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Does Remote Work Reinforce Gender Gaps in (Un)Paid Labor?

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Abstract

I study how the rise in working from home (WFH) affects the gender division of paid and unpaid labor (caregiving, domestic tasks). Identification uses differences in individuals' exposure to the Covid-induced WFH shock, measured by the WFH feasibility of their job in 2019. Using panel data from the German SOEP, I estimate 2SLS models that instrument realized WFH in 2022 with WFH feasibility. Results show that WFH reduces paid hours and increases domestic work and leisure (including sleep) among women. Men's time use remains largely unchanged, partly because WFH induces moves toward larger, more distant homes, offsetting commuting time savings. Within-couple analyses confirm that the Big Shift to WFH intensifies gender gaps in paid and unpaid work, particularly caregiving. I find that gender norms, bargaining power, and childcare demands interact with WFH in ways that reinforce the unequal division of labor.

Keywords: Work from home; time use; unpaid work; division of labor; gender norms; bargaining power

JEL Codes: J16, J22, J13

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1 Introduction

Since the coordinated shift in 2020, working from home (WFH) has become a defining feature of the modern labor market (Aksoy *et al.*, 2022, 2025). Supported by network externalities, investment, and innovation in WFH technologies, employers have shed productivity concerns and extended new flexibility to a broad segment of the workforce (Barrero *et al.*, 2023, 2021; Bloom *et al.*, 2024).¹

This dual shift, in work arrangements and perceptions, has sparked competing views on WFH’s implications for gender inequality in paid and unpaid labor (caregiving, domestic tasks). Convergence optimists argue that WFH enables greater labor market participation for women and lowers barriers to men’s household involvement—also thanks to time savings and the fading stigma once tied to WFH. Skeptics counter that WFH reinforces traditional gender roles by providing the pretext to burden women with more unpaid work. Men would instead capitalize on WFH to boost their productivity and careers.

This paper estimates the causal impact of WFH on the gender division of (un)paid labor and leisure in the post-Covid economy. I use representative panel data from the German Socioeconomic Panel (SOEP v.39), which includes yearly time-use information at the individual and couple level until 2022. Identification uses individual-level differences in the exposure to the WFH shock, measured by 2019 *WFH feasibility*, i.e., whether a job *could* be done from home. I estimate intention-to-treat (ITT) effects of WFH using a difference-in-differences (DiD) design that compares individuals by WFH feasibility over time. To address non-compliance with initial WFH exposure, I instrument realized WFH in 2022 with pre-Covid WFH feasibility, separately by gender. At the couple level, the IV model links changes in individual time use to each partner’s WFH status in 2022, instrumented by each partner’s 2019 WFH feasibility.

The key takeaway is that the shift to WFH reinforces gender disparities in both paid and unpaid work. WFH reduces women’s working hours and increases their time spent on leisure and domestic labor. In contrast, men’s time allocation is barely affected by WFH, which can be reconciled with moves to larger homes that involve longer commutes, offsetting commuting time savings from WFH. The couple-level estimates corroborate the individual-level findings: WFH intensifies preexisting gender

¹As of early 2025, 26% of work days are performed from home in the US, from 5% before the pandemic. In Germany, 25% of employed persons work from home at least partly (Alipour *et al.*, 2024, Fig. 1). These shares have stayed remarkably stable since 2022, despite recurring media attention to a return-to-office “trend” which has yet to bear out in the data.

gaps in caregiving and paid labor in the average couple. Three mechanisms help explain these patterns: individuals with more conservative gender norms use WFH to reinforce traditional divisions of labor; men’s greater economic bargaining power allows them to protect time for paid work; and greater childcare demands—disproportionately borne by women—pull their time toward unpaid labor.

To date, we lack systematic evidence on how the WFH shock affects individuals’ time use or couples’ division of labor in the post-Covid economy. Importantly, earlier findings may not generalize as the scale, access, and attitudes toward WFH (by both firms and workers) have changed fundamentally since the pandemic (Barrero *et al.*, 2023). Harrington and Kahn (2023) find that pre-Covid, WFH appeared to reduce motherhood employment penalties in traditionally inflexible occupations such as finance. Similarly, pre-Covid data from Germany suggest that WFH correlates with increased paid hours, more so for women than men (Arntz *et al.*, 2022). Descriptive evidence from the pandemic suggests that WFH supported college-educated mothers’ employment but also intensified their total workloads; meanwhile, household divisions of labor shifted only temporarily toward greater parity (Goldin, 2022; Lyttelton *et al.*, 2020). In the Netherlands, von Gaudecker *et al.* (2024) find that both parents in WFH-feasible jobs increased childcare time equally, narrowing the gender care gap as men more often held teleworkable jobs. Observational data from the US similarly indicate that mothers and fathers working remotely increased childcare time equally during the crisis (Pablonia and Vernon, 2023). Yet importantly, pandemic-era conditions (especially school closures) likely inflated the burdens and understated WFH’s longer-term potential, especially for women (Goldin, 2022). Schüller (2025) corroborates this argument by showing that by 2023, fathers’ ability to WFH reduces the parental gap in domestic work, by increasing mothers’ market hours and reducing their time in domestic work. However, WFH does not appear to affect the division of childcare among couples.

My main contribution is to provide *causal* evidence on WFH and the gender division of (un)paid labor in the post-Covid economy. I estimate the effects of *realized* WFH using an IV strategy that uses individual-level exposure to the WFH shock. Importantly, the panel structure allows me to substantiate identifying assumptions—e.g., by testing for parallel time-use trends prior to the WFH shock. A key novelty is to identify mechanisms, i.e., how WFH interacts with gender norms, bargaining power, and childcare needs. To this end, I expand on prior work by including non-parents, thereby accounting for gendered effects absent parenting constraints. The rich data also allow me to analyze cross-partner spillovers and directly assess how WFH affects within-couple

gender gaps. Importantly, I account for time reallocation toward leisure—a key aspect of well-being that is typically lacking in the literature.

The core analysis uses a panel of 5,505 individuals employed in 2019 and reinterviewed in 2022. The SOEP includes annual information on time use across key activities (leisure, caregiving, domestic work, paid work) on an “average weekday” as well as hours worked from home in 2022.

Correlations between WFH and time use are confounded by unobserved factors driving self-selection into WFH. To address this endogeneity, I instrument realized WFH with a pre-pandemic measure of *WFH feasibility*, i.e., whether an individual’s job *could* be done remotely in 2019. This measure strongly predicts realized WFH in 2022 and thus captures exposure to the Covid-induced WFH shock. The validity of the IV approach hinges on the exogeneity of WFH feasibility: First, because the pandemic was unanticipated, it is unlikely that individuals selected into jobs based on expected WFH opportunities.² Second, I impute WFH feasibility in the SOEP using prediction weights from a classification model trained on the 2018 BIBB-BAuA Employment Survey, based on pre-pandemic characteristics—occupation, industry, skill requirement, age, gender, and immigration background. This imputation purges potential bias from idiosyncratic factors affecting self-reported WFH feasibility (e.g., employer policies or living conditions) and thus approximates whether a job can be done remotely based solely on its task profile. Third, event-study results show no differential time-use trends by WFH feasibility before the pandemic, supporting the exogeneity assumption; namely, that WFH feasibility is uncorrelated with co-determinants of time-use changes. Fourth, I verify that 2SLS results are robust to comparing individuals only within the same industry, occupation, and federal state, minimizing the risk that Covid-related labor market shocks drive the results.

The 2SLS estimates reveal pronounced gender asymmetries in time-use responses to WFH. Among women, an additional hour of WFH per weekday increases domestic work by 0.10 hours and leisure by 0.12 hours. Scaled to a full 7-hour WFH day, these translate to a 28% rise in domestic work and a 10% increase in leisure in 2022 relative to 2019. The impacts on care work and Do-it-yourself (DIY) activities (gardening, repairs) are also positive but insignificant. These increases are mirrored by a drop in time spent on job-related activities (including commuting) by 0.27 hours per

²Again, the key observation here is that the nature and perception of WFH arrangements have fundamentally changed after the pandemic, such that even individuals with pre-Covid WFH experience should be considered “treated”.

hour worked remotely, reflecting both commuting time savings and fewer paid hours. Women who WFH at least once per week reduce paid hours by 0.54 hours or 8%, on average. By contrast, WFH *reduces* the likelihood of exiting employment relative to non-WFH peers, with effects nearly twice as large for women as for men. This aligns with pre-Covid evidence that WFH promotes labor force attachment for women (and mothers specifically) at the extensive margin (Harrington and Kahn, 2023). Thus crucially, the findings reveal a mixed pattern in women's labor supply: improved attachment at the extensive margin but reduced participation at the intensive margin.

Men, by contrast, show only small time-use responses to WFH. Domestic work rises modestly by 0.04 hours per hour of remote work, while effects on paid hours, leisure, and caregiving are insignificant. The muted response may seem puzzling given the time savings from reduced commuting. However, I find that this can be reconciled with results that WFH prompts moves to larger homes with longer commutes, and lowers the likelihood of leaving employment, i.e., eliminating commuting entirely.

At the couple level, IV results show that WFH amplifies gender gaps in paid and unpaid labor between heterosexual partners. Domestic and caregiving workloads shift disproportionately to women when only they work remotely, whereas effects are smaller and statistically weaker when only men do. When both partners WFH, gender gaps in paid hours and caregiving widen significantly. For the average couple, the gender gaps widen by 22% for caregiving and 18% for paid hours, relative to 2019. Gaps in leisure and DIY time remain unchanged, on average. Overall, the findings confirm that the transition to remote work reinforces rather than alleviates preexisting gender disparities. Importantly, I find that OLS estimates suggest the opposite narrative; namely, that WFH *reduces* gender disparities, particularly in paid hours and caregiving. The contrast between the IV and OLS results highlights that distinguishing selection from causation is essential to avoid misguided interpretations and policy recommendations.

I identify three mechanisms that help explain the gendered effects of WFH. First, an intra-household bargaining channel: WFH slows wage growth for women relative to non-WFH peers. I find no wage growth penalty for men. This pattern is consistent with firms sharing part of WFH's amenity value with female employees, who typically value flexibility more than men (Nagler *et al.*, 2024). But it may also reflect the interaction of WFH with domestic responsibilities, which can reduce productivity due to frequent work interruptions among women (Adams *et al.*, 2025). This asymmetry weakens women's bargaining position within the household, which tends to reinforce traditional divisions of labor. Consistent with this interpretation, the marginal effect

of WFH on individuals' non-market labor declines with their household income share, for both men and women. Men, who hold higher bargaining power on average, are better able to shield time for paid work. Second, the effects of WFH interact with political leaning, a proxy for gender role attitudes: more conservative individuals, both women and men, use WFH to reinforce traditional divisions of labor. Third, childcare needs moderate the impact of WFH. Among women, the shift from paid labor to caregiving is concentrated in households with young children. For men with young children, caregiving time also rises with remote work, but the effect is significantly smaller and accompanied by an *increase* in paid hours. I do not find that WFH affects the presence (or the number) of children in the household, nor marital status.

The evidence challenges the idea that increasing job flexibility alone necessarily fosters gender equality (Goldin, 2014, 2022; Alon *et al.*, 2020). While WFH expands individual autonomy and lowers the cost of (temporal and locational) flexibility, its interaction with preexisting gender norms and unequal bargaining power, typically favoring men, tends to reinforce the traditional gender division of labor. Institutional features, such as Germany's joint taxation system ("Ehegattensplitting"), further incentivize using WFH arrangements to support main-earner households. Thus, lacking institutional and normative shifts, the Big Shift to WFH is more likely to entrench rather than mitigate gender inequality at home and in the labor market.

The paper proceeds with a description of the data and variables of interest in [Section 2](#). [Section 3](#) lays out the empirical strategy and the identifying assumptions. [Section 4](#) presents the main results. [Section 5](#) explores heterogeneity and potential mechanisms explaining the results. [Section 6](#) concludes.

2 Data and variables of interest

2.1 German Socioeconomic Panel (SOEP)

The SOEP is a nationally representative annual panel of about 22,000 households in Germany. [Version 39](#) includes data through 2022.

Time-use data and WFH status. The time-use questionnaire elicits hours spent on various activities on an "average weekday", including the following categories:³

³I group some separate entries into one category; specifically, the entries for sleep, physical exercise, and "other leisure activities" are grouped into one "leisure" category. The results for "work" and "education" are combined into one group. I also count "running errands" as domestic work and combine childcare and eldercare into one "care work" category.

1. *Work & education* (including commuting, and trainings)
2. *Care work* (including childcare and elder care)
3. *Domestic work* (including laundry, cooking, cleaning, and running errands)
4. *Do-it-yourself (DIY) activities* (repairs, gardening)
5. *Leisure* (including sleep, physical exercise, and hobbies)

Employed individuals also report their *weekly* working hours (excluding commuting). For comparability with the time-use data, these entries are divided by five to obtain the average number of hours worked per weekday.

The 2022 wave includes information on workers' WFH status. I use a dummy for *WFH at least once per week* and *average hours worked from home per weekday* (weekly WFH hours divided by five) as the two explanatory variables of interest.

Individual-level panel. The main analysis uses a sample of individuals aged 16–64 and employed in 2019 (excluding military personnel, marginally employed, and freelancers), who completed the time-use questionnaire in 2019 and 2022. (2,513 men, 2,992 women). [Table 1](#) presents summary statistics by gender. By 2022, 26% of women and 32% of men WFH at least once per week. Remote workers spend about two-thirds of their working hours from home, with no significant gender difference. Across all employed individuals, women spend 19% of their working hours from home and men 25%.⁴

The likelihood of holding a WFH feasible job in 2019 (described in the next section) does not differ significantly by gender. Unsurprisingly, time-use patterns reveal pronounced gender gaps. In 2019, women spent similar time on leisure (8.5 hours on an average weekday) but less on their job (including studying and commuting) than men (7.4 vs. 9.3 hours). Women devoted one hour more than men to domestic work (2.6 vs. 1.5 hours) and more than twice as much to caregiving (1.9 vs. 0.8 hours). Women spent marginally less time on DIY activities (0.4 vs. 0.5 hours).

Couple-level panel. The data include 875 (heterosexual) cohabiting couples observed in 2019 and 2022, in which both partners are employed in 2019 and provided complete time-use data. The outcomes at the couple-level are gender gaps in time use—measured as the female-male difference in hours spent on an average weekday. [Table B.1](#) reports the summary statistics. Consistent with the individual-level data,

⁴These WFH rates in 2022 align with estimates from other representative worker and company surveys, including the ifo Business Survey and the German Mikrozensus (Destatis).

2019 WFH feasibility does not differ within couples, on average; but men are more likely to work remotely than their partners by 2022.

Table 1: Summary statistics (individual level)

	(1) Women N = 2992	(2) Men N = 2513	(3) Difference (Women-Men)
A. WFH variables			
WFH at least 1x/week, 2022	0.258 (0.438)	0.322 (0.467)	-0.064 (0.012)***
Weekly hours WFH, 2022 (all)	5.341 (10.977)	8.349 (14.109)	-3.008 (0.338)***
Weekly hours WFH, 2022 (only WFH 1+/week)	19.642 (12.729)	24.824 (13.744)	-5.182 (0.667)***
Share of hours WFH, 2022 (all)	0.187 (0.467)	0.253 (0.765)	-0.066 (0.018)***
Share of hours WFH, 2022 (only WFH 1+/week)	0.606 (0.687)	0.683 (1.157)	-0.076 (0.048)
predicted WFH feasibility (0/1), 2019	0.508 (0.500)	0.504 (0.500)	0.004 (0.014)
predicted WFH feasibility [0,1], 2019	0.373 (0.291)	0.370 (0.298)	0.002 (0.008)
B. Main outcome variables			
<i>B.1 Time use (hours on average weekday)</i>			
Hours leisure (incl. exercise and sleeping), 2019	8.541 (1.792)	8.466 (1.838)	0.075 (0.049)
Δ Hours leisure (incl. exercise and sleeping)	0.156 (1.982)	0.317 (2.110)	-0.161 (0.055)***
Hours working (incl. studying and commuting), 2019	7.470 (2.630)	9.308 (1.922)	-1.838 (0.063)***
Δ Hours working (incl. studying and commuting)	-0.767 (3.388)	-1.060 (3.123)	0.293 (0.088)***
Hours care work, 2019	1.923 (3.458)	0.814 (1.532)	1.109 (0.074)***
Δ Hours care work	0.175 (3.924)	0.146 (1.859)	0.029 (0.085)
Hours domestic work (incl. errands), 2019	2.590 (1.347)	1.496 (1.041)	1.093 (0.033)***
Δ Hours domestic work (incl. errands)	0.293 (1.530)	0.462 (1.431)	-0.168 (0.040)***
Hours DIY activities, 2019	0.373 (0.624)	0.473 (0.720)	-0.100 (0.018)***
Δ Hours DIY activities	0.297 (0.837)	0.420 (1.051)	-0.122 (0.025)***
<i>B.2 Hours worked (weekly)</i>			
Weekly hours worked, 2019	32.027 (12.090)	41.219 (9.579)	-9.192 (0.298)***
Δ Weekly hours worked	-3.580 (14.258)	-4.850 (14.313)	1.270 (0.386)***
C. Further variables			
Age, 2019	45.423 (10.904)	45.397 (11.227)	0.027 (0.299)
Partner in HH (0/1), 2019	0.686 (0.464)	0.756 (0.429)	-0.070 (0.012)***
Children under 14 in HH (0/1), 2019	0.355 (0.478)	0.353 (0.478)	0.002 (0.013)
No of children u14 in HH, 2019	0.544 (0.840)	0.588 (0.934)	-0.044 (0.024)*
Commuting distance (km), 2019	14.098 (18.963)	18.218 (20.589)	-4.120 (0.554)***
Gross monthly wage (EUR), 2019	2489.632 (1629.863)	4061.217 (2609.004)	-1571.584 (57.724)***
Firm tenure in years, 2019	10.626 (10.472)	11.970 (10.931)	-1.344 (0.289)***
Firm with 100+ employees (0/1), 2019	0.623 (0.485)	0.686 (0.464)	-0.063 (0.013)***
Moved b/w 2019 and 2022 (0/1)	0.103 (0.304)	0.111 (0.314)	-0.007 (0.008)
No of rooms, 2019	4.376 (1.791)	4.380 (1.831)	-0.004 (0.049)
Log living space, 2019	4.634 (0.427)	4.632 (0.445)	0.002 (0.012)
Exited employment b/w 2019 and 2022 (0/1)	0.123 (0.328)	0.097 (0.296)	0.026 (0.008)***
Changed employer b/w 2019 and 2022 (0/1)	0.186 (0.389)	0.145 (0.352)	0.041 (0.011)***
Married (0/1), 2019	0.586 (0.493)	0.641 (0.480)	-0.055 (0.013)***
Single (0/1), 2019	0.252 (0.434)	0.275 (0.447)	-0.023 (0.012)*

Notes: The table reports variable means and standard deviations (in parentheses) by gender (not weighted). Column 3 reports gender differences and standard errors (in parentheses). The sample includes individuals employed and aged 16–64 in 2019, who are observed again in 2022. The operator Δ denotes (individual-level) changes between 2019 and 2022. The data are from the SOEP. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

2.2 BIBB-BAuA Employment Survey 2018

To obtain a measure of WFH feasibility, I use information from the 2018 wave of the BIBB-BAuA Employment Survey (Hall *et al.*, 2020).⁵ The survey elicits working conditions and job features from a representative sample of the German workforce in 2018. I exclude marginal workers (“Minijobs”), military personnel, and freelancers, leaving a sample of 16,765 individuals.

Measuring WFH feasibility. When respondents in the BIBB-BAuA survey indicate that “WFH is impossible in my job” when asked whether they would accept a WFH offer, their job is coded as not WFH-feasible. In addition, I assume that a job cannot be worked from home if the respondent indicates *frequent* exposure to any of the following conditions:

1. Lifting or carrying loads of more than 10kg (women)/ 20kg (men)
2. Being exposed to smoke, dust, gases, or vapors
3. Being exposed to cold, heat, moisture, humidity, or droughts
4. Working with oil, grease, dirt
5. Handling microorganisms such as pathogens, bacteria, molds, or viruses
6. Working the majority of working hours outdoors
7. Repairing and renovating
8. Protecting, guarding, monitoring, regulating traffic
9. Cleaning, waste disposal, recycling
10. Monitoring, control of machines, plants, and technological processes

These additional restrictions help ensure that the measure captures jobs in which a substantial fraction of tasks can realistically be done from home. Under this definition, 39% of jobs are classified as WFH-feasible. This is broadly consistent with evidence that at the peak of the pandemic, about one-third of employed persons in Germany regularly worked from home (Alipour *et al.*, 2024, Fig. 1).

Imputing WFH feasibility in the SOEP. I capture individuals’ exposure to the Covid-induced WFH shock by the *WFH feasibility* of their 2019 job. The variable is constructed in two steps: First, I train a supervised classifier model using data from the 2018 BIBB-BAuA Employment Survey to estimate (binary) WFH feasibility as a

⁵The survey is conducted by the Federal Institute for Vocational Education and Training (BIBB), and the Federal Institute for Occupational Safety and Health (BAuA).

function of job and worker characteristics. Second, I apply the estimated prediction weights to impute 2019 WFH feasibility for individuals in the SOEP sample.

One advantage of this imputation approach is that it reduces idiosyncratic measurement error in self-reported WFH feasibility that arises from subjective constraints unrelated to a job's inherent task content, such as employer policies on WFH, local infrastructure, or individual living conditions (e.g., space at home). Under the assumption that these subjective factors are orthogonal to the attributes used in the prediction model, the imputation effectively filters out the noise component in the BIBB-BAuA data and retains only the systematic, task-related variation. Consequently, the predicted WFH-feasibility measure better captures exposure to the Covid-induced WFH shock independent of individual or firm-specific circumstances. A further advantage is that the resulting measure varies at the individual rather than the occupational level, allowing more precise identification.

The classification task is performed by a logistic model that estimates binary WFH feasibility as a function of occupation (KldB 3-digit, 139 categories), industry (NACE 2-digit, 85 categories), skill requirement (KldB 5-digit, 4 categories), age, age-squared, gender (0/1), and immigrant background (0/1). Including demographic characteristics can enhance the model's power by capturing sorting into specific jobs within occupations or industries. For identification purposes, I assume that this selection is orthogonal to anticipated WFH opportunities. This is plausible given that the Covid pandemic and the ensuing WFH shock were unexpected and fundamentally changed the nature (i.e., perception and organization) of WFH arrangements.

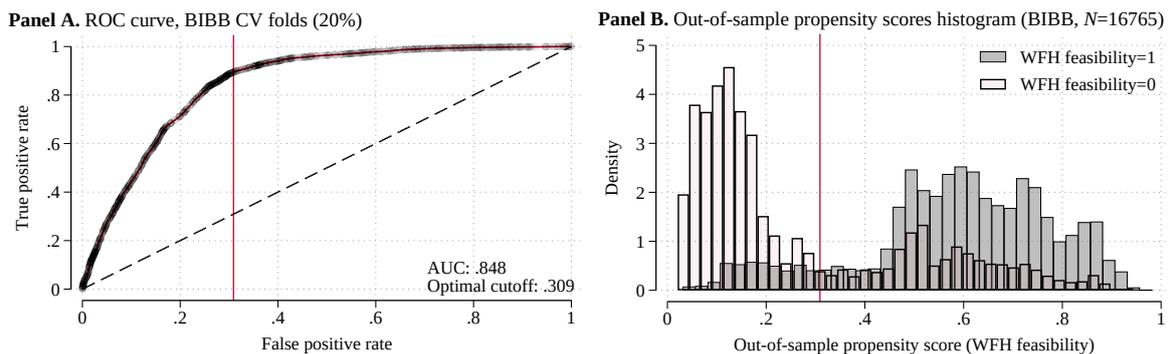
Predictors for the logistic model are selected by a LASSO regression with a penalty chosen by a 5-fold cross-validation to minimize the log-likelihood loss. The LASSO regularization penalizes coefficients, shrinking irrelevant predictors to zero and reducing overfitting. The cross-validation on random sub-samples improves the selection of the regularization parameter (λ), which controls the strength of the penalty.⁶

The LASSO procedure selects 209 out of 231 features. Dominance analysis using McFadden's pseudo- R^2 as the fit statistic suggests that occupation accounts for about two-thirds of the model's fit (65% of the pseudo- R^2), with industries (19%) and skill levels (15%) providing the remaining meaningful shares; selected demographic covariates

⁶I use STATA's `cvlassologit` package ([Ahrens et al., 2020](#)).

contribute little (<1% each).⁷ Model performance is summarized in Figure 1. Panel A depicts the ROC curve using out-of-sample predictions for WFH feasibility from the five cross-validation folds. The ROC curve visualizes the trade-off between true and false positives across various classification thresholds. The AUC (area under the curve) of 0.848 indicates an 84.8% probability that a randomly selected WFH-feasible job is assigned a higher propensity score than a randomly chosen non-feasible one.⁸ By conventional standards, an AUC above 0.8 indicates strong predictive performance. The vertical line at 0.309 marks the classification cutoff that maximizes the difference between the true positive and false positive rate (Youden’s J). This classification approach imposes equal weight to the two error rates. Panel B plots the distribution of propensity scores by WFH feasibility status. At the Youden’s J optimal cutoff (vertical line), the model correctly classifies 77% of cases (accuracy).

Figure 1: Out-of-sample performance of the binary prediction model



Notes: Panel A shows the ROC curve using out-of-sample predictions for WFH feasibility from the five cross-validation folds. Panel B plots histograms of out-of-sample propensity scores by WFH feasibility (0/1). The vertical lines at 0.309 highlight the classification cutoff that maximizes the difference between the true positive rate and false positive rate (Youden’s J). Data are from the BIBB-BAuA Employment Survey 2018.

In the second step, I apply the trained model to predict WFH feasibility in the SOEP sample based on 2019 characteristics. This yields a continuous and a binary measure of (predicted) WFH feasibility, using the propensity scores and the classification threshold, respectively. There is no statistical gender difference in WFH feasibility (Ta-

⁷Dominance analysis for the LASSO-selected model averages each predictor’s marginal improvement in fit over all possible submodels, yielding a Shapley-value decomposition of explanatory power. I use STATA’s *domin* package (Luchman, 2021).

⁸A randomly guessing model would produce an AUC of 0.5, whereas a perfect model would produce an AUC of 1. The AUC summarizes model performance independently of any specific classification cutoff.

ble 1). The next section documents that WFH feasibility strongly predicts individuals' WFH status in 2022 and thus appropriately captures exposure to the Covid-induced WFH shock.

3 Empirical Strategy

3.1 Difference-in-differences (DiD) approach

At the individual level, I estimate a standard dynamic DiD specification, in which WFH feasibility in 2019 corresponds to (time-invariant) treatment status:

$$y_{it} = \sum_{k \neq 2019} [\beta^k \mathbb{1}(k = t) \times WFH_FEAS_i] + \gamma_i + \gamma_t + \epsilon_{it}, \quad (1)$$

where y_{it} denotes an outcome (e.g., hours spent on domestic work) for individual i in year t . WFH_FEAS_i is WFH feasibility (binary (0/1) or continuous [0,1]) of i 's job in 2019. The specification includes the standard individual (γ_i) and year γ_t fixed effects. The error term ϵ_{it} captures unobserved shocks, which are assumed to be uncorrelated with the treatment-year interactions. Then, the coefficients β^k trace the differential evolution of outcomes for individuals with WFH-feasible jobs from 2017 to 2022, relative to 2019 (the reference year). Standard errors are clustered by individual.

Parallel trends assumption. The validity of the DiD design rests on the parallel trends (PT) assumption. Given the unexpected nature of the Covid-induced WFH shock, the PT assumption is unlikely to be violated by selection on expected returns to WFH. A more salient concern is that WFH feasibility may be correlated with other determinants of time-use changes. For instance, WFH-feasible jobs are more common among highly educated workers and typically involve greater cognitive task content (see e.g., [Alipour et al., 2023](#)). If time-use changes differ systematically across education groups, the DiD estimates may pick up a preexisting trend rather than reflecting the causal effects of WFH. Checking for pretrends in the DiD plot offers a diagnostic for such confounding; though, their absence never guarantees that the PT assumption holds post-treatment.

3.2 Instrumental variable (IV) approach

The DiD estimates deliver intention-to-treat (ITT) effects due to non-compliance in the sense that individuals with a WFH feasible job in 2019 may not realize WFH opportunities. Non-compliance arises because realized WFH depends on factors such as employer policy, living arrangements, and individual preferences, each of which

may also affect time use, thus diluting the ITT effect relative to the treatment effect of *actually* working from home.

The alternative of using OLS to estimate the effect of realized WFH is problematic: the decision to work remotely is endogenous to unobserved pandemic-specific shocks, such as changes in household needs, or health risks, that may simultaneously influence labor supply decisions. OLS therefore conflates *who* works from home with the causal impact of WFH, i.e., selection and omitted variable bias.

To address this, I estimate an IV model in which realized WFH status in 2022 is instrumented by 2019 WFH feasibility. The 2SLS estimates recover local average treatment effects (LATE) for compliers, i.e., individuals who work remotely in 2022 *because* they were exposed to the WFH shock through their job’s WFH feasibility.

Individual-level specification. I estimate the IV models in long differences of time use (2019–2022) to isolate the consequences of the WFH shock in the post-pandemic economy. The individual outcome equation is given by

$$\Delta y_i = \beta_0 + \beta_1 \times WFH22_i + \epsilon_i, \quad (2)$$

with the corresponding first stage:

$$WFH22_i = \pi_0 + \pi_1 \times WFH_FEAS_i + \vartheta_i, \quad (3)$$

where Δy_i is the *within-individual* change in time allocated to a given activity between 2019 and 2022. $WFH22_i$ is the individual’s WFH status in 2022, corresponding to a dummy (working from home at least once per week) or a count variable (number of hours worked from home per week). WFH status is instrumented by (predicted) WFH feasibility (WFH_FEAS_i), measured continuously [0,1] or as binary (0/1). The model is estimated separately by gender $g \in \{f, m\}$ using 2SLS.

Instrument relevance. For the IV strategy to be valid, we first require that the instrument be correlated with the endogenous variable (realized WFH). This is confirmed in [Figure 2](#), which presents binned scatter plots of 2022 WFH status against WFH feasibility [0,1] by gender. Panel A uses a dummy for working remotely at least once per week in 2022; in Panel B, WFH status is the average number of hours worked remotely per weekday.

In both panels, WFH feasibility strongly predicts WFH status after the Covid shock. While WFH feasibility does not differ by gender on average, the first-stage slopes are flatter among women, suggesting they are less likely than men to realize their WFH potential. Moving from 0 to 1 in WFH feasibility raises the likelihood of working remotely at least once per week by 0.87 for men, compared to 0.73 for women. Similarly, WFH feasibility increases the average number of hours working remotely per weekday by 4.78 among men, compared to 3.13 among women.⁹ The first-stage F -statistics are above 500, confirming that WFH feasibility is a strong instrument.

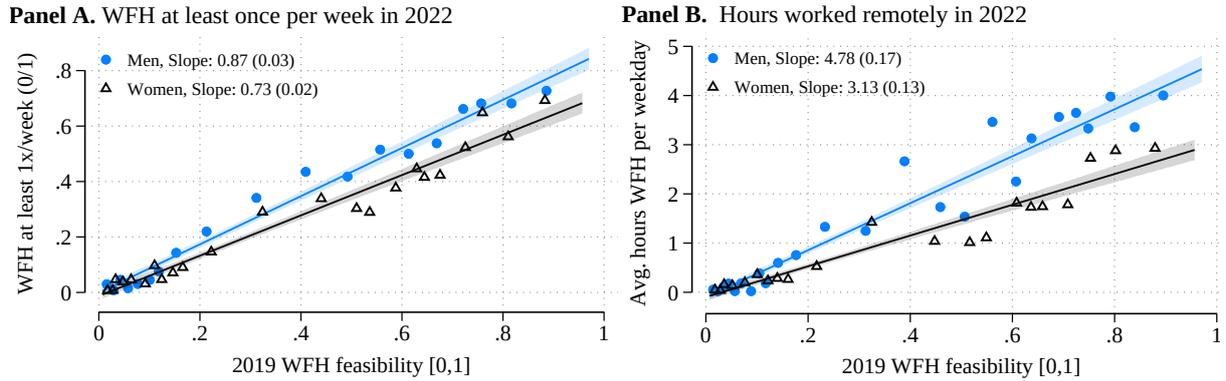
These gender gaps in take-up are somewhat puzzling, given that women generally report a higher willingness to pay for WFH (Nagler *et al.*, 2024; Barrero *et al.*, 2021; Mas and Pallais, 2017). One explanation may be differential constraints or perceived returns: women may face tighter employer-imposed restrictions or anticipate lower benefits from WFH—e.g., in terms of productivity or promotion chances. Supporting this view, Emanuel *et al.* (2023) find that switching to WFH reduces feedback by senior colleagues more for women than men. Adams *et al.* (2025) document that women face work interruptions more frequently at home than men. In contrast, Bloom *et al.* (2024) find no gender differences in realized WFH, productivity, and promotion chances in a field experiment. Moreover, men’s average commuting distance in 2019 is 4 kilometers longer than women’s (Table 1), suggesting that time-saving benefits—and thus the incentive to WFH—may be stronger for men.

Monotonicity. Second, the monotonicity assumption requires that individuals with *low* WFH feasibility who WFH in 2022 would also do so if assigned to a *high* WFH-feasibility job and conversely, that those with high WFH feasibility who *do not* WFH would likewise not do so when assigned to a low-WFH-feasibility job.¹⁰ A diagnostic for this assumption is to verify that the first-stage coefficients are non-negative across subsamples. Table B.2 confirms this for a large set of subsamples by industry, occupation, age cohort, skill level, and firm size (all measured in 2019). In all cases, the coefficient is positive and significant, with the sole exception of the “cleaning occupations”, where there is no variation in WFH status.

⁹These gender differences also hold conditional on total hours worked: Using the *fraction* of total hours worked from home as the dependent variable, the slopes are 0.73 among men, compared to 0.52 among women.

¹⁰Formally, let $D(z)$ denote the WFH status of an individual if assigned to a job with WFH feasibility level $z \in \{\text{low}, \text{high}\}$. Monotonicity requires $D(\text{high}) \geq D(\text{low})$ for all individuals, ruling out “defiers”.

Figure 2: 2019 WFH feasibility and WFH status in 2022



Notes: The figure shows binned scatter plots of WFH status in 2022 against WFH feasibility [0,1], estimated based on 2019 characteristics by gender (see Section 2.2 for details). In Panel A, WFH status is a dummy for working remotely at least once per week in 2022; in Panel B, WFH status is the average number of hours worked from home per weekday (weekly hours divided by five). Observations are grouped into equal-sized bins. The sample includes individuals employed and aged 16–64 in 2019, who are observed again in 2022. Slope estimates come from an OLS regression of WFH status on WFH feasibility. Standard errors are clustered by individual and reported in parentheses. The data are from the SOEP.

Exclusion restriction (ER). Third, the ER requires that WFH feasibility affect within-individual *changes* in time use only through realized WFH. Importantly, this means that any correlates of WFH feasibility are not problematic so long as they influence only time use levels. While the ER cannot be tested directly, three considerations support its plausibility: First, WFH feasibility is measured pre-Covid (2019) such that it is unaffected by the WFH shock or other shocks caused by the pandemic. Second, individuals are unlikely to have selected into jobs in anticipation of WFH opportunities created by the pandemic. Third, indirect tests of the ER deliver no evidence of differential pretrends by WFH feasibility, suggesting that it is not systematically related to co-determinants of time-use changes. A remaining concern is that the pandemic induced industry- or occupation-specific shocks correlated with both WFH feasibility and time-use trends, potentially eluding pretrend tests. Thus, I verify in robustness checks that results are robust to comparing individuals within the same industry and occupation.

Limitation. A limitation of the IV strategy is that, by relying on a single instrument, it cannot separately identify the extensive margin (whether individuals WFH at all) from the intensive margin (how many hours they WFH). Clearly, moving from 0 to 1 hour of WFH differs from moving from 1 to 2. The IV estimate of *hours worked from home* should therefore be interpreted as an average local effect, combining adjustments at both margins.

Couple-level specification. Among cohabiting couples, each partner’s WFH status can be linked to changes in their own time use, their partner’s time use, and the within-couple gender gap in time use. For example, we can investigate whether the male partner’s WFH status affects the female partner’s paid hours or household labor, and vice versa.

The corresponding IV model thus involves two endogenous variables (both partners’ realized WFH in 2022) and two instruments (both partners’ WFH feasibility) and is given by

$$\Delta y_c = \gamma_0 + \gamma_1 \times WFH22_c^f + \gamma_2 \times WFH22_c^m + v_c, \quad (4)$$

with the first-stage equations:

$$WFH22_c^f = \pi_0 + \pi_1 \times WFH_FEAS_c^f + \pi_2 \times WFH_FEAS_c^m + \varepsilon_c, \quad (5)$$

$$WFH22_c^m = \rho_0 + \rho_1 \times WFH_FEAS_c^m + \rho_2 \times WFH_FEAS_c^f + u_c, \quad (6)$$

where y_c is a partner’s time use or the *within-couple* time-use gap (female minus male) for a given activity. Δ denotes changes between 2019 and 2022. $WFH22_c^f$ and $WFH22_c^m$ are the WFH status in 2022 of the female and male partner in couple c . Each WFH status is instrumented by both partners’ WFH feasibility in 2019 ($WFH_FEAS_c^f$ and $WFH_FEAS_c^m$). Then, $\hat{\gamma}_1$ and $\hat{\gamma}_2$ deliver the causal impact of female and male partner WFH on a partner’s time use (or the couple’s gender gap) compared to a couple in which neither partner works from home. The combined effect ($\hat{\gamma}_1 + \hat{\gamma}_2$) gives the impact of both partners WFH compared to a non-WFH couple.

4 Main Results

4.1 Individual-level results

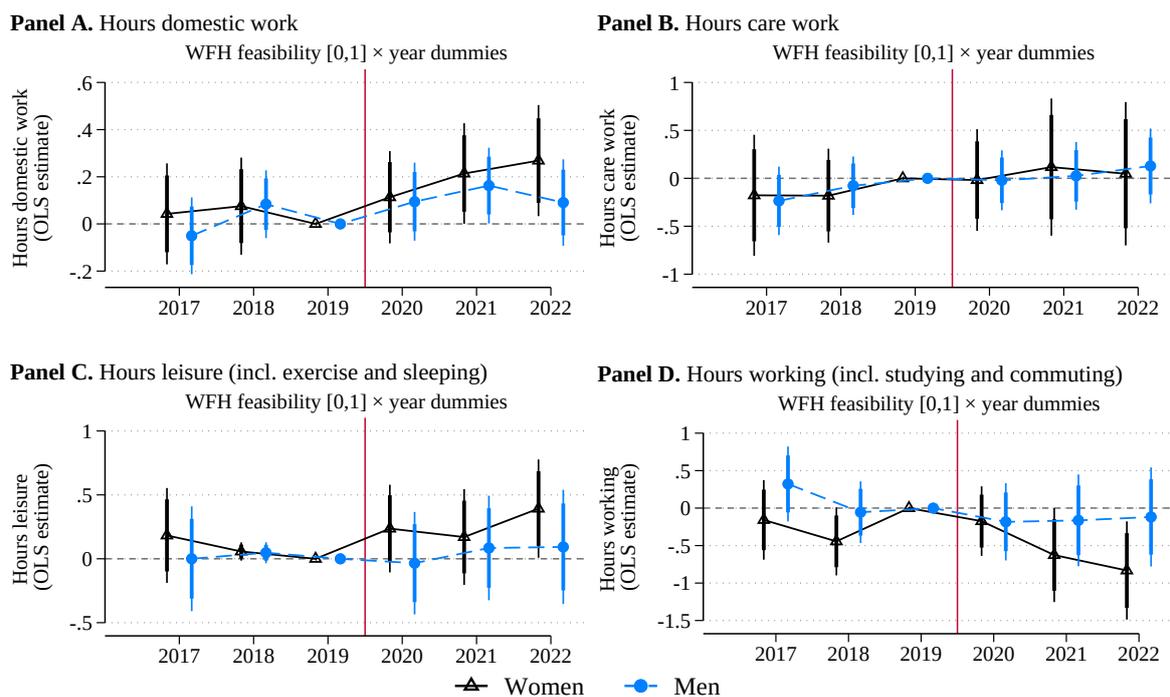
Intention-to-treat (ITT) effects of WFH. Figure 3 presents DiD results for the four most time-intensive activities, separately for women and men.¹¹ The sample includes all individuals of the main sample. Figure A.1 plots DiD results for the subsample that is balanced between 2017 and 2022, yielding virtually identical results. All pre-treatment coefficients are insignificant at the 1% level. F -tests of joint insignificance fail to reject the null that pre-treatment coefficients are equal to zero at the 5% level

¹¹Notice that there is no information on leisure in 2018; the individual coefficients are thus set to zero.

in all but one case: for women’s hours dedicated to work (including commuting), the pretrend is significant ($p=0.039$). However, the pretrend moves in the opposite direction of the treatment effect, suggesting that the treatment estimates may be conservative (Panel D). Overall, the evidence largely supports the PT assumption and suggests that WFH feasibility is not systematically correlated with determinants of time-use changes.

Following the WFH shock, women in WFH-feasible jobs shift time away from work (including commuting) toward domestic tasks and leisure. The impact estimates gradually intensify between 2020 and 2022. Among men, higher WFH feasibility is associated with a temporary increase in domestic work (Panel A) but does not lead to persistent changes in overall time allocation. For both genders, there is no discernible adjustment in caregiving hours, on average.

Figure 3: ITT effects of WFH on individual time use on an average weekday, balanced 2019–2022



Notes: The figure plots DiD estimates based on Equation 1. The sample includes individuals employed and aged 16–64 in 2019, balanced between 2019 and 2022. 99% and 95%-confidence intervals are drawn using standard errors clustered by individual. Data are from the SOEP.

LATEs on individual time use. As explained, the DiD estimates deliver ITT effects, which are independent of realized WFH opportunities. Figure 4 plots the results from the IV model estimated by 2SLS, which accounts for compliance with treatment assignment. The estimates correspond to the local causal effects of WFH on 2019–2022

time-use changes for individuals who work remotely *because* their 2019 job could be done from home. Panel A uses the binary measure of WFH at least once per week as the explanatory variable; Panel B uses the average number of hours worked remotely per weekday. Panel C plots the 2019 mean of the dependent variables by gender for reference. Rows 1–5 present 2SLS estimates for separate outcomes of the time-use questionnaire. The last row shows the effect on the average number of paid hours worked per weekday.¹² Tables B.3 and B.4 report the corresponding point estimates.

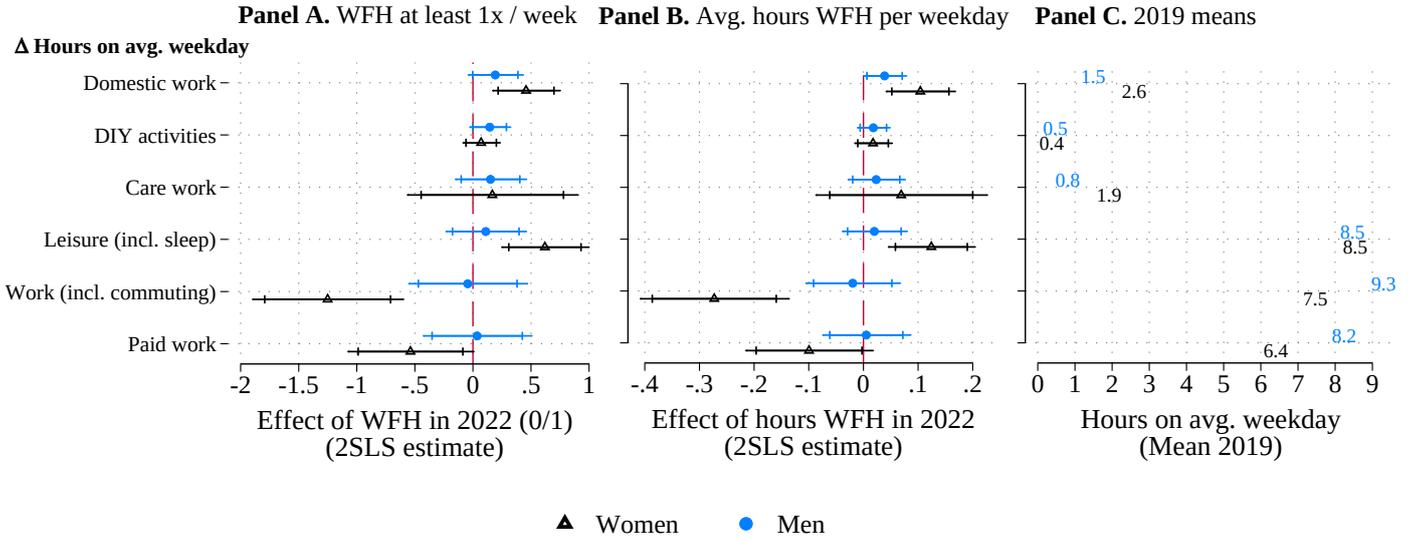
Among women, an additional hour of WFH per weekday significantly increases time spent on domestic tasks and leisure (including sleep) on an average weekday: 0.10 hours are reallocated to domestic work and 0.12 hours to leisure. Scaled to a full 7-hour remote workday, the effects translate to a 28% (10%) increase in domestic work and leisure relative to the 2019 means, respectively. Effects on DIY activities and care work are positive but insignificant. Women reduce time dedicated to their job (including studying and commuting) by 0.27 hours or 26% per 7-hour WFH day. Of this, 0.10 hours reflect reduced paid work, suggesting that roughly two-thirds of the total reduction comes from commuting time savings and the rest from shorter working hours. Women who WFH at least once per week reduce paid working hours by 8%, on average.

Among men, the only significant effect is a 0.04-hour increase in domestic work per additional hour WFH—equivalent to a 18% increase per 7-hour WFH day relative to 2019. This is smaller in absolute and relative terms than the corresponding effect for women. Effects on DIY activities, caregiving, and leisure are positive but statistically insignificant and weaker than for women. Interestingly, WFH has no discernible impact on men’s time spent on work-related activities (including commuting) or paid hours worked. This result may seem counterintuitive, given that commuting-time savings are a central benefit of remote work. However, it can be reconciled with the findings (presented in Section 5) that WFH opportunities also influence individuals’ work and living arrangements; in particular, by promoting moves to larger homes that involve *longer* commutes and by *reducing* the likelihood of exiting employment, i.e., not commuting at all.

Comparison with OLS. It is helpful to compare 2SLS to OLS to understand selection into WFH. The OLS results presented in Figure A.2 reveal that WFH take-up is correlated with a significant *increase* in women’s paid hours and a *decline* in their caregiving,

¹²Weekly hours worked are divided by five to match the weekday reference frame of the time-use module.

Figure 4: 2SLS estimates of the impact of WFH on individual time use



Notes: Panels A and B present 2SLS results based on Equations 2 and 3. Each coefficient comes from a separate IV regression of 2019–2022 time-use changes on WFH status, which corresponds to WFH at least once per week in 2022 (0/1) in Panel A and to the average number of hours WFH per weekday in 2022 (weekly hours WFH divided by five) in Panel B. The instrument is the WFH feasibility of individuals’ 2019 job (see Section 2.2 for details). Panel C shows the 2019 means of the dependent variables by gender. The sample includes individuals employed and aged 16–64 in 2019, who are observed again in 2022. 95% and 90%-confidence intervals are drawn using standard errors clustered by individual. Data are from the SOEP. Tables B.4 and B.3 present the corresponding point estimates and first-stage diagnostics.

in sharp contrast to the IV estimates. This pattern is consistent with the selection of women with higher caregiving demands and stronger labor market attachment into WFH to better reconcile market work and care. Indeed, the complier analysis in Section 5.3 shows that female always-takers (who work remotely regardless of baseline WFH feasibility) are younger, more likely to have children in the household, and more likely to desire an increase to their paid hours in 2019 than compliers and never-takers (who refuse WFH).

For men, OLS indicates that WFH comes with a significant rise in paid hours, whereas 2SLS shows no effect. This is consistent with performance-track selection: never-takers are older and more likely in 2019 to prefer a reduction in working hours than always-takers and compliers (Table B.9); meanwhile, career-oriented men face rising workloads and may adopt WFH to accommodate longer days (reverse causality). Firms may also be more inclined to grant WFH to employees on steeper career paths. In contrast, the IV estimate isolates compliers, whose WFH is induced by feasibility rather than career momentum, yielding an average effect close to zero.

Robustness. The 2SLS results are robust to alternative specifications and assumptions about the error structure, presented in [Table B.5](#). Row 1 in Panels A and B reproduces the baseline results for men and women, respectively using the binary WFH measure (standard errors clustered by individual; no controls). Row 2 shows that inference is unchanged when adjusting standard errors for two-way clustering by individual (to account for serially correlated shocks within persons) and household (allowing for correlated shocks among cohabiting partners) ([Cameron et al., 2011](#)). Row 3 reports p -values from a wild cluster bootstrap-t procedure with the null imposed to mitigate finite-sample distortions in 2SLS ([Young, 2022](#)). Inference remains unaffected.

A remaining concern is that pandemic-related shocks vary across industries and occupations and may correlate with changes in market and non-market labor supply. To address this, row 4 adds occupation fixed effects (14 segments, [Matthes et al., 2015](#)) and row 5 adds industry fixed effects (10 NACE-2 macro categories) to ensure that individuals are compared only *within* occupation and industry cells, respectively. Row 6 adds pre-determined covariates (measured in 2019) to further mitigate the risk of differential shocks. E.g., behavioral responses to the pandemic may depend on age and affect both infection risk and labor supply. Note that first differencing already nets out any time-invariant influences on time-use levels; thus, shocks are problematic if correlated with WFH feasibility and time-use *trends*. Covariates include demographics (age, age-squared, immigration background, educational attainment (3 categories)); household structure (dummies for cohabiting and marital status, the number of children under 14, dwelling size); location (state fixed effects); and job characteristics (firm tenure in years and firm size fixed effects (4 categories)). Row 7 estimates the most demanding specification with industry \times occupation fixed effects plus covariates. Across all variants, the core results are stable: WFH raises women’s domestic labor and lowers their paid hours; if anything, effect magnitudes increase relative to the baseline when including controls. There are no meaningful changes to men’s time use, on average. The positive effect of WFH on women’s leisure persists but is less precisely estimated when adding fixed effects; likely due to fixed effects absorbing part of the relevant variation in WFH feasibility across occupations and industries.

4.2 Couple-level results

The couple-level analysis allows us to study whether a partner’s WFH status influences individuals’ own time use. By focusing on cohabiting couples, the design isolates within-household differences and ensures that contextual factors, including (re)relocation or household composition, are constant across partners.

Table 2 presents the IV estimates of WFH’s impact on time use within couples. Panel A reports effects on the female partner’s time use; Panel B shows results for the male partner. Panel C relates each partner’s WFH status to the within-couple gender gap in time use (female minus male hours per weekday). By construction, these estimates equal the difference between the coefficients in Panels A and B.

WFH status is defined as WFH at least once per week (0/1). Results using average remote hours per weekday are similar and reported in Table B.8. In both cases, the Lewis-Mertens statistics (g_{min}) exceed the critical values at a significance level of $\alpha = 0.05$ and a relative bias threshold of $\tau = 0.1$, rejecting the null of weak instruments.¹³

Panel A shows that the estimates mirror the individual-level results: Women’s own WFH raises their time in domestic labor and lowers their time in market work (including commuting). The impact on care work is large (about 50% of the 2019 mean) but estimated imprecisely. In contrast, male partner WFH has no significant effect on women’s time use, on average. When both partners WFH, caregiving time rises significantly by 1.9 hours, while effects on leisure remain small and insignificant.

Panel B suggests that men’s own WFH raises their domestic and care work, though the effects are much smaller than for women. When the female partner works remotely, men tend to reduce their participation in domestic and care work. Male WFH is also associated with more time spent on paid work, though the estimates are imprecise.

Taken together, the estimates indicate that WFH widens gender gaps within couples (Panel C). When only the woman WFH, the domestic work gap increases by 0.83 hours; when only the man WFH, it narrows, but to a lesser extent. When both partners WFH, the gap increases modestly by 0.11 hours per day (column 1). Scaling the coefficients by the average WFH rates of both partners, the impact is nearly zero.

A similar pattern emerges for caregiving. Male WFH does not significantly affect the care gap, but female WFH increases it. When both partners work remotely, the gender gap in care work rises by 1.2 hours. In the average couple, the gap increases by 0.34 hours or 23% relative to 2019 (column 3). DIY and leisure gaps show no significant change.

For paid work, both partners’ WFH contributes to a widening gender gap (columns 5 and 6). While individual effects are not or only marginally significant, their sum

¹³Lewis *et al.* (2024) generalize the Olea and Pflueger (2013) robust effective F -statistic for testing weak instruments based on a worst-case benchmark for the 2SLS bias to models with multiple endogenous regressors under heteroskedasticity and serial correlation.

is sizable: when both partners WFH, the paid hours gap increases by 1.4 hours per weekday (column 6). For the average couple, this implies a rise of 0.42 hours, or 18% relative to 2019.

In sum, the couple-level analysis corroborates the individual-level findings: among the population employed shortly before the Covid crisis, the Big Shift to WFH intensifies gender inequality in both paid and unpaid labor.

Robustness. Table B.6 presents robustness checks for the couple-level estimates. For brevity, I focus on the effects on the within-couple gender gap (female-male differences in time use). Panel I reproduces the baseline from Panel C of Table 2 (no controls, standard errors clustered by couple). p -values from a wild-cluster bootstrap with the null imposed are reported in square brackets (Young, 2022); despite the smaller couple sample, inference remains consistent. Panel II adds household-level covariates (the number of children under 14 living in the household, dwelling size, state fixed effects, household size, and household net income.). Panel III introduces two sets of fixed effects for the male and female partners' industries in 2019, respectively. Panel IV further adds fixed effects for both partners' occupations. The results from the alternative specifications bolster the baseline: WFH widens gaps in caregiving and paid hours in the average couple. Only in the most stringent specification (Panel IV), the caregiving effect turns insignificant, likely due to fixed effects leaving limited within-cell variation, which reduces precision.

Table 2: 2SLS estimates of the impact of WFH (at least once per week) on couples' time-use

	(1)	(2)	(3)	(4)	(5)	(6)
	Δ Time use for					
	Dom. work (incl. errands)	DIY activities	Care work	Leisure (incl. sleep, exercise)	Work (incl. studying, commuting)	Paid work
Panel A: Effect on female partner's time use						
Female partner's WFH, 2022 (0/1)	0.647** (0.293)	-0.182 (0.155)	1.311 (0.893)	-0.049 (0.328)	-1.209** (0.610)	-0.518 (0.517)
Male partner's WFH, 2022 (0/1)	-0.268 (0.234)	0.142 (0.131)	0.611 (0.755)	-0.054 (0.288)	0.108 (0.518)	-0.080 (0.429)
Combined effect ($\hat{\gamma}_1 + \hat{\gamma}_2$)	.379 (.236)	-.041 (.117)	1.921*** (.706)	-.103 (.273)	-1.101** (.512)	-.597 (.436)
2019 DV mean	2.825	.401	2.571	8.498	7.019	6.063
Panel B: Effect on male partner's time use						
Female partner's WFH, 2022 (0/1)	-0.178 (0.267)	-0.256 (0.169)	-0.056 (0.375)	-0.055 (0.395)	0.096 (0.536)	0.279 (0.491)
Male partner's WFH, 2022 (0/1)	0.449** (0.198)	0.266* (0.143)	0.755** (0.312)	-0.084 (0.326)	0.067 (0.451)	0.505 (0.419)
Combined effect ($\hat{\gamma}_1 + \hat{\gamma}_2$)	.271 (.276)	.01 (.165)	.699** (.303)	-.14 (.361)	.163 (.479)	.784* (.451)
2019 DV mean	1.437	.582	1.057	8.295	9.352	8.364
Panel C: Effect on couple's time-use gap (W-M)						
Female partner's WFH, 2022 (0/1)	0.825** (0.381)	0.074 (0.218)	1.367* (0.786)	0.006 (0.458)	-1.305* (0.747)	-0.797 (0.636)
Male partner's WFH, 2022 (0/1)	-0.717** (0.300)	-0.124 (0.186)	-0.144 (0.669)	0.030 (0.385)	0.041 (0.643)	-0.585 (0.530)
Combined effect ($\hat{\gamma}_1 + \hat{\gamma}_2$)	.109 (.35)	-.05 (.181)	1.222** (.607)	.036 (.396)	-1.264* (.648)	-1.381** (.571)
Average effect ($\hat{\gamma}_1 \times \overline{WFH22^f} + \hat{\gamma}_2 \times \overline{WFH22^m}$)	.002 (.104)	-.019 (.054)	.341* (.18)	.011 (.118)	-.357* (.194)	-.415** (.17)
2019 DV mean	1.389	-.181	1.514	.203	-2.333	-2.301
#Couples	875	875	875	875	875	875
<i>First-stage diagnostics</i>						
Lewis-Mertens statistic (g_{min})	80.51	80.51	80.51	80.51	80.51	80.51
g_{min} critical values ($\alpha = 0.05, \tau = 0.1$)	20.22	20.22	20.22	20.22	20.22	20.22

Notes: The table presents 2SLS results based on Equations 4–6. Time-use gaps (Panel C) refer to the female-male differences in hours spent on a given activity on an average weekday within a couple. The instruments are the WFH feasibility [0,1] of each partner's 2019 job (see Section 2.2 for details). The sample includes couples in which both partners are employed and aged 16–64 in 2019, and observed again in 2022. Standard errors are clustered by couple and reported in parentheses. Data are from the SOEP. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

5 Heterogeneity and Mechanisms

5.1 Effects on individual work and living conditions

To examine potential mechanisms, [Table 3](#) reports 2SLS results of the impact of WFH on work and living conditions by gender. WFH status corresponds to a dummy for WFH at least once per week in 2022. [Table B.7](#) presents results using average hours WFH per weekday.

For men, WFH increases the probability of moving to a different dwelling by 6.5 percentage points (p.p.), with no significant effect for women (column 1). This gender difference is consistent with persistently higher job-related mobility among men ([Jayachandran et al., 2024](#)). Conditional on moving, WFH changes housing conditions for both genders: the number of rooms increases significantly, and living space tends to expand relative to 2019 (columns 2 and 3); the effects are stronger with more intensive WFH ([Table B.7](#)). These findings substantiate evidence from the urban and real estate literature that WFH raises demand for space and facilitates moves to peripheral areas of cities ([Akan et al., 2025](#); [Althoff et al., 2022](#); [Gupta et al., 2022](#); [Delventhal and Parkhomenko, 2023](#); [Coskun et al., 2024](#)).¹⁴

WFH also reduces the likelihood of exiting employment (column 4).¹⁵ The impact is larger for women (albeit not statistically significant), aligning with pre-Covid evidence that WFH narrows the motherhood employment penalty and improves women's labor market attachment ([Harrington and Kahn, 2023](#)). Importantly, the results highlight an asymmetry in female labor supply: WFH strengthens participation at the extensive margin, but reduces it at the intensive margin, as employed women cut back on hours.

Column 5 shows that WFH reduces the likelihood of changing employer, especially for women. This corroborates evidence from field and discrete choice experiments that WFH increases worker retention by conferring a valuable amenity, which women tend to appreciate more strongly than men ([Bloom et al., 2024, 2015](#); [Nagler et al., 2024](#); [Mas and Pallais, 2017](#)). The reduction in women's paid hours when WFH is accompanied by a slower wage growth of about 0.20 log points (column 6). Roughly 45% of this decline reflects a penalty on hourly wage growth of 0.09 log points (column 7). This is consistent with employers sharing part of WFH's amenity value with female employees. At the same time, prior evidence also suggests that WFH combined with

¹⁴Unfortunately, the 2022 wave of the SOEP does not elicit commuting distance.

¹⁵Individuals who exit employment (by leaving the labor force or going into unemployment) have zero working hours (from home).

domestic care responsibilities may reduce women’s productivity (and possibly hourly wages) through more frequent work interruptions (Adams *et al.*, 2025). Notably, no wage growth penalty is observed for men working remotely. This asymmetry suggests that WFH tends to weaken women’s bargaining position in the household and potentially their ability to negotiate a more equal division of labor. Section 5.2 further investigates the intra-household bargaining channel.

Finally, WFH has no significant impact on marital status or the presence of children under 14 in the household (columns 8–10). Likewise, the number of children is not affected by WFH (not shown in the table), suggesting little short-run effect on household structure or fertility, on average.

Table 3: 2SLS estimates of the impact of WFH (at least once per week) on work and living conditions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Moved (0/1)	Δ #Rooms	Δ Log living space	Left employm. (0/1)	Employer change (0/1)	Δ Log gross labor income	Δ Log gross hrly wage	Δ Married (0/1)	Δ Single (0/1)	Δ Children <14 (0/1)
Panel A: Women										
WFH at least 1x/week in 2022	-0.017 (0.029)	0.301** (0.118)	0.039 (0.026)	-0.076** (0.031)	-0.160*** (0.036)	-0.199*** (0.050)	-0.091** (0.046)	0.000 (0.026)	-0.027 (0.017)	0.027 (0.036)
#Individuals	2,992	2,972	2,992	2,992	2,624	2,624	2,607	2,991	2,991	2,992
DV mean	.103	4.376	4.634	.123	.186	7.575	2.748	.586	.252	.355
First-stage coef.	0.39 [738.6]	0.39 [735.3]	0.39 [738.6]	0.39 [738.6]	0.43 [784.3]	0.43 [772.2]	0.43 [777.9]	0.39 [739.2]	0.39 [739.2]	0.39 [738.6]
Panel B: Men										
WFH at least 1x/week in 2022	0.065** (0.026)	0.230** (0.112)	0.041* (0.022)	-0.048** (0.024)	-0.037 (0.028)	-0.005 (0.036)	0.043 (0.039)	0.010 (0.021)	-0.015 (0.016)	0.001 (0.030)
#Individuals	2,513	2,488	2,513	2,513	2,270	2,269	2,256	2,511	2,511	2,513
2019 DV mean	.111	4.38	4.632	.097	.145	8.122	2.979	.641	.275	.353
First-stage coef.	0.48 [926.3]	0.48 [914.2]	0.48 [926.3]	0.48 [926.3]	0.53 [1001.0]	0.52 [985.7]	0.53 [995.8]	0.48 [927.0]	0.48 [927.0]	0.48 [926.3]
<i>p</i> -values test of equal effects	0.0337	0.6613	0.9467	0.4766	0.0065	0.0015	0.0258	0.7517	0.6090	0.5831

Notes: The table presents 2SLS results based on Equations 2 and 3, estimated separately by gender. The instrument is the WFH feasibility (0/1) of individuals’ 2019 job (see Section 2.2 for details). The sample includes individuals employed and aged 16–64 in 2019, who are observed again in 2022. Columns 5–7 exclude individuals who are not employed in 2022. Kleibergen-Paap *F*-statistic for the first-stage regression in brackets. Standard errors are clustered by individual and reported in parentheses. Data are from SOEP. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

5.2 Interactions with gender norms, bargaining power, and caregiving needs

To understand why WFH reinforces a more traditional gender division of labor on average, I explore heterogeneity along three determinants of labor supply: norms, constraints, and bargaining. First, political leaning plausibly captures variation in gender norms, which influence preferences over the allocation of (un)paid labor. Second, the presence and age of children capture time constraints and caregiving demands, and condition how individuals can use the flexibility afforded by WFH. And third, individuals' relative income share within the household reflect intra-couple bargaining power and may influence time-use negotiations in the context of WFH.

I estimate separate 2SLS models with an interaction term between WFH and each dimension and report the marginal effects of WFH across their distributions; specifically the outcome equation at the individual level corresponds to:

$$\Delta y_i = \alpha_0 + \alpha_1 \times WFH22_i \times Z_i + \alpha_2 \times WFH22_i + \alpha_3 \times Z_i + \epsilon_i, \quad (7)$$

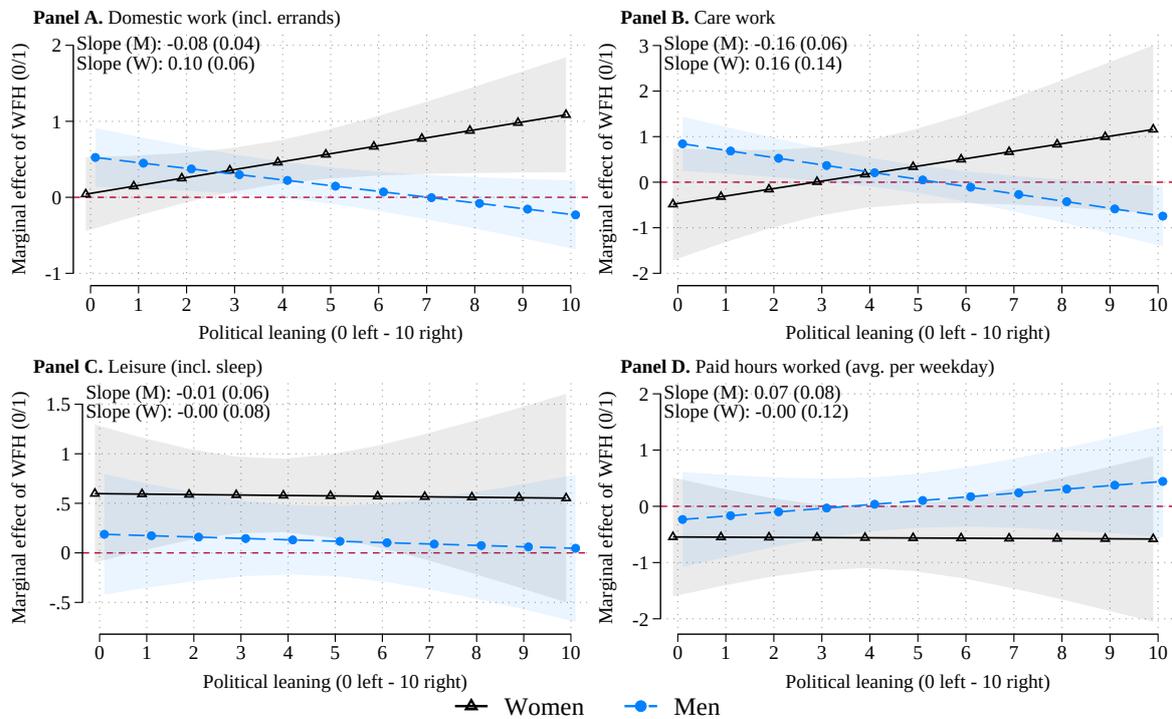
where Z_i denotes a (time-invariant) candidate moderator. The 2SLS estimate is obtained by instrumenting WFH status (WFH at least once per week 0/1) and the interaction term with Z_i by WFH feasibility and an analogous interaction with WFH feasibility.

Gender norms. First, I examine effect heterogeneity by individuals' political leaning, which is elicited on a 10-point scale from 0 (left) to 10 (right). Political leaning typically correlates strongly with gender role attitudes ([Nennstiel and Hudde, 2025](#); [Oswald and Powdthavee, 2010](#)). On average, men are somewhat more conservative than women (4.61 vs. 4.36). The question is whether individuals may use WFH differently in ways that reflect their gender norms. If so, we would expect WFH to reinforce traditional divisions of labor among more conservative individuals and to shift time-use toward a more egalitarian division among those with progressive attitudes.

[Figure 5](#) plots the marginal effects of WFH at least once per week (0/1) on time-use changes across the distribution of individuals' political leaning. Panels A and B clearly support the gender norm channel: among women, the effects of WFH on domestic work and caregiving become more positive with increasingly conservative views. The pattern is reversed among men: WFH increases participation in household labor as attitudes become more progressive. Given average political attitudes, WFH interacts with gender norms to widen the gender gap in household labor. I find no clear interaction between WFH and political leaning for leisure and a suggestive interaction

for paid hours: the marginal effect of WFH on working hours increases slightly with conservative views among men.

Figure 5: Marginal effects of WFH (0/1) on time use by political leaning (2SLS estimates)



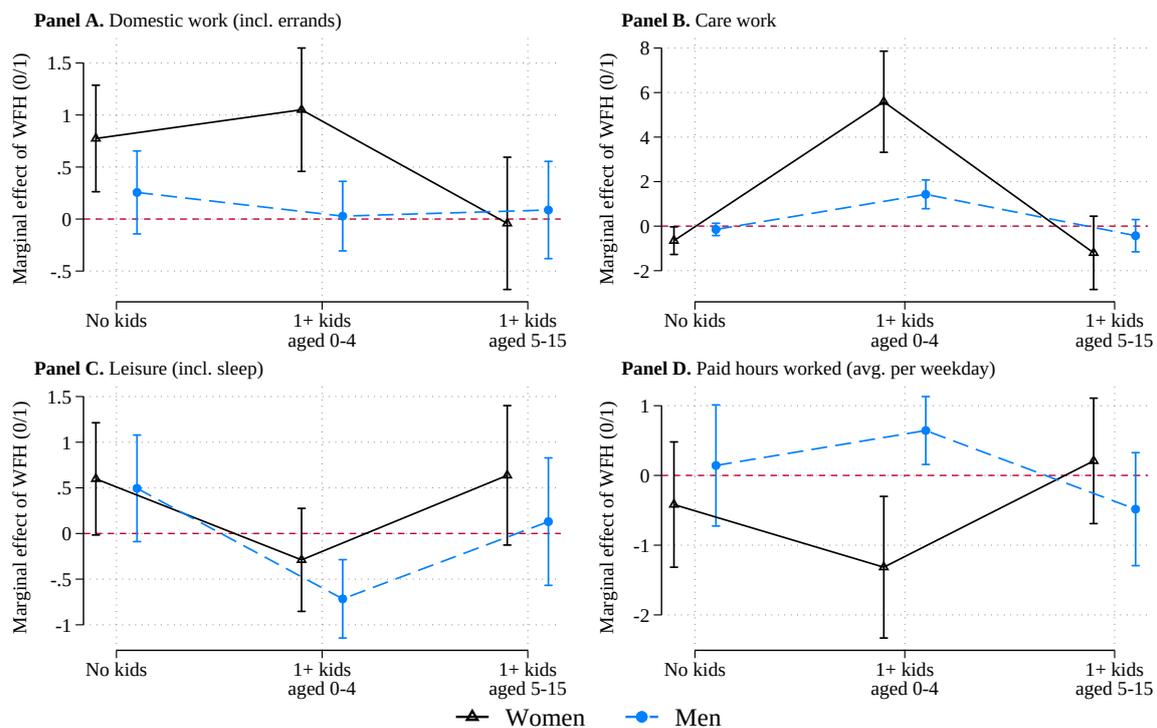
Notes: Panels A–D show 2SLS estimates based on Equation 7, estimated separately by gender. Plotted are the marginal effects of WFH at least once per week in 2022 (0/1) on time-use changes (2019–2022) across the distribution of individuals’ political leaning, elicited on a 10-point scale from 0 (left) to 10 (right). The sample includes individuals employed and aged 16–64 in 2019. Confidence bands are drawn at the 95% level using standard errors clustered by individual. Data are from the SOEP.

Children. Second, childcare needs raise time constraints and the opportunity costs of alternative time uses, including leisure or market labor (Aguiar and Hurst, 2007). Consequently, relaxing the time budget constraint via WFH likely causes different reallocation of time depending on the presence and age of children. Primarily, parents are expected to divert more time toward household labor. I examine possible heterogeneity by caregiving needs using a categorical variable that distinguishes between households without children, those with at least one child aged 0–4, and those with at least one child aged 5–15.

Figure 6 plots the marginal effects of WFH at least once per week (0/1) on time-use changes by the presence and age of children. The results show clear gender asymmetries. Among women, WFH increases time spent on domestic and care work, particularly when a young child is present, consistent with heightened caregiving demands

(Panels A and B). These effects are muted or absent for older children or when no children are present. Among men, time use remains largely unaffected across child age groups. Care work increases slightly with young children, but the effect is small relative to that for women (Panel B). For leisure, WFH reduces time use when caregiving needs are high and increases time use for childless households. For paid work, WFH reduces hours primarily for women with young children. Interestingly, WFH has the opposite effect for men with young children. When caregiving demands are minimal or absent, WFH does not significantly affect paid work hours for either gender. Taken together, the results suggest that childcare needs amplify gendered responses to WFH as women reallocate time toward unpaid labor, while men’s time allocation remains largely stable or shifts toward market work.

Figure 6: Marginal effects of WFH (0/1) on time use by presence of children (2SLS estimates)



Notes: Panels A–D show 2SLS estimates based on Equation 7, estimated separately by gender. Plotted are the marginal effects of WFH at least once per week in 2022 (0/1) on time-use changes (2019–2022) by the presence of children in the household, measured by 3 mutually exclusive categories (no children, at least one child aged 0–4, at least one child aged 5–15). The sample includes individuals with a cohabiting partner, and who are employed and aged 16–64 in 2019. Confidence intervals are drawn at the 95% level using standard errors clustered by individual. Data are from the SOEP.

Bargaining power. Third, I examine effect heterogeneity by individuals’ labor share of household income among individuals with a cohabiting partner. A higher share approximates a greater economic bargaining weight in the collective household bar-

gaining framework. The idea is that individuals with stronger bargaining positions may more effectively use WFH to negotiate favorable changes to the division of labor according to their preferences.

Figure 7 plots the marginal effects of WFH at least once per week (0/1) on time-use changes across the distribution of household income shares. In Panels A and B, the marginal effect curves are downward sloping for both genders, suggesting that WFH is used to reduce unpaid labor when bargaining power is higher. No clear effect is detectable for leisure. If anything, women with higher relative income use WFH to reduce leisure time and increase their market labor supply (Panel D). The opposite pattern holds for men, but the estimates are imprecise. Overall, these results align with bargaining models: partners with greater relative income—especially women—appear more able to shield their time for paid work and reduce the burden of unpaid labor under WFH. Ultimately, the bargaining channel strengthens the inequality in the division of labor as household income is disproportionately concentrated among men relative to women (63.22% vs. 36.25%).

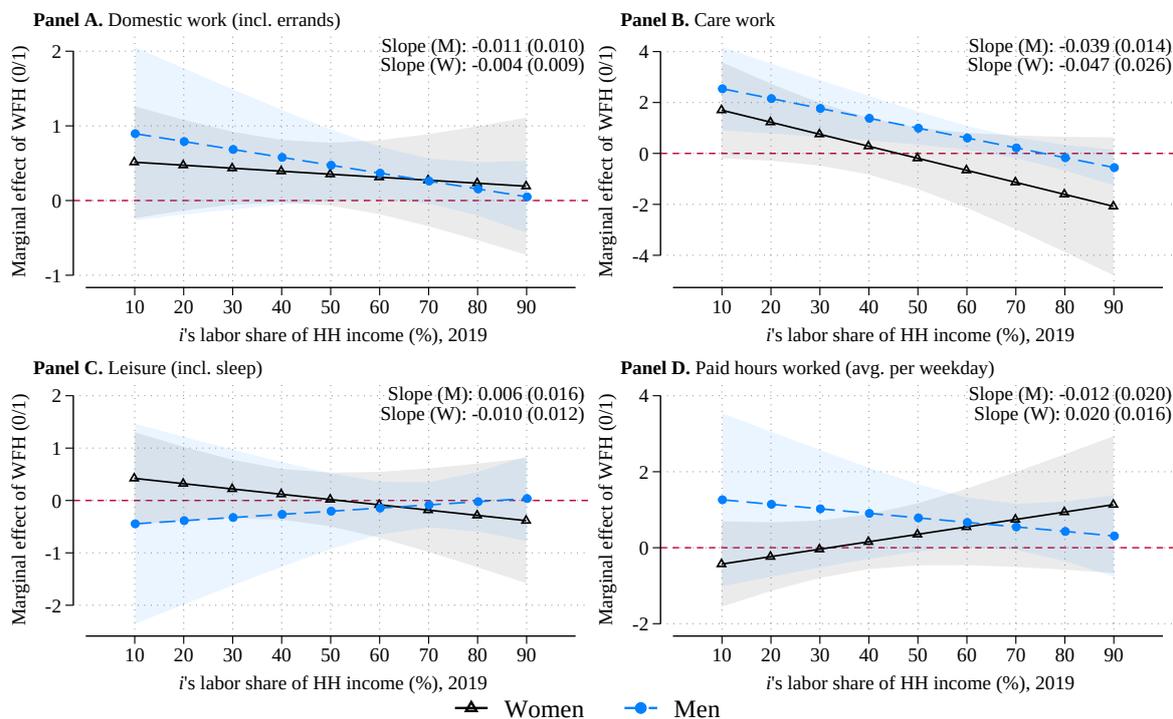
5.3 Complier analysis

The IV estimates identify local average treatment effects (LATE) for the subpopulation of compliers, i.e., individuals who work remotely if and only if their 2019 job is WFH feasible. Results may not be generalizable if treatment effects are heterogeneous and compliers differ strongly from the broader sample. I assess differences in pre-determined characteristics using the methodology by [Marbach and Hangartner \(2020\)](#); [Hangartner et al. \(2021\)](#). The approach provides a simple way of identifying and characterizing compliers relative to never-takers (who refuse to WFH) and always-takers (who WFH regardless of initial WFH feasibility).¹⁶

Figure 8 presents covariate means with 95%-confidence intervals for the full sample and the complier, never-taker, and always-taker subpopulations by gender (corresponding point estimates in [Table B.9](#)). Compliers are a sizable share of the sample: 39% of women and 48% of men; never-takers account for 55% (women) and 44% (men), and always-takers for 6% and 8%, respectively. Hence, the 2SLS estimates speak to a meaningful subpopulation. Indeed, standardized differences between sam-

¹⁶Under the standard IV assumptions, observable always-takers (individuals assigned to control who take the treatment) and never-takers (treated who refuse treatment) have identical covariate distributions as their non-observable counterparts, allowing direct estimation of their covariate means. Complier means are identified indirectly by subtracting the weighted covariate means of always-takers and never-takers from the overall sample mean ([Marbach and Hangartner, 2020](#)).

Figure 7: Marginal effects of WFH (0/1) on time use by labor share of household income (2SLS estimates)



Notes: Panels A–D show 2SLS estimates based on Equation 7, estimated separately by gender. Plotted are the marginal effects of WFH at least once per week in 2022 (0/1) on time-use changes (2019–2022) across the distribution of individuals’ labor share of household income. The sample includes individuals with a cohabiting partner, and who are employed and aged 16–64 in 2019. Confidence bands are drawn at the 95% level using standard errors clustered by individual. Data are from the SOEP.

ple and complier means fall below the conventional 0.25 threshold for nearly all covariates, indicating limited imbalances (Imbens and Rubin, 2015).

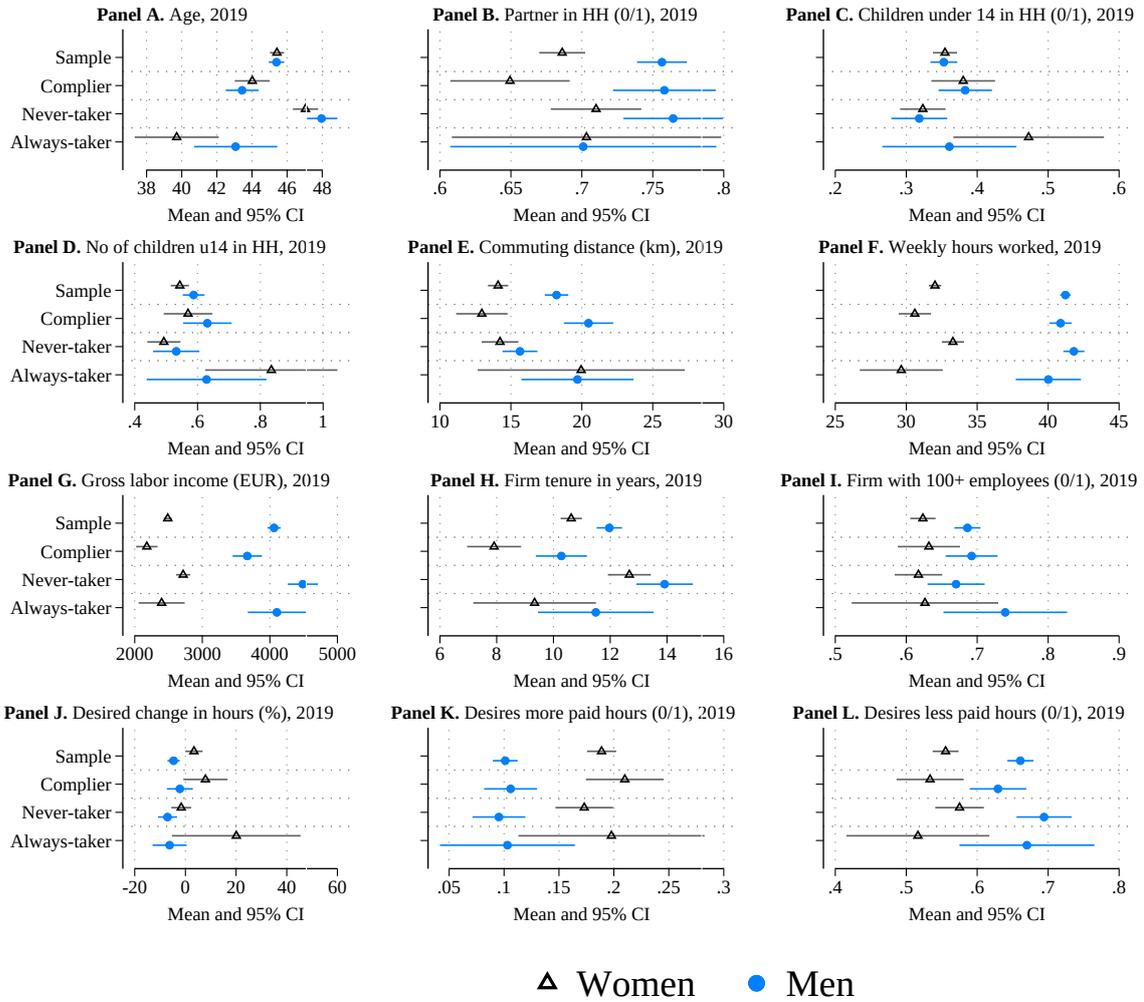
However, compliers differ relative to never-takers and always-takers in some dimensions. For both genders, there is an age gradient in WFH adoption: always-takers are youngest, compliers intermediate, never-takers oldest (Panel A). Subsequently, compliers have shorter firm tenures, lower incomes, and fewer paid hours in 2019 compared to never-takers (Panels F, G, H). On desired market work, female never-takers target a 1.62% reduction in hours in 2019 versus +7.9% hours for compliers and +20% for always-takers (Panel J). They are also less likely to have children under 14 in the household and show lower commuting distance than always-takers, underscoring self-selection into WFH based on flexibility demands. These pre-treatment differences help explain OLS-IV differences (see Section 4.1). OLS loads on selection: the treated group contains always-takers with large time-saving and scheduling gains (long commutes, young children), yielding higher paid hours and lower caregiving; the control

group is dominated by never-takers, who already wanted to reduce market hours in 2019 and tend to reduce hours even without WFH. Consequently, once selection on gains is purged by IV, the impact of WFH on women's paid hours and caregiving flips sign.

Similarly, male never-takers are already more likely to desire a reduction in paid hours and show a higher discrepancy between desired and actual hours in 2019 (Panels J and L). Thus, the OLS estimate of WFH on paid hours is likely to misattribute a reduction in market work to *not* working from home. These patterns also provide little support for the concern that workers systematically select into WFH to “shirk from home”.

Extrapolating treatment effects beyond compliers is speculative: never-takers are more inclined to prefer fewer hours at baseline and exhibit weaker time potentials from WFH. Given that WFH's flexibility helps better accommodate time-use preferences (see [Section 5.2](#)), it is plausible that, if induced to WFH, never-takers (both male and female) would cut paid hours more strongly than compliers.

Figure 8: Complier analysis



Notes: The figure plots covariate means for the whole sample and the complier, never-taker, and always-taker subpopulations based on the methodology by [Marbach and Hangartner \(2020\)](#); [Hangartner et al. \(2021\)](#). The instrument is WFH feasibility (0/1), and the treatment is WFH at least once per week in 2022 (0/1). Among women, 39% of individuals are identified as compliers, 55% are never-takers, and 6% are always-takers. Among men, the proportions are 48% compliers, 44% never-takers, and 8% always-takers. The sample includes individuals employed and aged 16–64 in 2019, who are observed again in 2022. 95%-confidence intervals are calculated using bootstrapped standard errors (1,000 replications). [Table B.9](#) reports the corresponding point estimates and tests of equal means.

6 Conclusion

This paper investigates how the large-scale transition to WFH, triggered by the Covid-19 pandemic, impacts the gender division of labor. Drawing on plausibly exogenous individual-level variation in the exposure to the WFH shock, I estimate the effects of WFH on changes in time allocation to unpaid labor, paid work, and leisure. The results reveal marked asymmetries: women transitioning to WFH reduce time spent on paid work and shift it toward domestic labor and leisure. Men, by contrast, show little adjustment across time-use categories due to WFH, which can be explained by residential moves to larger, more distant homes that offset commuting time savings. Couple-level analyses of partners' time-use gaps bolster the finding that WFH exacerbates gender disparities. For the average couple, the gender gaps in market labor and unpaid work, notably in caregiving, intensify.

Three mechanisms help explain these patterns. First, individuals with more conservative gender norms use WFH to reinforce traditional divisions of labor. Second, men's greater economic bargaining power allows them to protect time for paid work. And third, greater childcare demands—disproportionately met by women—draw their time toward unpaid labor. These results challenge the view that greater job flexibility inherently advances gender equality. When the autonomy afforded by WFH interacts with existing social expectations and institutional incentives (e.g., the tax system), it ultimately tends to reinforce rather than mitigate the gendered division of labor.

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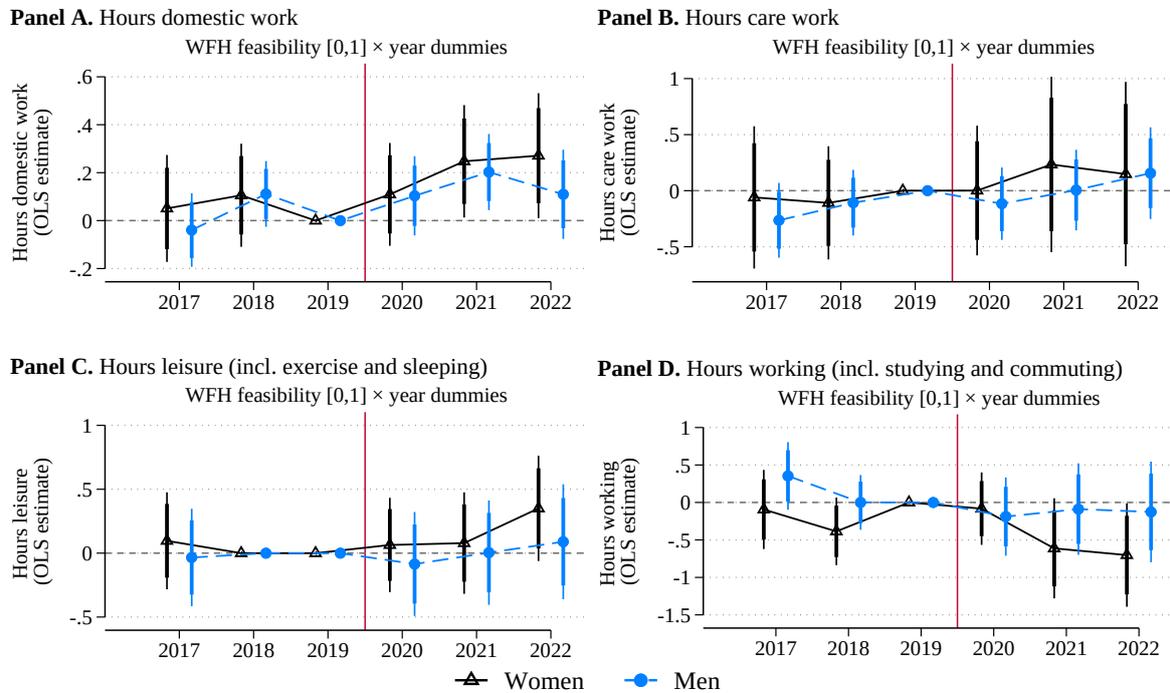
Appendix

Does Remote Work Reinforce Gender Gaps in (Un)Paid Labor?

by *Jean-Victor Alipour*

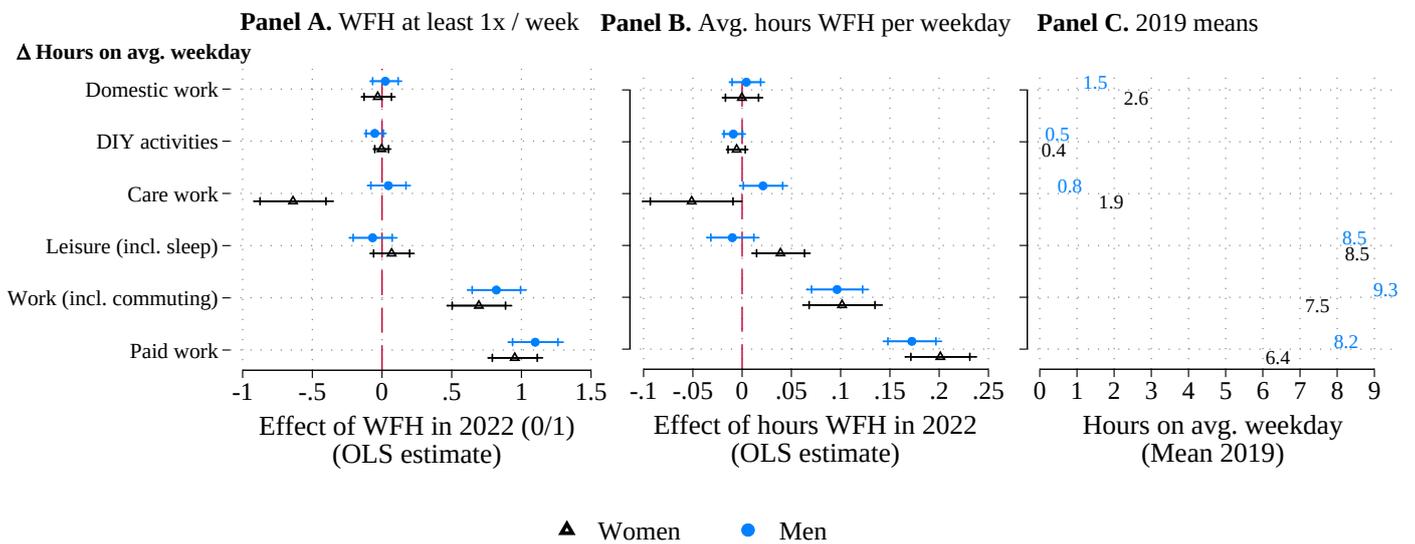
Appendix A Figures

Figure A.1: ITT effects of WFH on individual time use on an average weekday, balanced 2017–2022



Notes: The figure plots DiD estimates based on Equation 1. The sample includes individuals employed and aged 16–64 in 2019, balanced between 2017–2022. 99% and 95%-confidence intervals are drawn using standard errors clustered by individual. Data are from the SOEP.

Figure A.2: OLS estimates of the impact of WFH on individual time use



Notes: Panels A and B present OLS results based on Equation 2. Each coefficient comes from a separate OLS regression of 2019–2022 time-use changes on WFH status, which corresponds to WFH at least once per week in 2022 (0/1) in Panel A and to the average number of hours WFH per weekday in 2022 (weekly hours WFH divided by five) in Panel B. Panel C shows the 2019 means of the dependent variables by gender. The sample includes individuals employed and aged 16–64 in 2019, who are observed again in 2022. 95% and 90%-confidence intervals are drawn using standard errors clustered by individual. Data are from the SOEP.

Appendix B Tables

Table B.1: Summary statistics (couple level)

	(1) Women N = 875	(2) Men N = 875	(3) Within-couple gender gap (W-M)
A. WFH variables			
WFH at least 1x/week, 2022	0.283 (0.451)	0.323 (0.468)	-0.040 (0.568)
Weekly hours WFH, 2022 (all)	5.329 (10.588)	8.411 (14.220)	-3.083 (16.197)
Weekly hours WFH, 2022 (only WFH 1+/week)	18.373 (12.217)	24.802 (14.159)	-8.137 (16.766)
Share of hours WFH, 2022 (all)	0.181 (0.327)	0.200 (0.338)	-0.019 (0.421)
Share of hours WFH, 2022 (only WFH 1+/week)	0.561 (0.347)	0.591 (0.333)	-0.064 (0.446)
WFH feasibility (0/1), 2019	0.506 (0.500)	0.509 (0.500)	-0.002 (0.592)
WFH feasibility [0,1], 2019	0.372 (0.290)	0.370 (0.296)	0.002 (0.339)
B. Main outcome variables			
Hours leisure (incl. exercise and sleeping), 2019	8.498 (1.632)	8.295 (1.647)	0.203 (1.913)
Δ Hours leisure (incl. exercise and sleeping)	0.124 (1.769)	0.329 (2.116)	-0.205 (2.411)
Hours working (incl. studying and commuting), 2019	7.019 (2.625)	9.352 (1.771)	-2.333 (3.158)
Δ Hours working (incl. studying and commuting)	-0.549 (3.183)	-1.094 (3.075)	0.545 (4.132)
Hours care work, 2019	2.571 (3.627)	1.057 (1.654)	1.514 (3.061)
Δ Hours care work	0.144 (4.482)	0.089 (1.934)	0.055 (3.952)
Hours domestic work (incl. errands), 2019	2.825 (1.321)	1.437 (1.028)	1.389 (1.727)
Δ Hours domestic work (incl. errands)	0.271 (1.508)	0.502 (1.562)	-0.231 (2.065)
Hours DIY activities, 2019	0.401 (0.582)	0.582 (0.805)	-0.181 (0.877)
Δ Hours DIY activities	0.321 (0.769)	0.472 (1.019)	-0.151 (1.183)
Weekly hours worked, 2019	30.316 (11.801)	41.822 (8.194)	-11.505 (14.677)
Δ Weekly hours worked	-2.737 (13.289)	-5.151 (14.340)	2.414 (17.784)

Notes: The table reports variable means and standard deviations (in parentheses) for female and male partners of the same couple. Column 3 reports within-couple gender differences. The sample includes couples in which both partners are employed and aged 16–64 in 2019, and who completed the time-use questionnaire in 2019 and 2022. The operator Δ denotes changes between 2019 and 2022. The data are from the SOEP.

Table B.2: First stage by individual characteristic

Sample	Dep. variable		(3) Observations (#Individuals)
	(1) Avg. hours WFH per weekday	(2) WFH at least 1x/week (0/1)	
Sector: Agriculture & natural resources (A, B)	1.779 (1.046)*	0.660 (0.306)**	52
Sector: Food, beverages, tobacco (C10–12)	2.466 (0.982)**	0.653 (0.212)***	96
Sector: Machinery & transport equipment (C28–30)	4.958 (0.434)***	0.873 (0.069)***	372
Sector: Other manufacturing (C13–27, C31–33)	4.398 (0.362)***	0.810 (0.058)***	609
Sector: Other industry incl. construction (D, E, F)	3.052 (0.390)***	0.744 (0.075)***	311
Sector: Trade, transport, tourism (G, H, I)	3.421 (0.383)***	0.653 (0.064)***	927
Sector: Knowledge-intensive services (J, K, L, M)	2.637 (0.625)***	0.497 (0.092)***	748
Sector: Other business & personal services (N, R, S)	2.814 (0.331)***	0.726 (0.064)***	389
Sector: Public admin & education (O, P)	2.959 (0.242)***	0.739 (0.047)***	1,050
Sector: Health, social & other non-market services (Q, T, U)	2.324 (0.310)***	0.615 (0.065)***	951
Occupation: S11 Land/forestry/horticulture	5.242 (2.086)**	1.797 (0.583)***	72
Occupation: S12 Manufacturing/crafts	4.301 (0.948)***	0.948 (0.135)***	208
Occupation: S13 Engineering & manuf. tech	4.499 (0.488)***	0.902 (0.084)***	529
Occupation: S14 Construction & building services	4.047 (0.795)***	0.948 (0.143)***	220
Occupation: S21 Food & hospitality	5.916 (1.432)***	0.784 (0.189)***	196
Occupation: S22 Health (medical & non-medical)	1.230 (0.463)***	0.478 (0.143)***	556
Occupation: S23 Social & cultural services	3.818 (0.313)***	0.818 (0.054)***	872
Occupation: S31 Trade & sales	4.638 (0.446)***	0.903 (0.069)***	462
Occupation: S32 Management & organisation	6.072 (0.858)***	1.077 (0.138)***	681
Occupation: S33 Business services (finance, law, media)	4.945 (0.690)***	0.966 (0.123)***	820
Occupation: S41 IT & natural sciences	6.338 (0.765)***	0.874 (0.110)***	298
Occupation: S51 Security	7.842 (3.404)**	1.500 (0.579)**	110
Occupation: S52 Transport & logistics	6.220 (1.418)***	0.991 (0.210)***	351
Occupation: S53 Cleaning	0.000 (0.000)	0.000 (0.000)	130
Job skill level: Unskilled	1.575 (0.689)**	0.384 (0.130)***	455
Job skill level: Skilled	2.933 (0.177)***	0.666 (0.033)***	2,643
Job skill level: Specialist	3.366 (0.291)***	0.639 (0.052)***	992
Job skill level: Expert	4.582 (0.316)***	0.818 (0.051)***	1,415
Age: 16-25	4.144 (0.588)***	0.727 (0.102)***	275
Age: 26-30	5.159 (0.417)***	0.938 (0.056)***	414
Age: 31-35	4.414 (0.392)***	0.882 (0.059)***	449
Age: 36-40	4.255 (0.305)***	0.828 (0.051)***	652
Age: 41-45	4.168 (0.283)***	0.878 (0.047)***	743
Age: 46-50	4.307 (0.257)***	0.909 (0.041)***	910
Age: 51-55	3.890 (0.246)***	0.804 (0.041)***	921
Age: 56-60	2.816 (0.286)***	0.607 (0.049)***	735
Age: 61-64	1.663 (0.349)***	0.368 (0.058)***	406
Firm size: under 5	2.816 (0.579)***	0.573 (0.089)***	272
Firm size: 5-9	1.898 (0.400)***	0.415 (0.073)***	351
Firm size: 10-19	2.869 (0.450)***	0.524 (0.076)***	374
Firm size: 20-99	3.085 (0.255)***	0.690 (0.044)***	907
Firm size: 100-199	2.675 (0.321)***	0.682 (0.062)***	449
Firm size: 200-1999	3.971 (0.218)***	0.832 (0.036)***	1,244
Firm size: 2000+	4.795 (0.186)***	0.916 (0.028)***	1,877
College degree: 0	3.051 (0.145)***	0.658 (0.026)***	3,617
College degree: 1	4.207 (0.225)***	0.766 (0.038)***	1,869

Notes: The table reports first-stage regressions of WFH status on WFH feasibility [0,1] at the individual level. WFH status corresponds to the average number of hours WFH per weekday in 2022 (weekly hours WFH divided by five) in column 1 and to a dummy for WFH at least once per week in 2022 in column 2. Each coefficient comes from an OLS regression estimated on a different subsample determined by an individual characteristic measured in 2019. Standard errors are clustered by individual and reported in parentheses. Data are from the SOEP. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table B.3: 2SLS estimates of the impact of WFH (at least once per week) on individual time use

	(1)	(2)	(3)	(4)	(5)	(6)
	Δ Hours spent on average weekday on					
	Dom. work (incl. errands)	DIY activities	Care work	Leisure (incl. sleep, exercise)	Work (incl. studying, commuting)	Paid work
Panel A: Women						
WFH at least 1x/week in 2022	0.457*** (0.146)	0.071 (0.079)	0.167 (0.372)	0.620*** (0.189)	-1.251*** (0.329)	-0.538** (0.274)
#Individuals	2,992	2,992	2,992	2,992	2,992	2,992
2019 DV mean	2.59	.373	1.923	8.541	7.47	6.405
Prop. effect at the mean	.177	.189	.087	.073	-.167	-.084
First-stage coef.	0.39 [738.55]	0.39 [738.55]	0.39 [738.55]	0.39 [738.55]	0.39 [738.55]	0.39 [738.55]
Panel B: Men						
WFH at least 1x/week in 2022	0.193 (0.118)	0.145* (0.087)	0.151 (0.154)	0.111 (0.174)	-0.045 (0.258)	0.037 (0.236)
#Individuals	2,513	2,513	2,513	2,513	2,513	2,513
2019 DV mean	1.496	.473	.814	8.47	9.308	8.244
Prop. effect at the mean	.129	.306	.186	.013	-.005	.004
First-stage coef.	0.48 [926.31]	0.48 [926.31]	0.48 [926.31]	0.48 [926.31]	0.48 [926.31]	0.48 [926.31]
<i>p</i> -values test of equal effects	0.1597	0.5295	0.9694	0.0477	0.0040	0.1124

Notes: The table presents 2SLS results based on Equations 2 and 3, estimated separately by gender. The explanatory variable of interest is a dummy identifying individuals who WFH at least once per week in 2022. The instrument is the WFH feasibility (0/1) of individuals' 2019 job (see Section 2.2 for details). The sample includes individuals employed and aged 16–64 in 2019, who are observed again in 2022. Kleibergen-Paap *F*-statistic for the first-stage regression in brackets. Standard errors are clustered by individual and reported in parentheses. Data are from the SOEP. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table B.4: 2SLS estimates of the impact of WFH (hours per weekday) on individual time use

	(1)	(2)	(3)	(4)	(5)	(6)
	Δ Hours spent on average weekday on					
	Dom. work (incl. errands)	DIY activities	Care work	Leisure (incl. sleep, exercise)	Work (incl. studying, commuting)	Paid work
Panel A: Women						
Hours WFH per weekday, 2022	0.104*** (0.032)	0.018 (0.017)	0.069 (0.080)	0.124*** (0.040)	-0.273*** (0.069)	-0.099* (0.059)
#Individuals	2,992	2,992	2,992	2,992	2,992	2,992
2019 DV mean	2.59	.373	1.923	8.541	7.47	6.405
Prop. effect at the mean	.04	.047	.036	.015	-.037	-.016
First-stage coef.	3.13 [543.86]	3.13 [543.86]	3.13 [543.86]	3.13 [543.86]	3.13 [543.86]	3.13 [543.86]
Panel B: Men						
Hours WFH per weekday, 2022	0.039** (0.020)	0.018 (0.015)	0.023 (0.026)	0.020 (0.030)	-0.020 (0.044)	0.005 (0.041)
#Individuals	2,513	2,513	2,513	2,513	2,513	2,513
2019 DV mean	1.496	.473	.814	8.466	9.308	8.244
Prop. effect at the mean	.026	.038	.029	.002	-.002	.001
First-stage coef.	4.78 [803.21]	4.78 [803.21]	4.78 [803.21]	4.78 [803.21]	4.78 [803.21]	4.78 [803.21]
<i>p</i> -values test of equal effects	0.0795	0.9809	0.5846	0.0364	0.0019	0.1429

Notes: The table presents 2SLS results based on Equations 2 and 3, estimated separately by gender. The explanatory variable of interest is the average number of hours worked from home per weekday in 2022 (weekly hours WFH divided by five). The instrument is the WFH feasibility [0,1] of individuals' 2019 job (see Section 2.2 for details). The sample includes individuals employed and aged 16–64 in 2019, who are observed again in 2022. Kleibergen-Paap *F*-statistic for the first-stage regression in brackets. Standard errors are clustered by individual and reported in parentheses. Data are from the SOEP. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table B.5: Robustness: 2SLS estimates of the impact of WFH (at least once per week) on individual time use

	Δ Hours spent on average weekday on					
	(1)	(2)	(3)	(4)	(5)	(6)
	Dom. work (incl. errands)	DIY activities	Care work	Leisure (incl. sleep, exercise)	Work (incl. studying, commuting)	Paid work
Panel A: Women						
1 Baseline (Clustering by person, no controls)	0.457*** (0.146)	0.071 (0.079)	0.167 (0.372)	0.620*** (0.189)	-1.251*** (0.329)	-0.538** (0.274)
2 Two-way clustering by person & household	0.457*** (0.146)	0.071 (0.079)	0.167 (0.372)	0.620*** (0.189)	-1.251*** (0.330)	-0.538** (0.274)
3 Wild cluster bootstrap-t by person	0.457*** [.0019]	0.071 [.3852]	0.167 [.6508]	0.620*** [.0008]	-1.251*** [.0001]	-0.538** [.0496]
4 Occupation FE	0.483** (0.240)	0.096 (0.134)	0.011 (0.654)	0.807** (0.329)	-2.054*** (0.614)	-1.105** (0.499)
5 Occupation FE + industry FE	0.512* (0.281)	0.121 (0.154)	-0.202 (0.781)	0.611 (0.384)	-2.287*** (0.719)	-1.121* (0.594)
6 Controls + industry FE + occupation FE	0.988** (0.436)	0.161 (0.229)	-0.359 (1.039)	0.591 (0.562)	-3.071*** (1.021)	-1.629** (0.824)
7 Controls + industry × occupation FE	1.009** (0.493)	0.133 (0.252)	-0.315 (1.239)	0.582 (0.631)	-3.335*** (1.193)	-1.825* (0.949)
Panel B: Men						
1 Baseline (Clustering by person, no controls)	0.193 (0.118)	0.145* (0.087)	0.151 (0.154)	0.111 (0.174)	-0.045 (0.258)	0.037 (0.236)
2 Two-way clustering by person & household	0.193 (0.118)	0.145* (0.087)	0.151 (0.153)	0.111 (0.174)	-0.045 (0.258)	0.037 (0.236)
3 Wild cluster bootstrap-t by person	0.193 [.1031]	0.145* [.0996]	0.151 [.3148]	0.111 [.5268]	-0.045 [.8643]	0.037 [.8823]
4 Occupation FE	0.120 (0.197)	0.271* (0.139)	0.099 (0.251)	-0.201 (0.279)	-0.067 (0.429)	-0.080 (0.389)
5 Occupation FE + industry FE	0.053 (0.245)	0.334* (0.180)	-0.003 (0.321)	-0.346 (0.347)	-0.042 (0.536)	-0.262 (0.485)
6 Controls + industry FE + occupation FE	-0.144 (0.366)	0.389 (0.260)	0.142 (0.480)	-0.702 (0.507)	-0.481 (0.731)	-1.024 (0.680)
7 Controls + industry × occupation FE	-0.302 (0.377)	0.418 (0.255)	0.050 (0.490)	-0.521 (0.514)	-0.690 (0.735)	-0.970 (0.668)

Notes: The table presents 2SLS results based on extensions of Equations 2 and 3, estimated separately by gender. The explanatory variable of interest is a dummy identifying individuals who WFH at least once per week in 2022. The instrument is the WFH feasibility (0/1) of individuals' 2019 job (see Section 2.2 for details). Row 1 in Panels A and B reproduce the results from Panel A Figure 4 (Table B.3) for reference. The sample includes individuals employed and aged 16–64 in 2019, who are observed again in 2022. Occupation fixed effects at the level of segments (14 categories, Matthes *et al.*, 2015). Industry fixed effects at the level of 10 NACE 2 macro categories. Individual-level controls are measured in 2019 and include demographics (age, age-squared, immigration background, educational attainment (3 categories)); household structure (dummies for cohabiting with a partner and marital status, the number of children under 14, dwelling size); location (state fixed effects); and job characteristics (firm tenure in years and firm size fixed effects (4 categories)). *p*-values from a wild cluster bootstrap-t procedure with the null imposed (10,000 replications) are reported in brackets. Unless specified otherwise, standard errors are clustered by individual and reported in parentheses. Data are from the SOEP. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table B.6: Robustness: 2SLS estimates of the impact of WFH on couples' gender time-use gaps

	(1)	(2)	(3)	(4)	(5)	(6)
	Δ Couple's time-use gap (W-M)					
	Dom. work (incl. errands)	DIY activities	Care work	Leisure (incl. sleep, exercise)	Work (incl. studying, commuting)	Paid work
Panel I. Baseline						
Female partner's WFH (0/1), 2022	0.825** (0.381) [0.021]	0.074 (0.218) [0.738]	1.367* (0.786) [0.078]	0.006 (0.458) [0.993]	-1.305* (0.747) [0.083]	-0.797 (0.636) [0.206]
Male partner's WFH (0/1), 2022	-0.717** (0.300) [0.018]	-0.124 (0.186) [0.512]	-0.144 (0.669) [0.855]	0.030 (0.385) [0.926]	0.041 (0.643) [0.947]	-0.585 (0.530) [0.278]
Combined effect ($\hat{\gamma}_1 + \hat{\gamma}_2$)	0.109 (0.350) [0.728]	-0.050 (0.181) [0.781]	1.222** (0.607) [0.058]	0.036 (0.396) [0.927]	-1.264* (0.648) [0.044]	-1.381** (0.571) [0.014]
Average effect ($\hat{\gamma}_1 \times \overline{WFH22}^f + \hat{\gamma}_2 \times \overline{WFH22}^m$)	0.002 (0.104) [0.983]	-0.019 (0.054) [0.721]	0.341* (0.180) [0.063]	0.011 (0.118) [0.919]	-0.357* (0.194) [0.061]	-0.415** (0.170) [0.011]
Panel II. Controls						
Female partner's WFH (0/1), 2022	0.857** (0.418)	-0.004 (0.243)	1.752** (0.840)	-0.249 (0.540)	-1.524* (0.816)	-1.072 (0.708)
Male partner's WFH (0/1), 2022	-0.554* (0.313)	-0.187 (0.194)	0.594 (0.645)	0.313 (0.434)	-0.693 (0.684)	-1.028* (0.561)
Combined effect ($\hat{\gamma}_1 + \hat{\gamma}_2$)	0.303 (0.438)	-0.191 (0.240)	2.346*** (0.780)	0.065 (0.624)	-2.217*** (0.846)	-2.101*** (0.779)
Average effect ($\hat{\gamma}_1 \times \overline{WFH22}^f + \hat{\gamma}_2 \times \overline{WFH22}^m$)	0.064 (0.130)	-0.062 (0.071)	0.689*** (0.231)	0.031 (0.187)	-0.656*** (0.253)	-0.636*** (0.232)
Panel III. Controls + Industry FE						
Female partner's WFH (0/1), 2022	1.462** (0.589)	0.080 (0.347)	3.287*** (1.120)	-0.485 (0.739)	-2.716** (1.222)	-2.285** (1.029)
Male partner's WFH (0/1), 2022	-0.883** (0.448)	-0.156 (0.264)	0.729 (0.875)	0.349 (0.535)	-0.727 (0.882)	-0.573 (0.725)
Combined effect ($\hat{\gamma}_1 + \hat{\gamma}_2$)	0.579 (0.616)	-0.076 (0.337)	4.016*** (1.094)	-0.137 (0.820)	-3.443*** (1.240)	-2.858*** (1.107)
Average effect ($\hat{\gamma}_1 \times \overline{WFH22}^f + \hat{\gamma}_2 \times \overline{WFH22}^m$)	0.129 (0.183)	-0.028 (0.100)	1.167*** (0.324)	-0.025 (0.243)	-1.005*** (0.366)	-0.833** (0.327)
Panel IV. Controls + Industry FE + Occupation FE						
Female partner's WFH (0/1), 2022	1.484** (0.692)	0.461 (0.423)	1.639 (1.185)	-0.729 (0.916)	-2.808* (1.453)	-2.850** (1.296)
Male partner's WFH (0/1), 2022	-0.684 (0.647)	-0.365 (0.307)	-1.175 (1.138)	0.349 (0.677)	-0.346 (1.249)	-0.076 (0.925)
Combined effect ($\hat{\gamma}_1 + \hat{\gamma}_2$)	0.800 (0.860)	0.097 (0.442)	0.464 (1.372)	-0.380 (0.998)	-3.154* (1.618)	-2.926** (1.384)
Average effect ($\hat{\gamma}_1 \times \overline{WFH22}^f + \hat{\gamma}_2 \times \overline{WFH22}^m$)	0.199 (0.260)	0.013 (0.131)	0.085 (0.416)	-0.094 (0.296)	-0.908* (0.486)	-0.832** (0.409)

Notes: The table presents 2SLS results based on extensions of Equations 4–6. Panel I reproduces results from Panel C Table 2. Time-use gaps refer to the female-male differences in hours spent on a given activity on an average weekday within a couple. The instruments are the WFH feasibility [0,1] of each partner's 2019 job (see Section 2.2 for details). The sample includes couples in which both partners are employed and aged 16–64 in 2019, and observed again in 2022. Standard errors are clustered by couple and reported in parentheses. Occupation fixed effects at the level of segments (14 categories, Matthes *et al.*, 2015). Industry fixed effects at the level of 10 NACE 2 macro categories. Couple-level controls are measured in 2019 and include the number of children under 14 living in the household, dwelling size, state fixed effects, household size, and household net income. *p*-values from a wild cluster bootstrap procedure with the null imposed (10,000 replications) are reported in brackets. Data are from the SOEP. ****p* < 0.01, ***p* < 0.05, **p* < 0.1

Table B.7: 2SLS estimates of the impact of WFH (hours per weekday) on work and living conditions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Moved (0/1)	Δ #Rooms	Δ Log living space	Left employm. (0/1)	Employer change (0/1)	Δ Log gross labor income	Δ Log gross hrly wage	Δ Married (0/1)	Δ Single (0/1)	Δ Children <14 (0/1)
Panel A: Women										
Hours WFH per weekday in 2022	-0.001 (0.006)	0.069*** (0.025)	0.009* (0.005)	-0.020*** (0.006)	-0.028*** (0.008)	-0.039*** (0.011)	-0.015 (0.010)	0.001 (0.005)	-0.006* (0.004)	0.006 (0.008)
#Individuals	2,992	2,972	2,992	2,992	2,624	2,624	2,607	2,991	2,991	2,992
DV mean	.103	4.376	4.634	.123	.186	7.575	2.748	.586	.252	.355
First-stage coef.	3.13 [543.9]	3.14 [544.0]	3.13 [543.9]	3.13 [543.9]	3.47 [575.2]	3.43 [564.1]	3.45 [569.2]	3.13 [544.0]	3.13 [544.0]	3.13 [543.9]
Panel B: Men										
Hours WFH per weekday in 2022	0.012** (0.005)	0.039* (0.020)	0.008** (0.004)	-0.008* (0.004)	-0.006 (0.005)	0.003 (0.006)	0.012* (0.007)	0.001 (0.004)	-0.002 (0.003)	0.002 (0.005)
#Individuals	2,513	2,488	2,513	2,513	2,270	2,269	2,256	2,511	2,511	2,513
2019 DV mean	.111	4.38	4.632	.097	.145	8.122	2.979	.641	.275	.353
First-stage coef.	4.78 [803.2]	4.78 [796.3]	4.78 [803.2]	4.78 [803.2]	5.21 [878.8]	5.18 [863.5]	5.23 [875.3]	4.78 [803.0]	4.78 [803.0]	4.78 [803.2]
<i>p</i> -values test of equal effects	0.1055	0.3404	0.7696	0.1100	0.0132	0.0004	0.0205	0.9725	0.3593	0.5955

Notes: The table presents 2SLS results based on Equations 2 and 3, estimated separately by gender. The instrument is the WFH feasibility [0,1] of individuals' 2019 job (see Section 2.2 for details). The sample includes individuals employed and aged 16–64 in 2019, who are observed again in 2022. Columns 5–7 exclude individuals who are not employed in 2022. Kleibergen-Paap *F*-statistic for the first-stage regression in brackets. Standard errors are clustered by individual and reported in parentheses. Data are from SOEP. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table B.8: 2SLS estimates of the impact of WFH (hours per weekday) on couples' gender time-use gaps

	(1)	(2)	(3)	(4)	(5)	(6)
	Δ Time use for					
	Dom. work (incl. errands)	DIY activities	Care work	Leisure (incl. sleep, exercise)	Work (incl. studying, commuting)	Paid work
Panel A: Effect on female partner's time use						
Female partner's hours WFH, 2022	0.151** (0.069)	-0.042 (0.036)	0.316 (0.207)	-0.012 (0.076)	-0.285** (0.142)	-0.123 (0.121)
Male partner's hours WFH, 2022	-0.030 (0.038)	0.021 (0.021)	0.151 (0.123)	-0.011 (0.047)	-0.016 (0.085)	-0.030 (0.071)
#Couples	875	875	875	875	875	875
Combined effect ($\hat{\gamma}_1 + \hat{\gamma}_2$)	.121* (.062)	-.021 (.031)	.467** (.183)	-.024 (.069)	-.301** (.131)	-.153 (.112)
2019 DV mean	2.825	.401	2.571	8.498	7.019	6.063
Panel B: Effect on male partner's time use						
Female partner's hours WFH, 2022	-0.038 (0.062)	-0.058 (0.040)	-0.007 (0.087)	-0.014 (0.092)	0.023 (0.125)	0.070 (0.114)
Male partner's hours WFH, 2022	0.077** (0.034)	0.041* (0.025)	0.137*** (0.051)	-0.017 (0.055)	0.015 (0.075)	0.101 (0.070)
Combined effect ($\hat{\gamma}_1 + \hat{\gamma}_2$)	.039 (.069)	-.017 (.041)	.13* (.078)	-.031 (.091)	.039 (.121)	.171 (.113)
2019 DV mean	1.437	.582	1.057	8.295	9.352	8.364
Panel C: Effect on couple's time-use gap (W-M)						
Female partner's hours WFH, 2022	0.189** (0.089)	0.016 (0.051)	0.322* (0.180)	0.002 (0.106)	-0.309* (0.175)	-0.194 (0.150)
Male partner's hours WFH, 2022	-0.107** (0.050)	-0.021 (0.031)	0.014 (0.108)	0.006 (0.064)	-0.031 (0.107)	-0.131 (0.089)
Combined effect ($\hat{\gamma}_1 + \hat{\gamma}_2$)	.082 (.089)	-.004 (.046)	.337** (.157)	.007 (.1)	-.34** (.165)	-.325** (.145)
Average effect ($\hat{\gamma}_1 \times \overline{WFH22}^f + \hat{\gamma}_2 \times \overline{WFH22}^m$)	.022 (.108)	-.017 (.056)	.368** (.187)	.011 (.122)	-.382* (.201)	-.427** (.177)
2019 DV mean	1.389	-.181	1.514	.203	-2.333	-2.301
#Couples	875	875	875	875	875	875
<i>First-stage diagnostics</i>						
Lewis-Mertens statistic (g_{min})	67.60	67.60	67.60	67.60	67.60	67.60
g_{min} critical values ($\alpha = 0.05, \tau = 0.1$)	20.63	20.63	20.63	20.63	20.63	20.63

Notes: The table presents 2SLS results based on Equations 4–6. Time-use gaps (Panel C) refer to the female-male differences in hours spent on a given activity on an average weekday within a couple. The instruments are the WFH feasibility [0,1] of each partner's 2019 job (see Section 2.2 for details). The sample includes couples in which both partners are employed and aged 16–64 in 2019, and observed again in 2022. Standard errors are clustered by couple and reported in parentheses. Data are from the SOEP. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table B.9: Complier analysis

	(1) Sample	(2) Complier	(3) Never-taker	(4) Always-taker	(5) Std. difference (Sample-Complier)
Panel A: Women					
Age, 2019	45.42 (0.20)	44.02 (0.51)	47.05 (0.37)	39.71 (1.22)	0.13
Partner in HH (0/1), 2019	0.69 (0.01)	0.65 (0.02)	0.71 (0.02)	0.70 (0.05)	0.08
Children under 14 in HH (0/1), 2019	0.35 (0.01)	0.38 (0.02)	0.32 (0.02)	0.47 (0.05)	-0.05
No of children u14 in HH, 2019	0.54 (0.01)	0.57 (0.04)	0.49 (0.03)	0.84 (0.11)	-0.03
Commuting distance (km), 2019	14.10 (0.36)	12.95 (0.92)	14.23 (0.66)	19.95 (3.72)	0.06
Weekly hours worked, 2019	32.03 (0.22)	30.60 (0.58)	33.29 (0.40)	29.65 (1.49)	0.12
Gross labor income (EUR), 2019	2489.63 (30.38)	2179.25 (81.03)	2717.29 (53.20)	2398.71 (173.57)	0.19
Firm tenure in years, 2019	10.63 (0.19)	7.91 (0.48)	12.68 (0.39)	9.34 (1.10)	0.26
Firm with 100+ employees (0/1), 2019	0.62 (0.01)	0.63 (0.02)	0.62 (0.02)	0.63 (0.05)	-0.02
Desired change in hours (%), 2019	3.40 (1.73)	7.93 (4.45)	-1.62 (2.00)	20.09 (12.94)	-0.05
Desires more paid hours (0/1), 2019	0.19 (0.01)	0.21 (0.02)	0.17 (0.01)	0.20 (0.04)	-0.06
Desires less paid hours (0/1), 2019	0.56 (0.01)	0.53 (0.02)	0.58 (0.02)	0.52 (0.05)	0.04
Panel B: Men					
Age, 2019	45.40 (0.22)	43.44 (0.48)	47.96 (0.46)	43.07 (1.21)	0.17
Partner in HH (0/1), 2019	0.76 (0.01)	0.76 (0.02)	0.76 (0.02)	0.70 (0.05)	-0.00
Children under 14 in HH (0/1), 2019	0.35 (0.01)	0.38 (0.02)	0.32 (0.02)	0.36 (0.05)	-0.06
No of children u14 in HH, 2019	0.59 (0.02)	0.63 (0.04)	0.53 (0.04)	0.63 (0.10)	-0.05
Commuting distance (km), 2019	18.22 (0.42)	20.47 (0.89)	15.64 (0.63)	19.69 (2.02)	-0.11
Weekly hours worked, 2019	41.22 (0.19)	40.87 (0.40)	41.81 (0.38)	40.02 (1.17)	0.04
Gross labor income (EUR), 2019	4061.22 (50.14)	3666.81 (110.49)	4487.92 (113.75)	4104.53 (219.40)	0.16
Firm tenure in years, 2019	11.97 (0.23)	10.28 (0.46)	13.92 (0.51)	11.49 (1.04)	0.15
Firm with 100+ employees (0/1), 2019	0.69 (0.01)	0.69 (0.02)	0.67 (0.02)	0.74 (0.04)	-0.01
Desired change in hours (%), 2019	-4.65 (1.23)	-2.19 (2.61)	-7.04 (1.92)	-6.21 (3.43)	-0.04
Desires more paid hours (0/1), 2019	0.10 (0.01)	0.11 (0.01)	0.10 (0.01)	0.10 (0.03)	-0.02
Desires less paid hours (0/1), 2019	0.66 (0.01)	0.63 (0.02)	0.69 (0.02)	0.67 (0.05)	0.07

Notes: The table reports covariate means for the whole sample and subsamples of compliers, never-takers, and always-takers based on the methodology by [Marbach and Hangartner \(2020\)](#); [Hangartner et al. \(2021\)](#). Column 5 shows standardized differences in means between the sample and compliers. The instrument or “treatment assignment” is WFH feasibility (0/1), and the treatment is WFH at least once per week in 2022 (0/1). Compliers work remotely if and only if assigned to treatment. Never-takers (always-takers) refuse (obtain) treatment irrespective of assignment. The sample includes individuals employed and aged 16–64 in 2019, who are observed again in 2022. Among women, 39% of individuals are identified as compliers, 55% are never-takers, and 6% are always-takers. Among men, the proportions are 48% compliers, 44% never-takers, and 8% always-takers. Bootstrapped standard errors (1,000 replications) in parentheses.