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The Impact of Telework on Labor Productivity and Exercise Habits: Evidence from Regional Japan*

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Abstract

This paper estimates the causal effects of telework (TW) adoption on labor outcomes, health behaviors, and time use, leveraging Japan's unique reliance on voluntary pandemic measures. Using original retrospective survey data from 373 firm-based employees in the Shikoku and Kyushu regions, we examine behavioral changes across three periods: before the pandemic (November 2019), during the infection surge (August 2021), and after its decline (December 2021). To address endogeneity arising from self-selection into TW, we employ a two-stage least squares (2SLS) strategy using municipality-level COVID-19 infection rates as an instrumental variable. Our findings show that infection-driven increases in TW significantly reduce overtime hours and commuting time while improving life satisfaction, largely through the reallocation of time toward sleep, childcare, and leisure. While self-reported work efficiency remains unchanged, TW shifts job content toward internal coordination, external liaison, and accounting tasks. These effects are strongest during high-infection periods and weaken as risks subside, underscoring the context-dependent nature of TW. Leveraging exogenous regional variation, the study provides credible causal evidence and informs the design of flexible work arrangements beyond crisis settings.

Keywords: Instrumental variables regression, COVID-19, Telework, Employee, Shikoku and Kyushu Regions

JEL Classification Codes: I31, J22, J24

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1. Introduction

The COVID-19 pandemic triggered an unprecedented global expansion of telework (TW), with governments worldwide imposing mandatory lockdowns and remote work mandates[1]. In contrast, Japan adopted a "soft-commitment" strategy, relying on non-binding requests for firms to reduce in-person operations. Consequently, TW adoption in Japan was highly discretionary, driven not by uniform regulations but by local infection risks, firm-level discretion, and individual choices.[2] The Japanese reliance on voluntary workplace closures, combined with sharp regional variation in COVID-19 cases, generated exogenous differences in telework adoption—offering a natural experiment to identify its causal effects on work and lifestyle behaviors.

This paper estimates the causal effects of TW on labor outcomes, exercise habits, life satisfaction, job content, and the use of time saved from not commuting, using original retrospective survey data from 373 employees in the Shikoku and Kyushu regions of Japan. Respondents reported TW frequency and behavioral outcomes at three reference points—before the pandemic (November 2019), during the infection surge (August 2021), and after its decline (December 2021). We exploit this structured recall design to estimate fixed effects (FE) models for outcomes observed over multiple periods and value-added (VA) models for outcomes measured only at the time of the survey. To address endogeneity concerns such as selection bias and reverse causality, we implement a two-stage least squares (2SLS) strategy, using municipality-level COVID-19 infection rates as an instrument for TW intensity. This approach exploits plausibly exogenous variation in local pandemic conditions to identify the causal impact of telework adoption on the behavior and well-being of firm-based workers.

A growing body of research has examined how telework affects productivity, mental health, and time use during the COVID-19 pandemic (Barrero et al., 2023; Bloom et al., 2024; Hackney et al., 2022; Hall et al., 2023). In Japan, Morikawa (2022, 2024) reported that telework productivity was generally lower than in-office work, while Kitagawa et al.

[1] WHO officially declared COVID-19 a global pandemic on March 11, 2020. See WHO (2020) for the official statement.
[2] For instance, data from Tokyo Shoko Research indicate that over 50% of firms adopted telecommuting or remote work during Japan's first state of emergency in fiscal year 2020 (April 23–May 12) and in the immediate aftermath (May 28–June 9). However, the telework implementation rate dropped to 31% by late June (as of June 29) and remained in the low 30% range through mid-November (surveyed November 9–16). A modest rebound to 38% was observed in early March 2021 (surveyed March 1–8).

(2021) and Okubo (2022) showed task- and occupation-level differences that can mitigate or amplify those productivity effects. Overall findings remain mixed, in part because data sources vary widely—covering different regions, populations, and measurement periods—and in part because the methodologies themselves differ. Some studies rely on basic controls or fixed effects without fully addressing selection bias, which arises when individuals or firms that are already more productive or better resourced opt into telework. Recent research has turned to FD-IV to reduce endogeneity, using factors such as pre-pandemic job suitability, occupational teleworkability, or regional broadband infrastructure as instruments (Hara & Kawaguchi, n.d.; Inoue et al., 2024). Nonetheless, only a handful of studies have leveraged time-varying, municipality-level infection data to isolate plausibly exogenous variation in telework. Moreover, previous analyses often focus on broad productivity or health outcomes, overlooking how telework reshapes specific tasks or how the commuting hours saved might be reallocated.

Our results show that during the pandemic expansion phase (November 2019 to August 2021), an exogenous one-day increase in TW reduced overtime work, commuting time, and daily exercise, while increasing life satisfaction. These effects range from 48% to 82% of a standard deviation, indicating substantial behavioral changes. During the contraction phase (August to December 2021), a decline in TW led to increases in overtime work, commuting time, and walking—reversing earlier gains. By the time of the survey (January–April 2022), respondents who had experienced greater TW exposure were significantly more likely to report engaging in coordination and accounting tasks during TW and to have reallocated time savings to hobbies, sleep, and childcare. These long-run effects underscore how TW reshaped both professional and personal routines.

This study contributes to the literature in five ways. First, we develop a novel identification strategy using municipality-level COVID-19 infection rates at respondents' workplace or home locations as an IV for TW intensity. Second, we estimate both FE/FEIV and VA/IV-VA models, thereby addressing omitted variable bias, selection bias, and reverse causality. Third, we leverage structured recall to construct quasi-panel outcomes from a single-wave survey, showing how one-time data can be used for causal inference. Fourth, we examine not only work outcomes but also the content of tasks performed during TW and the reallocation of commuting time, offering a richer behavioral perspective. Fifth, we distinguish between TW expansion and contraction periods, uncovering asymmetric responses and informing debates about post-pandemic work arrangements.

The remainder of the paper is organized as follows. Section 2 reviews the relevant literature on telework, both before and during the pandemic, and explains how our research builds on and differs from prior work. Section 3 outlines the evolution of COVID-19 infections and telework trends in Shikoku and Kyushu, and Section 4 describes our dataset and variables. Section 5 explains the empirical framework, including the 2SLS model using infection rates as an instrument. Section 6 reports the estimation results and discusses their implications. Section 7 concludes with a reflection on policy ramifications and avenues for future research.

2. Literature review

Research on telework has expanded rapidly in response to the COVID-19 pandemic, but its roots stretch back to the pre-pandemic era when digital tools and flexible work arrangements were already emerging in some regions. Early studies in Japan, such as Kazekami (2020), demonstrated a positive correlation between telework adoption and labor productivity based on data from 2017–2018. However, longer durations of telework sometimes showed diminishing returns, suggesting that remote work efficiency depends on how telework is structured. Outside Japan, Melo & de Abreu e Silva (2017) and Silva & Melo (2017) examined British commuting behavior using data from 2005–2012 and found that teleworkers tend to travel longer distances overall but do not commute more frequently, whereas Elldér (2020) studied Swedish survey data from 2011–2016, concluding that telework can reduce congestion and cut the total number of commutes.

When the pandemic began, many countries rapidly scaled up telework, with varying implications for productivity. Some scholars have argued that productivity either stayed the same or increased, thanks to saved commuting time and improved work–life balance (Barrero et al., 2023; Criscuolo et al., 2022). For instance, Choudhury et al. (2021) documented a 4.4% productivity gain among patent examiners at the U.S. Patent and Trademark Office under work-from-anywhere policies, while Deole et al. (2023) noted positive correlations between telework frequency and self-reported productivity in Britain, especially for women in remote-friendly jobs and men with long commutes. Bloom et al., (2024) found that hybrid work in a Chinese tech firm reduced attrition and boosted satisfaction without harming performance metrics.

Nonetheless, some scholars reported that telework eroded productivity under certain conditions. van der Lippe & Lippényi (2020) used data from nine European countries and highlighted that team-based tasks suffered when many coworkers teleworked simultaneously, while Weitzer et al. (2021) linked remote work in Austria to decreased perceived productivity despite an overall improvement in quality of life. Gibbs et al., (2023) suggested that parents with school-age children struggled to maintain performance levels, indicating that individual circumstances critically shape telework's outcomes.

Researchers have also examined how telework can reshape tasks and human resource management. Kawaguchi & Motegi (2021), using December 2019 data on remote work availability, found that telework was more common among professionals performing non-routine tasks and in firms with performance-based HR practices. Jiang et al. (2024) argued that telework in Japan led to a shift from routine manual tasks to non-routine, analytical ones, thus improving productivity and wages. Okubo (2022), relying on a unique panel survey, emphasized how young, educated, ICT-skilled individuals are likelier to adopt telework, while teamwork-intensive and routine-heavy occupations remain largely office-based.

Another significant strand of research addresses the broader time allocation effects of telework. Inoue, Ishihata, and Yamaguchi (2024) found that an additional day of telework in Japan increased housework, childcare, and time with family, while Restrepo & Zeballos (2022) noted that American workers tend to expand working hours and reduce social activities when working from home. These changes reflect a reconfiguration of daily routines that can either bolster or undermine well-being, depending on individual preferences and life circumstances.

Moreover, telework has distinct implications for commuting behavior. Reiffer et al., (2023) analyzed German Mobility Panel data from 2018 to 2020, noting a surge in telecommuting among households with children beyond the effect of commuting distance. As stated above, Deole et al., (2023) noted positive correlations between telework frequency and self-reported productivity in Britain, especially for men with long commutes. Adachi et al. (2023) reported that telework reduced commuting rates and rail demand in Japan, with longer-distance commuters proving especially likely to adopt remote work. Obeid et al., (2024) used U.S. smartphone data to show that telecommuters made more non-work trips but nonetheless cut weekly travel distances by about 15 kilometers.

Within the broader telework literature, increasing attention is being paid to causal identification strategies. Many early studies relied on observational methods that risk selection bias, given that higher-skilled workers or progressive firms may adopt telework first. As a response, some authors have turned to instrumental variable approaches. Hara and Kawaguchi (2022) and Denzer & Grunau (2024) used technology or occupation-based instruments, while Inoue, Ishihata, and Yamaguchi (2024) examined the share of telework-capable jobs in 2019 as an FD-IV, finding no significant reduction in productivity during the pandemic. Our study builds on this line of research by using municipal-level infection rates to generate exogenous variation in telework adoption. This approach is particularly pertinent in Japan, where infection surges triggered calls for voluntary reductions in face-to-face work, thereby providing a quasi-experimental environment for analyzing telework's effects on productivity, commuting, and everyday activities.

In summary, prior research highlights telework's diverse implications for performance, well-being, and commuting. Yet a crucial gap remains around how short-term, localized triggers—such as changes in infection rates—can alter telework patterns and thus shape a broad range of outcomes. The following sections build on these findings by examining how Japan's voluntary self-restraint model, combined with substantial regional variation in COVID-19 case numbers, offers fresh evidence on the causal effects of telework on labor and lifestyle dimensions.

3. COVID-19 Infection Rates in Shikoku and Kyushu Regions

The spread of COVID-19 in Japan exhibited considerable variability across time and regions. Table 1 summarizes the emergency declarations and semi-emergency measures ("Manbou") applied nationwide as well as in 11 prefectures of Shikoku and Kyushu (excluding Okinawa Prefecture) regions during 2020 and 2021.

(Table 1 around here)

From Table 1, a total of four emergency declarations and one "Manbou" period were imposed nationwide between 2020 and 2021. By prefecture, most Shikoku and Kyushu prefectures (except Fukuoka) experienced only one emergency declaration between April 16, 2020, and May 14, 2020, when the initial outbreak occurred. In contrast, Fukuoka Prefecture faced four emergency declarations over the same period. These declarations and semi-emergency measures aligned closely with the progression of COVID-19 nationwide.

The issuance of emergency declarations and "Manbou" measures closely followed the progression of the COVID-19 pandemic. Figures 1 and 2 report the monthly number of new positive cases per 100,000 people for 2020 and 2021, both nationwide and in Shikoku and Kyushu regions.

(Figures 1–2 around here)

These figures illustrate successive waves of rising and declining COVID-19 infections from March 2020 to July 2021. In August 2021, the number of new positive cases surged markedly—roughly 9 to 19 times the typical monthly average (Appendix Table 1). However, by September 2021, case counts had fallen sharply, indicating a temporary nationwide contraction in infections.

4. Data

4.1. Data Summary

To examine how TW adoption impacts workers, this study combines questionnaire surveys with administrative data on new COVID-19 positive cases and population statistics. The survey was conducted between January and April 2022. Specifically, surveys were distributed to 338 member companies of the Kyushu Economic Federation (January–March) and to 100 member companies of the Shikoku Economic Federation (February–April). Participants accessed a web-based questionnaire via a QR code provided on the paper survey. In total, 400 responses were received—337 from Kyushu and 63 from Shikoku. Excluding individuals without necessary information (e.g., home/workplace zip codes) and those in Tokyo or Okinawa prefectures (where infection trends differed sharply from other prefectures in August 2021), the final sample size for analysis was 373.[3] Regarding administrative data, the number of new COVID-19 positive cases by municipality was collected from open data, websites, or information provided by prefectural officials.

4.2. Description of Variables Used in the Analysis

This study utilizes a set of variables constructed from a retrospective survey administered between January and April 2022 to employees residing in the Shikoku and Kyushu regions of Japan. The analysis centers on TW adoption, local COVID-19 exposure, labor outcomes, health-related behaviors, and time-use patterns. Individual-level responses are merged with municipality-level infection data using zip code identifiers to construct exogenous variation in pandemic intensity.

The endogenous treatment variable is the number of telework days per week, measured at three points in time: (i) prior to the pandemic (November 2019), (ii) during the infection expansion phase (August 2021), and (iii) during the contraction phase (December 2021). To address the potential endogeneity of TW adoption, we construct an instrumental variable based on the cumulative number of newly confirmed COVID-19 cases per 100,000 residents in the respondent's municipality of work or residence. This variable is publicly reported by official sources and does not require population normalization by researchers. We aggregate the data by municipality for two periods—May to August 2021 and September to December 2021—corresponding to the reference months for TW behavior (August and December 2021, respectively). The aggregated infection rates are then linked to respondents using zip code-level information on work or home location.

Although the survey was conducted only once, its inclusion of retrospective questions enables us to construct panel-like outcome measures. Specifically, we examine six labor and health-related outcomes for both August and December 2021: (1) overtime

[3] Information on new positive COVID-19 cases was not available for three municipalities (Osaka City and Sakai City, Osaka Prefecture, and Chiba City, Chiba Prefecture), and one prefecture (Hyogo Prefecture).

work, (2) work efficiency, (3) life satisfaction, (4) commuting time, (5) daily walking (excluding formal exercise), and (6) daily physical exercise. Each outcome is based on a question asking how the respondent's experience in August or December 2021 compared with November 2019. Responses are collected on a five-point ordinal scale: 1 = "decreased very much," 2 = "slightly decreased," 3 = "no change," 4 = "slightly increased," and 5 = "increased very much." For analytical consistency, we fix the November 2019 baseline at 3 and recode responses by subtracting 3, yielding a centered scale from –2 (decreased very much) to +2 (increased very much), with zero indicating no change from the pre-pandemic baseline.

In addition to these retrospective panel outcomes, we analyze cross-sectional measures reported at the time of the survey (January–April 2022). These consist of two domains. First, we examine whether respondents engaged in any of eleven specific tasks while teleworking since the onset of the pandemic: (1) documentation, (2) information gathering, (3) data processing, (4) accounting work, (5) planning and development, (6) design, (7) online meetings, (8) internal coordination, (9) external coordination, (10) internal training, and (11) external training. Each task is coded as a binary indicator equal to one if the respondent reported performing it at any point since March 2020.

Second, we analyze how respondents allocated time saved from not commuting due to TW. The survey asked whether such time was used for any of the following eight activities: (1) hobbies and recreation, (2) sleep, (3) skill development, (4) housework, (5) family time, (6) shopping, (7) additional work tasks, and (8) childcare. These responses are likewise coded as binary indicators.

Throughout all specifications, we control for two predetermined individual characteristics: age (in years) and a binary indicator for female respondents. Definitions of all treatment, outcome, instrumental, and control variables are summarized in Appendix Table A2. Descriptive statistics are provided in Section 4.3 and Appendix Tables 2–3, documenting the evolution of TW adoption, local infection rates, and outcome variables over time.

4.3. Descriptive Statistics

Descriptive Table 2 and Table 3 summarize descriptive statistics for the main variables used in the analysis across three reference periods: November 2019 (pre-pandemic baseline), August 2021 (pandemic expansion), and December 2021 (pandemic contraction). These tables document notable shifts in telework intensity, infection exposure, and individual behaviors.

(Tables 2–3 around here)

TW adoption increased markedly during the pandemic. The average number of TW days per week rose from 0.20 days in November 2019 to 1.34 days in August 2021, before declining to 0.80 days by December 2021. This change was accompanied by a sharp increase in the amount of commute time saved due to TW—from 13.5 minutes per week in 2019 to 105 minutes in August 2021 and 63.1 minutes in December 2021. These figures illustrate both the uptake and partial reversal of TW practices over time.

Local COVID-19 exposure patterns mirrored these trends. Workplace municipalities experienced an average of 909 new cases per 100,000 residents during May–August 2021, followed by a sharp decline to 191 cases in September–December 2021. A similar pattern is observed for home municipalities, with average exposure declining from 706 to 159 cases per 100,000. These figures reflect the infection waves that plausibly influenced firm- and worker-level TW decisions.

Labor and health outcomes also exhibit meaningful variation across periods. Between November 2019 and August 2021, respondents reported average decreases in overtime work (–0.037), life satisfaction (–0.412), commuting time (–0.294), walking (–0.352), and exercise (–0.362), with only modest gains in work efficiency (+0.045). These patterns suggest that while TW likely reduced commuting burdens, it coincided with declines in physical activity and subjective well-being. By December 2021, some of these trends partially reversed: the mean reported change in overtime work turned slightly positive (+0.024), and life satisfaction remained below baseline (–0.349), though slightly improved compared to August. Across outcomes, the standard deviations ranged from 0.58 to 1.01, indicating considerable individual heterogeneity in pandemic responses.

Descriptive statistics for the cross-sectional outcomes measured at the survey time (January–April 2022) are presented in Table 3. A large share of respondents reported having performed documentation (64%), information gathering (50%), and data processing (43%) during telework since the pandemic began. More specialized tasks such as accounting work (9.7%), planning (20%), and design (5.3%) were less common. Coordination activities were widespread: 52% of respondents engaged in internal coordination and 39% in external coordination, underscoring the communicative demands of remote work.

In terms of time-use reallocation, 33.6% reported spending saved commuting time on housework, 32.5% on sleep, 24.9% on family time, and 21.5% on hobbies and recreation. By contrast, fewer individuals used that time for skill development (7.6%), shopping (11.3%), or additional work (11.0%). Only 8.4% reported allocating this time to childcare.

Appendix Table 4 includes the frequency of home and work zip codes by municipality, along with the number of new cases per 100,000 and 2021 population. Figures 3 and 4 reveal no strong correlation between population size and local infection counts. In municipalities of 200,000 or more, respondents were more likely to report their home municipality rather than their workplace, especially below the 45-degree line in Figure 3. Saga City, Chuo-ku (Fukuoka City), and Hakata-ku (Fukuoka City) appeared more often as workplace areas. Figure 4 further shows a widespread decrease in new cases from May–August to September–December 2021 across most municipalities.

(Figures 3–4 around here)

5. Estimation Method

Estimating the causal impact of TW adoption during the COVID-19 pandemic on outcomes such as productivity, exercise habits, and time use presents several empirical challenges. Because TW is not randomly assigned, individual adoption decisions are likely correlated with unobserved determinants of outcomes—including job characteristics, workplace norms, and health-related constraints—giving rise to selection bias and potential reverse causality.

To address these concerns, we implement a two-stage least squares (2SLS) strategy using local COVID-19 infection rates as an instrument for TW adoption. Specifically, we use the cumulative number of new COVID-19 cases per 100,000 population in respondents' workplace municipalities as a plausibly exogenous determinant of TW. This measure captures local variation in pandemic severity that plausibly influenced firm-level telework policies but is unlikely to affect individual outcomes directly after conditioning on observed controls. Instrument relevance is assessed through first-stage F-statistics, and robustness checks using home municipality infection rates are provided in the Appendix.

Our empirical approach differs depending on the temporal structure of the outcomes. For repeated outcomes—such as overtime work, work efficiency, life satisfaction, commuting time, walking, and physical exercise—we exploit the panel structure of the data and estimate two-way fixed effects (FE) and fixed effects instrumental variables (FEIV) models. These specifications control for both individual-specific time-invariant unobservables (e.g., occupation, baseline health, personality traits) and time-specific shocks common to all individuals, thereby addressing two major sources of omitted variable bias. When combined with our instrumental variables strategy, which mitigates endogeneity from selection and reverse causality, the FEIV approach provides a credible framework for causal inference. The model structure, identification assumptions, and variable definitions are described in detail in Section 5.1. For outcomes observed only at the time of the survey—namely, the types of tasks performed during telework and the use of time saved from not commuting—we estimate value-added (VA) and IV-value-added (IV-VA) models. These cross-sectional specifications control for predetermined characteristics such as age and gender and exploit the same exogenous variation in local COVID-19 exposure. Details of these specifications and their identifying assumptions are provided in Section 5.2.

5.1. Telework and Effects on Labor Outcomes and Exercise Habits

5.1.1. Pre- and Post-Pandemic Comparisons (Nov. 2019 – Aug/Dec. 2021)

We begin by estimating the effect of TW adoption on labor outcomes and exercise habits between the pre-pandemic baseline (November 2019) and either the pandemic peak (August 2021) or contraction phase (December 2021). Let Y_{it} denote the outcome for individual i at time t, and $telework_{it}$ the number of TW days per week. Outcomes include six self-reported measures rated on a five-point scale: overtime work, work efficiency, life satisfaction, commuting time, daily walking, and daily physical exercise.

To control for unobserved time-invariant heterogeneity and common shocks across survey waves, we estimate the following two-way fixed effects model:

$$Y_{it} = \beta_1^{FE} telework_{it} + \mu_i + \mu_t + \varepsilon_{it}^{FE} \tag{1}$$

where the terms μ_i and μ_t denote individual and time fixed effects, respectively. Standard errors are clustered at the municipality level to allow for correlated local shocks. To address the endogeneity of $telework_{it}$, we instrument this variable using exogenous variation in COVID-19 infection rates at the municipality level. Specifically, we define $NewPositiveCases_{it}$ as the cumulative number of new COVID-19 cases per 100,000 people in the respondent's workplace municipality during the relevant period. The first-stage regression of the fixed effects instrumental variables (FEIV) model is given by:

$$telework_{it} = \alpha_1^{FEIV} NewPositiveCases_{it} + \alpha_2^{FEIV} W_{it} + \mu_i + \mu_t + \varepsilon_{it}^{FEIV} \tag{2}$$

and the corresponding second stage is:

$$Y_{it} = \beta_1^{FEIV}\, \widehat{telework}_{it} + \beta_2^{FEIV} W_{it} + \mu_i + \mu_t + \eta_{it}^{FEIV} \tag{3}$$

The validity of our identification strategy hinges on two conditions. First, the instrument must be relevant—that is, variation in local COVID-19 incidence should strongly predict telework adoption. Formally, this requires:

$$Cov(telework_{it}, NewPositiveCases_{it}) \neq 0 \tag{4}$$

Second, the exclusion restriction must be satisfied. This condition requires that, conditional on observed covariates and individual and time fixed effects, local infection rates affect outcomes solely through their influence on telework adoption—not through any direct or unobserved pathways. Formally, this implies:

$$Cov(\eta_{it}^{FEIV}, NewPositiveCases_{it}) = 0 \tag{5}$$

This implies that local COVID-19 incidence affects outcomes only through its impact on TW adoption. While this assumption is untestable, we support its plausibility by including individual and time fixed effects and excluding respondents whose TW adoption likely reflects firm-level restructurings rather than local pandemic severity.

Instrument strength is assessed via the first-stage F-statistic. The instrumental variable $NewPositiveCases_{it}$ varies depending on the comparison period. For the Nov. 2019–Aug. 2021 specification, we use the cumulative number of new COVID-19 cases per 100,000 people in the respondent's workplace municipality from March to August 2021. For the Nov. 2019–Dec. 2021 specification, we use the cumulative infection counts from September to December 2021. To mitigate potential bias from firm-level telework policies unrelated to pandemic severity, we exclude individuals whose TW days increased monotonically from 2019 to 2021. We interpret the difference between the FE and FEIV estimates of β_1 as evidence of the magnitude and direction of endogeneity bias.

5.1.2. Pandemic Contraction Phase (Aug. – Dec. 2021)

We next examine the contraction phase of the pandemic, spanning August to December 2021, during which COVID-19 infection rates declined substantially. This period is analytically distinct from earlier phases of the pandemic because the factors driving TW adoption may have shifted. In particular, decisions to maintain or terminate TW arrangements were likely less influenced by acute public health concerns and more shaped by firm-level strategies and worker preferences. Estimating the causal effects of TW during this transition allows us to test whether the behavioral and productivity consequences of telework persisted even as the external pandemic shock receded.

To this end, we estimate the same two-way fixed effects (FE) and fixed effects instrumental variables (FEIV) specifications described above, using panel data from August and December 2021. In this setting, Y_{it} and $telework_{it}$ represent the outcome and TW intensity for individual i at time $t \in \{Aug. 2021, Dec. 2021\}$. The instrument $NewPositiveCases_{it}$ is defined as the cumulative number of new COVID-19 cases per 100,000 people in the respondent's workplace municipality from September to December 2021. This variable captures the local infection risk following the August 2021 peak. The regression equations follow Equations (1)–(3). To construct $NewPositiveCases_{it}$, we aggregate official case counts by municipality over the relevant months and merge them with individual survey data by workplace location.

We exclude individuals whose TW usage increased monotonically from August to December 2021, as such changes may reflect firm-level reorganizations or other institutional shifts unrelated to infection dynamics. By focusing on a period in which public health pressures were easing, this analysis isolates variation in TW that is more plausibly driven by structural or behavioral inertia. Comparisons of the estimated TW effects across periods, particularly the magnitude and statistical significance of β_1 across periods provide evidence of heterogeneity in the causal effects of TW depending on the broader epidemiological environment.

5.2. Telework and Effects on Survey-Time Outcomes

To evaluate the longer-run effects of TW adoption, we examine outcomes that were measured only once, at the time of the retrospective survey conducted between January and April 2022. These outcomes capture two domains: (i) tasks performed while teleworking (11 items) and (ii) activities enabled by time saved from not commuting (8 items). Each outcome is recorded as a binary variable indicating whether the respondent ever engaged in the corresponding task or activity. Although the survey items do not specify a reference time point, we interpret these variables as stock indicators—persistent markers of prior TW exposure that reflect accumulated behavioral changes rather than transitory flows.[4]

Because TW status at the time of the survey was not directly recorded, we estimate value-added (VA) and IV-value-added (IV-VA) models using retrospective changes in TW days as the key regressors. We define two separate endogenous variables: the change in weekly TW days between November 2019 and August 2021, denoted $\Delta telework_i^{Aug}$, and the change between November 2019 and December 2021, denoted $\Delta telework_i^{Dec}$. Each specification is estimated separately.

We use the cumulative number of new COVID-19 cases per 100,000 people in the respondent's workplace municipality as an instrument, denoted $NewPositiveCases_i^{Aug}$ and $NewPositiveCases_i^{Dec}$, corresponding to May–August 2021 and September–December 2021, respectively. These instruments are assumed to be relevant for TW adoption and orthogonal to unobserved determinants of survey-time outcomes, conditional on controls.

4 In particular, in August 2021, when a state of emergency was declared, many prefectures recorded the highest number of new positive cases since the onset of the COVID-19 pandemic. For example, Figure 2 and Appendix Table 1, which show the number of new positive cases per 100,000 people per month since the COVID-19 pandemic in the prefectures of Shikoku and Kyushu, show that the number of new positive cases in August 2021 was approximately 9-19 times higher than the average for other months.

The baseline VA model is specified as:

$$Y_i = \gamma_0^p + \gamma_1^p \Delta telework_i^p + \gamma_2^p Age_i + \gamma_3^p Female_i + \varepsilon_i \quad (6)$$

To address endogeneity, we estimate the following 2SLS specification. The first-stage regression of the fixed effects instrumental variables (IV-VA) model is given by:

$$\Delta telework_i^p = \pi_0^p + \pi_1^p NewPositiveCases_i^p + \pi_2^p Age_i + \pi_3^p Female_i + u_i \quad (7)$$

and the corresponding second stage is:

$$Y_i = \gamma_0^p + \gamma_1^p \, \Delta \widehat{telework}_i^p + \gamma_2^p Age_i + \gamma_3^p Female_i + \eta_i \quad (8)$$

The instrument relevance condition requires:

$$Cov\left(\Delta telework_i^p, NewPositiveCases_i^p\right) \neq 0 \quad (9)$$

and the exclusion restriction assumes:

$$Cov\left(\eta_i, NewPositiveCases_i^p\right) = 0 \quad (10)$$

Instrument strength is assessed using the first-stage F-statistic. Standard errors are clustered at the municipality level to allow for correlated local shocks. No individual or time fixed effects are included due to the cross-sectional nature of the outcomes. All specifications control for predetermined characteristics, including respondent age and gender.

To mitigate confounding from firm-level transitions or delayed TW adoption, we exclude individuals whose TW use increased monotonically from August to December 2021, or who began teleworking only after August 2021. For those reporting zero TW days in both August and December 2021, we impute zero TW exposure at the time of the survey.

While the IV estimation strategy helps correct for selection and reverse causality, the VA and IV-VA models do not control for unobserved time-invariant individual heterogeneity. Thus, compared to the panel-based FE and FEIV models in Section 5.1, these estimates are more vulnerable to omitted variable bias. Nonetheless, they offer complementary evidence on how cumulative exposure to TW shaped work and personal routines by early 2022.

6. Estimated Results

This section presents the main empirical findings on the causal effects of TW adoption during the COVID-19 pandemic, drawing on two complementary estimation strategies: fixed effects instrumental variable (FEIV) models for panel outcomes and IV-value-added (IV-VA) models for cross-sectional outcomes. These approaches address endogeneity concerns—including selection bias and reverse causality—by leveraging exogenous variation in COVID-19 infection rates across municipalities as an instrument for TW adoption.[5]

6.1. Telework and Effects on Labor Outcomes and Exercise Habits

6.1.1. Pre- and Post-Pandemic Comparisons (Nov. 2019 – Aug/Dec. 2021)

We begin by assessing the relationship between COVID-19 exposure and telework adoption during the pandemic. Table 4 presents the first-stage 2SLS results, which show that the cumulative number of new COVID-19 cases in respondents' workplace municipalities significantly predicts the number of TW days between November 2019 and both August and December 2021. The estimated coefficients are 0.0003 for the Nov. 2019–Aug. 2021 period (F-statistic = 17.2) and 0.0003 for the Aug.–Dec. 2021 period (F-statistic = 15.1), both statistically significant at the 1% level and exceeding the conventional threshold ($F > 10$) for instrument strength. In contrast, the coefficient for the Nov. 2019–Dec. 2021 period is not statistically significant, and the associated F-statistic (4.57) falls well below conventional thresholds. As a result, we exclude this specification from the main analysis and report it in Appendix Table A4.

(Table 4 around here)

Table 5 presents the second-stage estimates from the fixed effects (FE) and fixed effects instrumental variables (FEIV) models examining the impact of TW adoption on labor outcomes and exercise habits between November 2019 and August 2021. While the signs

5 The results of the analysis using the number of new positive COVID-19 cases per 100,000 people for May-August and September-December for the municipalities containing the zip codes of the respondents' homes are omitted from this report because the results are similar to those in this section.

of the coefficients are generally consistent across models, the magnitudes and significance levels differ, highlighting the role of endogeneity.

(Table 5 around here)

In the FE model, a one-day increase in TW is significantly associated with reductions in overtime work (–0.117, $p < 0.01$), commuting time (–0.192, $p < 0.01$), daily walking (–0.198, $p < 0.01$), and daily exercise (–0.109, $p < 0.01$), as well as an increase in life satisfaction (0.138, $p < 0.01$). TW is also positively associated with work efficiency (0.050, $p < 0.05$). In contrast, the FEIV model—which instruments TW days using workplace-level COVID-19 case counts—yields larger estimated effects: a one-day increase in TW significantly reduces overtime work (–0.373, $p < 0.1$), commuting time (–0.496, $p < 0.01$), and daily exercise (–0.440, $p < 0.1$), and significantly increases life satisfaction (0.436, $p < 0.01$). The coefficients for work efficiency and daily walking lose statistical significance once endogeneity is addressed. These shifts in magnitude and significance suggest that the FE estimates may be attenuated due to unobserved confounding or simultaneity bias.

To assess the magnitude of the estimated effects in substantive terms, we multiply the FEIV coefficients by the average increase in TW days between November 2019 and August 2021, which was 1.13 days. The resulting changes are sizable: commuting time decreases by 0.56 units, daily exercise by 0.50 units, and overtime work by 0.42 units, while life satisfaction increases by 0.49 units. When scaled relative to the standard deviations of the respective outcomes in August 2021—0.683 for commuting time, 0.818 for daily exercise, 0.739 for overtime work, and 1.010 for life satisfaction—these effects correspond to approximately 82%, 61%, 57%, and 49% of one standard deviation. These magnitudes indicate that TW adoption during the pandemic peak had large and economically meaningful effects on both work and lifestyle behaviors.

6.1.2. Pandemic Contraction Phase (Aug. – Dec. 2021)

We next examine the period from August to December 2021, during which COVID-19 cases declined and TW adoption correspondingly fell. Table 6 presents the FE and

FEIV estimates of how this reduction in telework influenced labor outcomes and exercise habits. In the FEIV model, a one-day decrease in TW days significantly increased overtime work (–0.134, $p < 0.05$), commuting time (–0.315, $p < 0.01$), and daily walking (–0.261, $p < 0.05$). Other outcomes—such as work efficiency, life satisfaction, and daily exercise—do not show statistically significant effects in the IV specification, although some remain significant in the FE estimates.

To interpret the magnitude of these effects, we multiply the FEIV coefficients by the average reduction in TW days during this period, which was approximately 0.542 days. This yields estimated increases of 0.073 units in overtime work, 0.171 units in commuting time, and 0.141 units in daily walking. Relative to the standard deviations of the respective outcomes in December 2021 (0.697 for overtime work, 0.584 for commuting time, and 0.753 for daily walking; see Table 2), these effects amount to approximately 10.5%, 29.3%, and 18.7% of one standard deviation, respectively. These magnitudes suggest that the reversal of TW adoption during the pandemic's contraction phase had modest but noticeable effects on commuting behavior and physical activity. (Table 6 around here)

6.2. Telework and Effects on Survey-Time Outcomes

We next turn to survey-time outcomes, examining whether individuals who experienced an exogenous increase in TW days in August 2021—as instrumented by local COVID-19 infection rates—were more likely to have engaged in specific tasks while teleworking and to have reallocated time saved from not commuting by the time of the survey conducted in January–April 2022.

Table 7 shows that cumulative COVID-19 cases in May–August 2021 significantly predicted TW days in August 2021, with a coefficient of 0.0003 ($p < 0.01$). However, the associated first-stage F-statistic is 8.18, which falls below the conventional threshold of 10 for strong instruments. The December 2021 specification performed even worse, with a statistically insignificant first-stage coefficient and an F-statistic of 1.50, indicating a very weak instrument. Given these results, we retain only the August 2021 specification for the main analysis, as it provides the most credible identification despite a marginally weak instrument. In contrast, the December 2021 results are excluded from the main text due to weak instrument concerns and are reported separately in Appendix Tables A5–A6 for transparency and completeness.

(Table 7 around here)

Table 8 reports IV-VA estimates for job content. Respondents who experienced an exogenous increase in TW days by August 2021 were significantly more likely to report engaging in internal coordination (0.333, $p < 0.01$), external coordination (0.242, $p < 0.05$), and accounting work (0.334, $p < 0.01$) during telework. Information gathering was also positively associated (0.243, $p < 0.1$), though other activities such as documentation, planning, or training showed no significant relationship. To interpret the size of these estimates, we scale them by the standard deviations of each binary outcome variable (see Table 3): 0.500 for internal coordination, 0.489 for external coordination, and 0.297 for accounting work. The implied differences correspond to 66.6%, 49.5%, and 112.5% of one standard deviation, respectively—indicating substantial differences in the composition of work associated with increased TW adoption.

(Table 8 around here)

Table 9 turns to time-use outcomes. Individuals with greater TW exposure by August 2021 were significantly more likely to report engaging in hobbies and leisure (0.290, $p < 0.05$) and childcare (0.128, $p < 0.01$) with time saved from not commuting. While the estimate for sleep was positive (0.226), it did not reach statistical significance ($p > 0.1$). Scaling these estimates by the standard deviations of each outcome—0.412 for hobbies, 0.278 for childcare, and 0.469 for sleep—yields relative effect sizes of 70.4%, 46.0%, and 48.2% of one standard deviation, respectively. These findings suggest that individuals who experienced an exogenous increase in TW days during the peak phase of the pandemic not only altered the structure of their job content but also reallocated freed-up commuting time toward leisure, rest, and family-related activities.

(Table 9 around here)

7. Conclusion

This study examines the causal impact of TW adoption on labor outcomes, exercise habits, and time use during and after the COVID-19 pandemic, using original survey data collected from approximately 400 employees in the Shikoku and Kyushu regions of Japan. To address endogeneity concerns—arising from self-selection into TW and reverse causality—we employ an instrumental variable strategy that leverages variation in the COVID-19 infection rates per 100,000 people in respondents' workplace or home municipalities as an instrumental variable for TW intensity. By distinguishing between the infection expansion phase (November 2019 to August 2021) and the contraction phase (August to December 2021), we examine heterogeneity in TW effects across different pandemic periods.

Our identification strategy allows us to isolate plausibly exogenous shifts in TW intensity induced by the pandemic, enabling credible estimation of its effects across different phases of the crisis. For repeated retrospective outcomes—such as overtime work, commuting time, life satisfaction, and daily exercise—we estimate fixed effects and fixed effects IV (FEIV) models. For survey-only outcomes—such as tasks performed during telework and time-use activities enabled by reduced commuting—we apply IV-value-added (IV-VA) models, using retrospective variation in TW days as the endogenous regressor.

The results reveal substantial behavioral responses to exogenous changes in TW intensity. During the expansion phase, a one-day increase in TW significantly reduced overtime work, commuting time, and daily exercise, while increasing life satisfaction. When scaled by the average TW increase (1.13 days), these effects represent between 48% and 61% of one standard deviation, indicating meaningful improvements in time efficiency and well-being. In contrast, during the contraction phase, a decline in TW intensity (–0.54 days on average) led to increases in overtime work, commuting time, and walking, with magnitudes equivalent to 11%–29% of one standard deviation. These patterns suggest that even moderate reversals in TW can undermine some of the earlier gains in physical activity and work-life balance.

We also find longer-run effects among those who experienced sustained TW exposure as of August 2021. These individuals were significantly more likely to report engaging in internal coordination (67% of one SD), external coordination (50%), and accounting work (113%) during telework. In terms of time allocation, they were more likely to have devoted time saved from commuting to hobbies and recreation (70%), sleep (48%), and childcare (46%), relative to their peers.

These findings contribute to a nuanced understanding of how TW reshapes both work behavior and personal time use. Our results suggest that TW adoption—particularly during the pandemic's peak—generated meaningful improvements in worker well-being and efficiency. Reductions in overtime work, commuting time, and daily exercise, alongside gains in life satisfaction and reallocation of time toward hobbies, sleep, and caregiving, indicate that TW played a substantive role in reshaping work-life balance. These behavioral adjustments persisted into early 2022, suggesting that the effects of TW exposure were not merely transitory.

Nevertheless, many organizations in Japan and abroad have begun scaling back remote work and reinstating traditional workplace routines. This "return to work" trend may be driven by managerial preferences, peer pressure, or beliefs in the superiority of face-to-face collaboration. However, our findings caution against a wholesale reversion to pre-pandemic norms. Rather than abandoning TW altogether, institutions should consider hybrid or flexible arrangements that preserve its benefits while addressing its limitations. Policymakers and employers should continue to explore how TW can be effectively integrated into post-pandemic labor markets to enhance productivity, equity, and work-life balance.

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Figures

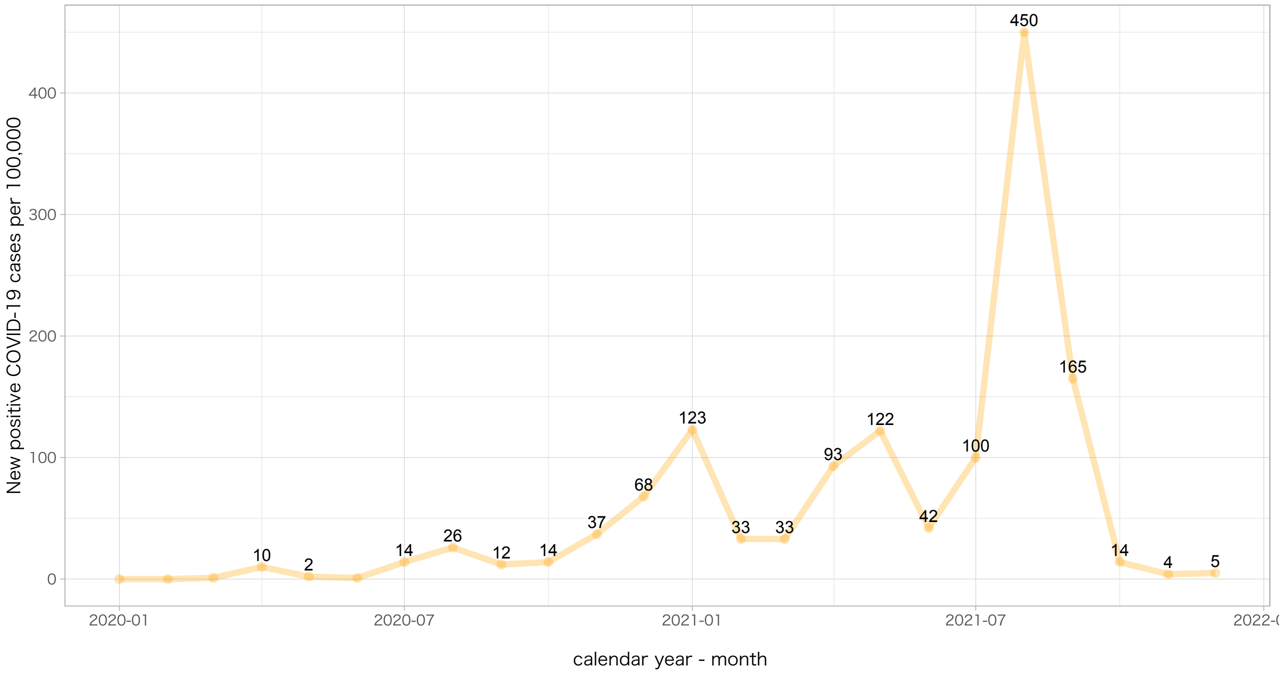

Figure 1: New positive COVID-19 cases per 100,000 people nationwide (January 2020-December 2021)

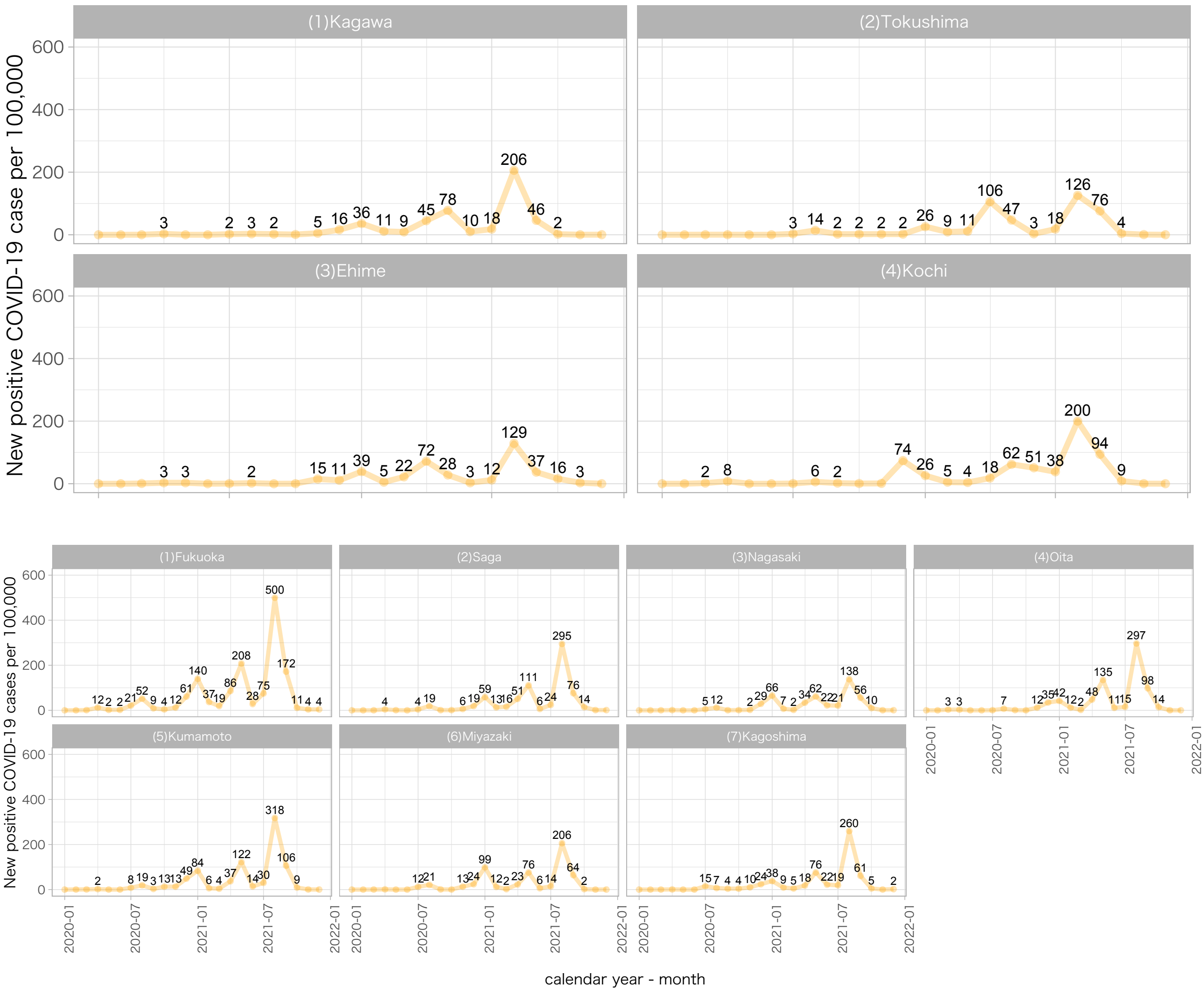

Figure 2: New positive COVID-19 cases per 100,000 people in Shikoku and Kyushu regions (January 2020-December 2021)

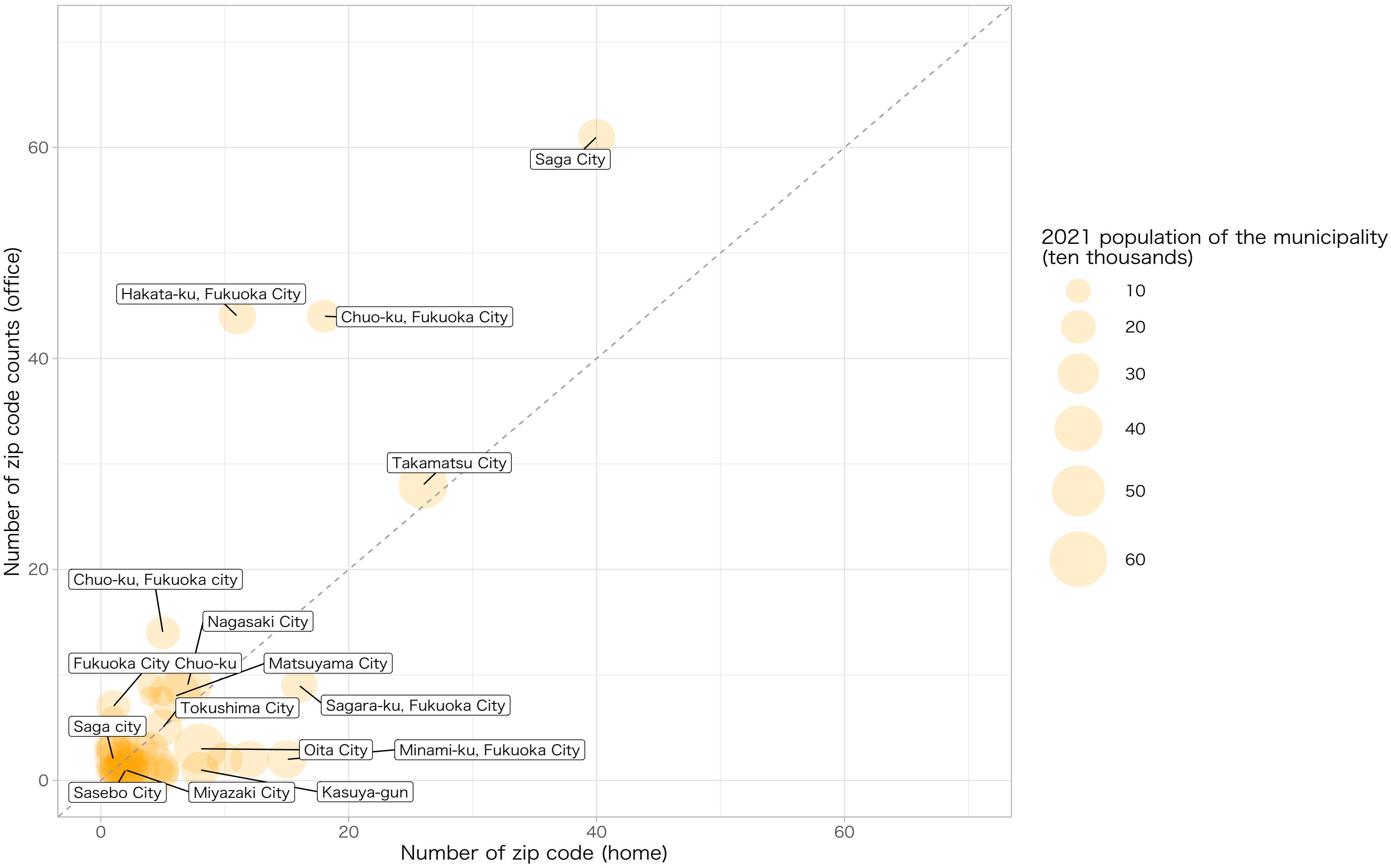

Figure 3: Comparison of the number of zip codes between work and home by municipality

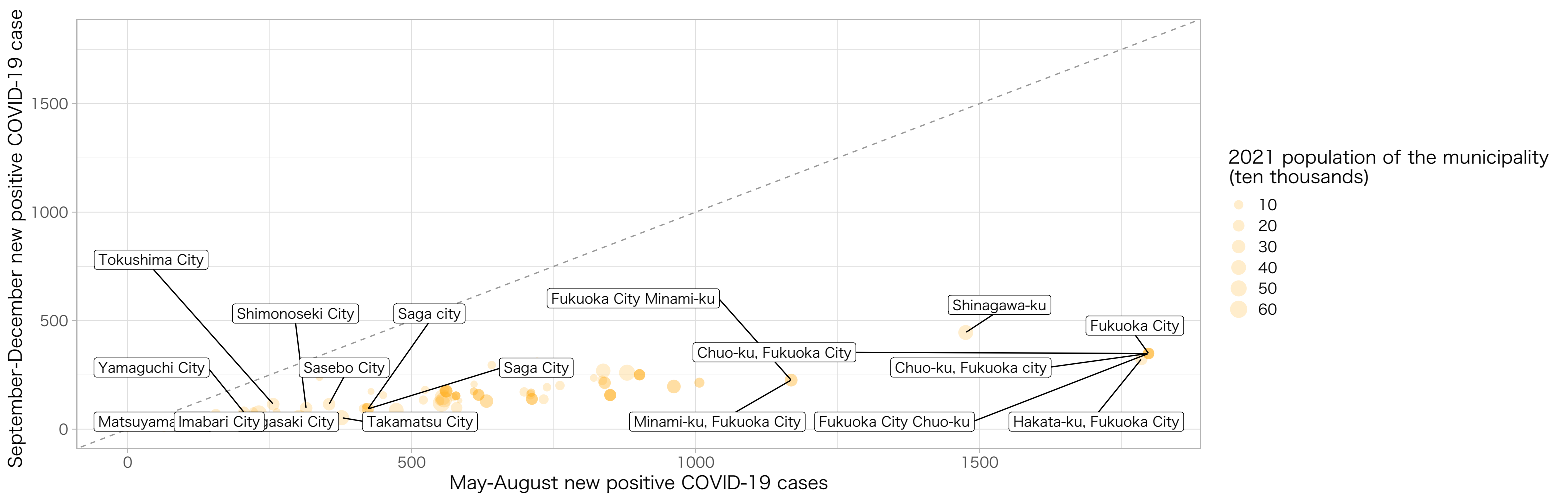

Figure 4: New positive COVID-19 cases from May-August and September-December by municipality

List of Tables

Table 1: Status of Emergency Declarations and Priority Measures in Kyushu (Excluding Okinawa) and Shikoku, 2020–2021

Name of prefecture	period of emergency declaration	period of priority measures to prevent the spread of disease
Nationwide	April 7, 2020 (Tue.) – May 25, 2020 (Mon.) January 8, 2021 (Fri.) – March 21, 2021 (Sun.) April 25, 2021 (Sun.) – June 20, 2021 (Sun.) July 12, 2021 (Mon.) – September 30, 2021 (Thu.)	April 5, 2021 (Mon.) – September 30, 2021 (Thu.)
Tokushima Prefecture	April 16, 2020 (Thu.) – May 14, 2020 (Thu.)	
Kagawa Prefecture	April 16, 2020 (Thu.) – May 14, 2020 (Thu.)	August 20, 2021 (Fri.) – September 30, 2021 (Thu.)
Ehime Prefecture	April 16, 2020 (Thu.) – May 14, 2020 (Thu.)	April 25, 2021 (Sun.) – May 22, 2021 (Sat.) August 20, 2021 (Fri.) – September 12, 2021 (Sun.)
Kochi Prefecture	April 16, 2020 (Thu.) – May 14, 2020 (Thu.)	August 27, 2021 (Fri.) – September 12, 2021 (Sun.)
Fukuoka Prefecture	April 7, 2020 (Tue.) – May 14, 2020 (Thu.) January 14, 2021 (Thu.) – February 28, 2021 (Sun.) May 12, 2021 (Wed.) – June 20, 2021 (Sun.) August 20, 2021 (Fri.) – September 30, 2021 (Thu.)	June 21, 2021 (Mon.) – July 11, 2021 (Sun.) August 2, 2021 (Mon.) – August 19, 2021 (Thu.)
Saga Prefecture	April 16, 2020 (Thu.) – May 14, 2020 (Thu.)	August 27, 2021 (Fri.) – September 12, 2021 (Sun.)
Nagasaki Prefecture	April 16, 2020 (Thu.) – May 14, 2020 (Thu.)	August 27, 2021 (Fri.) – September 12, 2021 (Sun.)
Kumamoto Prefecture	April 16, 2020 (Thu.) – May 14, 2020 (Thu.)	May 16, 2021 (Sun.) – June 13, 2021 (Sun.) August 8, 2021 (Sun.) – September 30, 2021 (Thu.)
Oita Prefecture	April 16, 2020 (Thu.) – May 14, 2020 (Thu.)	
Miyazaki Prefecture	April 16, 2020 (Thu.) – May 14, 2020 (Thu.)	August 27, 2021 (Fri.) – September 30, 2021 (Thu.)
Kagoshima Prefecture	April 16, 2020 (Thu.) – May 14, 2020 (Thu.)	August 20, 2021 (Fri.) – September 30, 2021 (Thu.)

Table 2: Summary Statistics (1)

Timing	(1) Nov.2019				(2) Aug.2021				(3) Dec.2021			
Variable	Obs	NA	Mean	S.D.	Obs	NA	Mean	S.D.	Obs	NA	Mean	S.D.
Telework frequency												
TW days	380	763	0.202	0.678	381	762	1.34	1.35	381	762	0.797	1.23
D2D commuting time reduced by TW	380	763	13.5	51	381	762	105	156	381	762	63.1	137
New positive COVID-19 cases												
New positive COVID-19 cases (workplace)	381	762	0	0	379	764	909	625	379	764	191	114
New positive COVID-19 cases (home)	381	762	0	0	380	763	706	440	380	763	159	87.2
Labor outcomes and exercise habits												
Overtime work	381	762	0	0	381	762	-0.0367	0.739	381	762	0.0236	0.697
Work efficiency	381	762	0	0	381	762	0.0446	0.685	381	762	0.0945	0.666
Life satisfaction	381	762	0	0	381	762	-0.412	1.01	381	762	-0.349	0.944
Commuting time	381	762	0	0	381	762	-0.294	0.683	381	762	-0.202	0.584
Daily walking	381	762	0	0	381	762	-0.352	0.816	381	762	-0.273	0.753
Daily exercise	381	762	0	0	381	762	-0.362	0.818	381	762	-0.331	0.775

Table 3: Summary Statistics (2)

Variable	Obs	NA	Mean	S.D.	Min.	Max.
Jobs during TW						
Documentation	381	0	0.64	0.481	0	1
Information gathering	381	0	0.504	0.501	0	1
Data processing	381	0	0.428	0.495	0	1
Accounting work	381	0	0.0971	0.297	0	1
Planning and development	381	0	0.197	0.398	0	1
Design	381	0	0.0525	0.223	0	1
Online meeting	381	0	0.486	0.5	0	1
Internal coordination	381	0	0.52	0.5	0	1
External coordination	381	0	0.394	0.489	0	1
Internal training	381	0	0.165	0.372	0	1
External training	381	0	0.0919	0.289	0	1
Time use of saved time due to TW						
Hobbies / Recreation	381	0	0.215	0.412	0	1
Sleep	381	0	0.325	0.469	0	1
Skill Development	381	0	0.0761	0.266	0	1
Housework	381	0	0.336	0.473	0	1
Family time	381	0	0.249	0.433	0	1
Shopping	381	0	0.113	0.317	0	1
Additional work	381	0	0.11	0.314	0	1
Child care	381	0	0.084	0.278	0	1
Individual characteristics						
Age	381	0	42.3	12.1	21	76
Female dummy	381	0	0.273	0.446	0	1
Change in TW days						
Aug 2021 - Nov 2019	380	1	1.13	1.31	-2.5	5
Dec 2021 - Nov 2019	380	1	0.597	1.22	-2.5	6
Dec 2021 - Aug 2021	381	0	-0.542	1.11	-5	6
Change in new positive COVID-19 cases						
Dec - Aug 2021(workplace)	379	2	-718	519	-1851	0
Dec - Aug 2021(home)	380	1	-548	362	-1654	0
Change in labor outcomes and exercise habits						
Change in overtime work (Dec - Aug 2021)	381	0	0.0604	0.446	-2	2
Change in work efficiency (Dec - Aug 2021)	381	0	0.0499	0.513	-2	2
Change in life satisfaction (Dec - Aug 2021)	381	0	0.063	0.437	-2	2
Change in commuting time (Dec - Aug 2021)	381	0	0.0919	0.486	-4	2
Change in daily walking (Dec - Aug 2021)	381	0	0.0787	0.434	-1	2
Change in daily exercise (Dec - Aug 2021)	381	0	0.0315	0.396	-2	2

Table 4: Effect of Changes in COVID-19 Positive Cases on Telework Days (1st Stage, FE and FEIV Models; IV: Workplace Municipality-Level Cases)

	Endogenous Variable: Telework Days		
Periods	Nov. 2019 and Aug. 2021	Nov. 2019 and Dec. 2021	Aug. 2021 and Dec. 2021
New COVID-19 positive cases	0.0003***	0.0008	0.0003***
	(0.0001)	(0.0006)	(5.81e-5)
Observations	759	711	710

Note: Parentheses indicate cluster-robust standard errors (SEs) that are robust to clustering at the municipal level based on the workplace zip code. Exogenous variables include age and female dummy. ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$

Table 5: Effect of the Increase in Telework Days (Nov. 2019–Aug. 2021) on Labor Outcomes and Exercise Habits (2nd Stage, FE and FEIV Models; IV: Workplace Municipality-Level Cases)

Outcome Variable	Overtime Work		Work Efficiency		Life Satisfaction		Commuting Time		Daily Walking		Daily Exercise	
	FE	FEIV	FE	FEIV	FE	FEIV	FE	FEIV	FE	FEIV	FE	FEIV
TW days	-0.117***	-0.373*	0.050**	0.042	0.138***	0.436***	-0.192***	-0.496***	-0.198***	-0.126	-0.109***	-0.440*
	(0.028)	(0.187)	(0.023)	(0.156)	(0.032)	(0.096)	(0.015)	(0.127)	(0.019)	(0.087)	(0.017)	(0.219)
Observations	761	759	761	759	761	759	761	759	761	759	761	759
1st stage F-stat.	–	17.2	–	17.2	–	17.2	–	17.2	–	17.2	–	17.2
Adj. R2	0.044	-0.170	0.006	0.003	0.102	-0.029	0.205	-0.106	0.173	0.158	0.113	-0.152

Note: FE and FEIV refer to the results from Fixed Effects (FE) Estimation and Fixed Effects Instrumental Variables (FE-IV) Estimation. Parentheses indicate cluster-robust standard errors (SEs) that are robust to clustering at the municipal level based on the workplace zip code. Exogenous variables include age and a female dummy. Fit statistics include the number of observations, Adjusted R-squared, and the 1st stage F-statistic (for detecting weak instruments in IV estimation). ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$

Table 6: Effect of the Decrease in Telework Days (Aug.–Dec. 2021) on Labor Outcomes and Exercise Habits (2nd Stage, FE and FEIV Models; IV: Workplace Municipality-Level Cases)

Outcome Variable	Overtime Work		Work Efficiency		Life Satisfaction		Commuting Time		Daily Walking		Daily Exercise	
	FE	FEIV	FE	FEIV	FE	FEIV	FE	FEIV	FE	FEIV	FE	FEIV
TW days	-0.065***	-0.134**	-0.011	-0.164	0.024	-0.212**	-0.175***	-0.315***	-0.153***	-0.261**	-0.083***	-0.114
	(0.011)	(0.051)	(0.010)	(0.125)	(0.018)	(0.074)	(0.015)	(0.098)	(0.024)	(0.096)	(0.021)	(0.109)
Observations	714	710	714	710	714	710	714	710	714	710	714	710
1st stage F-stat.	–	15.1	–	15.1	–	15.1	–	15.1	–	15.1	–	15.1
Adj. R2	0.810	0.803	0.699	0.670	0.891	0.860	0.729	0.706	0.858	0.854	0.875	0.874

Note: FE and FEIV refer to the results from Fixed Effects (FE) Estimation and Fixed Effects Instrumental Variables (FE-IV) Estimation. Parentheses indicate cluster-robust standard errors (SEs) that are robust to clustering at the municipal level based on the workplace zip code. Exogenous variables include age and a female dummy. Fit statistics include the number of observations, Adjusted R-squared, and the 1st stage F-statistic (for detecting weak instruments in IV estimation). ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$

Table 7: Effect of Increases in COVID-19 Cases at the Municipal Level (Based on Workplace Zip Code) on Telework Days (1st Stage, VA Model)

	Endogenous Variable: Telework Days	
Periods	Aug. 2021	Dec. 2021
New Positive COVID-19 Cases	0.0003***	0.0007
	(0.0001)	(0.0004)
Observations	354	354
Dep. Var. mean	1.12	0.470

Note: Parentheses indicate cluster-robust standard errors (SEs) that are robust to clustering at the municipal level based on the workplace zip code. Exogenous variables include age and female dummy. ***: p < 0.01, **: p < 0.05, *: p < 0.1

Table 8: Effect of the Increase in Telework Days (Nov. 2019–Aug. 2021) on Tasks Performed During Telework (2nd Stage, VA and IV-VA Models; IV: Workplace Municipality-Level Cases)

Outcome Variable	Documentation		Information Gathering		Data Processing		Accounting Work		Planning and Development		Design	
	VA	IV-VA	VA	IV-VA	VA	IV-VA	VA	IV-VA	VA	IV-VA	VA	IV-VA
TW days (Aug 2021)	0.140***	0.061	0.152***	0.243*	0.150***	0.299*	0.028***	0.334***	0.054*	0.141	0.019	-0.004
	(0.031)	(0.087)	(0.030)	(0.129)	(0.021)	(0.144)	(0.005)	(0.107)	(0.029)	(0.092)	(0.011)	(0.070)
Observations	356	354	356	354	356	354	356	354	356	354	356	354
1st stage F-stat.	–	8.18	–	8.18	–	8.18	–	8.18	–	8.18	–	8.18
Adj. R2	0.151	0.159	0.164	0.091	0.157	-0.021	0.008	-2.14	0.024	-0.097	0.022	0.006

Outcome Variable	Online Meetings		Internal Coordination		External Coordination		Internal Training		External Training	
	VA	IV-VA	VA	IV-VA	VA	IV-VA	VA	IV-VA	VA	IV-VA
TW days (Aug 2021)	0.167***	0.269	0.162***	0.333***	0.176***	0.242**	0.052	-0.025	0.037**	0.007
	(0.024)	(0.169)	(0.036)	(0.105)	(0.024)	(0.094)	(0.034)	(0.075)	(0.016)	(0.061)
Observations	356	354	356	354	356	354	356	354	356	354
1st stage F-stat.	–	8.18	–	8.18	–	8.18	–	8.18	–	8.18
Adj. R2	0.194	0.117	0.178	-0.016	0.225	0.197	0.033	-0.060	0.028	-0.015

Note: “VA” refers to the value-added model, and “IV-VA” refers to the IV value-added model. Parentheses indicate cluster-robust standard errors (SEs) that are robust to clustering at the municipal level based on the workplace zip code. Exogenous variables include age and female dummy. Fit statistics include the number of observations, Adjusted R-squared, F-statistic and its p-value (for testing the joint significance of regressors), and the 1st stage F-statistic (for detecting weak instruments in IV estimation). ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$

Table 9: Effect of the Increase in Telework Days (Nov. 2019–Aug. 2021) on Time-Use Activities During Saved Commute Time (2nd Stage, VA and IV-VA Models; IV: Workplace Municipality-Level Cases)

Outcome Variable	Hobbies and Leisure		Sleep		Skill Development		Housework	
	VA	IV-VA	VA	IV-VA	VA	IV-VA	VA	IV-VA
TW days (Aug 2021)	0.089***	0.290**	0.124***	0.226	0.045**	0.044	0.084**	0.134*
	(0.008)	(0.107)	(0.015)	(0.128)	(0.017)	(0.032)	(0.031)	(0.063)
Observations	356	354	356	354	356	354	356	354
1st stage F-stat.	–	8.18	–	8.18	–	8.18	–	8.18
Adj. R2	0.088	-0.397	0.146	0.083	0.053	0.053	0.065	0.081

Outcome Variable	Time with Family		Shopping		Additional Work Tasks		Childcare	
	VA	IV-VA	VA	IV-VA	VA	IV-VA	VA	IV-VA
TW days (Aug 2021)	0.060**	0.140	0.055***	0.008	0.051***	0.053	0.015***	0.128***
	(0.022)	(0.104)	(0.008)	(0.093)	(0.012)	(0.066)	(0.003)	(0.030)
Observations	356	354	356	354	356	354	356	354
1st stage F-stat.	–	8.18	–	8.18	–	8.18	–	8.18
Adj. R2	0.037	-0.030	0.060	0.002	0.063	0.055	0.004	-0.253

Note: “VA” refers to the value-added model, and “IV-VA” refers to the IV value-added model. Parentheses indicate cluster-robust standard errors (SEs) that are robust to clustering at the municipal level based on the workplace zip code. Parentheses indicate cluster-robust standard errors (SEs) that are robust to clustering at the municipal level based on the workplace zip code. Exogenous variables include age and female dummy. Fit statistics include the number of observations, Adjusted R-squared, and the 1st stage F-statistic (for detecting weak instruments in IV estimation). ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$

Appendix Table A1 : Comparison of new positive COVID-19 cases per 100,000 population (comparison of August 2021 with other months in 2020-21)

Prefecture Name	New positive COVID-19 cases per 100,000 population		Ratio of August 2021 to Other Months
	August 2021	Other Months in August 2021	
Nationwide	450	40.0	11.3
Tokushima	126	14.2	8.9
Kagawa	206	12.5	16.5
Ehime	129	11.9	10.9
Kochi	200	17.5	11.4
Fukuoka	500	41.7	12.0
Saga	295	18.5	15.9
Nagasaki	138	14.4	9.6
Kumamoto	318	22.6	14.0
Oita	297	19.1	15.6
Miyazaki	206	16.1	12.8
Kagoshima	260	13.9	18.7

Appendix Table A2 : Definitions of Key Variables

Variable Name	Definition
Exogenous Variables (Pre-COVID Baseline)	
TW days (Nov. 2019)	Average number of telework (TW) days per week in November 2019.
D2D commuting time reduced by TW (Nov. 2019)	Estimated weekly time saved from commuting, calculated as TW days/week × round-trip D2D commuting time (minutes).
Endogenous Variables (Post-COVID Behavior)	
TW days (Aug. 2021 / Dec. 2021)	Average number of TW days per week in August or December 2021.
D2D commuting time reduced by TW (Aug. 2021 / Dec. 2021)	Weekly commuting time saved due to TW, calculated as TW days/week × round-trip D2D commuting time (minutes).
Instrumental Variables (Municipality-Level COVID-19 Cases)	
New positive COVID-19 cases (workplace / home, May–Aug. 2021 or Sep.–Dec. 2021)	Cumulative new positive COVID-19 cases per 100,000 persons in the municipality including the respondent ' s workplace or home zip code, respectively.
Labor Outcomes and Exercise Habits	
The response in November 2019 is fixed at 3. Responses for August and December 2021 were recoded so that the baseline (November 2019) corresponds to 0, with values ranging from -2 (Very much decreased) to +2 (Very much increased). The original response categories were: 5 = Very much increased, 4 = Slightly increased, 3 = No change, 2 = Slightly decreased, 1 = Very much decreased.	
Overtime work (Nov. 2019 / Aug. 2021 / Dec. 2021)	5-point ordinal scale based on the question: "How has your overtime work changed in August 2021 / December 2021 compared to before the COVID-19 pandemic (i.e., November 2019)?"
Work efficiency (Nov. 2019 / Aug. 2021 / Dec. 2021)	5-point ordinal scale based on the question: "How has your work efficiency changed in August 2021 / December 2021 compared to before the COVID-19 pandemic (i.e., November 2019)?"
Life satisfaction (Nov. 2019 / Aug. 2021 / Dec. 2021)	5-point ordinal scale based on the question: "How has your life satisfaction changed in August 2021 / December 2021 compared to before the COVID-19 pandemic (i.e., November 2019)?"
Commuting time (Nov. 2019 / Aug. 2021 / Dec. 2021)	5-point ordinal scale based on the question: "How has your commuting time changed in August 2021 / December 2021 compared to before the COVID-19 pandemic (i.e., November 2019)?"

Daily walking (Nov. 2019 / Aug. 2021 / Dec. 2021)	5-point ordinal scale based on the question: "How has your amount of daily walking changed in August 2021 / December 2021 compared to before the COVID-19 pandemic (i.e., November 2019)?"
Daily exercise (Nov. 2019 / Aug. 2021 / Dec. 2021)	5-point ordinal scale based on the question: "How has your frequency of daily exercise changed in August 2021 / December 2021 compared to before the COVID-19 pandemic (i.e., November 2019)?"
Tasks Performed During TW (Multiple Responses Allowed)	
Documentation	Dummy variable = 1 if selected; 0 otherwise.
Information gathering	
Data processing	
Accounting work	
Planning and development	
Design	
Online meeting	
Internal coordination	
External coordination	
Internal training	
External training	
Time-Use Activities with Saved Commuting Time	
Hobbies / Recreation	Dummy variable = 1 if selected as an activity using time saved from commuting; 0 otherwise.
Sleep	
Skill development	
Housework	
Family time	
Shopping	
Additional work	
Child care	
Other Exogenous Variables	
Age	Age at time of response.
Female dummy	Dummy variable = 1 if female; 0 otherwise.
Marriage dummy	Dummy variable = 1 if married; 0 otherwise.
Preschooler / Elementary / Junior high / High school / 19+ child dummy	Dummy variable = 1 if the respondent lives with a child in the corresponding age group.
D2D commuting time (minutes)	Round-trip commuting time from home to work (in minutes).
2021 population (workplace / home)	Population of the municipality including the respondent's workplace or home zip code in 2021.

Appendix Table A3 : Number of postal codes by prefecture and municipality (home and workplace) + 2021 population scale

		Frequency of postal codes		New COVID-19 positive cases (persons)		
Name	Municipality Name	Home	Workplace	May.-Aug.ust	September-December	2021 Population (10,000)
Kagoshima	Kagoshima City	4	2	552.41	119.86	60.15
Ehime	Matsuyama City	6	8	230.82	72.23	50.95
Chiba	Matsudo City	1	0	879.31	260.20	49.85
Okayama	Kurashiki City	1	0	557.17	136.85	48.15
Oita	Oita City	8	3	554.48	146.51	47.85
Kagawa	Takamatsu City	26	32	376.53	52.78	42.63
Nagasaki	Nagasaki City	7	10	302.06	54.68	41.15
Miyazaki	Miyazaki City	2	3	472.84	87.06	40.20
Osaka	Suita City	1	0	837.28	269.08	37.61
Fukuoka	Fukuoka City, Higashi Ward	12	1	961.72	196.59	31.59
Fukuoka	Kurume City	4	1	631.84	129.32	30.47
Fukuoka	Fukuoka City, Minami Ward	16	2	1168.17	226.07	26.45
Yamaguchi	Shimonoseki City	3	4	314.11	96.68	25.76
Fukuoka	Kitakyushu City, Yahatanishi Ward	16	8	560.81	175.18	25.23
Tokushima	Tokushima City	5	6	256.25	115.04	25.21
Nagasaki	Sasebo City	2	1	354.65	114.83	24.64
Fukuoka	Kasuya District	9	1	839.81	213.56	23.55
Fukuoka	Fukuoka City, Hakata Ward	11	45	1784.81	322.54	23.53
Saga	Saga City	41	63	423.06	93.24	23.16
Fukuoka	Fukuoka City, Sawara Ward	21	12	849.68	157.13	22.02
Fukuoka	Kitakyushu City, Kokura Minami Ward	11	4	617.82	158.02	21.01
Fukuoka	Fukuoka City, Nishi Ward	12	2	711.73	139.27	20.82
Fukuoka	Fukuoka City, Chuo Ward	25	70	1797.52	348.81	19.27
Kumamoto	Kumamoto City, Higashi Ward	1	0	579.20	99.07	19.08
Yamaguchi	Yamaguchi City	1	0	204.55	78.15	19.07
Fukuoka	Kitakyushu City, Kokura Kita Ward	9	12	901.27	250.66	18.15
Ehime	Imabari City	1	1	133.76	37.12	15.63
Yamaguchi	Shunan City	1	1	170.92	47.52	14.10
Nagasaki	Isahaya City	2	1	155.30	69.92	13.59
Fukuoka	Fukuoka City, Jonan Ward	11	0	1006.68	214.36	12.60
Saga	Karatsu City	1	0	732.47	137.65	11.99
Yamaguchi	Hofu City	1	1	315.41	54.59	11.54
Oita	Beppu City	4	9	557.35	179.99	11.50

Fukuoka	Kasuga City	4	0	835.74	225.04	11.33
Kagawa	Marugame City	2	5	325.87	39.07	11.26
Fukuoka	Chikushino City	3	1	709.26	158.68	10.46
Fukuoka	Itoshima City	2	0	698.22	171.63	10.25
Fukuoka	Onojo City	5	1	761.16	201.08	10.20
Nagasaki	Omura City	1	0	190.06	47.26	9.73
Fukuoka	Munakata City	5	0	549.38	129.63	9.72
Fukuoka	Kitakyushu City, Moji Ward	2	0	414.97	94.41	9.64
Fukuoka	Onga District	3	0	520.58	134.20	9.24
Fukuoka	Kitakyushu City, Wakamatsu Ward	7	8	578.08	153.67	8.20
Kagoshima	Aira City	1	0	221.33	81.07	7.77
Fukuoka	Dazaifu City	2	0	738.30	193.26	7.19
Aichi	Kiyosu City	1	1	641.01	295.30	6.94
Fukuoka	Fukutsu City	5	8	573.92	147.20	6.73
Fukuoka	Kitakyushu City, Yahatan Higashi Ward	6	19	710.44	168.06	6.55
Fukuoka	Koga City	3	1	720.93	311.85	5.96
Fukuoka	Ogori City	2	0	523.62	181.25	5.96
Kagawa	Kanonji City	1	0	217.73	35.44	5.92
Fukuoka	Kitakyushu City, Tobata Ward	6	4	609.39	173.86	5.69
Fukuoka	Nogata City	2	0	449.86	156.47	5.62
Kagawa	Sakado City	2	0	235.89	38.36	5.21
Fukuoka	Nakagawa City	1	0	820.71	235.91	5.04
Saga	Takeo City	2	0	379.33	113.25	4.80
Oita	Nakatsu City	4	1	301.90	73.45	4.73
Fukuoka	Kurume City	2	1	658.66	161.20	4.27
Fukuoka	Yame City	3	3	537.54	126.32	3.93
Kumamoto	Tamana City	1	0	390.19	126.63	3.74
Okinawa	Nago City	1	0	108.48	29.27	3.69
Okinawa	Urasoe City	1	0	125.35	32.88	3.37
Okinawa	Nakagusuku Village	1	0	74.27	18.69	3.33
Okinawa	Itoman City	1	0	159.11	30.58	2.69
Okinawa	Ginowan City	1	0	156.15	32.41	2.46
Okinawa	Nanjo City	1	0	115.55	25.37	2.45
Okinawa	Naha City	1	0	113.60	26.14	1.69
Okinawa	Chatan Town	1	0	50.54	13.72	1.57

Appendix Table A4 : Effect of the Increase in Telework Days (Nov. 2019–Dec. 2021) on Labor Outcomes and Exercise Habits (2nd Stage, FE and FEIV Models; IV: Workplace Municipality-Level Cases)

Outcome Variable	Overtime Work		Work Efficiency		Life Satisfaction		Commuting Time		Daily Walking		Daily Exercise	
	FE	FEIV	FE	FEIV	FE	FEIV	FE	FEIV	FE	FEIV	FE	FEIV
TW days	-0.097**	-0.390	0.075***	0.267	0.172***	1.30*	-0.241***	-0.801*	-0.237***	-0.138	-0.092***	-0.935
	(0.034)	(0.361)	(0.019)	(0.361)	(0.024)	(0.701)	(0.023)	(0.392)	(0.026)	(0.287)	(0.026)	(0.692)
Observations	713	711	713	711	713	711	713	711	713	711	713	711
1st stage F-stat.	–	4.57	–	4.57	–	4.57	–	4.57	–	4.57	–	4.57
Adj. R2	0.026	-0.184	0.016	-0.097	0.096	-1.58	0.250	-0.878	0.174	0.149	0.088	-1.30

Note: FE and FEIV refer to the results from Fixed Effects (FE) Estimation and Fixed Effects Instrumental Variables (FE-IV) Estimation. Parentheses indicate cluster-robust standard errors (SEs) that are robust to clustering at the municipal level based on the workplace zip code. Exogenous variables include age and a female dummy. Fit statistics include the number of observations, Adjusted R-squared, and the 1st stage F-statistic (for detecting weak instruments in IV estimation). ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$

Appendix Table A5 : Effect of the Increase in Telework Days (Nov. 2019–Dec. 2021) on Tasks Performed During Telework (2nd Stage, VA and IV-VA Models; IV: Workplace Municipality-Level Cases)

Outcome Variable	Documentation		Information Gathering		Data Processing		Accounting Work		Planning and Development		Design	
	VA	IV-VA	VA	IV-VA	VA	IV-VA	VA	IV-VA	VA	IV-VA	VA	IV-VA
TW days (Dec 2021)	0.099***	0.067	0.120***	0.618	0.155***	0.966*	0.030***	0.768	0.034**	0.343	-0.007	19.5
	(0.021)	(0.384)	(0.022)	(0.463)	(0.024)	(0.444)	(0.009)	(0.490)	(0.012)	(0.391)	(0.013)	(719.1)
Observations	356	354	356	354	356	354	356	354	356	354	356	355
1st stage F-stat.	–	1.5	–	1.5	–	1.5	–	1.5	–	1.5	–	1.5
Adj. R2	0.054	0.106	0.071	-1.14	0.112	-3.16	0.005	-8.33	0.001	-0.742	0.011	-8,729.7

Outcome Variable	Online Meetings		Internal Coordination		External Coordination		Internal Training		External Training	
	VA	IV-VA	VA	IV-VA	VA	IV-VA	VA	IV-VA	VA	IV-VA
TW days (Dec 2021)	0.129***	0.836	0.136***	0.745	0.144***	0.530	0.073*	-0.154	0.035**	0.025
	(0.016)	(0.555)	(0.013)	(0.522)	(0.015)	(0.367)	(0.036)	(0.267)	(0.016)	(0.123)
Observations	356	354	356	354	356	354	356	354	356	354
1st stage F-stat.	–	1.5	–	1.5	–	1.5	–	1.5	–	1.5
Adj. R2	0.079	-2.28	0.083	-1.63	0.100	-0.624	0.047	-0.482	0.017	-0.011

Note: “ VA ” refers to the value-added model, and “ IV-VA ” refers to the IV value-added model. Parentheses indicate cluster-robust standard errors (SEs) that are robust to clustering at the municipal level based on the workplace zip code. Exogenous variables include age and female dummy. Fit statistics include the number of observations, Adjusted R-squared, F-statistic and its p-value (for testing the joint significance of regressors), and the 1st stage F-statistic (for detecting weak instruments in IV estimation). ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$

Appendix Table A6 : Effect of the Increase in Telework Days (Nov. 2019–Dec. 2021) on Time-Use Activities During Saved Commute Time (2nd Stage, VA and IV-VA Models; IV: Workplace Municipality-Level Cases)

Outcome Variable	Hobbies and Leisure		Sleep		Skill Development		Housework	
	VA	IV-VA	VA	IV-VA	VA	IV-VA	VA	IV-VA
TW days (Dec 2021)	0.048***	0.569*	0.121***	0.554	0.037**	0.142	0.067*	0.381
	(0.011)	(0.269)	(0.014)	(0.312)	(0.016)	(0.112)	(0.031)	(0.230)
Observations	356	354	356	354	356	354	356	354
1st stage F-stat.	–	1.5	–	1.5	–	1.5	–	1.5
Adj. R2	0.021	-2.03	0.103	-0.931	0.025	-0.188	0.033	-0.400

Outcome Variable	Time with Family		Shopping		Additional Work Tasks		Childcare	
	VA	IV-VA	VA	IV-VA	VA	IV-VA	VA	IV-VA
TW days (Dec 2021)	0.028	0.339	0.051***	0.020	0.051***	0.361	0.006	0.313*
	(0.018)	(0.485)	(0.011)	(0.163)	(0.010)	(0.231)	(0.009)	(0.168)
Observations	356	354	356	354	356	354	356	354
1st stage F-stat.	–	1.5	–	1.5	–	1.5	–	1.5
Adj. R2	0.008	-0.624	0.036	0.014	0.048	-1.15	-0.001	-1.41

Note: “ VA ” refers to the value-added model, and “ IV-VA ” refers to the IV value-added model. Parentheses indicate cluster-robust standard errors (SEs) that are robust to clustering at the municipal level based on the workplace zip code. Parentheses indicate cluster-robust standard errors (SEs) that are robust to clustering at the municipal level based on the workplace zip code. Exogenous variables include age and female dummy. Fit statistics include the number of observations, Adjusted R-squared, and the 1st stage F-statistic (for detecting weak instruments in IV estimation). ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$