Remote Work vs Part-Time Employment: a New Work-Family Balance?

Thea Jansen [1] (corresponding author)

thea.jansen@gssi.it

0009-0003-0990-3513

[1] *Gran Sasso Science Institute, L'Aquila, Italy*

Marina De Angelis [2]

ma.deangelis@inapp.gov.it

0000-0003-4516-6891

[2] *National Institute for Public Policies Analysis (INAPP), Rome, Italy*

ABSTRACT

This paper examines whether remote work can reduce reliance on part-time employment – a work arrangement predominantly used by women to balance work and family responsibilities but often associated with lower earnings, limited career prospects, and reduced pension benefits. Focusing on Italy, where female under-employment is particularly high, we investigate whether the flexibility offered by remote and hybrid work can serve as a substitute for part-time employment, enabling some necessity-driven part-time workers to transition to full-time contracts. Using a difference-in-differences framework and weighted logistic regression, we analyze panel and cross-sectional data from the National Institute for Public Policies Analysis (INAPP)'s Participation, Labor, and Unemployment Survey (PLUS) for the 2018–2021 period. Our findings show that remote work significantly reduces the probability of working part-time in the following year, with women showing the highest increase in the likelihood of having a full-time contract.

Keywords: remote work, part-time, gender, difference-in-differences, logit, Italy

JEL: J16, J22, J41

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1. INTRODUCTION

This paper investigates whether and how remote work influences part-time employment in the Italian context. According to 2018 data, Italy has the European Union's 3rd highest gap in overall earnings between men and women of working age. According to the Gender Overall Earnings Gap (GOEG), a synthetic indicator that jointly accounts for differences in average hourly earnings, hours paid per month, and employment rates, Italian women earn 43% less than men on average, against an EU average of 36.2%. Closer analysis of the components driving GEOG in Italy reveals that the overall inequality is mainly driven by female under-employment and much less so by pay discrimination for those working[1]. In 2018, the pay gap explained 9.9% of Italian GEOG (against an EU average of 36.7%), while the gap in hours worked per month explained 34.7% (EU average: 29.3%) and the employment rate gap 55.4% (EU average: 34%) (Eurostat, European Commission 2024). Tackling female under-employment, both in the form of low labour force participation and reliance on part-time, should therefore be a primary policy focus to reduce gender inequality and female poverty. It would moreover ensure a more efficient use of human capital in a country affected by low productivity, demographic decline and high public debt, as this would expand the labour force, tax base and improve the sustainability of the pension system (Pissarides et al. 2005; OECD 2017).

The feminist economics literature has extensively explored the determinants of low female employment, finding childcare, family, and home care to be the most prominent ones, as women still shoulder the bulk of unpaid care work and thus have more limited time and possibilities to engage in formal employment (Folbre 2012; Thévenon 2013; Aloè 2023). The growth in part-time work represented an important enabler for many women to enter the formal labor force in the past decades, as working fewer hours helped them balance paid work with family life (Buddelmeyer et al. 2004; OECD 2011). This benefit however comes at the cost of a generally lower professional status, hourly earnings, career prospects, job security, and pension benefits, which translate to a higher risk of poverty in old-age (OECD 2010; 2012; Addabbo 2020).

Statistical definitions typically distinguish between "voluntary" and "involuntary" part-time as a way to distinguish whether the arrangement is mainly motivated by the employee or the employer, i.e. by labor supply or labor demand (OECD 2010). The word "voluntary" might however be misleading, as motivations are nuanced and vary. For many women, the advantages of working part-time outweigh its negative consequences and doing so is a voluntary, empowered choice to spend more time with their families (Hakim 1992, 2000, 2008). Others may have opted for the arrangement due to necessity and lack of better alternatives, rather than choice. This is the case for many women in Italy, where early childhood education and care (ECEC) services, although increasing, are still scarce, with the country falling below the EU minimum standard of 33% of children under 3 years of age enrolled in ECEC programs nationwide, and significant territorial disparities in

[1] Italy's relatively low pay gap is likely due to selection bias: as the employment rate is much lower for women than for men, those women who are in paid employment may have comparatively higher skills and education levels on average than men (Eurostat 2024b).

day care center availability (European Commission, Directorate-General for Justice 2013; Del Boca et al. 2019).

Other practices facilitating work-family balance are flexible work arrangements, generally defined as workplace flexibility options in terms of work time and/or location (Allen et al. 2013). However, job interruptions, shorter hours, and flexibility during the workday, like working part-time, come at a cost in terms of status, pay, and career advancement (Goldin and Katz 2011). Before the pandemic, also remote work was mainly used and perceived as a family-friendly work practice and was similarly associated with negative career trade-offs. The pandemic however changed the way remote work is perceived. Its unprecedented surge and widespread adoption for both women and men, as well as better-than-expected experiences and productivity outcomes, normalized and legitimized its use for both genders (Barrero et al. 2021; Harrington and Kahn 2023). As working remotely no longer signals low workplace attachment, the flexibility that comes with it – and its potential benefits for work-family conciliation – no longer comes with the traditionally associated career-related costs. Those working remotely therefore benefit from "free" flexibility, making picking up children from school, being present for sick relatives, doing chores and running errands much less costly than reduced working hours. Working remotely could therefore provide the flexibility needed by necessity part-time workers, enabling some of them to increase their working hours and earnings.

COVID-19 containment measures led to the large scale adoption of a working modality previously unavailable to most, as working remotely was particularly rare in Italy[2]. The pandemic therefore introduced a new work-family conciliation benefit, which continues to be available after the immediate health crisis as remote work continues to be relied upon, albeit to a lesser extent.

We rely on panel and cross-sectional data from the National Institute for Public Policies Analysis' (INAPP) Participation Labor Unemployment Survey (PLUS). Leveraging the large scale adoption of remote work, we employ a difference-in-differences (DiD) framework to investigate how working remotely in 2020 affected the likelihood of being engaged in part-time work in 2021. This allows us to explore the lagged impact between remote work and hours worked, suggesting that adjustments may occur after a trial period of working remotely. Our findings contribute to ongoing debates on gender equality, labor market dynamics, and the role of remote work in supporting work-family balance.

This article is structured as follows: Section 2 outlines the theoretical framework and the existing background literature. Section 3 describes the data used and offers summary statistics. Section 4 discusses the methodology and Section 5 presents preliminary results. Section 6 concludes with some policy implications.

[2] In 2019, only 3.6% of Italians worked remotely usually (EU average: 5.4%) and 1.1% did so sometimes (EU average: 9%) (Eurostat 2023).

2. LITERATURE

The impact of childbirth and childcare on women's earnings and employment, often referred to as the "motherhood penalty," has been widely documented (Waldfogel 1998; Budig and England 2001; Kleven et al. 2019). Research highlights significant gender disparities in occupational outcomes following the birth of a first child, showing that women are more likely than their male partners to experience unemployment, part-time work, or low-paying positions (Barbieri et al., 2024). Mothers moreover tend to work in firms that are less productive, with lower capital, revenues and average wages (Casarico and Lattanzio 2023). The motherhood penalty is however particularly pronounced in high-paying careers, where working long hours is rewarded – despite being hard to reconcile with family life – and career interruptions are costly due to high returns to experience (Wood et al. 1993; Bertrand et al. 2010; Wilde et al. 2010; England et al. 2016). In Southern Europe, structural deficiencies in family services, policy support, and rigid labor markets make it especially difficult for women to balance work and family life, leading to a polarization between those with strong labor market attachment and those who spend much of their lives underemployed or out of the workforce (Barbieri et al. 2019).

The expansion of part-time work from the 1950s onward has played a crucial role in increasing women's labor market participation (Goldin 2006). Part-time work reduces work-life conflict, providing an opportunity to engage in formal employment to individuals who would not otherwise be active in the labor force (Booth and van Ours 2013). However, as mostly women engaged in part-time work, it became socially unacceptable for men to request it, reinforcing gender segregation in employment (Epstein et al. 2014). Workplace flexibility policies have similarly been used predominantly by women, often at the cost of lower wages, reduced professional status, and limited career advancement (Goldin and Katz 2011). Research on career preferences suggests that while women are more likely to seek flexible work arrangements, these choices are often driven by structural constraints rather than personal preferences alone (Hakim 2000; Thévenon 2013).

Various studies have highlighted the role of flexible working *hours* in reducing work-family conflict (Goldin 2014; Goldin and Katz 2016; Cortés and Pan 2023; Bolotnyy and Emanuel 2022), but the role of flexibility in working *location* is less understood. Studies on pre-pandemic data find either no significant link between remote work and work-family conflict (Allen et al. 2013) or indicated that remote work increased mothers' working hours, exacerbating work-life tensions rather than alleviating them (Arntz et al. 2022). However, more recent studies using post-pandemic data suggest a shift. Although remote employees worked longer hours before COVID-19, their hours had converged by 2021 (Pabilonia and Vernon 2025). Other studies report a reduction in the "motherhood penalty" in employment, with mothers in teleworkable professions returning to work more quickly post-childbirth (Harrington and Kahn 2023) and women with remote work options more willing to accept better-paying jobs with long commutes (Nagler et al. 2024).

While remote work has the potential to increase women's labor market participation, some scholars argue it may also lead to professional isolation and reduced workplace visibility, ultimately hindering career progression (Del Boca et al. 2020; Cannito and Scavarda 2020). Others suggest that the widespread adoption of remote work during the pandemic, as well as better-than-expected productivity outcomes (Bloom et al. 2015; Emanuel and Harrington 2023; Gibbs et al. 2023), normalized and legitimized its use, reducing its associated stigma (Barrero et al. 2021; Harrington and Kahn 2023). Supporting this view, Pabilonia and Vernon (2025) report that remote workers in the United States now receive a wage premium across most occupations. However, the benefits of remote work vary by individual circumstances, such as parental status and the availability of a suitable home workspace (Song and Gao 2020; Möhring et al. 2021; Arntz et al. 2022).

The impact of remote work on intra-household dynamics is also mixed. Some studies suggest it reinforces traditional gender roles in caregiving (Möhring et al. 2021), while others find it enables a more equitable distribution of domestic labor (Cowan 2024). Remote work also affects life satisfaction differently depending on gender and family structure. Married men and women with no school-age children were largely unaffected in terms of life satisfaction, while unmarried men saw a worsening in life satisfaction, as did women with school-aged children during the pandemic's initial phases (Senik et al. 2024). These findings are echoed by Han and Kaiser (2024), who highlighting a disproportionate impact of the pandemic on women's well-being. The negative impact on women with school-age children however disappeared by 2021, suggesting improved circumstances in reconciling remote work and childcare (Senik et al. 2024).

Despite the potential advantages of remote work, women remain underrepresented among remote workers even after accounting for occupational differences, suggesting barriers to accessibility (Alon et al. 2022) including gender gaps in digital skills (Arntz et al. 2022).

Focusing on Italy, experimental evidence suggests that remote work improves productivity, well-being, and work-life balance, particularly for women (Angelici and Profeta 2023). However, other studies highlight drawbacks, such as increased work-life blurring and negative well-being effects (Turrini 2024). Research on the gender wage gap in teleworkable occupations shows that while remote work facilitates female labor force participation, it is also associated with higher earnings gaps (Bonacini et al. 2021, 2023). Additionally, remote work opportunities are not evenly distributed across sectors, and access is influenced by education level and digital proficiency, further reinforcing existing inequalities (Turrini 2024).

Building on this literature, this study investigates whether remote work can serve as a substitute for part-time employment by providing the flexibility needed for necessity part-timers to increase their working hours. To the best of our knowledge, no prior research has explored whether remote work reduces reliance on part-time employment, making this study a novel contribution. Given that remote work opportunities are more prevalent in high-skill, high-income professions (Dingel and Neiman 2020; Mongey and Weinberg 2020; Barbieri et al. 2022), we expect this substitution pattern to be particularly strong among highly skilled workers facing significant work-family conflict.

3. DATA

We use secondary survey data from the National Institute for Public Policy Analysis (INAPP)'s *Participation Labor Unemployment Survey* (PLUS), already used in research published in the Journal of Population Economics (Bonacini et al., 2021). This survey is designed to explore specific labor market dynamics that are only partially addressed by the EU Labor Force Survey, such as detailed insights into female underemployment and, starting with the 2021 wave, remote work.

The survey is structured as a repeated cross-section, with approximately 45,000 observations per wave. About 25% of the sample consists of panel data, where the same individuals are re-interviewed in consecutive years. For our analysis, we use the panel data from 2018 and 2021. To validate our findings on a larger sample and further investigate the determinants of part-time work, we also utilize the full cross-sectional wave from 2021, which includes retrospective questions on respondents' remote work habits before the COVID-19 pandemic.

The PLUS survey employs a stratified quota sampling method to ensure reliable estimates for specific population subgroups, including region, urban classification, gender, and age group. Its rich dataset makes it particularly well-suited for examining whether and how remote work influences working hours.

Summary statistics

We only retain employees in our dataset, i.e. those whose work entails the possibility of having a part-time contract. Free professionals, entrepreneurs, or occasional workers are therefore excluded, as well as the unemployed and inactive. We adjust our sample weights to this subgroup's characteristics, which makes our sample representative of all employees with part- or full-time contracts at the national level.

After cleaning the data from missing values in key variables, a dataset of 1,945 observations per wave results for the panel, and a sample of 13,796 observations results for the 2021 cross-section. There is no apparent bias among non-respondents, such as in gender or other factors, ensuring our final panel[3] and cross-sectional[4] samples are comparable to the original ones.

[3] Observations dropped from the panel due to missing values in key variables only account for 3.08%. In terms of gender, 42% of non-respondents were men and 58% were women, which mirrors the sample's overall composition exactly. In terms of age, 27% of non-respondents were from the 18–29 group, 31% from the 30–49 group and 42% from the 50+ group, which also almost exactly mirrors the overall sample's composition (26%, 31% and 43% respectively). Overall sample shares are also exactly mirrored among non-respondents in terms of macro area (58% North, 22% Centre and 20% South), urban classification (13% from metropolitan areas and 87% from non-metropolitan areas), and employment type (39% public sector and 61% private).

[4] Observations dropped from the cross-section due to missing values account for 4%. In terms of gender, non-respondents are 51% men and 49% women, while in the original sample they were 47% and 53% respectively. In terms or age, non-respondents were in the 18–29 group for 35%, in the 30–49 group for 28% and in the 50+ group for 36%. The groups in the original sample accounted for 40%, 32% and 28% respectively. As for macro-area, non-respondents were 52% from the North (while 55% in the original sample), 18% from the Centre (19% from the original sample), and 30% from the South and Islands (26% in the original sample). In terms of employment type, non-respondents were 43% from the public sector and 57% from the private one, while shares in the original sample were 26% and 74% respectively. 16% of non-respondents were from a metropolitan area, compared to 15% in the original sample.

Tables 1 and 2 provide summary statistics for our dependent variable, in the panel and the cross-section respectively.

Table 1: Summary statistics for contract type in panel data, by year and gender

Gender	*Contract type categories*	*2018*	*%*	*2021*	*%*
Full sample	= 1 if part-time	404	20.77	327	16.18
	= 0 if full-time	1,541	79.23	1,618	83.19
	Total	*1,945*		*1,945*	
Women	= 1 if part-time	345	30.69	283	25.18
	= 0 if full-time	779	69.31	841	74.82
	Total	*1,124*	*57. 79*	*1,124*	*57. 79*
Men	= 1 if part-time	59	7.19	44	5.36
	= 0 if full-time	762	92.81	777	94.64
	Total	*821*	*42.21*	*821*	*42.21*

Data sources: INAPP PLUS 2018 and INAPP PLUS 2021

Table 1 provides summary statistics for the 2018-2021 panel, which follows the same 1,945 individuals over two time periods. Women represent the majority of the sample, with about 58% of observations.

We can observe that the share of respondents working part-time decreased by 22% from 2018 to 2021, going from about 21% to about 16%. The large majority (about 86%) of all part-time workers are women, and while part-time workers represent about 31% of all women in the sample in 2018, they only represent about 7% of men. Looking at women only we also observe a decrease in part-timers from 2018 to 2021, going from about 31% to 25%. Part-times for men went from about 7% to about 5% in the same period. These statistics suggest a general increase in full-time work for both women and men.

Table 2: Summary statistics for contract type in 2021 cross-section, by gender

Contract type categories	*Full sample*	*%*	*Women*	*%*	*Men*	*%*
= 1 if part-time	2,513	18.22	1,821	24.91	692	10.67
= 0 if full-time	11,283	81.78	5,490	75.09	5,793	89.33
Total	*13,796*		*7,311*	*52.99*	*6,485*	*47.01*

Data sources: INAPP PLUS 2021

Table 2 provides summary statistics for the 2021 full-sample, which includes the 2021 respondents in Table 1 with the addition of observations that were only interviewed in 2021 and not followed in other time periods. The sample, with 13,796 observations, is much larger than the panel, lending power to our estimates. About 53% of the sample are woman and 47% are men. Also in this case, as expected, the shares of part-times among women are significantly higher than for men, representing about 25% and 10% of the sample respectively.

Tables 3 and 4 provide summary statistics for our treatment variables – in the panel and in the cross-section respectively.

Table 3: Summary statistics for remote work in panel data, pre- and post-pandemic

Variable	*Categories*	*Pre-pandemic*	*%*	*2020*	*%*
Remote work	= 1 if respondent worked remotely	0	0.00	952	48.95
	= 0 if respondent did not work remotely	1,945	100.00	993	51.05
	Total	*1,945*		*1,945*	

Data sources: INAPP PLUS 2021

Table 3 outlines the respondents' pre- and post-pandemic remote work arrangements. The information about both periods was collected in the PLUS 2021 wave, through retrospective questions. Our panel contains no individuals who worked remotely before the pandemic, as we chose to exclude these cases from our analysis due to their small number (178 observations) and because their remote work status was driven by factors unrelated to the exogenous shock of COVID-19, making them a selected group. Treated observations therefore only appear in 2020 – where about half of the sample worked remotely.

Table 4: Summary statistics for remote work in 2021 cross-section

Variable	*Categories*	*Obs.*	*%*
Remote work	= 1 if respondent worked remotely in 2020	5,820	42.19
	= 0 if respondent did not work remotely (either in the pre- or post-pandemic period)	7,976	57.81
	Total	*13,796*	

Data sources: INAPP PLUS 2021

Similarly to the panel outlined in Table 3, pre-pandemic remote workers were also excluded from the cross-section given their selected nature. Treated observations in Table 4 therefore certainly refer to respondents who could not work remotely before the pandemic, but who do so in 2020 – these account for about 42%. Controls, which account for 58%, represent respondents who could not work remotely before the pandemic and who also do not work remotely following its outbreak.

Table A1 and A2 (in the Appendix) provide summary statistics for the other covariates which are included in the panel and in the cross-section respectively, after having checked they are not collinear with each other (see Table A3 and A4 in Appendix).

Table A1 in Appendix shows no variation in gender or university degree between 2018 and 2021. These variables are therefore not included as controls. However, it is noteworthy that approximately 58% of the panel consists of women and 43% hold a university degree. In terms of age, some respondents transition into older age groups between 2018 and 2021. Most respondents are aged 50+ (increasing from 40% to 46%), about a third are aged 30–49 (rising slightly from 30% to 33%), while the youngest group, aged 18–29, shrinks from 31% to 21%. Other covariates remain largely stable across the two periods. Geographically, most respondents reside in the North of the country (~58%), with the remainder evenly split between the Centre (~22%) and the South and Islands (~20%). Urban respondents are a minority, accounting for ~13%. In terms of profession, white-collar workers dominate the sample (~86%), as do private-sector employees (~61%), most of whom work in companies with fewer than 250 staff (~90%). Regarding family characteristics, about 43-46% are not partnered (or provide no information on their partner). Among those partnered, the majority of respondents have a partner with a full-time permanent contract (~35%), about 10% are unemployed, while fewer partners are self-employed (~6%), work part-time, on a fixed-term contract or occasionally (~3%). About half of respondents have no biological children with their partner (~49%), while ~17% has one child, ~27% has two children, and 6% had three or more children. About 3% of the sample has at least one child in the 0-3 age group. 11% of respondents have grandparents supporting them with childcare. As for pandemic-related controls, which are included as a robustness check to account for the extraordinary circumstances of the health emergency, approximately 30% of the sample report having children in distance learning, while most respondents (~79%) report no pandemic-related economic consequences.

Table A2 in Appendix outlines summary statistics for the 2021 cross-section and shows that sample composition is roughly comparable to the panel one.

4. METHODOLOGY

Taking advantage of the significant expansion of remote work opportunities following the COVID-19 pandemic in 2020, we use a difference-in-differences (DiD) framework to analyze how working remotely in 2020 affected the likelihood of being engaged in part-time versus full-time work in 2021. Our treatment variable is remote work, with the treatment group comprising individuals who worked remotely in 2020, while the control group consists of those who worked exclusively in person. This setup examines the *lagged impact* of remote work in 2020 on working hours in 2021, the subsequent year.

To ensure the validity of the analysis, we exclude respondents who already worked remotely before the pandemic, as they likely did so for reasons unrelated to the exogenous pandemic shock. Including them would risk biasing the results, given their pre-existing and potentially selective engagement in remote work.

Assumptions and limitations

In our empirical design, the treatment assignment is determined by the exogenous shock of the COVID-19 pandemic, its subsequent government-mandated social distancing measures and the rapid expansion of remote work arrangements. As treatment and control groups were differently impacted by the legal mandate to work from home due to their differential possibility to work remotely, we account for a wide range of pre-treatment characteristics and time-varying confounders, which the literature identifies as influencing both remote work adoption and part-time employment.

A limitation of the analysis lies in the fact, due to data availability, the we investigate substitution effects between remote work and part-time in the exceptional setting of the COVID-19 economic shock. Although layoffs were legally restricted during the pandemic, adjustments to working hours – such as involuntary shifts to part-time – were still possible. At the same time, the closing of childcare centers, schools and distance learning significantly worsened work-life balance for parents. We therefore include fixed effects to control for unobserved heterogeneity across individuals and time. To further isolate the impact of remote work from broader pandemic-related disruptions, we moreover add additional pandemic-specific controls, such as whether respondents had children in distance learning or experienced negative economic consequences due to the pandemic. However, both involuntary shifts to part-time and increased childcare burdens likely increased reliance on part-time. The fact that our results show a reduction in part-time among remote workers instead suggests a possible downward bias in the observed impact – strengthening the credibility of our findings.

A critical component of the DiD methodology is the parallel trends assumption, which requires that, in the absence of treatment, the treatment and control groups would have exhibited similar trends in outcomes over time. Despite the limitation of investigating remote and part-time work trends in the exceptional context of COVID-19, it is reasonable to assume that, if the possibility to work remotely was absent for the whole workforce, trends in part-time work would have followed similar trajectories for treated and control groups. This assumption is further supported by Eurostat (2024a) data and Figures 1 and 2 in Appendix illustrate that, prior to 2020, trends in full-time and part-time employment for occupations with varying teleworkability levels were largely parallel in Italy.

Pre-treatment trends were most likely not affected by the anticipation of treatment, as the outbreak of the COVID-19 pandemic and its related lockdown measures were unpredictable and happened relatively quickly.

As the same individuals are observed before and after the pandemic in the panel, the composition of both the treatment and control groups remains stable over time. Covariates show little variation between 2018 and 2021, as outlined in the descriptive analysis, which supports the assumption of stability. Job sorting between professions with differing levels of teleworkability is moreover minimal, as evidenced by the fact that 83% of the 2021 sample reports being employed in the same profession as in 2018. The Italian labor market, characterized by high rigidity and limited mobility across regions, occupations, and sectors (Bussolo et al. 2022; OECD 2019), further reduces the likelihood of significant sorting into higher teleworkability professions.

Model specification

To compare changes in the likelihood of being engaged in part-time versus full-time employment across individuals who worked remotely and those who did not before and after the onset of the COVID-19 pandemic, we implement a two-way fixed effects DiD model (Bell and McCaffrey 2002; Donald and Lang 2007). Despite our outcome being binomial, we employ a linear probability model to obtain an unbiased estimate of average treatment effects, given that our primary interest does not lie in precise probability estimation (Gomila 2021).

The regression equation can be expressed as follows:

$$PartTime2021_i = \beta_0 + \beta_1 RemoteWork2020_i + \beta_2 X_{it} + \gamma_t + \delta_t + \varepsilon_{it}$$

where $PartTime2021_{it}$ is the dependent variable, indicating whether individual i is employed part-time or full-time in 2021. β_0 represents the baseline average value of the dependent variable for the control group before the treatment is applied, i.e. the predicted part-time employment rate in 2018 for individuals who did not work remotely, considering their characteristics. $RemoteWork2020_i$ is the treatment variable capturing whether individual i worked remotely in 2020. This allows us to investigate the 1-year lagged impact of remote work on working hours in 2021. X_{it} is a vector of individual-level covariates, including controls for socio-economic, geographic, occupational, and family characteristics. γ_t are year fixed effects, controlling for time-specific shocks affecting all individuals, while δ_t are individual fixed effects, controlling for time-invariant unobservable characteristics. Errors are clustered at individual level to account for within-individual correlation over time and ε_{it} is the idiosyncratic error term.

By controlling for both time and unit effects, the model isolates the treatment effect β_1 from confounding factors that could bias the estimation. β_1 therefore represents the Average Treatment Effect on the Treated (ATET), i.e. the average change in part-time employment for those who worked remotely, compared to the average change in part-time for those who worked in person only.

To validate our DiD findings on a larger sample, we rerun the analysis using a weighted logit model on the cross-sectional PLUS 2021 dataset. Unlike the linear probability model used in the DiD, the logit model accounts for the bounded nature of probabilities within the 0-1 range. To improve balance between treated and control units, we moreover apply entropy balancing, which reweights control units so that the means and higher moments of selected covariates match those of the treatment group (Hainmueller 2012). After obtaining the entropy balancing weights, we multiply them by the sample weights to ensure that our results remain representative of employees eligible for part-time work at the national level.

The model specification, consistent with the DiD approach, is as follows:

$$PartTime2021_i = \beta_1 RemoteWork2020_i + \beta_2 X_{it} + \varepsilon_{it}$$

where $PartTime2021_i$ is the binary outcome variable, $RemoteWork2020_i$ is the treatment variable, and X_{it} is a vector of individual-level socio-economic, geographic, occupational, and family characteristics. ε_{it} is the error term, and errors are clustered at the 4-digit profession level.

5. RESULTS

Table 5 summarizes the estimates obtained through the two-way fixed effects DiD estimator, after rescaling population weights to focus on employees eligible for either part-time or full-time contracts. Results are representative of this specific subgroup, reflecting their demographic and geographic characteristics, but are not generalizable to broader populations, such as the unemployed, free professionals, entrepreneurs, or occasional workers.

Table 5: Weighted diff-in-diff estimates with individual and year fixed effects, panel data

	(1) Part-time in 2021
ATET	
Remote work in 2020	-0.031**
	(0.015)
Controls	
Age *(reference category: 50+ years)*	
18–29 years	0.024
	(0.048)
30–49 years	-0.012
	(0.024)
Italy macro area *(reference category: South and Islands)*	
North	0.058
	(0.061)
Center	0.120
	(0.099)
Metropolitan area	0.065
	(0.043)
White-collar worker	-0.042
	(0.034)
Private sector	0.016
	(0.028)

Large company (250+ staff)	0.003
	(0.025)
Child up to 3 years old	-0.035
	(0.033)
Year (*reference category: 2018)*	
2021	-0.006
	(0.010)
_cons	0.158***
	(0.061)
N	3749

Standard errors clustered at the individual level in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
Data sources: INAPP PLUS 2018 and INAPP PLUS 2021

The ATET in Table 5 indicates that individuals who worked remotely in 2020 had a 3.1 percentage point lower probability of working part-time – and consequently a 3.1 percentage point higher probability of working full-time – in 2021, a result significant at the 5% level. This supports our hypothesis that the flexibility offered by remote work enhances work-family balance, enabling some part-time workers to increase their hours and earnings the following year.

As for the controls, it is important to note that their insignificance reflects that the *change* in their impact on the outcome between the pre- and post-treatment periods is not significant. This does not mean that these controls are unimportant in determining part-time employment overall. Rather, it suggests that their relationship with part-time work remained stable over time within the context of the DiD framework. Running a logistic regression using the larger cross-sectional sample allows us to not only test our DiD findings on a more robust dataset, but also to gain a better understanding of the overall association of these controls with part-time work.

The resulting estimates are summarized in Table 6. The results are presented as odd ratios, with errors clustered at the 4-digit profession level in parenthesis. All the included variables are binomial or categorical, hence the coefficient for each category can be interpreted as the difference in the likelihood of working part-time relative to the reference group. Results are representative of employees eligible for part-time/full-time contracts.

Table 6: Weighted logit of part-time employment on remote work, 2021 cross-sectional data

	(1) Part-time in 2021 – Full sample	(2) Part-time in 2021 – Women only
Remote work in 2020	0.704***	0.653***
	(0.066)	(0.058)
Woman	6.550***	1.000

	(0.691)	(.)
University degree	0.534***	0.518***
	(0.052)	(0.059)
Age group (reference: 50+ years)		
18–29 years	1.160	0.817
	(0.134)	(0.125)
30–49 years	1.297***	1.224**
	(0.111)	(0.104)
Italy macro area *(reference category: South and Islands)*		
North	0.871	1.033
	(0.095)	(0.127)
Center	0.911	1.086
	(0.085)	(0.122)
Metropolitan area	0.833*	0.743***
	(0.084)	(0.079)
White-collar worker	0.853	0.687*
	(0.169)	(0.153)
Private sector	3.562***	3.234***
	(0.409)	(0.383)
Large company (250+ staff)	0.602***	0.804
	(0.063)	(0.111)
Services sector	1.847***	1.703***
	(0.347)	(0.303)
Child up to 3 years old	0.885	0.911
	(0.136)	(0.130)
N	13796	7311

Odd ratios; Standard errors clustered at the 4-digit profession level in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
Data source: INAPP PLUS 2021

Column 1 of Table 6 presents the estimates from a logit model applied to the full 2021 cross-sectional sample, using the same covariates as the DiD estimation[5]. Column 2 focuses exclusively on women, as examining potential remote work benefits for this group is particularly relevant for policy, given their disproportionate representation among part-time workers.

Column 1 shows that working remotely in 2020 decreased the odds of working part-time in the following year by approximately 30%, compared to working in person only. When considering women only, the increase in

[5] The variables gender, university degree and employment sector were not included in the DiD estimation as they showed no variation between 2018 and 2021, but are included in the logit model.

full-time work is even larger, as working remotely in 2020 decreased the odds of working part-time in the following year by 35%. Both estimates are significant at the 1% level.

Looking at the determinants of part-time employment, we observe that, as expected, women are much more likely to have reduced working hours, while university graduates are more likely to work fulltime. People in the 30-49 age group are more likely to work part-time than the 50+ baseline. Macro-area in Italy seems to be insignificantly associated with part-time work, while metropolitan dwellers – particularly women – are more likely to work full-time. Women in white-collar jobs are also more likely to work full-time, although in a weakly significant way. Private sector workers are strongly and significantly more likely to work part-time than their public sector counterparts, as do workers in services, while large company employees are significantly more likely to work full-time. Having a child in the 0-3 age range is not significantly associated with higher rates of part-time.

Robustness checks

We test the robustness of our estimates by re-running the DiD estimation, imposing covariate balance for university degree, age group, Italy macro area, and metropolitan area in the pre-treatment period using entropy balancing. After obtaining the entropy balancing weights, we multiply them by the sample weights to ensure that our results remain representative of employees eligible for part-time work at the national level.

We then add additional covariates to both our DiD estimation and our logit model, including – where present – the employment status of the respondent's partner, the number of children, grandparents' support, and pandemic-related factors. Specifically, we account for whether respondents had children in distance learning or experienced economic consequences from the pandemic. While these variables help further disentangle the influence of remote work on part-time employment from broader pandemic-related disruptions, they may also be influenced by remote work itself. To ensure our baseline estimates remain unaffected by potential post-treatment bias, we include these controls as a robustness check, in a separate regression.

Table 7 shows the results of our DiD estimates with an improved covariate balance in the pre-treatment period (column 1) and with improved covariate balance as well as additional controls (column 2). The ATET in column 1 shows the same magnitude of impact and significance level as the baseline, indicating that those who worked remotely in 2020 had a 3 percentage point lower probability of working part-time in 2021, a result significant at the 5% level. The ATET in column 2 shows a similar magnitude, with those who worked remotely in 2020 having a 2.8 percentage point lower probability of working part-time in 2021, a result significant at the 10% level, but very close to the 5% level threshold (p-value: 0.058).

Table 7: Weighted diff-in-diff estimates with additional childcare and pandemic controls, panel data

	(1) Part-time in 2021 (w. pre-period covariate balance)	(2) Part-time in 2021 (w. covariate balance + additional controls)
ATET		
Remote work in 2020	-0.030**	-0.028*
	(0.015)	(0.015)
Controls		
Age *(reference category: 50+ years)*		
18–29 years	0.024	0.020
	(0.042)	(0.042)
30–49 years	-0.015	-0.016
	(0.019)	(0.020)
Italy macro area *(reference category: South and Islands)*		
North	0.114	0.118
	(0.086)	(0.088)
Center	0.183	0.186
	(0.126)	(0.130)
Metropolitan area	0.085	0.088*
	(0.052)	(0.052)
White-collar worker	-0.048*	-0.051*
	(0.027)	(0.028)
Private sector	0.043	0.041
	(0.027)	(0.026)
Large company (250+ staff)	-0.016	-0.021
	(0.016)	(0.017)
Child up to 3 years old	-0.049	-0.061
	(0.047)	(0.050)
Year *(reference category: 2018)*		
2021	-0.008	-0.011
	(0.011)	(0.011)
Partner's employment status *(reference category: missing info / not partnered)*		
Permanent contract		-0.034
		(0.030)
Self-employed		-0.018
		(0.048)
Part-time, fixed-term contract, occasional worker		-0.032
		(0.023)
Unemployed, inactive, on leave		-0.032
		(0.025)
Nr. of children *(reference category: 3+ children)*		

No children		-0.005
		(0.047)
One child		0.003
		(0.049)
Two children		0.026
		(0.047)
Grandparents' support		0.037
		(0.025)
Child in distance-learning		-0.003
		(0.017)
COVID-19 economic impact		0.009
		(0.023)
_cons	0.100	0.110
	(0.078)	(0.094)
N	3768	3767

Standard errors clustered at the individual level in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
Data sources: INAPP PLUS 2018 and INAPP PLUS 2021

Also in Table 8, the magnitude and significance level of the variable of interest is consistent with our baseline weighted logit in Table 6. Looking at the additional covariates, we can infer that the employment status of the partner significantly influences the respondent's likelihood to work part-time – particularly for women. Women are significantly more likely to work part-time when their partner is employed – if they have a full-time permanent contract, but even more so if they are self-employed or have part-time, fixed-term or occasional contracts. The presence of children seems to drive the likelihood of working part-time less that the partner's occupational status, with only respondents with two children being slightly more likely to work part-time. Respondents – particularly women – with a child in the 0-3 age range are, on the contrary, more likely to work full-time. Benefiting from grandparent's support does not seem to play a significant role in the choice to work part-time. The reasons underlying these working time decisions could be an interesting avenue for future research.

As for pandemic controls, while having had a child in distance learning does not have a significant association with contract type, having suffered economic consequences from the pandemic is strongly associated with part-time engagement.

Although magnitudes and significance level may vary slightly between the baseline estimates in Tables 5 and 6 and the robustness checks in Tables 7 and 8 respectively, the substantial interpretation of the results remains unchanged.

Table 8: Weighted logit of part-time employment on remote work with additional childcare and pandemic controls, 2021 cross-sectional data

	(1) Part-time in 2021 – Full sample	(2) Part-time in 2021 – Women only
Remote work in 2020	0.701***	0.636***
	(0.066)	(0.060)
Woman	6.857***	
	(0.719)	
University degree	0.539***	0.512***
	(0.053)	(0.059)
Age group *(reference: 50+ years)*		
18–29 years	1.501***	1.242
	(0.173)	(0.166)
30–49 years	1.347***	1.291**
	(0.134)	(0.134)
Italy macro area *(reference category: South and Islands)*		
North	0.940	1.148
	(0.106)	(0.148)
Center	0.978	1.201
	(0.095)	(0.145)
Metropolitan area	0.802**	0.712***
	(0.081)	(0.075)
White-collar worker	0.911	0.724
	(0.187)	(0.166)
Private sector	3.340***	3.163***
	(0.405)	(0.412)
Large company (250+ staff)	0.604***	0.812
	(0.062)	(0.108)
Services sector	1.868***	1.810***
	(0.332)	(0.305)
Partner's employment status (*reference category: missing info / not partnered)*		
Permanent contract	1.196	1.454**
	(0.162)	(0.261)
Self-employed	2.011***	2.229***
	(0.290)	(0.414)
Part-time, fixed-term contract, occasional worker	1.733***	2.399***
	(0.263)	(0.500)
Unemployed, inactive, on leave	1.267	1.247
	(0.236)	(0.232)
Nr. of children *(reference category: 3+ children)*		

No children	0.979	0.789
	(0.195)	(0.160)
One child	1.039	0.886
	(0.192)	(0.175)
Two children	1.355*	1.255
	(0.226)	(0.228)
Child up to 3 years old	0.737*	0.684**
	(0.127)	(0.104)
Grandparents' support	0.970	0.945
	(0.124)	(0.120)
Child in distance-learning	1.001	1.107
	(0.123)	(0.126)
COVID-19 economic impact	1.448***	1.158
	(0.117)	(0.123)
N	13796	7311

Odd ratios; Standard errors clustered at the 4-digit profession level in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
Data source: INAPP PLUS 2021

6. CONCLUSIONS

This study examines a timely and relevant topic: the recent adoption of remote work as a tool to support work-family balance and its potential to enable longer working hours and higher earnings, particularly for working mothers. We build on several strands of literature: the extensive feminist economics literature on the determinants of female under-employment; the literature on part-time and flexible work arrangements; the rapidly growing literature on the changed nature of remote work and its impact on women's care burdens and well-being. We contribute to the literature by providing empirical evidence on the importance of flexibility in working location in reducing work-family conflict. Moreover, to the best of our knowledge, this is the first attempt at investigating substitution effects between remote work and part-time, making it a novel contribution.

Our analysis investigates whether working remotely in 2020 influenced transitions away from part-time employment in the subsequent year. Using both a difference-in-differences (DiD) approach and a weighted logistic regression model, we find robust evidence that remote work significantly reduces the likelihood of part-time employment, especially among women. The DiD analysis, tracking individuals from 2018 to 2021, suggests a lagged impact, where remote work adopted in 2020 is associated with a shift toward full-time employment in 2021. The weighted logistic regression confirms this relationship in a larger cross-sectional sample. These results suggest that remote work can be an enabling factor for some necessity-driven part-time workers, allowing them to transition into full-time roles, and thereby increasing their earnings and pension scheme contributions.

Importantly, this impact is observed despite the extreme childcare burdens that characterized the pandemic period – pressures which typically push women out of the labor market or into part-time work. The fact that we still detect a reduction in part-time employment suggests that the impact of remote work may be understated in our estimates, lending additional credibility to our conclusions. However, as the pandemic represents an exceptional context for the economy and labor markets, an important avenue for future research would be to investigate remote work / part-time substitution effects in a subsequent, non-pandemic context.

Policy implications

Our findings have important implications for labor market, family, and equal opportunity policies. Although remote work is not a panacea – and only a subset of jobs can be performed remotely – it offers a relatively inexpensive and scalable tool to help mitigate the structural weaknesses of work-family reconciliation policies for the segment of the labor force in teleworkable professions. This is particularly relevant in countries like Italy, where access to formal childcare services and flexible job opportunities remains limited.

To harness the potential of remote work in promoting full-time employment and gender equality, policies should focus on improving access to remote and hybrid work. Workers whose jobs are compatible with remote work should be granted the option to work from home to a reasonable extent, especially when they need flexibility due to caregiving responsibilities or health conditions. This flexibility should not be denied merely because of rigid workplace norms or managerial resistance to change.

One concrete policy option is to guarantee the right to remote work for specific categories of workers, such as parents of young children or individuals with certified health needs. More broadly, incentivizing employers through tax benefits, grants, or workplace flexibility certifications can encourage the adoption of remote work policies for all employees. Such initiatives would help normalize flexible work and reduce the risk of "flexibility stigma", where remote workers are penalized or perceived as less committed.

Promoting remote work among men is also crucial, as increasing men's participation in caregiving through greater access to remote work can promote more balanced gender roles at home and help prevent remote work from becoming gender segregated, in a similar way to what has happened with part-time employment.

Another key challenge is overcoming entrenched workplace cultures. In countries like Italy, managerial practices often rely on in-person supervision and traditional models of productivity. Training managers in outcomes-based performance evaluation and inclusive remote team management can help shift this mindset and support a broader cultural transition toward flexible work.

At the same time, it is important to ensure that the expansion of remote work does not deepen existing inequalities. Targeted digital skills training should be offered to age groups and social categories at greater risk of exclusion or career stagnation in remote settings. This will help ensure that the benefits of remote work are equitably distributed and that disadvantaged groups are not left behind.

Finally, while remote work can ease some work-family conflicts, it is not a substitute for comprehensive family support policies. Persistently high rates of part-time work and female unemployment indicate that many women, especially mothers, are constrained by care responsibilities. Our findings suggest that many would like to increase their working hours and earnings but are held back by the lack of support. Investments in affordable, high-quality childcare are therefore essential. By reducing the unpaid care burden – especially for women – such investments would raise labor force participation, improve income security, increase tax revenues, and ensure a more efficient use of human capital.

REFERENCES

Addabbo T (2020) ‘Italy’, book chapter in Extended Working Life Policies pp. 319-328. International Gender and Health Perspectives https://dx.doi.org/10.1007/978-3-030-40985-2_24

Allen TD, Johnson RC, Kiburz KM, Shockley KM (2013) Work–Family Conflict and Flexible Work Arrangements: Deconstructing Flexibility. Personnel Psychology, 66, 345-376.

Aloè E (2023). Time and income poverty measurement. An ongoing debate on the inclusion of time in poverty assessment. Social Indicators Research, 169(1), 283-322.

Alon T, Coskun S, Doepke M, Koll D, Tertilt M (2022) From Mancession to Shecession: Women’s Employment in Regular and Pandemic Recessions, NBER Macroeconomics Annual, University of Chicago Press, vol. 36(1), pages 83-151.

Angelici M, Profeta P (2023) Smart Working: Work Flexibility Without Constraints. Management Science 70(3):1680-1705. https://doi.org/10.1287/mnsc.2023.4767

Arntz M, Ben Yahmed S, Berlingieri F (2022) Working from home, hours worked and wages: Heterogeneity by gender and parenthood. Labour Econ 76(C). https://doi.org/10.1016/j.labeco.2022.102169

Barbieri P, Cutuli G, Guetto R, Scherer S (2019) Part-time employment as a way to increase women’s employment: (Where) does it work? International Journal of Comparative Sociology, 60(4), 249-268. https://doi.org/10.1177/0020715219849463

Barbieri T, Basso G, Scicchitano S (2022) Italian Workers at Risk During the COVID-19 Epidemic. Ital Econ J 8, 175–195. https://doi.org/10.1007/s40797-021-00164-1

Barbieri T, Bavaro M, Cirillo V (2024) Trapped in the care burden: occupational downward mobility of Italian couples after childbirth, GLO Discussion Paper Series 1475, Global Labor Organization (GLO).

Barrero JM, Bloom N, Davis SJ (2021) Why Working From Home Will Stick. NBER Working Paper No. 28731

Bell RM, McCaffrey DF (2002) Bias reduction in standard errors for linear regression with multi-stage samples. Survey Methodology 28: 169-181.

Bertrand M, Goldin C, Katz LF (2010) Dynamics of the gender gap for young professionals in the financial and corporate sectors, American economic journal: applied economics, 2 (3), 228–55.

Bloom N, Liang J, Roberts J, Ying ZJ (2015) Does Working from Home Work? Evidence from a Chinese Experiment, The Quarterly Journal of Economics, Volume 130, Issue 1, Pages 165–218. https://doi.org/10.1093/qje/qju032

Bolotnyy V, Emanuel N (2022) Why Do Women Earn Less than Men? Evidence from Bus and Train Operators, Journal of Labor Economics, University of Chicago Press, vol. 40(2), pages 283-323.

Bonacini L, Gallo G, Scicchitano S (2021) Working from home and income inequality: risks of a 'new normal' with COVID-19. J Popul Econ 34, 303–360 (2021). https://doi.org/10.1007/s00148-020-00800-7

Bonacini L, Gallo G, Scicchitano S (2023). Does Working from Home Increase the Gender Wage Gap? Insights from an Italian Survey of Occupations. Feminist Economics, 30(2), 53–88. https://doi.org/10.1080/13545701.2024.2326509

Booth AL, van Ours JC (2013) Part-time jobs: what women want?. J Popul Econ 26, 263–283. https://doi.org/10.1007/s00148-012-0417-9

Buddelmeyer H, Mourre G, Ward M (2004) Recent Developments in Part-Time Work in EU-15 Countries: Trends and Policy, IZA Discussion Paper, No. 1415, Institüt zur Zukunft der Arbeit (Institute for the Study of Labour), Bonn.

Budig MJ, England P (2001) The Wage Penalty for Motherhood. American Sociological Review 66(2): 204–225.

Bussolo M, Capelle D, Lokshin M, Torre I, Winkler HJ (2022) Explaining the Evolution of Job Tenure in Europe, 1995–2020. Policy Research Working Paper Series 10205, The World Bank.

Cannito M, Scavarda A (2020) Childcare and Remote Work during the COVID-19 Pandemic. Ideal Worker Model, Parenthood and Gender Inequalities in Italy. Italian Sociological Review, 10 (3S), 801-820.

Casarico, A., Lattanzio, S. (2023) Behind the child penalty: understanding what contributes to the labour market costs of motherhood. J Popul Econ 36, 1489–1511. https://doi.org/10.1007/s00148-023-00937-1

Cortés P, Pan J (2023) Children and the Remaining Gender Gaps in the Labor Market. Journal of Economic Literature, 61 (4): 1359-1409.

Cowan B (2024) Time use, college attainment, and the working-from-home revolution. J Popul Econ 37, 60. https://doi.org/10.1007/s00148-024-01036-5

Del Boca D, Martino EM, Meroni EC, Piazzalunga D (2019) Early education and gender differences. IZA Discussion Paper No. 12484. Available at: https://www.econstor.eu/bitstream/10419/202830/1/dp12484.pdf

Del Boca D, Oggero N, Profeta P, Rossi M (2020) Women's and men's work, housework and childcare, before and during COVID-19. Review of Economics of the Household 18, 1001–1017.

Dingel JI, Neiman B (2020) How Many Jobs Can Be Done at Home? J Public Econ 189:104235. https://doi.org/10.1016/j.jpubeco.2020.104235

Donald SG, Lang K (2007) Inference with difference-in-differences and other panel data. Review of Economics and Statistics 89: 221-233. https://doi.org/10.1162/rest.89.2.221

Emanuel N, Harrington E (2023) Working Remotely? Selection, Treatment, and the Market for Remote Work. FRB of New York Staff Report No. 1061. http://dx.doi.org/10.2139/ssrn.4466130

England P, Bearak J, Budig MJ, Hodges MJ (2016) Do Highly Paid, Highly Skilled Women Experience the Largest Motherhood Penalty? American Sociological Review, 81(6), 1161–1189.

Epstein CF, Seron C, Oglensky B, Saute R (2014) The part-time paradox: Time norms, professional life, family and gender. Routledge.

European Commission, Directorate-General for Justice (2013) Barcelona objectives – The development of childcare facilities for young children in Europe with a view to sustainable and inclusive growth, Publications Office, https://data.europa.eu/doi/10.2838/43161

Eurostat (2023) Employed persons working from home as a percentage of the total employment, by sex, age and professional status (%) [Data set] https://ec.europa.eu/eurostat/databrowser/view/lfsa_ehomp/default/table?lang=en

Eurostat (2024a) Full-time and part-time employment by sex, age and occupation (1000) [Data set] https://ec.europa.eu/eurostat/databrowser/view/lfsa_epgais__custom_11366107/default/line?lang=en

Eurostat (2024b) Gender pay gap statistics. Eurostat Statistics Explained. Retrieved from https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Gender_pay_gap_statistics

Eurostat, European Commission (2024) Gender statistics. Eurostat Statistics Explained. Retrieved from https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Gender_statistics#:~:text=Table%202%20shows%20contributions%20to,the%20gender%20overall%20earnings%20gap.

Folbre N (Ed.) (2012) For love or money: Care provision in the United States. Russell Sage Foundation.

Gibbs M, Mengel F, Siemroth C (2023) Work from Home and Productivity: Evidence from Personnel and Analytics Data on Information Technology Professionals. Journal of Political Economy Microeconomics, 1(1), 7–41. https://dx.doi.org/10.2139/ssrn.3841457

Goldin C (2006) The Quiet Revolution That Transformed Women's Employment, Education, and Family. American Economic Review, 96 (2): 1-21. DOI: 10.1257/000282806777212350

Goldin C (2014) A Grand Gender Convergence: Its Last Chapter. American Economic Review, 104 (4): 1091–1119. DOI: 10.1257/aer.104.4.1091

Goldin C, Katz LF (2011) The Cost of Workplace Flexibility for High-Powered Professionals. The Annals of the American Academy of Political and Social Science, 638, 45–67.

Goldin C, Katz LF (2016) A Most Egalitarian Profession: Pharmacy and the Evolution of a Family Friendly Occupation. Journal of Labor Economics. 34 (3) :705-745.

Gomila R (2021) Logistic or linear? Estimating causal effects of experimental treatments on binary outcomes using regression analysis. J Exp Psychol Gen. 150(4):700-709. doi: 10.1037/xge0000920

Hainmueller J (2012) Entropy Balancing for Causal Effects: A Multivariate Reweighting Method to Produce Balanced Samples in Observational Studies. Political Analysis. 20(1):25-46. doi:10.1093/pan/mpr025

Hakim C (1992) Explaining trends in occupational segregation: The measurement, causes and consequences of the sexual division of labour. European Sociological Review 8(2): 127–152.

Hakim C (2000) Work-Lifestyle Choices in the 21st Century: Preference Theory. Oxford: Oxford University Press.

Hakim C (2008) Is gender equality legislation becoming counter-productive? Public Policy Research 15(3): 133–136.

Han J, Kaiser C (2024) Time use and happiness: US evidence across three decades. J Popul Econ 37, 15. https://doi.org/10.1007/s00148-024-00982-4

Harrington E, Kahn ME (2023) Has the Rise of Work-from-Home Reduced the Motherhood Penalty in the Labor Market? Working paper.

Kleven H, Landais C, Posch J, Steinhauer A, Zweimüller J (2019) Child Penalties across Countries: Evidence and Explanations. AEA Papers and Proceedings, 109: 122-26.

Möhring K, Naumann E, Reifenscheid M, Wenz A, Rettig T, Krieger U et al. (2021) The COVID-19 pandemic and subjective well-being: longitudinal evidence on satisfaction with work and family. Eur Soc 23 (sup1), S601–S617. https://doi.org/10.1080/14616696.2020.1833066

Mongey S, Weinberg A (2020) Characteristics of Workers in Low Work-from-Home and High Personal-Proximity Occupations. Becker Friedman Institute for Economic White Paper.

Nagler M, Rincke J, Winkler E (2024) Working from home, commuting, and gender. J Popul Econ 37, 58. https://doi.org/10.1007/s00148-024-01035-6

OECD (2010) How Good is Part-Time Work?, in Employment Outlook, OECD Publishing, Paris, pp. 201-266.

OECD (2011) Doing Better for Families, OECD Publishing, Paris, https://doi.org/10.1787/9789264098732-en.

OECD (2012), Closing the Gender Gap: Acting Now! OECD Publishing, Paris.

OECD (2017) Pensions at a Glance: OECD and G20 Indicators. Paris: OECD Publishing.

OECD (2019), Strengthening Active Labour Market Policies in Italy, Connecting People with Jobs, OECD Publishing, Paris, https://doi.org/10.1787/160a3c28-en

Pabilonia SW, Vernon V (2025) Remote work, wages, and hours worked in the United States. J Popul Econ 38, 18. https://doi.org/10.1007/s00148-025-01064-9

Pissarides C, Garibaldi P, Olivetti C, Petrongolo B, Wasmer E (2005) Women in the Labour Force: How Well is Europe Doing ?, Sciences Po publications info:hdl:2441/9081, Sciences Po.

Senik C, Clark AE, D'Ambrosio C et al. (2024) Teleworking and life satisfaction during COVID-19: the importance of family structure. J Popul Econ 37, 8. https://doi.org/10.1007/s00148-024-00979-z

Song Y, Gao J (2020) Does Telework Stress Employees Out? A Study on Working at Home and Subjective Well-Being for Wage/Salary Workers. J Happiness Stud 21(7), 2649–2668. https://doi.org/10.1007/s10902-019-00196-6

Thévenon O (2013) Drivers of Female Labour Force Participation in the OECD, OECD Social, Employment and Migration Working Papers, No. 145, OECD Publishing, Paris, https://doi.org/10.1787/5k46cvrgnms6-en

Turrin M (2024). Telework as a driver of inequalities in the labour market. Italian Labour Law E-Journal, 17(2), 371–386. https://doi.org/10.6092/issn.1561-8048/20833

Waldfogel J (1998) Understanding the "Family Gap" in Pay for Women with Children. Journal of Economic Perspectives, 12 (1): 137-156.

Wilde ET, Batchelder L, Ellwood D (2010) The Mommy Track Divides: The Impact of Childbearing on Wages of Women of Differing Skill Levels. NBER Working Paper 16582.

APPENDIX

Table A1: Summary statistics of the control variables, 2018-2021 panel

Variable name	*Categories*	*2018*	*%*	*2021*	*%*
Women	= 1 if woman	1,124	57.79	1,124	57.79
	= 0 if man	821	42.21	821	42.21
University degree	= 1 if university degree	828	42.57	828	42.57
	= 0 if no university degree	1,117	57.43	1,117	57.43
Age group	= 1 if 18-29 years old	599	30.80	413	21.23
	= 1 if 30-49 years old	577	29.67	640	32.90
	= 1 if 50+ years old	769	39.54	892	45.86
Italy macro area	= 1 if North	1,120	57.58	1,131	58.15
	= 1 if Centre	431	22.16	432	22.21
	= 1 if South and Islands	394	20.26	382	19.64
Metropolitan area	= 1 if metropolitan area	270	13.88	247	12.70
	= 0 if other	1,675	86.12	1,698	87.30
White-collar worker	= 1 if professional / white-collar worker	1,665	86.05	1,608	87.01
	= 0 if manual labor / blue-collar worker	270	13.95	240	12.99
Private sector	= 1 if private company	1,166	60.41	1,211	62.26
	= 0 if public sector	764	39.59	734	37.74
Large company (250+ staff)	= 1 if large company (250+ staff)	216	11.11	139	7.15
	= 0 if other company (up to 249 staff)	1,729	88.89	1,806	92.85
Partner's employment status	Missing info / not partnered	899	46.22	827	42.52
	Permanent contract	656	33.73	710	36.50
	Self-employed	123	6.32	126	6.48
	Part-time, fixed-term contract, occasional worker	76	3.91	57	2.93
	Unemployed, inactive, on leave	191	9.82	225	11.57

Nr. of children	No children	965	49.61	960	49.38
	Respondent has one child	309	15.89	335	17.23
	Respondent has two children	542	27.87	534	27.47
	Respondent has three or more children	129	6.63	115	5.92
Child up to 3 years old	= 1 has child up to 3 years old	86	4.42	55	2.83
	= 0 does not have child up to 3 years old	1,859	95.58	1,890	97.17
Grandparents' support	= 1 if grandparents support with childcare	179	9.20	218	11.21
	= 0 if no support / missing information	1,766	90.80	1,727	88.79
Child in distance-learning	= 1 child in distance-learning	0	0.00	582	29.92
	= 0 no child in distance-learning	1,945	100.00	1,363	70.08
COVID-19 economic impact	= 1 had negative consequences	0	0.00	416	21.39
	= 0 no COVID-19 consequences	1,945	100.00	1,529	78.61

Data sources: INAPP PLUS 2018 and INAPP PLUS 2021

Table A2: Summary statistics of the control variables, 2021 cross-section

Variable name	*Categories*	*Obs.*	*%*
Women	= 1 if woman	7,311	52.99
	= 0 if man	6,485	47.01
University degree	= 1 if university degree	5,675	41.14
	= 0 if no university degree	8,121	58.86
Age group	18-29 years old	5,514	39.97
	30-49 years old	4,423	32.06
	50+ years old	3,859	27.97
Italy macro area	North	7,600	55.09
	Centre	2,682	19.44
	South and Islands	3,514	25.47
Metropolitan area	= 1 if metropolitan area	2,108	15.28
	= 0 if other	11,688	84.72
White-collar worker	= 1 if professional / white-collar worker	11,872	86.05
	= 0 if manual labour / blue-collar worker	1,924	13.95
Private sector	= 1 if private company	10,284	74.54
	= 0 if public sector	3,512	25.46
Large company (250+ staff)	= 1 if large company (250+ staff)	1,438	10.42
	= 0 if other company (up to 249 staff)	12,358	89.58
Services sector	= 1 if production of services	10,801	78.029
	= 0 if production of goods	2,995	21.71
Partner's employment status	Missing info / not partnered	6,412	46.48
	Permanent contract	4,547	32.96
	Self-employed	744	5.39
	Part-time, fixed-term contract, occasional worker	963	6.98

	Unemployed, inactive, on leave	1,130	8.19
Nr. of children	No children	8,615	62.45
	Respondent has one child	2,295	16.64
	Respondent has two children	2,416	17.51
	Respondent has three or more children	470	3.41
Child up to 3 years old	= 1 has child up to 3 years old	887	6.43
	= 0 does not have child up to 3 years old	12,909	93.57
Grandparents' support	= 1 if grandparents support with childcare	2,156	15.63
	= 0 if no support / missing information	11,640	84.37
Child in distance-learning	= 1 child in distance-learning	3,314	24.02
	= 0 no child in distance-learning	10,482	75.98
COVID-19 economic impact	= 1 had negative consequences	4,392	31.84
	= 0 no COVID-19 consequences	9,404	68.16

Data sources: INAPP PLUS 2021

Figure 1: Full-time employment by occupation, 2014-2023, Italy

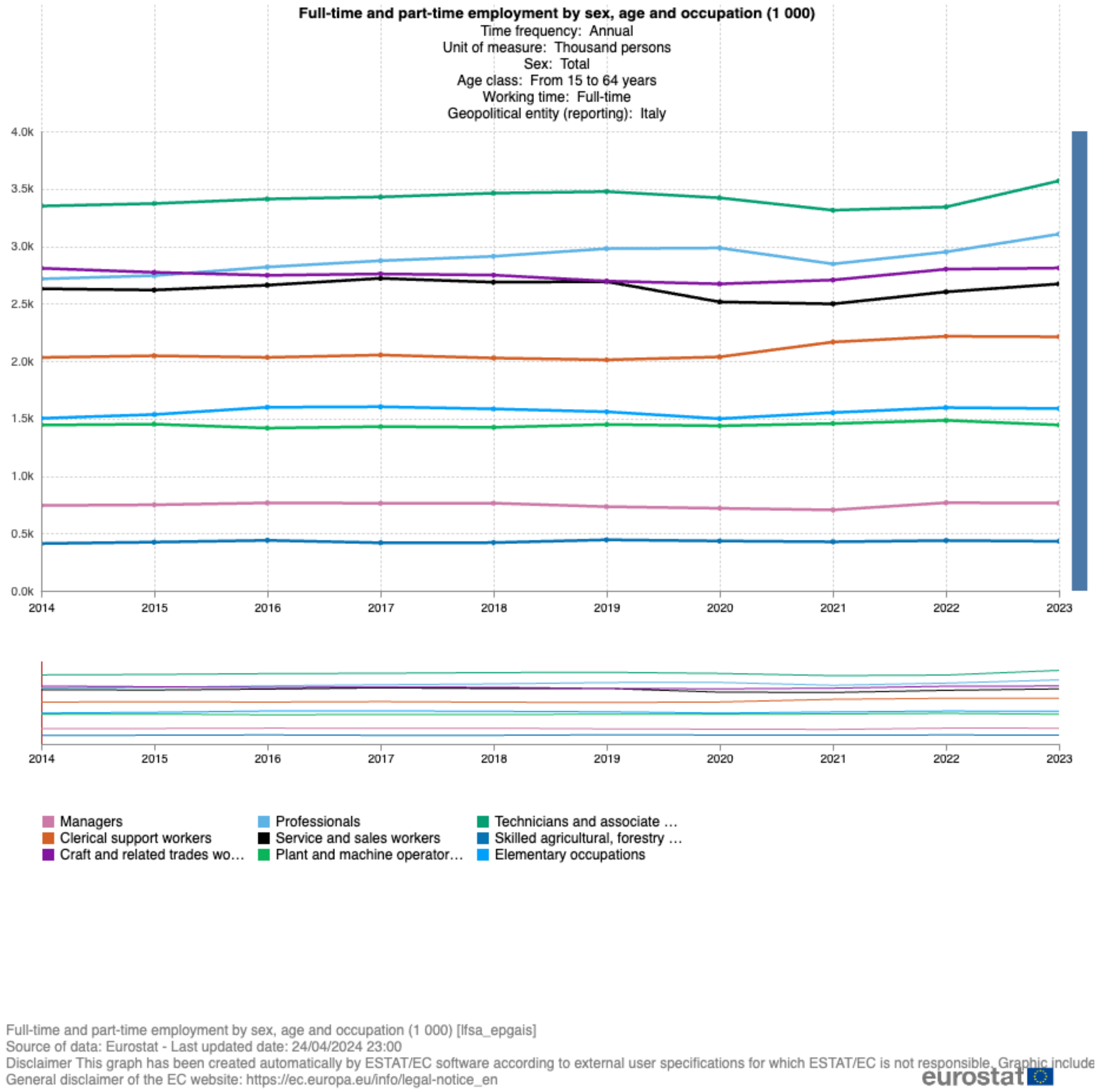
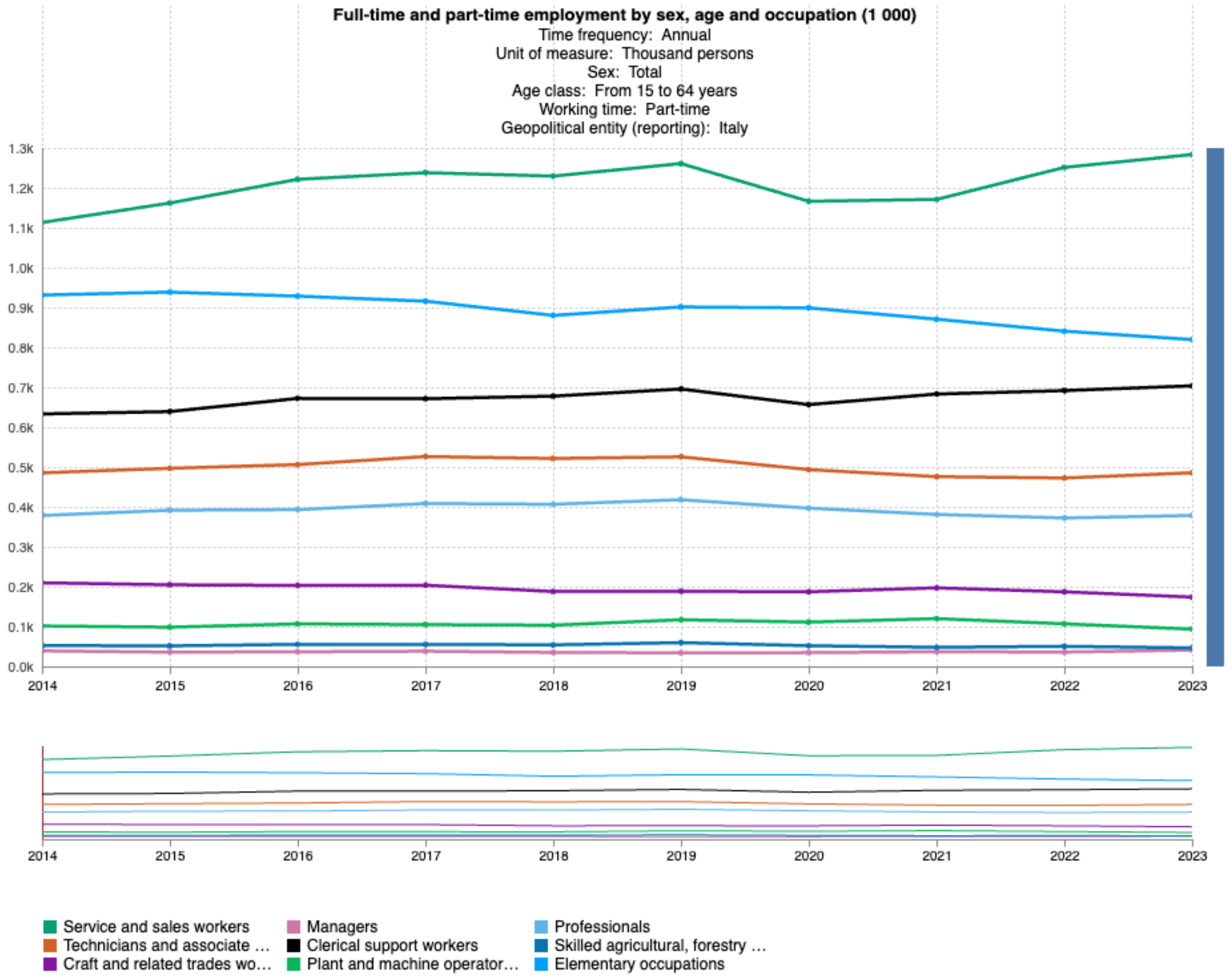


Figure 2: Part-time employment by occupation, 2014-2023, Italy



Full-time and part-time employment by sex, age and occupation (1 000) [lfsa_epgais]
Source of data: Eurostat - Last updated date: 24/04/2024 23:00

Table A3: Correlation matrix for the control variables, panel

Pairwise correlations

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
(1) cl_eta3	1.000												
(2) area_g3	0.096*	1.000											
	(0.000)												
(3) comune_metro	0.010	0.051*	1.000										
	(0.530)	(0.001)											
(4) whiteblue_collar	0.005	0.020	0.060*	1.000									
	(0.764)	(0.228)	(0.000)										
(5) pubb_priv	-0.363*	-0.167*	-0.025	-0.234*	1.000								
	(0.000)	(0.000)	(0.116)	(0.000)									
(6) grande_azienda	-0.073*	-0.039	0.068*	-0.062*	0.291*	1.000							
	(0.000)	(0.014)	(0.000)	(0.000)	(0.000)								
(7) figli	-0.572*	-0.070*	0.072*	-0.001	0.239*	0.039	1.000						
	(0.000)	(0.000)	(0.000)	(0.964)	(0.000)	(0.016)							
(8) figlio_upto3	-0.085*	-0.009	0.001	-0.007	0.038	0.018	-0.193*	1.000					
	(0.000)	(0.575)	(0.954)	(0.686)	(0.017)	(0.253)	(0.000)						
(9) salute	-0.110*	-0.086*	0.021	0.058*	0.069*	-0.025	0.099*	0.015	1.000				
	(0.000)	(0.000)	(0.192)	(0.000)	(0.000)	(0.128)	(0.000)	(0.350)					
(10) scuole_val_ne~a	0.002	0.119*	-0.018	-0.014	0.041	-0.010	0.014	-0.021	-0.032	1.000			
	(0.921)	(0.000)	(0.261)	(0.394)	(0.010)	(0.544)	(0.384)	(0.191)	(0.045)				
(11) supp_cura_nonni	-0.054*	-0.010	-0.056*	0.043*	0.016	0.038	-0.333*	0.364*	0.030	-0.005	1.000		
	(0.001)	(0.545)	(0.000)	(0.009)	(0.332)	(0.017)	(0.000)	(0.000)	(0.066)	(0.774)			
(12) dad	0.218*	0.005	-0.032	0.017	-0.073*	0.019	-0.415*	-0.019	-0.005	-0.026	0.243*	1.000	
	(0.000)	(0.769)	(0.049)	(0.309)	(0.000)	(0.225)	(0.000)	(0.226)	(0.751)	(0.106)	(0.000)		
(13) impatto_covid	-0.041	-0.019	-0.017	-0.046*	0.141*	0.034	0.023	-0.027	-0.012	0.035	0.025	0.161*	1.000
	(0.012)	(0.228)	(0.284)	(0.004)	(0.000)	(0.035)	(0.159)	(0.093)	(0.454)	(0.031)	(0.119)	(0.000)	

**** p<0.01, ** p<0.05, * p<0.1*

Table A4: Correlation matrix for the control variables, cross-section

Pairwise correlations

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
(1) donna	1.000													
(2) universita	0.117*	1.000												
	(0.000)													
(3) cl_eta3	-0.009	0.041*	1.000											
	(0.280)	(0.000)												
(4) area_g3	-0.022*	0.029*	0.038*	1.000										
	(0.010)	(0.001)	(0.000)											
(5) comune_metro	0.035*	0.141*	0.059*	0.020	1.000									
	(0.000)	(0.000)	(0.000)	(0.018)										
(6) whiteblue_collar	0.160*	0.286*	0.050*	-0.010	0.088*	1.000								
	(0.000)	(0.000)	(0.000)	(0.259)	(0.000)									
(7) pubb_priv	-0.065*	-0.242*	-0.237*	-0.096*	-0.016	-0.128*	1.000							
	(0.000)	(0.000)	(0.000)	(0.000)	(0.060)	(0.000)								
(8) grande_azienda	-0.089*	0.056*	0.067*	-0.058*	0.060*	0.006	0.202*	1.000						
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.446)	(0.000)							
(9) servizi	0.112*	0.135*	0.026*	0.061*	0.070*	0.296*	-0.276*	-0.075*	1.000					
	(0.000)	(0.000)	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)						
(10) figli	0.012	0.018	0.537*	0.069*	0.022*	0.036*	-0.144*	0.051*	0.022*	1.000				
	(0.156)	(0.030)	(0.000)	(0.000)	(0.008)	(0.000)	(0.000)	(0.000)	(0.010)					
(11) figlio_upto6	0.049*	0.089*	-0.047*	0.031*	0.015	0.036*	0.005	0.025*	0.024*	0.454*	1.000			
	(0.000)	(0.000)	(0.000)	(0.000)	(0.080)	(0.000)	(0.516)	(0.002)	(0.004)	(0.000)				
(12) salute	-0.048*	0.018	-0.127*	-0.024*	-0.018	0.012	0.023*	-0.011	0.006	-0.084*	-0.020	1.000		
	(0.000)	(0.035)	(0.000)	(0.004)	(0.036)	(0.148)	(0.007)	(0.202)	(0.463)	(0.000)	(0.015)			
(13) scuole_val_ne~a	0.013	-0.066*	-0.002	0.104*	-0.006	-0.029*	0.070*	-0.008	-0.019	0.012	0.035*	-0.099*	1.000	
	(0.129)	(0.000)	(0.792)	(0.000)	(0.460)	(0.001)	(0.000)	(0.352)	(0.021)	(0.142)	(0.000)	(0.000)		
(14) supp_cura_nonni	0.042*	0.084*	0.027*	0.037*	0.011	0.042*	0.000	0.029*	0.017	0.550*	0.706*	-0.025*	0.039*	1.000
	(0.000)	(0.000)	(0.001)	(0.000)	(0.207)	(0.000)	(0.976)	(0.000)	(0.040)	(0.000)	(0.000)	(0.003)	(0.000)	

**** $p<0.01$, ** $p<0.05$, * $p<0.1$*