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Abstract

Flexible working arrangements, such as telework, have the potential to serve as a mechanism for promoting female workforce participation and concurrently encouraging childbearing, particularly in rapidly aging societies. This study employs longitudinal data from the Japan Panel Study of Employment Dynamics (JPSED) to estimate the impact of being employed in an occupation characterized by a high proportion of teleworkers on the likelihood of women experiencing a birth or pregnancy within a given year. Employing a difference-in-differences framework in combination with fixed effects logistic regression, the study exploits the exogenous increase in occupations' teleworker ratios driven by the COVID-19 pandemic. The findings suggest that women in occupations with high teleworking ratios exhibit a 1.5 times increase in odds of being pregnant. While the results for the odds of giving birth are positive, they lack statistical significance. Furthermore, the treatment effects are heterogeneous, demonstrating more pronounced effects on women with higher levels of education, full-time employment, and above-median income. These results are reinforced with propensity score matching and random permutation tests. This study sheds light on the potential influence of telework on family planning decisions and underscores the importance of considering various demographic factors in understanding the nuanced effects of flexible working arrangements on fertility outcomes.

Keywords: telework; Japan; fertility; female LFP; family formation; difference-in-differences

JEL Classifications: J13; J22

1. Introduction

When it comes to Japan, the demographic challenges posed by population aging and decline is one of the most common economic and socio-political issues to be discussed in the country. The Japan Statistical Yearbook (Statistical Bureau of Japan (SBJ), 2023) has recorded a negative population growth rate since 2011, accompanied by a continuous decline in the total fertility rate over the past five years (SBJ, 2022). The implications of a shrinking population are manifold, ranging from labor force shortages to the mounting burden of public debt associated with social security obligations (Stawasz et al., 2018). As a result, a shrinking labor force poses enormous long-term challenges for the Japanese government's strategic planning and policy formulation.

Among the array of policy options discussed, this study addresses two specific types. The first entails targeting under-utilized labor sources in the country, especially by increasing female labor force participation (LFP), as emphasized in Prime Minister Abe's comprehensive policy framework, *Abenomics* (Stawasz et al, 2018). The second, more long-term solution aims to boost the birth rate, definitively reversing population decline. Measures such as the New Angel Plan and the Plus One Policy (Centre for Public Impact, 2017) have been proposed for this purpose. However, it is important to note the inherent contradiction between these two options, as they require Japanese women to both work more and raise more children. This places significant pressure on a demographic already known to bear a disproportionate burden of household work, even while employed (Kohara & Maity, 2021; Tsuya et al., 2013).

In the backdrop of the COVID-19 pandemic in Japan, telecommuting has garnered considerable attention as a valid strategy of realizing "work-life balance". Telework, also known as remote work and work from home, is one possible method of both promoting female LFP and possibly encouraging higher birth rates. Considerable amounts of research have been conducted on telework's effect on work productivity, life satisfaction, stress, and various other aspects within the fields of labor and health economics. However, due to its relatively new prominence, there has been limited study on its effect on family formation.

We outline two possible mechanisms. The first mechanism revolves around relocation, wherein telework enables individuals in the pre-childbearing phase the opportunity to change their place of residence due to reduced spatial constraints compared to traditional work arrangements. This newfound flexibility allows young couples planning for children to migrate to areas considered more suitable for child-rearing, especially in terms of childcare facilities. Moreover, this flexibility grants them greater freedom to navigate housing transitions, such as moving to larger homes in anticipation of a growing family or relocating closer to family members who offer childcare support. Bernard et al. (2014) globally observe a strong relationship between "the age spread of union and family formation and the degree of concentration of migration are strongly related, with [significant at $p < 0.01$] correlation coefficients above 0.70 for both men and women." Li (2019) employs panel data analysis to examine the causal impact of fertility intentions on the likelihood of moving house in Australia. This study estimates that, compared to the annual mobility rate of 0.14, "a one-unit higher fertility intention reported is associated with a 3.16% increase in the likelihood for moving." Haslag and Weagley (2022) leverage the appearance of COVID-19 and utilize a questionnaire-based approach to directly inquire about respondents' motivations for relocation. This approach establishes a link between migration and remote work capabilities. Furthermore, descriptive analysis conducted by Fielding and Ishikawa (2021) finds notable reversals in inter-prefectural migration patterns in relation to the availability of remote work capabilities, with Tokyo experiencing greater increase in outmigration and a decrease in in-migration.

The second possible mechanism through which telework may affect the fertility rate is by the reduction in commute time, consequently leading to an increase in leisure time. Heckman's benchmark labor-leisure choice model (1974) posits that the decision to work involves a trade-off between the utility of consumption facilitated by wages and the utility of leisure enabled by free time. Since then, many studies on family formation have focused on the opportunity cost of having children, considering both lost working hours and lost leisure time, such as in Craig and Bittman's 2008 study. One of the hidden time costs associated with employment is the time spent commuting, which neither contributes to income nor allows for engagement in leisure, household work, or childcare. Telework eliminates the need for commuting, thus creating additional free time that could potentially be allocated to parenting. However, previous studies on this topic have found conflicting results. Nomaguchi (2006) investigated the relationship between leisure time and motherhood in Japan, finding that married Japanese women who spend more leisure time are less likely to become mothers within a two-year period. Conversely, Becker and Lois (2012) found that "strongly leisure-oriented women exhibited a lower likelihood of first motherhood only if no close family members lived nearby who could provide informal child care support."

Finally, telework may serve as a means to facilitate women's re-entry into the workforce during the early years of child-rearing, thereby addressing the issue of the "M-shaped curve" as identified by the Gender Equality Bureau Cabinet Office (GEBCO) (2020). This curve highlights the tendency of Japanese women to leave the workforce in the middle of their careers to have children[1]. Nakanishi (2016) estimates that if telework can effectively eliminate the M-shaped curve, then approximately 980,000 women could reintegrate into the labor force. Additionally,

[1] GEBCO (2020) conducts a specific analysis comparing Japan's female LFP across age groups with Sweden, France, Germany, and the United States. The study concludes that these similarly wealthy developed countries no longer exhibit the M-shaped curve in female LFP.

Sakai and Asaoka (2007) provide evidence suggesting that family-friendly practices, such as telecommuting and flexible working hours, contribute to increased female LFP. However, Sato (2019) warns that women with young children disproportionately constitute Japan's *zaitaku* workers, who engage in contract-based freelance telework from home. This type of employment is often associated with low wages, unstable work flows, and has been shown to have adverse effects on health and mental well-being. Therefore, efforts to promote telework for women as a means of increasing LFP must be balanced with measures to protect their health and wellbeing.

In this study, we investigate the effect of telework adoption on the fertility decisions of Japanese women. To address this research question, we utilize the onset of the COVID-19 pandemic as an exogenous shock that compelled Japanese workers in telework-capable occupations to transition to remote work from home. We employed a combination of difference-in-differences estimation and fixed-effects logistic estimation on longitudinal panel data. By comparing individuals working in occupations with a low ratio of teleworkers to those in high-ratio occupations, we estimate the change in odds of pregnancy or giving birth. We find statistically significant and positive results for pregnancy, indicating telework encourages childbearing. However, while results are also positive for birth, they remain statistically insignificant. This is attributed to the nine-month gestation period of pregnancies, resulting in outcomes not yet observed, as the dataset at the time of analysis extends only until the end of 2022. To ensure the robustness of our findings, we conduct robustness tests using propensity score matching and random permutation tests. These tests provide little evidence of sample selection bias, suggesting that women dropping out of the workforce do not significantly impact the results. Furthermore, an examination of the heterogeneous treatment effects reveals that the effects are particularly pronounced for highly educated full-time workers with above-median household annual income, aligning with expectations.

The remainder of this paper is as follows. Section 2 briefly covers the institutional background of telework and female LFP in Japan, while Section 3 summarises previous literature on telework and fertility rates. Sections 4 and 5 describe the data and explain the econometric strategy. Section 6 presents the results, with a short discussion in Section 7. Section 8 concludes with policy implications and suggests avenues for further research.

2. Institutional background

While Japan has advanced digital infrastructure, leading to predictions in the 1990s that telework would become a significant component of the economy in the next decade or two (Higa & Shin, 2003), these predictions have not entirely materialised. Since 2013, the Ministry of Internal Affairs and Communications, the Ministry of Health, Labour, and Welfare, and the Ministry of Economy, Trade, and Industry have all actively promoted and subsidised various forms of teleworking, as outlined by Sato (2019). Furthermore, the Prime Minister's Office of Japan identified telework as a key initiative for work style reform in 2017. Despite these initiatives, Japan's entrenched workplace culture and organizational barriers have deterred companies from readily embracing telework for their employees (Ono, 2022).

The global lockdown policies and social distancing requirements implemented during the COVID-19 pandemic caused sizeable increases in teleworking rates worldwide, leading to a surge in interest in studying the effects of telework. According to the "Teleworker Population Survey," conducted by the Ministry of Land, Infrastructure, Transport and Tourism in Japan, the teleworker ratio for employed workers experienced a rapid increase from 15% in 2019 to 27% in 2022[2].

Despite this increase, Japan's telework rates continue to stand in contrast to those of other highly developed countries. The Organisation for Economic Co-operation and Development (OECD)'s international figures indicate that countries with already higher telework rates, such as France, Australia and Great Britain, saw 47% of employees engaging in telework during lockdowns, while Japan's teleworker ratio increased from 10% to 28% in 2020 (OECD, 2021). Hosoda (2021) finds organizational, technological and environmental barriers contributing to Japan's lower adoption of telework during the pandemic, particularly among small- and medium-sized companies. As previously mentioned, existing telework literature primarily focuses on labor productivity and life satisfaction, with Japanese evidence generally suggesting a positive effect of telework on these outcomes (Kazekami, 2020; Okubo et al., 2021), although there are some mixed findings. For example, Kitagawa et al. (2021) find declines in productivity among those who work from home but improvements in mental health. Notably, life satisfaction is often relevant to fertility intentions.

Regarding female LFP in Japan, women face lower employment rates, earn less, and are less likely to secure full-time positions. The OECD's Japan Policy Brief (2017) highlights a 17% gender employment gap and a 27% gender pay gap. Additionally, the brief reveals that women account for two-thirds of non-regular workers in 2015. According to The Global Gender Gap Index by the World Economic Forum, Japan ranked 121st in the economic participation and opportunity subindex in 2022. These disparities prompted the GEBCO to establish numerical targets in its Fifth Basic Plan for Gender Equality for 2025 (2022). As of 2021, the employment rate for women aged

[2] From 2002 to 2012, the teleworking ratios experienced rapid growth, increasing from 6% to 20% for employed workers and from 8% to 28% for self-employed workers. Subsequently, the ratios gradually declined, reaching 13% for employed workers and 21% for self-employed workers by 2016. However, during the COVID-19 pandemic, both ratios saw a resurgence, reaching 26-27% and returning to the levels seen in 2012. Further information on the survey can be found at the Ministry of Land, Infrastructure, Transport and Tourism's website: https://www.mlit.go.jp/crd/daisei/telework/p2.html (accessed on 25th January, 2024)

25-44 is 78.6%, with a target to increase it to 82%. The percentage of women continuing to work before and after giving birth to their first child is 53.1% in 2015, with the goal of raising it to 70% by 2025. LFP rates of women in Japan typically exhibit an “M-shaped curve” over age, reflecting the childcare burden for women in their 30s. However, this M-shaped curve has diminished over time in other developed countries (GEBCO, 2020). The same GEBCO 2020 pamphlet shows that as of 2018, women outnumber men in the financing and insurance, real estate, and services industry.

3. Previous Literature

Prior to the COVID-19 pandemic, quantitative and individual-level studies on telework faced limitations due to its limited prevalence and challenges associated with microdata collection. While telework has been a subject of study since the 1990s, available data was often cross-sectional or based on samples of teleworkers until the 2010s. This restricted the generalisation and inference capacity of contemporary research, particularly in areas such as fertility intentions where birth outcomes are delayed by nine months. Notwithstanding these limitations, Sinyavskaya and Billingsley (2015) stand out for directly addressing the research topic. They employ a three-wave panel survey in Russia to estimate ordered logistic regressions, focusing on the impact of various job characteristics on fertility intention and rate. Although their findings indicate that the ability to work from home is a strong predictor of fertility intentions, they do not explore its impact on actual conceptions or births. Furthermore, Billari et al. (2019) analyse the effect of high-speed internet access on fertility rates using panel data. While their primary focus lies in investigating the relationship between broadband availability and fertility among highly educated women in Germany, their approach indirectly touches upon the role of telework as a potential driver of birth rates. They also explore other aspects of the link between internet access and fertility, including increased reproductive health. Several studies also delve into the implications of telework for women’s labor supply after childbirth, as seen in Chung and van der Horst (2018), and the allocation of time spent on childcare (Troup & Rose, 2012; Pabilonia & Vernon, 2022).

With the emergence of the COVID-19 pandemic, there has been a notable surge in research related to telework. Luppi et al. (2022) conducted a cross-sectional survey on fertility intentions conducted in Italy, finding that the widespread adoption of teleworking was associated with “improved couple relationship quality, increased partner contribution in household tasks, and positive return in work-family reconciliation.” These factors served as motivations for planning births. In Belgium, a qualitative study collecting experiences from pregnant women during COVID-19 revealed that telework was a positive experience for the majority of respondents (Vermeulen et al., 2022). Examining the effects of the pandemic on telework-capable occupations, Heggeness and Suri (2021) use a difference-in-differences model and found reduced LFP for highly educated mothers in telework-capable occupations due to limited childcare availability during the pandemic. While "the option for telework kept many attached to the labor market and working," teleworking mothers also faced higher levels of "simultaneous multitasking of childcare with work" (Heggeness and Suri, 2021). In contrast, Minetaki (2023) found that telework in Japan increases satisfaction with childcare, but this effect was observed only for male employees. However, post-COVID-19 studies are focused on women who have already given birth, leaving limited evidence regarding whether telework actually increases the likelihood of giving birth. Matsuda et al. (2022) examined the effect of telework on family planning among couples with at least one child during the pandemic. Their primary outcome was the desire to have a child. They found no significant effect for women, but telework suppressed the desire to have children for men. At the same time, they also found that couples are motivated to have additional children when housework and childcare are more evenly shared, a positive effect of telework. While fertility intentions reliably serve as strong predictors of actual births for individuals with existing children (Dommermuth et al., 2015; Régnier-Loilier et al., 2011), Matsuda et al. (2022) face limitations due to their cross-sectional survey design. Consequently, they lack data on births or pregnancies, as well as fertility intentions for couples without children. In a similar vein, Inoue et al. (2023) conducted a study on men and found that working from home leads to increased time spent on family and housework. However, unlike Matsuda et al. (2022), their research indicates that working from home raises the proportion of men who consider themselves more life than work oriented.

Existing literature reveals a limited number of studies that have directly investigated the association between telework and pregnancy or childbirth. To fill this research gap, we employ a longitudinal survey that leverages the COVID-19 pandemic as an exogenous shock. This unprecedented event prompted Japanese workers in telework-enabled occupations to shift towards remote work from home. Our aim is to scrutinize the repercussions of this shift in work arrangement on the decision-making related to pregnancy or giving a birth among Japanese women.

4. Data and descriptive statistics

We use the Japanese Panel Study of Employment Dynamics (JPSED) dataset, a yearly online survey conducted by Recruit Works Institute. Acquired through a sample survey, this dataset is nationally representative, with the allocation of participants based on the data from the "Labour Force Survey" provided by the Japanese Statistics Bureau, Ministry of Internal Affairs and Communications. Allocation factors include gender, stratified age group, type of employment, district block, and educational background (Recruit Works Institute, 2023). The JPSED dataset encompasses comprehensive information on individual attributes, employment status, and living dynamics, all collected in January of each year for the past twelve months. Notably, the JPSED is a longitudinal dataset, allowing for the tracking of individuals over time.[3]

First, responses for the year 2015 were excluded due to a lack of relevant telework-related questions. Consequently, this study encompasses the years 2016 to 2021 inclusive, incorporating two years of data collected during the COVID-19 pandemic. Subsequently, the dataset is refined by retaining observations solely for female respondents[4]. Moreover, we exclude all observations of female respondents aged 55 and older, considering this age range as the typical upper limit for menopause. While instances of pregnancy and birth are reported for women over the age of 55 in this dataset, none of these cases appear to have resulted in viable births, given that the reported youngest child's age is at least 20 years old. Consequently, we keep only female observations that are potentially associated with women capable of having children.

The JPSED provides an extensive list of 224 occupation codes, ranging from occupations such as bus driver to civil engineering construction management and fashion designer. These occupation codes are categorized under various subheadings such as “occupations related to agriculture, forestry and fisheries” or “finance-related professionals,” as presented to the respondents. Due to the presence of rare occupation codes with only one or two observations per year, potentially resulting in misleading 100% teleworker rates, our study adopts a more aggregated approach. Specifically, we employ 44 broader occupation labels to assess the effect of teleworker ratios across occupations. To calculate the impact of teleworker ratio by occupation, we restrict the dataset to individuals who recorded an occupation in the same year as their recorded birth or pregnancy, even if they were on leave or unemployed at some point in the year. It is important to note that this approach may lead to sample selection bias, as some women might choose to exit the workforce to focus on raising children. We acknowledge and address the implications of this potential bias in the robustness tests conducted in our analysis.

The sample analysed by this study thus consists of a representative group of employed Japanese women aged 15-55 years old, surveyed from 2016 to 2021. However, out of 110,506

[3] The response rates for individuals participating continuously from 2017 to 2022 range from 75.2% to 80.0%. Furthermore, accounting for the inclusion of new respondents each year, the dataset comprises an average of approximately 54,000 observations annually.

[4] While the analysis of birth and pregnancy outcomes for male respondents was feasible, as they reported whether their spouses experienced a birth or pregnancy, there was an absence of telework data for spouses. Furthermore, information on spouses’ occupations was recorded in much less detail, making it impossible to extract the occupation teleworker ratio, which serves as the independent variable in our investigation. Notably, the birth and pregnancy outcomes for male respondents were statistically insignificant. Consequently, due to these reasons, we have chosen not to include their results in this paper.

person-year observations, only 6,215 observations belong to women who reported either a birth or a pregnancy during this time period. The limitation on the number of observations is a result of using a logistic fixed effects regression model, which will be further elaborated upon in the methodology section. Despite the unbalanced nature of the panel data, where respondents enter and exit the survey over time, the regressions conducted indicate an average of 3.4 observations per individual. This allows for longitudinal analysis and provides a sufficient basis for examining trends over time. Table 1 presents characteristics of both the larger sample and the final subsample used for analysis, showing descriptive statistics of the person-year observations.[5]

[Table 1 here]

In the dataset's time frame, women who are recorded as having a birth or pregnancy exhibit certain distinct characteristics. Firstly, they tend to be younger, suggesting that childbirth or pregnancy is more common among younger women in the sample, aligning with standard models of fertility. Additionally, they are more likely to be married and to have a higher level of education compared to those who did not report a birth or pregnancy. Interestingly, the subsample of women who experienced births or pregnancies also seem to work slightly more days and hours per week, though there is no significant difference in the number of hours worked per day. Moreover, their household annual income tends to be higher, possibly reflecting a higher socioeconomic status, the financial support needed to cover child-related expenses, or simply a consequence of being more likely to be married and thus having a second source of income in the household. Predictably, women in the subsample spend more time on childcare on average, and are less likely to be the main income earner in their households.

In this sample, women tend to have their children in their early 30's, while the frequency of pregnancies diminishes at a lower rate with increase in age[6]. It is noteworthy that pregnancies somewhat outnumber births, attributed to factors such as abortions or miscarriages, naturally leading to a higher number of pregnancies reported than births. Figure 1 shows the rates of women in the whole sample reporting being on leave or not having a job at least one month out of twelve-month periods. Combined, almost all women experience a period of not working (though not necessarily being unemployed) for at least one month during the year in which they give birth. However, concerning the proportion of women who have exited the workforce for at least one month during the year, the proportion is higher in the year following birth. While our focus is on those in the workforce—excluding respondents who are permanently out of the workforce while

[5] Please refer to Appendix A for a list of occupations in the JPSED stratified by gender.

[6] Please refer to Appendix B for summary statistics figures, including a frequency table of age at the time of birth/pregnancy.

still including those on leave during the year of childbirth—we also utilize LFP as a robustness check.

[Figure 1 here]

5. Econometric strategy

In this study, we assess the impact of telecommuting on the likelihood of childbirth and pregnancy, considering time periods before and after the COVID-19 pandemic. For this purpose, we employ a differences-in-differences (DID) model combined with a logit fixed effects approach. We also utilize an event study model to reinforce the parallel trend assumption, a prerequisite for DID models. The estimation for all models discussed in the following analysis were conducted using Stata 17.0 statistical software.

5.1. Logit fixed effects model for a binary outcome variable

Firstly, using a panel data fixed effects model is a sound approach when assessing the impacts of telecommuting on the binary outcome of childbirth or pregnancy, especially when handling individual unobserved effects that remain constant over time. The desire to have a child is indeed influenced by various factors such as an educational attainment, cognitive and non-cognitive abilities and skills, cultural upbringing, spouse's personality, personal opinion on parenthood, and other unobservable characteristics. These factors are likely to remain relatively stable over the course of a panel study and may be correlated with explanatory variables like employment status and current parental responsibilities. To control for these unobserved fixed effects denoted by a_i, the data can be transformed through time demeaning, by subtracting the individual mean from each observation for that individual. This helps eliminate the individual-specific fixed effects, allowing for a more accurate assessment of the impact of telecommuting on the likelihood of childbirth or pregnancy. Without yet considering a logistic binary response function, this approach can be outlined as follows. Let $i = (1,2,\ldots,N)$ stand for individuals, and $t = (1,2,\ldots,T)$ for time period; and let μ_{it} be the error term for a specific individual and given time period.

$$\begin{aligned} y_{it} &= \boldsymbol{\beta}\mathbf{x}_{it} + a_i + \mu_{it} \\ \bar{y}_i &= \frac{1}{T}\sum_{t=1}^{T} y_{it} = \boldsymbol{\beta}\bar{\mathbf{x}}_i + a_i + \bar{\mu}_i \\ y_{it} - \bar{y}_i &= \boldsymbol{\beta}(\mathbf{x}_{it} - \bar{\mathbf{x}}_i) + \mu_{it} - \bar{\mu}_i \end{aligned} \tag{1}$$

Here, $\boldsymbol{\beta}$ represents a vector of coefficients corresponding to the vector of explanatory variables denoted as $\mathbf{x}$. For an unobserved effects logit estimator, which is also referred to as the conditional logit (CL) estimator, the approach employs "the individual [total] number of successes $t_{1i} = \Sigma_t y_{it}$ as sufficient statistics to concentrate the incidental parameters out of the log-likelihood function.

Thus, β obtained by CL is consistent for $N \to \infty$ and fixed T" (Stammann et al, 2019). The log-likelihood function is then given as

$$L_n(\beta) = \sum_{i=1}^{N} \log[f(\mathbf{y}_i \,|\mathbf{x}_i, \boldsymbol{\beta}, t_{1i})] \tag{2}$$

Wooldridge (2010) finds that for the logit model, the joint distribution of $\mathbf{y}_i$ conditional on $\mathbf{x}_i$, t_i, and a_i does not depend on a_i. This property allows for the use of standard conditional maximum likelihood estimation (CMLE) to estimate $\boldsymbol{\beta}$. This is a characteristic specific to the logit functional form. In this study, the logistic distribution for the error term is chosen, enabling the inclusion of fixed effects. While ongoing research explores fixed effects specification using the probit model (Kunz et al., 2021; Cruz-Gonzalez et al., 2017), the logit model has consistently demonstrated its ability to account for fixed effects within the likelihood framework (Greene, 2008). Furthermore, considering the relatively small sample size in this study, the probit model and linear probability estimation methods are considered unsuitable. Although these methods may yield similar results asymptotically, they are not appropriate for this dataset[7]. The linear probability model in particular includes all cases of never-takers, referring to individuals who never had intentions to have pregnancies or births regardless of changes in treatment variable, thus greatly diluting estimates. Therefore, the logit estimator is deemed the most consistent and unbiased choice for this study's dataset and model.

Due to the absence of an option for cluster-robust standard errors with fixed effects logit, the variables are clustered using the bootstrap method. This approach is recommended by Cameron and Trivedi (2010, p.609). It is worth noting that standard errors in fixed effects models tend to be larger, due to the focus on within-variation of the explanatory variables. For fixed effects logit estimation, respondents with $\sum_{t=1}^{T} y_{it} = 0$ or $\sum_{t=1}^{T} y_{it} = T_i$ are omitted as they exhibit no variation in the outcome variable over the panel's time period. The omission contributes to an increase in standard errors due to the resulting smaller sample size. In this context, when examining year-to-year transitions regarding whether an individual experiences a new birth or pregnancy, a notable persistence is evident among those who have not had children. Specifically, 96.78% of women without a prior birth remain childless, and 96.79% of those without a prior pregnancy continue to remain pregnancy-free. Consequently, many observations are necessarily excluded from the sample size.

[7] Cameron and Trivedi's second edition of *Microeconometrics Using Stata* (2022) continues to advise using logit when fitting binary outcome models with fixed effects.

The coefficients derived from the fixed effects logit model are interpretable as log odds ratios. When using Stata's *-xtlogit-* command, there exists an option to directly report the coefficient estimator as an odds ratio for each variable. For example, if the reported value for the dummy variable "belongs to occupation with high teleworker ratio" is 3, it signifies that if an individual's occupation has a high ratio of teleworkers, the individual's odds of reporting a new birth are multiplied by 3. Similarly, if the reported value for the log-transformed continuous variable "total hours spent commuting and working per week" is 1.03, it indicates that for every 1% increase in hours worked, the odds of reporting a new birth increase by 3%.

Wooldridge (2010) outlines three drawbacks associated with the fixed effects logit model. First, estimating partial effects on response probabilities is not feasible, due to the necessity of having an expected value for unobserved effects denoted as a. Second, estimating average partial effects requires a distribution for a_i, the individual-specific unobserved effect, making it unfeasible. Finally, for consistency, the conditional logit approach assumes conditional independence of y_{it}, implying that the occurrence of birth or pregnancy in a given year is independent. The yearly temporal unit used in the analysis of the JPSED poses challenges in assessing whether pregnancy or birth in a given year is serially dependent on events in the next year. For instance, if the temporal unit were only three months, it would be logically impossible for an individual to give birth three months after previously giving birth. However, in the context of the JPSED, it is entirely possible for a mother to give birth in January of year *t* and then again in November of *t+1*, with a full 12 months gap between the birth of the first child and the conception of the next child. Thus, consecutive births in *t* and *t+1* may be recorded. By testing pairwise correlations of the two outcome variables and their respective lags, it is evident that no two years have a correlation coefficient of higher than 0.1, indicating a very low correlation. Therefore, we assume that y_{it} is serially independent, thus satisfying the consistency assumptions.

5.2. DID model utilizing logit fixed effects

To assess the effects of telework on the likelihood of childbirth and pregnancy before and after the COVID-19 pandemic, we combine the logit fixed effects estimator with the DID framework. This approach employs an exogenous intervention to compare the control and treatment groups. In this specific context, the intervention utilized is the onset of COVID-19 and subsequent increase in the ratio of teleworkers within occupations. The DID model is estimated as follows:

$$y_{it} = \beta_0 + \beta_1 Ratio_i + +\beta_2(Ratio_i \times COVID_t) + \boldsymbol{\beta}\mathbf{x}_{it} + \varepsilon_t + \mu_{it} \tag{3}$$

where y_{it} is one of two binary outcome variables: the log odds that an individual reported a pregnancy in a given year, and the log odds that an individual reported a birth in a given year. The treatment variable $Ratio_i$ is one of two binary treatment variables taking value 1 if the individual's occupation belongs in the 3rd or 4th quartile of ratio of teleworkers; we explain the creation of the treatment variable in greater detail below. We do not include $COVID_t$, a binary variable taking value 1 if the observation year is 2020 or 2021, as a standalone variable due to including time fixed effects. Instead, $COVID_t$ is only used in the interaction term, which estimates the effect of belonging to an occupation that has a high rate of teleworkers during the exogenous shock of COVID-19. This interaction term is the coefficient of interest, which measures the difference between the control and treatment groups before and after the exogenous intervention. These terms can be effectively incorporated into the logit fixed effects estimator, yielding the final empirical model in this study. Other control variables in $\mathbf{x}_{it}$ are the log transformation of household annual income; whether the individual is already raising a child under the age of 20; whether the individual is the main household income earner; and the log transformation of sum of hours per week spent on working and commuting. Lastly, as previously stated, we include individual fixed effects and additionally time fixed effects[8], denoted as ε_t. μ_{it} is an error term for individual *i* at time *t*.

We employ two outcome variables for several reasons. Firstly, considering the yearly basis of data collection in the JPSED, it is possible for births and pregnancies to be reported either within the same year or across two consecutive years. At the same time, it is essential to acknowledge that a pregnancy does not always result in a successful birth and may be terminated through miscarriage or abortion, the latter being a legal and widely practiced means in Japan. The dataset used in this study notably does not report abortions. Lastly, when examining the post-intervention time periods, there are only two years of available data after the onset of the COVID-19 pandemic. Specifically, there is a limited window of approximately 12 months spanning from April 2020 to March 2021 in which a nine-month pregnancy could occur and culminate in a birth by December 2021. Meanwhile, other pregnancies that occur between March and December 2021 will not have a corresponding birth observed yet. Therefore, due to these data limitations, it is expected that the effect of occupation teleworker ratio on birth will not be as strong as the effect on pregnancy.

The treatment variable is a binary variable determined by the ratio of teleworkers within an individual's occupation. Optimally, the preferred approach would have been to directly use the individual's teleworker status as the treatment variable.[9] However, in a DID framework, isolating and interpreting results solely based on an individual's belonging to the treatment or control group

[8] Though we attempted to incorporate region and industry fixed effects, this unfortunately led to the failure of bootstrap replications due to the limited sample size.

[9] Please refer to Appendix C for a comprehensive overview of the outcomes derived from a basic logit fixed effects model, independently estimated for the pre-COVID-19 era. In this supplementary model, the treatment variable used was the teleworking status.

becomes challenging. The estimated interaction effect in that case would combine the effect of being a teleworker both before and after COVID-19, along with the effect of transitioning into being a teleworker after COVID-19. Restricting the control group to individuals who were consistently teleworkers before and after COVID-19 or to those who never teleworked both periods resulted in sample sizes too small to obtain reliable estimates. Finally, the decision to telework is somewhat endogenous. While factors such as education and personal preferences can be addressed through fixed effects modelling, other unobservable factors—such as the individual's workplace policies and willingness to allow teleworking—introduce omitted variable bias. To mitigate this endogeneity concern, this study utilizes the ratio of teleworkers within an individual's occupation as the treatment variable. This approach reduces endogeneity and facilitates easier identification of the treatment and control groups. While the occupation's teleworker ratio is effectively a continuous variable, we define the thresholds based on a specific criterion, allowing for the creation of the binary treatment variable.

The treatment variable is constructed as follows. First, a binary variable is assigned based on individuals' self-reported hours of telework to indicate whether they are teleworkers. This variable takes the value 1 if a person works more than 7 hours per week remotely, and 0 otherwise. It is important to note that in Japan, the legal maximum number of working hours per day is 8[10], although overwork is prevalent. The dataset used in this study shows an average of 7.84 hours worked per day. Therefore, if a person works 7 hours per week remotely in a full-time job, it is likely that they are working at least one full day remotely, or perhaps two days on a part-time basis. We employ this definition to exclude cases where individuals engage in telework for such a limited number of hours that the impact is negligible. For example, individuals who only work 5 hours per week in total and primarily focus on household duties or those who telework for an hour per day during their commute to a full-time work position. Subsequently, we calculate the ratio of teleworkers for each of the 44 occupations in 2016. These ratios are then sorted and divided into four quartiles. In Figure 2, the teleworker ratio for each year is plotted, with the occupations grouped according to the quartiles assigned in 2016. Lastly, the trends of each quartile before and after the COVID-19 pandemic's onset are illustrated. There is a clear jump in teleworker ratio in years 2020 and 2021 for occupations belonging to the third and fourth quartiles, while the first and second quartiles experience minimal change. This increase can be attributed to Japan's state of emergency and subsequent changes in workplace policies during that period.

[Figure 2 here]

[10] Statutory working hours are determined by Article 32 of Japan's Labor Standards Act. The official translation can be found in the Japanese Law Translation Database System: https://www.japaneselawtranslation.go.jp/en/laws/view/3567/ (accessed on 25th January, 2024)

One concern in the analysis pertains to the potential for individuals to change occupations, leading to a shift in quartile assignment over time. Such change could introduce contamination in the treatment group, particularly if individuals switch occupations due to COVID-19-related unemployment. To address this concern, we exclude all individuals who change quartiles in 2020 or 2021 from the analysis. However, it is worth noting that while individuals may switch occupations more frequently, such switches typically occur within the same quartile. This pattern is likely due to the carryover of skillsets from their previous occupations. In the final sample used for analysis, the probability of individuals switching quartiles over the waves of the dataset is only 12-13%. Another potential source of contamination is the possibility of occupations themselves switching quartiles. Unfortunately, due to the relatively small sample size, imposing further restrictions, such as testing occupations that never change quartiles, yields too few observations for meaningful analysis. Appendix D shows a crosswalk of occupations and their movement between quartiles over the years. Upon manual inspection, it is observed that while some movement between quartiles exists, by 2021, the first and fourth quartiles exhibit stability, with changes primarily occurring between their nearest quartiles (e.g. an occupation moving from second to first quartile). Additionally, approximately half of the occupations in both the first and fourth quartiles remain in the same quartile throughout the entire survey period.

To address potential contamination issues, two versions of the treatment variable are estimated. The first version exclusively uses only the first quartile as the control group and the fourth quartile as treatment group. This selection minimizes the likelihood of contamination in treatment group but results in a halving of the number of observations. The second version uses the first two quartiles as the control group and the last two quartiles as the treatment group. This broader treatment group allows for a larger sample size and a more comprehensive analysis of the effect. We refer to models estimated with these treatment variables respectively as Model 1 and Model 2 hereafter. The inclusion of these two models allows for the examination of different treatment group compositions and their effects on the outcomes of interest.

Control variables are chosen for the analysis utilizing a stepwise approach. The baseline model in Eq. (3) is estimated by incrementally incorporating one additional control variable at a time. Any control variables found to be statistically insignificant are discarded, while those demonstrating significance are retained for inclusion in the final multi-covariate analysis. It is worth noting that in Japan, extramarital births are extremely rare, as supported by Suzuki (2006) and Raymo et al (2009)[11]. This greatly simplifies the analysis by eliminating the need to consider

[11] According to Suzuki (2006) and Raymo et al (2009), the proportion of children born to unmarried couples in Japan is negligible, accounting for only 1.93% of all births in 2003. In the JPSED dataset used for this analysis, only 137 (or 3%) of 4,226 new births reported were to unmarried women.

marital status as a grouping variable, which is often important in models of birth likelihood in other countries. Furthermore, fixed characteristics such as education, noted as a significant predictor of parenthood for women (Nomaguchi, 2006), are not included as control variables. This omission is due to the utilization of a fixed effects model, which effectively mitigates the influence of time-invariant factors. In subsequent heterogeneity analysis, education, employment status (full-time or part-time), and having above or below median household income are utilized to explore potential variations in the effect of the treatment variable.

Lastly, we include year fixed effects, in addition to the individual fixed effects already controlled for.[12] The inclusion of year fixed effects allows the capturing of time-specific factors, such as medical technological advancements and societal changes, which may influence birth and pregnancy outcomes. It is worth noting that age is initially found to be a significant control variable. However, when year fixed effects are included, both age and year fixed effects become insignificant due to multicollinearity between them. This multicollinearity naturally arises as age consistently increases at a constant rate over time. While age is certainly an important factor in understanding birth and pregnancy outcomes, the decision is made to prioritise year fixed effects as they encompass not only age but also a broader range of time-varying factors that may impact fertility outcomes. Given that the primary focus of this study is to establish a relationship between telework and fertility choices, the choice is made to forgo the ability to isolate the specific effect of age. Age is a well-studied topic in the fields of family and health economics, and the inclusion of year fixed effects allows for the examination of broader temporal dynamics in relation to telework and birth outcomes.

5.3. Event study model

One of the fundamental assumptions for the validity of the DID approach is the parallel trend assumption, which posits that before the intervention, the difference in outcomes between the treatment and control groups should have followed a similar trend over time. To address this assumption, we conduct an event study employing ordinary least squares (OLS) regression with the following model:

$$y_{it} = \gamma_0 + \sum_{k=-3}^{2} \gamma_k Ratio_i \times COVID_{s(t+k)} + \boldsymbol{\gamma}\mathbf{x}_{it} + v_{it} \tag{4}$$

[12] While it is typical for area fixed effects—in this case, Japanese prefecture fixed effects—to be included in fixed effects models, the low sample size precludes their incorporation. With 47 prefectures and approximately 450 individuals in the multivariate models, even assuming uniform distribution, this would lead to fewer than 10 individuals per observation. Therefore, prefecture fixed effects are regretfully omitted.

where the outcome variable y_{it}, representing either the birth or pregnancy outcomes, is regressed on the interaction of the treatment $Ratio_i$ and the year dummy $COVID_{s(t+k)}$. We utilize the year 2019 as the base year of comparison, considering three years prior to and two years post-2019 as the temporal groups for comparison. We include the same control variables $\mathbf{x}_{it}$ as in the main DID models for greater precision, with error terms for given individuals and time periods indicated by v_{it}. The coefficient γ_k then represents the change in difference between treated and control groups over time. Optimally, if the null hypothesis that $\gamma_k = 0, k < 0$ cannot be rejected, it implies that the parallel trend assumption holds, indicating no significant change in the difference between treatment and control groups over time prior to the intervention.

6. Results

6.1. Event study for pre-trend assumption

First, we examine the results of the event study presented in Eq. (4) for both birth and pregnancy outcomes. Figures depicting the coefficients from the event studies, normalized to 2019 (the year prior to COVID-19), are available in Appendix E. Across all models, it is observed that the pre-trend assumption holds for all cases. The confidence intervals for years 2016, 2017, and 2018 fall within the range of 0, suggesting no significant change in the difference between control and treatment before the intervention. Unfortunately, there does not appear to be a corresponding post-trend increase in any model, except for pregnancy in the year 2020. However, this finding aligns with the expectation that the event study may not exhibit a distinct post-trend increase for the birth outcome, given the nine-month-long delay between pregnancy and birth.

6.2. Basic statistics stratified by treatment and control group

After validating the legitimacy of the DID approach concerning the parallel trend assumption, our analysis proceeds to comparison between the control and treatment groups. Table 2 recapitulates a summary of statistics, delineated this time between individuals in the control group falling within the first and second quartile of teleworker ratios by occupation, and those in the treatment group within the third and fourth quartiles. Notable differences in characteristics emerge: as expected, individuals in the treatment group are more likely to be teleworkers and engage in more teleworking hours. However, individuals in the treatment group also tend to have significantly higher levels of education and income. To address concerns regarding the comparability of the control and treatment groups, we control for observed differences in the baseline models, and extend this control further in the propensity score matching robustness test.

[Table 2 here]

6.3. Main results

Tables 3 and 4 show the results for both Models 1 and 2. The effect of the teleworker ratio by occupation on birth outcomes is largely insignificant, albeit exhibiting a positive trend. Notably, the interaction term for birth attains significance only in the estimation of Model 1, pertaining to the 1st and 4th quartiles of teleworker ratio. This finding suggests that individuals in an occupation characterized by a high teleworker ratio during the COVID-19 pandemic are 1.78 times more likely to experience childbirth. Meanwhile, the interaction term appears to have a more pronounced effect on the odds of reporting a pregnancy. In the more restricted Model 1, the teleworker ratio loses its significance when control variables are included in the model, while Model 2 finds a significant 1.53 increase in odds of pregnancy with control variables. Although omitted here for brevity, it is worth noting that the coefficients are highly significant and align with logical expectations and previous literature. For instance, women are more likely to report both births and pregnancies if they possess a higher household annual income and are less likely to do so if they work longer hours per week, serve as the main income earner in the household, or already have a child under the age of 20. Additionally, the validity of the fixed effects approach over random effects is confirmed through the Hausman test conducted for all models, consistently rejecting the null hypothesis (indicating that a random effects model's coefficients are consistent and efficient) with p-values of 0.000.

[Table 3 here]

[Table 4 here]

6.4. Robustness tests

Utilizing a fixed effects model helps control for many of the unobservable innate characteristics that may affect an individual's assignment to either the treatment or control group. For example, innate ability, motivation, and personal preference for telework are likely to have affected whether an individual chooses an occupation with a high teleworker ratio. Despite utilizing a fixed effects model and finding no significant change in pre-trend difference over time between the treatment and control groups though the event study, uncertainty persists regarding the comparability of the two groups. To address this concern, a robustness test is conducted by employing propensity score matching. First, propensity scores are generated, representing the conditional probability of an individual being assigned to the treatment or control group, considering a vector of control variables. These control variables align with those used in the DID models, supplemented by age, education, and employment status (full-time or part-time). Then, treatment individuals are matched with control individuals based on their propensity scores using nearest neighbour matching. In Appendix F, a figure illustrating the distribution of propensity scores for Models 1 and 2 after the matching process is included, alongside estimates for the average treatment effect and corresponding covariate balances. The matching process does not perfectly eliminate differences in covariates, and in fact marginally amplifies differences in some variables. However, of paramount significance is that propensity score matching effectively mitigated dissimilarities in educational attainment and full-time versus part-time employment across all 4x4 model arrangements involving birth/pregnancy and Model 1/Model 2. Pre-matching, these two variables exhibited the largest differences and were precluded from inclusion as control variables due to their time invariance or within-variation. Consequently, the results of propensity score matching are retained for meticulous consideration, acknowledging the inherent imperfections in the matching process.

To ensure comparability between the treatment and control groups, observations outside the overlap assumption or lacking common support are excluded from the analysis. This selective procedure results in a set of matched observations. Consequently, the baseline models are re-estimated, now restricted to the propensity score-matched observations. Detailed tables presenting the findings of the propensity score matching can be found in Appendix F.

The results obtained from propensity score-matched observations appear robust. While Model 1, concerning pregnancy, lacks significance in its interaction term, Model 2 continues to suggest that individuals in occupations with a high teleworker ratio experience a 1.605 times increase in the odds of having a pregnancy at the 5% level of significance. The results for birth outcomes, irrespective of the treatment used, remain positive yet statistically insignificant.

To further validate the findings, a random permutation placebo test is conducted. This test involves the random assignment of treatment to observations, with the expectation that if the original treatment does have a significant effect, the resulting estimates from repeated randomization should be insignificant. As per Heß (2017), the null hypothesis tested is that the observed outcome for an individual remains the same regardless of whether they are under treatment or not. Rejecting the null hypothesis implies that treatment does indeed have a significant effect. The random permutation tests are conducted using the -*ritest*- Stata command, involving 500 random permutations of the treatment effect with bootstrapped standard error computed 20 times for each permutation. In Model 1, the p-value remains insignificant for both birth and pregnancy, while Model 2's pregnancy estimate suggests that the null hypothesis can be rejected at the 10% level of significance. The coefficients of the random permutation test are reported as log odds, unlike the preceding estimations presented as odds ratios. Converting the odds ratios for pregnancy, the insignificant Model 1 suggests a 1.809 multiplier to the odds of experiencing a pregnancy, and the significant Model 2 estimates a 1.5302 multiplier. Notably, Model 2's estimated coefficient aligns with the results obtained in both Table 4 and the propensity score-matched robustness test, implying a high degree of robustness. More detailed results can be found in Appendix F.

To address potential sample selection bias due to women exiting the workforce in the year of pregnancy or childbirth, a final robustness test is conducted. As indicated in Figure 1, 48% of women did not have a job in the year they gave birth. While this dropout is unavoidable, it becomes a concern if the decision to withdraw from the labor force is influenced by the treatment of being in an occupation with a high teleworker ratio. For example, it is possible that teleworking women, who are more likely to work from home during pregnancy, are more likely to retain their jobs. This question is examined by generating a new treatment variable for years in which an individual does not have a job for at least one month out of twelve. This new treatment variable assumes the same occupation value as the preceding year if the current year lacks an occupation recorded, allowing for estimation of the effect of their occupation even in unemployed years. The outcome variable, indicating labor force participation, is then regressed on the new treatment, thus including individuals without a job. The same control variables as in previous models are included, excluding total hours worked and commuted, which would otherwise limit the sample by excluding those who do not work or commute.

The results of this new DID model[13], which regresses labor force participation on "persistent" occupation, find that the treatment assignment is not a significant predictor of unemployment regardless of the quartile model or considered control variables. Therefore, even if women are dropping out of the employed sample, this phenomenon does not occur disproportionately between the treatment and control groups. This implies that the effect of telework is confined to those who choose to stay in the labor force. However, it can be seen that the number of individuals in this estimation has decreased compared to previous models, which may compromise the reliability of the results. This limitation arises from the dataset itself and cannot be overcome without a larger sample size.

To further examine the relationship between treatment effect and unemployment, an additional analysis is conducted utilizing LFP as a robustness check. The sample is stratified based on employment status, followed by testing the effect of the treatment for each subgroup. Intuitively, the effect of belonging to an occupation with a high telework ratio should logically only be evident among those who are currently employed. The expectation is that an unemployed person who previously held a telework-capable job should not experience changes in their likelihood of experiencing a birth or pregnancy once they have left the job. If significant effects are estimated even for the unemployed individuals, it raises the possibility of an omitted variable

[13] To access detailed results, please refer to Table F10, Appendix F.

common to occupations with high telework ratios, potentially biasing the previous results. Therefore, regressions comparing the treatment effect on two groups are conducted: those in the labor force and those who are not.

For pregnancy outcomes in the "has job" group, the results align with expectations[14], as the coefficients of the interaction terms are significant and greater than one in both models, indicating a positive effect on pregnancy rates. In addition, the estimated odds ratio of 1.593 for Model 2 is consistent with previous estimates. However, the lack of statistical significance in the "does not have job" group in both models, though consistent with the expected results of this robustness test, may be attributed to the insufficient sample size of less than 400 individuals per regression. Consequently, it remains challenging to definitively conclude that the interaction term is indeed insignificant for those not in the labor force. For the same reason, the coefficient estimates for birth outcomes are insignificant in all cases. Nevertheless, certain factors support the validity of the pregnancy results. The pseudo R^2 values, indicating the goodness-of-fit of the models, are slightly higher for "does not have job" groups of both Model 1 and 2 than for "has job" groups. In addition, the pseudo R^2 values for the models involving individuals without jobs are slightly higher than even the baseline results presented in section 6.3. Considering these factors, these results are included for consideration. It is important to exercise caution and interpret these results for individuals without jobs while keeping in mind the limitations posed by the small sample size.

6.5. Heterogeneous treatment effects

To assess the heterogeneous treatment effects, the analysis is stratified into three binary categories: education (secondary or tertiary), employment status (full-time or part-time), and household income (above or below median). For the education variable, given Japan's robust secondary school education system[15], a binary variable is created where 1 represents tertiary-level education and 0 otherwise. Since the majority of individuals in the sample do not change educational level during the survey's timespan, the logistic fixed effects model allows for the assessment of the otherwise time-invariant conditional effect. Regarding the employment status, the statutory working hours per week in Japan (40 hours) serve as a threshold for creating a binary variable.[16] This variable takes value 1 if an individual works more than 40 hours a week and 0 otherwise. The regression stratified by employment status also includes the logarithm of total

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[14] To access detailed results, please refer to Tables F11 and F12, Appendix F.

[15] The proportion of individuals with only pre-high school education represents a mere 2.97% of the entire dataset in the JPSED. For the analytical sample, this figure further diminishes to 2.17%.

[16] Statutory working hours are determined by Article 32 of Japan's Labor Standards Act. The official translation can be found in the Japanese Law Translation Database System: https://www.japaneselawtranslation.go.jp/en/laws/view/3567/ (accessed on 25th January, 2024)

working hours as a control variable. Lastly, the median household income of the sample is 6 million JPY, or roughly USD $43,000 at time of analysis. Similar to the full-time versus part-time variable, a binary variable is generated, taking the value of 1 if an individual has above-median income and 0 otherwise. The logarithm of household annual income continues to be included as a control variable. Upon further division into smaller subsamples, the low sample size of Model 1 leads to unreliable estimations for all three binary categories. Consequently, only the results from Model 2, along with the propensity score-matched version of Model 2, are reported. For brevity, the results for birth outcomes, which remain positive yet statistically insignificant, are omitted, and only the outcomes for pregnancy outcomes are presented.[17]

Tables 5, 6 and 7 report the results of heterogeneity analysis for education, full-time versus part-time, and median income respectively. The consistent findings across all three categories indicate that being in an occupation with a high teleworker ratio is associated with increased odds of pregnancy. This effect is particularly pronounced for individuals with tertiary education, those working full-time, and those with above-median income. These results make intuitive sense. Higher education is often linked to the necessary computer skills for telework, and full-time employees are more likely to benefit from increased leisure time through telework. Both of these effects also interact with income levels. Higher education leads to higher earnings, and full-time workers naturally earn more than their part-time counterparts.

[Table 5 here]

[Table 6 here]

[Table 7 here]

7. Discussion

This study contributes to the existing literature by highlighting the potential impact of telework on fertility outcomes, taking advantage of the unique context of the COVID-19 pandemic. The inclusion of various factors highlighted in previous literature, coupled with robustness tests, enhances the validity of the findings. Our results indicate that employment in a telework-intensive occupation is positively associated with the likelihood of experiencing a pregnancy, resulting in a 1.5 times increase in the odds. Moreover, the effect of telework on fertility is observed to vary across groups with different demographic and socio-economic characteristics, with a more pronounced impact on women with higher education, those working full-time, and those with above-median income. However, it is essential to note that this study did not uncover the precise mechanisms through which telework affects fertility outcomes. Regardless, it presents a novel

[17] Heterogeneous treatment results for birth outcomes can be found in Appendix G.

contribution to existing research by investigating the actual fertility outcomes, encompassing both women without children and women who already have children. This stands in contrast to previous studies that primarily focused on fertility intentions and were largely limited to women who had already had children.

One of the principal drawbacks to this study stems from the relatively small sample size, necessitated by the use of a logistic regression model. This constraint precluded the inclusion of important fixed effects, specifically region and industry, in all models due to the limited number of individuals per category within these fixed effects. Efforts to address this limitation, including attempts during bootstrapping, often resulted in convergence failure. Similarly, this study faced sample size constraints in conducting a more comprehensive heterogeneous analysis, encompassing variables such as age brackets, firm size, and industry. Unfortunately, this is a data limitation that cannot be overcome without a significantly larger sample size.

Another noteworthy limitation is the inability to estimate the long-term effects of telework on fertility rates, particularly whether change in behaviour and telework rates persist. While the study hypothesised that the statistically significant effect of telework is observed only for pregnancies, potentially due to the limited survey time period post-COVID-19 pandemic, other factors may be responsible for this outcome. Telework may influence pregnancy odds by granting workers more leisure time with their partners, even if the pregnancies are unplanned and may not be carried to term. Individuals might also perceive telework as a temporary shift in their working conditions rather than a permanent one. Attitudes towards telework and return-to-office further complicate the assessment of long-term effects. Some studies, like Bick et al. (2023), suggest that the increase in the prevalence of telework is permanent in the United States. However, a survey report by Persol Research and Consulting Co. (2023) found that Japan's telework rates in July 2023 were the lowest since the beginning of the pandemic[18]. The uncertainty regarding Japanese workers' and firms' preferences for continued telework makes it unclear whether workers can count on a stable future of teleworking when making ex-ante fertility decisions.

While the current study does not explicitly employ causal inference to analyse the mechanism of telework, the descriptive statistics from the dataset align with both the work-leisure time allocation hypothesis and the effect of enabled relocation outlined in this paper's introduction.

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[18] The data from Persol (2023), a private think tank, offers valuable insights into the prevalence of telework in Japan. According to their sample of over 20,000 individuals at companies with minimum 10 employees, the teleworking rate was 22.2% in July 2023, a notable increase from 13.2% reported in March 2020. The data also reveals a peak teleworking rate of 28.5% in February 2022. For those interested in more detailed information, the survey conducted by Persol can be accessed on their website at the following link : https://rc.persol-group.co.jp/thinktank/data/telework-survey8.html (accessed on 25th January, 2024)

Among both women and men in remote-capable jobs, a higher proportion of teleworkers (ranging from 5.6% to 9.2%) reported relocating during the survey period compared to non-teleworkers (ranging from 6.4% to 7.9%), with a notable increase post-COVID-19. This finding supports the notion that telework facilitates greater flexibility in residential choices. As for commute time, although teleworkers report a higher daily commute length, their total commute time per week is lower by approximately one hour. This discrepancy is likely due to high-commute workers deliberately choosing to telework to reduce the number of days they need to commute. The promising results of the effect of telework on pregnancy, coupled with the recognition of the need for larger bodies of evidence regarding telework and LFP, suggest that this area of research holds potential for yielding further insightful findings.

8. Conclusion

Working in an occupation characterized by a high proportion of teleworkers indeed has a significant positive effect on the likelihood of having a pregnancy. However, while the results are positive for the likelihood of having a birth, they lack statistical significance. The absence of significance may be attributed to the limited time period covered in this study, during which some pregnancies may not yet have reached their conclusion. Hence, it would be worthwhile to revisit this topic in the future using data from additional years. This topic is particularly noteworthy in the aftermath of the COVID-19 pandemic, which may have caused a paradigm shift in both employees' and employers' attitudes towards telework. Although this study sheds light on potential insights that may assist Japanese women in balancing their family and professional lives, the underlying mechanisms through which telework affects fertility outcomes remain unclear and deserve further investigation. Further research efforts should be directed towards gaining a deeper understanding of these mechanisms to provide more comprehensive insights into the effects of telework on family formation dynamics and career trajectories. This will contribute to a more nuanced comprehension of the impact of telework on various aspects of individuals' lives and may inform policy discussions and workplace practices.

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Figures and Tables

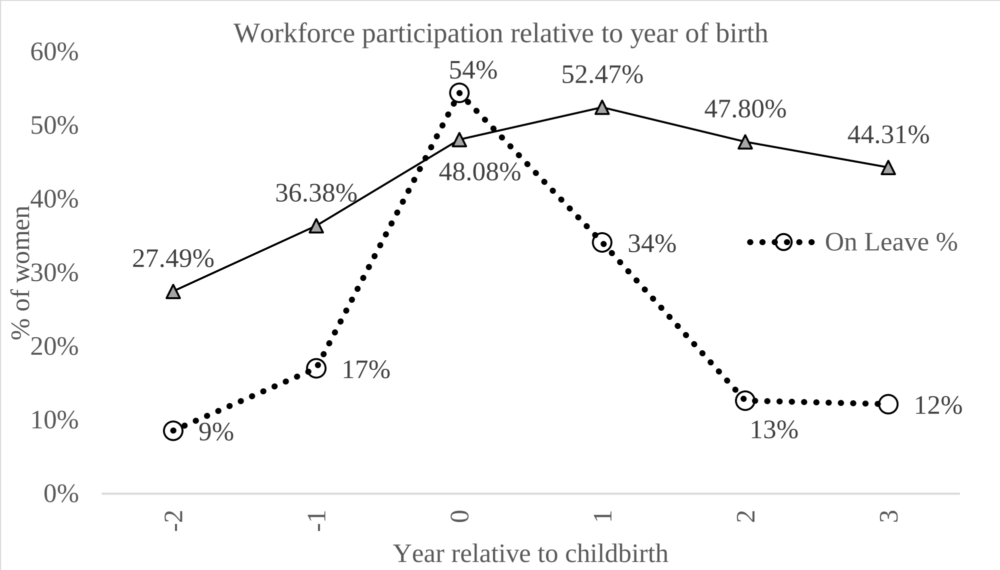

Figure 1: Workforce participation relative to year of birth.

Source: Estimated based on the JPSED.

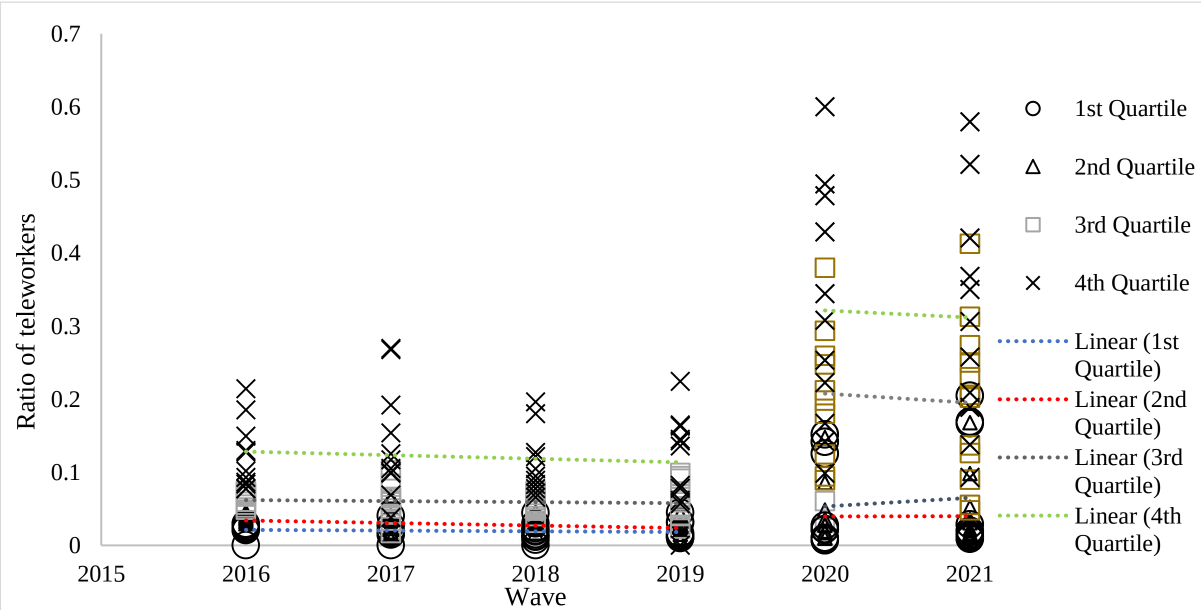

Figure 2: Trend of occupations' teleworker ratios pre- and post-COVID-19.

Source: Estimated based on the JPSED. Quartiles are based on assignment in 2016.

Table 1: Descriptive statistics of employed Japanese women, ages 15-55

	Whole sample			Analytical subsample		
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Count	Mean	SD	Count	Mean	SD
Age	87,690	37.24	10.5	6,215	32.21	5.995
Raising child under age of 20	87,690	0.281	0.45	6,215	0.419	0.493
Number of children	35,680	1.814	0.7774	4,247	1.694	0.844
Married	87,690	0.468	0.499	6,215	0.824	0.381
Birth in last year	87,690	0.0328	0.178	6,215	0.241	0.427
Pregnancy in last year	87,690	0.0406	0.197	6,215	0.305	0.46
Highest level of education:						
Pre-high school	81,469	0.0231	0.1502	6,115	0.0217	0.1459
High school	81,469	0.3195	0.4662	6,115	0.2597	0.4385
Tertiary	81,469	0.64	0.4799	6,115	0.6983	0.459
Postgraduate	81,469	0.0174	0.1309	6,115	0.0203	0.1409
Work days/week	82,609	4.591	1.102	6,191	4.612	1.139
Work hours/week	82,609	32.32	13.89	6,191	32.49	13.62
Work hours/day	82,609	6.851	2.294	6,191	6.787	2.316
Teleworker	87,316	0.0519	0.222	6,215	0.0502	0.218
Telework hours/week	4,534	22.63	15.31	312	21.59	15.59
Have second job:						
No	87,690	0.8551	0.3519	6,215	0.8747	0.3311
1 other job	87,690	0.1113	0.3145	6,215	0.0983	0.2976
More than 1 other job	87,690	0.0336	0.1801	6,215	0.027	0.1622
Daily time (min) spent on:						
Childcare, weekday	82,899	165.2	192.1	6,215	308.7	317.7
Childcare, weekend	82,899	245.8	279.7	6,215	492.3	417.3
Two-way commute	82,899	52.73	58.87	6,215	51.66	52.8
Household annual income (10,000 yen)	87,690	464.9	388.9	6,215	611.5	355.2
Is main household income earner	87,690	0.3267	0.469	6,215	0.157	0.364
Number of respondents	38,374	38,374	38,374	1,697	1,697	1,697

Source: Estimated based on the JPSED

Table 2: Descriptive statistics of control and treatment group

	Control			Treatment			Difference in Means	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	Count	Mean	SD	Count	Mean	SD	Difference	P-Value
Age	6,413	31.98	5.96	1,601	31.4	6.1	0.58	0.00
Number of children	4,366	1.70	0.84	1,091	1.67	0.85	0.03	0.27
Highest level of education:								
Pre-high school	6,413	0.02	0.16	1,601	0.02	0.15	0.00	0.78
High school	6,413	0.27	0.44	1,601	0.23	0.42	0.04	0.00
Tertiary	6,413	0.67	0.47	1,601	0.69	0.46	-0.02	0.14
Postgraduate	6,413	0.02	0.13	1,601	0.03	0.17	-0.01	0.00
Work days/week	6,384	4.56	1.16	1,599	4.44	1.3	0.12	0.00
Work hours/week	6,384	31.84	13.54	1,599	30.42	15.85	1.42	0.00
Work hours/day	6,384	6.72	2.24	1,599	6.49	2.79	0.23	0.00
Teleworker	6,413	0.03	0.18	1,601	0.1	0.3	-0.07	0.00
Telework hours/week	6,413	0.84	5.04	1,601	2.56	7.95	-1.72	0.00
Have second job:								
No	6,413	0.88	0.33	1,601	0.86	0.35	0.02	0.02
1 other job	6,413	0.09	0.29	1,601	0.11	0.31	-0.01	0.10
More than 1 other job	6,413	0.03	0.16	1,601	0.03	0.18	-0.01	0.08
Daily time (min) spent on:								
Childcare, weekday	6,413	311.29	319.12	1,601	337.3	344.05	-26.01	0.00
Childcare, weekend	6,413	494.97	417.97	1,601	501.91	435.18	-6.94	0.56
Two-way commute	6,413	50.22	51.10	1,601	54.27	62.39	-4.05	0.01
Household annual income (10,000 yen)	6,413	588.33	341.18	1,601	617.76	417.74	-29.43	0.00
Is main household income earner	6,413	0.15	0.35	1,601	0.15	0.36	-0.01	0.32

Source: Estimated based on the JPSED

Table 3: Effect of occupation's teleworker ratio on birth				
	Model 1		Model 2	
	(1)	(2)	(3)	(4)
Independent Variable				
Birth (birth = 1, 0 otherwise)				
Teleworker ratio	1.581	1.825	1.109	1.228
	(1.329)	(2.544)	(0.158)	(0.305)
Interaction	1.784*	1.319	1.152	1.065
	(0.624)	(0.811)	(0.214)	(0.336)
Year fixed effects	X	X	X	X
Control variables		X		X
Observations	1,563	1,526	4,621	4,517
Number of individuals	464	456	1,285	1,259
Pseudo R^2	0.00969	0.594	0.00224	0.597

Notes: The reported results are in the form of odds ratios. Panel-robust standard errors, presented in parentheses, are calculated using 1000 bootstrap repetitions. The goodness of fit is estimated by pseudo R^2. In Model 1, "teleworker ratio" binary treatment variable takes 1 if the individual belongs to the 4th quartile of occupation's teleworker ratio and 0 if the individual belongs to the 1st quartile. For Model 2, the treatment variable takes 1 if the individual belongs to the 3rd or 4th quartile, and 0 otherwise. Control variables include the logarithm of household annual income, the logarithm of total work and commute hours per week, household main earner, and whether the individual is already raising a child under the age of 20. P-values indicated as follows: *** p<0.01, ** p<0.05, * p<0.1.

Source: Estimated based on the JPSED.

Table 4: Effect of occupation's teleworker ratio on pregnancy				
	Model 1		Model 2	
Independent Variable	(1)	(2)	(3)	(4)
Pregnancy (pregnancy = 1, 0 otherwise)				
Teleworker ratio	1.129	1.901	1.003	1.165
	(0.584)	(1.037)	(0.132)	(0.171)
Interaction	2.297**	1.809	1.549**	1.530**
	(0.855)	(0.694)	(0.306)	(0.309)
Year fixed effects	X	X	X	X
Control variables		X		X
Observations	1,836	1,788	5,150	5,024
Number of individuals	543	532	1,469	1,438
Pseudo R^2	0.0104	0.183	0.00721	0.191

Notes: The reported results are in the form of odds ratios. Panel-robust standard errors, presented in parentheses, are calculated using 1000 bootstrap repetitions. The goodness of fit is estimated by pseudo R^2. In Model 1, "teleworker ratio" binary treatment variable takes 1 if the individual belongs to the 4th quartile of occupation's teleworker ratio and 0 if the individual belongs to the 1st quartile. For Model 2, the treatment variable takes 1 if the individual belongs to the 3rd or 4th quartile, and 0 otherwise. Control variables include the logarithm of household annual income, the logarithm of total work and commute hours per week, household main earner, and whether the individual is already raising a child under the age of 20. P-values indicated as follows: *** p<0.01, ** p<0.05, * p<0.1.

Source: Estimated based on the JPSED.

Table 5: Effect of occupation's teleworker ratio on pregnancy, split by education level

	Model 2		Model 2 (PSM)	
	(1)	(2)	(3)	(4)
Independent Variable	Secondary	Tertiary	Secondary	Tertiary
Pregnancy (pregnancy = 1, 0 otherwise)				
Teleworker ratio	1.377	0.997	1.377	0.997
	(0.345)	(0.200)	(0.331)	(0.192)
Interaction	1.168	1.630**	1.168	1.630**
	(0.654)	(0.371)	(0.628)	(0.362)
Year fixed effects	X	X	X	X
Control variables	X	X	X	X
Observations	1,330	3,552	1,330	3,552
Number of individuals	394	1,011	394	1,011
Pseudo R^2	0.155	0.207	0.155	0.207

Notes: The reported results are in the form of odds ratios. Panel-robust standard errors, presented in parentheses, are calculated using 1000 bootstrap repetitions. The goodness of fit is estimated by pseudo R^2. P-values indicated as follows: *** p<0.01, ** p<0.05, * p<0.1.
Source: Estimated based on the JPSED.

Table 6: Effect of occupation's teleworker ratio on pregnancy, split by part-time/full-time work

	Model 2		Model 2 (PSM)	
	(1)	(2)	(3)	(4)
Independent Variable	Part-time	Full-time	Part-time	Full-time
Pregnancy (pregnancy = 1, 0 otherwise)				
Teleworker ratio	1.111	0.853	1.059	0.839
	(0.241)	(0.218)	(0.254)	(0.211)
Interaction	1.349	1.718*	1.469	1.775*
	(0.475)	(0.515)	(0.526)	(0.522)
Year fixed effects	X	X	X	X
Control variables	X	X	X	X
Observations	1,863	2,031	1,863	2,031
Number of individuals	616	619	616	619
Pseudo R^2	0.138	0.237	0.138	0.237

Notes: The reported results are in the form of odds ratios. Panel-robust standard errors, presented in parentheses, are calculated using 1000 bootstrap repetitions. The goodness of fit is estimated by pseudo R^2. P-values indicated as follows: *** p<0.01, ** p<0.05, * p<0.1.
Source: Estimated based on the JPSED.

Table 7: Effect of occupation's teleworker ratio on pregnancy, split by median income

	Model 2		Model 2 (PSM)	
Independent Variable	(1) Below median income	(2) Above median income	(3) Below median income	(4) Above median income
Pregnancy (pregnancy = 1, 0 otherwise)				
Teleworker ratio	1.198	1.204	1.135	1.180
	(0.282)	(0.301)	(0.272)	(0.310)
Interaction	1.318	1.790**	1.369	1.879**
	(0.464)	(0.476)	(0.528)	(0.531)
Year fixed effects	X	X	X	X
Control variables	X	X	X	X
Observations	1,719	2,172	1,660	2,149
Number of individuals	556	683	541	676
Pseudo R^2	0.168	0.141	0.168	0.142

Notes: The reported results are in the form of odds ratios. Panel-robust standard errors, presented in parentheses, are calculated using 1000 bootstrap repetitions. The goodness of fit is estimated by pseudo R^2. P-values indicated as follows: *** p<0.01, ** p<0.05, * p<0.1.
Source: Estimated based on the JPSED.

Appendix A: List of occupations by gender, individuals aged 15-55 years

	2016			2021		
Occupation	Male	Female	Total	Male	Female	Total
Service occupations related to domestic housekeepers, home helpers	46	105	151	54	74	128
Environmental sanitation service workers	115	170	285	112	176	288
Food and drink preparation occupations	265	283	548	267	313	580
Hospitality attendant and waiter occupations	465	1,131	1,596	497	1,150	1,647
Facility keeping services	130	16	146	117	11	128
Miscellaneous service workers	482	198	680	496	161	657
Security and protective occupations	345	28	373	506	42	548
Occupations related to agriculture, forestry and fisheries	112	45	157	179	80	259
Drivers	615	34	649	722	36	758
Miscellaneous service workers related to transport and communications	263	31	294	361	45	406
Manufacturing and production process workers	1,782	541	2,323	2,028	619	2,647
Miscellaneous labor workers	384	375	759	585	457	1,042
Managers of companies, organisations, etc	1,338	185	1,523	1,432	240	1,672
General clerical occupations	1,811	4,274	6,085	2,239	4,274	6,513
Planning and promotion business occupations	235	141	376	281	178	459
Financial clerks, accountants, numerical clerks	250	567	817	247	432	679
Sales occupations	860	277	1,137	1,059	302	1,361
Office automation device operators	50	148	198	50	93	143
Merchandise salespersons	360	832	1,192	475	936	1,411
Brokerage and agent	18	13	31	18	7	25
Miscellaneous office workers	65	69	134	71	66	137
Technicians for agriculture, forestry, fisheries and food	101	57	158	146	74	220
Mechanical and electrical engineers	472	28	500	579	41	620
Mining and industrial engineers	30	0	30	32	2	34
Construction, earth moving, survey engineers	615	74	689	638	92	730
Engineers related to software and internet	866	161	1,027	932	193	1,125
Internet-related professionals	59	42	101	61	43	104
Miscellaneous engineers	237	24	261	256	48	304
Medical doctors, dentists, veterinarians, pharmacist	92	59	151	134	140	274
Health, midwifery, nursing professionals	62	435	497	115	610	725
Medical engineers	168	181	349	291	282	573
Miscellaneous medical health professionals	62	131	193	80	177	257
Social welfare professionals	290	588	878	441	710	1,151
Professionals related to legal affairs	46	4	50	63	12	75
Professionals related to management	32	10	42	46	23	69
Literature writers, journalists, editors	30	29	59	39	33	72
Artists, photographers, designers	58	56	114	46	45	91
Consultants	18	8	26	20	9	29
Finance-related professionals	42	34	76	43	22	65
Game-related professionals	9	4	13	12	8	20
Advertising, publishing and media professionals	49	26	75	59	34	93
Printing-related professionals	68	32	100	63	26	89

Professionals related to fashion and interior	19	37	56	18	25	43
Miscellaneous professionals and technical occupations	431	406	837	606	443	1,049
Uncategorized	1,335	1,244	2,579	1,512	1,251	2,763
Total	15,182	13,133	28,315	18,028	14,035	32,063

Source: Estimated based on the JPSED.

Appendix B: Summary statistics figures

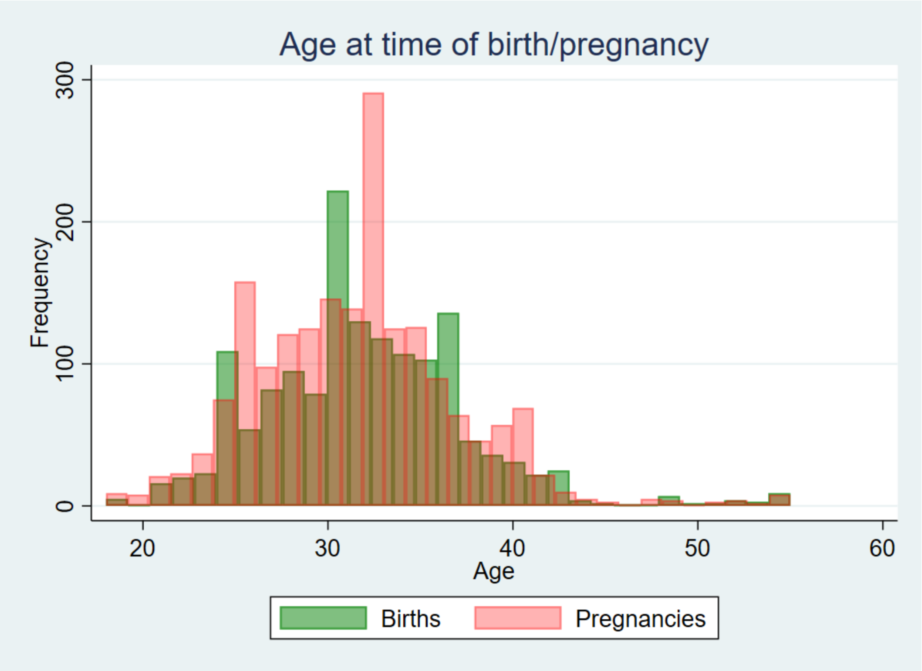

Figure B1: Age at time of birth/pregnancy. Source: Estimated based on the JPSED.

Appendix C: Pre-COVID-19 logit fixed effects model

This appendix covers the supplementary results of logistic fixed effects regression, focusing on the variable of being a teleworker as the main explanatory variable. Unlike the main study, which considers the teleworker ratios of occupations, this analysis directly incorporates individual telework status. A the study lacks a DID framework enabled by a natural experiment like the COVID-19 pandemic, data from 2016 to 2019 is utilized, with a brief inclusion of 2020 to construct an indicator variable for remote-capable jobs.

To ensure the relevance of the analysis, female respondents aged 55 and older are excluded, approximating the upper age for menopause. In contrast to the main study, male respondents are retained, as the hypothesis suggests that men's telework status may contribute to family formation in terms of the labor-leisure time use hypothesis. Outcome variables are specified in terms of the marital unit, considering whether the respondent or their spouse has a child. Male observations are retained regardless of age as their spouse's ages are not recorded. However, this avenue of analysis is limited due to the availability of fewer variables regarding the respondent's spouse than the respondent. For example, it is not possible to know the spouse's telework status, occupation, time use, education and more. Lastly, survey responses do not contain any household identification variables, creating the possibility that two individuals in the sample could be from the same household and may be referring to each other. This situation poses challenges, particularly in terms of un-clustered standard errors, which may lead to biased estimates. Unfortunately, there is no straightforward way to overcome this issue given the available data constraints.

The dataset is split into two components: those with remote-capable jobs and those without. The JPSED provides a list of 224 possible occupation codes, such as bus driver, civil engineering construction management, and fashion designer. In 2020, many jobs were forced to become telework jobs in order to limit the spread of COVID-19. Using ex-post reasoning, we create a list of all occupations that were worked remotely in 2020 from home, and therefore should have been remote-capable in all previous years. We then limit the dataset to only those with remote-capable observations.

The analytical sample consists of a representative sample of individuals in remote-capable occupations, ages 15 years old and older, capped at age 55 for female respondents. The dataset spans four year-periods from 2016-2019, with 49,169 person-year observations (an average of 2.7 years per individual), allowing for longitudinal analysis despite unbalanced data.

Logit fixed effects methodology is employed, examining two outcome variables: birth and pregnancy. The main variable of interest is telework, explored through a dummy variable taking the value 1 if a person works more than 7 hours a week remotely, and 0 otherwise. A continuous variable of the number of telework hours per week is also considered. Regressions with and without lagged telework variables are included, expecting lagged telework to be more significant for birth than pregnancy, following the labor-leisure choice model. If telework increases leisure time and thus leads to pregnancy, then current telework status should be more important for pregnancy than the previous year's telework status.

Control variables include living with their spouse, current child-rearing status, employment status (current and lagged), annual income, and year fixed effects.

Table C1 first confirms the multicollinearity among the explanatory variables, crucial due to the use of one-year lagged telework and employed variables, which may be serially correlated and so may impact standard errors.

Table C1: correlation matrix of explanatory variables

	Teleworker	Teleworker lagged	Employed	Employed lagged	Childraiser	Spouse cohabitation
Teleworker	1.00					
Teleworker lagged	0.20***	1.00				
Employed	0.00	-0.00	1.00			
Employed lagged	-0.00	0.00	0.17***	1.00		
Childraiser	-0.01***	-0.01***	-0.08***	-0.04***	1.00	
Spouse cohabitation	0.01***	0.01**	-0.03***	-0.01***	0.49***	1.00
HH annual income	0.05***	0.03***	0.02***	0.01***	0.22***	0.44***

Source: Estimated based on the JPSED.
Note: * p<0.05 ** p<0.01 *** p<0.001

The results show that none of the variables demonstrate excessive collinearity. Both the teleworker and employed variables show correlation coefficients of at most 0.2, which are not a cause of concern. The results for the telework hours variable have been omitted, due to a correlation coefficient of 0.16 with its lag, accompanied by p-value less than 0.001. Variables such as whether the respondent is raising a child, cohabitating with their spouse, and their household's annual income exhibit moderate correlation with each other but have not reached a level of concern.

These explanatory variables underwent a rigorous selection process, involving testing and discarding several other variables in reduced-form regressions, which are omitted from this discussion. The excluded variables either presented excessive missing data or lacked sufficient within-variation, resulting in subsample sizes too small for asymptotically normal estimates. This set includes considerations such as whether the individual is the main household's main income earner, whether telework was offered by the individual's place of employment for workers with childcare responsibilities, and whether the individual took maternity leave during their pregnancy. Furthermore, interaction terms between explanatory variables were largely found to be insignificant, and, as such, have not been reported.

Table C2: Effect of telework on birth	Female		Male	
	(1)	(2)	(3)	(4)
Independent Variable				
Birth (1 if family unit gave birth to a child, 0 otherwise)				
Teleworker	3.496**	3.017**	0.978	0.979
	(2.024)	(1.372)	(0.177)	(0.237)
Teleworker lagged		0.706		0.710*
		(0.263)		(0.139)
Year fixed effects	X	X	X	X
Control variables	X	X	X	X
Observations	1,665	1,403	3,961	3,567
Number of respondents	581	492	1,451	1,325

Source: Estimated based on the JPSED.

Table C3: Effect of telework on pregnancy	Female		Male	
	(1)	(2)	(3)	(4)
Independent Variable				
Pregnancy (1 if family unit had pregnancy, 0 otherwise)				
Teleworker	1.328	1.747	1.179	1.083
	(0.494)	(0.750)	(0.266)	(0.235)
Teleworker lagged		1.025		0.883
		(0.362)		(0.211)
Year fixed effects	X	X	X	X
Control variables	X	X	X	X
Observations	1,795	1,499	3,362	2,984
Number of respondents	629	526	1,240	1,110

Source: Estimated based on the JPSED.
Notes: The reported results are in the form of odds ratios. Panel-robust standard errors, presented in parentheses, are calculated using 200 bootstrap repetitions. P-values indicated as follows: *** p<0.01, ** p<0.05, * p<0.1.

Tables C2 and C3 present the findings for birth and pregnancy outcomes, respectively. Notably, the effect of telework on birth outcomes is positively significant for women. Even after including the lagged teleworker variable, which is unexpectedly insignificant itself, women engaged in telework are at least 3.017 times more likely to give birth compared to those not teleworking in a remote-capable occupation. However, the hypothesised effects of telework and employment on birth outcomes are not observed in men. Surprisingly, if a male respondent engaged in telework in the previous year, the odds of his spouse giving birth in the current year decreased by 29%. This counterintuitive result contradicts the labor-leisure choice hypothesis, albeit at a significance level of 90%. Furthermore, employed men demonstrate an 89% lower odds of their spouse giving birth, a result significant at the 99% level. This deviation from common family formation theory, suggesting that job insecurity may delay births, is highly unusual. Moreover, it is unlikely that men leave their jobs in a manner that compels them to focus on childrearing, as women might. The anomalous nature of these results raises the possibility that estimators for male respondents are biased due to a lack of information regarding their spouses. Contrary to hypotheses, telework has no significant effect on whether a respondent's marital unit experiences a pregnancy, irrespective of gender.

Appendix D: Occupations' teleworker ratio quartiles

Occupations are categorized into quartiles of their teleworker ratio, and the table tracks changes in their quartiles over the survey's time periods. Occupations in italics remain in the same quartiles relative to the initial period of 2016. For years 2017 onwards, the "Relative Place" column records any change in quartile relative to 2016. For example, the occupation "Drivers" transitions from the 2nd quartile in 2016 to the 1st quartile in subsequent years.

	2016
1st Quartile	Facility keeping services
	Financial clerks, accountants, numerical clerks
	Health, midwifery, nursing professionals
	Hospitality attendant and waiter occupations
	Manufacturing and production process workers
	Medical engineers
	Merchandise salespersons
	Mining and industrial engineers
	Miscellaneous labor workers
	Miscellaneous service workers related to transport and communications
	Security and protective occupations
	Technicians for agriculture, forestry, fisheries and food
2nd Quartile	Drivers
	Environmental sanitation service workers
	Food and drink preparation occupations
	General clerical occupations
	Medical doctors, dentists, veterinarians, pharmacists
	Miscellaneous medical health professionals
	Miscellaneous service workers
	Occupations related to agriculture, forestry and fisheries
	Printing-related professionals
	Social welfare professionals
3rd Quartile	Uncategorized
	Construction, earth moving, survey engineers
	Finance-related professionals
	Managers of companies, organisations, etc
	Mechanical and electrical engineers
	Miscellaneous engineers
	Miscellaneous office workers
	Miscellaneous professionals and technical occupations
	Planning and promotion business occupations
	Professionals related to legal affairs
	Professionals related to management
	Service occupations related to domestic housekeepers, home helpers
4th Quartile	*Advertising, publishing and media professionals*
	Artists, photographers, designers
	Brokerage and agent
	Consultants
	Engineers related to software and internet
	Game-related professionals
	Internet-related professionals
	Literature writers, journalists, editors
	Office automation device operators
	Professionals related to fashion and interior
	Sales occupations

	2017	Relative Place
1st Quartile	Drivers	-1
	Facility keeping services	
	Health, midwifery, nursing professionals	
	Hospitality attendant and waiter occupations	
	Manufacturing and production process workers	
	Medical engineers	
	Merchandise salespersons	
	Mining and industrial engineers	
	Miscellaneous labor workers	
	Miscellaneous office workers	-2
	Occupations related to agriculture, forestry and fisheries	-1
	Printing-related professionals	-1
2nd Quartile	Financial clerks, accountants, numerical clerks	1
	Food and drink preparation occupations	
	General clerical occupations	
	Mechanical and electrical engineers	-1
	Medical doctors, dentists, veterinarians, pharmacists	
	Miscellaneous medical health professionals	
	Miscellaneous service workers related to transport and communications	1
	Office automation device operators	-2
	Security and protective occupations	1
	Social welfare professionals	
3rd Quartile	Uncategorized	
	Construction, earth moving, survey engineers	
	Environmental sanitation service workers	1
	Finance-related professionals	
	Miscellaneous engineers	
	Miscellaneous professionals and technical occupations	
	Miscellaneous service workers	1
	Professionals related to legal affairs	
	Professionals related to management	
	Service occupations related to domestic housekeepers, home helpers	
	Technicians for agriculture, forestry, fisheries and food	2
4th Quartile	Advertising, publishing and media professionals	
	Artists, photographers, designers	
	Brokerage and agent	
	Consultants	
	Engineers related to software and internet	
	Game-related professionals	
	Internet-related professionals	
	Literature writers, journalists, editors	
	Managers of companies, organisations, etc	1
	Planning and promotion business occupations	1
	Professionals related to fashion and interior	
	Sales occupations	

	2018	Relative Place
1st Quartile	Drivers	-1
	Health, midwifery, nursing professionals	
	Hospitality attendant and waiter occupations	
	Manufacturing and production process workers	
	Medical engineers	
	Merchandise salespersons	
	Mining and industrial engineers	
	Miscellaneous labor workers	
	Miscellaneous service workers related to transport and communications	
	Security and protective occupations	
	Social welfare professionals	-1
2nd Quartile	Facility keeping services	1
	Financial clerks, accountants, numerical clerks	1
	Food and drink preparation occupations	
	General clerical occupations	
	Mechanical and electrical engineers	-1
	Medical doctors, dentists, veterinarians, pharmacists	
	Miscellaneous medical health professionals	
	Miscellaneous office workers	-1
	Miscellaneous service workers	
	Occupations related to agriculture, forestry and fisheries	
	Printing-related professionals	
3rd Quartile	Uncategorized	
	Construction, earth moving, survey engineers	
	Engineers related to software and internet	-1
	Environmental sanitation service workers	1
	Finance-related professionals	
	Managers of companies, organisations, etc	
	Miscellaneous engineers	
	Miscellaneous professionals and technical occupations	
	Professionals related to management	
	Sales occupations	-1
	Service occupations related to domestic housekeepers, home helpers	
4th Quartile	*Advertising, publishing and media professionals*	
	Artists, photographers, designers	
	Brokerage and agent	
	Consultants	
	Game-related professionals	
	Internet-related professionals	
	Literature writers, journalists, editors	
	Office automation device operators	
	Planning and promotion business occupations	1
	Professionals related to fashion and interior	
	Professionals related to legal affairs	1

	2019	Relative Place
1st Quartile	Drivers	-1
	Food and drink preparation occupations	-1
	Game-related professionals	-3
	Health, midwifery, nursing professionals	
	Hospitality attendant and waiter occupations	
	Manufacturing and production process workers	
	Medical doctors, dentists, veterinarians, pharmacists	-1
	Medical engineers	
	Merchandise salespersons	
	Miscellaneous labor workers	
	Miscellaneous service workers related to transport and communications	
	Security and protective occupations	
2nd Quartile	Construction, earth moving, survey engineers	-1
	Environmental sanitation service workers	
	Facility keeping services	1
	Financial clerks, accountants, numerical clerks	1
	General clerical occupations	
	Miscellaneous office workers	-1
	Miscellaneous service workers	
	Printing-related professionals	
	Social welfare professionals	
	Technicians for agriculture, forestry, fisheries and food	1
3rd Quartile	Uncategorized	
	Managers of companies, organisations, etc	
	Mechanical and electrical engineers	
	Mining and industrial engineers	2
	Miscellaneous engineers	
	Miscellaneous medical health professionals	1
	Miscellaneous professionals and technical occupations	
	Occupations related to agriculture, forestry and fisheries	1
	Office automation device operators	-1
	Sales occupations	-1
4th Quartile	*Advertising, publishing and media professionals*	
	Artists, photographers, designers	
	Brokerage and agent	
	Consultants	
	Engineers related to software and internet	
	Finance-related professionals	1
	Internet-related professionals	
	Literature writers, journalists, editors	
	Planning and promotion business occupations	1
	Professionals related to fashion and interior	
	Professionals related to legal affairs	1
	Professionals related to management	1

	2020	Relative Place
1st Quartile	Drivers	-1
	Food and drink preparation occupations	-1
	Health, midwifery, nursing professionals	
	Hospitality attendant and waiter occupations	
	Manufacturing and production process workers	
	Medical engineers	
	Merchandise salespersons	
	Miscellaneous labor workers	
	Occupations related to agriculture, forestry and fisheries	-1
	Security and protective occupations	
	Social welfare professionals	-1
2nd Quartile	Uncategorized	-1
	Brokerage and agent	-2
	Environmental sanitation service workers	
	Facility keeping services	1
	Medical doctors, dentists, veterinarians, pharmacists	
	Miscellaneous medical health professionals	
	Miscellaneous office workers	-1
	Miscellaneous professionals and technical occupations	-1
	Miscellaneous service workers	
	Miscellaneous service workers related to transport and communications	1
	Printing-related professionals	
	Service occupations related to domestic housekeepers, home helpers	-1
3rd Quartile	Construction, earth moving, survey engineers	
	Financial clerks, accountants, numerical clerks	2
	General clerical occupations	1
	Managers of companies, organisations, etc	
	Mining and industrial engineers	2
	Office automation device operators	-1
	Professionals related to fashion and interior	-1
	Professionals related to legal affairs	
	Professionals related to management	
	Technicians for agriculture, forestry, fisheries and food	2
4th Quartile	*Advertising, publishing and media professionals*	
	Artists, photographers, designers	
	Consultants	
	Engineers related to software and internet	
	Finance-related professionals	1
	Game-related professionals	
	Internet-related professionals	
	Literature writers, journalists, editors	
	Mechanical and electrical engineers	1
	Miscellaneous engineers	1
	Planning and promotion business occupations	1
	Sales occupations	

	2021	**Relative Place**
1st Quartile	Drivers	-1
	Facility keeping services	
	Health, midwifery, nursing professionals	
	Hospitality attendant and waiter occupations	
	Manufacturing and production process workers	
	Medical doctors, dentists, veterinarians, pharmacists	-1
	Medical engineers	
	Merchandise salespersons	
	Miscellaneous labor workers	
	Occupations related to agriculture, forestry and fisheries	-1
	Security and protective occupations	
	Social welfare professionals	-1
2nd Quartile	Uncategorized	-1
	Brokerage and agent	-2
	Environmental sanitation service workers	
	Food and drink preparation occupations	
	Miscellaneous medical health professionals	
	Miscellaneous professionals and technical occupations	-1
	Miscellaneous service workers	
	Miscellaneous service workers related to transport and communications	1
	Printing-related professionals	
	Service occupations related to domestic housekeepers, home helpers	-1
3rd Quartile	Construction, earth moving, survey engineers	
	Financial clerks, accountants, numerical clerks	2
	General clerical occupations	1
	Managers of companies, organisations, etc	
	Mining and industrial engineers	2
	Miscellaneous office workers	
	Office automation device operators	-1
	Professionals related to fashion and interior	-1
	Professionals related to legal affairs	
	Sales occupations	-1
	Technicians for agriculture, forestry, fisheries and food	2
4th Quartile	*Advertising, publishing and media professionals*	
	Artists, photographers, designers	
	Consultants	
	Engineers related to software and internet	
	Finance-related professionals	1
	Game-related professionals	
	Internet-related professionals	
	Literature writers, journalists, editors	
	Mechanical and electrical engineers	1
	Miscellaneous engineers	1
	Planning and promotion business occupations	1
	Professionals related to management	1

Source: Based on the JPSED.

Appendix E: Event study figures

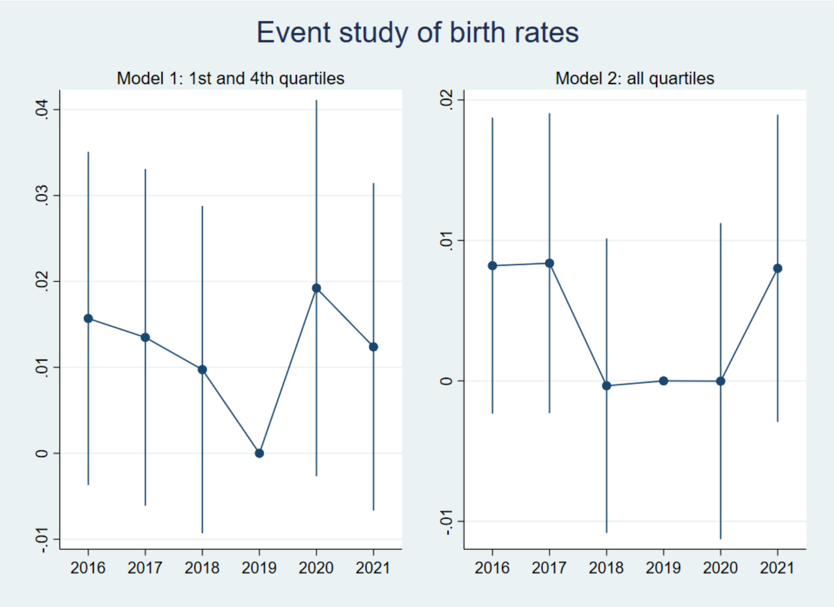

Figure E1: Event study of birth rates.

Source: Estimated based on the JPSED. Birth rates are calculated as percentage of women aged 15-55 years who reported a birth in a given year. Data points are normalized to 2019 as the base year.

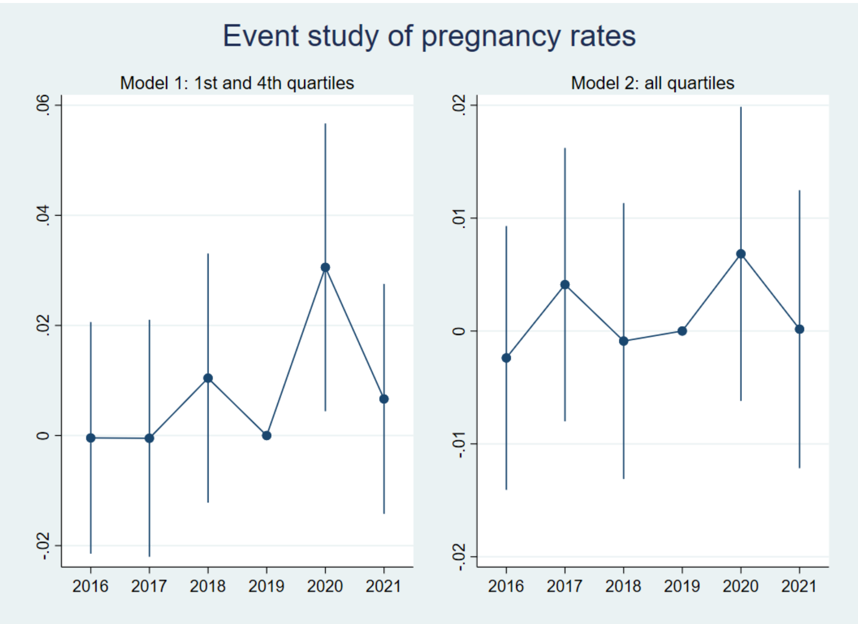

Figure E2: Event study of pregnancy rates.

Source: Estimated based on the JPSED. Pregnancy rates are calculated as percentage of women aged 15-55 years who reported a pregnancy in a given year. Data points are normalized to 2019 as the base year.

Appendix F: Robustness tests' results

Propensity Score Matching

Figure F1: Propensity Score Histogram for Treated and Untreated. Source: Estimated based on the JPSED.

Table F1 shows the average treatment effect estimators of the treatment's effect on birth and pregnancy, using nearest-neighbor propensity score matching. The outcomes do not lend themselves to a straightforward interpretation in comparison to the logit fixed effects DID results. The only discernible conclusions drawn from these results are that the treatments in both models have a significant and non-negative effect on birth and pregnancy rates.

Table F1: PSM ATE estimators

Outcome	Birth		Pregnancy	
	(1) Model 1	(2) Model 2	(3) Model 1	(4) Model 2
Average Treatment Effect	0.138***	-0.00603	0.139**	0.0420**
	(0.0458)	(0.0198)	(0.0551)	(0.0211)
Observations	1,544	4,558	1,805	5,044

Notes: Standard errors in parentheses. In Model 1, "teleworker ratio" binary treatment variable takes 1 if the individual belongs to the 4th quartile of occupation's teleworker ratio and 0 if the individual belongs to the 1st quartile. For Model 2, the treatment variable takes 1 if the individual belongs to the 3rd or 4th quartile, and 0 otherwise.
P-values indicated as follows: *** p<0.01, ** p<0.05, * p<0.1
Source: Estimated based on the JPSED.

Using these estimators, we can subsequently present the balance of covariates after propensity score matching for each 2x2 configuration of model and outcome. The details are presented in Tables F2-F5 below.

Table F2: PSM covariate balances – birth, Model 1

	Standardized differences		Variance ratio	
Independent variables	Raw	Matched	Raw	Matched
Household annual income	0.4837	0.1723	1.1096	0.7378
Total work and commute hours	0.4352	-0.0294	0.6354	0.8489
Main household earner	0.0841	-0.0544	1.1874	0.8855
Child raiser	0.0373	-0.1284	1.0093	0.9649
Age	0.0300	0.1850	0.9458	1.4696
Education	0.4472	0.0000	0.5782	1.0000
Full-time	0.3502	-0.0325	0.9555	0.9954
Treated observations	177			
Control observations	1367			

Source: Estimated based on the JPSED.

Table F3: PSM covariate balances – birth, Model 2

	Standardized differences		Variance ratio	
Independent variables	Raw	Matched	Raw	Matched
Household annual income	0.1818	0.0204	1.3130	1.1040
Total work and commute hours	0.0186	-0.0133	1.2361	1.1734
Main household earner	0.0455	-0.0091	1.1018	0.9801
Child raiser	-0.0772	0.0673	0.9865	1.0074
Age	-0.0539	0.0016	1.1614	1.2678
Education	0.2117	0.0040	0.7736	0.9959
Full-time	0.0472	-0.0404	0.9980	1.0000
Treated observations	827			
Control observations	3731			

Source: Estimated based on the JPSED.

Table F4: PSM covariate balances – pregnancy, Model 1

	Standardized differences		Variance ratio	
Independent variables	Raw	Matched	Raw	Matched
Household annual income	0.3017	0.1936	1.1494	0.8034
Total work and commute hours	0.4984	-0.0484	0.7752	1.1170
Main household earner	0.2928	-0.0774	1.4680	0.8752
Child raiser	-0.0415	-0.1033	0.9845	0.9460
Age	-0.0728	0.0011	0.7164	0.7811
Education	0.6006	0.0059	0.4403	0.9958
Full-time	0.5112	0.0066	0.8383	1.0002
Treated observations	211			
Control observations	1594			

Source: Estimated based on the JPSED.

Table F5: PSM covariate balances – pregnancy, Model 2

	Standardized differences		Variance ratio	
Independent variables	Raw	Matched	Raw	Matched
Household annual income	0.0957	0.0365	1.1218	1.0911
Total work and commute hours	0.0438	-0.0521	1.3497	1.4668
Main household earner	0.0774	-0.0241	1.1419	0.9572
Child raiser	-0.0539	0.0393	0.9757	1.0166
Age	-0.0820	-0.0117	1.0299	1.0983
Education	0.2247	-0.0168	0.7657	1.0165
Full-time	0.0883	-0.0305	0.9912	1.0012
Treated observations	943			
Control observations	4101			

Source: Estimated based on the JPSED.

Finally, we present the estimations of the propensity score matched DID models for both birth and pregnancy outcomes.

Table F6: PSM effect of occupation's teleworker ratio on birth

	(1)	(2)
Independent Variable	Model 1	Model 2
Pregnancy (pregnancy = 1, 0 otherwise)		
Teleworker ratio	1.762	1.182
	(2.721)	(0.291)
Interaction	1.210	1.071
	(0.783)	(0.329)
Year fixed effects	X	X
Control variables	X	X
Observations	1,510	4,441
Number of individuals	450	1,241
Pseudo R^2	0.604	0.601

Notes: The reported results are in the form of odds ratios. Panel-robust standard errors, presented in parentheses, are calculated using 1000 bootstrap repetitions. The goodness of fit is estimated by pseudo R^2. P-values indicated as follows: *** p<0.01, ** p<0.05, * p<0.1.
Source: Estimated based on the JPSED.

Table F7: PSM effect of occupation's teleworker ratio on pregnancy		
	(1)	(2)
Independent Variable	Model 1	Model 2
Pregnancy (pregnancy = 1, 0 otherwise)		
Teleworker ratio	2.192	1.131
	(1.339)	(0.171)
Interaction	1.794	1.605**
	(0.668)	(0.316)
Year fixed effects	X	X
Control variables	X	X
Observations	1,763	4,919
Number of individuals	523	1,415
Pseudo R^2	0.183	0.190

Notes: The reported results are in the form of odds ratios. Panel-robust standard errors, presented in parentheses, are calculated using 1000 bootstrap repetitions. The goodness of fit is estimated by pseudo R2. P-values indicated as follows: *** p<0.01, ** p<0.05, * p<0.1.Source: Estimated based on the JPSED.

Random Permutation Test

Table F8: Random permutation test					
Treatment effect	T(obs)	p	SE(p)	[95% Confidence Interval]	
Birth – Model 1	0.2768	0.8220	0.0171	0.7856	0.8545
Birth – Model 2	0.0629	0.8620	0.0154	0.8286	0.8910

Notes: Confidence intervals are calculated with respect to p. Coefficients are reported as log odds, not odds ratios.

Source: Estimated based on the JPSED.

Table F9: Random permutation test					
Treatment effect	Coefficient	P-value	Standard error	[95% Confidence Interval]	
Pregnancy – Model 1	0.5930	0.4000	0.0219	0.3567	0.4444
Pregnancy – Model 2	0.4254	0.0740	0.0117	0.0526	0.1006

Notes: Confidence intervals are with respect to p. Coefficients are reported as log odds, not odds ratios.

Source: Estimated based on the JPSED.

Labor Force Participation

Table F10: Effect of occupation's teleworker ratio on labor force participation

	Model 1		Model 2	
Independent Variable	(1)	(2)	(3)	(4)
Not having a job (1 if no job, 0 if has job)				
Teleworker ratio	0.827	0.615	1.165	0.919
	(0.650)	(1.271)	(0.240)	(0.216)
Interaction	1.034	0.993	1.151	1.369
	(0.574)	(2.054)	(0.284)	(0.540)
Year fixed effects	X	X	X	X
Control variables		X		X
Observations	1,407	746	3,379	1,690
Number of individuals	367	235	865	528
Pseudo R^2	0.105	0.0889	0.0828	0.0745

Notes: The reported results are in the form of odds ratios. Panel-robust standard errors, presented in parentheses, are calculated using 1000 bootstrap repetitions. The goodness of fit is estimated by pseudo R^2. The independent variable of "not having a job" takes value 1 if an individual has been without a job for at least one month within twelve-month period in a given year. This categorization excludes individuals who have a job but are currently on leave. P-values indicated as follows: *** p<0.01, ** p<0.05, * p<0.1.
Source: Estimated based on the JPSED.

Table F11: Effect of occupation's teleworker ratio on birth, split by labor force participation

	Model 1		Model 2	
	(1)	(2)	(3)	(4)
Independent Variable	Has job	Does not have job	Has job	Does not have job
Pregnancy (pregnancy = 1, 0 otherwise)				
Teleworker ratio	2.129	20.36	1.132	1.446
	(2.270)	(683.7)	(0.293)	(0.672)
Interaction	0.960	0.937	1.135	0.362
	(0.531)	(3.037)	(0.367)	(0.226)
Year fixed effects	X	X	X	X
Control variables	X	X	X	X
Observations	1,641	467	4,030	1,111
Number of individuals	474	151	1,126	359
Pseudo R^2	0.582	0.694	0.573	0.699

Notes: The table corresponds to estimation procedure used for Table 8 in main body. The reported results are in the form of odds ratios. Panel-robust standard errors, presented in parentheses, are calculated using 1000 bootstrap repetitions. The goodness of fit is estimated by pseudo R^2. P-values indicated as follows: *** p<0.01, ** p<0.05, * p<0.1.
Source: Estimated based on the JPSED.

Table F12: Effect of occupation's teleworker ratio on pregnancy, split by labor force participation

	Model 1		Model 2	
	(1)	(2)	(3)	(4)
Independent Variable	Has job	Does not have job	Has job	Does not have job
Pregnancy (pregnancy = 1, 0 otherwise)				
Teleworker ratio	0.343	9.782e+06***	1.039	2.822*
	(0.266)	(3.254e+07)	(0.180)	(1.560)
Interaction	2.315**	1.225	1.593**	0.799
	(0.761)	(2.765)	(0.335)	(0.322)
Year fixed effects	X	X	X	X
Control variables	X	X	X	X
Observations	1,846	422	4,390	999
Number of individuals	548	133	1,262	322
Pseudo R^2	0.189	0.228	0.198	0.225

Notes: The reported results are in the form of odds ratios. Panel-robust standard errors, presented in parentheses, are calculated using 1000 bootstrap repetitions. The goodness of fit is estimated by pseudo R^2. The stratification of "has job" and "does not have job" categories is based on whether an individual has been without a job for at least one month within twelve-months period in a given year. It is important to note that this categorization excludes individuals who have a job but are currently on leave. P-values indicated as follows: *** p<0.01, ** p<0.05, * p<0.1.
Source: Estimated based on the JPSED.

Appendix G: Estimations of effect of occupation's teleworker ratio on birth outcomes

Table G1: Effect of occupation's teleworker ratio on birth, split by education level

	Model 2		Model 2 (PSM)	
	(1)	(2)	(3)	(4)
Independent Variable	Secondary	Tertiary	Secondary	Tertiary
Birth (birth = 1, 0 otherwise)				
Teleworker ratio	6.388	0.377	1.358	1.005
	(25.15)	(1.557)	(0.580)	(0.316)
Interaction	0.250	1.344	0.922	1.007
	(1.552)	(0.870)	(1.223)	(0.358)
Year fixed effects	X	X	X	X
Control variables	X	X	X	X
Observations	479	1,019	1,191	3,222
Number of individuals	143	305	343	893
Pseudo R^2	0.643	0.606	0.615	0.606

Notes: The table corresponds to estimation procedure used for Table 5 in main body. The reported results are in the form of odds ratios. Panel-robust standard errors, presented in parentheses, are calculated using 1000 bootstrap repetitions. The goodness of fit is estimated by pseudo R^2. P-values indicated as follows: *** p<0.01, ** p<0.05, * p<0.1.
Source: Estimated based on the JPSED.

Table G2: Effect of occupation's teleworker ratio on birth, split by part-time/full-time work

	Model 2		Model 2 (PSM)	
	(1)	(2)	(3)	(4)
Independent Variable	Part-time	Full-time	Part-time	Full-time
Birth (birth = 1, 0 otherwise)				
Teleworker ratio	25.31	2.936	1.653	0.735
	(151.2)	(13.00)	(0.768)	(0.296)
Interaction	0.560	2.802	0.287	1.681
	(1.615)	(2.928)	(0.269)	(0.704)
Year fixed effects	X	X	X	X
Control variables	X	X	X	X
Observations	1,863	2,031	1,863	2,031
Number of individuals	616	619	616	619
Pseudo R^2	0.138	0.237	0.138	0.237

Notes: The table corresponds to estimation procedure used for Table 6 in main body. The reported results are in the form of odds ratios. Panel-robust standard errors, presented in parentheses, are calculated using 1000 bootstrap repetitions. The goodness of fit is estimated by pseudo R^2. P-values indicated as follows: *** p<0.01, ** p<0.05, * p<0.1.
Source: Estimated based on the JPSED.

Table G3: Effect of occupation's teleworker ratio on birth, split by median income				
	Model 2		Model 2 (PSM)	
Independent Variable	(1) Below median income	(2) Above median income	(3) Below median income	(4) Above median income
Birth (birth = 1, 0 otherwise)				
Teleworker ratio	1.065	34.27	1.004	2.090*
	(5.432)	(284.7)	(0.391)	(0.924)
Interaction	0.895	1.814	0.806	1.429
	(4.259)	(1.435)	(0.561)	(0.608)
Year fixed effects	X	X	X	X
Control variables	X	X	X	X
Observations	526	692	1,467	2,123
Number of individuals	182	218	478	644
Pseudo R^2	0.567	0.593	0.606	0.587

Notes: The table corresponds to estimation procedure used for Table 7 in main body. The reported results are r in the form of odds ratios. Panel-robust standard errors, presented in parentheses, are calculated using 1000 bootstrap repetitions. The goodness of fit is estimated by pseudo R^2. P-values indicated as follows: *** p<0.01, ** p<0.05, * p<0.1.
Source: Estimated based on the JPSED.