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The effect of COVID-19 on the gender gap in remote work

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Abstract

We examine changes in the gender gap in working from home (WFH) in response to the unanticipated first wave of the COVID-19 pandemic. Using data from the American Time Use Survey, we find a non-negligible widening of the gender gap with WFH being more prevalent among women than among men. Respondents' job traits played a significant role in the gender gap variations, those working in the private sector being the most affected. Young individuals, those more educated, and those living with a dependent person increased the gender gap more in terms of the proportion of time devoted to WFH. We further show evidence suggesting the mitigating effect of non-pharmaceutical interventions during the first wave of the pandemic, positively affecting the WFH tendency for men but not for women. Overall, the gender gap change proves robust to identification checks. In addition, the gender gap response has had a long-lasting impact on the gender gap.

Keywords: COVID-19, working from home (WFH), gender, American Time Use Survey (ATUS)

JEL Codes: D10, J16, J21, J22

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1. Introduction

Traditionally, women have shown a greater preference for family and work balance than men even in developed countries, wherein telework or remote work may have played an important role. Women are more likely to avoid *greedy* jobs and be involved in family-friendly jobs with short commutes and possibilities of working from home (WFH) (Gálvez et al., 2021; Goldin, 2021; Marcén & Morales, 2021a), whereas, for example, men reported the coordination of work with personal/family needs as a main reason for WFH in the early twenty-first century in the US six times less than women (Wight & Raley, 2009).[1] After the COVID-19 lockdowns, this could have changed. The worldwide unexpected COVID pandemic gave many men and women the opportunity to experience the full-time work-family-life environment during the lockdown weeks. The return to the "new normality" of pre-pandemic life gives rise to three possible scenarios: (1) a return to the usual work locations; (2) an increase in men's remote work (or a decrease in women's remote work), reducing the gender gap in WFH; or (3) reinforcement of the asymmetry between men and women in remote work. In this paper, we shed some light on this issue by analyzing how the gender gap in WFH has evolved, with a detailed focus on the extensive and intensive margin.

Despite the importance given to telework, the growing research on this issue appears to be incomplete. There is solid evidence of a considerable increase in the percentage of voluntary WFH workers after a pre-pandemic randomized Chinese experiment that explored the positive impact of WFH on the productivity, profitability, and work satisfaction of home workers (Bloom et al., 2015). The unexpected physical COVID-19 distancing measures and lockdowns, like in a mass social experiment, forced many people toward a learning process, combining all their spheres (work-family-life) at the same time. From the supply side in the labor market, it is not clear whether COVID-19 made WFH more attractive to workers and/or whether this is gendered. The positive WFH benefits are related to the freedom of the work schedule, savings in commuting time, the possible increase in time devoted to leisure and family, and the availability of time to care for the children. There are also adverse effects possibly counteracting these, such as work isolation; difficulties with access to and use of technology; obesity risks; mental health problems; difficulties in the coordination of the work, family, and life environment; social isolation; and disruption of children's educational processes during school closures (Birimoglu Okuyan & Begen, 2022; Bloom et al., 2021; Mann & Holdsworth, 2003). From the demand side, the attractiveness of the WFH option is not clear. In contrast to the Chinese pre-pandemic experiment, researchers did not observe an increase in productivity from the WFH practice, seeing reductions of around 30–40 percent in workers' productivity in the case of two Japanese surveys during the COVID-19 lockdowns (Bloom et al., 2015; Kitagawa et al., 2021; Morikawa, 2022). Direct supervisors had no role in the WFH setting because there is a lack of direct oversight of workers. Those workers, to avoid losing their own jobs, could exert pressure to return (or partial return) to the usual work locations based on the lack of working transparency. Additionally, firms could not immediately reduce office rental costs since their rental contracts did not disappear with COVID-19, further reducing their immediate economic incentives for the WFH option. The dominant effect and how WFH has evolved is an empirical issue that needs to be explored. Our work fills this gap using US data on workers

[1] WFH, also known as telework, telecommuting, or remote work, refers to the formal or informal arrangement that permits workers to work from another location (normally their own home) than the usual worksite.

from the Integrated Public Use Microdata Series Time Use (IPUMS Time Use, ATUS) database for the period 2015–2022 (Flood et al., 2023). ATUS is a daily diary allowing us to identify pre- and post-lockdowns remote workers through the location of working activities and daily time devoted to WFH.

We use pre- and post-lockdown data to answer the following two research questions: (1) Has the asymmetry between men and women in remote work being reinforced following the hard lockdowns? (2) Does the intensity of non-pharmaceutical interventions (NPIs) play a role in the telework choice? Our paper is novel because we examine a long period of time, considering the choice of the telework option and the proportion of time devoted to WFH and combining this with the intensity of NPIs. We also explore heterogeneity in the WFH response by age, level of education, class of worker, and marital and dependence status.

We contribute to three strands of the literature: gender economics, COVID-19, and telework literature. The existing research on gender differences in the labor market has focused on the role of human capital, attitudes toward risk and competition, and discrimination in explaining gender gaps (Bertrand, 2011; Blau & Kahn, 2017; Olivetti & Petrongolo, 2016). A recent line of research emphasizes the importance of the structure of work to achieve gender equality in the world of work (Benny et al., 2021; Bertrand et al., 2010; Cortes et al., 2021; Cortes & Pan, 2018, 2019, 2021; Goldin, 2014, 2021; Goldin & Katz, 2011, 2016). These papers point to technological changes promoting workplace flexibility as a key to increase women's representation in high-paying occupations and therefore reduce gender gaps in the labor market. In this framework, an increase in the time men work from home might increase their family life involvement, rebalancing traditional family arrangements (Boca et al., 2021). We add to this literature by showing that the pandemic has amplified the gender gap in WFH in the US.

We also contribute to the growing literature on the COVID-19 effect on socio-economic variables. Our research is closely related to those papers seeking the impact of NPIs on labor markets, such as those studying the changes in labor supply in response to the unanticipated school closures, stay at home orders, and business closures, among others NPIs (Amuedo-Dorantes et al., 2022; Kalenkoski & Pabilonia, 2022; Marcén & Morales, 2021b). We extend this literature by merging individual ATUS data with an index capturing the intensity of NPIs at state level to assess how the gender gap in WFH relates to the intensity of NPIs. We find that a higher intensity of NPIs during the pandemic reduced the probability of WFH and the proportion of time spent working from home for women relative to men.

Lastly, we add to the still scarce telework literature. In the early stages of the pandemic, it was predicted that 20 percent of full workdays could be supplied from home after the pandemic ended compared with just 5 percent before (Barrero et al., 2020; Dingel & Neiman, 2020). There are a few papers using pre-pandemic time use data, most of them examining the relationship between WFH, wages, and wellbeing (see a review in Pabilonia & Vernon, 2022). In our case, we provide evidence on how telework has evolved in the post-pandemic period. The analysis is extended by studying other work-related outcomes such as having an unpredictable or non-standard schedule, interrupted work (with several work episodes), and commuting time.

The rest of the research work is organized as follows. Section 2 describes the data used. The methodology is described in section 3, and the results are presented in section 4. Section 5 concludes.

2. Data

We use data from the 2015–2022 American Time Use Survey (ATUS) (Flood et al., 2023) to analyze the WFH of US workers. The ATUS is the nation's only representative survey containing continuous information on time use in the United States and administered by the Bureau of Labor Statistics. This survey measures the amount of time people spend doing various activities such as paid work, childcare, eldercare, sleeping, doing leisure activities, volunteering, and socializing. The ATUS sample is drawn from the Current Population Survey (CPS). Households that have completed their 8th CPS interview are eligible for selection in the ATUS. Two to five months after the last CPS interview, a selected sample is asked to fill out a diary for the 24 hours of the previous day (from 4:00 AM to 4:00 AM).[2] For our purposes, this dataset has some advantages because of the detailed information on time allocation and the information provided on how long the activity lasted, who was there, and where the activity took place. We are able to add up the time devoted to work in any place, and specifically at home. The main drawback is that time diary data are only available for one individual from each selected household.

We restrict the sample to workers aged 18 to 64 years who reported any work episode on the day of the survey. Regarding the time devoted to WFH, we consider the activities "working" and "work-related activities".[3] The ATUS also provides information on the specific date respondents completed the survey, which allows us to disentangle individuals responding during the periods pre- and post-first wave COVID-19 when COVID-19 and NPIs were unexpected and intense. All responses after mid-May 2020 are considered post-first wave COVID-19 answers.[4] Our main sample consists of 24,092 individuals interviewed from January 2015 to December 2022.

Figure 1 shows WFH measures by gender during the pre- and post-COVID-19 periods. We observe that the gender gap in WGH has almost tripled (from 3 to 8 percentage points) since the pandemic hit. While only 27 percent of men and 30 percent of women reported any WFH episode pre-COVID-19, 39 percent of men and 47 percent of women reported WFH after the pandemic first-wave outbreak. Similarly, the percentage of the total work time workers spent WFH has increased from 18 percent to 32 percent in the case of men and has almost doubled for women, rising from 21 percent to 40 percent. Note that differences by gender are statistically significant (see Table A1).

To provide a sense of the evolution of WFH over time, we split the post-COVID period considered here into two different sub-periods, separating the initial stage hardest hit by the pandemic (from May 2020 to February 2021) from later stage of the pandemic (from March 2021 to December 2022).[5] Then, we calculated the variation rate of WFH measures between the pre-COVID and the two post-COVID stages. Figures 2.1 and 2.2 present maps showing the variation rates of the average proportion of workers reporting any work from home episode by state and the average proportion of time devoted to WFH by state, respectively. Panel A plots the variation rate between pre-COVID and the first stage of post-COVID; panel B shows the variation between pre-COVID and the second stage of post-COVID. Darker colors correspond to higher variation of WFH in each state

[2] Respondents are then randomly assigned a designated reference day. The diary days are distributed across the weeks of the year and the days of the week, with 10 percent allocated to each of the weekdays, 25 percent to Saturdays, and 25 percent to Sundays.

[3] Activity codes from 50101 to 50299 located in "Respondent's home or yard" coded 101.

[4] Data collection was suspended in 2020 from mid-March to mid-May for the safety of ATUS staff. For more information, please see the https://www.bls.gov/tus/covid19.htm

[5] The worst COVID-19 waves (considering infections and deaths) are included in the first period considered. https://covid.cdc.gov/covid-data-tracker/#trends_weeklycases_select_00

and period. The majority of the variation rates are positive, suggesting that WFH increased not only in the first post-COVID stage, but also during the second one. It is observed that the highest increase in the proportion of individuals reporting WFH is concentrated in the middle-north of the US but the highest increase in the proportion of time devoted to WFH takes place in the middle-south and in the northeast. In any case, geographical differences should be taken into consideration in our analysis. Similarly, Figure 3 illustrates the evolution of the gender gap in reporting any WFH episode and the gender gap in the proportion of total working time devoted to WFH. While, again, we detect a change in the geographical distribution of the gender gap in WFH with the highest gender gaps moving from the north to the south and northeast during the first stage of the pandemic, this change appears to reverse, at least in part, during the second stage of COVID-19, albeit the gender gaps are higher than in the pre-pandemic period.

Table B1 in Appendix B reports the descriptive statistics for the rest of the variables. The average age in our sample is around 43 years; 49 percent of respondents are females; 80 percent are white individuals; 48 percent have completed more than four years of college education; and around 47 percent live in a metropolitan area. More than half of the interviewed workers (60%) live with a partner, most of them (98%) being heterosexual individuals. In addition, 51 percent of respondents have children living in the household, 19 percent, 25 percent, and 20 percent living with a child aged 5 years or below, aged 6 to 12 years, or aged 12 to 18 years, respectively. Only 7 percent of respondents live with an older adult in the household. By class of worker, 16 percent of respondents are public employees, while 73 percent are employed privately and 11 percent are self-employed.

For the additional work-related outcomes considered here, interviewed were asked about the time an activity started and ended, which gives us information about respondents' available work time, their work schedule, and the number of different work episodes reported in a day. Data revealed that only 5 percent of workers had an unpredictable schedule; 24 percent worked during non-standard hours, and they report two separate work episodes on average. Most (74%) reported a commute episode in a working day.

3. Empirical Strategy

To estimate the effect of the first wave of COVID-19 and the presence of gender asymmetries, we mainly estimate the following equation:

$$Y_{ikt} = \beta_0 + \beta_1 Female_i + \beta_2\, PostCovid_t\, + \beta_3 (Female_i * PostCovid_t) + \boldsymbol{X'_{ikt}}\beta_4 + \boldsymbol{\delta_k} + \boldsymbol{\theta_t} + \varepsilon_{ikt} \quad (1)$$

where the dependent variable is the WFH measure of interest. Y_{ikt} captures whether the *i*th respondent living in state *k* in period *t* reports any WFH episode during the day of the survey, and the proportion of total working time devoted to WFH.[6] The explanatory variables include a gender indicator: the variable $Female_i$ is a dummy variable that takes the value of one if the individual is a female and zero otherwise. To identify the differential effect post-COVID across genders and over time, we include an interaction between the gender dummy and a post-first wave indicator called $PostCovid_t$, being a dummy variable taking the value of one after May 2020 and zero otherwise. Our coefficient of interest is β_3, which captures the role of the unexpected lockdowns in

[6] We compute the total WFH time as the sum of all working episodes located in the respondent's home reported throughout the day. We calculate the proportion of WFH as the total WFH time divided by the total time working, calculated as the sum of all working episodes located anywhere throughout the day.

explaining gender differences in working remotely. A positive β_3 would indicate that the post-first wave COVID period is associated with a greater gender gap in WFH. The vector $\boldsymbol{X_{ikt}}$ includes a set of individual characteristics of respondent *i*. Controls are age, educational level (more college or not), race (white or not), and geographic location (living in a metropolitan area or not), which may affect the time workers devote to WFH.[7] These individual characteristics are also interacted with the female indicator to capture other gender differences that could be captured by our coefficient of interest. Controls for unobserved characteristics of the place of residence are added by using state fixed effects, denoted by $\boldsymbol{\delta_k}$.[8] To capture the time-variant unobserved characteristics, we add time (year, month) fixed effects, $\boldsymbol{\theta_t}$.[9]

Our work is extended by studying the differential gender response over time. In this case, we are able to examine whether any change in the gender differences WFH is lasting. The empirical strategy is detailed below. We also mitigate possible concerns as to the plausible exogeneity of the measures that took place during the first wave of the COVID-19 by presenting an event study. Our empirical strategy is based on the exogeneity of COVID-19, but although the COVID-19 was unexpected, no policy is ever adopted arbitrarily. There could be some concerns on whether changes in WFH pre-dated the first wave of COVID-19.

Additionally, to disentangle the differential gender response of WFH to NPIs' intensity, we exploit the temporal and geographic variations in the adoption of NPIs during the first-wave. To gauge the NPIs, we consider the weighted index COVINDEX (Marcén & Morales, 2021b). This captures the timing and intensity of NPIs by state and month in an easy way by using daily information on the announcement of five NPIs and their expiration at the state level, if any (state of emergency, school closures, partial business closures, stay-at-home orders, and non-essential business closures combine with the out-of-home mobility data provided by Google [Google LLC, 2020]).

4. Results

4.1. Main Results

Table 1 presents the estimates of Equation (1). Panels A and B show the results at the extensive and intensive margins, respectively. The results indicate that working women are more likely to report WFH and more proportion of time WFH over the total working time. The results indicate that working women are more likely to report WFH and to spend a greater proportion of working time WFH. Column (1) reveals that working women are around 4 percentage points more likely than men to report WFH, representing the 11 percent of the average number of individuals reporting any WFH episode during the day of the survey. Working women also outperform men in the time devoted to WFH over the total time working by 4.3 percentage points (18 percent of the average proportion of time devoted to WFH). Table 1 also points to the increase in WFH (again in both intensive and extensive margins) generated after the first COVID-19 wave. The estimated coefficient on the *PostCovid* dummy is also positive and statistically significant. Our results say that the percentage of individuals reporting WFH increased by around 21 percentage points after the first wave of COVID and the time devoted to WFH over the total time spent working rose by 22.8 percentage points. These findings are in line with those papers using the Current Population Survey that highlight the importance of

[7] We enlarged the set of socio-demographic characteristics and our results were maintained. See the results below.

[8] Our results are maintained when using MSA fixed effects.

[9] All the estimates are repeated with/without weights. The results do not vary.

telework in the first COVID-19 wave and later (Amuedo-Dorantes et al., 2022; Kalenkoski & Pabilonia, 2022; Marcén & Morales, 2021b; Pabilonia & Vernon, 2022).

To explore the gender differences in WFH after the first wave of COVID-19, we add the term of interaction between the *female* and the *PostCovid* dummies in column (2) of Table 1. The estimated coefficient for the interaction term is positive and statistically significant in both panels, suggesting that the gender gap increased at the extensive and intensive margins in comparison to the pre-pandemic period. We find that, after the end of the first wave, the gender gap in reporting any WFH episode increased by 7 percentage points, tripling the average gap in the pre-pandemic period. Similarly, our findings suggest that the post-first wave COVID period is associated with an increase of 6 percentage points, doubling the average pre-pandemic gender gap in the time that women, relative to men, devoted to WFH over the total working time. These findings are consistent with the conclusions derived from the parental time investments literature, which has documented how childcare activities are the responsibility of mothers (Adams-Prassl et al., 2020; Alon et al., 2020; Sevilla & Smith, 2020; Zamarro & Prados, 2021).[10]

The estimated coefficients for the rest of the controls also reveal that older, white, highly educated individuals and those living in metropolitan areas have a greater probability of reporting any WFH episode and a higher time devoted to WFH (see Table A2 in Appendix A). Our conclusions are maintained after the inclusion of additional controls in Table A3 in Appendix A. We control for the day of the week respondents complete the survey and whether they did so during holidays. We also enlarge the set of socio-demographic and job characteristics by controlling for partners' characteristics, respondents' work classification as part- or full-time workers, and self-employment status.

A reasonable concern with the results described above is the possibility that our coefficient of interest could be capturing gender differences in occupational choices and/or industry. As shown in prior literature, women may tend to choose family-friendly occupations (Marcén & Morales, 2023). Thus, women may be more likely than men to choose occupations allowing WFH. To mitigate this possible concern, we control for ATUS occupation and industry categories in Table A4 in Appendix A. Our results do not change. In addition, we follow a classification of teleworkable occupations (Dingel & Neiman, 2020) and re-run our estimates using only a sample of individuals employed in occupations allowing telework (see Table A5 in Appendix A) (Dingel & Neiman, 2020). Our conclusions are maintained. The same can be concluded when we use a sample of full-time workers as in Pabilonia and Vernon (2022) and when we further restrict the sample to those working during at least two hours on the day of the survey (see Tables A6 and A7).

4.2. Dynamic Response and Identification

In this subsection, we explore the dynamic response of the gender differences in WFH to the unexpected shock of COVID-19, focusing on the aftermath of the first wave. It is arguable that during the early post-first wave months, after May 2020, individuals maintained their remote working because employers, employees, and self-employed individuals still had concerns about the evolution of the pandemic. However, it is not clear whether the gender differences in WFH increase, decrease, or do not change after some months. After the unexpected COVID-19, individuals can re-adapt their behavior

[10] This can also be rationalized in light of social norms that mainly consider childcare as a female responsibility (Akerlof & Kranton, 2000; Bertrand et al., 2015; Sevilla-Sanz, 2010). However, our results are not in line with the standard economic models of the household, which would suggest a symmetrical response, ceteris paribus.

over time and the new waves of COVID-19 could also be affecting the evolution of the WFH. But, again, both women and men are affected by COVID-19, and so the differential response by gender in terms of WFH is not due to the evolution of the pandemic. Gender differences in preferences for family and work balance which made women choose to telework in the pre-pandemic period could have varied after the first wave of the pandemic. This is what we analyzed with a static analysis in the previous subsection, and now with a dynamic analysis. We follow Wolfers' (2006) methodology to determine the dynamic effect of COVID-19. Formally, we estimate the following model:

$$Y_{ikt} = \alpha + \sum_{j=0}^{2} \rho_j 1\{t^p = \text{j}\} + \sum_{j=0}^{2} \beta_j 1\{t^p = \text{j}\} Female_i + Female_i + \\ + \boldsymbol{X'_{ikt}}\mu \quad + \boldsymbol{\delta_k} + + \boldsymbol{\theta_t} + \varepsilon_{ijkt} \qquad (2)$$

where the indicator function $1\{t^p = \text{j}\}$ represents the *t*th periods after our period of interest.[11] In this way, Equation (2) includes dummies showing whether COVID-19 has affected WFH for t*th* periods. Also included is the term of interaction with $Female_i$, which allows us to explore the dynamic effect of COVID-19 on the gender differences in WFH. In this case, β_j parameters show whether COVID-19 affected the gender gap in WFH in periods after the pandemic hit. The rest of the variables are defined as in Equation (1). Table 2 shows the estimated coefficients of Equation (2) without the female and post-COVID interactions, whereas Table 3 shows the estimates of Equation (2) including all variables. There appears to be empirical evidence in favor of an increase in both WFH and the gender gap in WFH at the extensive and intensive margins in almost all periods subsequent to the onset of COVID-19. The impact on WFH in both the intensive and extensive margins appears to be long-lasting, albeit the magnitude of the impact varies over time and it is not statistically significant in the period capturing the impact in 2021. Our conclusions do not change when we control for the number of cases and deaths (see Tables A8 and A9 in Appendix A).

Another feasible concern with the results in Table 1 refers to the possibility that the estimated impacts might be biased due to pre-existing WFH and gender differences trends. Additionally, it is possible to surmise that changes pre-dated the unexpected COVID-19 pandemic (Goodman-Bacon & Marcus, 2020). To tackle this, we first conduct event studies enabling us to gauge if the estimated impacts pre-dated the start of the pandemic. Specifically, the event-study takes the following form:

$$Y_{ikt} = \alpha + \sum_{j=-2}^{-5} \tau_j 1\{t^p = \text{j}\} + \sum_{j=0}^{2} \rho_j 1\{t^m = \text{j}\} + \sum_{j=-2}^{-5} \beta_j 1\{t^p = \\ \text{j}\} Female_i + \sum_{j=0}^{2} \eta_j 1\{t^p = \text{j}\} Female_i + Female_i + \boldsymbol{X'_{ikt}}\mu + \boldsymbol{\delta_k} + \boldsymbol{\theta_t} + \\ + \varepsilon_{ijkt} \qquad (3)$$

where Y_{ikt} are the two WFH measures defined above. The indicator function $1\{t^p = \text{j}\}$ represents the *t*th period before or after our period of interest. The reference period in all event studies is the period before the event occurred when $\text{j} = -1$, which in our case corresponds with the year 2019.[12] We examine the existence of pre-trends during the

[11] The period of the event is May to December 2020. The two periods after the event refer to the years 2021 and 2022, respectively.

[12] The period of the event includes May 2020 to December 2020. The first period before the event refers to the year 2019. The period January to March 2020 is excluded here to maintain a similar number of months in all pre-COVID periods. The rest of the periods before the event refer to the years 2018, 2017 and so on. The two periods after the event refer to the years 2021 and 2022, respectively.

years prior to COVID-19. The coefficients β_j measure the dynamics of the interaction between the female indicator and COVID-19. The length of the event-time window is similar to those papers using data since 2015 or 2016 (Béland et al., 2020). The rest of the variables have been defined previously.

Figure 4 displays the coefficients from the event study along with 95 percent confidence intervals, with and without including the term of interaction between the female indicator and COVID-19.[13] The estimates for the years prior to the COVID-19 outbreak are close to zero, strongly supporting the assumption of no differential pre-trends. Moreover, there are clear breaks in both WFH measures when the pandemic hits, with the impact remaining similar to the dynamic analysis. This is not surprising since the pre-COVID coefficients are not statistically significant when jointly considered. Our results do not change after controlling for the number of cases and deaths (see Figure A1 in Appendix A).

4.3. Heterogeneity

We also examine whether the effect of the unexpected shock of COVID-19 on the gender gap in WFH varies across different subgroups of individuals. Table 4 explores whether COVID-19 had a differential effect according to respondents' age and educational level, and Table 5 focuses on marital status. The results suggest that young individuals, those more educated, and those living with a dependent person particularly increase the gender gap in the proportion of time devoted to WFH. We observe that the gender gap in the time devoted to WFH increased more than threefold in those aged 18 to 33 compared to the average pre-pandemic gender gap. However, for those aged 48 to 64, the gender gap increased more in the proportion of individuals reporting WFH. By educational level, the increase in the gender gap is greater in the case of non-highly educated individuals compared with the average gap in the pre-pandemic period, but the increase in the proportion of time devoted to WFH over the total working time is greater for those who are highly educated. Also, it is observed that those women with a different-sex partner significantly increased both the probability of working and the time devoted to WFH after the first-wave of the pandemic relative to men.

Table 6 considers dependence status. Columns (1) to (4) look at parenthood status and estimate the differential response to WFH by age group of the child (if any) separately. Interestingly, we observe that, relative to men, women without children and those with children aged 6 to 12, who may require more hours helping with home schooling, are the only ones who increased their WFH time during the post-first wave COVID-19 period in both the extensive and the intensive margins. Columns (5) and (6) consider the presence of older individuals in the household. Even though our coefficient of interest is positive and statistically significant regardless of the presence of an older adult in the household, the impact on the proportion of time WFH is greater for those with older individuals living in the household than for those without.

Additionally, we pay attention to the heterogeneous WFH response to COVID-19 by class of worker. Table 7 presents the results. Our findings reveal that privately employed women significantly increased both the probability of WFH and the time devoted to WFH relative to men during the post-COVID period. However, workers in the public sector appear to have increased the time devoted to WFH but not the gender gap in the intensive and extensive margins. The same is detected for the self-employed. We have further explored the dynamic response of WFH to COVID-19 focusing on employment differences. The results are presented in Tables A12 and A13 in Appendix

[13] The estimated coefficients are presented in Tables A10 and A11 in Appendix A.

A. We find that time devoted to WFH of both private and public employees significantly increased throughout the post-COVID period. In line with our previous results, we also find an increase in the gender gap in WFH which is maintained over time, but only for those working in the private sector.

4.4. Mechanisms

4.4.1. Mechanism #1: The Intensity of COVID-19 Non-Pharmaceutical Interventions and WFH

We consider a complementary exercise to understand better how the role of NPIs in the first wave impacted WFH. We analyze whether the intensity of NPIs during the COVID-19 pandemic has affected WFH decisions and whether it has differentially impacted the gender gap. NPIs took place at distinct geographic levels (some at county level, others at state level) and for different periods of time. Thus, it is possible that differences in the exposure to NPIs across US states may be related to different gender responses in WFH. To capture the timing and intensity of the NPIs at state level, we use the COVINDEX (Marcén & Morales, 2021b). The COVINDEX captures the intensity of NPIs, measured in terms of the duration of the NPIs and weighted by the estimated share of the population that changes mobility patterns as a consequence of the NPIs at the state and month levels in the first wave of the pandemic. We estimate the following equation:

$$Y_{ik}^{2021} = \beta_0 + \beta_1 Female_i + \beta_2\, COVINDEX_s^{2020} + \beta_3 (Female_i * COVINDEX_s^{2020}) + \boldsymbol{X'_{ik}}\mu + \boldsymbol{\delta_k} + \varepsilon_{ik} \quad (4)$$

where $COVINDEX_s^{2020}$ is the average of the COVINDEX presented by Marcén and Morales (2021b) for the months of March, April, and May in state s.[14] The more intense (effective) the NPIs are at reducing social interactions, the closer the value of the COVINDEX to -5. The average COVINDEX is -1.02. The rest of the variables are the same as before. Positive values for the coefficient β_3 should be interpreted as a reduction of the gender gap. We now limit our analysis to the years 2021 and 2022 to mitigate any concerns about the possible relationship between the COVID-19 evolution and the NPIs during the whole of 2020.

Table 8 presents the results. As expected, we observe that the increase in the intensity of the NPIs that occurred from March to May 2020 did significantly affect the structure of work through an increase in both the intensive and the extensive margins. We also find that the exposure to social distancing measures at the beginning of the pandemic differentially affected the propensity of men and women to WFH during the post-first wave COVID period, but this is not observed in the case of the proportion of time spent working from home. The estimated coefficient on the interaction term between the *female* dummy and *COVINDEX* is positive and statistically significant, suggesting that the gender gap has been reduced in those areas with more intense NPIs. Furthermore, we explore the dynamic response of WFH to the intensity of the NPIs. The results reveal that our conclusions are maintained over time (see Tables A14 and A15 in Appendix A). All these findings suggest that an increase in the duration and intensity of social distancing measures (such as stay at home orders) could be an opportunity for changing traditional family roles through an increase in men's involvement in family life and/or a reduction in that of women.

[14] The COVINDEX over the post-COVID period (March, April, and May 2020) averaged -1.02 and fluctuated between 0.05 and -2.6.

4.4.2. Mechanism #2: Other Work-related Outcomes

Until now, we have shown that while remote work has increased for both men and women as a result of COVID-19, the gender gap in WFH has also increased from the pandemic outbreak onwards. In this subsection, we explore what happens with other work-related issues. We focus our analysis here on unpredictable hours, working during non-standard hours, interrupted work, the logarithm of weekly work hours, and commuting time. We re-run our main analysis by redefining the dependent variable. Table 9 shows the estimated coefficients. If we look at the term of interaction between the *female* and *PostCovid* dummies, all but one (commuting) seem to have risen for women during the post-COVID period, albeit the coefficient is not statistically significant in the case of a non-standard schedule. As a result of COVID-19, women are more likely than men to have an unpredictable schedule, to be interrupted, and to work longer hours than before the pandemic hit (see columns (1) to (8)). In addition, women have increased the gender gap in commuting by reducing their already lower tendency to commute (see columns (9) and (10)). These results suggest that COVID-19 also differentially changed the structure of work in significant ways for men and women.

5. Conclusions

COVID-19 enforced alternate arrangements from the traditional working day, namely working from home. Since a large shift to WFH by both partners in the household could lead to a more balance division of household labor (Boca et al., 2021), scholars have raised interest about the extent to which it will persist after the first unexpected wave. Some initial studies suggest that most workers welcome the option to work remotely part of the week (Barrero et al., 2020, 2021). However, whether WFH will stick or not among women and men remained an open question. In this paper, we analyze the effect of COVID-19 on WFH in the US and whether it varies by gender.

Using data from the American Time Use Survey, we find a positive and significant effect of COVID-19 on WFH more than two years after the pandemic hit. The post-first wave COVID period is associated with an increase of 7 percentage points in the gender gap relating to WFH and an increase of 6 percentage points in the gender gap pertaining to time devoted to WFH over the total working time. Additionally, the pandemic impacted individuals differently depending on their characteristics: those who are younger, those with a different-sex partner, and private employees significantly increased the gender gap in the proportion of time devoted to working remotely. A supplementary analysis also identifies that, relative to men, women are now more likely than before the pandemic to have an unpredictable schedule, interrupted working, and long hours of work.

Additionally, we exploit differences in the timing and duration of NPIs across US states to analyze whether higher exposure to social distancing measures at the beginning of the pandemic could lead to a greater WFH tendency after the pandemic and how this affects the gender gap. We find that the gender gap decreases in those areas with more intense NPIs.

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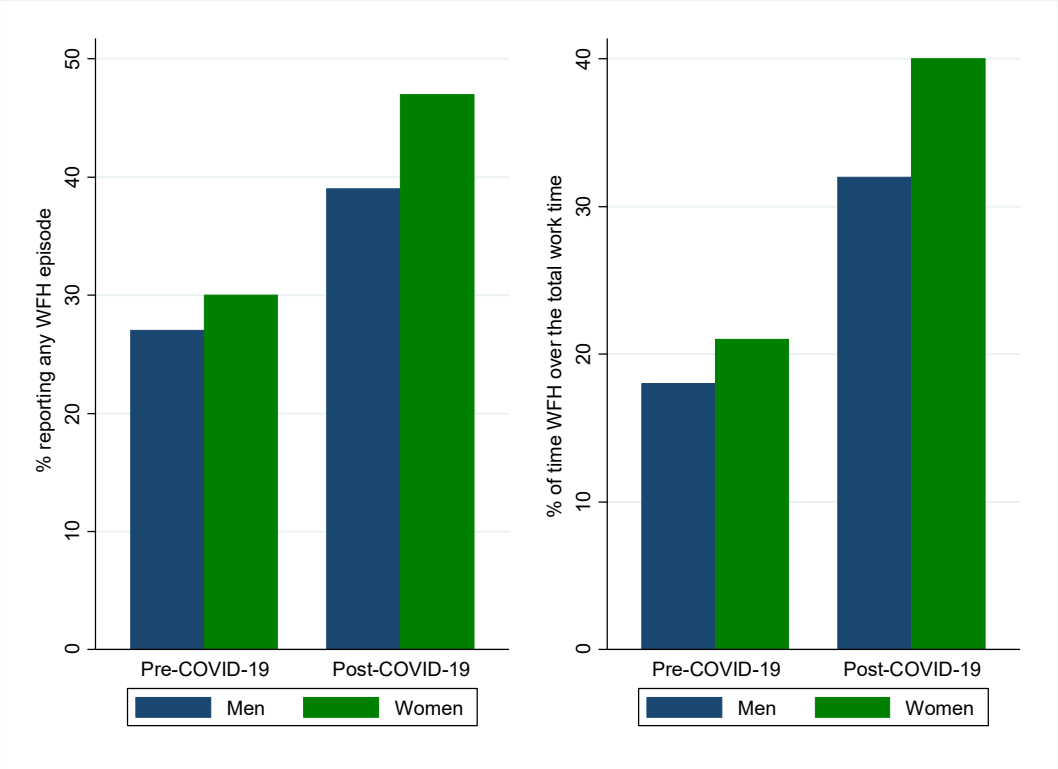
Figure 1. Summary statistics of WFH measures by gender during pre- and post-COVID-19 periods



Notes: Data come from the 2015–2022 ATUS. We use a sample of workers aged between 18 and 64 years who reported a work episode on the day of the survey. Table A1 in the Appendix A shows the estimated coefficients.

Figure 2. Variation rates of WFH between pre- and post-COVID periods

Figure 2.1. Variation rate in the average WFH by state

Panel A: Pre- and initial stage of post-COVID **Panel B: Pre- and last stage of post-COVID**

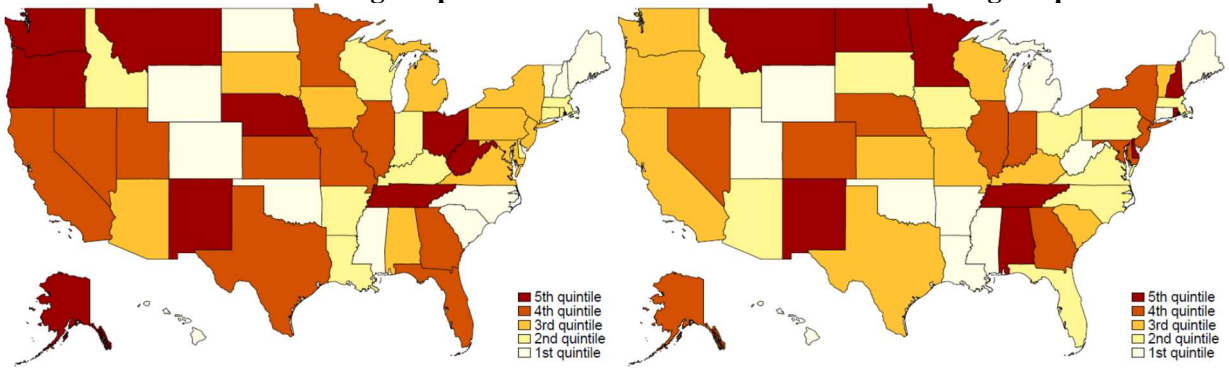
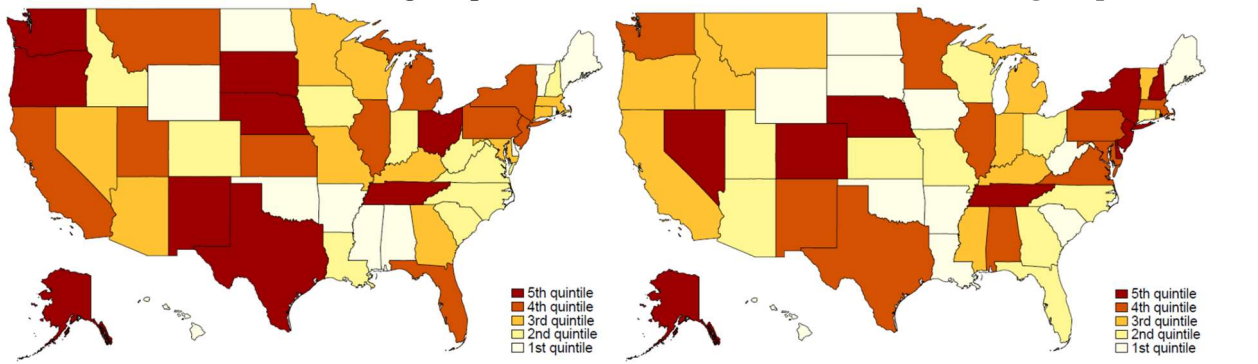


Figure 2.2. Variation rate in the average proportion of WFH time over the total work time by state

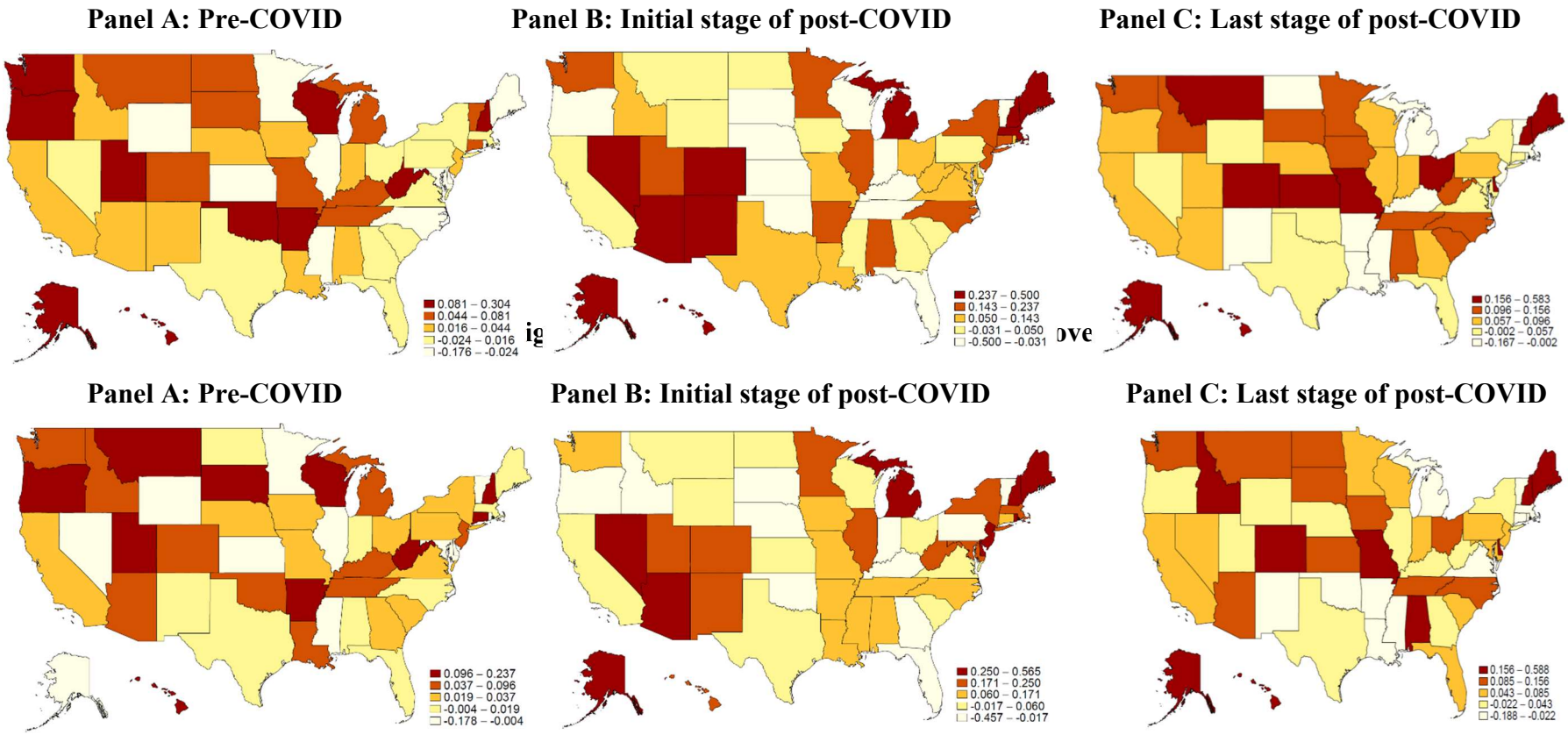
Panel A: Pre- and initial stage of post-COVID **Panel B: Pre- and last stage of post-COVID**



Notes: These figures show the variation rate between pre-COVID and each of the two post-COVID sub-periods in the average proportion of workers reporting any WFH episode and the proportion of time devoted to WFH over the total working time by state. The pre-COVID period is from January 2015 to March 2020. The initial stage of post-COVID is from May 2020 to February 2021. The last stage of post-COVID is from March 2021 to December 2022.

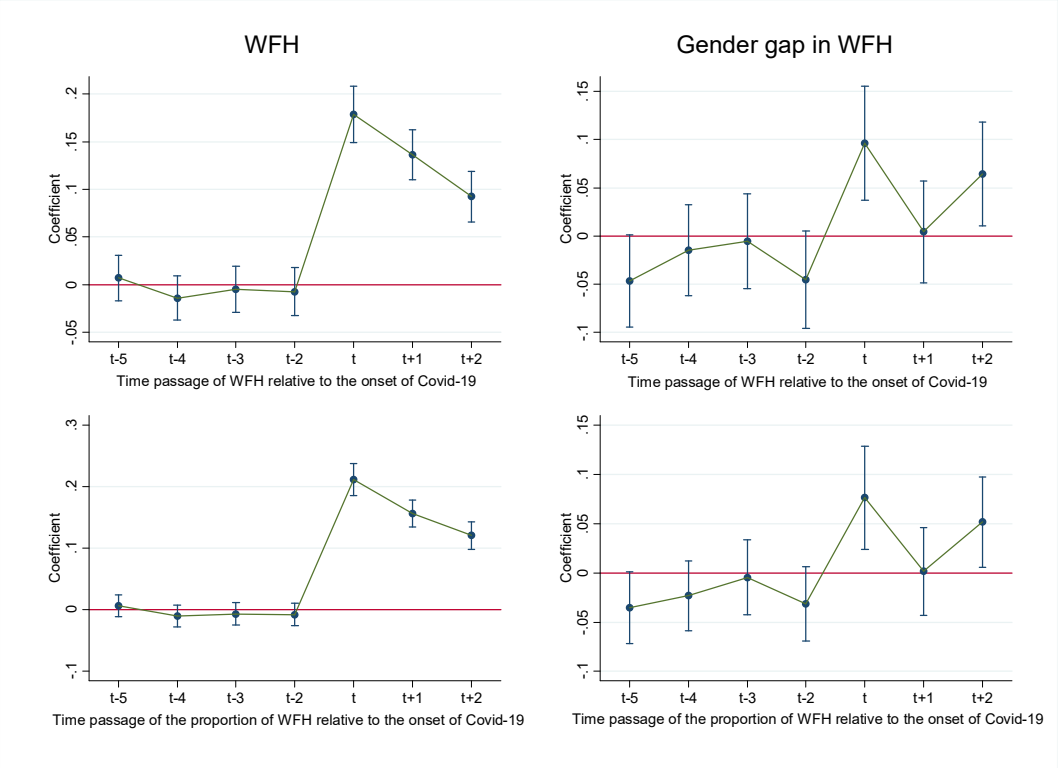
Figure 3. Evolution of the gender gap in WFH over time

Figure 3.1. Average WFH by state



Notes: These figures show the average gender gap in the proportion of workers reporting any WFH episode and the proportion of time devoted to WFH over the total working time by state and period. The pre-COVID period is from January 2015 to March 2020. The initial stage of post-COVID is from May 2020 to February 2021. The last stage of post-COVID is from March 2021 to December 2022.

Figure 4. Event study



Notes: These figures display the coefficients from the event study for our main sample, along with 95 percent confidence intervals. We estimate Equation (3). Estimates are provided in Appendix A in Tables A10 and A11.

Table 1. Main results

	(1)	(2)
Panel A: WFH		
Female----------	0.037***	0.036
	(0.007)	(0.027)
Post Covid	0.209***	0.177***
	(0.024)	(0.024)
Post Covid x Female		0.070***
		(0.015)
Observations	24,094	24,094
R-squared	0.130	0.132
D.V. Mean	0.33	0.33
D.V. Std. Dev.	0.47	0.47
Pre Covid D.V. diff (Female-Male)	0.02***	0.02***
Panel B: Proportion of time WFH over the total work time		
Female	0.043***	0.039*
	(0.006)	(0.022)
Post Covid	0.228***	0.201***
	(0.020)	(0.020)
Post Covid x Female		0.057***
		(0.013)
Observations	24,094	24,094
R-squared	0.129	0.131
D.V. Mean	0.24	0.24
D.V. Std. Dev.	0.41	0.41
Pre Covid D.V. diff (Female-Male)	0.03***	0.03***
For all		
State FE	Yes	Yes
Month FE	Yes	Yes
Year FE	Yes	Yes

Notes: The sample in all columns includes workers between 18 and 64 years old who reported a work episode on the day of the survey. We estimate Equation (1). The dependent variable is the probability of working from home in Panel A and the proportion of WFH time over the total work time in Panel B. The post-COVID dummy takes the value 1 from May 2020 to December 2022 and 0 otherwise. All regressions include a constant, as well as demographic and geographic controls for age, race, educational attainment, and a dummy variable controlling for whether or not respondents live in a metropolitan area. The controls are interacted with the female dummy in column (2). Table A2 in Appendix A presents all estimated coefficients. Estimates are weighted using ATUS weights. Robust standard errors are clustered at the state level and reported in parentheses. *** Significant at the 1% level; ** significant at the 5% level; * significant at the 10% level.

Table 2. The effect of COVID-19 on WFH over time

Dependent variable:	(1) WFH	(2) Proportion of time WFH over the total work time
The period of the event (May20-Dec20)	0.183***	0.215***
	(0.013)	(0.012)
1 period after the event (2021)	0.141***	0.161***
	(0.011)	(0.010)
2 periods after the event (2022)	0.097***	0.125***
	(0.011)	(0.010)
Observations	24,094	24,094
R-squared	0.130	0.129
State FE	Yes	Yes
Month FE	Yes	Yes

Notes: This table presents the estimated coefficients of the dynamic response of WFH to COVID-19. The sample in all columns includes workers between 18 and 64 years old who reported a work episode on the day of the survey. We estimate Equation (2). All regressions include a constant, as well as demographic and geographic controls for age, race, educational attainment, and a dummy variable controlling for whether or not respondents live in a metropolitan area. Estimates are weighted using ATUS weights. Robust standard errors are clustered at the state level and reported in parentheses. *** Significant at the 1% level; ** significant at the 5% level; * significant at the 10% level.

Table 3. The effect of COVID-19 on the gender gap in WFH over time

Dependent variable:	(1) WFH	(2) Proportion of time WFH over the total work time
The period of the event (May20-Dec20) x Female	0.117***	0.095***
	(0.025)	(0.024)
1 period after the event (2021) x Female	0.025	0.021
	(0.022)	(0.019)
2 periods after the event (2022) x Female	0.086***	0.071***
	(0.022)	(0.020)
Observations	24,094	24,094
R-squared	0.132	0.131
State FE	Yes	Yes
Month FE	Yes	Yes

Notes: This table presents the estimated coefficients of the dynamic response of the gender gap in WFH to COVID-19. The sample in all columns includes workers between 18 and 64 years old who reported a work episode on the day of the survey. We estimate Equation (2). All regressions include a constant, as well as demographic and geographic controls for age, race, educational attainment, and a dummy variable controlling for whether or not respondents live in a metropolitan area. The controls are interacted with the female dummy in all columns. Estimates are weighted using ATUS weights. Robust standard errors are clustered at the state level and reported in parentheses. *** Significant at the 1% level; ** significant at the 5% level; * significant at the 10% level.

Table 4. Heterogeneity analysis considering individual characteristics

	(1) Aged 18 to 33	(2) Aged 34 to 48	(3) Aged 49 to 64	(4) High educated	(7) Non-high educated
Panel A: WFH					
Female	-0.053	-0.042	0.047	0.067*	0.011
	(0.077)	(0.102)	(0.142)	(0.036)	(0.037)
Post Covid	0.212***	0.178***	0.142***	0.237***	0.025
	(0.044)	(0.040)	(0.042)	(0.032)	(0.038)
Post Covid x Female	0.080***	0.077***	0.054**	0.055***	0.069***
	(0.027)	(0.024)	(0.025)	(0.019)	(0.025)
Observations	6,003	9,768	8,323	18,170	5,924
R-squared	0.141	0.137	0.131	0.068	0.029
D.V. Mean	0.23	0.37	0.34	0.39	0.13
D.V. Std. Dev.	0.42	0.48	0.48	0.49	0.34
Pre Covid D.V. diff (Female-Male)	0.02**	0.05***	0.0001	0.01	0.01
Panel B: Proportion of time WFH over the total work time					
Female	-0.068	-0.052	0.036	0.071**	0.008
	(0.067)	(0.085)	(0.119)	(0.029)	(0.030)
Post Covid	0.210***	0.207***	0.188***	0.264***	0.060**
	(0.037)	(0.033)	(0.035)	(0.027)	(0.027)
Post Covid x Female	0.069***	0.066***	0.037*	0.046***	0.032
	(0.024)	(0.021)	(0.021)	(0.017)	(0.020)
Observations	6,003	9,768	8,323	18,170	5,924
R-squared	0.137	0.148	0.120	0.095	0.030
D.V. Mean	0.19	0.27	0.26	0.29	0.09
D.V. Std. Dev.	0.36	0.43	0.42	0.44	0.27
Pre Covid D.V. diff (Female-Male)	0.02**	0.05***	0.02*	0.01	0.02***
For all					
State FE	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes

Notes: The sample in all columns includes workers who reported a work episode on the day of the survey. We estimate Equation (1). The dependent variable is the probability of working from home in Panel A and the proportion of WFH time over the total work time in Panel B. All regressions include a constant, as well as demographic and geographic controls for age, race, educational attainment, and a dummy variable controlling for whether or not respondents live in a metropolitan area. The controls are interacted with the female dummy in all columns. See Table B1 in the Appendix B for a detailed description of all subsamples. Estimates are weighted using ATUS weights. Robust standard errors are clustered at the state level and reported in parentheses. *** Significant at the 1% level; ** significant at the 5% level; * significant at the 10% level.

Table 5. Heterogeneity analysis by marital status

	(1) Two-partnered HH	(2) Single HH	(3) Different-sex two-partnered HH	(4) Same-sex two-partnered HH
Panel A: WFH				
Female	0.036	0.046	0.033	0.523*
	(0.041)	(0.035)	(0.042)	(0.315)
Post Covid	0.187***	0.162***	0.183***	1.040***
	(0.030)	(0.041)	(0.030)	(0.358)
Post Covid x Female	0.085***	0.049**	0.084***	-0.051
	(0.019)	(0.023)	(0.019)	(0.172)
Observations	14,419	9,675	14,196	223
R-squared	0.125	0.138	0.124	0.449
D.V. Mean	0.36	0.28	0.36	0.48
D.V. Std. Dev.	0.48	0.44	0.48	0.50
Pre Covid D.V. diff (Female-Male)	0.03***	0.03***	0.03***	-0.04
Panel B: Proportion of time WFH over the total work time				
Female	0.056	0.037	0.053	0.472*
	(0.034)	(0.029)	(0.035)	(0.273)
Post Covid	0.217***	0.177***	0.216***	0.846**
	(0.025)	(0.033)	(0.025)	(0.349)
Post Covid x Female	0.067***	0.045**	0.068***	-0.067
	(0.017)	(0.020)	(0.017)	(0.147)
Observations	14,419	9,675	14,196	223
R-squared	0.126	0.139	0.125	0.503
D.V. Mean	0.27	0.20	0.27	0.39
D.V. Std. Dev.	0.42	0.39	0.42	0.47
Pre Covid D.V. diff (Female-Male)	0.04***	0.04***	0.04***	-0.02
For all				
State FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Notes: The sample in all columns includes workers who reported a work episode on the day of the survey. We estimate Equation (1). The dependent variable is the probability of working from home in Panel A and the proportion of WFH time over the total work time in Panel B. All regressions include a constant, as well as demographic and geographic controls for age, race, educational attainment, and a dummy variable controlling for whether or not respondents live in a metropolitan area. The controls are interacted with the female dummy in all columns. See Table B1 in the Appendix B for a detailed description of all subsamples. Estimates are weighted using ATUS weights. Robust standard errors are clustered at the state level and reported in parentheses. *** Significant at the 1% level; ** significant at the 5% level; * significant at the 10% level.

Table 6. Heterogeneity analysis by dependence status

	(1) Non-children	(2) Children aged 5 years or below	(3) Children aged 6-12 years	(4) Children aged 13-18 years	(5) Older adult in the HH	(6) Non-older adult in the HH
Panel A: WFH						
Female	0.034	0.057	-0.120	0.046	0.026	0.042
	(0.034)	(0.087)	(0.081)	(0.095)	(0.066)	(0.032)
Post Covid	0.172***	0.247***	0.088*	0.237***	0.119*	0.186***
	(0.034)	(0.052)	(0.052)	(0.053)	(0.069)	(0.026)
Post Covid x Female	0.100***	0.015	0.079***	0.036	0.098**	0.064***
	(0.021)	(0.033)	(0.029)	(0.033)	(0.043)	(0.015)
Observations	11,725	4,625	6,110	4,911	1,699	22,395
R-squared	0.130	0.171	0.142	0.149	0.135	0.127
D.V. Mean	0.30	0.34	0.36	0.36	0.19	0.34
D.V. Std. Dev.	0.46	0.47	0.48	0.48	0.39	0.47
Pre Covid D.V. diff (Female-Male)	0.04***	0.02	0.005	-0.01	0.04*	0.02***
Panel B: Proportion of time WFH over the total work time						
Female	0.030	0.081	-0.042	0.037	0.042	0.048*
	(0.029)	(0.068)	(0.064)	(0.079)	(0.053)	(0.026)
Post Covid	0.180***	0.256***	0.144***	0.245***	0.138**	0.212***
	(0.029)	(0.044)	(0.041)	(0.045)	(0.055)	(0.022)
Post Covid x Female	0.082***	-0.002	0.069***	0.034	0.096**	0.050***
	(0.018)	(0.029)	(0.025)	(0.029)	(0.038)	(0.014)
Observations	11,725	4,625	6,110	4,911	1,699	22,395
R-squared	0.133	0.172	0.138	0.142	0.122	0.130
D.V. Mean	0.22	0.25	0.26	0.26	0.14	0.25
D.V. Std. Dev.	0.40	0.42	0.42	0.42	0.34	0.41
Pre Covid D.V. diff (Female-Male)	0.04***	0.03**	0.01	0.01	0.03	0.03***
For all						
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The sample in all columns includes workers between 18 and 64 years old who reported a work episode on the day of the survey. We also limit the sample to those without any children, with a child aged 5 years or below, with a child aged 6 to 12 years old, and with a child aged 13 to 18 years old living in the household in columns (1), (2), (3), and (4), respectively. We estimate Equation (1). The dependent variable is the probability of working from home in Panel A and the proportion of WFH time over the total work time in Panel B. All regressions include a constant, as well as demographic and geographic controls for age, race, educational attainment, and a dummy variable controlling for whether or not respondents live in a metropolitan area. The controls are interacted with the female dummy in all columns. Estimates are weighted using ATUS weights. Robust standard errors are clustered at the state level and reported in parentheses. *** Significant at the 1% level; ** significant at the 5% level; * significant at the 10% level.

Table 7. Heterogeneity analysis by class of worker

	(1) Public employed	(2) Private employed	(3) Self-employed
Panel A: WFH			
Female	-0.025	0.041	0.179
	(0.070)	(0.029)	(0.129)
Post Covid	0.259***	0.154***	0.184**
	(0.062)	(0.028)	(0.089)
Post Covid x Female	0.040	0.083***	-0.007
	(0.038)	(0.017)	(0.052)
Observations	3,967	17,536	2,591
R-squared	0.145	0.148	0.143
D.V. Mean	0.35	0.29	0.56
D.V. Std. Dev.	0.48	0.45	0.50
Pre Covid D.V. diff (Female-Male)	0.05***	0.003	0.18***
Panel B: Proportion of time WFH over the total work time			
Female	0.015	0.031	0.229*
	(0.057)	(0.024)	(0.119)
Post Covid	0.351***	0.180***	0.102
	(0.049)	(0.023)	(0.082)
Post Covid x Female	0.046	0.060***	0.013
	(0.033)	(0.015)	(0.049)
Observations	3,967	17,536	2,591
R-squared	0.154	0.150	0.147
D.V. Mean	0.25	0.21	0.43
D.V. Std. Dev.	0.41	0.39	0.46
Pre Covid D.V. diff (Female-Male)	0.04***	0.02**	0.19***
For all			
State FE	Yes	Yes	Yes
Month FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

Notes: The sample in all columns includes workers between 18 and 64 years old who reported a work episode on the day of the survey. We also limit the sample to public employees, private employees, and self-employed individuals in columns (1), (2), and (3), respectively. We estimate Equation (1). The dependent variable is the probability of working from home in Panel A and the proportion of WFH time over the total work time in Panel B. All regressions include a constant, as well as demographic and geographic controls for age, race, educational attainment, and a dummy variable controlling for whether or not respondents live in a metropolitan area. The controls are interacted with the female dummy in all columns. Estimates are weighted using ATUS weights. Robust standard errors are clustered at the state level and reported in parentheses. *** Significant at the 1% level; ** significant at the 5% level; * significant at the 10% level.

Table 8. The intensity of COVID-19 non-pharmaceutical interventions and WFH

Dependent variable:	(1) WFH	(2) WFH	(3) Proportion of time WFH over the total work time	(4) Proportion of time WFH over the total work time
Female	0.062***	0.219***	0.060***	0.161**
	(0.015)	(0.076)	(0.013)	(0.068)
COVINDEX	-0.027	-0.075**	-0.059***	-0.081***
	(0.025)	(0.031)	(0.022)	(0.027)
COVINDEX x Female		0.104**		0.049
		(0.051)		(0.045)
Observations	5,198	5,198	5,198	5,198
R-squared	0.158	0.160	0.142	0.141
State FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
D.V. Mean	0.42	0.42	0.35	0.35
D.V. Std. Dev.	0.49	0.49	0.46	0.46
COVINDEX Mean	-1.02	-1.02	-1.02	-1.02
COVINDEX Std. Dev.	0.32	0.32	0.32	0.32

Notes: The sample in all columns includes workers between 18 and 64 years old who reported a work episode on the day of the survey. We limit the sample to the years 2021 and 2022. We estimate Equation (4). The more intense (effective) the NPIs are at reducing social interactions, the closer the value of the COVINDEX to -5. The dependent variable is the probability of working from home in columns (1) and (2), and the proportion of WFH time over the total work time in columns (3) and (4). All regressions include a constant, as well as demographic and geographic controls for age, race, educational attainment, and a dummy variable controlling for whether or not respondents live in a metropolitan area. The controls are interacted with the female dummy in all columns. Estimates are weighted using ATUS weights. Robust standard errors are clustered at the state level and reported in parentheses. *** Significant at the 1% level; ** significant at the 5% level; * significant at the 10% level.

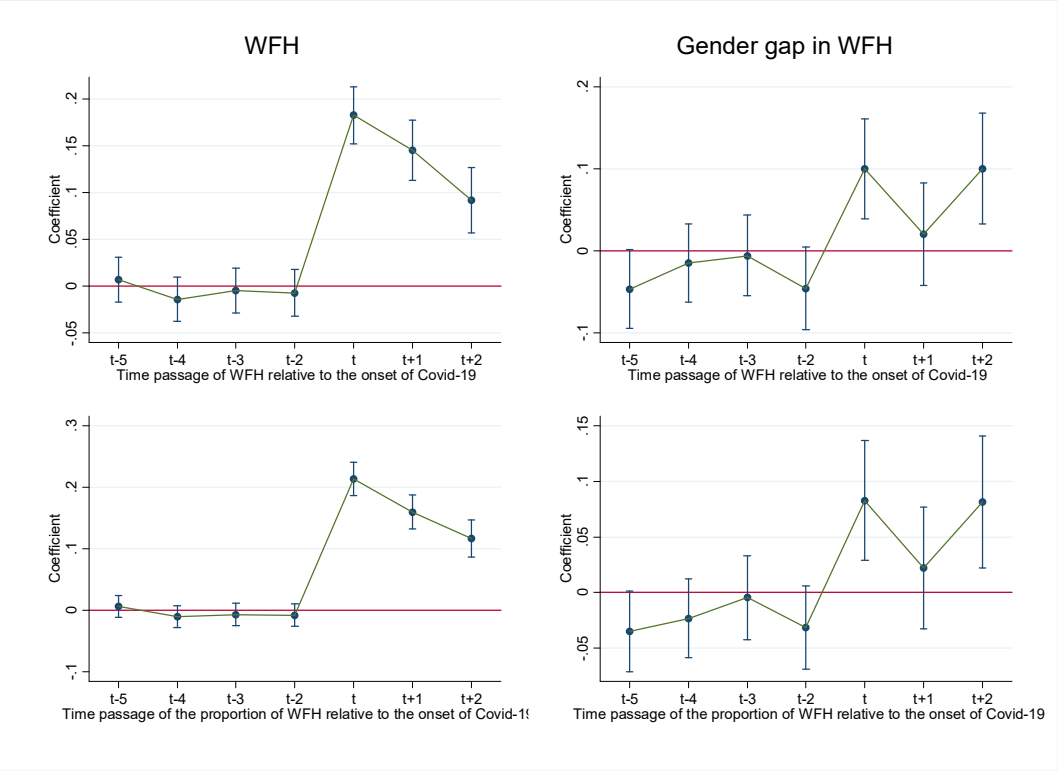
Table 9. Other work-related outcomes

Dependent variable:	(1) Unpredictable schedule	(2) Unpredictable schedule	(3) Non-standard schedule	(4) Non-standard schedule	(5) Interrupted work (number of work episodes)	(6) Interrupted work (number of work episodes)	(7) Log (weekly work hours)	(8) Log (weekly work hours)	(9) Commuting	(10) Commuting
Female	-0.488***	-0.524*	-0.074***	-0.043	-0.132***	-0.254**	-0.126***	-0.034	-0.027***	-0.023
	(0.066)	(0.297)	(0.007)	(0.031)	(0.023)	(0.103)	(0.006)	(0.030)	(0.006)	(0.027)
Post Covid	-0.077	-0.449*	-0.010	0.012	-0.159**	-0.215**	-0.035*	-0.060***	-0.194***	-0.157***
	(0.070)	(0.243)	(0.007)	(0.023)	(0.080)	(0.084)	(0.020)	(0.021)	(0.023)	(0.024)
Post Covid x Female		0.383***		0.022		0.119**		0.057***		-0.078***
		(0.141)		(0.015)		(0.049)		(0.013)		(0.015)
Observations	24,094	24,094	24,094	24,094	24,094	24,094	22,875	22,875	24,094	24,094
R-squared	0.014	0.017	0.022	0.026	0.014	0.015	0.057	0.061	0.085	0.087
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
D.V. Mean	5.03	5.03	0.24	0.24	2.35	2.35	3.70	3.70	0.73	0.73
D.V. Std. Dev.	4.25	4.25	0.43	0.43	1.33	1.33	0.36	0.36	0.44	0.44

Notes: The sample in all columns includes workers between 18 and 64 years old who reported a work episode on the day of the survey. We also limit the sample to those individuals reporting information on weekly work hours in columns (7) and (8). We estimate Equation (1). In columns (1) and (2), the dependent variable is the difference between the time at which the first and the last work episode start for a respondent in a day. In columns (3) and (4), it is a dummy variable taking the value 1 if the respondent works during non-standard hours and 0 otherwise. In columns (5) and (6), it is the number of different work episodes reported by the respondent in a day. In columns (7) and (8), it has been redefined as the logarithm of the weekly work hours, and as a dummy variable taking the value 1 if the respondent reports any commuting episode and 0 otherwise in columns (9) and (10). See Table B1 in the Appendix B for a detailed description. All regressions include a constant, as well as demographic and geographic controls for age, race, educational attainment, and a dummy variable controlling for whether or not respondents live in a metropolitan area. Estimates are weighted using ATUS weights. Robust standard errors are clustered at the state level and reported in parentheses. *** Significant at the 1% level; ** significant at the 5% level; * significant at the 10% level.

Appendix A

Figure A1: Event study controlling for the number of cases and deaths



Notes: These figures display the coefficients from the event study controlling for the number of cases and deaths, along with 95 percent confidence intervals. We estimate Equation (3).

Table A1. Summary statistics by gender

	Pre-covid (from Jan 2015 to March 2020)			Post-covid (from May 2020 to Dec 2022)		
Variable	Female	Male	Diff (Female-Male)	Female	Male	Diff (Female-Male)
WFH	0.30	0.27	0.02***	0.47	0.39	0.08***
Proportion of time WFH over the total work time	0.21	0.18	0.03***	0.40	0.32	0.08***

Notes: Data come from the 2010–2022 ATUS. We use a sample of workers between 18 and 68 years old who reported a work episode on the day of the survey.

Table A2. Main results showing all coefficients

	(1)	(2)
Panel A: WFH		
Female----------	0.037***	0.036
	(0.007)	(0.027)
Post Covid	0.209***	0.177***
	(0.024)	(0.024)
Post Covid x Female		0.070***
		(0.015)
Age	0.003***	0.004***
	(0.000)	(0.000)
Age x Female		-0.001*
		(0.001)
White	0.031***	0.023**
	(0.008)	(0.011)
White x Female		0.015
		(0.016)
High educated	0.257***	0.261***
	(0.007)	(0.009)
High educated x Female		-0.009
		(0.014)
Metropolitan area	0.021***	0.016
	(0.008)	(0.010)
Metropolitan area x Female		0.013
		(0.013)
Observations	24,094	24,094
R-squared	0.130	0.132
D.V. Mean	0.33	0.33
D.V. Std. Dev.	0.47	0.47
Panel B: Proportion of time WFH over the total work time		
Female	0.043***	0.039*
	(0.006)	(0.022)
Post Covid	0.228***	0.201***
	(0.020)	(0.020)
Post Covid x Female		0.057***
		(0.013)
Age	0.002***	0.002***
	(0.000)	(0.000)
Age x Female		-0.001
		(0.000)
White	0.013*	0.009
	(0.007)	(0.009)
White x Female		0.007
		(0.013)
High educated	0.188***	0.193***
	(0.006)	(0.007)
High educated x Female		-0.012
		(0.011)
Metropolitan area	0.014**	0.006
	(0.007)	(0.008)
Metropolitan area x Female		0.018
		(0.011)
Observations	24,094	24,094
R-squared	0.129	0.131
D.V. Mean	0.24	0.24
D.V. Std. Dev.	0.41	0.41
For all		
State FE	Yes	Yes
Month FE	Yes	Yes
Year FE	Yes	Yes

Notes: The sample in all columns includes workers between 18 and 64 years old who reported a work episode on the day of the survey. We estimate Equation (1). The dependent variable is the probability of working from home in Panel A and the proportion of WFH time over the total work time in Panel B. The post-COVID dummy takes the value 1 from May 2020 to December 2022 and 0 otherwise. All regressions include a constant, as well as demographic and geographic controls for age, race, educational attainment, and a dummy variable controlling for whether or not respondents live in a metropolitan area. The controls are interacted with the female dummy in column (2). Estimates are weighted using ATUS weights. Robust standard errors are clustered at the state level and reported in parentheses. *** Significant at the 1% level; ** significant at the 5% level; * significant at the 10% level.

Table A3. Robustness checks adding more controls

	(1)	(2)
Panel A: WFH		
Female	0.046***	0.026
	(0.007)	(0.037)
Post Covid	0.208***	0.172***
	(0.023)	(0.024)
Post Covid x Female		0.070***
		(0.014)
Observations	24,094	24,094
R-squared	0.161	0.165
D.V. Mean	0.33	0.33
D.V. Std. Dev.	0.47	0.47
Panel B: Proportion of time WFH over the total work time		
Female	0.048***	0.039
	(0.006)	(0.031)
Post Covid	0.225***	0.196***
	(0.019)	(0.020)
Post Covid x Female		0.059***
		(0.013)
Observations	24,094	24,094
R-squared	0.157	0.163
D.V. Mean	0.24	0.24
D.V. Std. Dev.	0.41	0.41
For all		
State FE	Yes	Yes
Month FE	Yes	Yes
Year FE	Yes	Yes

Notes: The sample in all columns includes workers between 18 and 64 years old who reported a work episode on the day of the survey. We estimate Equation (1). The dependent variable is the probability of working from home in Panel A and the proportion of WFH time over the total work time in Panel B. The post-COVID dummy takes the value 1 from May 2020 to December 2022 and 0 otherwise. All regressions include a constant, as well as demographic and geographic controls for age, race, educational attainment, and a dummy variable controlling for whether or not respondents live in a metropolitan area. Additionally, we control for the day of the week respondents completed the survey and whether it was a holiday, whether the respondent lives with an employed and highly educated partner, respondents' work classification as part- or full-time workers, and self-employment status. The controls are interacted with the female dummy in column (2). Estimates are weighted using ATUS weights. Robust standard errors are clustered at the state level and reported in parentheses. *** Significant at the 1% level; ** significant at the 5% level; * significant at the 10% level.

Table A4. Robustness checks controlling for industry and occupation categories

	(1)	(2)
Panel A: WFH		
Female	0.021***	-0.008
	(0.007)	(0.026)
Post Covid	0.216***	0.185***
	(0.023)	(0.024)
Post Covid x Female		0.068***
		(0.014)
Observations	24,094	24,094
R-squared	0.192	0.193
D.V. Mean	0.33	0.33
D.V. Std. Dev.	0.47	0.47
Panel B: Proportion of time WFH over the total work time		
Female	0.036***	0.008
	(0.006)	(0.022)
Post Covid	0.234***	0.209***
	(0.020)	(0.020)
Post Covid x Female		0.054***
		(0.012)
Observations	24,094	24,094
R-squared	0.189	0.190
D.V. Mean	0.24	0.24
D.V. Std. Dev.	0.41	0.41
For all		
State FE	Yes	Yes
Month FE	Yes	Yes
Year FE	Yes	Yes

Notes: The sample in all columns includes workers between 18 and 64 years old who reported a work episode on the day of the survey. We estimate Equation (1). The dependent variable is the probability of working from home in Panel A and the proportion of WFH time over the total work time in Panel B. The post-COVID dummy takes the value 1 from May 2020 to December 2022 and 0 otherwise. All regressions include a constant, as well as demographic and geographic controls for age, race, educational attainment, and a dummy variable controlling for whether or not respondents live in a metropolitan area. The controls are interacted with the female dummy in column (2). Estimates are weighted using ATUS weights. Robust standard errors are clustered at the state level and reported in parentheses. *** Significant at the 1% level; ** significant at the 5% level; * significant at the 10% level.

Table A5. Robustness checks controlling for occupations allowing remote working

	(1)	(2)
Panel A: WFH		
Female	0.016**	0.011
	(0.006)	(0.026)
Post Covid	0.212***	0.182***
	(0.024)	(0.024)
Post Covid x Female		0.064***
		(0.014)
Observations	21,675	21,675
R-squared	0.161	0.162
D.V. Mean	0.33	0.33
D.V. Std. Dev.	0.47	0.47
Panel B: Proportion of time WFH over the total work time		
Female	0.025***	0.016
	(0.005)	(0.021)
Post Covid	0.230***	0.206***
	(0.020)	(0.020)
Post Covid x Female		0.052***
		(0.012)
Observations	21,675	21,675
R-squared	0.158	0.159
D.V. Mean	0.29	0.29
D.V. Std. Dev.	0.46	0.46
For all		
State FE	Yes	Yes
Month FE	Yes	Yes
Year FE	Yes	Yes
Industry FE	Yes	Yes
Occupation FE	Yes	Yes

Notes: The sample in all columns includes workers between 18 and 64 years old who reported a work episode on the day of the survey. We estimate Equation (1). The dependent variable is the probability of working from home in Panel A and the proportion of WFH time over the total work time in Panel B. The post-COVID dummy takes the value 1 from May 2020 to December 2022 and 0 otherwise. All regressions include a constant, as well as demographic and geographic controls for age, race, educational attainment, and a dummy variable controlling for whether respondents live in a metropolitan area or not. The controls are interacted with the female dummy in column (2). Estimates are weighted using ATUS weights. Robust standard errors are clustered at the state level and reported in parentheses. *** Significant at the 1% level; ** significant at the 5% level; * significant at the 10% level.

Table A6: Robustness checks using a sample of full-time workers

	(1)	(2)
Panel A: WFH		
Female	0.033***	0.041
	(0.007)	(0.031)
Post Covid	0.218***	0.180***
	(0.026)	(0.026)
Post Covid x Female		0.088***
		(0.016)
Observations	20,796	20,796
R-squared	0.129	0.131
D.V. Mean	0.33	0.33
D.V. Std. Dev.	0.47	0.47
Panel B: Proportion of time WFH over the total work time		
Female	0.038***	0.041*
	(0.006)	(0.025)
Post Covid	0.244***	0.211***
	(0.020)	(0.021)
Post Covid x Female		0.077***
		(0.014)
Observations	20,796	20,796
R-squared	0.133	0.136
D.V. Mean	0.24	0.24
D.V. Std. Dev.	0.41	0.41
For all		
State FE	Yes	Yes
Month FE	Yes	Yes
Year FE	Yes	Yes

Notes: The sample in all columns includes full-time workers between 18 and 64 years old who reported a work episode on the day of the survey. We estimate Equation (1). The dependent variable is the probability of working from home in Panel A and the proportion of WFH time over the total work time in Panel B. The post-COVID dummy takes the value 1 from May 2020 to December 2022 and 0 otherwise. All regressions include a constant, as well as demographic and geographic controls for age, race, educational attainment, and a dummy variable controlling for whether respondents live in a metropolitan area or not. The controls are interacted with the female dummy in column (2). Estimates are weighted using ATUS weights. Robust standard errors are clustered at the state level and reported in parentheses. *** Significant at the 1% level; ** significant at the 5% level; * significant at the 10% level.

Table A7. Robustness checks using a sample of workers working at least two hours on the day of the survey

	(1)	(2)
Panel A: WFH		
Female	0.031***	0.036
	(0.007)	(0.027)
Post Covid	0.213***	0.180***
	(0.024)	(0.025)
Post Covid x Female		0.073***
		(0.015)
Observations	21,762	21,762
R-squared	0.131	0.133
D.V. Mean	0.28	0.28
D.V. Std. Dev.	0.45	0.45
Panel B: Proportion of time WFH over the total work time		
Female	0.036***	0.041*
	(0.005)	(0.021)
Post Covid	0.233***	0.206***
	(0.019)	(0.019)
Post Covid x Female		0.060***
		(0.013)
Observations	21,762	21,762
R-squared	0.138	0.140
D.V. Mean	0.19	0.19
D.V. Std. Dev.	0.37	0.37
For all		
State FE	Yes	Yes
Month FE	Yes	Yes
Year FE	Yes	Yes

Notes: The sample in all columns includes workers between 18 and 64 years old who reported working two or more hours on the day of the survey. We estimate Equation (1). The dependent variable is the probability of working from home in Panel A and the proportion of WFH time over the total work time in Panel B. The post-COVID dummy takes the value 1 from May 2020 to December 2022 and 0 otherwise. All regressions include a constant, as well as demographic and geographic controls for age, race, educational attainment, and a dummy variable controlling for whether or not respondents live in a metropolitan area. The controls are interacted with the female dummy in column (2). Estimates are weighted using ATUS weights. Robust standard errors are clustered at the state level and reported in parentheses. *** Significant at the 1% level; ** significant at the 5% level; * significant at the 10% level.

Table A8. The effect of COVID-19 on WFH over time controlling for the number of cases and deaths

Dependent variable:	(1) WFH	(2) Proportion of time WFH over the total work time
The period of the event (May20-Dec20)	0.187***	0.217***
	(0.013)	(0.013)
1 period after the event (2021)	0.151***	0.163***
	(0.014)	(0.013)
2 periods after the event (2022)	0.097***	0.121***
	(0.016)	(0.014)
Observations	24,094	24,094
R-squared	0.130	0.129
State FE	Yes	Yes
Month FE	Yes	Yes

Notes: This table presents the estimated coefficients of the dynamic response of WFH to COVID-19. The sample in all columns includes workers between 18 and 64 years old who reported a work episode on the day of the survey. We estimate Equation (2). All regressions include a constant, as well as demographic and geographic controls for age, race, educational attainment, and a dummy variable controlling for whether or not respondents live in a metropolitan area. Estimates are weighted using ATUS weights. Robust standard errors are clustered at the state level and reported in parentheses. *** Significant at the 1% level; ** significant at the 5% level; * significant at the 10% level.

Table A9. The effect of COVID-19 on the gender gap in WFH over time controlling for the number of cases and deaths

Dependent variable:	(1) WFH	(2) Proportion of time WFH over the total work time
The period of the event (May20-Dec20) x Female	0.121***	0.101***
	(0.026)	(0.025)
1 period after the event (2021) x Female	0.041	0.041
	(0.028)	(0.025)
2 periods after the event (2022) x Female	0.121***	0.100***
	(0.030)	(0.028)
Observations	24,094	24,094
R-squared	0.133	0.131
State FE	Yes	Yes
Month FE	Yes	Yes

Notes: This table presents the estimated coefficients of the dynamic response of the gender gap in WFH to COVID-19. The sample in all columns includes workers between 18 and 64 years old who reported a work episode on the day of the survey. We estimate Equation (2). All regressions include a constant, as well as demographic and geographic controls for age, race, educational attainment, and a dummy variable controlling for whether or not respondents live in a metropolitan area. The controls are interacted with the female dummy in all columns. Estimates are weighted using ATUS weights. Robust standard errors are clustered at the state level and reported in parentheses. *** Significant at the 1% level; ** significant at the 5% level; * significant at the 10% level.

Table A10. Event study (WFH)

Dependent variable:	(1) WFH	(2) Proportion of time WFH over the total work time
4 periods before the event (2015)	0.007	0.007
	(0.012)	(0.009)
3 periods before the event (2016)	-0.014	-0.010
	(0.012)	(0.009)
2 periods before the event (2017)	-0.005	-0.006
	(0.012)	(0.009)
1 period before the event (2018)	-0.007	-0.008
	(0.013)	(0.009)
The period of the event (May20-Dec20)	0.179***	0.212***
	(0.015)	(0.013)
1 period after the event (2021)	0.136***	0.157***
	(0.013)	(0.011)
2 periods after the event (2022)	0.092***	0.121***
	(0.014)	(0.011)
Observations	23,433	23,433
R-squared	0.131	0.130
State FE	Yes	Yes
Month FE	Yes	Yes

Notes: The sample in all columns includes workers between 18 and 64 years old who reported a work episode on the day of the survey. We estimate Equation (3). The period from January 2020 to March 2020 has been dropped from the sample. All regressions include a constant, as well as demographic and geographic controls for age, race, educational attainment, and a dummy variable controlling for whether or not respondents live in a metropolitan area. Estimates are weighted using ATUS weights. Robust standard errors are clustered at the state level and reported in parentheses. *** Significant at the 1% level; ** significant at the 5% level; * significant at the 10% level.

Table A11. Event study (gender gap in WFH)

Dependent variable:	(1) WFH	(2) Proportion of time WFH over the total work time
4 periods before the event (2015)	-0.047*	-0.035*
	(0.025)	(0.019)
3 periods before the event (2016)	-0.015	-0.023
	(0.024)	(0.018)
2 periods before the event (2017)	-0.006	-0.004
	(0.025)	(0.019)
1 period before the event (2018)	-0.046*	-0.031
	(0.026)	(0.019)
The period of the event (May20-Dec20)	0.096***	0.076***
	(0.030)	(0.027)
1 period after the event (2021)	0.004	0.002
	(0.027)	(0.023)
2 periods after the event (2022)	0.065**	0.052**
	(0.027)	(0.023)
Observations	23,433	23,433
R-squared	0.134	0.133
State FE	Yes	Yes
Month FE	Yes	Yes

Notes: The sample in all columns includes workers between 18 and 64 years old who reported a work episode on the day of the survey. We estimate Equation (3). The period from January 2020 to March 2020 has been dropped from the sample. All regressions include a constant, as well as demographic and geographic controls for age, race, educational attainment, and a dummy variable controlling for whether or not respondents live in a metropolitan area. Estimates are weighted using ATUS weights. Robust standard errors are clustered at the state level and reported in parentheses. *** Significant at the 1% level; ** significant at the 5% level; * significant at the 10% level.

Table A12. The effect of COVID-19 on WFH over time by class of worker

	(1) Public employed	(2) Private employed	(3) Self-employed
Panel A: WFH			
The period of the event (May20-Dec20)	0.256***	0.182***	0.059
	(0.033)	(0.015)	(0.044)
1 period after the event (2021)	0.192***	0.148***	0.054
	(0.028)	(0.012)	(0.037)
2 periods after the event (2022)	0.082***	0.115***	-0.011
	(0.028)	(0.012)	(0.037)
Observations	3,967	17,536	2,591
R-squared	0.141	0.145	0.140
Panel B: Proportion of time WFH over the total work time			
The period of the event (May20-Dec20)	0.321***	0.210***	0.079*
	(0.031)	(0.014)	(0.041)
1 period after the event (2021)	0.219***	0.163***	0.084**
	(0.026)	(0.011)	(0.033)
2 periods after the event (2022)	0.106***	0.144***	0.007
	(0.024)	(0.011)	(0.033)
Observations	3,967	17,536	2,591
R-squared	0.151	0.147	0.143
For all			
State FE	Yes	Yes	Yes
Month FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

Notes: This table presents the estimated coefficients of the dynamic response of the gender gap in WFH to COVID-19. The sample in all columns includes workers between 18 and 64 years old who reported a work episode on the day of the survey. We estimate Equation (2). All regressions include a constant, as well as demographic and geographic controls for age, race, educational attainment, and a dummy variable controlling for whether or not respondents live in a metropolitan area. Estimates are weighted using ATUS weights. Robust standard errors are clustered at the state level and reported in parentheses. *** Significant at the 1% level; ** significant at the 5% level; * significant at the 10% level.

Table A13. The effect of COVID-19 on the gender gap in WFH over time by class of worker

	(1) Public employed	(2) Private employed	(3) Self-employed
Panel A: WFH			
The period of the event (May20-Dec20) x Female	0.095	0.113***	0.093
	(0.065)	(0.029)	(0.084)
1 period after the event (2021) x Female	0.042	0.033	-0.108
	(0.057)	(0.024)	(0.077)
2 periods after the event (2022) x Female	0.002	0.114***	0.013
	(0.057)	(0.025)	(0.079)
Observations	3,967	17,536	2,591
R-squared	0.143	0.148	0.142
Panel B: Proportion of time WFH over the total work time			
The period of the event (May20-Dec20) x Female	0.100	0.073***	0.138*
	(0.061)	(0.027)	(0.079)
1 period after the event (2021) x Female	0.044	0.019	-0.060
	(0.051)	(0.022)	(0.073)
2 periods after the event (2022) x Female	0.015	0.094***	-0.011
	(0.049)	(0.023)	(0.074)
Observations	3,967	17,536	2,591
R-squared	0.153	0.150	0.147
For all			
State FE	Yes	Yes	Yes
Month FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

Notes: This table presents the estimated coefficients of the dynamic response of the gender gap in WFH to COVID-19. The sample in all columns includes workers between 18 and 64 years old who reported a work episode on the day of the survey. We estimate Equation (2). All regressions include a constant, as well as demographic and geographic controls for age, race, educational attainment, and a dummy variable controlling for whether or not respondents live in a metropolitan area. The controls are interacted with the female dummy in all columns. Estimates are weighted using ATUS weights. Robust standard errors are clustered at the state level and reported in parentheses. *** Significant at the 1% level; ** significant at the 5% level; * significant at the 10% level.

Table A14. The intensity of COVID-19 non-pharmaceutical interventions and WFH over time

Dependent variable:	(1) WFH	(2) Proportion of time WFH over the total work time
The period of the event (May20-Dec20) x COVINDEX	-0.115***	-0.163***
	(0.044)	(0.040)
1 period after the event (2021) x COVINDEX	-0.036	-0.109***
	(0.036)	(0.031)
2 periods after the event (2022) x COVINDEX	-0.018	-0.065**
	(0.035)	(0.031)
Observations	24,094	24,094
R-squared	0.131	0.131
State FE	Yes	Yes
Month FE	Yes	Yes

Notes: This table presents the estimated coefficients of the dynamic response of WFH to COVID-19. The sample in all columns includes workers between 18 and 64 years old who reported a work episode on the day of the survey. We estimate Equation (2). The more intense (effective) the NPIs are at reducing social interactions, the closer the value of the COVINDEX to -5. All regressions include a constant, as well as demographic and geographic controls for age, race, educational attainment, and a dummy variable controlling for whether or not respondents live in a metropolitan area. Estimates are weighted using ATUS weights. Robust standard errors are clustered at the state level and reported in parentheses. *** Significant at the 1% level; ** significant at the 5% level; * significant at the 10% level.

Table A15. The intensity of COVID-19 non-pharmaceutical interventions and the gender gap in WFH over time

Dependent variable:	(1) WFH	(2) Proportion of time WFH over the total work time
The period of the event (May20-Dec20) x COVINDEX x Female	-0.119***	-0.107***
	(0.022)	(0.020)
1 period after the event (2021) x COVINDEX x Female	-0.013	-0.022
	(0.019)	(0.017)
2 periods after the event (2022) x COVINDEX x Female	-0.065***	-0.063***
	(0.019)	(0.018)
Observations	24,094	24,094
R-squared	0.133	0.132
State FE	Yes	Yes
Month FE	Yes	Yes

Notes: This table presents the estimated coefficients of the dynamic response of the gender gap in WFH to COVID-19. The sample in all columns includes workers between 18 and 64 years old who reported a work episode on the day of the survey. We estimate Equation (2). The more intense (effective) the NPIs are at reducing social interactions, the closer the value of the COVINDEX to -5. All regressions include a constant, as well as demographic and geographic controls for age, race, educational attainment, and a dummy variable controlling for whether or not respondents live in a metropolitan area. The controls are interacted with the female dummy in all columns. Estimates are weighted using ATUS weights. Robust standard errors are clustered at the state level and reported in parentheses. *** Significant at the 1% level; ** significant at the 5% level; * significant at the 10% level.

Appendix B

Table B1. Summary statistics and definitions of ATUS variables

Name	CPS variable	Definition	Mean	S.D.
WFH Outcomes				
WFH time	ACTIVITY reports the respondent's activity. DURATION reports the length of the activity in minutes. The sum of duration for all activities results in one 24-hour period (1440 minutes). WHERE reports the location of the activity	The sum of all minutes per day reported by a respondent in the activities "working" and "work-related activities", with the activity codes from "50101" to "50299" located in "Respondent's home or yard" with where code "101"	75.00	164.25
Proportion of time WFH over the total work time	See ACTIVITY and DURATION above	WFH time divided by the sum of all minutes per day reported by a respondent in the activity "work" wherever it takes place	0.24	0.41
WFH	See ACTIVITY and WHERE above	Dummy variable taking value 1 if the respondent reports any work from home episode in the day of the survey, and 0 otherwise	0.33	0.47
Other work-related outcomes				
Unpredictable schedule	START reports the time the activity started	We calculate the difference	5.03	4.25

		between the time at which the first and the last work episode start. We assume that a large available work time is equivalent to an unpredictable schedule		
Non-standard schedule	See START above	Dummy variable equal to 1 if the respondent starts some work episode between 20pm and 6 am	0.24	0.42
Interrupted work (number of work episodes)	See ACTIVITY above	The number of the different work episodes reported by the respondent in a day	2.35	1.33
Log (weekly work hours)	UHRSWORKT reports the total number of hours the respondent usually works per week at all jobs	Logarithm of usually hours worked per week	3.70	0.36
Commuter	See ACTIVITY above.	Dummy variable taking value 1 if the respondent devotes any time in the activity "commuting" with the activity code "180501"	0.73	0.44
Individual controls				
Age	AGE gives each person's age at last birthday	Years	42.81	11.77
Female	SEX gives each person's sex. Values of this variable:		0.49	0.50

	Male	1	Dummy variable equal to 1 if SEX==2		
	Female	2			
More college	EDUC reports the respondent's highest completed level of education		Dummy variable equal to 1 if EDUC>=40	0.48	0.50
	Less than 1st grade	10			
	1st, 2nd, 3rd, or 4th grade	11			
	5th or 6th grade	12			
	7th or 8th grade	13			
	9th grade	14			
	10th grade	15			
	11th grade	16			
	12th grade - no diploma	17			
	HS diploma, no college				
	High school graduate - GED	20			
	High school graduate diploma	21			
	Some college				
	Some college but no degree	30			
	Associate degree occupational vocational	31			
	Associate degree - academic program	32			
	College degree +				
	Bachelor's degree (BA, AB, BS, etc.)	40			
	Master's degree (MA, MS, MEng, MEd, MSW, etc.)	41			
	Professional school degree (MD, DDS, DVM, etc.)	42			
	Doctoral degree (PhD, EdD, etc.)	43			

White	RACE reports the racial category of all household members White only 100 Black only 110 American Indian, Alaskan Native 120 Asian or Pacific Islander 130 Asian only 131 Hawaiian Pacific Islander only 132 Two or more races >132		Dummy variable equal to 1 if race=100	0.80	0.40
Metropolitan area	METRO reports whether a household was located in a metropolitan area Metropolitan, central city 1 Metropolitan, balance of MSA 2 Metropolitan, not identified 3 Nonmetropolitan 4 Not identified 5		Dummy variable equal to 1 if METRO=1 or METRO=2	0.47	0.50
Additional variables used in the heterogeneity analysis					
High educated	See EDUC above		Dummy variable equal to 1 if EDUC>=30	0.75	0.43
Two-partnered HH	RELATE reports the relationship of each household member to the ATUS respondent Self 10 Spouse 20 Unmarried Partner 21 Own household child 22 Grandchild 23 Parent 24 Brother/Sister 25		Dummy variable equal to 1 if any of the members in the household reports relate=20 or relate=21	0.60	0.49

	Other relative	26			
	Foster child	27			
	Housemate/roommate	28			
	Roomer/boarder	29			
	Other nonrelative	30			
	Own non-household child lt 18	40			
Different-sex two-partnered HH	See RELATE and SEX above		Dummy variable equal to 1 if any of the members in the household reports relate=20 or relate=21 & SEX is different form the self	0.98	0.12
Children	See RELATE above		Dummy variable equal to 1 if any of the members in the household reports relate=22	0.51	0.50
Children aged 5 years or below	See RELATE and AGE above		Dummy variable equal to 1 if any of the members in the household reports relate=22 and AGE<=5	0.19	0.40
Children aged 6 to 12 years old	See RELATE and AGE above		Dummy variable equal to 1 if any of the members in the household reports relate=22 and AGE>=6 & AGE<=12	0.25	0.44
Children aged 13 to 18 years old	See RELATE and AGE above		Dummy variable equal to 1 if any of the members in the household reports relate=22 and AGE>=13 & AGE<=18	0.20	0.40
Older adult	See Relate above		Dummy variable equal to 1 if any of the members in the household reports relate=24	0.07	0.26

Public employee	CLWKR reports the worker classification for the respondent's main job. Government, federal 1 Government, state 2 Government, local 3 Private, for profit 4 Private, nonprofit 5 Self-employed, incorporated 6 Self-employed, unincorporated 7		Dummy variable equal to 1 if CLWKR=1 or CLWKR=2 or CLWKR=3	0.16	0.37
Private employee	See CLWKR above		Dummy variable equal to 1 if CLWKR=4 or CLWKR=5	0.73	0.45
Self-employee	See CLWKR above		Dummy variable equal to 1 if CLWKR=6 or CLWKR=7	0.11	0.31
Additional controls					
High educ partner	SPEDUC reports the highest completed level of education of the respondent's spouse or unmarried partner. See EDUC categories above		Dummy variable equal to 1 if SPEDUC>=30	0.86	0.35

Fulltime worker	FULLPART indicates whether the individual usually works full time or part time. Full time employment is considered to be 35 or more hours per week		Dummy variable equal to 1 if FULLPART= 1	0.86	0.35
	Full time	1			
	Part time	2			
Partner working	SPEMPNOT reports whether the respondent's spouse or unmarried partner is employed		Dummy variable equal to 1 if SPEMPNOT= 1	0.46	0.50
	Not employed	0			
	Employed	1			
Occupation	OCC reports the four-digit Census occupational code for the respondent's main job. "occupation" relates to the worker's specific technical function. IND reports the four-digit Census industry code. More than 250 industries are represented.				
	Management, Business, Science, and Arts Occupations	0010-3540	Dummy variable equal to 1 if OCC>=0010 and OCC<=3540	0.50	0.50
	Service Occupations	3600-4650	Dummy variable equal to 1 if OCC>=3600 and OCC<=4650	0.14	0.34
	Sales and Office Occupations	4700-5940	Dummy variable equal to 1 if OCC>=4700 and OCC<=5940	0.19	0.39
	Natural Resources, Construction, and Maintenance Occupations	6005-7630	Dummy variable equal to 1 if OCC>=6005	0.07	0.26

			and OCC<=7630		
	Production, Transportation, and Material Moving Occupations	7700-9750	Dummy variable equal to 1 if OCC>=7700 and OCC<=9750	0.10	0.30
	IND reports the type of industry in which the person performed his or her primary occupation. "Industry" refers to the work setting and economic sector.				
Industry	Agriculture, Forestry, Fishing, Hunting, and Mining	0170-0490	Dummy variable equal to 1 if IND>=0170 and IND<=0490	0.02	0.14
	Construction	770	Dummy variable equal to 1 if IND=770	0.05	0.23
	Manufacturing	1070-3990	Dummy variable equal to 1 if IND>=1070 and IND<=3990	0.11	0.31
	Wholesale Trade	4070-4590	Dummy variable equal to 1 if IND>=4070 and IND<=4590	0.02	0.16
	Retail Trade	4670-5790	Dummy variable equal to 1 if IND>=4670 and IND<=5790	0.09	0.29
	Transportation	6070-6390, 0570-0690	Dummy variable equal to 1 if (IND>=6070 and	0.05	0.22

		IND<=6390) or (IND>=0570 and IND<=0690)		
Information	6470-6780	Dummy variable equal to 1 if IND>=6470 and IND<=6780	0.02	0.15
Financial activities	6870-7190	Dummy variable equal to 1 if IND>=6870 and IND<=7190	0.07	0.26
Professional and business	7270-7790	Dummy variable equal to 1 if IND>=7270 and IND<=7790	0.13	0.34
Educational, Health and Social Assistance	7860-8470	Dummy variable equal to 1 if IND>=7860 and IND<=8470	0.25	0.43
Arts, Entertainment, Recreation, Accommodation and Food Services	8560-8690	Dummy variable equal to 1 if IND>=8560 and IND<=8690	0.07	0.26
Other Services	8770-9290	Dummy variable equal to 1 if IND>=8770 and IND<=9290	0.04	0.21
Public Administration	9370-9590	Dummy variable equal to 1 if IND>=9370 and IND<=9590	0.05	0.23

Employed in an occupation allowing remote work	See OCC above	Dummy variable taking value 1 if the respondent is employed in an occupation allowing telework according to the classification in Dingel & Neiman (2020)	0.51	0.50