual- and year-fixed effects, respectively. e_{it} is the unobserved error term. In other words, the IV of this study is $T_i \times After_t$ and we see the coefficient π to determine whether the first stage works.

Figure 2 illustrates the WFH implementation rates for both the treatment and control groups. It is evident that the WFH implementation rate for the treatment group experienced a significant increase from 2020, coinciding with JPSED2021, or the COVID-19 outbreak. Subsequently, in 2021, the treatment group maintains a notably high WFH implementation rate, while the control group's rate remains comparatively low. This setup is instrumental in mitigating endogeneity resulting from unobserved time-variant shocks.

Additionally, this study employs fixed effects analysis, including θ_i, to address unobserved time-independent effects. Such effects, which encompass individual preferences regarding work style and career, can introduce bias into the estimates if left unaccounted for.

3.2 Assumption for identification

We aim to verify the assumptions of this identification strategy, with particular focus on the estimated equation (2).

To assess the DID model's assumptions, we investigate whether the treatment and control groups exhibit similar attributes. The results are presented in Table 2, showing whether the demographic characteristics of the treatment and control groups were statistically different during the 2020 survey period. The analysis reveals that the number of children and the percentage of children under six years of age does not exhibit significant differences between the two groups. However, statistically significant differences are observed in the percentage of women, age, and the percentage of individuals with a spouse. Despite statistical significance, the magnitude of these differences is relatively small, ranging from approximately 2.9% to 5.7%, calculated as the difference between the two groups divided by the control group's worker rate. Notably, a statistically and economically significant difference is identified in educational level, with a mean difference of 44.8% between the treatment and control groups.

Regarding firm size, the percentage of each firm size category displays statistical significance, with differences in magnitude that cannot be overlooked: -15.1% (small; 1–99), -7,8% (medium; 100–999), and 20.5% (large; 1000+). However, much of this variance can be attributed to differences in educational levels between the two groups. Upon estimating firm size differences after controlling for education level, the variances in the proportions of small, medium, and large firms were reduced to 7.6%, 9.3%, and 12.4%, respectively. Furthermore, the difference in the proportion of public employees between the two groups is 38.9% after controlling for education level, while it stands at 51.6% before such control. Previous studies, such as Kawaguchi and Motegi (2021), indicate that firm size plays a crucial role in WFH adoption in Japan. Moreover, an individual's firm size is correlated with their educational background, and controlling for this factor can mitigate potential biases. Thus, it is imperative to include educational background and firm size as controls in the estimation equation. The demographic variables are generally balanced between the treatment and control groups, but the education level and percentage of civil servants differ. It would be better to control for these attributes, which means controlling for different trends in education and firm size levels.

To see whether the common trend assumption holds in this DID model, we estimate equation (3) as an event study model.

$$y_{it} = \alpha_0 + \sum_{k=2017, k\neq 2020}^{2022} [\delta_k T_i \times 1\{t = k\}] + x'_{it}\gamma + \theta_i + \phi_t + \varepsilon_{it}, \tag{3}$$

Here, δ_k indicates whether the difference between the two groups in year k is statistically significant from the mean difference in the explained variables between the treatment and control groups in 2020. For example, if no statistically significant coefficients are obtained for 2017-2019, then we can infer that the explained variable remained parallel between the treatment and control groups during the pre-COVID-19 period. Additionally, statistically significant coefficients obtained for 2021 and 2022 indicate that there was some change in the difference between the treatment and control groups during COVID-19 for the explained variable.

The estimation results are depicted in Figure 3a. The coefficients δ_k are plotted as follows: after 2020, they are statistically significant positive coefficients. This indicates that individuals in occupations with higher availability of WFH programs during COVID-19 actually had higher WFH rates only after 2020. Regarding 2017 to 2019, the target coefficients are small and not statistically significant. The results are more pronounced in the 40+% in Figure 3b compared to the magnitude of the coefficient after 2021. In the 40% or more case, the impact of the coefficient is more significant since the pre-pandemic mean among treated is 0.013. These two figures imply that the common trend assumption for the DID estimates is valid. We address this issue with a robustness check of the estimation results in Section 4 for another important condition for identifying DID estimates: no compositional change or selection.

4 Results

4.1 Main results

We first interpret the estimation results, starting with the first-stage results. Columns (1) and (2) of Table 3 show that the estimated results are both statistically significant. The magnitudes of the coefficients of percent change are also large, at 12.3% and 9.8%, respectively.

When using the IV strategy, we often encounter weak instruments; if IVs are weakly correlated with the endogenous variable, the IV estimates can be biased, and statistical tests for the estimates may not be precisely implemented. We investigate the possibility of weak instruments using the effective F-statistics introduced by Olea and Pflueger (2013) and the rule-of-thumb value of 10, as suggested by Andrews et al. (2019): if the effective F-statistics are over the rule-of-thumb value, we can conclude that the IVs have a certain power to predict the included endogenous variable. The effective F-statistics are 28.2 and 22.7 for the WFH dummy and the WFH at least 40% per week dummy, respectively, and are over the rule-of-thumb value of 10. This finding implies that the IVs are less likely to suffer from weak instrument problems.

Next, we discuss the main results of the second-stage estimation. The results are shown in Panel A of Table 4. Interpreting the results from the statistically significant ones, we found that WFH implementation increases self-learning by 14.1%. This is economically significant, representing a 44.4% increase in the self-learning ratio compared to non-WFH workers. For online-KoL, there is also a significant increase of 15.6%. This translates to a 113.8% increase in the online learning ratio compared with non-WFH workers. The result of increased online learning is intuitive, given that WFH itself involves much online work, and learning tends to be facilitated by the Internet. However, in-person-KoL shows a decrease of 8.9% for WFH practitioners. This underscores the importance of compensating for in-person learning when implementing WFH. This decrease can be attributed to the reduced opportunities for face-to-face contact with people when working from home. Additionally, there is a 9.9% increase in All-KoL, indicating a 19.2% overall increase in engagement in some type of learning. This increase is noteworthy, especially considering that 51% of workers do not engage in WFH.

Although not statistically significant, there is a trend towards promotion for OJT and Off-JT (6.4% and 7.2%, respectively). These are also notable, considering that the implementation rates for those not engaging in WFH are, 21.3% and 20.5%, respectively. However, the results for OJT may seem counterintuitive, as one would expect the quality of communication to decline when WFH is implemented. In this study, the opposite is true. It would be impossible to decrease the amount of OJT training if IT equipment and other tools are well utilized. As mentioned earlier, firm-provided training and WFH are two types of HRM, but they appear to be complementary HRM systems. It has been suggested that the two could be used in conjunction to invest efficiently in human capital. Overall, we conclude that WFH increases various human capital investments, except for in-person learning.

The results are then discussed for the second definition case, in which WFH is conducted at least 40% of the time per week. The results are also shown in Panel B of Table 4. The trends are the same as those observed in the main WFH results. The significance levels and direction of impact are consistent. However, the magnitudes of the coefficients are larger. Among them, online-KoL and in-person-KoL nets are larger by 32.6% (-0.118 compared to -0.089) and 25.7% (0.093 compared to 0.074), respectively, and the differences are more pronounced. As previously noted, these results are highly complementary to WFH and are intuitive. Self-learning also increased by 25.5% (0.177 compared with 0.141) relative to the first definition of WFH. The same trend is also observed for All-KoL, with an increase of 11.9%. The ratio of WFH to workdays and other factors are often discussed in terms of corporate human resources. Companies are increasingly requesting that their employees return to office settings. However, from the perspective of human capital investment, it would be desirable to have at least some WFH hours.

4.2 Robustness checks

In this subsection, we conduct a robustness check. Section 3 examines the common trend assumption, which is fundamental to our identification strategy.

Our analysis reveals no systematic compositional changes between the treatment and control groups. Specifically, we investigate individuals who transitioned between these groups. In our study, changes in employment status, such as job transitions and resignations, are particularly pertinent. These factors carry significance in both pre- and post-COVID-19 outbreak analyses. During the pandemic, certain industries, such as the service sector experienced significant upheaval due to the challenges of implementing WFH. Workers may have left their jobs or switched to positions that allowed remote work. Such transitions could introduce bias into our estimates, skewing them upwards due to selection bias. Conversely, some individuals may have secured new employment opportunities in response to heightened labor demand during the pandemic. This dynamic employment landscape amid COVID-19 is documented in Fukai et al. (2021) (for the Japanese context) and Bluedorn et al. (2023). Figures 4 (a)–(c) depict the variations in these events between the treatment and control groups. Essentially, we replace the outcomes of the event study model in Section 3 with specific life and work events. Our analysis reveals no statistically significant results or discernible trends. There is no notable difference in unemployment rates before or after COVID-19, and no systematic pattern emerges. Consequently, we conclude that job changes and resignations did not significantly influence our findings.

During COVID-19, personnel experienced reallocation within the same company. Some divisions became redundant due to the pandemic, leading to the redistribution of employees across different divisions. In Japanese companies, such departmental reallocations often coincide with promotions or demotions. Hence, we examine differences in personnel transfers, promotions, and demotions between the treatment and control groups. The results, depicted in (d), (e), and (f) of Figure 4, show no statistically significant differences or systematic trends.

There were shifts in industries and occupations during this period. Similar to the previous checks, individuals may have changed occupations within the same industry or moved to different industries within the same occupation due to COVID-19. Another significant life event could be a residential move, such as relocating to the suburbs. We investigate whether there were differences in transitions between the treatment and control groups. The results are presented in Figure 5. Apart from changing industries, where statistically significant results are obtained, no systematic trends are observed in the treatment-control groups before or after the COVID-19 outbreak.

Furthermore, we assess whether our IVs satisfy the exclusion restrictions from other perspectives. Regional characteristics play a crucial role in WFH feasibility, particularly because white-collar occupations are concentrated in metropolitan areas, where WFH is likely more feasible, as indicated by Inoue et al. (2023). To address this, we conduct analyses for our main results, incorporating prefecture-level fixed effects as robustness checks, following Inoue et al. (2023).

Additionally, it is crucial to consider industry effects, as highlighted by Inoue et al. (2023). Previously, we conducted an event study on a sample that changed industries and found that the effect of selection was insignificant, except for 2021. Next, we repeat the analysis, excluding the samples that changed industries. The results are presented in Panel A of Table 5, where the impact is slightly weaker for self-learning, OJT, and Off-JT, but the trend remains consistent. Panel A in Table 6 displays the scenario where the definition of WFH hours is adjusted to 40% or more of weekly working hours; here, the impact is slightly weaker for self-learning, OJT, and Off-JT, but the trend remains largely unchanged.

We further segment the sample by dividing it into workers with ten or more years of tenure. Some workers may prioritize whether the firm offers a WFH program in their employment decisions. If such an unobservable work preference exists, the control variable does not satisfy the exclusion restriction. For instance, a worker might anticipate a career shift and opt for a firm with a WFH program, thereby accumulating human capital. Therefore, we conduct a similar analysis by restricting the sample to workers with over five years of tenure. Additionally, many Japanese firms likely implemented a WFH system over five years ago. For individuals who joined the firm over five years ago, the WFH system is less likely to have influenced their employment decisions.

The estimated results are presented in Panel B of Table 5. Consequently, the significance of the estimated results weakened, particularly becoming insignificant for self-learning. However, the results remain consistent for online-based learning and in-person learning. Panel B in Table 6 illustrates the scenario where the definition of WFH hours is adjusted to 40% or more of the weekly working hours, and the impact is slightly weaker for self-learning, OJT, and Off-JT, but the trend remains largely consistent.

4.3 Heterogeneity

Finally, we examine heterogeneity. The results are depicted in Figure 6.[17] The coefficient in the estimation equation is divided by the mean outcome for those who did not engage in WFH, and then plotted. To compare the coefficients, they are interpreted as percentage changes. The coefficients themselves are challenging to interpret due to the differences in the levels of each group.

If time constraints hinder human capital investment, especially in self-learning, childcare is expected to be a significant factor. Therefore, we first analyze the results based on the presence of children under six years of age, as time is more constrained for parents with young children owing to daycare attendance and other factors. The trends in the results are consistent, except for Off-JT. When there are no children, only online-KoL shows statistical significance, whereas with children, self-learning, online-KoL, and in-person-KoL are significant. Particularly noteworthy is the greater impact of coefficients for all human capital investments when children are present. The coefficient for self-learning is more than twice as large for those with children, albeit on a percentage scale. This suggests that employees with children are likely to face more significant time constraints than those without children. In other words, while childcare responsibilities may limit their ability to invest in human capital, WFH enables them to do so by providing more flexible time for childcare and daycare

[17]Each characteristic for heterogeneity analysis is as of 2019.

arrangements.

We then analyze heterogeneity with respect to working hours to investigate time constraints in more detail. Using 40 hours as the boundary for a full-time workweek, we observe consistent trends across all variables except for OJT. For those working less than 40 hours, OJT, Off-JT, and online-KoL are statistically significant. Conversely, for those working more than 40 hours, only online-KoL shows statistical significance. However, the coefficients are larger for all human capital investments for those working fewer than 40 hours. This contrasts with the previous analysis based on the presence of children under six years of age. Despite the expectation that individuals working more than 40 hours would face time constraints, the results are counterintuitive.

To further explore this, we analyze employment status separately. Differences in in-firm training based on employment status have been frequently discussed in Japan. We found similar results for both regular and non-regular workers. Non-regular workers include part-time, dispatched, contract, and temporary workers. In this study, those corresponding to non-regular workers worked fewer than 40 hours, while those corresponding to regular workers worked more than 40 hours. The estimated results in this case mirror those obtained by dividing the sample by 40 hours. Essentially, the impact is greater for non-regular workers, although it is not statistically significant for non-Off-JT. As non-regular workers generally have lower incomes and education levels, they may have stronger incentives to invest in human capital to increase their income and enhance their career prospects. Non-regular workers were not originally able to engage in human capital investment but may have benefited from the introduction of WFH support.

In Japan, the disparity in human capital investment between regular and non-regular workers has often been highlighted. For instance, according to the Basic Survey on Capacity Development, as of 2022, 60.2% of companies implemented OJT for regular workers, compared to only 23.9% for non-regular workers. Similarly, for Off-JT, the percentages are 70.4%

for regular workers and 29.6% for non-regular workers. Firm-provided training is notably less common among non-regular employees, contributing to the observed wage gap. These findings suggest that the introduction of more flexible work arrangements may help narrow the gap between regular and non-regular workers.

To summarize the analysis of heterogeneity, the presence of children serves as both a time constraint and a hindrance to human capital investment. Moreover, it indicates that a certain segment of workers, depending on their income and career status, aims to enhance their careers by investing in human capital.

4.4 Discussion

These results underscore the significance of reskilling, a concept acknowledged by the government, which has implemented various policies in response. Active labor market programs, as summarized by Card et al. (2018), have been instrumental in this regard. In Japan, one of the most frequently utilized educational training benefits is provided by the MHLW. This system entails reimbursing a portion of the costs associated with attending and completing qualification courses, universities, graduate schools, and similar educational endeavors, with funding sourced from unemployment insurance.[18] Evidence from studies such as Yokoyama et al. (2019) and Hara (2022) suggests that such government support has proven effective in encouraging workers, both formal and informal, to participate in high-return training programs.

These effects are often limited to individuals facing liquidity constraints, preventing them from investing in human capital despite their desire to do so. Lack of time is a significant barrier, as indicated by supplementary data from JPSED2018, where 15.0% of respondents

[18]Subsidies are available for human resource development support, which cover training expenses and wages during the training period when employers provide vocational training to workers. The Ministry of Economy, Trade and Industry (METI) and the Ministry of Education, Culture, Sports, Science and Technology (MEXT) also offer subsidies to support working individuals in their learning endeavors.

cited being busy with work, housework, or childcare as a reason for not studying. Financial constraints, while also a factor, were cited by 7.7% of respondents.[19]

This suggests that while government-prepared educational and training programs can be effective, encouraging individuals to voluntarily invest in human capital based on their needs and interests may yield better results. Even with government subsidies, effectiveness hinges on other conducive conditions. One implication from this study is that flexible work arrangements, such as WFH, can boost voluntary human capital investment, particularly among individuals juggling household responsibilities. This is also pertinent for those seeking higher wages, such as informal workers, who can benefit from the compatibility of WFH with on-line learning. The government's recent subsidization of such investments underscores their importance.

The significance of reskilling and adult education has gained prominence in Japan, with active government support. While these programs are often costly and financed through sources such as employment insurance, they complement various subsidies and flexible work arrangements such as WFH. It is crucial to promote them as a cohesive strategy to maximize effectiveness. Additionally, in some scenarios, individuals may naturally invest in human capital without subsidies when left to the free labor market. In such cases, funds from unemployment insurance can be redirected to passive labor market programs, including unemployment benefits.

5 Conclusion

This study investigated the impact of WFH on the human capital investment of working individuals, a relationship that has become increasingly significant in an era marked by longer working years. To the best of our knowledge, the exploration of WFH's enduring

[19] Incidentally, "no specific reason" was ranked first, at 51.2%; thus, substantial research still needs to be done to encourage human capital investment.

relevance beyond the COVID-19 era and its influence on human capital investment is unique to this study. To mitigate the endogeneity of WFH implementation, we employed an IV approach, utilizing the combination of macro shocks from COVID-19, promoting WFH, and differences in pre-pandemic implementability of WFH among occupations. Our first-stage estimation employed a DID analysis, designating occupations more likely to adapt to WFH as the treatment group and those less likely as the control group. We observed the effects before and after the COVID-19 outbreak in 2020 to capture exogenous shocks.

Our findings revealed that WFH enhances self-learning by approximately 14.1%, along with a notable increase of about 15.6% in online-based learning. However, they showed a decrease of 8.9% in in-person-based learning. While not statistically significant for OJT and Off-JT, WFH exhibits positive effects on both. Interestingly, despite initial expectations of incompatibility, no adverse impact on OJT was observed. Moreover, we identified varying effects based on lifestyle factors, such as the presence or absence of children and working style, with WFH proving particularly effective in promoting human capital investment among individuals with children.

Moving forward, future research should explore effective human resource policies that complement WFH to further enhance human capital investment. This is especially pertinent for company-initiated investments such as OJT. While our study focuses on job type as an identification strategy, further analysis could explore the nuanced relationship between WFH and human capital investment across different job types, possibly through alternative IVs.

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Appendix

We present the specific questions that are key to the creation of the variables in this appendix.

- Questions about remote work

  As of last December, how long did you engage in remote work per week? Remote work is defined as working from your home, a satellite office, a cafe/family restaurant, or a workplace (This refers to working at a location other than the company and its customers).

  Total hours per week: ( ) hours As of last December, you did remote work for a total of (Previous Answer) hours in an average week. The answer is "yes". If there are no mistakes, please click the "Next Page" button. If you need to make a correction, please click the "Back" button and try again.

- Questions about the remote work system

  As of last December, did your workplace have a remote work system in place? Were you eligible for the system and did you apply for it? A remote work system refers to a system that allows employees to work from locations other than the workplace (your company and your customers), such as your home, a satellite office, or a cafe. A remote work system refers to a system that allows employees to work from locations other than the workplace (your company and your customers), such as your home, a satellite office, or a cafe/family restaurant.

  1. It was introduced as a system and applied to me. 2. It was introduced as a system, but did not apply to me. 3. It had not been introduced as a system. 4. I don't know.

- Questions about OJT

  During the last year, did you have any opportunities to acquire new knowledge or skills through your work practice?

1. I received guidance from my supervisor, senior employees, etc. based on a certain program. 2. I received guidance from my supervisor, senior employees, etc. as needed, although it was not based on a fixed training program. 3. I did not receive guidance from my supervisor or senior employees, but I acquired new knowledge and skills by observing their (others') work. 4. I did not receive instruction from supervisors or senior employees, but I learned by referring to manuals. 5. I had no opportunity to acquire new knowledge or skills at all.

- Questions about Off-JT

During the last year, did you have any opportunities to temporarily leave your regular work duties to receive education or training, either inside or outside the company?

1. I did not have the opportunity 2. I had the opportunity but did not take it. 3. Had the opportunity and actually took it (less than 5 hours in total during the year) 4. Opportunity existed and actually received (5-9 hours or less in total during the year) 5. Opportunity existed and was actually received (10-19 hours or less in total during the year) 6. Opportunities existed and were actually received (20-49 hours or less total in a year) 7. Opportunities existed and were taken (more than 50 hours in total during the year)

- Questions about self-learning (worker-initiated training)

In the last year, have you voluntarily made any efforts to improve your job-related knowledge or skills (e.g., read books, talked to people who know more about the subject, studied on your own, took courses, etc.)?

1. I did. 2. I did not.

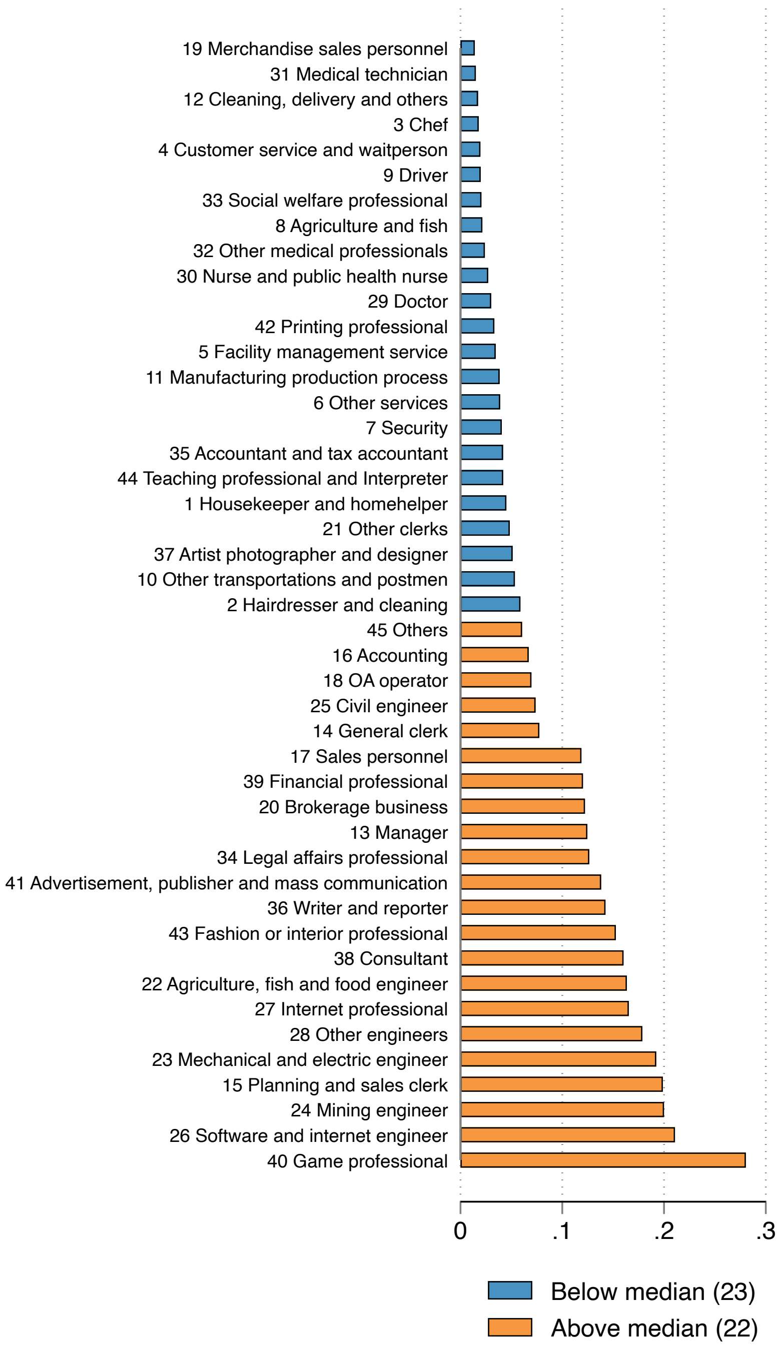


Figure 1: Proportion of workers at companies allowing them to work from home before the pandemic by occupation

Note: The sampling weight in 2017 is used for the calculations of the proportions. The occupations are divided by the median of the proportions over occupation: "below median"(blue) and "above median"(orange).

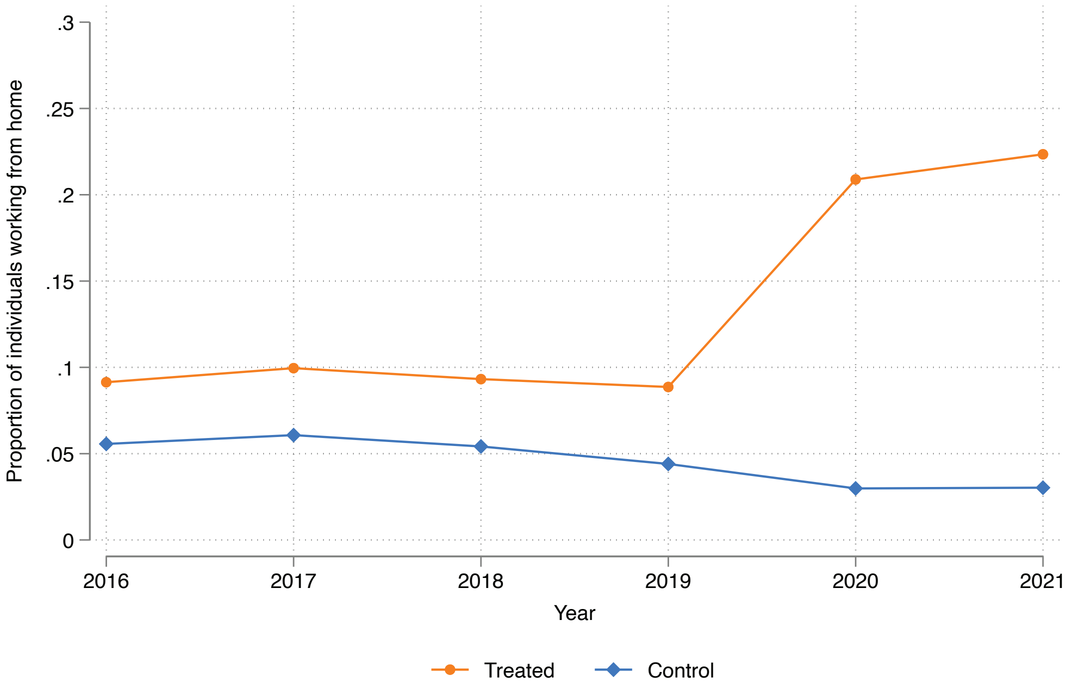
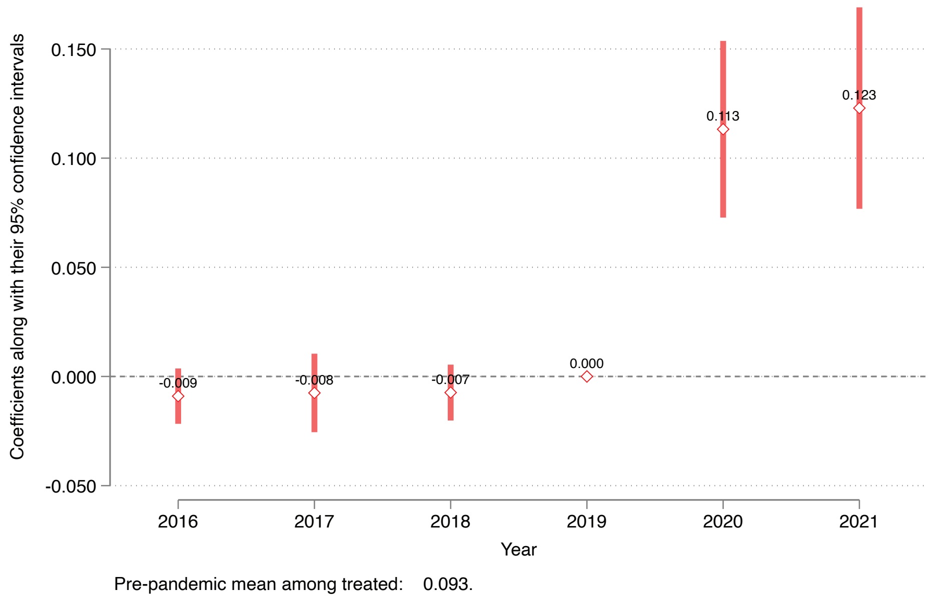
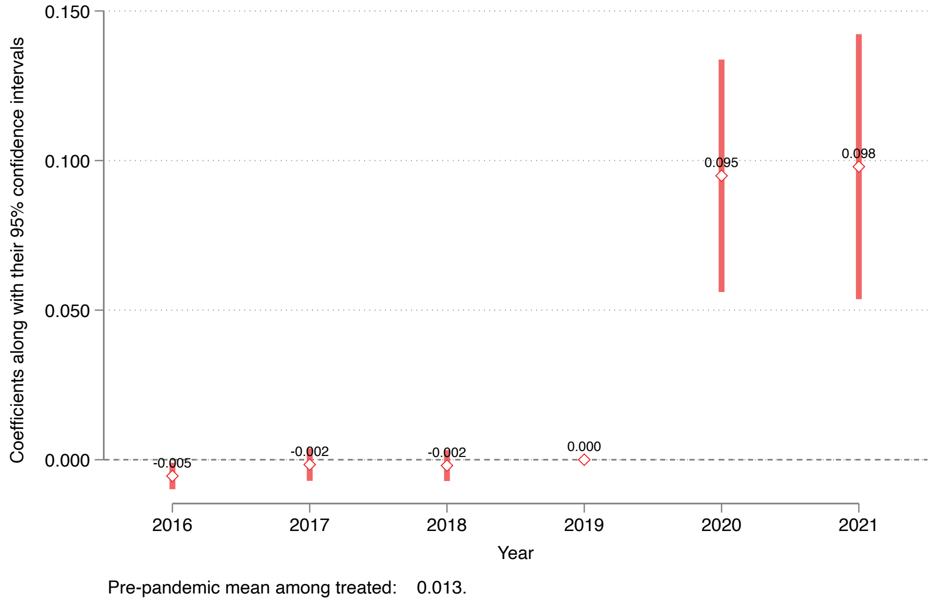


Figure 2: Change in proportion of individuals working from home by treatment status

Note: The sampling weight in 2017 is used for the calculation.



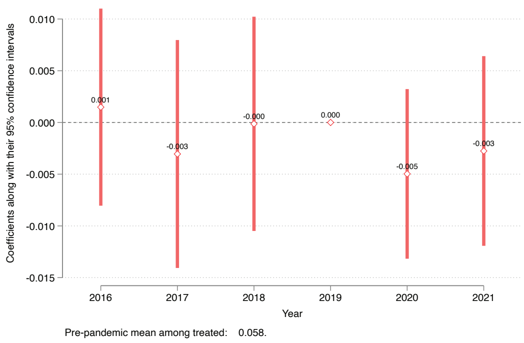
(a) Working from home



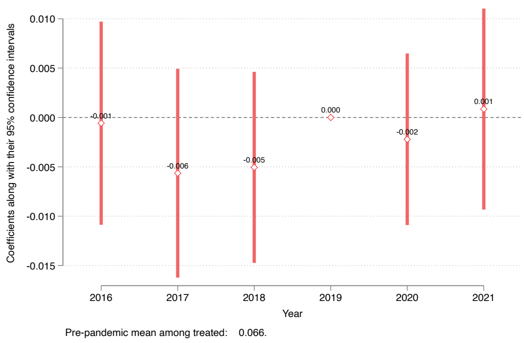
(b) Working from home for 40% or more of weekly working hours

Figure 3: Results of event study model for working from home variables

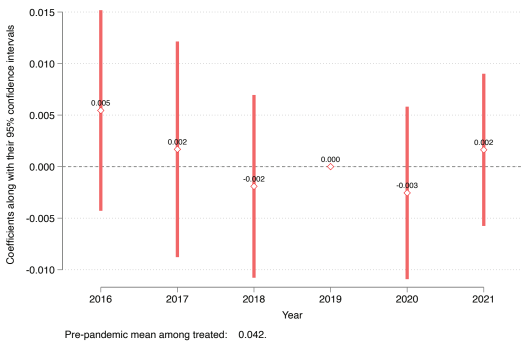
Note: The diamond symbols indicate the estimated coefficients on the cross term of the treatment dummy and the year dummy variables, and the bars represent the 95% confidence intervals for the estimates. We set 2020 as the reference time period. The confidence intervals are calculated using standard errors robust against occupation as of December 2019 level clustering.



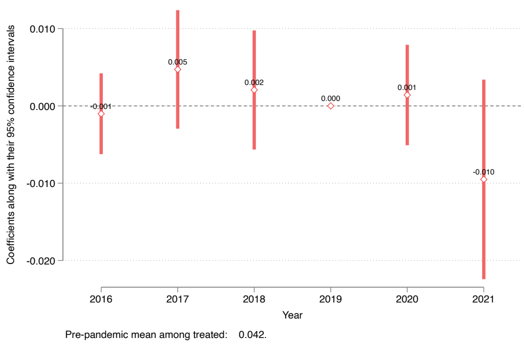
(a) Quit job



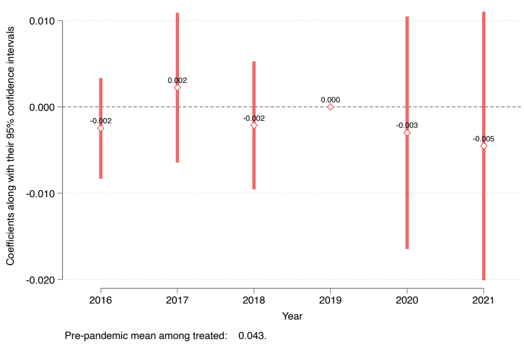
(b) Get job



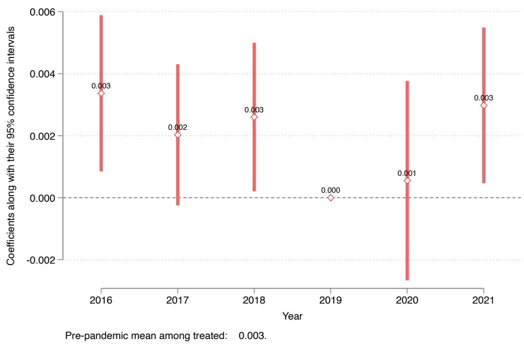
(c) Change job



(d) Reshuffle

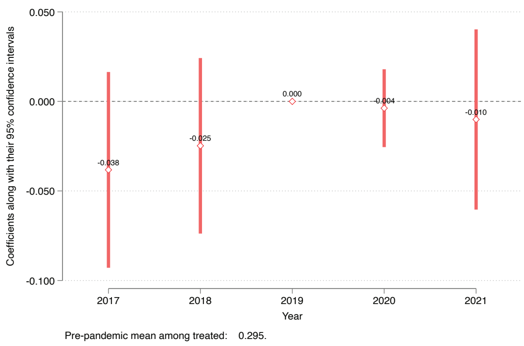


(e) Promoted

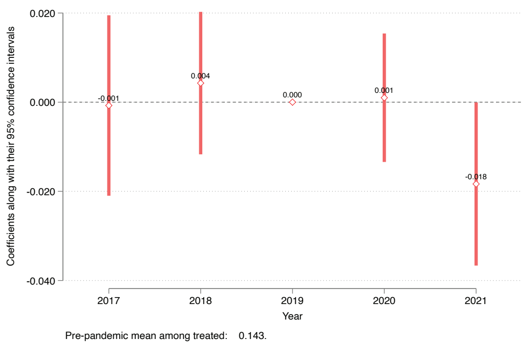


(f) Demoted

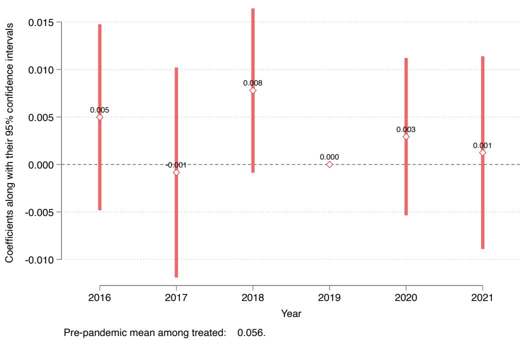
Figure 4: Results of event study model for other career-related events 1



(a) Change occupation



(b) Change industry



(c) Moving

Figure 5: Results of event study model for other career-related events 2

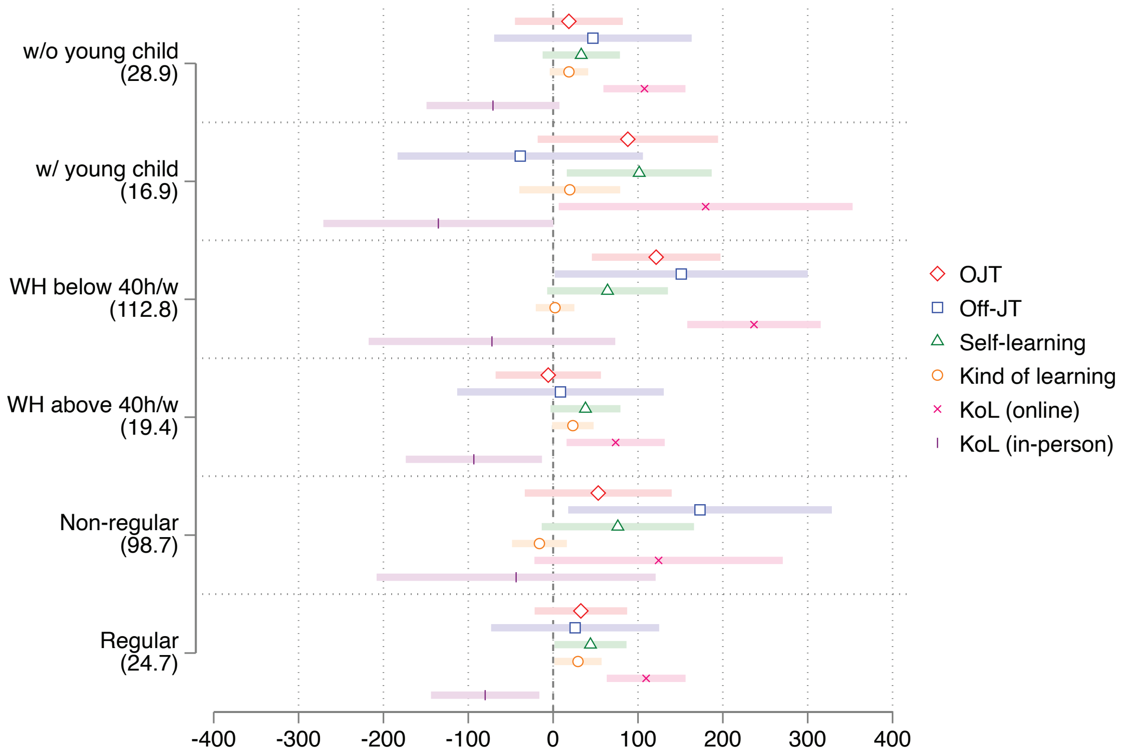


Figure 6: Heterogeneous effects

Note: The diamond symbols indicate the magnitude of the estimated coefficients of the working-from-home dummy in percent change, and the bars represent 95% confidence intervals. The confidence intervals are calculated using standard errors robust against occupation as of December 2019 level clustering. The parenthesis under the subgroup names indicates the first stage F-statistics. The sampling weight in 2017 is used for the estimations.

Table 1: Summary Statistics

	Mean	SD
Demographics		
Female	0.45	0.50
Age	43.72	9.32
Married	0.59	0.49
Having children	0.52	0.50
Number of children	0.99	1.09
Having a child under 6 years old	0.14	0.35
College or above	0.33	0.47
Employment		
Regular employees	0.70	0.46
Firm size		
1-99	0.42	0.49
100-999	0.27	0.44
1000+	0.23	0.42
Public sector	0.08	0.27
Years of tenure	11.78	10.19
Working from home		
working from home	0.10	0.29
working from home for 40% or more of weekly working hours	0.03	0.17
companies allowing employees to work from home	0.14	0.35
Human capital investment		
OJT	0.22	0.41
Off-JT	0.21	0.41
Self-learning	0.33	0.47
Kind of learning	0.53	0.50
Online	0.15	0.35
In-person	0.13	0.33

Note: The sample consists of observations from 2017 and 2022. The sampling weight in 2017 is used for the calculations.

Table 2: Balancing between treated and control groups in December 2019

	Mean		Differences			
	Control (1)	Treated (2)	raw (3)	(%) (4)	adjusted (5)	(%) (6)
Female	0.42	0.44	0.01* (0.01)	3.15* (1.87)		
Age	43.54	44.83	1.29*** (0.15)	2.92*** (0.34)		
Married	0.57	0.60	0.03*** (0.01)	5.71*** (1.37)		
Number of children	1.00	0.99	-0.00 (0.02)	-0.38 (1.79)		
Having a child under 6 years old	0.13	0.13	-0.00 (0.01)	-3.34 (4.23)		
College or above	0.25	0.40	0.14*** (0.01)	44.82*** (2.35)		
Hours worked	38.53	40.26	1.72*** (0.21)	4.37*** (0.53)		
Firm size						
1-99	0.46	0.39	-0.06*** (0.01)	-15.13*** (1.88)	-0.03*** (0.01)	-7.59*** (1.89)
100-999	0.28	0.26	-0.02*** (0.01)	-7.77*** (2.66)	-0.03*** (0.01)	-9.27*** (2.71)
1000+	0.21	0.25	0.05*** (0.01)	20.52*** (2.98)	0.03*** (0.01)	12.44*** (3.01)
Public sector	0.05	0.09	0.04*** (0.00)	51.59*** (5.88)	0.03*** (0.00)	38.92*** (5.95)
Years of tenure	10.33	13.17	2.84*** (0.17)	24.21*** (1.41)	3.08*** (0.17)	26.22*** (1.43)

Note: the sampling weight in 2017 is used for the calculations of the proportions. Columns (1) and (2) show the mean of the variables for the control and treated groups, respectively, and Columns (3) and (4) show the difference and percentage difference between the two columns, respectively. Columns (5) and (6) represent the difference and percentage difference in the variables between the treated and control groups after we controlled for the level of education.

Table 3: Results of reduced form estimation

	Working from home				Kind of learning			
	(1) > 0	(2) $\geq 40\%$	(3) OJT	(4) Off-JT	(5) Self-learning	(6) All	(7) Online	(8) In-person
DID estimates	0.123***	0.098***	0.008	0.009	0.017*	0.012*	0.019***	-0.011**
	(0.023)	(0.021)	(0.007)	(0.014)	(0.009)	(0.006)	(0.005)	(0.004)
Number of observations	80105	79842	80105	80105	80105	80105	80105	80105
Pre-pandemic mean among the treated	0.093	0.013	0.205	0.232	0.355	0.548	0.162	0.139
Magnitude of the coefficient in percent change	132.7	732.0	3.8	3.8	4.9	2.2	11.9	-8.0

Note: The unit of observation is the individual and year. The dependent variables are dummy variables for working from home and human capital investment. Standard errors robust against occupation as of December 2019 with level clustering are shown in parentheses. All specifications are estimated using an individual-level fixed effects model and include age (quadratic function), a dummy indicating whether an individual has a partner, the number of children, a dummy indicating whether an individual has preschoolers, education category dummies, firm size category dummies, years of tenure (quadratic function), cross-terms for graduation in 2020 and year dummy variables, cross-terms for firm size in 2020 and year dummy variables, and prefecture-year fixed effects. Inference: * $p < .1$, ** $p < .05$, *** $p < .01$. The sampling weight in 2017 is used for the estimations.

Table 4: Effects of working from home on human capital investment

				Kind of learning		
	(1) OJT	(2) Off-JT	(3) Self-learning	(4) All	(5) Online	(6) In-person
Panel A						
Work from home	0.064	0.072	0.141**	0.099*	0.156***	-0.089**
	(0.058)	(0.109)	(0.067)	(0.049)	(0.031)	(0.039)
Number of observations	80105	80105	80105	80105	80105	80105
Mean among people not working from home	0.213	0.205	0.318	0.515	0.137	0.117
Magnitude of the coefficient in percent change	29.9	34.9	44.4	19.2	113.8	-76.6
Panel B						
WFH 40% and over of weekly working hours	0.080	0.086	0.177*	0.119*	0.191***	-0.118**
	(0.081)	(0.144)	(0.095)	(0.060)	(0.045)	(0.047)
Number of observations	79842	79842	79842	79842	79842	79842
Mean among people not WFH for 40% and over of weekly working hours	0.219	0.215	0.335	0.529	0.147	0.126
Magnitude of the coefficient in percent change	36.4	40.3	52.9	22.6	129.8	-93.4

Table 5: Robustness check (working from home)

				Kind of learning		
	(1) OJT	(2) Off-JT	(3) Self-learning	(4) All	(5) Online	(6) In-person
Panel A: no change in one's industry during the pandemic						
Work from home	0.047	0.030	0.118*	0.084	0.147***	-0.080*
	(0.051)	(0.102)	(0.059)	(0.057)	(0.033)	(0.044)
Number of observations	57103	57103	57103	57103	57103	57103
Mean among people not working from home	0.196	0.204	0.318	0.517	0.137	0.113
Magnitude of the coefficient in percent change	23.9	14.5	37.1	16.2	107.5	-70.9
Panel B: year of tenure $\geq$ 5 years						
Work from home	0.045	0.059	0.098	0.104*	0.128***	-0.113**
	(0.077)	(0.118)	(0.072)	(0.062)	(0.043)	(0.043)
Number of observations	54781	54781	54781	54781	54781	54781
Mean among people not working from home	0.171	0.206	0.313	0.511	0.137	0.113
Magnitude of the coefficient in percent change	26.1	28.7	31.3	20.5	93.6	-99.8

Note: The unit of observation is the individual and year. The dependent variables are dummy variables for human capital investment. Standard errors robust against occupation as of December 2019 with level clustering are shown in parentheses. The estimations in Panel A use workers who did not change their industry during the pandemic (surveys in 2021 and 2022), whereas those in Panel B use workers with five or more years of tenure as of December 2019. All specifications are estimated using an individual-level fixed effects model and include age (quadratic function), a dummy indicating whether an individual has a partner, the number of children, a dummy indicating whether an individual has preschoolers, education category dummies, firm size category dummies, years of tenure (quadratic function), cross-terms for graduation in 2020 and year dummy variables, cross-terms for firm size as of 2020 and year dummy variables, and prefecture-year fixed effects. Inference: * $p < .1$, ** $p < .05$, *** $p < .01$. The effective F-statistics are 26.0 and 26.2 for Panels A and B, respectively, and are over the rule-of-thumb value, 10. The sampling weight in 2017 is used for the estimations.

Table 6: Robustness check (working from home 40 % and over of weekly working hours)

	(1) OJT	(2) Off-JT	(3) Self-learning	Kind of learning (4) All	Kind of learning (5) Online	Kind of learning (6) In-person
Panel A: no change in one's industry during the pandemic						
WFH 40% and over of weekly working hours	0.060	0.035	0.145*	0.105	0.183***	-0.105*
	(0.069)	(0.133)	(0.081)	(0.070)	(0.051)	(0.053)
Number of observations	56941	56941	56941	56941	56941	56941
Mean among people not WFH for 40% and over of weekly working hours	0.201	0.213	0.335	0.530	0.147	0.122
Magnitude of the coefficient in percent change	29.8	16.3	43.2	19.9	124.7	-86.3
Panel B: year of tenure $\geq$ 5 years						
WFH 40% and over of weekly working hours	0.058	0.074	0.124	0.130	0.161***	-0.151***
	(0.102)	(0.151)	(0.096)	(0.078)	(0.053)	(0.056)
Number of observations	54615	54615	54615	54615	54615	54615
Mean among people not WFH for 40% and over of weekly working hours	0.178	0.216	0.331	0.525	0.148	0.122
Magnitude of the coefficient in percent change	32.7	34.1	37.5	24.9	109.3	-123.9

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