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

Miriam Marcén[1] and Marina Morales[1]

[1]Universidad de Zaragoza

Abstract

In this paper, we analyze gender differences in working from home (WFH) from the time the pandemic hardest hit onwards in the US. The first unexpected wave of the COVID-19 caused a shift in many people's regular workplaces, facing increased demands for housework and childcare while working remotely. After that, it is not clear how men and women has reacted to the normality. Using data from the American Time Use Survey (ATUS), we find that WFH is more prevalent among women than men and the gender gap is considerably widest after the first wave of the pandemic with heterogeneous results by age, level of education, and marital and dependence status. The dynamic analysis also reveals changes over time. The event study points to the no existence of pre-trends. However, we further show suggestive evidence on the fact that a longer and greater exposure to more intense non-pharmaceutical interventions (NPIs) during the first wave of the pandemic positively affected the tendency of WFH for men but not for women considerably reducing the gender gap by 18 percentage points in a typical state. Additional results also point to more work-related issues differentially affected by gender after the pandemic hits. We find an increase in unpredictable schedules, interrupted work, weekly work hours, and a decrease in commuting time only for women.

Keywords: COVID-19, Working from home (WFH), gender, ATUS

JEL Codes: J16, J21, J22

1. Introduction

Traditionally, women have shown greater preferences for family and work balance than men even in developed countries. Whereas men reported 6 times less than women the coordination of work with personal/family needs as main reason for WFH in the early 21st century in the US (Wight & Raley, 2009), women tend to avoid greedy jobs and involve in family-friendly jobs with short commutes and possibilities of working from home (WFH) or telework (Gálvez et al., 2021; Goldin, 2021; Marcén & Morales, 2021a).[1] But after COVID-19 lockdowns this could have changed or get worse. The worldwide unexpected COVID pandemic gave the opportunity to many men and women to experience the full-time work-family-life environment during the lockdown weeks. The return to the pre-pandemic life "new normality" could arise three possible scenarios: (1) A return to the usual work locations; (2) An increase in men remote work reducing the gender gap in WFH; or (3) A reinforcement in 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 on a considerable increase, doubling the percentage of voluntary workers, in the WFH option after a pre-pandemic randomized Chinese experiment that explored the positive impact of the WFH on the productivity, profitability, as well as work satisfaction of home workers (Bloom et al., 2015). The physical unexpected distancing measures and lockdowns as a result of COVID-19, like in a mass social experiment, forced many people to a learning process of the WFH with a combination of all their spheres (work-family-life) at the same time. From the supply side in the labor market, it is not clear whether the COVID-19 makes WFH more attractive to workers and whether this is gendered. The positive WFH benefits are related to the freedom of work schedule, savings in commuting time, the possible increase in the time devoted to leisure and family, and the availability of time to care for the children. But, there are also adverse effects possibly counteracting previous ones such as work isolation, difficulties in the access 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 neither clear. In contrast to the Chinese pre-pandemic experiment, researchers did not observe an increase in the productivity from the WFH practice with reductions around 30-40% of the workers′ productivity in the case of two Japanese surveys during the COVID-19 lockdowns (Bloom et al., 2015; Kitagawa et al., 2021; Morikawa, 2022) . All the direct supervisors had no role in the setting of the WFH because there is a lack of direct oversight of workers. Those workers could make pressure to force the return to the usual work locations or to partly return to them based on the lack of working transparency to avoid losing their own jobs. Additionally, firms could not immediately reduce office rental costs since their rental contracts do not disappear with the COVID-19, reducing even more their immediate economic incentives for the WFH option. The dominant effect and how the WFH has evolved is an empirical issue that needs to be explored, our work fills this gap using US data on workers from the Integrated Public Use Microdata Series Time Use

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

(IPUMS Time Use, ATUS) database for the period 2015–2021 (Flood et al., 2022). ATUS is a daily diary allowing us to identify pre- and post-lockdowns remote workers through the location of working activities and the daily time devoted to the WFH.

We use the pre- and post-lockdowns data to answer the following two research questions: (1) Has the asymmetry between men and women in remote work being reinforced after the hard lockdowns? (2) Does the intensity of the 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 the NPIs. We also explore heterogeneity in the WFH response by age, level of education, marital status, and dependence status.

We contribute to three strands of the literature: gender economics, COVID-19 impact, and telework literature. The existing research on gender differences in the labor market has focused on the role of human capital, attitudes towards 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 representation in high-paying occupations and therefore to reduce gender gaps in the labor market. In this framework, an increase in the time men works from home might raise their family life involvement rebalancing traditional family arrangements (Boca et al., 2021). We add to this literature 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 market such as those works that study the changes in labor supply in response to the unanticipated school closures, stay at home orders, 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 non-pharmaceutical interventions (NPIs) at state level to assess how the gender gap in WFH relates to the intensity of the NPIs. After considering the intensity of the NPIs, we find that a higher intensity of non- NPIs during the pandemic reduced the probability of WFH and also the time WFH for women relative to men.

We lastly add to the still scarce telework literature. In the early stages of the pandemic, it was predicted that 20% of full workdays could be supplied from home after the pandemic ends compared with just 5% of WFH detected before or that 37 of all U.S. jobs will be entirely do from home (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 well-being (see a review in Pabilonia & Vernon, 2022). In our case, we provide evidence on how the telework has evolved in the post-pandemic period. The analysis is extended by studying other work-related outcomes such as having unpredictable schedule or non-standard schedules, 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 2015-2021 American Time Use Survey (ATUS) (Flood et al., 2022) to analyze remote work 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. After 2-5 months of the last CPS interview, a selected sample is asked to fill out a diary throughout 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 at anyplace, and specifically at home. The main drawback is that time diary data is only available for one individual from each selected household.

We restrict the sample to workers aged 15 to 65 years old who report any work episode in 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 complete the survey which allow us to disentangle individuals responding during the period pre- and post-first-wave COVID-19 when the COVID-19 and NPIs were unexpected and intense. All responses after May 2020 are considered as post-COVID-19 answers.[4]

Figure 1 shows WFH measures by gender during both the pre- and post-COVID-19 periods. We observe that the gender gap in remote work has tripled after the pandemic hit. While only 28% and 31% of men and women respectively, reported any remote work episode during the pre-COVID-19, 40% and 49% do after the pandemic first wave outbreak. Similarly, the percentage of time workers spend WFH over the total work time has increased from 19% to 33% in the case of men and almost double in the case of women rising from 22% to 41%. Differences by gender are statistically significant, see table A1. A more detailed analysis is needed. Table B1 in the Appendix B reports the descriptive statistics for the rest of variables. The average age in our sample is 43 years, 47% of respondents are females, 80% are white individuals, 48% have completed more college education and around 46% of them live in a metropolitan area. More than half of the interviewed workers (59%) live with a partner, with most of them (98%) being heterosexual individuals. In addition, 51% of respondents have children living in the household and 19%, 25% and 20% of them lives with a child aged 5 years or below, aged 6 to 12 years old or aged 12 to 18 years old, respectively. Only 8% of respondents live with an older adult in the household.

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[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% allocated to each of the weekdays, 25% to Saturdays, and 25% to Sundays.

[3] Activity codes from "50101" to "50299" located in "Respondent's home or yard" with where code "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

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:

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

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 remote work episode during the day of the survey, and the proportion of time devoted to telework from home over total working time.[5] The explanatory variables include a gender indicator, the variable $Female_i$, which is a dummy variable that takes the value of one if the individual is a female, and zero otherwise. To identify the differential effect of the COVID-19 first wave across genders, we include an interaction between the gender dummy and a Post-first wave indicator called, $PostCovid_t$ which is the dummy variable taking 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 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. These individual 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.[6] These individual characteristics are also interacted with the female indicator. Controls for unobserved characteristics of the place of residence are added by using state fixed effects, denoted by $\boldsymbol{\delta_k}$.[7] To capture the time-variant unobserved characteristics, we add time (year, month) fixed effects, $\boldsymbol{\theta_t}$.[8]

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 in telework is lasting. The description of the empirical strategy is described below. The dynamic analysis also mitigates the possible concerns on 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 that exogeneity, but although the COVID-19 was unexpected, no policy is ever adopted arbitrarily. There could be some concerns on whether the changes in the telework pre-dated the COVID-19 first-wave.

Additionally, to disentangle the differential gender response of the telework to the 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 novel weighted index called COVINDEX (Marcén & Morales, 2021b). This captures the timing and intensity of the 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

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

[6] We enlarge the set of socio-demographic characteristics, and our results are maintained. See the results below.

[7] Our results are maintained when using MSA fixed effects, and controls for occupation and industry.

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

closures combine with the out-of-home mobility data provided by Google (Google LLC, 2020)). The empirical strategy is described below.

4. Results

4.1. Main Results

Table 1 presents the estimates of Equation (1). Panel A and B shows the results at the extensive and intensive margins, respectively. Column (1) reveals that working women are around 3 percentage points more likely than men to spend some time working remotely representing the 9% of the average number of individuals reporting any remote work episode during the day of the survey. Working women also overperform men in the time devoted to WFH over the total time working by 3.5 percentage points (the 15% of the average proportion of time devoted to WFH). The estimated coefficient on the *PostCovid* dummy is also positive and statistically significant. Our results say that the individuals reporting WFH increased by more than 6 percentage points after the first wave of the COVID and the time devoted to WFH over the total time spend working rose by 4.9%. These findings are in line with those papers using the Current Population Survey that highlight the importance of 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 the COVID-19, we add the term of interaction between the *female* and the *PostCovid* dummies in column (2). 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 increases by almost 7 percentage points. Similarly, our findings suggest that the post-first-wave Covid period is associated with an increase of 6 percentage points in the time that women relative to men devote to WFH over total working time. Our conclusions are maintained after the inclusion of additional controls in Table A2 in Appendix A. We 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 above refers to the possibility that our coefficient of interest may be capturing gender differences in occupational choices and/or industry. As shown in prior literature, women may tend to choose family-friendly occupations. Thus, women may be more likely than men choosing occupations allowing telework. To mitigate this possible concern, we control for ATUS occupation and industry categories in Table A3 in Appendix A and 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 in Table A4 in Appendix A (Dingel & Neiman, 2020). Our conclusions are maintained.

4.2. Dynamic response and Identification

In this subsection, we explore the dynamic response of the gender differences in WFH to the COVID-19 unexpected shock focusing on the aftermath of the first wave. It is arguable that during the first months after May-2020 individuals maintain their remote work because employers, employees, and self-employed individuals have still concerns on 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 over time and the COVID-19 new waves could also be affecting the evolution of the telework. But, again, both women and men are affected by COVID-19, and so the differential response by gender on telework is not due to the evolution of the pandemic. Gender differences in the preferences for family and work balance which in the pre-pandemic period make women to choose telework could have varied after the first wave of the pandemic. This is what we are analyzing with a static analysis in the previous subsection and now with a dynamic analysis. Another feasible concern with the results in Table 1 refers to the possibility that the estimated impacts might be biased due to the existence of pre-existing WFH trends and gender differences trends. Additionally, it is also 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:

$$Y_{ikt} = \alpha + \sum_{j=-2}^{-63} \tau_j 1\{t^m = \mathrm{j}\} + \sum_{j=0}^{15} \rho_j 1\{t^m = \mathrm{j}\} + \boldsymbol{X'}_{\boldsymbol{ikt}}\beta_3 + \boldsymbol{\delta_k} + \boldsymbol{\theta_t} + \varepsilon_{ijkt} \qquad (2)$$

where Y_{ikt} is the WFH measures defined above. The indicator function $1\{t^m = \mathrm{j}\}$represents the *t*th month before or after our period of interest. The reference period in all event studies is the period before the event occurred when $\mathrm{j} = -1$. We examine the existence of pre-trends during the sixty-three months prior, as captured by coefficients τ_j. The coefficients ρ_j measure the dynamics of COVID-19. The length of the event-time "window" is not so long in comparison to those papers using data since 2015 or 2016 (Béland et al., 2020).The rest of the variables are defined as in Equation (1).

Table 2 displays the estimated coefficients. All estimates for the months 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 statistically different from zero during one to fifteen months later.

4.3.Heterogeneity

We also examine whether the effect of the unexpected shock of the COVID-19 on the gender gap in WFH varies across different subgroups of individuals. Table 3 explores whether COVID-19 has a differential effect according to respondents' age, educational level, marital status, and the presence of older individuals in the household. We observe that younger, with a different-sex partner as well as more educated women are those who have increased significantly more the time devoted to work remotely relative to men, after the first-wave of the pandemic (see columns (1) to (10)). For individuals aged 15 to 35, the increase in the gender gap represents the 46% (10 percentage points) of the average number of working individuals WFH over the total number of working individuals, while that in the case of the time devoted to WFH over the total working time represents the 54% of the average time devoted to WFH over the total working time. Note that these results should be taken with caution due to the low number of observations for same-sex couples. Even though our coefficient of interest is positive and statistically significant regardless of the presence of an older adult in the household, the impact is more than twice as large for those with older individuals living in the household than without older individuals (see columns (11) and (12)).

Table 4 considers parenthood status and estimates the differential response of WFH by age group of the child if any, separately. Interestingly, we observe that women without children and those with children 6 to 12, who may require more hours helping with home schooling, are the only ones who have increased their WFH time relatively more than men during the post-first-wave COVID-19 period in both the extensive and the intensive margin.

4.4. Mechanisms

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

A complementary exercise to understand better how the first wave and the NPIs amplified, we consider here the intensity of the NPIs. We now analyze whether the intensity of Non-Pharmaceutical Interventions (NPIs) during the COVID-19 pandemic has affected remote work decisions and whether it has differentially impacted the gender gap in remote work. NPIs took place at distinct geographic levels (some at the county, others at the state), and for different periods of time. Thus, it is possible that differences in the exposure to NPIs across U.S. states may be related with different gender responses in remote work. To capture the timing and intensity of the NPIs at state level. we use the COVINDEX (Marcén & Morales, 2021b). $COVINDEX$ is the index capturing the intensity of the 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:

$$Y_{ik}^{2021} = \beta_0 + \beta_1 Female_i + \beta_2\, COVINDEX_s^{2020} + \beta_3 (Female_i * COVINDEX_s^{2020}) + \boldsymbol{X'}_{ik}\beta_3 + \boldsymbol{\delta_k} + \varepsilon_{ik} \quad (3)$$

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.[9] Negative values should be interpreted as a reduction of social distancing. The more intense (effective) the NPIs are at reducing social interactions, the closer the value that the COVINDEX is to -5. The COVINDEX can take positive values when at least one of the NPIs encourages social interaction (this happens when the total number of visitors exceeds that of the baseline period as a consequence of the NPI implementation) and none of the other NPIs has statistically significant effects or, if significant, they cannot compensate for the estimated positive effect. The rest of variables are the same as before. We now limit our analysis to the year 2021 to mitigate any concerns on the possible role of the COVID-19 evolution during the whole 2020 year.

Table 5 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 the proportion of time devoted to WFH (see column (3)). We also find that the exposure to social distancing measures at the beginning

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

of the pandemic differentially affected the propensity of men and women to work remotely during the post-first-wave COVID period. 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. 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 of that for women.

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 raised from the pandemic outbreak onwards. In this subsection, we further 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 6 shows the estimated coefficients. If we look at the term of interaction between *female* and the *PostCovid* dummies, all but one (commuting), seem to have raised for women during the post-Covid period. As a result of COVID-19, women are, relatively to men, more likely to have an unpredictable and non-standard schedule, working interrupted and during long hours of work than before the pandemic hits (see columns (1) to (8)). In addition, women have increased their gender gap in commuting by reducing their already relatively fewer tendency to commute (see columns (9) and (10)). These results suggests that while COVID-19 facilitated women's work by promoting WFH, it also changed the structure of work in significant ways making difficult the combination between family and work (Goldin, 2014).

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 to what extend it will persist long 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). Yet, whether WFH will stick or not among women and men remains and 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 (ATUS), we find a positive and significant effect of COVID-19 on WFH even 19 months after the pandemic hit. The post-first-wave Covid period is associated with an increase of 7 percentage points in the gender gap in WFH relative to the pre-pandemic period and an increase of 6 percentage points in the gender gap of the time devoted to WFH over total working time. Additionally, the effect of the pandemic has differentially impacted remote work by gender, being younger, with a different-sex partner as well as more educated have increased significantly more the gender gap proportion of time devoted to work remotely. A supplementary analysis also identifies that relative to men women are now more likely to have an unpredictable and non-standard schedule, working interrupted and during long hours of work than before the pandemic.

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

References

Amuedo-Dorantes, C., Marcén, M., Morales, M., & Sevilla, A. (2022). Schooling and Parental Labor Supply: Evidence from COVID-19 School Closures in the United States. *ILR Review*, 001979392210991. https://doi.org/10.1177/00197939221099184

Barrero, J. M., Bloom, N., & Davis, S. J. (2020). Why Working From Home Will Stick. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3741644

Barrero, J. M., Bloom, N., & Davis, S. J. (2021). Let Me Work From Home, or I Will Find Another Job. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3890988

Benny, L., Sierra, M., & Bhalotra, S. (2021). *Flexibility and the gender pay gap - evidence from an equilibrium model for the UK*.

Bertrand, M. (2011). New perspectives on gender. In *Handbook of Labor Economics* (Vol. 4, Issue PART B). https://doi.org/10.1016/S0169-7218(11)02415-4

Bertrand, M., Goldin, C., & Katz, L. F. (2010). Dynamics of the gender gap for young professionals in the financial and corporate sectors. *American Economic Journal: Applied Economics*, *2*(3), 228–255. https://doi.org/10.1257/app.2.3.228

Birimoglu Okuyan, C., & Begen, M. A. (2022). Working from home during the COVID-19 pandemic, its effects on health, and recommendations: The pandemic and beyond. *Perspectives in Psychiatric Care*, *58*(1), 173–179. https://doi.org/10.1111/ppc.12847

Blau, F. D., & Kahn, L. M. (2017). The gender wage gap: Extent, trends, & explanations. *Journal of Economic Literature*, *55*(3), 789–865. https://doi.org/10.1257/jel.20160995

Bloom, N., Davis, S. J., & Zhestkova, Y. (2021). COVID-19 Shifted Patent Applications toward Technologies That Support Working from Home. *AEA*

Papers and Proceedings, *111*, 263–266. https://doi.org/10.1257/pandp.20211057

Bloom, N., Liang, J., Roberts, J., & Ying, Z. J. (2015). Does working from home work? Evidence from a Chinese experiment. *Quarterly Journal of Economics*, *130*(1), 165–218. https://doi.org/10.1093/qje/qju032

Boca, D. Del, Oggero, N., Profeta, P., & Rossi, M. C. (2021). Did Covid-19 Affect the Division of Labor within the Household? Evidence from Two Waves of the Pandemic in Italy. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3870183

Cortes, P., & Pan, J. (2018). Occupation and gender. In L. M. A. and S. D. H. (eds. Susan L. Averett (Ed.), *The Oxford Handbook of Women and the Economy*. https://doi.org/10.1093/oxfordhb/9780190628963.001.0001

Cortes, P., & Pan, J. (2019). Gender, occupational segregation, and automation. *Economics Studies at Brookings*.

Cortes, P., & Pan, J. (2021). Prevalence of Long Hours and Skilled Women's Occupational Choices. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.2846316

Cortes, P., Pan, J., & Guida-Johnson, N. (2021). *Automation and Gender: Implications for Occupational Segregation and Skill Gaps*.

Dingel, J. I., & Neiman, B. (2020). How many jobs can be done at home? *Journal of Public Economics*, *189*, 104235. https://doi.org/10.1016/j.jpubeco.2020.104235

Flood, S. M., Sayer, L. C., & Backman, D. (2022). American Time Use Survey Data Extract Builder: Version 3.1 [dataset]. *College Park, MD: University of Maryland and Minneapolis, MN: IPUMS*. https://doi.org/https://doi.org/10.18128/D060.V3.1

Gálvez, A., Tirado, F., & Alcaraz, J. M. (2021). Resisting Patriarchal Cultures: The Case of Female Spanish Home-Based Teleworkers. *Https://Doi.Org/10.1177/0950017020987390*, *35*(2), 369–385. https://doi.org/10.1177/0950017020987390

Goldin, C. (2014). A grand gender convergence: Its last chapter. *American Economic Review*, *104*(4), 1091–1119. https://doi.org/10.1257/aer.104.4.1091

Goldin, C. (2021). *Career and Family: Women's Century, Long Journey toward Equity*. Princeton University Press.

Goldin, C., & Katz, L. F. (2011). The Cost of Workplace Flexibility for High-Powered Professionals. *Annals of the American Academy of Political and Social Science*, *638*(1), 45–67. https://doi.org/10.1177/0002716211414398

Goldin, C., & Katz, L. F. (2016). A most egalitarian profession: Pharmacy and the evolution of a family-friendly occupation. *Journal of Labor Economics*, *34*(3), 705–746. https://doi.org/10.1086/685505

Goodman-Bacon, A., & Marcus, J. (2020). Using difference-in-differences to identify causal effects of COVID-19 policies. *Survey Research Methods*, 14 (2), 153-158. https://doi:10.18148/srm/2020.v14i2.7723

Google LLC. (2020). *Google COVID-19 Community Mobility Reports*.

Kalenkoski, C. M., & Pabilonia, S. W. (2022). Impacts of COVID-19 on the self-employed. *Small Business Economics*, *58*(2), 741–768. https://doi.org/10.1007/S11187-021-00522-4/TABLES/15

Kitagawa, R., Kuroda, S., Okudaira, H., & Owan, H. (2021). Working from home and productivity under the COVID-19 pandemic: Using survey data of four manufacturing firms. *PLOS ONE*, *16*(12), e0261761. https://doi.org/10.1371/journal.pone.0261761

Mann, S., & Holdsworth, L. (2003). The psychological impact of teleworking: stress, emotions and health. *New Technology, Work and Employment*, *18*(3), 196–211. https://doi.org/10.1111/1468-005X.00121

Marcén, M., & Morales, M. (2021a). Culture and the cross-country differences in the gender commuting gap. *Journal of Transport Geography*, *96*, 103184. https://doi.org/10.1016/j.jtrangeo.2021.103184

Marcén, M., & Morales, M. (2021b). The intensity of COVID-19 nonpharmaceutical interventions and labor market outcomes in the public sector. *Journal of Regional Science*, *61*(4), 775–798. https://doi.org/10.1111/JORS.12535

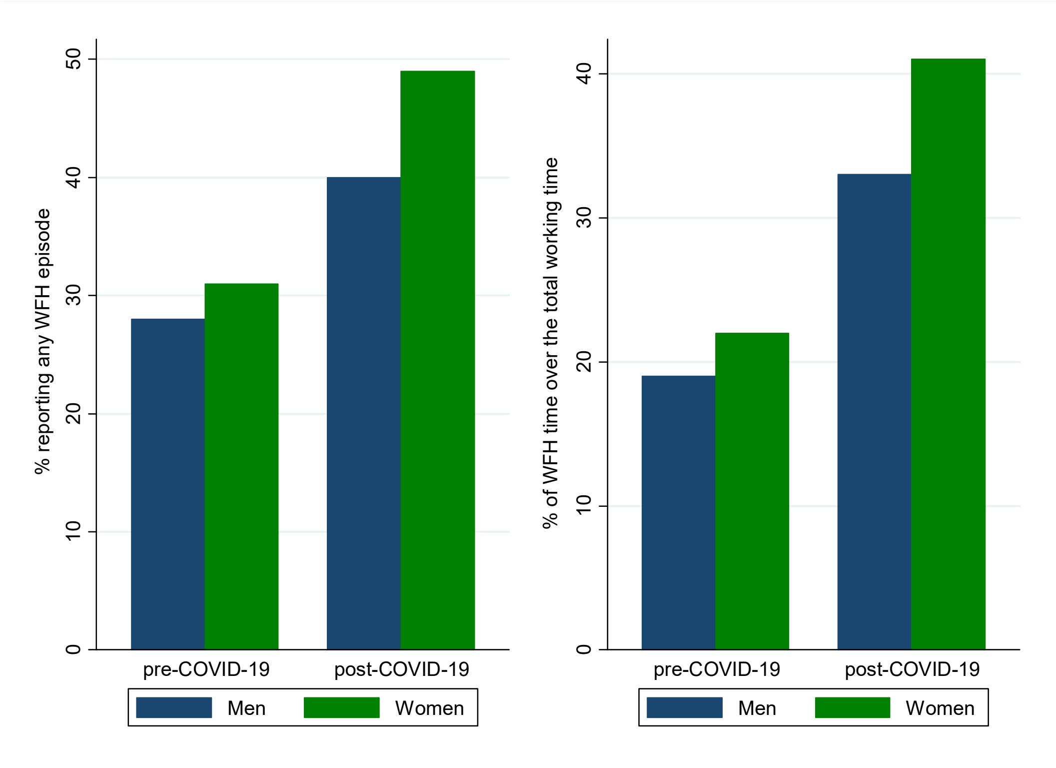
Morikawa, M. (2022). Work-from-home productivity during the COVID-19 pandemic: Evidence from Japan. *Economic Inquiry*, *60*(2), 508–527. https://doi.org/10.1111/ecin.13056

Olivetti, C., & Petrongolo, B. (2016). The Evolution of Gender Gaps in Industrialized Countries. In *Annual Review of Economics* (Vol. 8, pp. 405–434). Annual Reviews Inc. https://doi.org/10.1146/annurev-economics-080614-115329

Pabilonia, S. W., & Vernon. V., (2022). Telework, Wages, and Time Use in the United States. *Review of Economics of the Household*, *20*(3), 687–734. https://doi.org/10.1007/S11150-022-09601-1/TABLES/11

Wight, V. R., & Raley, S. B. (2009). When home becomes work: Work and family time among workers at home. *Social Indicators Research*, *93*(1), 197–202. https://doi.org/10.1007/s11205-008-9377-6

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



Notes: Data comes from 2015-2021 ATUS. We use a sample of workers between 15 to 65 years old who report a work episode on the day of the survey. Table A1 in the Appendix A shows the estimated coefficients.

Table 1: Main results

	(1)	(2)
Panel A: WFH		
Female	0.028***	0.024
	(0.007)	(0.027)
Post Covid	0.063***	0.045**
	(0.018)	(0.018)
Post Covid x Female		0.067***
		(0.017)
Observations	22,157	22,157
R-squared	0.126	0.127
D.V. Mean	0.32	0.32
D.V. Std. Dev.	0.46	0.46
Panel B: Proportion of time WFH over the total work time		
Female	0.035***	0.029
	(0.006)	(0.022)
Post Covid	0.049***	0.033**
	(0.015)	(0.016)
Post Covid x Female		0.059***
		(0.015)
Observations	22,157	22,157
R-squared	0.120	0.121
D.V. Mean	0.23	0.23
D.V. Std. Dev.	0.40	0.40
For all		
State FE	Yes	Yes
Month FE	Yes	Yes
Year FE	Yes	Yes
Post Covid Std. Dev.	0.37	0.37

Notes: The sample in all columns includes workers between 15 to 65 years old who report 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 time WFH over the total work time in Panel B. The Post Covid dummy takes value 1 from May 2020 to December 2021, and 0 for the rest. 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. This 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 2: Event study

	(1)	(2)
Dependent variable:	WFH	Proportion of time WFH over the total work time
63 months before the event	0.027	0.017
	(0.034)	(0.024)
62 months before the event	-0.020	0.012
	(0.031)	(0.023)
61 months before the event	0.073*	0.033
	(0.042)	(0.028)
60 months before the event	-0.014	-0.020
	(0.038)	(0.025)
59 months before the event	0.049	0.052*
	(0.039)	(0.030)
58 months before the event	0.011	0.024
	(0.036)	(0.028)
57 months before the event	0.104***	0.073**
	(0.039)	(0.030)
56 months before the event	-0.003	0.009
	(0.033)	(0.024)
55 months before the event	0.108***	0.070**
	(0.042)	(0.031)
54 months before the event	0.039	0.032
	(0.041)	(0.032)
53 months before the event	0.029	0.034
	(0.037)	(0.028)
52 months before the event	0.017	0.041
	(0.035)	(0.026)
51 months before the event	0.035	0.029
	(0.036)	(0.027)
50 months before the event	-0.007	-0.027
	(0.038)	(0.024)
49 months before the event	0.032	-0.003
	(0.038)	(0.026)
48 months before the event	0.034	0.017
	(0.039)	(0.027)
47 months before the event	0.004	0.006
	(0.036)	(0.026)
46 months before the event	0.033	0.019
	(0.042)	(0.032)
45 months before the event	-0.014	0.002
	(0.033)	(0.023)
44 months before the event	-0.003	-0.004
	(0.036)	(0.025)
43 months before the event	-0.012	-0.011
	(0.035)	(0.023)
42 months before the event	-0.016	-0.004
	(0.035)	(0.025)
41 months before the event	0.067*	0.072**
	(0.039)	(0.032)

40 months before the event	0.048	0.018
	(0.036)	(0.025)
39 months before the event	0.040	0.025
	(0.042)	(0.033)
38 months before the event	0.025	0.029
	(0.034)	(0.025)
37 months before the event	0.013	-0.002
	(0.036)	(0.025)
36 months before the event	0.021	0.001
	(0.039)	(0.028)
35 months before the event	-0.028	-0.000
	(0.038)	(0.030)
34 months before the event	0.009	0.004
	(0.046)	(0.035)
33 months before the event	-0.008	0.002
	(0.041)	(0.029)
32 months before the event	0.065	0.025
	(0.040)	(0.029)
31 months before the even	0.024	0.009
	(0.038)	(0.028)
30 months before the event	0.034	0.037
	(0.037)	(0.028)
29 months before the event	0.028	0.027
	(0.037)	(0.027)
28 months before the event	0.065	0.063*
	(0.042)	(0.034)
27 months before the event	-0.011	0.021
	(0.042)	(0.030)
26 months before the event	0.039	0.030
	(0.039)	(0.028)
25 months before the event	0.024	-0.004
	(0.037)	(0.024)
24 months before the event	0.012	-0.004
	(0.042)	(0.026)
23 months before the event	-0.010	0.010
	(0.038)	(0.027)
22 months before the event	0.046	0.022
	(0.040)	(0.026)
21 months before the event	0.009	0.007
	(0.038)	(0.027)
20 months before the event	0.013	-0.001
	(0.041)	(0.028)
19 months before the event	0.052	0.016
	(0.042)	(0.027)
18 months before the event	-0.045	-0.020
	(0.036)	(0.026)
17 months before the event	0.029	0.018
	(0.039)	(0.028)
16 months before the event	0.033	0.012
	(0.041)	(0.027)

15 months before the event	0.091**	0.049*
	(0.043)	(0.029)
14 months before the event	0.039	-0.007
	(0.040)	(0.023)
13 months before the event	0.022	0.002
	(0.040)	(0.028)
12 months before the event	0.002	-0.012
	(0.036)	(0.025)
11 months before the event	-0.009	0.027
	(0.037)	(0.029)
10 months before the event	0.036	0.023
	(0.041)	(0.027)
9 months before the event	0.013	0.028
	(0.038)	(0.029)
8 months before the event	0.030	0.027
	(0.038)	(0.028)
7 months before the event	0.012	0.011
	(0.038)	(0.029)
6 months before the event	0.050	0.063**
	(0.036)	(0.029)
5 months before the event	0.012	0.038
	(0.035)	(0.027)
4 months before the event	0.027	0.025
	(0.037)	(0.027)
3 months before the event	-0.012	-0.007
	(0.040)	(0.028)
2 months before the event	0.008	0.041
	(0.045)	(0.036)
The month of the event	0.354***	0.402***
	(0.047)	(0.044)
1 months after the event	0.225***	0.276***
	(0.040)	(0.034)
2 months after the event	0.193***	0.212***
	(0.042)	(0.037)
3 months after the event	0.160***	0.178***
	(0.041)	(0.033)
4 months after the event	0.174***	0.187***
	(0.040)	(0.034)
5 months after the event	0.187***	0.235***
	(0.041)	(0.036)
6 months after the event	0.152***	0.183***
	(0.040)	(0.033)
7 months after the event	0.210***	0.213***
	(0.045)	(0.038)
8 months after the event	0.189***	0.199***
	(0.039)	(0.032)
9 months after the event	0.197***	0.241***
	(0.042)	(0.037)
10 months after the event	0.218***	0.237***
	(0.041)	(0.037)

11 months after the event	0.161***	0.203***
	(0.044)	(0.038)
12 months after the event	0.169***	0.165***
	(0.043)	(0.035)
13 months after the event	0.103***	0.133***
	(0.040)	(0.033)
14 months after the event	0.144***	0.151***
	(0.042)	(0.034)
15 months after the event	0.192***	0.184***
	(0.039)	(0.032)
16 months after the event	0.164***	0.183***
	(0.046)	(0.037)
17 months after the event	0.183***	0.160***
	(0.044)	(0.034)
18 months after the event	0.157***	0.150***
	(0.043)	(0.036)
19 months after the event	0.067	0.101***
	(0.041)	(0.034)
State FE	Yes	Yes
Observations	22,157	22,157
R-squared	0.134	0.133

Notes: The sample in all columns includes workers between 16 to 65 years old who report 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 respondents live in a metropolitan area or not. 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: Heterogeneity analysis

	(1)	(2)	(3)	(4)	(7)	(8)	(9)	(10)	(11)	(12)
	Aged 15 to 35	Aged 36 to 65	High educated	Non-high educated	Two-partnered HH	Single HH	Different-sex two-partnered HH	Same-sex two-partnered HH	Older adult in the HH	Non-older adult in the HH
Panel A: WFH										
Female	-0.036	0.069	0.059	0.013	0.015	0.042	0.010	0.591	0.003	0.029
	(0.063)	(0.054)	(0.037)	(0.037)	(0.043)	(0.034)	(0.043)	(0.361)	(0.066)	(0.033)
Post Covid	0.018	0.037	0.045*	-0.024	0.043*	0.008	0.040	0.322	-0.037	0.040**
	(0.033)	(0.024)	(0.025)	(0.030)	(0.024)	(0.031)	(0.024)	(0.263)	(0.055)	(0.020)
Post Covid x Female	0.105***	0.056**	0.069***	0.054*	0.086***	0.060**	0.084***	0.077	0.118**	0.068***
	(0.032)	(0.023)	(0.024)	(0.032)	(0.025)	(0.029)	(0.025)	(0.232)	(0.054)	(0.020)
Observations	6,741	15,416	16,517	5,640	13,078	9,079	12,884	194	1,725	20,432
R-squared	0.129	0.120	0.065	0.030	0.117	0.133	0.116	0.479	0.123	0.121
D.V. Mean	0.23	0.35	0.38	0.13	0.36	0.26	0.35	0.47	0.17	0.33
D.V. Std. Dev.	0.42	0.48	0.49	0.34	0.48	0.44	0.48	0.50	0.38	0.47
Panel B: Proportion of time WFH over the total work time										
Female	-0.058	0.080*	0.064**	0.012	0.038	0.038	0.034	0.509	0.020	0.040
	(0.053)	(0.043)	(0.030)	(0.029)	(0.035)	(0.028)	(0.036)	(0.316)	(0.053)	(0.027)
Post Covid	-0.015	0.044**	0.046**	-0.029	0.044**	-0.013	0.043**	0.225	-0.072	0.038**
	(0.029)	(0.020)	(0.023)	(0.023)	(0.021)	(0.027)	(0.021)	(0.227)	(0.046)	(0.018)
Post Covid x Female	0.092***	0.039*	0.049**	0.031	0.061***	0.063**	0.057**	0.081	0.118***	0.050***
	(0.029)	(0.021)	(0.022)	(0.025)	(0.022)	(0.026)	(0.023)	(0.209)	(0.046)	(0.018)
Observations	6,741	15,416	16,517	5,640	13,078	9,079	12,884	194	1,725	20,432
R-squared	0.120	0.118	0.088	0.030	0.116	0.130	0.114	0.506	0.107	0.120
D.V. Mean	0.17	0.26	0.28	0.09	0.26	0.19	0.26	0.39	0.13	0.24
D.V. Std. Dev.	0.36	0.42	0.43	0.27	0.42	0.38	0.42	0.47	0.32	0.41
For all										
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
Post Covid Std. Dev.	0.37	0.37	0.38	0.36	0.38	0.37	0.37	0.43	0.39	0.37

Notes: The sample in all columns includes workers who report 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 time WFH 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 respondents live in a metropolitan area or not. This 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 4: Heterogeneity analysis by parenthood status

	(1) Non-children	(2) Children aged 5 years or below	(3) Children aged 6-12 years	(4) Children aged 13-18 years
Panel A: WFH				
Female	0.019	0.125	-0.194**	0.040
	(0.034)	(0.087)	(0.085)	(0.097)
Post Covid	0.054**	0.046	-0.031	0.095**
	(0.025)	(0.039)	(0.036)	(0.040)
Post Covid x Female	0.106***	-0.019	0.103***	0.013
	(0.024)	(0.038)	(0.034)	(0.038)
Observations	10,898	4,216	5,560	4,467
R-squared	0.128	0.157	0.142	0.141
D.V. Mean	0.29	0.33	0.36	0.35
D.V. Std. Dev.	0.45	0.47	0.48	0.48
Panel B: Proportion of time WFH over the total work time				
Female	0.015	0.105	-0.110*	0.045
	(0.028)	(0.072)	(0.065)	(0.079)
Post Covid	0.027	0.043	-0.021	0.072**
	(0.022)	(0.035)	(0.031)	(0.035)
Post Covid x Female	0.093***	-0.018	0.106***	0.010
	(0.021)	(0.034)	(0.030)	(0.034)
Observations	10,898	4,216	5,560	4,467
R-squared	0.129	0.151	0.137	0.133
D.V. Mean	0.21	0.24	0.25	0.25
D.V. Std. Dev.	0.39	0.41	0.41	0.41
For all				
State FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Post Covid Std. Dev.	0.38	0.36	0.37	0.36

Notes: The sample in all columns includes workers between 15 to 65 years old who report a work episode on the day of the survey. We also limit the sample to those without any children, with some child aged 5 years or below, aged 6 to 12 years old, and aged 13 to 18 years old living in the HH 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 time WFH 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 respondents live in a metropolitan area or not. This 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 5: WFH and the intensity of NPIs (COVINDEX)

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	0.028	0.218**	0.035**	0.191**
	(0.020)	(0.099)	(0.018)	(0.087)
COVINDEX	-0.032	-0.115**	-0.074**	-0.125***
	(0.035)	(0.047)	(0.030)	(0.041)
COVINDEX x Female		0.176**		0.105*
		(0.070)		(0.061)
Observations	2,851	2,851	2,851	2,851
R-squared	0.180	0.183	0.167	0.169
State FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
D.V. Mean	0.43	0.43	0.36	0.36
D.V. Std. Dev.	0.50	0.50	0.46	0.46
COVINDEX Std. Dev.	0.30	0.30	0.30	0.30

Notes: The sample in all columns includes workers between 16 to 65 years old who report a work episode on the day of the survey. We limit the sample to the year 2021. We estimate Equation (3). The dependent variable in column (2) is a dummy variable taking value 1 if the respondent works during non-standard hours. In column (3) the dependent variable has been redefined as the logarithm of the weekly work hours. We limit the sample to individuals with own children living in the HH in column (4), and the dependent variable is a dummy variable taking value 1 if the child is present in any of the work-reported episodes. See data appendix 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 respondents live in a metropolitan area or not. 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: Other work-related outcomes

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Dependent variable:	Unpredictable schedule	Unpredictable schedule	Non-standard schedule	Non-standard schedule	Interrupted work (number of work episodes)	Interrupted work (number of work episodes)	Log (weekly work hours)	Log (weekly work hours)	Commuting	Commuting
Female	-0.531***	-0.518*	-0.073***	-0.038	-0.139***	-0.245**	-0.132***	-0.014	-0.016**	-0.022
	(0.069)	(0.300)	(0.007)	(0.032)	(0.025)	(0.105)	(0.007)	(0.033)	(0.006)	(0.027)
Post Covid	0.050	-0.140	-0.007	0.003	-0.094	-0.168***	-0.031**	-0.047***	-0.042**	-0.010
	(0.088)	(0.181)	(0.009)	(0.019)	(0.058)	(0.061)	(0.015)	(0.017)	(0.017)	(0.019)
Post Covid x Female		0.408**		0.052***		0.165**		0.039**		-0.068***
		(0.176)		(0.018)		(0.067)		(0.018)		(0.019)
Observations	22,157	22,157	22,157	22,157	22,157	22,157	20,980	20,980	22,157	22,157
R-squared	0.018	0.020	0.021	0.026	0.015	0.016	0.067	0.070	0.075	0.077
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	5.00	5.00	0.24	0.24	2.34	2.34	3.69	3.69	0.74	0.74
D.V. Std. Dev.	4.25	4.25	0.42	0.42	1.35	1.35	0.38	0.38	0.44	0.44
Post Covid Std. Dev.	0.37	0.37	0.37	0.37	0.37	0.37	0.37	0.37	0.37	0.37

Notes: The sample in all columns includes workers between 15 to 64 years old who report a work episode on the day of the survey. We also limit the sample to those individuals reporting information on the 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 value 1 if the respondent works during non-standard hours, and 0 otherwise. In columns (5) and (6) it is the number of the 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 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 respondents live in a metropolitan area or not. 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

Table A1: Summary statistics by gender

	Pre-covid (from Jan 2015 to March 2020)			Post-covid (from May 2020 to Dec 2021)		
Variable	Female	Male	Diff (Male-Female)	Female	Male	Diff (Male-Female)
WFH	0.31	0.28	-0.02***	0.49	0.40	-0.08***
Proportion of time WFH over the total work time	0.22	0.19	-0.03***	0.41	0.33	-0.08***

Notes: Data comes from 2010-2021 ATUS. We use a sample of workers between 15 to 65 years old who report a work episode on the day of the survey.

Table A2: Robustness checks adding more controls

	(1)	(2)
Panel A: WFH		
Female	0.035***	0.024
	(0.007)	(0.034)
Post Covid	0.065***	0.031*
	(0.017)	(0.019)
Post Covid x Female		0.072***
		(0.019)
Observations	22,147	22,147
R-squared	0.158	0.162
D.V. Mean	0.32	0.32
D.V. Std. Dev.	0.46	0.46
Panel B: Proportion of time WFH over the total work time		
Female	0.039***	0.035
	(0.006)	(0.028)
Post Covid	0.049***	0.023
	(0.015)	(0.017)
Post Covid x Female		0.058***
		(0.017)
Observations	22,147	22,147
R-squared	0.151	0.157
D.V. Mean	0.23	0.23
D.V. Std. Dev.	0.40	0.40
For all		
State FE	Yes	Yes
Month FE	Yes	Yes
Year FE	Yes	Yes
Post Covid Std. Dev.	0.37	0.37

Notes: The sample in all columns includes workers between 15 to 65 years old who report 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 time WFH over the total work time in Panel B. The Post Covid dummy takes value 1 from May 2020 to December 2021, and 0 for the rest. 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. Additionally, we also control for whether the respondent lives with an employed and high educated partner, respondents' work classification as part- or full-time workers, and self-employment status. This 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 controlling for industry and occupation categories

	(1)	(2)
Panel A: WFH		
Female	0.010	-0.017
	(0.008)	(0.027)
Post Covid	0.069***	0.039**
	(0.017)	(0.019)
Post Covid x Female		0.065***
		(0.018)
Observations	22,157	22,157
R-squared	0.183	0.184
D.V. Mean	0.32	0.32
D.V. Std. Dev.	0.46	0.46
Panel B: Proportion of time WFH over the total work time		
Female	0.026***	0.004
	(0.006)	(0.022)
Post Covid	0.054***	0.032*
	(0.015)	(0.016)
Post Covid x Female		0.050***
		(0.016)
Observations	22,157	22,157
R-squared	0.173	0.174
D.V. Mean	0.23	0.23
D.V. Std. Dev.	0.40	0.40
For all		
State FE	Yes	Yes
Month FE	Yes	Yes
Year FE	Yes	Yes
Industry FE	Yes	Yes
Occupation FE	Yes	Yes
Post Covid Std. Dev.	0.37	0.37

Notes: The sample in all columns includes workers between 15 to 65 years old who report 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 time WFH over the total work time in Panel B. The Post Covid dummy takes value 1 from May 2020 to December 2021, and 0 for the rest. 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. This 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 occupations allowing remote work

	(1)	(2)
Panel A: WFH		
Female	0.009	0.003
	(0.007)	(0.026)
Post Covid	0.064***	0.034*
	(0.017)	(0.019)
Post Covid x Female		0.066***
		(0.018)
Observations	22,157	22,157
R-squared	0.158	0.159
D.V. Mean	0.32	0.32
D.V. Std. Dev.	0.46	0.46
Panel B: Proportion of time WFH over the total work time		
Female	0.020***	0.012
	(0.005)	(0.021)
Post Covid	0.050***	0.025
	(0.015)	(0.016)
Post Covid x Female		0.053***
		(0.016)
Observations	22,157	22,157
R-squared	0.151	0.152
D.V. Mean	0.23	0.23
D.V. Std. Dev.	0.40	0.40
For all		
State FE	Yes	Yes
Month FE	Yes	Yes
Year FE	Yes	Yes
Industry FE	Yes	Yes
Occupation FE	Yes	Yes
Post Covid Std. Dev.	0.37	0.37

Notes: The sample in all columns includes workers between 15 to 65 years old who report 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 time WFH over the total work time in Panel B. The Post Covid dummy takes value 1 from May 2020 to December 2021, and 0 for the rest. 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. This 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.

Appendix B

Table B1: Sum stats 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 activies", with the activity codes from "50101" to "50299" located in "Respondent's home or yard" with where code "101"	69.72	158.45
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	0.23	0.40
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	0.32	0.46
Other work-related outcomes				
Unpredictable schedule	START reports the time the activity started	We calculate the difference	5.00	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	1.35
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	3.69	0.38
Commuter	See ACTIVITY above.	Dummy variable taking value 1 if the respondent devotes any time in the activity "commuting" with the activity code "180501"	0.74	0.44
Individual controls				
Age	AGE gives each person's age at last birthday	Years	43	12.16
Female	SEX gives each person's sex. Values of this variable:		0.47	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		Dummy variable equal to 1 if race=100	0.80	0.40
	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			
Metropolitan area	METRO reports whether a household was located in a metropolitan area		Dummy variable equal to 1 if METRO=1 or METRO=2	0.46	0.50
	Metropolitan, central city	1			
	Metropolitan, balance of MSA	2			
	Metropolitan, not identified	3			
	Nonmetropolitan	4			
	Not identified	5			
Additional variables used in the heterogeneity analysis					
High educated	See EDUC above		Dummy variable equal to 1 if EDUC>=30	0.74	0.43
Two-partnered HH	RELATE reports the relationship of each household member to the ATUS respondent		Dummy variable equal to 1 if any of the members in the household reports relate=20 or relate=21	0.59	0.49
	Self	10			
	Spouse	20			
	Unmarried Partner	21			
	Own household child	22			
	Grandchild	23			
	Parent	24			
	Brother/Sister	25			

	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	0.49
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	0.39
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	0.43
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	0.08	0.27

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 Full time 1 Part time 2	Dummy variable equal to 1 if FULLPART=1	0.85	0.35
Partner working	SPEMPNOT reports whether the respondent's spouse or unmarried partner is employed Not employed 0 Employed 1	Dummy variable equal to 1 if SPEMPNOT=1	0.77	0.42
Self-employed	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=6 or CLWKR=7	0.11	0.31
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	0.49	0.50
	Service Occupations	3600-4650	Dummy variable equal to 1 if OCC>=3600 and OCC<=4650	0.14	0.35
	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 and OCC<=7630	0.07	0.26
	Production, Transportation, and Material Moving Occupations	7700-9750	Dummy variable equal to 1 if OCC>=7700 and OCC<=9750	0.10	0.30
Industry	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.				
	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	0.22

Manufacturing	1070-3990	Dummy variable equal to 1 if IND>=1070 and IND<=3990	0.10	0.31
Wholesale Trade	4070-4590	Dummy variable equal to 1 if IND>=4070 and IND<=4590	0.02	0.15
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 IND<=6390) or (IND>=0570 and IND<=0690)	0.05	0.22
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	0.08	0.27
	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	0.22
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)	0.50	0.50