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The gender gap in working from home after the onset of COVID-19

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Abstract
This study examines changes in the gender gap in the take up and intensity of working from home following the unexpected onset of the COVID-19 pandemic. Using data from the American Time Use Survey, we find that working from home became more prevalent among women than men, thus widening the gender gap. Job characteristics played a crucial role in this trend, particularly among private sector workers. The gender gap widened most significantly among young, highly educated individuals and those living with dependents. Moreover, our results suggest that social distancing measures increased working from home time for men but did not have the same effect on women. We also extend our analysis to other work-related outcomes, finding that women experienced less favorable outcomes, particularly an increase in unpredictable or non-standard schedules. Overall, this shift in the gender gap is statistically significant over time and remains robust.

Keywords COVID-19 · Working from home (WFH) · Gender · American Time Use Survey (ATUS)

JEL Codes J16 · J21 · J22

1 Introduction

In developed countries, women have historically prioritized a better work-life balance compared to men—a factor that may have influenced their adoption of flexible work arrangements such as telework or remote work. Women are more likely to avoid 'greedy jobs' and seek family-friendly jobs with short commutes and options for working from home (WFH) (Gálvez et al., 2021; Goldin, 2021; Marcén & Morales, 2021a). In contrast, in the early twenty-first century, men reported balancing work with personal or family needs as their main reason for WFH six times less

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often than women in the U.S. (Wight & Raley, 2009).[1] Following the strict COVID-19 lockdowns from March to April 2020, this dynamic may have changed. The unexpected global pandemic gave many men and women the opportunity to experience full-time work and family life during those lockdown weeks. The subsequent return to "normal life" presented three potential scenarios regarding WFH gender dynamics: (1) a return to traditional work locations; (2) an increase in men's remote work (or a decrease in women's remote work), thus narrowing the gender gap in WFH; or (3) a reinforcement of the asymmetry between men and women in remote work. In this paper, we shed light on this issue by analyzing how the gender gap in WFH has evolved, with particular attention to both the extensive and intensive margins.

Despite the importance given to telework, the growing research on this issue appears to be incomplete. During the pre-pandemic period, a randomized experiment in China resulted in a significant increase in the percentage of voluntary WFH workers. Employees who voluntarily worked from home reported higher levels of productivity, profitability, and job satisfaction. Given the experiment's success for both workers and employers, the company allowed employees to choose between working from home or at the office, leading to a growing preference for WFH in the firm (Bloom et al., 2015). In the wake of COVID-19, the evolution of remote work presents a complex picture from both supply-side and demand-side considerations. For workers, the benefits included flexible schedules, the elimination of commutes, and more time for personal pursuits, such as family and leisure, which enhanced quality of life (e.g., food preparation and eating at home, or sleeping) (Restrepo & Zeballos, 2020; 2022). However, these advantages were offset by challenges such as social isolation, technical difficulties, health concerns (both physical and mental), work-life balance struggles, and the disruption of children's educational processes during school closures (Birimoglu Okuyan & Begen, 2022; Bloom et al., 2021; Mann & Holdsworth, 2003). From the employers' side, the business case for WFH was similarly mixed. Unlike the pre-pandemic study in China that showed productivity gains, Japanese research during COVID-19 found productivity declines of 30–40 percent (Bloom et al., 2015; Kitagawa et al., 2021; Morikawa, 2022). A similar reduction was found by Barrero et al., (2023) in the American context. Managers struggled with reduced oversight of their teams, potentially motivating them to push for office returns to maintain better supervision. Companies also faced ongoing office lease obligations, reducing their immediate economic incentives to offer the WFH option.

Given these competing factors, understanding how WFH has actually evolved requires empirical study. Our work fills this gap using U.S. data on workers from the Integrated Public Use Microdata Series Time Use (IPUMS Time Use) database for the period 2015–2022 (Flood et al., 2023). ATUS is a daily diary that allows us to identify remote workers through their work location and the daily time allocated to WFH. We answer the following two research questions: (1) Has the asymmetry between men and women in remote work been reinforced following the strict

[1] WFH, also known as telework, telecommuting, or remote work, refers to a formal or informal arrangement that allows employees to work from a location other than the usual worksite—typically their own home.

lockdowns? (2) Does the intensity of social distancing measures play a role in the telework choice? Our paper is novel in that we examine a long period, considering both the choice to telework (the extensive margin) and the proportion of time allocated to WFH (the intensive margin). We combine this analysis with the intensity of social distancing measures, known as non-pharmaceutical interventions (NPIs). We also explore heterogeneity in the WFH response by age, level of education, class of worker, marital status, and presence of children and older adults in the household.

We contribute to three strands of the literature: gender economics, the COVID-19 literature, and the telework literature. 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 workplace (Benny et al., 2021; Bertrand et al., 2010; Cortes et al., 2021; Cortes & Pan, 2016, 2018, 2019 ; Goldin, 2014, 2021; Goldin & Katz, 2011, 2016). These papers identify technological changes promoting workplace flexibility as a key to increasing women's representation in high-paying occupations and therefore reducing gender gaps in the labor market. Closely related to our paper is the study by Chen et al., (2023). That work provided a descriptive overview of WFH rates in the U.S. during specific months in what they term the "post-COVID-19" period, which corresponds to the post-first-wave period (May 2020). They found that the incidence of WFH was higher than pre-pandemic levels. Our paper contributes to this literature by documenting the unequal WFH response between women and men after May 2020.

Our paper also contributes to the growing literature on the COVID-19 effect on socio-economic variables. Our research is closely related to papers examining the impact of NPIs on labor markets, such as those studying the changes in labor supply in response to unanticipated school closures, stay-at-home orders, and business closures, among other NPIs (Amuedo-Dorantes et al., 2023; Kalenkoski & Pabilonia, 2022; Marcén & Morales, 2021b). We extend this literature by merging individual ATUS data with an index capturing the intensity of NPIs at the 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 early 2020 reduced the probability of WFH and the proportion of time spent working from home for women relative to men.

Furthermore, we add to the 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, 2022a). In this paper, we provide evidence on how telework in the U.S. has evolved over a long period from 2015 to 2022. Lastly, we extend the analysis by studying other work-related outcomes such as unpredictable or non-standard schedules, work interruptions (with several work episodes), and commuting.

The rest of the paper is organized as follows. Section 2 describes the data used. Section 3 describes the methodology, and Section 4 presents the results. Section 5 concludes.

2 Data

This study uses data from the IPUMS Time Use harmonized version of the American Time Use Survey (ATUS) for the period 2015–2022 (Flood et al., 2023). The ATUS is the only nationally representative survey providing information on time use in the United States and is administered by the Bureau of Labor Statistics. This survey measures the amount of time (in minutes) people spend on various activities such as paid work, childcare, eldercare, sleeping, 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 individual is asked to fill out a diary for the 24 h of the previous day (from 4:00 AM to 4:00 AM).[2] This dataset is useful for our study as it provides detailed time allocation, activity duration, participants, and location information. We are able to calculate the time allocated to work at any location, 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 allocated 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 pre-COVID-19 (pre-mid-March 2020) and post-May 2020 periods. Data collection was suspended in 2020 from mid-March to mid-May for the safety of ATUS staff, coinciding with the first wave of the COVID-19 pandemic, when the NPIs were sudden and particularly intense.[4] The period starting after mid-May 2020 constitutes our primary period of interest and will henceforth be referred to as the "post-May 2020 period". 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-COVID-19 and post-May 2020 periods. We observe that the gender gap in WFH has almost tripled (from 3 to 8 percentage points) since the pandemic began. 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 post-May 2020. Similarly, the percentage of total work time workers spent WFH has increased from 18 percent to 32 percent for men and has almost doubled for women, rising from 21

[2] Respondents are then randomly assigned a designated reference day. The diary days are distributed throughout the year and across the days of the week, with 10 percent allocated to each weekday, 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] For more information, please see the https://www.bls.gov/tus/covid19.htm.

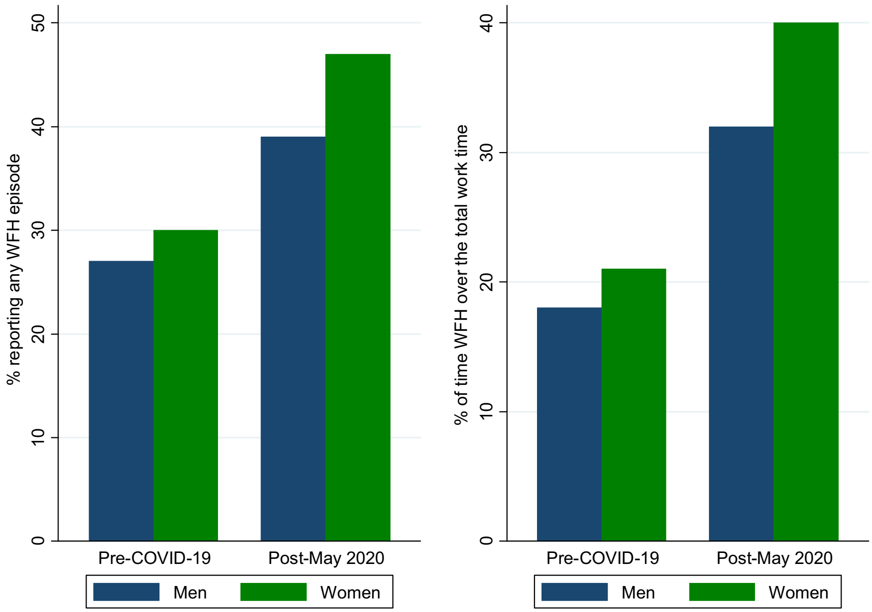

Fig. 1 Summary statistics of WFH measures by gender. Notes: Data come from the 2015–2022 ATUS. We use a sample of workers aged 18 to 64 who reported a work episode on the day of the survey. Table A1 in Appendix A shows the gender-specific averages and other descriptive statistics

percent to 40 percent. Gender differences are statistically significant (see Table A1 in Appendix A).

Table B1 in Appendix B reports the descriptive statistics for the rest of the variables. The average age in our sample is approximately 43 years; 49 percent of respondents are women; 80 percent are white. Furthermore, 48 percent are highly educated (have completed college or higher); and approximately 47 percent live in a metropolitan area. More than half of the respondents (60 percent) live with a partner, of whom 98 percent are heterosexual. In addition, 51 percent of respondents have children living in the household. Of these respondents, 19 percent live with a child aged 5 years or below, 25 percent live with a child aged 6 to 12 years, and 18 percent live with a child aged 13 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 privately employed and 11 percent are self-employed.

For the additional work-related outcomes considered here, respondents were asked about the start and end times of activities, which provides information on respondents' available work time, their work schedule, and the number of different work episodes reported in a day. Data reveal that the average span between the first and the last work episode on the day of the survey is 5 h; 24 percent worked during non-standard hours, and they report two separate work episodes on average. Most (74 percent) reported a commute episode on the survey day.

3 Empirical Strategy

To study how the gender gap in WFH has evolved and the presence of gender asymmetries, we first estimate the following equation:

$$
\begin{aligned}
Y_{ikt} = {} & \beta_0 + \beta_1 Female_i + \beta_2\, PostMay2020_t \; + \beta_3 (Female_i * PostMay2020_t) \\
& + \boldsymbol{X'}_{ikt}\beta_4 + (\boldsymbol{X'}_{ikt} * Female_i)\beta_5 + \boldsymbol{\delta_k} + \boldsymbol{\theta_t} + \varepsilon_{ikt}
\end{aligned}
\tag{1}
$$

where the dependent variable Y_{ikt} represents either an indicator variable for whether the i^{th} respondent living in state k in period t reports any WFH episode during the day of the survey, or the proportion of total working time allocated to WFH.[5] 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 woman and zero otherwise. To identify the differential effect across genders and over time, we include an interaction between the gender dummy and $PostMay2020_t$, which is a dummy variable equal to one for observations from mid-May 2020 onwards and zero otherwise. Our coefficient of interest is β_3, which captures the differential change in WFH for women relative to men in the post-May 2020 period. A positive β_3 would indicate that the post-May 2020 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 (highly educated or not), race (white or not), and geographic location (living in a metropolitan area or not), which may affect the time workers allocate to WFH.[6] These individual characteristics are also interacted with the female indicator to allow the effects of these characteristics to differ by gender. Controls for unobserved characteristics of the place of residence are added by using state fixed effects, denoted by $\boldsymbol{\delta_k}$.[7] To capture time-variant unobserved characteristics, we add time (year, month) fixed effects, $\boldsymbol{\theta_t}$.[8]

We further extend our work by studying the differential gender response over time. This extension allows us to examine whether any change in gender differences in WFH is persistent. The empirical strategy is detailed below. We also address potential concerns regarding the timing of the observed changes relative to the pandemic onset using an event study design. 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 about whether changes in WFH pre-dated the COVID-19 pandemic.

Additionally, to disentangle the differential gender response of WFH to NPI intensity, we exploit the temporal and geographic variations in the adoption of NPIs during the first wave of COVID-19. To measure NPI intensity, we consider the weighted index COVINDEX (Marcén & Morales, 2021b). This index captures the timing and intensity of NPIs by state and month by using daily information on the

[5] 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 work time, calculated as the sum of all working episodes located anywhere throughout the day.

[6] We enlarged the set of socio-demographic characteristics and our results were maintained (see the results below).

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

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

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), combining this information with out-of-home mobility data provided by Google [Google LLC, 2020]).

4 Results

4.1 Main Results

Table 1 presents the estimates of Eq. (1). Panels A and B show the results at the extensive and intensive margins, respectively. The estimates in column (1) indicate that working women are more likely to report WFH and to spend a greater proportion of their working time to WFH for the whole period. Specifically, working women are approximately 4 percentage points more likely than men to report WFH. This difference is equivalent to approximately 11 percent of the average rate of individuals reporting any WFH episode during the day of the survey. Working women also allocate a higher proportion of total work time to WFH than men by 4.3 percentage points (approximately 18 percent of the average proportion of time allocated to WFH). Consistently with Chen et al., (2023), our results also point to the increase in WFH at both the intensive and extensive margins since May 2020. The estimated coefficient on the *post-May 2020* dummy is also positive and statistically significant. Our results show that the percentage of individuals reporting WFH increased by approximately 21 percentage points since May 2020 and the proportion of total work time allocated to WFH rose by 22.8 percentage points. These findings are in line with studies using the Current Population Survey that highlight the importance of telework after the onset of COVID-19 (Amuedo-Dorantes et al., 2023; Kalenkoski & Pabilonia, 2022; Marcén & Morales, 2021b; Pabilonia & Vernon, 2022a).

To explore the gender differences in WFH in the post-May 2020 period, we add an interaction term between the *female* and the *post-May 2020* 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 both the extensive and intensive margins compared to the pre-pandemic period. We find that 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-May 2020 period is associated with an increase of 6 percentage points, doubling the average pre-pandemic gender gap in the proportion of total working time that women, relative to men, allocated to WFH. [9] Although the post-May 2020 period may differ from previous economic crises due to its structural transformation of the labor market, these results align with those of Kapteyn & Stancanelli (2024). Using ATUS data, the authors also find that the Great Recession had a gendered impact on work-from-home (WFH) arrangements, with women experiencing an increase.

[9] We have re-run our main estimates for the probability of WFH using a Probit model. The marginal effects are presented in Table A2 in Appendix A. Our conclusions do not change, and the magnitude of the estimated coefficients is quite similar to those in Table 1. We have also experimented with estimating a Tobit model with WFH time as the dependent variable, and our conclusions remain unchanged.

Table 1 Main results

	(1)	(2)
Panel A: WFH		
Female	0.037*** (0.007)	0.036 (0.027)
Post-May 2020	0.209*** (0.024)	0.177*** (0.024)
Post-May 2020 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*** (0.006)	0.039* (0.022)
Post-May 2020	0.228*** (0.020)	0.201*** (0.020)
Post-May 2020 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: This table presents individual-level WLS regressions. The sample in all columns includes workers aged 18 to 64 who reported a work episode on the day of the survey. We estimate Eq. (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-May 2020 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, highest educational attainment (Highly educated dummy: completed college or higher), 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 10% level

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 allocate a higher proportion of their working time on WFH (see Table A3 in Appendix A). Our conclusions are maintained after the inclusion of additional controls in columns (1) and (2) of Table A4 in

Appendix A. We control for the day of the week respondents completed the survey and whether they completed it during holidays. We also enlarge the set of socio-demographic and job characteristics by controlling for partners' characteristics, the presence of children in the household, respondents' work classification as part- or full-time workers, self-employment status, and hourly wage. 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 (Morales & Marcén, 2024). Thus, women may be more likely than men to choose occupations allowing WFH. To mitigate this possible concern, we also control for ATUS occupation and industry categories. Similarly, as Pabilonia & Vernon (2022a) find that some teleworkers may earn a wage premium, we control for the logarithm of hourly earnings in columns (3) and (4) of Table A4 in Appendix A. Our results do not change after adding these additional controls. In addition, we follow a classification of teleworkable occupations (Dingel & Neiman, 2020) and rerun our estimates using only a sample of individuals employed in occupations allowing telework (see Table A5 in Appendix A). Our conclusions are maintained. Similarly, our conclusions remain robust when we use a sample of full-time workers as in Pabilonia & Vernon (2022a) and when we further restrict the sample to those working for at least two hours on a weekday (see Tables A6 and A7).

4.2 Dynamic Response and Identification

In this subsection, we explore the dynamic response of gender differences in WFH since May 2020. It is arguable that during the early months after the onset of COVID-19, individuals continued working remotely because employers, employees, and self-employed individuals still had concerns about the evolution of the pandemic. However, it is not clear whether gender differences in WFH increased, decreased, or remained unchanged in subsequent months. Individuals can adapt their behavior over time, and subsequent waves of COVID-19 could also be affecting the evolution of WFH. However, gender differences in preferences for work-life balance, which influenced women's choice to telework in the pre-pandemic period, could have changed following the initial pandemic shock. We consider Wolfers' (2006) methodology to determine the dynamic response. Formally, we estimate the following model:

$$Y_{ikt} = \alpha + \sum_{j=0}^{2} \rho_j 1\{t^p = \mathrm{j}\} + \sum_{j=0}^{2} \beta_j 1\{t^p = \mathrm{j}\} Female_i + Female_i + \boldsymbol{X'}_{\boldsymbol{ikt}} \boldsymbol{\mu}_1 + (\boldsymbol{X'}_{\boldsymbol{ikt}} * Female_i) \boldsymbol{\mu}_2 + \boldsymbol{\delta_k} + \boldsymbol{\theta_t} + \varepsilon_{ijkt} \quad (2)$$

where Y_{ikt} are the two WFH measures defined above. The indicator function $1\{t^p = \mathrm{j}\}$ represents a set of dummy variables for the periods: May-December 2020 (t = 0), 2021 (t = 1), and 2022 (t = 2).[10] In this way, Eq. (2) includes dummies to capture changes in WFH for each period t. Also included are interaction terms

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

between those dummies and $Female_i$, which allow us to explore the dynamic response of gender differences in WFH. In this case, the β_j parameters represent the estimated difference in the gender gap in WFH in period t relative to the pre-pandemic baseline. The rest of the variables are defined as in Eq. (1). Columns (1) and (2) in Table 2 show the estimated coefficients of Eq. (2) without interactions, whereas columns (3) and (4) show the estimates of Eq. (2) including all variables. The results provide 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 since May 2020. 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 smaller and not statistically significant in the period capturing the impact in 2021. A reduction in childcare burdens following school reopenings, combined with widespread return-to-office mandates, likely contributed to a temporary narrowing of the gender gap in telework rates in 2021. However, as employers began implementing formal hybrid work policies in 2022 (Barrero et al., 2023)—allowing employees to work remotely part of the week—many women continued to benefit from flexible work arrangements. In contrast, men were more likely to return to full-time in-person work, reinforcing again the gender gap. Our conclusions do not change when we control for the number of cases and deaths (see Tables A8 and A9 in Appendix A).

Another potential concern with the results in Table 1 is the possibility that the estimated impacts might be biased due to pre-existing WFH and trends in gender differences. Furthermore, these changes may have pre-dated the unexpected COVID-19 pandemic (Goodman-Bacon & Marcus, 2020). To address this concern, we first conduct an event study to assess whether the estimated impacts pre-dated the start of the pandemic. Specifically, the event-study takes the following form:

$$\begin{aligned} Y_{ikt} = \alpha + \sum_{j=-2}^{-5} \tau_j 1\{t^p = \mathrm{j}\} + \sum_{j=0}^{2} \rho_j 1\{t^m = \mathrm{j}\} + \sum_{j=-2}^{-5} \beta_j 1\{t^p = \mathrm{j}\} Female_i \\ + \sum_{j=0}^{2} \eta_j 1\{t^p = \mathrm{j}\} Female_i + Female_i + \boldsymbol{X}'_{\boldsymbol{ikt}\boldsymbol{\mu}_1} \\ + (\boldsymbol{X}_{\boldsymbol{ikt}} * Female_i)\boldsymbol{\mu}_2 + \boldsymbol{\delta_k} + \boldsymbol{\theta_t} + \varepsilon_{ijkt} \end{aligned} \tag{3}$$

where Y_{ikt} are the two WFH measures defined above. The indicator function $1\{t^p = \mathrm{j}\}$ represents a set of dummy variables indicating time periods t relative to the event. The reference period (omitted category) is the year prior to the event ($\mathrm{t} = -1$), which in our case corresponds to 2019.[11] We examine the existence of pre-trends during the years prior to COVID-19. The coefficients β_j capture the evolution of the gender gap relative to the baseline period. 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.

[11] 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.

Table 2 The response of WFH over time

	(1)	(2)	(3)	(4)
Dependent variable:	WFH	Proportion of time WFH over the total work time	WFH	Proportion of time WFH over the total work time
The period of the event (May20-Dec20)	0.183*** (0.013)	0.215*** (0.012)	0.130*** (0.017)	0.173*** (0.015)
1 period after the event (2021)	0.141*** (0.011)	0.161*** (0.010)	0.130*** (0.014)	0.151*** (0.012)
2 periods after the event (2022)	0.097*** (0.011)	0.125*** (0.010)	0.059*** (0.014)	0.093*** (0.012)
The period of the event (May20-Dec20) x Female			0.117*** (0.025)	0.095*** (0.024)
1 period after the event (2021) x Female			0.025 (0.022)	0.021 (0.019)
2 periods after the event (2022) x Female			0.086*** (0.022)	0.071*** (0.020)
Observations	24,094	24,094	24,094	24,094
R-squared	0.130	0.129	0.132	0.131
State FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes

Notes: This table presents the estimated coefficients of individual-level WLS regressions for the dynamic response of WFH. The sample in all columns includes workers aged 18 to 64 who reported a work episode on the day of the survey. We estimate Eq. (2). All regressions include a constant, as well as demographic and geographic controls for age, race, highest educational attainment (Highly educated dummy: completed college or higher), and a dummy variable controlling for whether or not respondents live in a metropolitan area. The controls are interacted with the female dummy in columns (3) and (4). Estimates are weighted using ATUS weights. Robust standard errors are clustered at the state level and reported in parentheses. *** Significant at the 1% level.

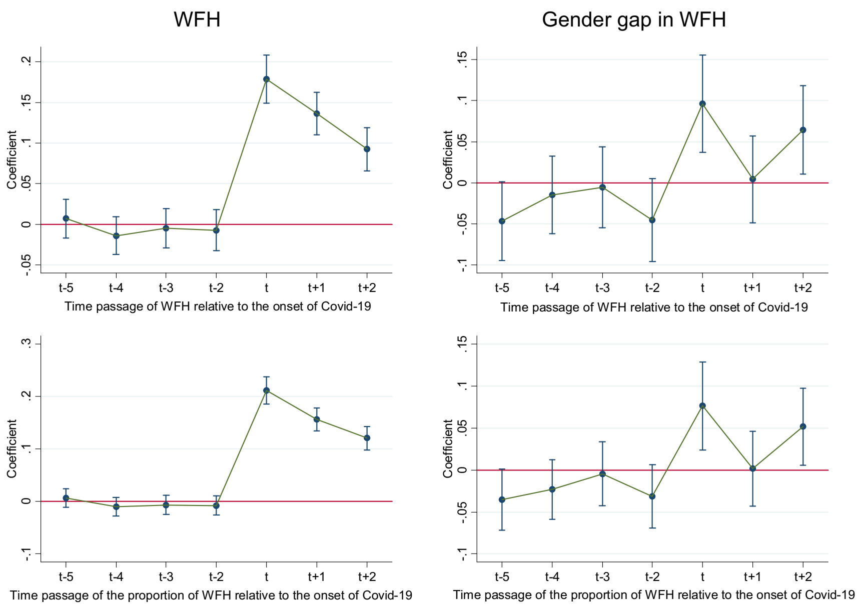

Fig. 2 Event study. Notes: These figures display the coefficients from the event study for our main sample, along with 95 percent confidence intervals. We estimate Eq. (3). Estimates are provided in Appendix A in Tables A10 and A11

Figure 2 displays the estimated event-study coefficients along with their 95 percent confidence intervals, with and without interaction terms.[12] 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 began, and the post-May 2020 pattern is similar to that found in the previous 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 Fig. A1 in Appendix A).

4.3 Heterogeneity

We also examine whether the effect on the gender gap in WFH varies across different subgroups of individuals. Table 3 explores a differential effect according to respondents' age and educational level. Table 4 focuses on marital status. Table 5 considers parenthood status and the presence of adults in the household. The results suggest that young individuals, those with some college completed, and those living with dependents experienced a particularly large increase in the gender gap in the proportion of time allocated to WFH. We observe that the gender gap in the proportion of time allocated to WFH increased more than threefold for those aged 18 to 33 compared to the average pre-pandemic gender gap. However, for those aged 48 to

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

Table 3 Heterogeneity analysis considering individual characteristics

	(1) Aged 18 to 33	(2) Aged 34 to 48	(3) Aged 49 to 64	(4) Some college	(7) No college
Panel A: WFH					
Female	−0.053 (0.077)	−0.042 (0.102)	0.047 (0.142)	0.067* (0.036)	0.011 (0.037)
Post-May 2020	0.212*** (0.044)	0.178*** (0.040)	0.142*** (0.042)	0.237*** (0.032)	0.025 (0.038)
Post-May 2020 x Female	0.080*** (0.027)	0.077*** (0.024)	0.054** (0.025)	0.055*** (0.019)	0.069*** (0.025)
Observations	6003	9768	8323	18,170	5924
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 (0.067)	−0.052 (0.085)	0.036 (0.119)	0.071** (0.029)	0.008 (0.030)
Post-May 2020	0.210*** (0.037)	0.207*** (0.033)	0.188*** (0.035)	0.264*** (0.027)	0.060** (0.027)
Post-May 2020 x Female	0.069*** (0.024)	0.066*** (0.021)	0.037* (0.021)	0.046*** (0.017)	0.032 (0.020)
Observations	6003	9768	8323	18,170	5924
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: This table presents individual-level WLS regressions. The sample in all columns includes workers who reported a work episode on the day of the survey. We estimate Eq. (1). All regressions include a constant, as well as demographic and geographic controls for age, race, and a dummy variable controlling for whether or not respondents live in a metropolitan area. Columns (1) to (3) also add controls for highest educational attainment (Highly educated dummy: completed college or higher). The controls are interacted with the female dummy in all columns. See Table B1 in 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

64, the gender gap increased more for the extensive margin (reporting WFH). By educational level, the increase in the gender gap (extensive margin) is greater in the case of individuals without some college compared with the average gap in the pre-pandemic period, but the increase in the proportion of total work time allocated to WFH is greater for those who have completed some college. Furthermore, we

Table 4 Heterogeneity analysis by marital status

	(1) Partnered HH	(2) Single HH	(3) Different-sex partnered HH	(4) Same-sex partnered HH
Panel A: WFH				
Female	0.036 (0.041)	0.046 (0.035)	0.033 (0.042)	0.523* (0.315)
Post-May 2020	0.187*** (0.030)	0.162*** (0.041)	0.183*** (0.030)	1.040*** (0.358)
Post-May 2020 x Female	0.085*** (0.019)	0.049** (0.023)	0.084*** (0.019)	−0.051 (0.172)
Observations	14,419	9675	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 (0.034)	0.037 (0.029)	0.053 (0.035)	0.472* (0.273)
Post-May 2020	0.217*** (0.025)	0.177*** (0.033)	0.216*** (0.025)	0.846** (0.349)
Post-May 2020 x Female	0.067*** (0.017)	0.045** (0.020)	0.068*** (0.017)	−0.067 (0.147)
Observations	14,419	9675	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: This table presents individual-level WLS regressions. The sample in all columns includes workers who reported a work episode on the day of the survey. We estimate Eq. (1). All regressions include a constant, as well as demographic and geographic controls for age, race, highest educational attainment (Highly educated dummy: completed college or higher), 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 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

observe that those women with a different-sex partner significantly increased both the probability of working from home and the proportion of time allocated to WFH during the pandemic relative to men.

Columns (1) to (4) of Table 5 examine parenthood status and estimate the differential WFH response by age group of the child (if any) separately. Interestingly, we observe that, relative to men, women without children and those with children

Table 5 Heterogeneity analysis by caregiving status

	(1) No 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) No older adult in the HH
Panel A: WFH						
Female	0.034 (0.034)	0.057 (0.087)	−0.120 (0.081)	0.058 (0.104)	0.026 (0.066)	0.042 (0.032)
Post-May 2020	0.172*** (0.034)	0.247*** (0.052)	0.088* (0.052)	0.256*** (0.058)	0.119* (0.069)	0.186*** (0.026)
Post-May 2020 x Female	0.100*** (0.021)	0.015 (0.033)	0.079*** (0.029)	0.034 (0.036)	0.098** (0.043)	0.064*** (0.015)
Observations	11,725	4625	6110	4240	1699	22,395
R-squared	0.130	0.171	0.142	0.152	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	−0.02	0.04*	0.02***
Panel B: Proportion of time WFH over the total work time						
Female	0.030 (0.029)	0.081 (0.068)	−0.042 (0.064)	0.037 (0.079)	0.042 (0.053)	0.048* (0.026)
Post-May 2020	0.180*** (0.029)	0.256*** (0.044)	0.144*** (0.041)	0.245*** (0.045)	0.138** (0.055)	0.212*** (0.022)
Post-May 2020 x Female	0.082*** (0.018)	−0.002 (0.029)	0.069*** (0.025)	0.034 (0.029)	0.096** (0.038)	0.050*** (0.014)
Observations	11,725	4625	6110	4911	1699	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***

Table 5 continued

	(1) No 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) No older adult in the HH
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: This table presents individual-level WLS regressions. 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 Eq. (1). All regressions include a constant, as well as demographic and geographic controls for age, race, highest educational attainment (Highly educated dummy: completed college or higher), 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 aged 6 to 12, who may require more hours helping with homeschooling, are the only groups for whom both the extensive and intensive margins increased significantly since May 2020. Columns (5) and (6) consider the presence of older adults in the household. Our key coefficient is positive and statistically significant regardless of the presence of an older adult in the household. However, the impact on the proportion of total work time allocated to WFH is greater for those with older individuals than for those without. As household care responsibilities fell primarily on women (Marcén & Morales, 2022), our results may reflect a greater preference for workplace flexibility provided by WFH among women with dependents than without.

Additionally, we examine the heterogeneous WFH response by class of worker. Table 6 presents the results. Our findings reveal that privately employed women significantly increased both the probability of WFH and the proportion of total work time allocated to WFH relative to men from May 2020. However, workers in the public sector appear to have increased the proportion of total work time allocated to WFH but not the gender gap in the intensive and extensive margins. A similar pattern is observed for the self-employed. We have further explored the dynamic response of WFH focusing on differences by class of worker. The results are presented in Tables A12 and A13 in Appendix A. We find that the proportion of time allocated to WFH by both private and public employees significantly increased since May 2020. In line with our previous results, we also find an increase in the gender gap in WFH that persists over time, but only for those working in the private sector.[13]

4.4 The Intensity of COVID-19 Non-Pharmaceutical Interventions (NPIs) and WFH

We consider a complementary exercise to better understand the role of social distancing measures, known as non-pharmaceutical interventions (NPIs). We analyze whether the intensity of NPIs has affected WFH decisions and whether it has differentially impacted the gender gap. Early in the pandemic, the following five different NPIs were adopted to contain the spread of the virus by reducing social interactions in the U.S.: state of emergency, school closures, partial business closures, stay-at-home orders, and non-essential business closures. Approval of NPIs sparked political polarization, with Republicans displaying notably higher levels of skepticism compared to Democrats (Funk & Tyson, 2020). As a result, they took place at distinct geographic levels (some at county level, others at the state level) and for different periods of time. Thus, it is possible that differences in the exposure to NPIs across U.S. states may be related to different gender responses in WFH.

To capture the timing and intensity of the NPIs at the state level, we use the COVINDEX (Marcén & Morales, 2021b). The COVINDEX is a state-level weighted index that combines daily data on five NPI announcements, their expirations, and real-time mobility trends from Google Mobility Reports across five non-residential categories (retail and recreation, grocery and pharmacy, parks, transit stations, and

[13] Note that all these results should be taken with caution due to the small number of observations in some estimates. In addition, the pre-pandemic gender gap is small or not statistically significant among those aged 49 to 64, with children aged 6 to 18, in households with older adults, and same-sex partnered households.

Table 6 Heterogeneity analysis by class of worker

	(1) Public employed	(2) Private employed	(3) Self-employed
Panel A: WFH			
Female	−0.025 (0.070)	0.041 (0.029)	0.179 (0.129)
Post-May 2020	0.259*** (0.062)	0.154*** (0.028)	0.184** (0.089)
Post-May 2020 x Female	0.040 (0.038)	0.083*** (0.017)	−0.007 (0.052)
Observations	3967	17,536	2591
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 (0.057)	0.031 (0.024)	0.229* (0.119)
Post-May 2020	0.351*** (0.049)	0.180*** (0.023)	0.102 (0.082)
Post-May 2020 x Female	0.046 (0.033)	0.060*** (0.015)	0.013 (0.049)
Observations	3967	17,536	2591
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: This table presents individual-level WLS regressions. The sample in all columns includes workers between 18 and 64 years old who reported a work episode on the day of the survey. All regressions include a constant, as well as demographic and geographic controls for age, race, highest educational attainment (Highly educated dummy: completed college or higher), 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

workplaces). The COVINDEX is calculated using estimated coefficients capturing the average effect of each NPI on the relative change in visitors for each category of mobility by state. The COVINDEX is by definition bounded with a minimum value of −5, which occurs when NPIs result in zero visitors across five specified location categories in a given state during an entire month, representing maximum enforcement. A COVINDEX value of 0 (no enforcement) indicates either no NPIs are implemented or the declared NPIs have no statistically significant impact on mobility categories. More negative values indicate greater reductions in mobility due to NPIs. The more effectively NPIs reduce social interactions in a state, the closer the COVINDEX approaches −5. Conversely, the COVINDEX can take positive values when at least one of the NPIs stimulates social interaction resulting in visitor numbers exceeding the baseline period and none of the other NPIs has statistically significant effects or, if significant, cannot compensate for the estimated positive effect.[14] We estimate the following equation:

$$Y_{ik}^{2021} = \beta_0 + \beta_1 Female_i + \beta_2\, COVINDEX_s^{2020} + \beta_3(Female_i * COVINDEX_s^{2020}) + \\ + \boldsymbol{X'}_{\boldsymbol{ikt}}\boldsymbol{\mu}_1 + (\boldsymbol{X'}_{\boldsymbol{ikt}} * Female_i)\boldsymbol{\mu}_2 + \boldsymbol{\delta_k} + \varepsilon_{ik} \tag{4}$$

where $COVINDEX_s^{2020}$ is the average of the COVINDEX presented by Marcén & Morales (2021b) for the months of March, April, and May in state s.[15] 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. Thus, to evaluate the lasting impact of NPIs on WFH, we examine the correlation between state-level COVINDEX scores in 2020 (representing unexpected interventions) and the later WFH data. Following an approach similar to Amuedo-Dorantes et al., (2023), 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 all of 2020.

Table 7 presents the results. As expected, we observe that the increase in the intensity of the NPIs that occurred from March to May 2020 significantly affected the structure of work through an increase in WFH at both the intensive and 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 later on. The estimated coefficient on the interaction term between the *female* dummy and *COVINDEX* in columns (1) and (2) is positive and statistically significant, suggesting that the gender gap has been reduced in those areas with more intense NPIs, as a result of both a higher probability of WFH practices among men and a lower probability among women. However, this is only observed among men in the case of the proportion of time spent working from home. The estimated coefficient of interest is not statistically significant in columns (3) and (4), showing that non-pharmaceutical interventions during the early months of the pandemic positively affected the proportion of WFH time for men but not for women. These findings are not surprising due to the differing responses revealed in the probability of WFH across genders.

[14] This only happens in March when emergency declarations and school closures seem to correlate with increased visits to parks and grocery stores. Given the typically consistent nature of human mobility patterns, the COVINDEX would not normally surpass 0 without non-pharmaceutical interventions (NPIs). Our findings align with this expectation, with the maximum calculated value being 0.05.

[15] The COVINDEX over the COVID-19 period (March, April, and May 2020) averaged −1.02 and fluctuated between 0.05 and −2.6.

Table 7 The intensity of COVID-19 non-pharmaceutical interventions and WFH

Dependent variable:	(1)	(2)	(3)	(4)
	WFH	WFH	Proportion of time WFH over the total work time	Proportion of time WFH over the total work time
Female	0.062*** (0.015)	0.219*** (0.076)	0.060*** (0.013)	0.161** (0.068)
COVINDEX	−0.027 (0.025)	−0.075** (0.031)	−0.059*** (0.022)	−0.081*** (0.027)
COVINDEX x Female		0.104** (0.051)		0.049 (0.045)
Observations	5198	5198	5198	5198
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: This table presents individual-level WLS regressions. The sample in all columns includes workers aged 18 to 64 who reported a work episode on the day of the survey. We limit the sample to the years 2021 and 2022. We estimate Eq. (4). 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, highest educational attainment (Highly educated dummy: completed college or higher), and a dummy variable controlling for whether or not respondents live in a metropolitan area. The controls are interacted with the female dummy in columns (2) and (4). *** Significant at the 1% level; ** significant at the 5% level.

4.5 Other Work-related Outcomes

In this subsection, we further explore what happens to other work-related issues that existing literature highlights as key determinants of the work-family balance (Goldin, 2014). We focus our analysis on unpredictable schedules, non-standard working hours, work interruptions, the logarithm of weekly work hours, and commuting.[16] We rerun our main analysis by redefining the dependent variable, see Appendix B. Table 8 shows the estimated coefficients. The estimated coefficient on the female indicator reveals the existing lower tendency of women relative to men to have an unpredictable and non-standard schedule, to be interrupted, to work longer hours,

[16] Our analysis using work schedules relies on the START variable that captures the beginning times of work episodes. Unpredictable schedule is measured as the number of hours between the first and the last work episode. We assume that a large available work time is equivalent to an unpredictable schedule. A non-standard schedule is defined by a dummy variable taking the value one if the respondent starts some work episode between 8:00 p.m. and 6:00 a.m., and zero otherwise. Work interruptions is proxied by the number of work episodes. Commuting is a dummy variable taking value one if the respondent devotes any time in the activity ‘commuting’.

Table 8 Other work-related outcomes

Dependent variable:	(1) Unpredictable schedule	(2) Unpredictable schedule	(3) Non-standard schedule	(4) Non-standard schedule	(5) Work interruptions (number of work episodes)	(6) Work interruptions (number of work episodes)	(7) Log (weekly work hours)	(8) Log (weekly work hours)	(9) Commuting	(10) Commuting
Female	−0.488*** (0.066)	−0.524* (0.297)	−0.074*** (0.007)	−0.043 (0.031)	−0.132*** (0.023)	−0.254** (0.103)	−0.126*** (0.006)	−0.034 (0.030)	−0.027*** (0.006)	−0.023 (0.027)
Post-May 2020	−0.077 (0.070)	−0.449* (0.243)	−0.010 (0.007)	0.012 (0.023)	−0.159** (0.080)	−0.215** (0.084)	−0.035* (0.020)	−0.060*** (0.021)	−0.194*** (0.023)	−0.157*** (0.024)
Post-May 2020 x Female		0.383*** (0.141)		0.022 (0.015)		0.119** (0.049)		0.057*** (0.013)		−0.078*** (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: This table presents individual-level WLS regressions. The sample in all columns includes workers aged 18 to 64 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 Eq. (1). The dependent variable is the number of hours between the first and the last work episode in columns (1) and (2). In columns (3) and (4), the dependent variable is a dummy variable taking the value one for those working during non-standard hours, 0 otherwise. The number of work episodes is the dependent variable in columns (5) and (6). The logarithm of weekly work hours is the dependent variable in columns (7) and (8). Commuting time is a dummy variable taking value one if the respondent devotes any time in the activity commuting in columns (9) and (10). See Table B1 in Appendix B for a detailed description of dependent variables. All regressions include a constant, as well as demographic and geographic controls for age, race, highest educational attainment (Highly educated dummy: completed college or higher), and a dummy variable controlling for whether or not respondents live in a metropolitan area. The controls are interacted with the female dummy in columns (2), (4), (6), (8) and (10). 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 and to commute. These results are not surprising as women have traditionally demanded more predictable and regular schedules than men, avoiding greedy jobs (Bolotnyy & Emanuel, 2022; Morales & Marcén, 2024). However, these gender gaps may have reversed after May 2020. If we look at the interaction term, all but one (commuting) seem to have risen for women after May 2020, albeit the coefficient is not statistically significant in the case of a non-standard schedule. As a result, 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)), which is not surprising due to the higher tendency of women to WFH.

We further explore whether these findings might be due to the changes in time allocations of those who work from home. As shown in Giménez-Nadal et al., (2019) and Pabilonia & Vernon (2022b), telework provides workers with greater flexibility to adjust their work timing, potentially enabling them to better manage work and personal life responsibilities. For example, compared to those working in the office, teleworkers are less likely to be working during central hours. They also spend more time on household tasks, some of which occur during traditional working hours. Thus, by allowing workers to adjust their work schedules, telework may have resulted in less structured work hours and more extended and frequently disrupted workdays, making it even harder for women to maintain work-life balance. To address this issue, we rerun our analysis by separating the sample between those who report any WFH episode during the day of the survey and those who do not. Table 9 presents our results. Women are generally less likely to experience unpredictable schedules, non-standard working hours, work interruptions, longer working hours, and commuting, regardless of whether they WFH or not. For those WFH (Panel A), we find that the gender gap has only narrowed in weekly working hours. In contrast, among non-teleworkers (Panel B), the gender gaps in all other job features have decreased, though these changes are mostly significant only at the 10% level.[17] By considering the magnitude of the estimated coefficients, these results suggest that the increase in women's working hours—though not in other outcomes—may be linked to the flexibility provided by teleworking.

5 Conclusions

Since the onset of COVID-19 led to alternate arrangements from the traditional working day, namely working from home, scholars have raised questions 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 persist among women and men remained an open question. In this paper, we analyzed changes in the gender gap in working from home (WFH).

[17] Our conclusions remain consistent when analyzing a sample of mothers WFH controlling for ATUS occupation and industry categories.

Table 9 Other work-related outcomes by WFH status

Dependent variable:	(1) Unpredictable schedule	(2) Unpredictable schedule	(3) Non-standard schedule	(4) Non-standard schedule	(5) Work interruptions (number of work episodes)	(6) Work interruptions (number of work episodes)	(7) Log (weekly work hours)	(8) Log (weekly work hours)	(9) Commuting	(10) Commuting
Panel A: teleworkers										
Female	−0.430*** (0.133)	0.002 (0.699)	−0.029** (0.013)	0.023 (0.071)	−0.082** (0.039)	−0.097 (0.213)	−0.140*** (0.011)	−0.071 (0.073)	−0.059*** (0.013)	−0.176** (0.070)
Post-May 2020	−0.779*** (0.132)	−0.889* (0.506)	−0.134*** (0.013)	−0.054 (0.049)	−0.319* (0.168)	−0.345** (0.172)	−0.062 (0.040)	−0.113*** (0.041)	−0.232*** (0.053)	−0.234*** (0.054)
Post-May 2020 x Female		0.302 (0.265)		−0.018 (0.026)		0.043 (0.078)		0.089*** (0.022)		0.004 (0.027)
Observations	7901	7901	7901	7901	7901	7901	7455	7455	7901	7901
R-squared	0.019	0.022	0.035	0.039	0.020	0.020	0.057	0.065	0.087	0.090
D.V. Mean	5.95	5.95	0.31	0.31	2.48	2.48	3.73	3.73	0.33	0.33
D.V. Std. Dev.	5.06	5.06	0.46	0.46	1.46	1.46	0.39	0.39	0.47	0.47
Panel B: non-teleworkers										
Female	−0.597*** (0.073)	−0.616* (0.322)	−0.095*** (0.008)	−0.045 (0.035)	−0.172*** (0.028)	−0.277** (0.117)	−0.122*** (0.007)	−0.037 (0.033)	0.016*** (0.005)	0.007 (0.023)
Post-May 2020	−0.148* (0.083)	−0.677** (0.277)	0.014 (0.009)	0.013 (0.027)	−0.206** (0.092)	−0.252*** (0.098)	−0.026 (0.023)	−0.044* (0.024)	0.013 (0.019)	0.021 (0.019)
Post-May 2020 x Female		0.295* (0.168)		0.035* (0.018)		0.118* (0.064)		0.049*** (0.015)		−0.021* (0.012)
Observations	16,193	16,193	16,193	16,193	16,193	16,193	15,420	15,420	16,193	16,193
R-squared	0.018	0.022	0.049	0.053	0.025	0.026	0.064	0.067	0.010	0.011
D.V. Mean	4.48	4.48	0.19	0.19	2.28	2.28	3.69	3.69	0.92	0.92
D.V. Std. Dev.	3.70	3.70	0.40	0.40	1.26	1.26	0.34	0.34	0.26	0.26

Table 9 continued

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Dependent variable:	Unpredictable schedule	Unpredictable schedule	Non-standard schedule	Non-standard schedule	Work interruptions (number of work episodes)	Work interruptions (number of work episodes)	Log (weekly work hours)	Log (weekly work hours)	Commuting	Commuting
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

Notes: This table presents individual-level WLS regressions. The sample in all columns includes workers between 18 and 64 years old. Those who reported any work episode on the day of the survey are included in Panel A, and those reporting none are included in Panel B. We also limit the sample to those individuals reporting information on weekly work hours in columns (7) and (8). We estimate Eq. (1). See Table 8 and B1 in Appendix B for a detailed description of dependent variables. All regressions include a constant, as well as demographic and geographic controls for age, race, highest educational attainment (Highly educated dummy: completed college or higher), and a dummy variable controlling for whether or not respondents live in a metropolitan area. The controls are interacted with the female dummy in columns (2), (4), (6), (8) and (10). 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

Using data from the American Time Use Survey, we find that WFH became more prevalent among women than men two years after the pandemic hit. The post-May 2020 period is associated with an increase of 7 percentage points in the gender gap relating to the probability of WFH and an increase of 6 percentage points in the gender gap pertaining to the proportion of working time allocated to WFH. Additionally, we observe differential impacts depending on the characteristics of respondents. The gender gap in the proportion of time allocated to working remotely increased significantly for those who are younger, those with a different-sex partner, and private employees. A heterogeneous analysis based on parenthood status shows that, compared to men, only women without children and those with children aged 6 to 12—who may need to dedicate more time to assisting with homeschooling—increased their WFH hours in the post-May 2020 period, both in terms of participation and intensity.

We further exploited differences in the timing and duration of NPIs across U.S. states to analyze whether a higher exposure to social distancing measures at the beginning of the pandemic could differentially affect the WFH tendency across genders. We showed evidence suggesting a mitigating effect of non-pharmaceutical interventions during the early months of the pandemic, positively affecting the proportion of time WFH for men, but not for women, who even reduced their tendency to WFH. Long-term NPIs exposure may have helped reduce gender inequalities as men who balanced work and family duties during early lockdowns could have maintained greater family involvement afterward while WFH. A supplementary analysis also identified changes in other work-related outcomes hindering the work-family balance. Non-teleworker women are now more likely than before the pandemic to have an unpredictable schedule, work interruptions, and long work hours, while the opposite is found for non-teleworker men. For teleworkers, gender disparities have increased solely in terms of weekly working hours. Overall, our findings demonstrate a persistent gender gap in WFH, even after controlling for potential confounding factors. Further research is required to fully explore the mechanisms that contributed to the greater shift toward WFH among women compared to men.

Data availability No datasets were generated or analysed during the current study.

Supplementary information The online version contains supplementary material available at https://doi.org/10.1007/s11150-025-09809-x.

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