COVID-19 and the Adoption of Telework:

A Survey of Employees in the Shikoku and Kyushu Regions

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COVID-19 and the Adoption of Telework: A Survey of Employees in the Shikoku and Kyushu Regions[*]

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Abstract

This study examines the impact of telework (TW) adoption on labor and health outcomes, and time use, using a questionnaire survey for employees working in Kyushu and Shikoku regions. Using a two-stage least squares (2SLS) estimation with changes in the number of new positive COVID-19 cases per 100,000 people in respondents' local municipalities where their workplaces or homes are located as the instrumental variable, we identify the impact of exogenous TW adoption on workers' labor and health outcomes from the pre-pandemic period (November 2019) to the post-pandemic period (August and December 2021) and from the COVID-19 expansion period (August 2021) to the contraction period (December 2021). The results show that the exogenous TW adoption does not significantly affect work efficiency or productivity, it reduces overtime, commuting time, and daily physical activity, and increases life satisfaction. This increase in satisfaction is associated with more time spent on hobbies, sleep, and childcare. An exogenous increase in TW days is also associated with more accounting tasks and increased liaison and coordination within the company and with business partners.

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, declared by the World Health Organization in March 2020, triggered widespread restrictions on both domestic and international travel. These restrictions disrupted not only leisure activities but also daily commutes and workplace routines. In response, many organizations rapidly adopted telework (TW) through online conferencing tools such as Microsoft Teams, Webex, and Zoom. This shift marked the beginning of a new normal, where remote work became a prominent alternative to traditional office settings.

However, during the COVID-19 pandemic, many companies and workers were forced to transition to TW due to lockdowns, before proper TW environments were fully established. The impact of TW on worker productivity, mental health, and well-being varied greatly by country and region (Hackney et al. 2022; Hall et al. 2023; Lee 2023). In particular, workers who began working from home for the first time during the pandemic faced potential reductions in productivity, especially those experiencing poor mental health (Hall et al. 2023).

In Japan, the state of emergency declared in May 2020 accelerated the enhancement of IT infrastructure, such as high-speed internet and digital communication tools, to promote the transition to TW. However, obstacles such as employment regulations, compatibility with remote work, and company culture varied across industries, occupations, and company sizes, leading to significant differences in the duration and adoption rates of TW. Over time, the positive effects of TW adoption in Japan became more evident (Morikawa 2022, 2024; Kitagawa et al. 2021; Inoue, Ishihata, and Yamaguchi 2024). Morikawa (2022, 2024) analyzed the relationship between TW and workplace productivity through a web-based survey conducted in July 2021. The analysis found that the average productivity of TW workers was approximately 20% lower than that of in-office workers, and reallocating commuting time to work hours did not improve TW productivity. Kitagawa et al. (2022) examined four Japanese manufacturing companies and found that inadequate work-from-home setups and communication challenges led to reduced productivity. Conversely, Inoue, et. (2023) employed the percentage of TW-capable work in December 2019 as an instrumental variable and found that TW did not reduce labor productivity by December 2020.[5]

Self-selection in TW usage is crucial for identifying the causal effects of TW on work and health outcomes. To address endogeneity issues, existing studies employ instrumental variable (IV) estimation, using factors such as occupation, firm size, region of residence, personal attributes, and variation in mobile device availability as IVs (Hara and Kawaguchi 2022; Inoue, Ishihata, and Yamaguchi 2024; Denzer and Grunau 2024). However, decisions to adopt TW may have been influenced not only by worker and firm characteristics but also by COVID-19 infection rates. In Japan, TW was widely viewed as a measure to prevent the spread of infection. For instance, the Basic Policy on Measures against COVID-19, established on March 28, 2020, encouraged businesses to reduce the number of employees working on-site by 70% through the promotion of TW and the use of leave to curb infection rates.[6]

However, despite the presumed causal relationship between COVID-19 infection rates and TW adoption, few studies have examined how TW affected worker outcomes in the context of infection spread. Therefore, this study aims to explore how fluctuations in the number of new COVID-19 cases per 100,000 people in respondents' local municipalities influenced labor and health outcomes, TW patterns, and time allocation. Using a two-stage least squares (2SLS) estimation, we analyze data from a survey of employees in Kyushu and Shikoku conducted from January to April 2022.

The findings indicate that in August 2021, during the COVID-19 pandemic, an increase in TW days—driven by rising COVID-19 cases—led to significant reductions in overtime work, commuting time, and daily physical activity, while increasing life satisfaction. In December 2021, as infections declined, a reduction in TW days led to an increase in commuting and walking time, with no significant impact on other variables. Between

[5] In Japan, Analysis using data from before the COVID-19 pandemic has confirmed a positive correlation between TW use and productivity. For example, Kazekami (2020) analyzed the relationship between TW implementation time and labor productivity, utilizing a survey conducted by the Recruit Works Institute, whose survey period was 2017-2018. The results of the analysis indicate that TW increases labor productivity, but that longer implementation time has the opposite effect.

[6] For example, according to a survey by Tokyo Shoko Research, while more than 50% of companies implemented telecommuting/remote work in FY2020 under the state of emergency declaration (4/23-5/12) and immediately after its lifting (5/28-6/9), the percentage of companies implementing TW fell to 31% after the lifting (6/29). The telecommuting/remote work rate dropped to 31% by 7/8. Subsequently, the telecommuting/remote work rate remained in the low 30% range until the 11/9-11/16 survey, but rose to 38% in the 3/1-3/8 2021 survey (Ministry of Internal Affairs and Communications 2021).

January and April 2022, more TW days were associated with increased engagement in accounting tasks, internal coordination, and collaboration with business partners, as well as more time for hobbies, sleep, and childcare. Importantly, no significant impact on productivity was observed during these periods.

The remainder of this paper is structured as follows: Section 2 reviews relevant previous studies, Section 3 outlines the spread of COVID-19 in Japan and specifically in the Kyushu and Shikoku regions, Section 4 presents the data, and Section 5 details the estimation method. Section 6 presents the results of the empirical analysis, while Section 7 provides a summary and concludes.

2. Literature review

Prior research has explored the impact of work-from-home (WFH) and TW on various worker outcomes, such as labor productivity, life satisfaction, and commuting behavior, during the COVID-19 pandemic. Among these, labor productivity has garnered significant attention, though findings remain mixed. Some studies suggest that WFH and TW during the pandemic either maintained or improved labor productivity (Antolín, Rodríguez-Ruiz, and Menéndez 2024; Barrero, Bloom, and Davis 2021; Bloom, Han, and Liang 2024; Choudhury, Foroughi, and Larson 2021; Criscuolo et al. 2022; Deole, Deter, and Huang 2023). For example, Barrero, et al. (2021) analyzed survey data from over 30,000 Americans and found that WFH is expected to remain approximately four times more common post-pandemic, with a predicted 4.6% productivity boost from reduced commuting, primarily benefiting higher-educated, well-paid workers. Deole, et al. (2023) examined data from British households and found that increased WFH frequency positively correlates with self-reported productivity, especially among women in remote-friendly roles and men with long commutes. However, productivity decreased among parents of school-age children due to homeschooling demands. Choudhury, et al. (2021) analyzed work-from-anywhere policies at the U.S. Patent and Trademark Office, reporting a 4.4% productivity increase for patent examiners. Criscuolo et al. (2022) conducted a survey in 25 countries and found that both managers and workers viewed TW positively in terms of firm performance and personal well-being, with the ideal amount of TW being 2–3 days per week. Similarly, Antolín, et al. (2024) used a dataset of 542 professionals with previous or current experience in home-based TW in 2021 and showed that prior TW experience increased both the willingness to TW and self-reported productivity. Bloom, et al. (2024) conducted a randomized control trial with 1,612 employees from a Chinese tech company and found that hybrid work improved job satisfaction and reduced quit rates by one-third, especially for non-managers, women, and employees with long commutes, with no significant impact on performance grades, promotions, or lines of code.

On the other hand, some studies have reported negative effects of TW on productivity (van der Lippe and Lippényi 2020; Weitzer et al. 2021; Gibbs, Mengel, and Siemroth 2023). For instance, van der Lippe and Lippényi (2020) conducted a survey involving 11,011 employees in 259 offices and 869 teams across nine European countries and found that WFH by coworkers worsens labor productivity and team performance worsens when more coworkers work from home. Weitzer et al. (2021) examined data from 1,010 Austrians using an online survey and found that working from home was associated with enhanced quality of life but a decrease in perceived productivity varied by gender, age, and education level. Gibbs, et al. (2023) examined data from 3,846 individuals across approximately 40,000 British households and found that increased WFH frequency correlated with higher self-reported productivity, but this was not uniform across all workers, particularly parents managing homeschooling duties.

Studies show that task and human resource management policies make a difference to the utilization rate and productivity of TW (Jiang, Yasui, and Yugami 2024; Kawaguchi and Motegi 2021; Okubo 2022). Kawaguchi and Motegi (2021) analyzed December 2019 data on remote work availability and found that remote work availability was more accessible to professionals engaged in non-routine tasks than to service or manual workers. They also found that performance-based human resource management practices and higher income levels were associated with a greater likelihood of remote work. Jiang, et al. (2024) analyzed data from Japan's General Survey of Jobs and Working Conditions before and during the COVID-19 pandemic and found that WFH increased non-routine analytic tasks while reducing routine manual tasks, contributing positively to labor productivity and wages. Okubo (2022) uses the unique panel survey on telework and found that educated, high ICT-skilled, younger, and female workers who engage in less teamwork and less routine tasks tend to use telework.

TW has also been shown to influence how workers allocate their time (Inoue, Ishihata, and Yamaguchi 2024; Restrepo and Zeballos 2022). Inoue, et al. (2024) found that an increase of one day per week of TW in December 2020 would result in a 6.2% increase in time spent on housework and childcare and a 5.6% increase in time spent with family, and an 11.6% increase in the percentage of respondents who say their attitudes have changed to value life more than work. Similarly, Restrepo and Zeballos (2022) used American Time Use Survey (2010–2020) and found that WFH individuals increased work time significantly while reducing time spent on socializing and eating out. In contrast, those working away from home showed negligible changes.

Several studies have also explored the impact of TW on commuting behavior. Reiffer et al. (2023) analyzed German Mobility Panel data (2018-2020) and found that telecommuting significantly increased during the pandemic, particularly among households with children. Obeid et al. (2024) examined the travel impacts of telecommuting using the Point of Interest and survey data from U.S. smartphone users from January 2020 to December 2021 and found that telecommuters in the U.S. made one additional non-commute trip on telecommuting days, reducing weekly travel distance by about 15 km. Adachi et al. (2023) used data from a web-based survey conducted from February to March 2021 and showed that TW reduced commuting rates and rail demand in Japan, and that the likelihood of choosing TW increased with longer commuting times.[7]

The literature on the effects of WFH and TW during the COVID-19 pandemic highlights a wide range of impacts on labor productivity, life satisfaction, and commuting behavior. Despite valuable insights from previous studies, a key gap remains in understanding how regional variations in TW adoption, particularly in response to fluctuations in COVID-19 infection rates, affect labor and health outcomes of workers.

[7] Before the COVID-19 pandemic, Melo and Silva (2017) and Silva and Melo (2017), utilizing the National Travel Survey in the UK, whose study period was 2005-2012, analyzed the relationship between TW and transportation behavior (commuting behavior). The analysis results indicate that TW practitioners tend to commute longer distances, but not to commute more frequently. Elldér (2020) analyzed the relationship between TW and commuting behavior, utilizing the Swedish National Survey, whose survey period was 2011-2016. The results of the analysis indicate that TW contributes to reducing congestion as well as decreasing the number of commuting and trips.

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

The spread of COVID-19 in Japan showed significant temporal and regional variability. Table 1 summarizes the emergency declarations and semi-emergency measures ("Manbou") implemented nationwide and in 11 prefectures across the Kyushu (excluding Okinawa Prefecture) and Shikoku regions in 2020 and 2021.

(Table 1 around here)

Table 1 indicates that a total of four emergency declarations and one period of "Manbou" were issued nationwide between 2020 and 2021. By prefecture, only one emergency declaration was issued between April 16, 2020, and May 14, 2020, during the initial wave of the outbreak, in all prefectures in the Kyushu and Shikoku regions, except for Fukuoka and Okinawa Prefectures. In contrast, Fukuoka Prefecture experienced four emergency declarations since 2020.

The issuance of emergency declarations and "Manbou" measures closely followed the progression of the COVID-19 pandemic. Figures 1 and 2 show the monthly number of new positive cases per 100,000 people for 2020 and 2021 nationwide and in the Kyushu (excluding Okinawa Prefecture) and Shikoku regions. The figures illustrate the fluctuating pattern of COVID-19 spread, marked by successive waves of expansion and contraction, both nationwide and in the 11 prefectures of Kyushu and Shikoku from March 2020 to July 2021. In August 2021, the number of new positive COVID-19 cases surged dramatically, reaching 9 to 19 times the average for other months (see Appendix Table 1). However, by September 2021, the number of new cases declined sharply, indicating a temporary contraction phase across the country.

(Figures 1–2 around here)

4. Data

4.1. Data Summary

This study uses a combination of questionnaire surveys and administrative data on new positive COVID-19 cases and population figures to assess the impact of TW adoption on workers. The survey was conducted between January and April 2022. Specifically, questionnaires were sent to 338 member companies of the Kyushu Economic Federation from January to March, and to 100 member companies of the Shikoku Economic Federation from February to April. Participants accessed and completed the web-based survey via a QR code provided in the paper survey. Responses were received from 337 individuals in the Kyushu region and 63 individuals in the Shikoku region, totaling 400 respondents. After excluding individuals lacking necessary information such as home and workplace zip codes, as well as those residing in Tokyo and Okinawa prefectures, where COVID-19 trends diverged significantly from other prefectures in August 2021, the final sample size for analysis was 373.[8]

Regarding administrative data, the number of new positive COVID-19 cases by municipality was gathered from open data sources, websites, and data provided by prefectural officials. Population data for 2021 by municipality were obtained from the Basic Resident Register of the Ministry of Internal Affairs and Communications to account for population size variations.

4.2. Description of Variables Used in the Analysis

The variables used in the analysis are described below (see Appendix Table 2). First, variables were created to reflect respondents' TW adoption status, including the number of TW days per week before the pandemic (November 2019) and after the pandemic (August and December 2021). The number of TW days before the pandemic serves as an exogenous variable, while TW days following new positive COVID-19 cases is treated as an endogenous variable, varying with changes in the number of new cases.

Second, the total number of new positive COVID-19 cases per 100,000 people in the respondents' work or home municipalities (identified by zip code) was used as a control variable affecting the endogenous variable. This variable was calculated over a four-month period, covering May to August 2021 for August data and September to December 2021 for December data. The number of new positive cases per 100,000 people was

[8] 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).

determined using the total number of positive cases during each four-month period and the municipal population for 2021.

We have three outcome variables for different time points: August 2021, December 2021, and January-April 2022. For August and December 2021, identical questions were asked, varying only in the retrospective time frames. These questions, rated on a 5-point scale, covered changes since November 2019 in variables such as overtime work, work efficiency, life satisfaction, commuting time, daily walking (excluding exercise), and daily exercise. The responses were converted into an ordinal scale ranging from 1 (decreased very much) to 5 (increased very much). In contrast, the outcome variables for January-April 2022 related to tasks performed via TW (11 items) and activities undertaken with the additional time gained from not commuting (10 items). These items were multiple-choice, and dummy variables were created for each activity, coded as 1 if applicable.

Five exogenous variables were included in the analysis: respondent age, a female dummy variable, marriage status, dummy variables for the presence of children in various age groups, door-to-door (D2D) round-trip commuting time, and the population of the respondent's home or workplace municipality in 2021.

4.3. Descriptive Statistics

Descriptive statistics (Appendix Table 3) show significant shifts in TW adoption and COVID-19 cases, along with changes in TW-related outcomes and time allocation. The average number of TW days per week increased from 0.19 days in November 2019 to 1.33 days in August 2021 and 0.79 days in December 2021. A dummy variable was created for TW adoption, coded as 1 if respondents engaged in TW at least once per week. The percentage of respondents using TW rose from 12% in November 2019 to 67% in August 2021, then dropped to 42% in December 2021. During both May-August and September-December 2021, the mean and standard deviation of new positive COVID-19 cases per 100,000 people were higher in workplace municipalities than in home municipalities, with workplace municipalities reporting case numbers 4.5 to 4.7 times higher during May-August 2021.

For August and December 2021, the outcome variables (including overtime work,

work efficiency, life satisfaction, commuting time, daily walking, and daily exercise) showed a mean below 3 for many variables, indicating declines relative to November 2019. For January-April 2022, a significant portion of respondents reported engaging in various work tasks via TW, with document preparation (64%), information gathering (50%), and data processing (43%) being the most common tasks. However, fewer respondents reported involvement in accounting (9%), planning (20%), design (5%), internal training (16%), or external training (9%). As for time freed up by not commuting due to TW, respondents most frequently reported spending time on household chores (34%), sleep (32%), family time (25%), and hobbies/entertainment (21%). Lower percentages were reported for skill development (8%), shopping (11%), additional work duties (11%), childcare (8%), caregiving (0.3%), and volunteering (1%). Due to low representation, caregiving and volunteering were excluded from the analysis.

Finally, descriptive statistics for the exogenous variables show that the average respondent age was approximately 42, with women accounting for 27% of the sample. About 67.5% of respondents were married, and percentages of respondents living with children varied by age group. The average round-trip commuting time was approximately 35 minutes, and the populations of the workplace municipalities averaged 220,000, with home municipalities averaging 210,000.

Appendix Table 4 displays the frequency of home and work zip codes by municipality, along with the number of new positive COVID-19 cases per 100,000 people and the 2021 population. Figures 3 and 4 show no discernible correlation between population size, workplace or home location, and new positive COVID-19 cases. Respondents from larger municipalities (with populations of 200,000 or more) were more likely to report cases from their home rather than their workplace, particularly in municipalities situated below the 45-degree line in Figure 3. Saga City, Chuo-ku (Fukuoka City), and Hakata-ku (Fukuoka City) were more frequently identified as work areas. Figure 4 shows a decrease in new COVID-19 cases from May-August to September-December 2021 across most municipalities.

(Figures 3–4 around here)

Figures 3 and 4 show no clear correlation between population size, workplace or home location, and new positive COVID-19 cases. Moreover, comparing the frequency of each municipality's zip code inclusion in Figure 3 by workplace and home, it becomes evident that in municipalities with populations of approximately 200,000 or more, respondents more frequently identified cases as occurring at home rather than at the workplace, particularly in municipalities situated below the 45-degree line. In contrast, Saga City, Chuo-ku (Fukuoka City), and Hakata-ku (Fukuoka City) were more commonly identified as work areas rather than residential ones. Furthermore, Figure 4 shows a decrease in the number of new positive COVID-19 cases from May-August to September-December 2021 across most municipalities.

5. Estimation Method

When estimating the causal effects of TW adoption during the COVID-19 pandemic on various outcomes such as worker productivity, health status, and time use, a straightforward OLS regression of each outcome on TW variables may introduce biases. These biases typically fall into three categories: omitted variable bias, selection bias, and attenuation bias. Omitted variable bias occurs when unobservable factors influencing the outcome variables are correlated with TW adoption, leading to bias in the coefficient of the TW adoption variable. Selection bias arises when the magnitude of the causal effect of TW adoption influences the decision to adopt TW, resulting in inflated estimated coefficients of TW adoption, particularly in cross-sectional data. Attenuation bias occurs when the OLS estimator tends to bias the coefficients toward zero.

To address these endogeneity issues, we perform 2SLS estimation, treating the number of TW days as the endogenous variable and using the number of new positive COVID-19 cases per 100,000 people per municipality as the instrumental variable. To assess the direction of bias, we compare the coefficients from the 2SLS estimation with those from the OLS estimation, regressing each outcome variable on the number of TW days. Since TW adoption aims to reduce infection spread in workplaces, the primary estimation uses the number of new positive COVID-19 cases per 100,000 people in the respondents' workplace municipalities as the instrumental variable. As a robustness check, we provide results using the number of new positive COVID-19 cases per 100,000 people in the respondents' home municipalities as the instrumental variable in the Appendix.

The data were obtained from a cross-sectional retrospective survey conducted between January and April 2022. We estimate the causal effects of TW adoption by categorizing the outcome variable into three time points (August 2021, December 2021, and January-April 2022) based on the timing of the questionnaire.

5.1. Analysis of Labor and Health Outcomes for August 2021

The variable used as outcome Y_i^A for respondent i in August 2021 is the change in work and health outcomes from November 2019, before the onset of the COVID-19 pandemic, to August 2021. Specifically, the variables analyzed as outcomes included changes in six variables rated on a 4-point scale: overtime work, work efficiency, life satisfaction, commuting time, daily walking (excluding proactive exercise), and daily physical activity. The endogenous variable $telework_i^A$ represents the average number of days per week that respondent i engaged in TW in August 2021. The operational variable $posi\_Mar\_Aug_i$ indicates the total number of new positive COVID-19 cases for the four months from March to August 2021 in the municipality where respondent i's workplace is located. The exogenous variable W_i encompasses respondent i's number of TW days in November 2019, age, gender (female dummy), marriage status, school type of children living together, D2D commute time at the time of response, and the populations of the municipalities where home and work were located in 2021.

For the analysis spanning November 2019 to August 2021, both the outcome variable Y_i^A and the manipulation variable $posi\_Mar\_Aug_i$ represent differences between November 2019 and August 2021. The exogenous variable W_i includes the number of TW days in November 2019 for the endogenous variable $telework_i^A$ in August 2021. Therefore, we conduct a 2SLS estimation based on the value-added model using the difference between November 2019 and August 2021 for both the first and second stages. The regression equation for the first stage of 2SLS is as follows:

$$telework_i^A = \alpha_0^{A,2SLS} + \alpha_1^{A,2SLS}\, posi\_Mar\_Aug_i + \alpha_2^{A,2SLS} W_i + \varepsilon_i^{A,2SLS} \qquad (1)$$

However, we assume the following relationship between endogenous variables and operational variables:

$$Cov\left(telework_i^A, posi\_Mar\_Aug_i\right) \neq 0 \tag{2}$$

Here, as there is only one operating variable, we verify the assumption by examining whether the F statistic of the null hypothesis, stating that the coefficient α_1^A in Equation (1) equals zero, exceeds 10. The regression equation for the second stage of 2SLS is as follows:

$$Y_i^A = \beta_0^{A,2SLS} + \beta_1^{A,2SLS}\widehat{telework}_i^A + \beta_2^{A,2SLS}W_i + \eta_i^{A,2SLS} \tag{3}$$

$\widehat{telework}_i^A$ represents the predicted value of $telework_i^A$ for respondent i obtained from Equation (1) in the first step of the 2SLS. For $posi\_Mar\_Aug_i$ to be an operating variable, the following exogenous assumptions are required in addition to relevance:

$$E\left(\eta_i^{A,2SLS}, posi\_Mar\_Aug_i\right) = 0 \tag{4}$$

The assumption in Equation (4) implies that the variation in the new positive COVID-19 cases is assumed to be random for individual i. Furthermore, $(Y_i^A, W_i, telework_i^A, posi\_Mar\_Aug_i)$ are assumed to follow independent and identical distributions, with $(W_i, telework_i^A, posi\_Mar\_Aug_i)$ having moments up to the fourth order. To compare the results of the 2SLS and OLS estimations, the following equations are estimated simultaneously:

$$Y_i^A = \beta_0^{A,OLS} + \beta_1^{A,OLS}\widehat{telework}_i^A + \beta_2^{A,OLS}W_i + \eta_i^{A,OLS} \tag{5}$$

In this section, we assess the direction and magnitude of the OLS bias by comparing the magnitude and significance level of the coefficients of $\beta_1^{A,2SLS}$ in Equation (3) and $\beta_1^{A,OLS}$ in Equation (5).

5.2. Analysis of Labor and Health Outcomes for December 2021

The descriptive statistics in Appendix Table 2 confirm a decrease in the number of new positive COVID-19 cases per 100,000 people across municipalities encompassing both work and home locations of all respondents, transitioning from the infection expansion period in May-August 2021 to the contraction period in September-December 2021. However, 24 respondents exhibited more TW days in December 2021, during the contraction period, compared to August 2021, amidst the expansion period. For these respondents, the increase in TW days might be attributed to factors beyond COVID-19 spread, such as departmental changes or shifts in supervisory responsibilities.

This surge in TW facilitation counteracts the impact of declining new positive COVID-19 cases on TW days, leading to missing variable bias and underestimating the 2SLS estimation. However, the survey did not capture information on TW adoption ease. Therefore, we mitigate this bias by excluding respondents with increased TW days in December 2021 from the analysis involving outcome variables post-December.

5.2.1. Changes in labor and health outcomes before and after the COVID-19 pandemic (November 2019 to December 2021)

The variable used as outcome Y_i^D for respondent *i* in December 2021 is the change in work and health outcomes from November 2019, before the onset of the COVID-19 pandemic, to December 2021. The outcome variables are the same as those described in Section 5.1. The endogenous variable $telework_i^D$ is the average number of days per week respondent i engaged in TW in December 2021. The operational variable $posi\_Sep\_Dec_i$ signifies the total number of new positive COVID-19 cases for the four months from September to December 2021 in the municipality where respondent i's workplace is located. The exogenous variable W_i includes respondent *i*'s number of TW days in November 2019, gender (female dummy), age, and D2D commute time.

In the analysis spanning November 2019 to December 2021, both the outcome variable Y_i^D and the manipulation variable $posi\_Sep\_Dec_i$ reflect differences from November 2019 to December 2021. The exogenous variable W_i includes the number of TW days in November 2019 for the endogenous variable $telework_i^D$ in December 2021. Therefore, similar to Section 5.1, we perform 2SLS estimation based on the value-added model using the difference from November 2019 to December 2021 for both the first and second stages. The regression equation for the first stage of 2SLS is as follows:

$$telework_i^D = \alpha_0^{D,2SLS} + \alpha_1^{D,2SLS} posi\_Sep\_Dec_i + \alpha_2^{D,2SLS} W_i + \varepsilon_i^{D,2SLS} \quad (6)$$

However, we assume the following relationship between endogenous variables and operational variables

$$Cov(telework_i^D, posi\_Sep\_Dec_i) \neq 0 \quad (7)$$

Here, as there is only one operating variable, we verify the assumption by examining whether the F statistic of the null hypothesis, stating that the coefficient α_1^D in Equation (1) equals zero, is greater than 10. The regression equation for the second stage of 2SLS is as follows:

$$Y_i^D = \beta_0^{D,2SLS} + \beta_1^{D,2SLS} \widehat{telework}_i^D + \beta_2^{D,2SLS} W_i + \eta_i^{D,2SLS} \quad (8)$$

$\widehat{telework}_i^D$ represents the predicted value of $telework_i^D$ for respondent i obtained from Equation (6) in the first step of the 2SLS. For $posi\_Sep\_Dec_i$ to be an operating variable, the following exogenous assumptions are required:

$$E\left(\eta_i^{D,2SLS}, posi\_Sep\_Dec_i\right) = 0 \quad (9)$$

The assumption in Equation (9) also implies that the variation in the new positive COVID-19 cases is random for individual i, as in Equation (4). Furthermore, $(Y_i^D, W_i, telework_i^D, posi\_Sep\_Dec_i)$ is assumed to follow independent and identical distributions and $(W_i, telework_i^D, posi\_Sep\_Dec_i)$ is assumed to have moments up to the fourth order. To compare the results of the 2SLS and OLS estimations, the following equations are estimated simultaneously:

$$Y_i^D = \beta_0^{D,OLS} + \beta_1^{D,OLS} \widehat{telework}_i^D + \beta_2^{D,OLS} W_i + \eta_i^{D,OLS} \tag{10}$$

Here we assess the direction and magnitude of the OLS bias by comparing the magnitude and significance level of the coefficients of $\beta_1^{D,2SLS}$ in Equation (8) and $\beta_1^{D,OLS}$ in Equation (10).

5.2.2. Changes in occupational and health outcomes during the COVID-19 contraction period (August to December 2021)

As depicted in Figure 2, in Kyushu (excluding Okinawa) and Shikoku, the number of new COVID-19 cases continued to increase from early 2020, coinciding with the declaration of emergency, and entered a downward trend after August 2021. This trend suggests a potential difference in the impact of changes in TW days through alterations in new positive COVID-19 cases on labor and health outcomes during two distinct periods: from pre-COVID-19 to August 2021, representing the period of infection expansion, and from August to December 2021, representing the period of infection contraction.

To address this, we estimate the impact of a decrease in the number of new COVID-19 cases on the outcome variables from August 2021 (infection expansion) to December 2021 (infection contraction). In this analysis, we augment the exogenous variable W_i^N with a new outcome variable for August 2021: the number of TW days, along with the new positive COVID-19 cases from May-August 2021.

In the analysis spanning August 2021 to December 2021, both the outcome variable Y_i^D and the instrumental variable $posi\_Sep\_Dec_i$ represent differences from August to December 2021. The endogenous variable $telework_i^D$, denoting the TW days in December 2021, is also included in the exogenous variable W_i^N comprising the TW days in November 2019 and August 2021. Therefore, similar to Section 5.2.1, we perform a 2SLS estimation based on the value-added model, using the differences from August 2019 to December 2021 for both the first and second stages. The estimation equations for the 2SLS and OLS estimations are similar to Equations (6)–(10) and are therefore omitted.

5.3. *Analysis of Outcomes for January-April 2022*

For January-April 2022, the number of TW days at the time of the survey, an endogenous variable, was omitted from the questionnaire. Thus, we assessed the long-term impact of the increase in TW days in August and December 2021 due to the rise in new positive COVID-19 cases between the pre- and post-COVID-19 pandemic periods (November 2019 to May-August and September-December 2021) on the outcome variables at the time of the survey. Note that respondents with more TW days in December 2021 than in August 2021 were excluded from the analysis sample.

The two variables used as outcome Y_i^C for respondent i at the time of the survey (January-April 2022) comprised work performed through TW (11 items) and activities conducted with the time freed up by not commuting due to TW adoption (8 items). Although these variables do not specify a specific time point in the question items, they are considered as stock variables at the survey time since they are dummy variables that persist once experienced.[9] In the analysis, we estimate the differential effect of the exogenous number of TW days in August and December 2021 on stock variables at the survey time, controlling for the number of TW days prior to COVID-19 (November 2019). The endogenous variable $telework_i^C$ represents the average number of TW days per week in August and December 2021 for respondent i. We use $posi\_May\_Aug_i$ and $posi\_Sep\_Dec_i$ as instrumental variables corresponding to the respective endogenous variables. The exogenous variables W_i^C remain the same as in the previous sections.

This analysis using the outcome variables at the survey time differs from that in Sections 5.1 and 5.2 in terms of the time points of the outcome, endogenous, and instrumental variables. Concerns about underestimation arise if respondents initiated TW between past and survey time points. However, Figures 1 and 2 show that underestimation is limited because new positive COVID-19 cases were approximately 9-19 times higher in August 2021 compared to other months, indicating that the stock variable at the survey time likely depended on TW adoption in August 2021.

[9] 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 Kyushu (excluding Okinawa) and Shikoku, show that the number of new positive cases in August 2021 was approximately 9-19 times higher than the average for other months.

However, a few respondents initiated TW after September 2021, following the decline in new positive COVID-19 cases, suggesting that their adoption of TW may have been driven by factors other than pandemic-related concerns, such as departmental changes. Therefore, in the analysis using the endogenous variable for August 2021, we exclude respondents whose number of TW days was zero in both November 2019 and August 2021 but became positive in December 2021. If the number of TW days in December 2021 was zero, we assume that the TW days were also zero at the time of the survey.

Additionally, regarding the outcome variable concerning activities done with the time saved from not commuting due to TW, the commuting time varies among respondents. Therefore, even with the same number of TW days, the amount of leisure time gained through TW may differ, leading to variations in the outcome variable values. To address this issue, we exclude the D2D commute time used as a control variable in the estimation equations in Sections 5.1 and 5.2. Instead, we analyze the total commuting time per week multiplied by the number of TW days at the past time points as an endogenous variable for August and December 2021.

6. Estimated Results

The following section presents the results of the analysis utilizing the instrumental variable of new positive COVID-19 cases per 100,000 people for the periods of May-August and September-December in the respondents' workplace municipalities at the time of the survey.[10]

6.1. Analysis of Labor and Health Outcomes for August and December 2021

In this section, we investigate the impact of the increase in new positive COVID-19 cases from November 2019 to August-December 2021, as outlined in Sections 5.1 and 5.2.1, on the number of TW days in August-December 2021. Table 2 presents the outcomes of the first stage of the 2SLS estimation. The table shows $\alpha_1^{A,2SLS}$ from the estimation of Equation (1) as the outcome for August 2021 and $\alpha_1^{D,2SLS}$ from the

10 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.

estimation of Equation (6) as the result for December 2021.

(Table 2 around here)

Table 2 indicates a significant positive association between the number of new positive COVID-19 cases per 100,000 people and the number of TW days. The estimates are approximately 0.0003 and 0.001 for August and December 2021, respectively, significant at the 1% level for August and at the 10% level for December. The average increase in new positive COVID-19 cases per 100,000 people in workplace municipalities from November 2019 to August and December 2021 was approximately 898 and 190, respectively. Therefore, based on the estimates, the increase in new positive COVID-19 cases results in an average increase of approximately 0.27 (August 2021) and 0.19 (December 2021) TW days.

Next, we investigate the impact of the predicted number of TW days in August and December 2021, estimated in the first step, on the outcome variables at each time point. Tables 3 and 4 present the results of the second stage of the 2SLS estimation.

In Tables 3 and 4, we present the coefficients $\beta_1^{A,2SLS}$ from estimating Equation (3) of the 2SLS estimation and $\beta_1^{A,OLS}$ from estimating Equation (5) of the OLS estimation as results for August 2021. Similarly, we present the coefficients $\beta_1^{D,2SLS}$ from estimating Equation (8) for the 2SLS estimation and $\beta_1^{D,OLS}$ from estimating Equation (10) for the OLS estimation as results for December 2021. Before examining the estimates, we consider the first-stage F-value (Cragg-Donald statistic). The instrumental variable is deemed stronger for August 2021 with a value of 10.4, while concerns arise about the weak instrumental variable for December 2021, where the value is 5.57, corresponding to the period of reduced COVID-19 transmission. Therefore, the estimation results for August 2021 are considered as the main results, whereas those for December 2021 are provided for reference.

Comparing the estimated results of the OLS and 2SLS coefficients, Table 3 illustrates that all outcome variables in the OLS estimation exhibit a significant relationship with the number of TW days. However, in the 2SLS estimation, the outcome variables of operational efficiency and daily walking are non-significant. Based on these findings, concerns arise regarding potential bias in the OLS estimation results; therefore, we prioritize reporting the results of the 2SLS estimation.

(Tables 3–4 around here)

The 2SLS estimation results reveal that a one-day increase in the number of TW days significantly reduces overtime work at the 5% level, and commuting time and daily exercise at the 1% level in August 2021 (with coefficients approximately -0.41, -0.36, and -0.42, respectively). However, life satisfaction significantly increases at the 1% level, with a coefficient of approximately 0.38. No significant effects on work efficiency or daily walking were observed. To assess the magnitude of the estimates, we multiplied them by the average number of days of increased TW adoption for the outcome (approximately 0.27 days), revealing estimates of approximately -0.11 (overtime work), -0.10 (commuting time), -0.11 (daily exercise), and 0.10 (life satisfaction). Comparing the absolute values with the mean of the outcome variables confirmed that they were approximately 3% of the mean. Table 6 indicates that for December 2021, commuting time and daily exercise significantly decreased at the 1% level, with coefficients of approximately -0.46 and -0.71, respectively. Conversely, life satisfaction increased significantly at the 1% level, with a coefficient of approximately 0.88.

Based on these results, we conclude that from November 2019 to August 2021 (the period of increased infection) and December 2021 (the period of decreased infection), the increase in the number of TW days decreased commuting time and daily exercise while increasing life satisfaction. Overtime work significantly decreased only in August 2021.

Next, we examine the impact of the increase in new positive COVID-19 cases from August 2021 to December 2021, as described in Section 5.2.2, on the number of TW adoption days in December 2021. Table 5 presents the results of the first stage of the 2SLS estimation. In the table, because the August 2021 outcome variable controlled for by the exogenous variables differs depending on the outcome variable, we show the $\alpha_1^{D,2SLS}$ of the estimation of Equation (6) for each outcome variable.

Table 5 illustrates that an increase in the number of new positive cases per 100,000 people in the workplace municipality significantly augments the number of TW days at the 1% level for overtime work, work efficiency, and commuting time, and at the 5% level for life satisfaction, daily walking, and daily exercise (with estimates ranging from 0.0042 to 0.0046). When multiplying the estimates by the average decrease in new positive cases per 100,000 people in the workplace municipality from August to December 2021 (approximately 708 persons), we find that a decrease in the number of new positive COVID-19 cases reduces the number of TW days by about 2.97 to 3.26 days on average. Next, we examine the impact of the predicted number of TW days in December 2021, estimated in the first stage, on the labor and health outcome variables. Table 6 presents the results of the second stage of the 2SLS estimation.

(Tables 5–6 around here)

Table 6 displays the 2SLS and OLS estimates of the impact of a decrease in the number of TW days in December 2021 on the outcome variables for the same period. Prior to reviewing the estimates, the first-stage F-value (Cragg-Donald statistic) indicates that the instrumental variable is sufficiently robust, as all outcome variables have values above 10 (ranging from 10.5 to 11.9).

Upon comparing the results of the OLS and 2SLS estimations presented in Table 6, the OLS estimation shows a significant relationship with the number of TW days for all outcome variables. Conversely, the 2SLS estimation indicates no significance for the outcome variables of overtime work, work efficiency, life satisfaction, and daily exercise. Given these findings, concerns arise that the OLS estimation may introduce bias into the results, thus we primarily report the results of the 2SLS estimation.

The results of the 2SLS estimation reveal that a one-day decrease in the number of TW days from August to December 2021 significantly increased commuting time and daily walking at the 5% and 1% levels, respectively (with coefficients of approximately -0.36 and -0.39). No significant effects were observed for any other variables. To evaluate the magnitude of the estimates, we multiplied the coefficients in Table 6 by the average reduction in TW days for both outcomes (approximately 3.04 and 3.12 days). By multiplying the coefficients by the average decrease of approximately 708 new positive COVID-19 cases per 100,000 people in workplace municipalities from August to

December 2021, we calculated average reductions of approximately 1.09 and 1.22, respectively. Comparing these values to the average of 2.8 and 2.73 for the outcome variable, they represent approximately 39% and 45% of the average, respectively. Thus, we confirm that the decrease in the number of TW days from August 2021 (period of infection expansion) to December 2021 (period of infection contraction) had no significant impact on the decrease in commuting time and daily walking.

6.2. Analysis of Outcome Variables for January-April 2022

In this section, we initially explore the influence of the increase in new positive COVID-19 cases from November 2019 to May-August and September-December 2021, as outlined in Section 4.3, on the number of TW days in August and December 2021. Table 7 illustrates the findings of the first stage of the 2SLS estimation.

The distinction between Tables 7 and 2 lies in the analysis using the endogenous variable as the number of TW days in August 2021, excluding respondents who had more TW days in December than in August 2021. Consequently, only the initial step of the analysis involved the endogenous variable being the number of days of TW in August 2021. Table 8 indicates that with a higher number of new positive COVID-19 cases per 100,000 people, August 2021 had significantly more TW days at the 1% level in the analysis using the new sample, and the estimate is slightly larger (approximately 0.0004). Since the average increase in new positive COVID-19 cases per 100,000 people in workplace municipalities from November 2019 to August 2021 is about 898, when multiplied by the estimate, the increase in new positive COVID-19 cases increases the number of TW days by about 0.36 days on average (in August 2021).

(Table 7 around here)

Next, we examine the impact of the predicted number of TW days in August and December 2021, estimated in the first step, on the outcome variables at the time of the survey. Tables 8-11 present the results of the second stage of the 2SLS estimation.

(Tables 8–11 around here)

In Tables 8-11, alongside Tables 3 and 4, we present the results of the 2SLS and OLS estimations for each outcome variable for August and December 2021, respectively. Initially, examining the first-stage F-value (Cragg-Donald statistic), the instrumental variable remains sufficiently robust for August 2021, with an F-value of 9.71 for the new sample. However, given concerns about a weaker instrumental variable than 5.57 for December 2021, the period of reduced COVID-19 transmission, we emphasize the estimated results for August 2021 as the primary result.

We review the results presented in Tables 8 and 9, elucidating the impact of an increase in the number of TW days on the work performed during TW. Table 8 reveals that a one-day increase in the number of TW days in August 2021 significantly increased accounting work at the 1% level, internal liaison, and coordination work at the 5% level, and liaison and coordination work with business partners at the 10% level (coefficients are approximately 0.24, 0.25, and 0.18, respectively). To examine the magnitude of these estimates, when multiplied by the average number of days of increased TW adoption for each outcome (approximately 0.36 days), the average increases are calculated to be around 0.09, 0.09, and 0.06, respectively. Comparing these values with the averages of 0.08, 0.5, and 0.38 for the outcome variable, we find that these values are approximately 108%, 18%, and 17% of the average, respectively, indicating that a substantial proportion of respondents engaged in accounting and coordination tasks during TW. Table 9 indicates that a one-day increase in the number of TW days in December 2021 significantly increased only data processing at the 10% level (coefficient of approximately 0.42).

Next, we review the results presented in Tables 10 and 11, which elucidate the effects of increasing the number of TW days on the activities individuals pursued with their newfound time due to the absence of commuting. As shown in Table 10, a one-day increase in the number of TW days in August 2021 significantly boosts hobbies/entertainment and sleep at the 1% level, and childcare at the 10% level (coefficients are approximately 0.24, 0.18, and 0.06, respectively). To examine the significance of these estimates, we multiplied them by the average number of days of increased TW adoption for each outcome (approximately 0.36 days) and found the average increases to be approximately 0.09, 0.06, and 0.02, respectively. Comparing these values to the averages of 0.2, 0.31, and 0.08 for the outcome variables, they amount to approximately 40%, 20%, and 26% of the average, respectively, indicating that an increase in the number of TW days does not significantly impact hobbies/entertainment, sleep, and childcare. Table 11 reveals that a one-day increase in the number of TW days in December 2021 significantly increases hobbies and recreation at the 10% level and sleep at the 5% level (coefficients are approximately 0.29 and 0.28, respectively).

Based on these findings, we conclude that from November 2019 to August 2021 (the period of infection spread) and December 2021 (the period of infection contraction), an increase in the number of TW days typically increased accounting work, internal liaison, and coordination with business partners in terms of work conducted via TW. Moreover, the increased number of TW days facilitated engagement in hobbies/entertainment and sleep in terms of individuals' utilization of their free time due to the elimination of commuting.

Subsequently, we examine the impact of the rise in the number of new positive COVID-19 cases from November 2019 to August-December 2021 on the D2D commute time reduced by TW in August-December 2021, as outlined in Section 4.3. Table 12 provides the results of the first step of 2SLS estimation.

In Table 12, similar to Table 7, respondents with more TW days in December 2021 than in August 2021 were excluded from the analysis for August 2021. Table 12 indicates that an increase of one new positive case per 100,000 in the respondents' workplace municipalities significantly decreased the D2D commute time reduced by TW by 0.045 minutes per week in August 2021 at the 1% level, and significantly decreased it by 0.157 minutes per week in December 2021 at the 10% level. Furthermore, when the average number of new positive cases per 100,000 people in the workplace municipality from November 2019 to August and December 2021 is multiplied by the estimate of approximately 898 and 190, the average reduction in D2D commute time due to TW adoption amounted to approximately 40 and 30 minutes per week, respectively, corresponding to an increase in new positive cases of COVID-19 infection.

Next, we examine the impact of the increase in new positive COVID-19 cases from November 2019 to August-December 2021 on TW's reduced D2D commute time in August-December 2021, as described in Section 4.3. Table 12 presents the results of the first stage of 2SLS estimation.

(Table 12 around here)

In Tables 13 and 14, we present the 2SLS and OLS estimation results for each outcome variable, as in Table 7. Reviewing the first-stage F-value (Cragg-Donald statistic) before examining the estimates, the F-value is considered sufficiently robust for the instrumental variable, surpassing 10.7 in the analysis using the new positive COVID-19 cases in August 2021 as the instrumental variable. However, in the analysis utilizing the new positive COVID-19 cases in December 2021, a period of reduced COVID-19 infection, there is a concern about the instrumental variable's weaker operation, falling below 7.53. Hence, the estimation results using the new positive COVID-19 cases in August 2021 as the instrumental variable are reported as the primary results here.

(Tables 13–14 around here)

Table 13 demonstrates that a one-minute increase in D2D commute time reduced by TW in August 2021 significantly increases hobbies/entertainment and sleep at the 1% level, and child care at the 10% level (with coefficients of 0.002, 0.002, and 0.0005, respectively). To assess the magnitude of the estimates, we multiply them by the average D2D commute time reduced by TW (about 40 minutes) and find the average increase to be approximately 0.08, 0.08, and 0.02, respectively. Comparing these values to the average of approximately 0.2, 0.3, and 0.08 for the outcome variable, they are roughly 40%, 26%, and 24% of the average, respectively. This suggests that the impact of increased D2D commute time reduced by TW as of August 2021 on hobbies/entertainment, sleep, and child care is nearly equivalent to the impact of increased TW days. Table 14 further shows that a one-minute increase in D2D commute time reduced by TW in December 2021 significantly increases hobbies and recreation at the 10% level, sleep at the 5% level, housework at the 10% level, and work (additional duties) at the 1% level (with coefficient of 0.003, 0.003, 0.001, and 0.001, respectively).

7. Conclusion

Using a questionnaire survey conducted among employees affiliated with organizations in the Kyushu and Shikoku regions from January to April 2022, this study employs the instrumental variable method to examine the impact of changes in COVID-19 infection rates per 100,000 people in respondents' workplace or home municipalities on labor and health outcomes, tasks performed during TW, and time allocation, influenced by variations in the number of TW days.

The survey data distinguish between the COVID-19 expansion period (November 2019 to August 2021) and the contraction period (August to December 2021). To capture potential differences in the effects of individual TW adoption across these phases, post-COVID-19 outcome variables were analyzed at three points: August 2021 (infection expansion period), December 2021 (infection contraction period), and January-April 2022 (survey time point). The instrumental variable was the number of new positive COVID-19 cases in respondents' work and home municipalities (identified by zip codes) for May-August and September-December 2021. Two endogenous variables were used: the weekly number of TW days and the weekly amount of commute time saved due to TW adoption.

In estimating the 2SLS model within a value-added framework, we controlled for the November 2019 outcome variable in the August 2021 analysis (infection expansion period), for both November 2019 and August 2021 outcome variables in the December 2021 analysis (infection contraction period), and for November 2019 outcome variables in the January-April 2022 analysis (survey time point).

The estimations yielded notable findings. In August 2021, during the COVID-19 expansion, an additional TW day due to rising positive cases significantly reduced overtime work (-0.41), commuting time (-0.36), and daily exercise (-0.42), while significantly increasing life satisfaction (0.38). In December 2021, during the infection contraction period, a decrease in TW days significantly increased commuting time (-0.36) and daily walking (-0.39), with no significant effects on other variables. During the January-April 2022 survey period, an increase in TW days in August 2021, driven by rising COVID-19 cases, significantly increased accounting work (0.24), internal coordination (0.25), and coordination with business partners (0.18). Additionally, time spent on hobbies/entertainment, sleep, and childcare increased by 0.23, 0.18, and 0.06 percentage points, respectively. These findings indicate that the exogenous increase in TW, due to the rise in COVID-19 cases, mainly involved accounting and coordination tasks within the company and with business partners.

COVID-19's reclassification as a category 5 infection has led to a "return to work" trend both domestically and globally. For instance, U.S.-based Zoom, the online conferencing platform widely relied on during the TW period, ended its "full remote work" policy and required employees to return to the office (Owada 2023). However, reverting entirely to traditional onsite work is not the solution. Instead, efforts should focus on effectively integrating TW to maintain work-life balance and sustain productivity. This calls for continued exploration of innovative TW strategies.

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Figures

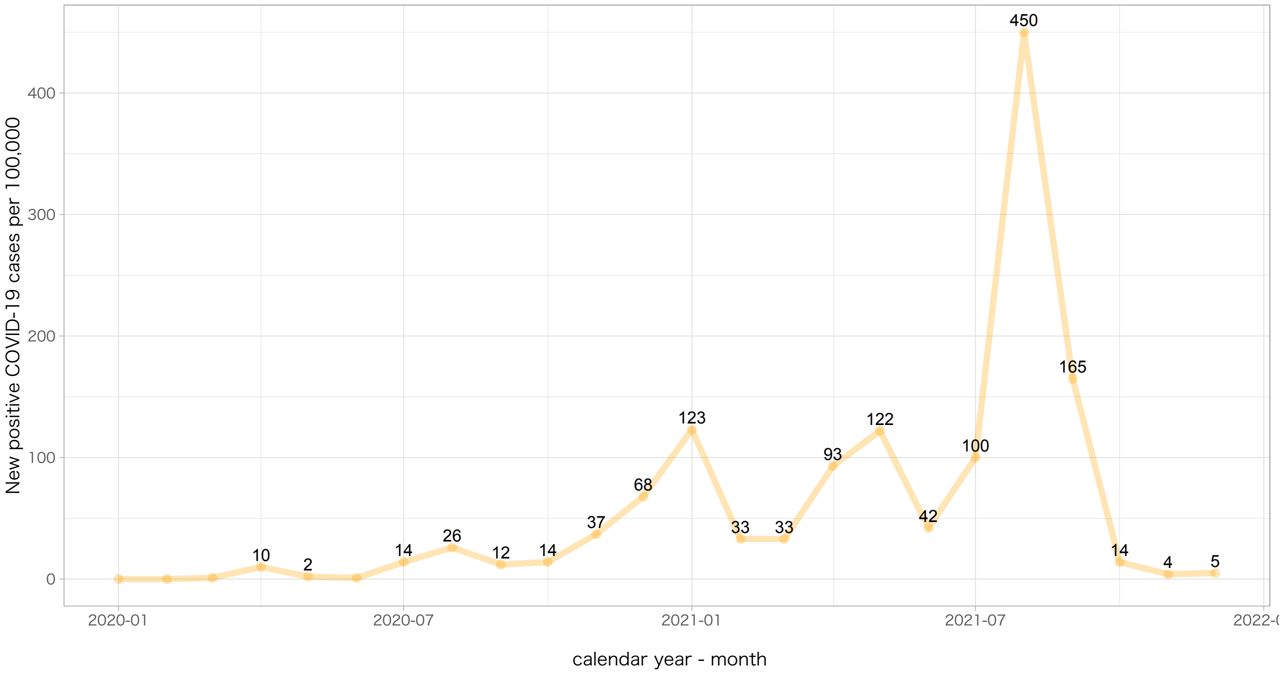

Figure 1: New positive COVID-19 cases per 100,000 people nationwide (January 2020-December 2021)

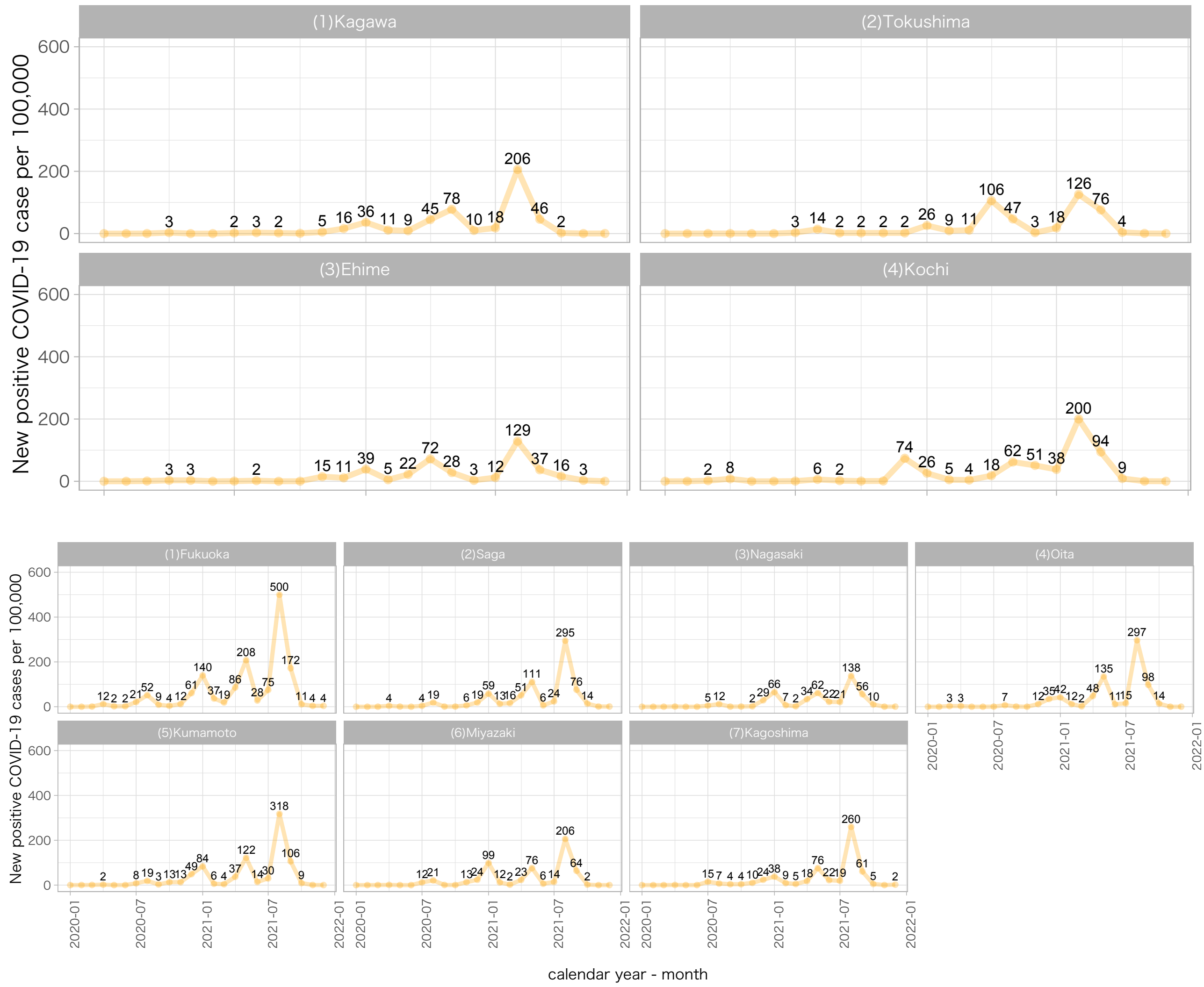

Figure 2: New positive COVID-19 cases per 100,000 people in Kyushu and Shikoku districts (January 2020-December 2021)

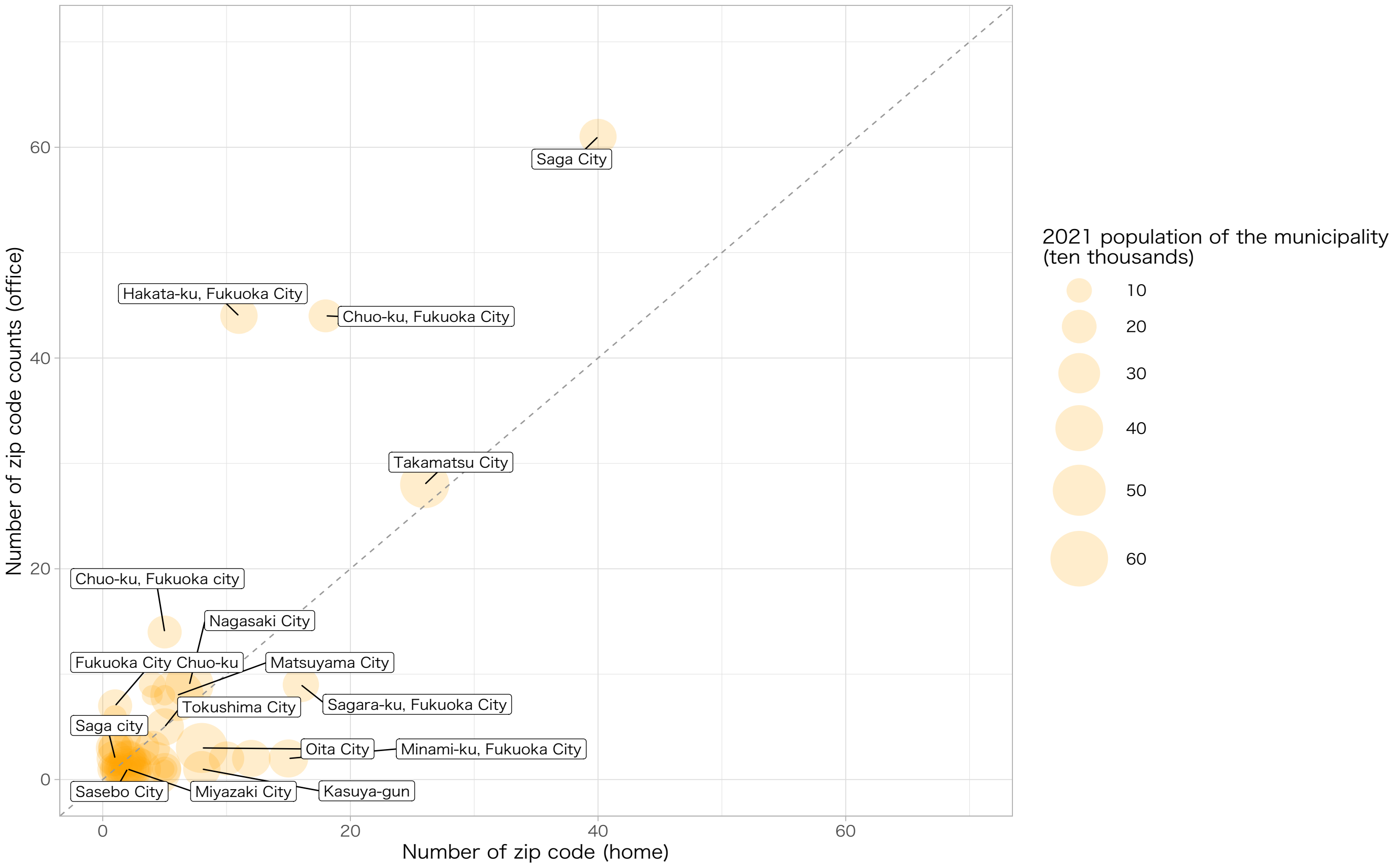

Figure 3: Comparison of the number of zip codes between work and home by municipality

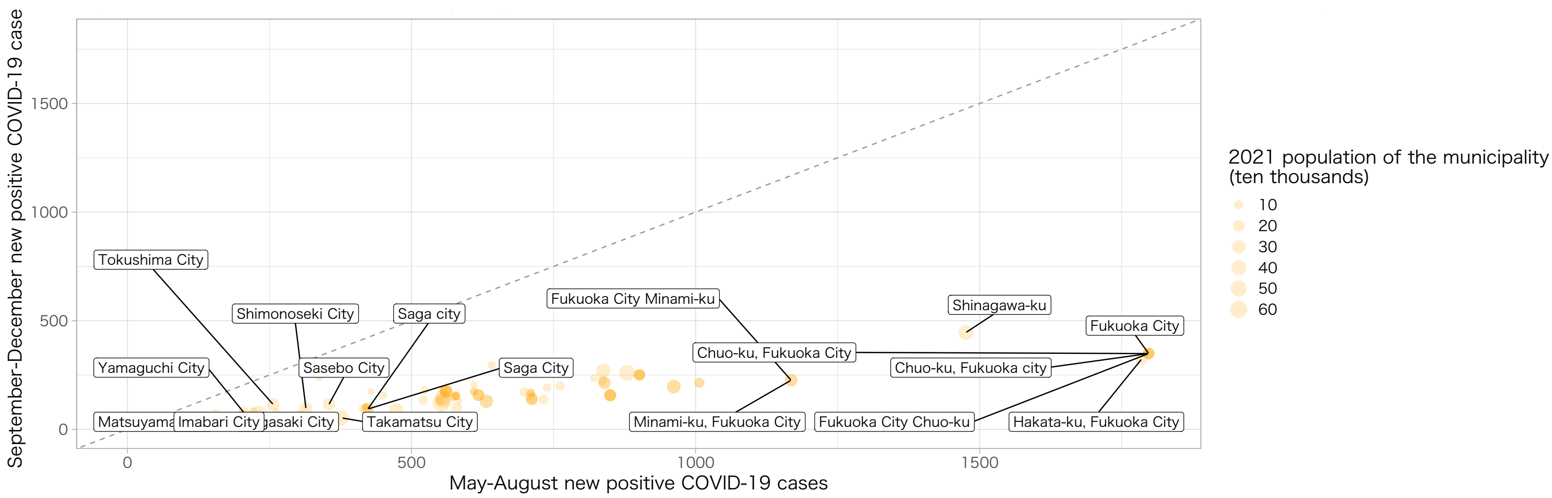

Figure 4: New positive COVID-19 cases from May-August and September-December by municipality

Table 1: Status of emergency declarations and priority measures to prevent the spread of disease in the Kyushu (excluding Okinawa) and Shikoku regions in 2020–21

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: The impact of the increase in new COVID-19 cases from November 2019 to August and December 2021 on the number of TW days (Instrumental variable: New cases at the workplace from May to August and September to December, 1st stage)

	Endogenous Variables	
	TW Days (August 2021)	TW Days (December 2021)
New COVID-19 Cases per 100,000 (workplace)	0.0003***	0.001*
	(8.27e-5)	(0.0006)
# of obs.	373	349
Mean of dep. vars	1.32	0.670

Note: For the analysis of the December 2021 outcome variable only, we excluded respondents whose number of TW days in December 2021 exceeded the number of TW days in November 2019 and August 2021. The figures in parentheses refer to the home/work cluster-robust standard errors. The exogenous variables were the November 2019 TW days, age, female dummy variables, door-to-door commute time (round trip), and population (home and workplace). ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$

Table 3: Impact of the increase in TW days from November 2019 to August 2021 on labor and health outcomes in August 2021 (Instrumental Variable: Number of positive cases in the workplace from May to August, 2nd stage)

	Overtime Work		Work Efficiency		Satisfaction with Life		Commuting Time		Daily Walking (Excluding Active Exercise)		Daily Exercise	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV
TW Days (August 2021)	-0.118***	-0.408**	0.053**	0.142	0.165***	0.382***	-0.199***	-0.357***	-0.206***	-0.064	-0.116***	-0.420***
	(0.032)	(0.154)	(0.020)	(0.100)	(0.048)	(0.061)	(0.015)	(0.087)	(0.024)	(0.088)	(0.019)	(0.075)
# of obs.	373	373	373	373	373	373	373	373	373	373	373	373
Mean of dep. varss	2.97	2.97	3.05	3.05	2.59	2.59	2.71	2.71	2.65	2.65	2.64	2.64
Cragg-Donald	–	10.4	–	10.4	–	10.4	–	10.4	–	10.4	–	10.4

Note: For the analysis of the December 2021 outcome variable only, we excluded respondents whose number of TW days in December 2021 exceeded the number of TW days in November 2019 and August 2021. The figures in parentheses refer to the home/work cluster-robust standard errors. The exogenous variables were the November 2019 TW days, age, female dummy variables, door-to-door commute time (round trip), and population (home and workplace). Cragg-Donald indicates the F-statistic value of the 1st stage. ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$

Table 4: Impact of the increase in TW days from November 2019 to December 2021 on labor and health outcomes in December 2021 (Instrumental Variable: Number of positive cases in the workplace from September to December, 2nd stage)

	Overtime Work		Work Efficiency		Satisfaction with Life		Commuting Time		Daily Walking (Excluding Active Exercise)		Daily Exercise	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV
TW Days (December 2021)	-0.115***	-0.365	0.085***	0.455	0.206***	0.884**	-0.277***	-0.457***	-0.262***	-0.108	-0.113***	-0.709**
	(0.034)	(0.305)	(0.018)	(0.262)	(0.028)	(0.348)	(0.032)	(0.083)	(0.033)	(0.184)	(0.032)	(0.251)
# of obs.	349	349	349	349	349	349	349	349	349	349	349	349
Mean of dep. varss	3.04	3.04	3.07	3.07	2.66	2.66	2.82	2.82	2.74	2.74	2.70	2.70
Cragg-Donald	–	5.57	–	5.57	–	5.57	–	5.57	–	5.57	–	5.57

Note: For the analysis of the December 2021 outcome variable only, we excluded respondents whose number of TW days in December 2021 exceeded the number of TW days in November 2019 and August 2021. The figures in parentheses refer to the home/work cluster-robust standard errors. The exogenous variables were the November 2019 TW days, age, female dummy variables, door-to-door commute time (round trip), and population (home and workplace). Cragg-Donald indicates the F-statistic value of the 1st stage. ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$

Table 5: Impact of the decrease in new COVID-19 cases from August to December 2021 on the reduction of TW Days (Instrumental Variable: Positive cases at the workplace from September to December, 1st stage)

First Stage Dependent Variable	TW Days					
Second-stage Dependent Variable	Overtime Work	Work Efficiency	Life Satisfaction	Commute Time	Daily Walking	Daily Exercise
New COVID-19 Cases	0.0046***	0.0043***	0.0042***	0.0043***	0.0042***	0.0044***
(workplace)	(0.0013)	(0.0012)	(0.0012)	(0.0011)	(0.0012)	(0.0013)
# of obs.	349	349	349	349	349	349
Mean of dep. varss	0.6703	0.6703	0.6703	0.6703	0.6703	0.6703

Note: For the analysis of the December 2021 outcome variable only, we excluded respondents whose number of TW days in December 2021 exceeded the number of TW days in November 2019 and August 2021. The figures in parentheses refer to the home/work cluster-robust standard errors. The exogenous variables were the November 2019 TW days, age, female dummy variables, door-to-door commute time (round trip), and population (home and workplace). ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$

Table 6: Impact of the reduction in TW Days from August to December 2021 on labor and health outcomes in December 2021 (Instrumental Variable: Positive cases at the workplace from September to December, 2nd stage)

	Overtime Work		Work Efficiency		Life Satisfaction		Commute Time		Daily Walking		Daily Exercise	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV
TW Days	-0.068***	0.074	0.020**	0.046	0.043***	0.102	-0.243***	-0.360**	-0.191***	-0.387***	-0.088***	-0.002
	(0.011)	(0.078)	(0.009)	(0.119)	(0.007)	(0.066)	(0.020)	(0.123)	(0.020)	(0.090)	(0.011)	(0.085)
# of obs.	349	349	349	349	349	349	349	349	349	349	349	349
Mean of dep. varss	3.04	3.04	3.07	3.07	2.66	2.66	2.82	2.82	2.74	2.74	2.70	2.70
Cragg-Donald	–	11.9	–	10.9	–	10.5	–	10.6	–	10.5	–	11.2

Note: For the analysis of the December 2021 outcome variable only, we excluded respondents whose number of TW days in December 2021 exceeded the number of TW days in November 2019 and August 2021. The figures in parentheses refer to the home/work cluster-robust standard errors. The exogenous variables were the November 2019 TW days, age, female dummy variables, door-to-door commute time (round trip), and population (home and workplace). Cragg-Donald is the F-statistic from the first stage, while Wu-Hausman, stat. and Wu-Hausman, p-value indicate the statistics and p-values from the endogeneity test. ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$

Table 7: The Impact of the Increase in New Positive COVID-19 Cases from November 2019 to August/December 2021 on the Increase in TW Days (Instrumental Variables: Workplace COVID-19 Cases from May to August and September to December, 1st stage)

	Endogenous Variables	
	TW Days (August 2021)	TW Days (December 2021)
New Positive COVID-19 Cases	0.0004***	0.001*
(workplace)	(8.01e-5)	(0.0006)
# of obs.	349	349
Mean of dep. vars	1.33	0.670

Note: For the analysis of the December 2021 outcome variable only, we excluded respondents whose number of TW days in December 2021 exceeded the number of TW days in November 2019 and August 2021. The figures in parentheses refer to the home/work cluster-robust standard errors. The exogenous variables were the November 2019 TW days, age, female dummy variables, population (home and workplace).

Table 8: The Impact of the Increase in TW Days from November 2019 to August 2021 on the Work Performed during TW at the Time of Survey (Instrumental Variables: Workplace COVID-19 Cases from May to August, 2nd stage)

	Document Creation		Information Gathering		Data Processing		Accounting Operations		Planning and Development		Design	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV
TW Days	0.150***	0.032	0.172***	0.157	0.154***	0.211	0.031***	0.242***	0.063**	0.115	0.021*	-0.066
(August 2021)	(0.029)	(0.128)	(0.023)	(0.112)	(0.019)	(0.127)	(0.008)	(0.067)	(0.027)	(0.072)	(0.011)	(0.043)
# of obs.	349	349	349	349	349	349	349	349	349	349	349	349
Mean of dep. vars	0.633	0.633	0.487	0.487	0.410	0.410	0.083	0.083	0.201	0.201	0.046	0.046
Cragg-Donald	–	9.71	–	9.71	–	9.71	–	9.71	–	9.71	–	9.71

	Online Meetings		LC within the company		External CC		TG within the company		TG for business partners	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV
TW Days	0.182***	0.137	0.174***	0.254**	0.186***	0.179*	0.066**	-0.081	0.036***	-0.002
(August 2021)	(0.021)	(0.129)	(0.033)	(0.096)	(0.024)	(0.099)	(0.025)	(0.069)	(0.006)	(0.026)
# of obs.	349	349	349	349	349	349	349	349	349	349
Mean of dep. vars	0.467	0.467	0.504	0.504	0.381	0.381	0.138	0.138	0.086	0.086
Cragg-Donald	–	9.71	–	9.71	–	9.71	–	9.71	–	9.71

Note: For the analysis of the December 2021 outcome variable only, we excluded respondents whose number of TW days in December 2021 exceeded the number of TW days in November 2019 and August 2021. The figures in parentheses refer to the home/work cluster-robust standard errors. The exogenous variables were the November 2019 TW days, age, female dummy variables, door-to-door commute time (round trip), and population (home and workplace).

Table 9: The impact of the increase in TW days from November 2019 to December 2021 on the tasks performed via TW at the time of the survey (Instrumental variable: Positive cases at the workplace from September to December, 2nd stage)

	Document Creation		Information Gathering		Data Processing		Accounting		Planning and Development		Design	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV
TW days (Dec 21)	0.116***	0.020	0.149***	0.223	0.166***	0.418**	0.033**	0.333	0.050***	0.189	-0.007	-0.034
	(0.020)	(0.189)	(0.018)	(0.206)	(0.023)	(0.138)	(0.013)	(0.192)	(0.016)	(0.176)	(0.016)	(0.060)
Observations	349	349	349	349	349	349	349	349	349	349	349	349
Mean of dep. vars	0.633	0.633	0.487	0.487	0.410	0.410	0.083	0.083	0.201	0.201	0.046	0.046
Cragg-Donald	–	5.57	–	5.57	–	5.57	–	5.57	–	5.57	–	1.07

	Online Meetings		LC within the company		External CC		TG within the company		TG for business partners	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV
TW days (Dec 21)	0.148***	0.299	0.150***	0.371	0.156***	0.274	0.091***	-0.153	0.038***	-2.74e-5
	(0.018)	(0.189)	(0.016)	(0.223)	(0.019)	(0.188)	(0.025)	(0.160)	(0.007)	(0.030)
Observations	349	349	349	349	349	349	349	349	349	349
Mean of dep. vars	0.467	0.467	0.504	0.504	0.381	0.381	0.138	0.138	0.086	0.086
Cragg-Donald	–	5.57	–	5.57	–	5.57	–	5.57	–	5.57

Note: For the analysis of the December 2021 outcome variable only, we excluded respondents whose number of TW days in December 2021 exceeded the number of TW days in November 2019 and August 2021. The figures in parentheses refer to the home/work cluster-robust standard errors. The exogenous variables were age, female dummy variables, door-to-door commute time (round trip), and population (home and workplace). Cragg-Donald refers to the value of the F-statistic from the 1st stage. ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$

Table 10: The impact of the increase in TW days from November 2019 to August 2021 on activities performed during the freed time due to the implementation of TW at the survey time (instrumental variable: positive COVID-19 cases at workplaces from May to August, 2nd stage)

	Hobbies / Recreation		Sleep		Skill Improvement		Housework	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV
TW days (August 2021)	0.097***	0.243***	0.121***	0.179***	0.053***	0.023	0.089***	0.069
	(0.011)	(0.057)	(0.016)	(0.048)	(0.011)	(0.044)	(0.026)	(0.042)
# of obs.	349	349	349	349	349	349	349	349
Mean of dep. varss	0.201	0.201	0.304	0.304	0.074	0.074	0.327	0.327
Cragg-Donald	–	9.71	–	9.71	–	9.71	–	9.71

	Time with Family		Shopping		Work (Additional Tasks)		Childcare	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV
TW days (August 2021)	0.063**	0.043	0.055***	-0.050	0.053***	0.022	0.016**	0.062*
	(0.023)	(0.098)	(0.008)	(0.051)	(0.012)	(0.053)	(0.007)	(0.029)
# of obs.	349	349	349	349	349	349	349	349
Mean of dep. varss	0.246	0.246	0.097	0.097	0.106	0.106	0.083	0.083
Cragg-Donald	–	9.71	–	9.71	–	9.71	–	9.71

Note: For the analysis of the December 2021 outcome variable only, we excluded respondents whose number of TW days in December 2021 exceeded the number of TW days in November 2019 and August 2021. The figures in parentheses refer to the home/work cluster-robust standard errors. The exogenous variables were age, female dummy variables, door-to-door commute time (round trip), and population (home and workplace). Cragg-Donald refers to the value of the F-statistic from the 1st stage. ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$

Table 11: The impact of the increase in TW days from November 2019 to December 2021 on activities performed during the freed time due to the implementation of TW at the survey time (instrumental variable: positive COVID-19 cases at workplaces from September to December, 2nd stage)

	Hobbies / Recreation		Sleep		Skill Improvement		Housework	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV
TW days (December 2021)	0.058***	0.293*	0.122***	0.277**	0.045***	0.023	0.080**	0.080
	(0.013)	(0.145)	(0.016)	(0.124)	(0.010)	(0.069)	(0.028)	(0.061)
# of obs.	349	349	349	349	349	349	349	349
Mean of dep. varss	0.201	0.201	0.304	0.304	0.074	0.074	0.327	0.327
Cragg-Donald	–	5.57	–	5.57	–	5.57	–	5.57

	Time with Family		Shopping		Work (Additional Tasks)		Childcare	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV
TW days (December 2021)	0.063**	0.043	0.055***	-0.050	0.053***	0.022	0.016**	0.062*
	(0.023)	(0.098)	(0.008)	(0.051)	(0.012)	(0.053)	(0.007)	(0.029)
# of obs.	349	349	349	349	349	349	349	349
Mean of dep. varss	0.246	0.246	0.097	0.097	0.106	0.106	0.083	0.083
Cragg-Donald	–	5.57	–	5.57	–	5.57	–	5.57

Note: For the analysis of the December 2021 outcome variable only, we excluded respondents whose number of TW days in December 2021 exceeded the number of TW days in November 2019 and December 2021. The figures in parentheses refer to the home/work cluster-robust standard errors. The exogenous variables were age, female dummy variables, door-to-door commute time (round trip), and population (home and workplace). Cragg-Donald refers to the value of the F-statistic from the 1st stage. ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$

Table 12: The impact of the increase in new positive COVID-19 cases from November 2019 to August and December 2021 on the D2D commute time reduced by TW (Instrumental variables: workplace positive cases from May to August and September to December, 1st stage)

	Endogenous Variables	
	D2D commute time reduced by TW (August 2021)	D2D commute time reduced by TW (December 2021)
New positive COVID-19 cases (workplace)	0.045***	0.157*
	(0.008)	(0.074)
Number of observations	349	349
Mean of the explained variable	106.8	53.6

Note: For the analysis of the December 2021 outcome variable only, we excluded respondents whose number of TW days in December 2021 exceeded the number of TW days in November 2019 and August 2021. The figures in parentheses refer to the home/work cluster-robust standard errors. The exogenous variables were the November 2019 TW days, age, female dummy variables, population (home and workplace). ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$

Table 13: The impact of the D2D commute time reduced by TW from November 2019 to August 2021 on activities done during the time saved from commuting due to TW (Instrumental variables: workplace positive cases from May to August, 2nd stage)

	Hobbies and Recreation		Sleep		Skill Improvement		Housework	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV
D2D commute time reduced by TW (August 2021)	0.0005***	0.002***	0.001***	0.002***	0.0002	0.0003	0.0007***	0.0009***
	(0.0001)	(0.0005)	(0.0001)	(0.0004)	(0.0001)	(0.0003)	(0.0002)	(0.0003)
Number of observations	349	349	349	349	349	349	349	349
Mean of the explained variable	0.201	0.201	0.304	0.304	0.074	0.074	0.327	0.327
Cragg-Donald	–	10.7	–	10.7	–	10.7	–	10.7

	Time with Family		Shopping		Work (additional tasks)		Childcare	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV
D2D commute time reduced by TW (August 2021)	0.0005**	0.0006	0.0006***	-5.71e-5	0.0004**	0.0003	0.0001**	0.0005*
	(0.0002)	(0.0007)	(5.5e-5)	(0.0003)	(0.0001)	(0.0004)	(5.01e-5)	(0.0003)
Number of observations	349	349	349	349	349	349	349	349
Mean of the explained variable	0.246	0.246	0.097	0.097	0.106	0.106	0.083	0.083
Cragg-Donald	–	10.7	–	10.7	–	10.7	–	10.7

Note: For the analysis of the December 2021 outcome variable only, we excluded respondents whose number of TW days in December 2021 exceeded the number of TW days in November 2019 and August 2021. The figures in parentheses refer to the home/work cluster-robust standard errors. The exogenous variables were age, female dummy variables, D2D commute time (round trip), and population (home and workplace). Cragg-Donald refers to the F-statistic value from the 1st stage. ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$

Table 14: The impact of the reduction in door-to-door commute time (D2D) due to TW from November 2019 to December 2021 on activities done with the saved time by not commuting (instrumental variable: positive COVID-19 cases from September to December at the workplace, 2nd stage)

	Hobbies and Entertainment		Sleep		Skill Development		Housework	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV
Reduction in D2D commute time (December 21)	0.0003**	0.003*	0.001***	0.003**	0.0002*	0.0003	0.0007**	0.001*
	(0.0001)	(0.001)	(0.0002)	(0.001)	(7.31e-5)	(0.0005)	(0.0002)	(0.0007)
# of obs.	349	349	349	349	349	349	349	349
Mean of dep. varss	0.201	0.201	0.304	0.304	0.074	0.074	0.327	0.327
Cragg-Donald	–	7.53	–	7.53	–	7.53	–	7.53

	Time with Family		Shopping		Work (Additional Tasks)		Childcare	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV
Reduction in D2D commute time (December 21)	0.0004**	0.0006	0.0005***	0.0001	0.0007***	0.001**	5.66e-5	0.0007
	(0.0001)	(0.001)	(9.38e-5)	(0.0005)	(0.0001)	(0.0005)	(6.35e-5)	(0.0007)
# of obs.	349	349	349	349	349	349	349	349
Mean of dep. varss	0.246	0.246	0.097	0.097	0.106	0.106	0.083	0.083
Cragg-Donald	–	7.53	–	7.53	–	7.53	–	7.53

Note: For the analysis of the December 2021 outcome variable only, we excluded respondents whose number of TW days in December 2021 exceeded the number of TW days in November 2019 and August 2021. The figures in parentheses refer to the home/work cluster-robust standard errors. The exogenous variables were age, female dummy variables, door-to-door commute time (round trip), and population (home and workplace). Cragg-Donald indicates the value of the F-statistic for the 1st stage. ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$

Appendix Table 1 : 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		
	August 2021	Other Months in August 2021	Ratio of August 2021 to Other Months
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 2 : Definitions of key variables

Variable Name	Definition
Exogenous variable: Number of TW days and commuting time reduction per week before COVID-19	
TW days (Nov. 2019)	Respondents' average number of TW days per week in November 2019
D2D commuting time reduced by TW (Nov. 2021)	the time obtained by multiplying the average number of TW days per week in November 2019 for the respondent by the round-trip D2D commuting time per day
Endogenous variable: Number of TW days and commuting time reduction per week after COVID-19	
TW days (Aug. 2021)	Respondents' average number of TW days per week in August 2021
TW days (Dec. 2021)	Respondents' average number of TW days per week in December 2021
D2D commuting time reduced by TW (Aug. 2021)	the time derived by multiplying the average number of TW days per week in August 2021 for the respondent by the round-trip D2D commuting time per day
D2D commuting time reduced by TW (Dec. 2021)	the time obtained by multiplying the average number of TW days per week in December 2021 for the respondent by the round-trip D2D commuting time per day
Instrument variable: New positive COVID-19 case, by municipality	
New positive COVID-19 cases (workplace, person, May.-Aug. 2021)	Total new positive COVID-19 cases per 100,000 persons in the municipality containing the respondent's workplace zip code

New positive COVID-19 cases (home, person, May.-Aug. 2021)	Total new positive COVID-19 cases per 100,000 persons in the municipality containing the respondent's home zip code
New positive COVID-19 cases (workplace, person, Sep.-Dec. 2021)	Total new positive COVID-19 cases per 100,000 persons in the municipalities containing the respondent's workplace zip code
New positive COVID-19 cases (home, person, Sep.-Dec. 2021)	Total new positive COVID-19 cases per 100,000 persons in the municipalities containing the respondent's home ZIP code
Outcome variable as of August 2021	
Overtime work (Aug., 2021)	5-point ordinal scale based on "Increase or decrease in overtime hours worked in December 2021 compared to pre-COVID-19" (Very much increased = 5, Slightly increased = 4, No change = 3, Slightly decreased = 2, Very much decreased = 1)
Work efficiency (Aug., 2021)	5-point ordinal scale based on "Change in work efficiency in December 2021 compared to before COVID-19" (Very much up = 5, Slightly up = 4, No change = 3, Slightly down = 2, Very much down = 1)
Life satisfaction (Aug., 2021)	5-point ordinal scale based on "Change in life satisfaction in December 2021 compared to before COVID-19" (Very much increased = 5, Slightly increased = 4, No change = 3, Slightly decreased = 2, Very much decreased = 1)
Commuting time (Aug., 2021)	5-point ordinal scale based on "Change in commuting time in December 2021 compared to before COVID-19" (Very much increased = 5, Slightly increased = 4, No change = 3, Slightly decreased = 2, Very much decreased = 1)
Daily walking (Aug., 2021)	5-point ordinal scale based on "Change in daily walking in December 2021 compared to pre-COVID-19" (Very much increased = 5, Slightly increased = 4, No change = 3, Slightly decreased = 2, Very much decreased = 1)
Daily Exercise (Aug., 2021)	5-point ordinal scale based on "Change in daily physical activity in December 2021 compared to pre-COVID-19" (Very much increased = 5, Slightly increased = 4, No change = 3, Slightly decreased = 2, Very much decreased = 1)
Outcome variable as of December 2021	
Overtime work (Dec., 2021)	5-point ordinal scale based on "Increase or decrease in overtime hours worked in December 2021 compared to pre-COVID-19" (Very much increased = 5, Slightly increased = 4, No change = 3, Slightly decreased = 2, Very much decreased = 1)
Work efficiency (Dec., 2021)	5-point ordinal scale based on "Change in work efficiency in December 2021 compared to before COVID-19" (Very much up = 5, Slightly up = 4, No change = 3, Slightly down = 2, Very much down = 1)

Life satisfaction (Dec., 2021)	5-point ordinal scale based on "Change in life satisfaction in December 2021 compared to before COVID-19" (Very much increased = 5, Slightly increased = 4, No change = 3, Slightly decreased = 2, Very much decreased = 1)
Commuting time (Dec., 2021)	5-point ordinal scale based on "Change in commuting time in December 2021 compared to before COVID-19" (Very much increased = 5, Slightly increased = 4, No change = 3, Slightly decreased = 2, Very much decreased = 1)
Daily walking (Dec., 2021)	5-point ordinal scale based on "Change in daily walking in December 2021 compared to pre-COVID-19" (Very much increased = 5, Slightly increased = 4, No change = 3, Slightly decreased = 2, Very much decreased = 1)
Daily Exercise (Dec., 2021)	5-point ordinal scale based on "Change in daily physical activity in December 2021 compared to pre-COVID-19" (Very much increased = 5, Slightly increased = 4, No change = 3, Slightly decreased = 2, Very much decreased = 1)
Jobs performed during the TW (multiple responses allowed)	
Documentation	Dummy variable that is 1 if the respondent selected "Documentation" and 0 otherwise
Information Gathering	Dummy variable that is 1 if the respondent selected "Information Gathering" and 0 otherwise
Data Processing	Dummy variable that is 1 if "Data Processing" is selected and 0 otherwise
Accounting work	Dummy variable that is 1 when "Accounting work" is selected and 0 otherwise
Planning and Development	Dummy variable that is 1 if "Planning and Development" is selected and 0 otherwise
Design	Dummy variable that is 1 if "Design" is selected and 0 otherwise
Online meeting	Dummy variable that is 1 if "Online meeting" is selected and 0 otherwise
LC within the company	Dummy variable if "Liaison and coordination within the company by e-mail and telephone" is selected, 0 otherwise
LC for business partners	Dummy variable that is 1 if the respondent selected "Liaison and coordination for business partners by e-mail and telephone," and 0 otherwise.
TM within the company	Dummy variable that is 1 if the respondent selected "Training and mentoring within the company" and 0 otherwise
TM for business partners	Dummy variable that equals 1 if "Training and mentoring for business partners" is selected and 0 otherwise.
Dummy variables for saved commuting time activities	
Hobbies / Recreation	Dummy variable that is 1 if the respondent selected "Hobbies / Recreation" and 0 otherwise
Sleep	Dummy variable that is 1 if the respondent selected "Sleep" and 0 otherwise

Skill Development	Dummy variable that is 1 if the respondent selected "Skill Development" and 0 otherwise
Housework	Dummy variable that is 1 if the respondent selected "Housework" and 0 otherwise
Family time	Dummy variable that is 1 if "Family time" is selected and 0 otherwise
Shopping	Dummy variable that is 1 if "Shopping" is selected and 0 otherwise
Work (additional work)	Dummy variable that is 1 if "Work (additional work)" is selected and 0 otherwise
Child care	Dummy variable that is 1 if "Child care" is selected and 0 otherwise
Other exogenous variables	
Age	Age at time of response
Female dummy	Dummy variable that is 1 if the respondent is female, 0 otherwise
Marriage dummy	Dummy variable that takes the value 1 if the respondent is married, 0 otherwise
Preschooler living with respondent dummy	dummy variable that takes the value 1 if the respondent lives with a preschooler
Elementary school student living with respondent dummy	dummy variable that takes the value 1 if the respondent lives with an elementary school student
Junior high school student living with respondent dummy	dummy variable that takes the value 1 if the respondent lives with a junior high school student
High school student living with respondent dummy	dummy variable that takes the value 1 if the respondent lives with a high school student
19 years old or older living with respondent dummy	A dummy variable that takes the value 1 if the respondent lives with a child who is 19 years old or older
D2D commuting time (round trip, minutes)	Variable obtained by doubling the "D2D commuting time from home to work (minutes)"
2021 Population (workplace, persons)	2021 population of the municipality that includes the respondent's work zip code.
2021 population (home, persons)	2021 population of the municipality containing the respondent's home zip code.

Appendix Table 3 : Definitions of key variables

Variable Name	Definition					
Exogenous variable						
TW days (Nov. 2019)	380	1	0.202	0.678	0	5
D2D commuting time reduced by TW (Nov. 2019)	380	1	13.5	51	0	500
Endogenous variable						
TW days (Aug. 2021)	381	0	1.34	1.35	0	6
TW days (Dec. 2021)	381	0	0.797	1.23	0	6
D2D commuting time reduced by TW (Aug. 2021)	381	0	105	156	0	1200
D2D commuting time reduced by TW (Dec. 2021)	381	0	63.1	137	0	1200
Instrument variable						
New positive COVID-19 cases (workplace, May.-Aug. 2021)	379	2	909	625	0	2425
New positive COVID-19 cases (home, May.-Aug. 2021)	380	1	706	440	0	2016
New positive COVID-19 cases (workplace, Sep.-Dec. 2021)	379	2	191	114	0	574
New positive COVID-19 cases (home, Sep.-Dec. 2021)	380	1	159	87.2	0	445
Outcome variable as of August 2021						
Overtime work (Aug., 2021)	381	0	2.96	0.739	1	5
Work efficiency (Aug., 2021)	381	0	3.04	0.685	1	5
Life satisfaction (Aug., 2021)	381	0	2.59	1.01	1	5
Commuting time (Aug., 2021)	381	0	2.71	0.683	1	5
Daily walking (Aug., 2021)	381	0	2.65	0.816	1	5
Daily Exercise (Aug., 2021)	381	0	2.64	0.818	1	5
Outcome variable as of December 2021						
Overtime work (Dec., 2021)	381	0	3.02	0.697	1	5
Work efficiency (Dec., 2021)	381	0	3.09	0.666	1	5
Life satisfaction (Dec., 2021)	381	0	2.65	0.944	1	5
Commuting time (Dec., 2021)	381	0	2.8	0.584	1	5
Daily walking (Dec., 2021)	381	0	2.73	0.753	1	5
Daily Exercise (Dec., 2021)	381	0	2.67	0.775	1	5
Jobs performed during the 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
LC within the company	381	0	0.52	0.5	0	1
LC for business partners	381	0	0.394	0.489	0	1
TM within the company	381	0	0.165	0.372	0	1
TM for business partners	381	0	0.0919	0.289	0	1
Dummy variables for saved commuting time activities						
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
Work (additional work)	381	0	0.11	0.314	0	1
Child care	381	0	0.084	0.278	0	1
Other exogenous variables						
Age	381	0	42.3	12.1	21	76
Female dummy	381	0	0.273	0.446	0	1
Marriage dummy	381	0	0.675	0.469	0	1
Living with preschooler dummy	381	0	0.178	0.383	0	1
Living with elementary school student dummy	381	0	0.194	0.396	0	1
Living with junior high school student dummy	381	0	0.0866	0.282	0	1
Living with high school student dummy	381	0	0.0735	0.261	0	1
Living with 19 years old or older dummy	381	0	0.123	0.329	0	1
D2D commuting time (round trip, minutes)	381	0	35.4	23.7	1	150
2021 Population (workplace)	379	2	223190	116305	12978	601546
2021 population (home)	380	1	215694	129091	9653	601546

Appendix Table 4 : 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