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

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ABSTRACT

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

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 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 part-time employment in the following year, suggesting that workers adjust their employment status after an initial trial period of remote work.

KEYWORDS: work-life balance, gender discrimination, wage inequality, remote work, part-time work

JEL CODES: J16, J22, J41

Questo articolo esamina se il lavoro da remoto possa ridurre l'utilizzo del lavoro part-time, una modalità lavorativa utilizzata prevalentemente dalle donne per conciliare lavoro e responsabilità familiari, ma spesso associata a retribuzioni più basse, prospettive di carriera limitate e benefici pensionistici ridotti. Concentrandoci sull'Italia, dove il sottoutilizzo dell'occupazione femminile è particolarmente elevato, analizziamo se la flessibilità offerta dal lavoro da remoto e ibrido possa rappresentare un'alternativa al part-time, consentendo ad alcune lavoratrici costrette a scegliere il part-time per necessità di passare a contratti a tempo pieno. Utilizzando un approccio difference-in-differences e regressioni logistiche, analizziamo dati panel e sezionali provenienti dall'indagine PLUS (Partecipazione, Lavoro e Unemployment Survey) dell'Istituto Nazionale per l'Analisi delle Politiche Pubbliche (Inapp) per il periodo 2018-2021. I nostri risultati mostrano che il lavoro agile riduce significativamente l'occupazione part-time nell'anno successivo, suggerendo che i lavoratori modificano il proprio status occupazionale dopo un periodo iniziale di prova del lavoro da remoto.

PAROLE CHIAVE: *conciliazione vita lavoro, discriminazione di genere, disuguaglianza salariale, lavoro a distanza, lavoro a tempo parziale*

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

Other practices facilitating work-family balance are flexible work arrangements, generally defined

[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).

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. 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

[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).

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 (Turrin 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 (Turrin 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). 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. The result is a dataset of 1,934 observations per wave for the panel. Observations dropped from this sample due to missing values in key variables only account for 3.08%, with no apparent bias among non-respondents[3]. Our final sample is therefore comparable to the original one and still representative of the employees subgroup at the national level, as shown in table A1 in Appendix. As for the 2021 cross-section wave, we have a sample of 14,351 observations. Observations dropped due to missing values account for 4%, and also in this case non-respondents do not show an apparent bias[4].
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	%
	= 1 if part-time	403	20.84	326	16.86
Full sample	= 0 if full-time	1,531	79.16	1,608	83.14
	Total	**1,934**		**1,934**	
	= 1 if part-time	344	30.69	282	25.16
Women	= 0 if full-time	777	69.31	839	74.84
	Total	**1,121**	**57.96**	**1,121**	**57.96**
	= 1 if part-time	59	7.26	44	5.41
Men	= 0 if full-time	754	92.74	769	94.59
	Total	**813**	**42.04**	**813**	**42.04**

Data source: Inapp PLUS 2018 and Inapp PLUS 2021

Table 1 provides summary statistics for the 2018-2021 panel, which follows the same 1,934 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 19% from 2018 to 2021, going from about 21% to about 17%. The large majority (about 85%) of all part-time workers are women,

[3] 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] 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.

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	2,588	18.03	1,879	24.78	709	10.47
= 0 if full-time	11,763	81.97	5,703	75.22	6,060	89.53
Total	**14,351**		**7,582**	**52.83**	**6,769**	**47.17**

Data source: 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 14,351 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	%
	= 1 if respondent worked remotely	0	0.00	949	49.07
Remote work	= 0 if respondent did not work remotely	1,934	100.00	985	50.93
	Total	**1,934**		**1,934**	

Data source: 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 (162 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.	%
	= 1 if respondent worked remotely in 2020	6,045	42.12
Remote work	= 0 if respondent did not work remotely (either in the pre- or post-pandemic period)	8,306	57.88
	Total	**14,351**	

Data source: 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 A2 and A3 (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 A4 and A5 in Appendix).

Table A2 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 39% 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 (~88%). Regarding family characteristics, 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 A3 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

The empirical design of this study adheres to the key assumptions required for the validity of the DiD framework. Treatment assignment is determined by the exogenous shock of the Covid-19 pandemic and the subsequent rapid expansion of remote work opportunities, rather than by intrinsic characteristics of the individuals. Aside from profession, which is controlled for, the allocation of treatment is not likely to be influenced by unobservable factors that could affect engagement in part-time work.

Furthermore, the composition of both the treatment and control groups remains stable over time, as the same individuals are observed before and after the pandemic in the panel. 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.

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. The sudden and unexpected nature of the pandemic provides a strong foundation for this assumption, as the shock affected treatment and control groups differently solely because of their differential possibility to work remotely. Absent this treatment, it is reasonable to assume that trends in part-time work engagement for individuals in high- and low-teleworkability professions would have followed similar trajectories. This assumption is further supported by Eurostat (2024a) data and Figures A1 and A2 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.

The model accounts for a wide range of pre-treatment characteristics and time-varying confounders that may influence both remote work adoption and part-time employment. Additionally, it includes fixed effects to control for unobserved heterogeneity across individuals and time. Aside from time fixed effects, to further isolate the impact of remote work from broader pandemic-related disruptions, we add additional pandemic-specific controls such as whether respondents had children in distance learning or experienced negative economic consequences due to the pandemic.

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:

$$PartTime_{it} = \beta_0 + \beta_1 RemoteWork_{it\text{-}1} + \beta_2 X_{it} + \gamma_t + \delta_t + \varepsilon_{it}$$

where $PartTime_{it}$ is the dependent variable, indicating whether individual i is employed part-time or full-time in year t. 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 the pre-pandemic period for individuals who did not work remotely, considering their characteristics. $RemoteWork_{it\text{-}1}$ is the treatment variable capturing whether individual i worked remotely in the year before t. 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 from confounding factors that could bias the estimation. 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 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, addressing the main limitation of the earlier approach. However, even though the logit model benefits from greater statistical power due to the larger sample, it captures correlations and may be influenced by unobserved confounding factors or sample composition differences.

To improve balance between treated and control units, we 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. Since combining entropy and sample weights may influence covariate balance, we verify the balance in table A6 in the Appendix. The results confirm that covariate balance has improved compared to the unweighted model, even after incorporating both weight adjustments. The model specification, consistent with the DiD approach, is as follows:

$$PartTime_{it} = \beta_1 RemoteWork_{it\text{-}1} + \beta_2 X_{it} + \varepsilon_{it}$$

where $PartTime_{it}$ is the binary outcome variable, $RemoteWork_{it\text{-}1}$ 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 source: 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^{***} (0.066)	0.653^{***} (0.058)
Woman	6.550^{***} (0.691)	1.000 (.)
University degree	0.534^{***} (0.052)	0.518^{***} (0.059)
Age group (reference: 50+ years)		
18–29 years	1.160 (0.134)	0.817 (0.125)
30–49 years	1.297^{***} (0.111)	1.224^{**} (0.104)
Italy macro area *(reference category: South and Islands)*		
North	0.871 (0.095)	1.033 (0.127)
Center	0.911 (0.085)	1.086 (0.122)
Metropolitan area	0.833^{*} (0.084)	0.743^{***} (0.079)
White-collar worker	0.853 (0.169)	0.687^{*} (0.153)
Private sector	3.562^{***} (0.409)	3.234^{***} (0.383)
Large company (250+ staff)	0.602^{***} (0.063)	0.804 (0.111)
Services sector	1.847^{***} (0.347)	1.703^{***} (0.303)
Child up to 3 years old	0.885 (0.136)	0.911 (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 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 now test the robustness of our estimates by re-running both our DiD estimation and our logit model with additional covariates, including 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 only as a robustness check.

The ATET of our DiD robustness checks in table 7 shows a similar magnitude of impact to the baseline model, indicating that those who worked remotely in 2020 had 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: 0.051). Looking at the additional covariates of the logit model in table 8, we can infer that women with no children are less likely to work part-time, as do women with a child in the 0-3 age range, while respondents with two children are more likely to. 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.

[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.

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

	(1) **Part-time in 2021**
ATET	
Remote work in 2020	-0.028* (0.014)
Controls Age *(reference category: 50+ years)*	
18–29 years	0.024 (0.048)
30–49 years	-0.015 (0.025)
Italy macro area *(reference category: South and Islands)*	
North	0.062 (0.059)
Center	0.127 (0.098)
Metropolitan area	0.067 (0.043)
White-collar worker	-0.042 (0.035)
Private sector	0.015 (0.028)
Large company (250+ staff)	-0.001 (0.025)
Child up to 3 years old	-0.047 (0.036)
Nr. of children *(reference category: 3+ children)*	
No children	0.006 (0.049)
One child	0.024 (0.052)
Two children	0.012 (0.051)
Grandparents' support	0.023 (0.025)
Child in distance-learning	-0.009 (0.018)
Covid-19 economic impact	0.017 (0.022)
Year (*reference category: 2018)*	
2021	-0.010 (0.011)
_cons	0.144* (0.075)
N	3748

Standard errors clustered at the individual level in parentheses

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

Data source: Inapp PLUS 2018 and Inapp PLUS 2021

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	0.716*** (0.067)	0.645*** (0.059)
Woman	6.647*** (0.712)	
University degree	0.552*** (0.053)	0.531*** (0.061)
Age group (reference: 50+ years)		
18–29 years	1.407*** (0.167)	1.145 (0.168)
30–49 years	1.352*** (0.135)	1.310*** (0.129)
Italy macro area (reference category: South and Islands)		
North	0.894 (0.097)	1.070 (0.132)
Center	0.930 (0.088)	1.104 (0.128)
Metropolitan area	0.812** (0.082)	0.735*** (0.078)
White-collar worker	0.882 (0.175)	0.709 (0.159)
Private sector	3.367*** (0.411)	3.220*** (0.421)
Large company (250+ staff)	0.597*** (0.062)	0.783* (0.106)
Services sector	1.864*** (0.335)	1.788*** (0.307)
Nr. of children *(reference category: 3+ children)*		
No children	0.901 (0.171)	0.702* (0.134)
One child	1.043 (0.181)	0.904 (0.170)
Two children	1.384** (0.226)	1.277 (0.229)
Child up to 3 years old	0.766 (0.132)	0.720** (0.110)
Grandparents’ support	1.005 (0.130)	1.012 (0.125)
Child in distance-learning	1.016 (0.121)	1.141 (0.129)
Covid-19 economic impact	1.509*** (0.120)	1.233* (0.132)
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 and policy implications

This study examines a current and relevant topic: the recent adoption of remote work as a tool for work-family balance and its potential impact on extending working hours and increasing earnings, in particular for working mothers. We draw from several strands of literature: the extensive feminist economics literature on the determinants of female under-employment; the literature on the pandemic's impact on women's labor market outcomes; the literature on flexible work arrangements and work-family conflict; the rapidly growing remote work literature on the changed nature of remote work.

The analysis examines the impact of working remotely in 2020 on part-time employment in the following year using both DiD and logistic regression approaches. The DiD model, which follows the same individuals from 2018 to 2021, finds significant evidence that remote work in 2020 reduced part-time employment in 2021, suggesting a lagged impact. The weighted logistic regression further tests the association on a larger cross-sectional dataset and shows a highly significant negative association between remote work and part-time employment, particularly for women. Taken together, the findings suggest that remote work can enable some necessity part-time workers to take on full-time roles, thereby increasing their earnings and pension scheme contributions.

Interestingly, despite the exceptional childcare burdens that characterized the pandemic period, which generally push more individuals, particularly women, into part-time employment, we still find a reduction in part-time work (in favor of full-time). This suggests that our results may be downwardly biased and that the observed impact of remote work on reducing part-time work engagement is likely understated, lending additional credibility to our findings.

This study bears implications for family, labor market, and equal opportunity policies. In a context of deep structural shortcomings in family support services and policies such as the Italian one, the flexibility offered by remote work alone is far from being a comprehensive solution to female under-employment – particularly since only a fraction of the workforce can work remotely. However, promoting remote work is a relatively low-budget measure that can mitigate work-family conflict and potentially increase working hours, earnings, and career prospects for some.

Appendix

Table A1. Comparison of key covariates: full sample vs analysis sample

	Full sample mean	DiD Sample Mean	Std. diff.
Remote work in 2020	0.184	0.183	0.001
Woman	0.444	0.451	-0.014
University degree	0.234	0.242	-0.016
Age group (reference: 50+ years)			
18-29 years old	0.132	0.137	-0.011
30-49 years old	0.473	0.467	0.012
Italy macro area (reference: South and Islands)			
North	0.596	0.595	0.004
Center	0.196	0.196	0.002
Metropolitan area	0.126	0.124	0.004
White/blue collar worker	0.731	0.731	-0.001
Private sector	0.689	0.692	-0.007
Large company (250+ staff)	0.132	0.133	-0.002
Child up to 3 years old	0.036	0.035	0.002

Data source: Inapp PLUS 2018 and Inapp PLUS 2021

Table A2. Summary statistics of the control variables, 2018-2021 panel

Variable name	Categories	2018	%	2021	%
Women	= 1 if woman	1,121	57.96	1,121	57.96
	= 0 if man	813	42.04	813	42.04
University degree	= 1 if university degree	825	42.66	825	42.66
	= 0 if no university degree	1,109	57.34	1,109	57.34
Age group	= 1 if 18-29 years old	598	30.92	413	21.35
	= 1 if 30-49 years old	572	29.58	634	32.78
	= 1 if 50+ years old	764	39.50	887	45.86
Italy macro area	= 1 if North	1,115	57.65	1,127	58.27
	= 1 if Centre	430	22.23	430	22.23
	= 1 if South and Islands	389	20.11	377	19.49
Metropolitan area	= 1 if metropolitan area	269	13.91	246	12.72
	= 0 if other	1,665	86.09	1,688	87.28
White-collar worker	= 1 if professional / white-collar worker	1,657	86.12	1,601	87.01
	= 0 if manual labor / blue-collar worker	267	13.88	239	12.99
Private sector	= 1 if private company	1,160	60.45	1,204	62.25
	= 0 if public sector	759	39.55	730	37.75
Large company (250+ staff)	= 1 if large company (250+ staff)	213	11.01	245	12.67
	= 0 if other company (up to 249 staff)	1,721	88.99	1,689	87.33
Nr. of children	= 1 if no children	960	49.64	955	49.38
	= 1 if respondent has one child	307	15.87	333	17.23
	= 1 if respondent has two children	539	27.87	531	27.47
	= 1 if respondent has three or more children	128	6.62	114	5.90
Child up to 3 years old	= 1 has child up to 3 years old	86	4.45	55	2.84
	= 0 does not have child up to 3 years old	1,848	95.55	1,879	97.16
Grandparents' support	= 1 if grandparents support with childcare	178	9.20	215	11.12
	= 0 if no support / missing information	1,756	90.80	1,719	88.88
Child in distance-learning	= 1 child in distance-learning	0	0.00	577	29.83
	= 0 no child in distance-learning	1,934	100.00	1,357	70.17
Covid-19 economic impact	= 1 had negative consequences	0	0.00	413	21.35
	= 0 no Covid-19 consequences	1,934	100.00	1,521	78.65

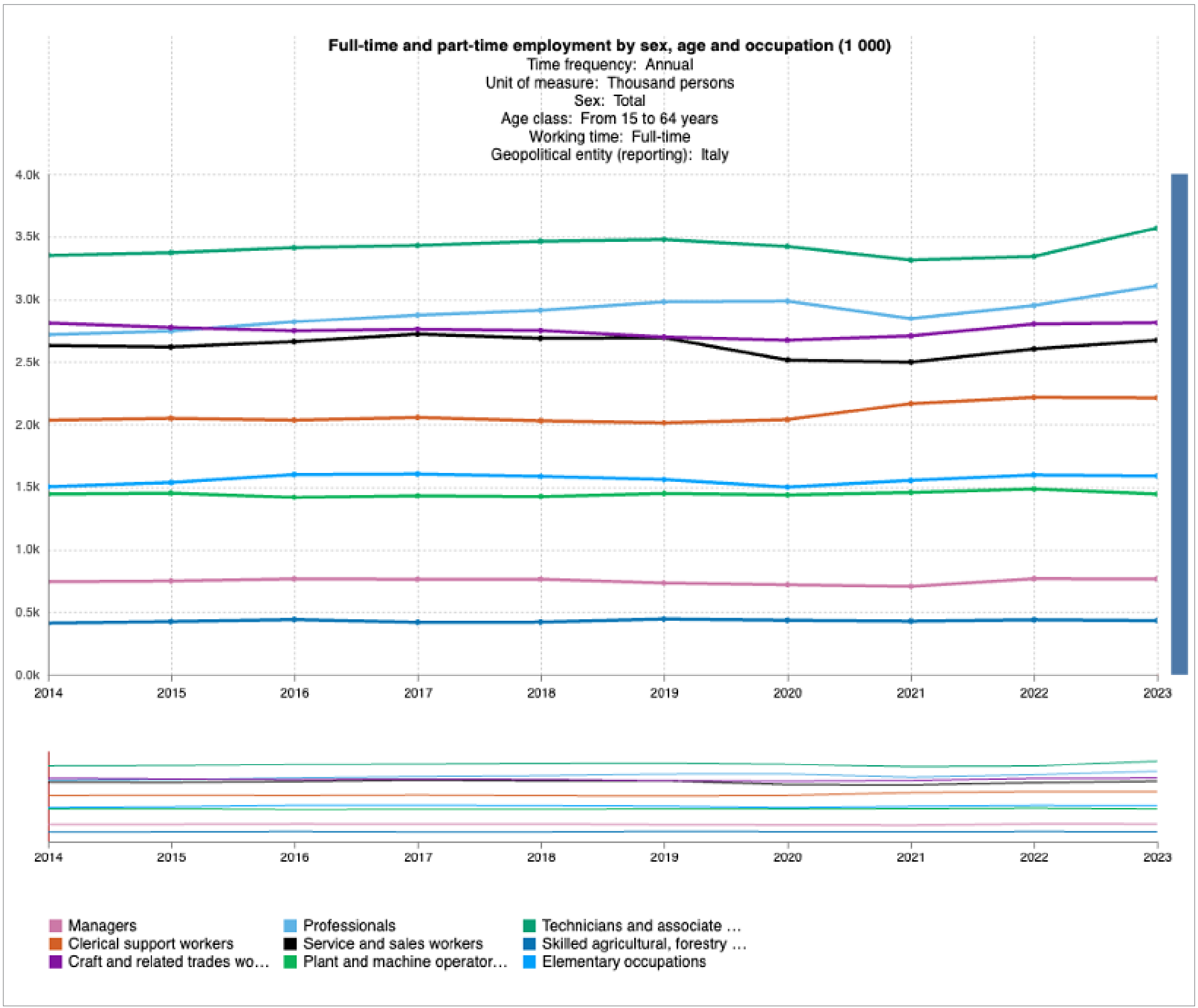
Data source: Inapp PLUS 2018 and Inapp PLUS 2021

Table A3. Summary statistics of the control variables, 2021 cross-section

Variable name	Categories	Obs.	%
Women	= 1 if woman	7,582	52.83
	= 0 if man	6,769	47.17
University degree	= 1 if university degree	5,884	41.00
	= 0 if no university degree	8,467	59.00
Age group	18-29 years old	5,710	39.79
	30-49 years old	4,580	31.91
	50+ years old	4,061	28.30
Italy macro area	North	7,888	54.96
	Centre	2,782	19.39
	South and Islands	3,681	25.65
Metropolitan area	= 1 if metropolitan area	2,196	15.30
	= 0 if other	12,155	84.70
White-collar worker	= 1 if professional / white-collar worker	11,877	86.06
	= 0 if manual labour / blue-collar worker	1,924	13.94
Private sector	= 1 if private company	10,598	73.85
	= 0 if public sector	3,753	26.15
Large company (250+ staff)	= 1 if large company (250+ staff)	1,480	10.31
	= 0 if other company (up to 249 staff)	12,871	89.69
Services sector	= 1 if production of services	11,203	78.06
	= 0 if production of goods	3,148	21.94
Nr. of children	= 1 if no children	8,902	62.05
	= 1 if respondent has one child	2,407	16.78
	= 1 if respondent has two children	2,540	17.71
	= 1 if respondent has three or more children	497	3.46
Child up to 3 years old	= 1 has child up to 3 years old	931	6.49
	= 0 does not have child up to 3 years old	13,420	93.51
Grandparents' support	= 1 if grandparents support with childcare	2,243	15.63
	= 0 if no support / missing information	12,108	84.37
Child in distance-learning	= 1 child in distance-learning	3,487	24.30
	= 0 no child in distance-learning	10,864	75.70
Covid-19 economic impact	= 1 had negative consequences	4,579	31.91
	= 0 no Covid-19 consequences	9,772	68.09

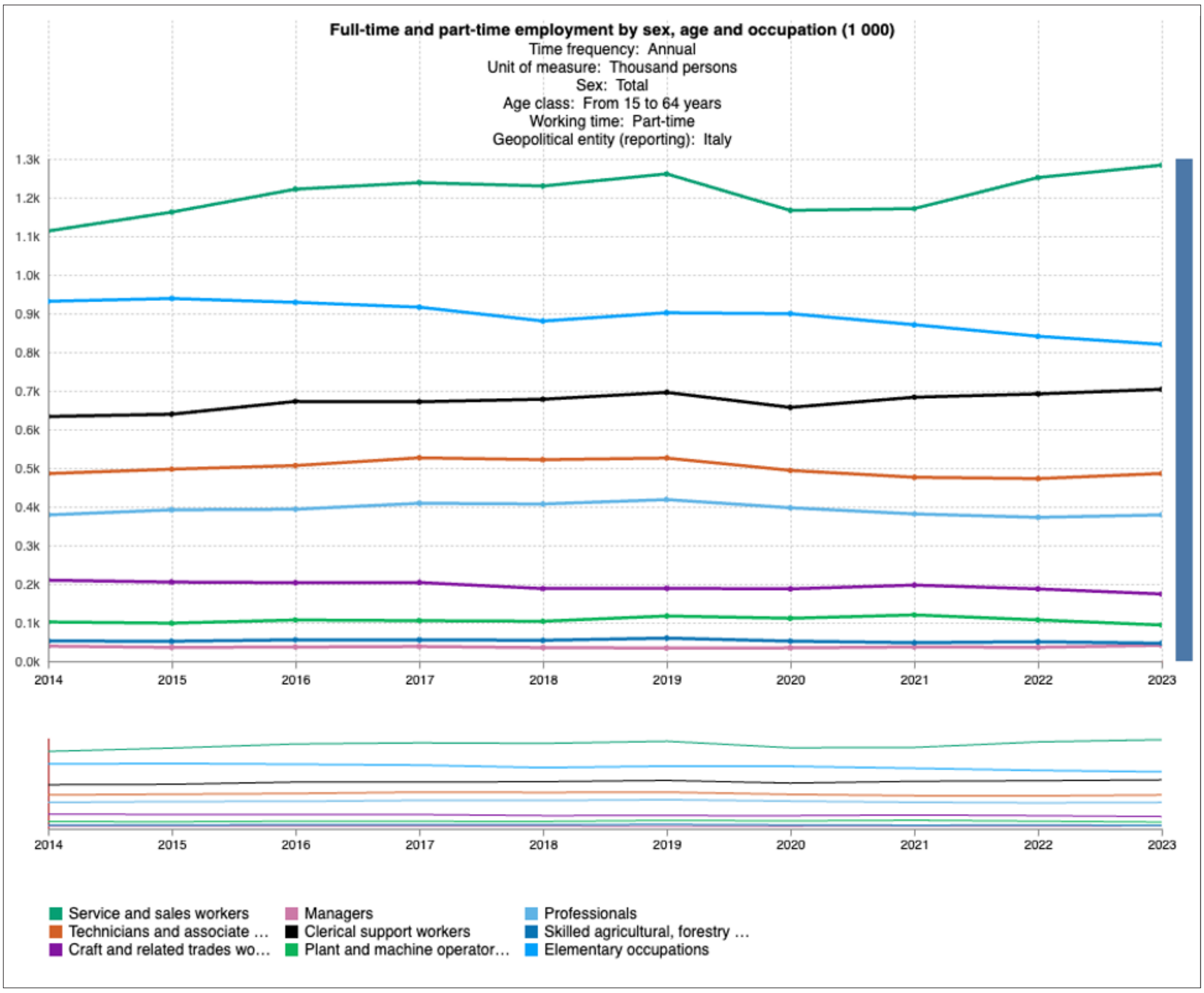
Data source: Inapp PLUS 2021

Figure A1. Full-time employment by occupation, 2014-2023, Italy



Data source: Eurostat 2024

Figure A2. Part-time employment by occupation, 2014-2023, Italy



Data source: Eurostat 2024

Table A4. 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)	

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

Data source: Author elaboration on Inapp PLUS data, 2018-2021

Table A5. 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*

Data source: Author elaboration on Inapp PLUS data, 2021

Table A6. Covariates balancing summary estimates for remote work treatment, normalized weights

	Standardized differences		Variance ratio	
	Raw	**Weighted**	**Raw**	**Weighted**
Woman	0.148	0.112	0.987	0.997
University degree	0.932	0.182	1.210	1.060
Age group (reference: 50+ years)				
18-29 years old	0.603	0.020	0.802	1.041
30-49 years old	0.327	0.056	1.187	1.000
Italy macro area *(*reference *category: South and Islands)*				
North	0.020	0.055	0.997	0.993
Center	0.078	0.034	1.089	0.970
Metropolitan area	0.362	0.055	1.618	1.072
White/blue collar worker	0.809	0.228	0.140	0.511
Private sector	0.582	0.096	1.537	1.043
Large company (250+ staff)	0.296	0.008	1.707	0.989
Services sector	0.248	0.118	0.778	0.879

Data source: Author elaboration on Inapp PLUS data, 2021

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