The Mental Health Impacts of the Work-from-Home Revolution

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Abstract

We examine trends in remote work and mental health from before to after the onset of the COVID-19 pandemic for workers in jobs with high telework potential versus those in jobs with low telework potential. Using panel data on U.K. workers in the Understanding Society dataset, we first show that those in "teleworkable" jobs prior to COVID see a jump in their likelihood of remote work relative to those in "non-teleworkable" jobs. We then examine whether this shift leads to a change in reported mental health, since factors such as time use, job satisfaction, and social interaction are key drivers of mental health. We use measures of mental health derived from the GHQ12 survey and the SF12 survey. Though naive initial estimates suggest that mental health worsened for remote workers following the pandemic relative to in-person workers, we do not find that this result is robust to alternative specifications which include controls or use weights to establish parallel pre-trends.

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1. Introduction

The sharp increase in remote work that occurred in conjunction with the COVID-19 pandemic has led to "new normal" in which many workers continue to work remotely part- or full-time. The share of workdays worked from home has stabilized at around 28% in the U.S over the past few years.[1] Many countries around the world have also seen large increases in remote work relative to pre-pandemic levels, with rates that are especially high in English-speaking countries such as the U.K. (Zarate et al, 2024).

The lasting change in remote working arrangements brought about by the pandemic has the potential to affect the health and well-being of affected workers. Job satisfaction is a major correlate of self-reported mental health (Faragher, Cass, and Cooper, 2005; Belloni, Carrino, and Meschi, 2022). Workers enjoy the additional autonomy and flexibility of remote work and are willing to pay some of their earnings to be able to work from home part of the week, on average (Aksoy et al., 2022). Recent evidence suggests that in some environments, hybrid or fully remote work is causally related to greater job satisfaction and work-life balance without harming productivity (Bloom et al., 2015; Choudhury et al., 2024; Davis, 2024). On the other hand, remote work could have negative effects on some employees' well-being by making it more difficult to keep home and work lives separate or leading to feelings of isolation and loneliness (Tavares, 2017; Miyake et al., 2021).

Remote work likely has different effects on worker well-being during a pandemic than it does in normal times. During the height of the COVID-19 pandemic in 2020 and early 2021, firms and workers were compelled to adjust their remote work practices rapidly and without forward planning as part of a larger public health effort to contain the spread of the virus prior to the

[1] https://wfhresearch.com/wp-content/uploads/2024/05/WFHResearch_updates_May2024.pdf.

widespread dissemination of vaccines. As COVID has receded and workers and firms have returned to greater flexibility in determining remote work arrangements, it is important to understand how the health and well-being of a large new class of remote and hybrid workers are affected by these arrangements.

In this paper, we examine how the increase in the incidence of remote work in the years 2020 and beyond affects the mental health of workers. We contribute to a recent set of working papers on this topic that attempt to isolate causal effects of remote work on mental health rather than simply measuring correlations.[2] Our main contributions to this literature are 1) we examine how remote work affects mental health in the years (2021-22) following the initial phase of COVID-19 (2020); 2) an identification strategy that leverages workers' pre-COVID occupational characteristics to compare trends in outcomes of workers in "teleworkable" occupations (as defined by Dingel and Neiman, 2020) with those in "non-teleworkable" occupations from before to after the initial phase of the pandemic; 3) the use of an extensive battery of questions available in our data (U.K. Understanding Society) to provide a more comprehensive analysis of mental health than the partial measures used in some other studies; 4) the use of a detailed panel data set which allows us to control for person fixed effects as well as other individual-level controls, assess pre-trends at a more granular (yearly) level; and 5) the use of synthetic differences-in-differences techniques which allow us to assess sensitivity of differences-in-differences estimates to comparison periods and units.

[2] Many papers examine correlations between remote work and various measures of mental health, with mixed results. For example, Islam, Baun, and Racette (2023) find that those who switched to remote work during the first year of the COVID pandemic experienced heightened depression and anxiety at that time, on average. Song and Gao (2020) find that before COVID, individuals who work in the office as well as at home experience more stress when teleworking. Orešković et al. (2023) find that those who work remotely do not experience worse job satisfaction or work-life balance.

Our identification strategy compares outcomes for two groups of workers: one group working in highly "teleworkable" occupations in 2019, and another working in occupations that are not highly "teleworkable" in 2019. From each group's perspective, the rapid increase in the propensity to work remotely in 2020 and beyond is an unexpected, exogenous shock, but it likely affected those already working in teleworkable occupations more than those who were working in non-teleworkable occupations. Under a parallel trends assumption that in the absence of the shock to remote work, changes in outcomes for both groups would have evolved in the same way, the differential trend in outcomes for the two groups can be informative about the effects of the working-from-home revolution.

We first document that individuals in occupations in 2019 that score highly in terms of "teleworkability" were significantly more likely to report that they were working remotely starting in 2020 and continuing through 2021 and 2022. This result is robust across all of our specifications, suggesting that pre-2020 occupation is highly predictive of the extent of the shock to one's working conditions in 2020 and beyond.

Two-way fixed effects regressions and event studies suggest two preliminary conclusions: the mental health of workers in teleworkable occupations worsened somewhat relative to those in other occupations in 2020 (the early stage of the pandemic), particularly among women. However, this change appears to reverse in subsequent years, even as the differential propensity to work remotely remains high. Secondly, there is evidence of deviations from strict parallel trends in the pre-treatment periods in the event studies, which calls into question the parallel trends assumption required to give a causal interpretation to these results.

We therefore assess the robustness of our results to including additional right-hand side controls, changing the sample to use only a balanced panel, and using a synthetic differences-in-differences approach (Arkhangelsky et al., 2021). We also redefine the panel at the occupation-level, averaging mental health across individuals in each occupation, and re-estimate results. The mental health estimates are very sensitive to changes in specification, and our most credible estimates that eliminate non-parallel pre-trends suggest a null result in the effect of the working-from-home revolution on mental health. Our results are consistent with the working-from-home revolution causing large changes in working conditions without generating large population-level changes in mental health outcomes.

2. Related Literature

As noted above, several recent papers have attempted to measure causal impacts of remote work on mental health and other measures of well-being using a variety of strategies and samples. Goux and Maurin (2024) examine a 2017 French reform that facilitated remote work agreements between employers and employees and led to a large increase in remote work among some occupation types. By comparing changes among those in occupations affected by the reform to those in unaffected occupations, combined with variation in whether firms adopted the reform (i.e., whether they actually signed telework agreements with employees), they study how the induced increase in telework affected measures of overall health including chronic disease incidence, activity limitations, and self-reported health. The authors find that overall health declines when employees shift to remote work, with effects that are concentrated among men. However, because their data is repeated cross-sections, it is possible that worker sorting across occupations and firms drives part of this result. Additionally, the paper does not consider mental health specifically as an outcome.

Bertoni et al. (2022) use a longitudinal sample of older European workers (age 50 and up) from the Survey of Health, Aging, and Retirement (SHARE) to examine how switching from onsite to remote work during the first wave of the pandemic (June and July 2020) affected feelings of sadness and depression. Exploiting differences in pre-COVID occupational characteristics (how well the job lends itself to telework) for exogenous variation in the likelihood of working remotely following the onset of the pandemic, the authors find that remote work increases the probability of depressive symptoms, especially for women, those with children living at home, and single individuals. It is unclear, however, how these results translate to a broader sample of workers and to the post-COVID era, when lockdowns and other restrictions have been lifted.

Nguyen (2023) examines the mental health outcomes of a cohort from the British Cohort Study (1970) in 2020 (when all respondents turned 50 years old). She focuses on a sample of individuals in "teleworkable" jobs and uses distance from a respondent's home to their physical workplace for exogenous variation in remote work in a structural model of labor supply. The results indicate that working from home has a negative effect on mental health compared with a traditional workplace arrangement, but a positive effect compared with not working at all. In addition to concerns about the generalizability of results beyond 2020, it is not clear whether distance to workplace is uncorrelated with unobserved characteristics that are correlated with mental health outcomes.

Bilgrami (2023) uses panel data from Australia to examine how working-from-home affects mental health. Two identification strategies are used: in the first, the author uses within-individual variation in remote work over time to trace out effects on mental health (i.e., individual fixed effects are included in the model). In the second, the author instruments for take-up of remote work with whether the individual's employer offers remote work to the employee. In both cases, there is clear potential for endogenous sorting into jobs in which workers who prefer to use remote-work arrangements select into jobs that offer remote work, potentially biasing estimates of the effect of remote work on mental health outcomes.

Lastly, using a longitudinal sample from Italy, Esposito et al. (2024) compare the evolution of job satisfaction between workers who transition to remote work between 2019 and 2021 and those who continuously work in a traditional workplace setting. They find that women experience a rise in job satisfaction, on average, when they transition to remote work. The average effect masks significant heterogeneity in effects by personality characteristics. This study focuses exclusively on job satisfaction rather than overall mental health and relies on the exogeneity of individual decisions to switch to remote work in the wake of COVID. In addition, this paper only uses two waves of the survey, and therefore cannot assess parallel pre-trends over a long pre-period or how estimates are sensitive to the comparison year.

We contribute to this budding literature on remote work and worker well-being in the wake of the pandemic by focusing on two detailed measures of mental health contained in our data, as described in the next section. Recognizing that any effects of remote work on mental health could be very different in 2020 than they are in later years, our sample period runs through 2022. Perhaps most importantly, to isolate the causal effects of remote work on mental health, we exploit the fact that many workers in "teleworkable" occupations were not working remotely in 2019 but did begin working remotely in 2020 and continued to do so in 2021 and 2022. We examine the trend in mental health outcomes for such workers compared to those outside of such occupations, who did not experience the large increase in remote work that the former group did. In this way, we rely on a pre-determined (relative to the onset of COVID) characteristic to obtain plausibly exogenous variation in the transition to remote work. We therefore do not rely on the exclusion restriction that the COVID pandemic only affected mental health via its effect on the propensity to remote work. We detail the assumptions that underly our strategy in Section 4.

Additionally, we exploit a detailed panel data set which allows us to test the robustness of our findings to which comparisons identify our effects. Whereas some studies (e.g., Nguyen, 2023) only use comparisons with the year 2019 to identify the effect of remote work, we have observations in every year from 2011 to 2019 and can therefore explore how far comparisons with different years might affect the estimates. The panel nature of our data set means that we can include person fixed effects to control for all characteristics that do not vary across time within individuals. We also assess the validity of the parallel-trends assumption underlying the identification strategy in much of this literature by testing the robustness of our estimates to the inclusion of controls and using synthetic differences-in-differences weights (Arkhangelsky et al., 2021).

3. Data

We link data from the Understanding Society data set,[3] a representative UK panel data set, with occupational teleworkability scores as defined by Dingel and Neiman (2020).

Understanding Society (U.K.)

Understanding Society is a large, representative UK panel data set. We use data from 2011 to 2023. Each wave of the survey is roughly annual, but waves can overlap and individuals may be interviewed in different months of the year due to their availability. As a result, respondents interviewed in subsequent waves may be interviewed in consecutive years, twice in the same year, or with one year's gap. On average, around 10% of people interviewed in one year are not

[3]University of Essex, Institute for Social and Economic Research. (2023). Understanding Society: Waves 1-13, 2009-2022 and Harmonised BHPS: Waves 1-18, 1991-2009. [data collection]. 18th Edition. UK Data Service. SN: 6614, http://doi.org/10.5255/UKDA-SN-6614-19.

interviewed in the subsequent year. Although the survey endeavors to follow individuals in every subsequent wave, sample attrition and reentry is not trivial (Lynn et al., 2012).[4]

Understanding Society provides detailed information about demographics, labor-market behavior, and health outcomes at an individual level.

Remote Work Outcomes

In even waves of the survey, respondents who work are asked about their right to use a remote work option and whether they indeed work remotely. Specifically, the survey asks respondents:

"I would like to ask about working arrangements at the place where you work. Which of the following arrangements are available at your workplace?"

One of the options is: "To work from home on a regular basis."

Additionally, the survey asks respondents who reply that some flexible arrangements are available, "Do you currently work in any of these ways?"

We define a person as working remotely if they report using the right to work remotely (and not working remotely if they do not). We also code respondents who do not work, or report that the right to work remotely is not offered at their workplace, as not working remotely. In our analysis, we do not make extensive use of the variable about being *offered* remote work, because the wording of this question refers specifically to the respondents' *workplace*, i.e., an affirmative response does not formally imply that the worker themselves has the right to work remotely.

[4] Average attrition across waves is 5% (Spearing, 2023). In the Appendix, we show average attrition from one year to the next, that is on average how many respondents in each year are not interviewed in the subsequent year. We also show how attrition relates to measured variables. Because waves overlap years, measuring attrition in terms of appearance in subsequent years gives us a higher estimate of the extent of attrition than if we measure attrition in terms of appearance in subsequent waves.

Mental health outcomes

We measure mental health using the GHQ12 survey and the SF12 indices. The GHQ12 survey is a battery of 12 questions that asks individuals about the severity of 12 mental health symptoms.[5] Individuals select from four ordered responses, normalized so that higher numbers reflect worse mental health.

We construct the GHQ12 caseness score as the sum of symptoms of mental illness in which a respondent scores 3 or 4. The caseness therefore varies between 0 (no symptoms) and 12 (the maximum number of symptoms) and can be understood as a measure of the number of adverse mental health symptoms a person experiences. Additionally, we construct the sub-indices as the sum of the respondent's scores on symptoms of each type: Anxiety and Depression; Loss of Confidence; and Social Dysfunction. Both the GHQ12 caseness and its subindices have been shown to be useful screening tools for mental illness (McCabe et al. 1996, Graetz 1991, Anjara et al. 2020), and have been used in economics research (e.g., Gathergood, 2013, Belloni, Carrino and Meschi, 2022, Spearing 2024).

The SF12 measure is derived from the SF12 survey, a series of 12 questions to which respondents give one of an ordered list of responses. These responses are then weighted and aggregated to provide a summary index of mental health, ranging from 100 (best) to 0 (worst) (Jenkinson and Layte, 1997). The SF12 index has been used effectively as a screening measure for mental illness (Kontodimopoulos et al. 2007, Tibubos and Kröger 2020), and as a summary

[5] The symptoms are the ability to concentrate, loss of sleep, whether they feel they are playing a useful role, whether they are capable of making decisions, whether they are constantly under strain, whether they have problems overcoming difficulties, whether they enjoy day-to-day activities, whether they have the ability to face problems, whether they are unhappy or depressed, whether they are losing confidence, whether the believe themselves to be worthless, and whether they are generally happy.

measure of mental health in economic research (e.g., Davalos and French 2011, Wallace, Nazroo, and Becares 2016, Jolivet and Postel-Vinay 2020).

Occupational telework potential ("Teleworkability")

We measure occupational "teleworkability" according to Dingel and Neiman's (2020) index. Dingel and Neiman define occupational teleworkability based on O*NET[6] variables, which summarize information about occupations in the United States: they assume that each occupation can be done remotely unless some information from the O*NET data suggests otherwise. For example, if the average person within an occupation reports that dealing with the public face-to-face is a requirement of the job, they assign a teleworkability score of 0 to this occupation. This process categorizes all occupations within the O*NET data set as teleworkable or not teleworkable.

We access a special license version of the Understanding Society dataset which contains information on occupation at the ISCO88 4-digit level, and link respondents' occupations to the SOC codes used in the O*NET data set using crosswalks provided by Hardy (2016). This linkage allows us to assign each ISCO88 occupation a teleworkability score of 1 or 0. In some cases, an ISCO88 occupation can be linked to multiple SOC occupations, only some of which are teleworkable. In those cases, we assign a value of 1 to the ISCO88 occupation if a majority of the SOC occupations it is linked to are teleworkable.

The Understanding Society data set is a UK panel data set, and the O*NET data is a US data set. We therefore implicitly rely on similarity between UK and US occupations. We are not the first to apply O*NET data to a European context (e.g., Goos, Manning, and Salomons 2014, Hardy, Keister, and Lewandowski 2018, Lewandowski 2020), including the UK (Jolivet and Postel-Vinay 2020, Spearing, 2024). Where researchers have assessed the similarity of

[6] O*NET 26.3 Database, by the US Department of Labor, Employment and Training Administration; https://creativecommons.org/licenses/by/4.0/

occupations measured in Europe and in the O*NET data set, results have generally pointed to a high correlation (CEDEFOP 2013, Spearing 2023). Furthermore, in our context, we are able to test to what extent the teleworkability scores from the US occupations predict remote working in the UK: a regression of remote working on the teleworkability of a respondent's occupation among those who work yields a coefficient of 0.112, with a p-value of 0.000. Overall, we are confident that the teleworkability of US occupations measured by Dingel and Neiman (2020) is informative about the propensity of UK workers in those occupations to work remotely.

Sample selection

Our sample is composed of all unique individuals who report working in 2019. We define two groups: one group of people who were working in 2019 in occupations measured as "teleworkable", and one group of people who were working in 2019 in occupations not measured as "teleworkable." Though the work-from-home revolution potentially affects all within the economy, we can think of the former of these groups as facing higher treatment intensity than the latter.

Summary Statistics

Figure 1 shows the percentage of workers who say they use the option to work remotely over time. This percentage trends up gradually over a period of 9 years prior to the onset of COVID in early 2020 and then nearly doubles after that. The percentage working remotely then remains roughly constant through the end of 2021. This finding is consistent with Barrero, Bloom, and Davis' (2023) finding that the incidence of working remotely has not returned to pre-pandemic levels even after vaccinations.

Table 1 shows overall summary statistics on key variables used in the analysis. Of note, our sample is 47% composed of workers who were working in a teleworkable occupation in 2019, but over the entire period of study (2011 to 2023), they actually work remotely only 6.5% of the time. Mean values for the GHQ12 caseness, Anxiety and Depression, Loss of Confidence and Social Dysfunction are 1.7, 7.5, 3.1 and 12.4 respectively. The SF12 measures of health both range between 0 and 100 and have an average score of around 50. Around 20% of our sample has biological children.

Table 2 compares characteristics of workers in teleworkable and non-teleworkable occupations in 2019. Workers in teleworkable jobs are slightly older and more likely to be female, white, married, have children, and own their own home. Their commute times to their traditional workplace are longer, and they work a little over one additional hour per week, on average. Unsurprisingly, since teleworkable jobs tend to require the use of computers, workers in such jobs tend to have higher degrees, be in jobs at the management/professional level, and earn substantially more than those in non-teleworkable jobs. However, average differences in mental health measures by occupational teleworkability are small.

Though our identification strategy (detailed in the next section) does not require balance on pre-treatment characteristics between treatment and control groups, the large differences in some characteristics seen in Table 2 may call into question whether these groups would have experienced parallel trends in outcomes in the absence of COVID (which is required for our strategy). We discuss our method for guarding against the possibility of violations of this assumption in the next section.

4. Empirical Strategy

We utilize the panel nature of Understanding Society to examine how the outcomes of workers in teleworkable occupations in 2019 changed after the onset of COVID relative to workers in non-teleworkable occupations.

4.1 Event-study specification

We begin with event-study comparisons of these two groups in the following specification:

$$y_{it} = \sum_{t \neq 2019} \beta_t \cdot (tele_i \cdot D_t) + \gamma_i + \delta_t + \epsilon_{it} \,. \tag{1}$$

In this equation, y_{it} is the outcome of individual i in year t; $tele_i$ is an indicator for whether the individual works in a teleworkable occupation in 2019; D_t is an indicator that takes a value of "1" for each year t in our sample frame (2010-2022, with 2019 as the excluded base year); γ_i is a person fixed effect; δ_t is a year fixed effect; and ϵ_{it} is the error term. The coefficients of interest are the β_t's, which indicate how outcomes evolve for those in teleworkable occupations relative to those in non-teleworkable occupations. In all regressions run throughout the paper, standard errors are clustered at the individual level to account for correlation within an individual's outcomes over time.

The main assumption needed for the β_t's to identify the differential effect of being in a teleworkable occupation (in 2019) starting in 2020 is that in the absence of the COVID shock to remote work, trends in the outcomes for those in teleworkable occupations would have been the same as for those in non-teleworkable occupations.[7] We can indirectly examine this possibility by looking at differences in trends up to 2019. Figure 2 shows that those individuals in teleworkable occupations in 2019 were already trending toward relatively higher rates of remote work prior up through 2019. This is somewhat expected, as remote work arrangements were growing (slowly) prior to COVID, and it is natural that these would be more common among individuals in occupations that lend themselves to telework.

[7] The "no anticipation" assumption requires that the COVID shock had no differential effect on outcomes for those in teleworkable occupations prior to its arrival, which we find plausible. For example, it seems unlikely that workers sorted into teleworkable occupations prior to 2020 based on the anticipation of a pandemic.

Figure 3 shows event study results with respect to our mental health outcomes by gender. The event studies show that, relative to those working in non-teleworkable occupations, respondents working in teleworkable occupations in 2019 saw deterioration in their mental health in the year 2020 as measured by the GHQ12 caseness score, symptoms of anxiety and depression, and the SF12 (for women). However, these effects do not generally persist beyond the year 2020. This pattern is more pronounced for women, although it can also be see in men's GHQ12 caseness score. On the other hand, while there are no systematic pre-trends, some pre-period coefficients are significant.

The biggest concern regarding the event studies in Figure 3 is that since workers in teleworkable and non-teleworkable occupations differ across many characteristics (see Table 2), differential experience during the pandemic may reflect differences in experience across some characteristics other than likelihood of working remotely. In order to assess how much systematic differences between our groups might affect the results, we re-estimate the event studies including controls. Specifically, we include: a full set of dummies for highest qualification earned in 2019, interacted with a full set of year dummies; a dummy variable for being a homeowner in 2019, interacted with a full set of year dummies; a dummy variable for having biological children in 2019, interacted with a full set of year dummies; and a dummy variable for job level (management and professional, intermediate, or routine) in 2019, interacted with a full set of year dummies. The resulting event studies are plotted in Figure 4.

Figure 4 shows stark changes in event-study estimates with controls included in the model. With the controls, men in teleworkable occupations no longer experience a relative degradation of their mental health in 2020; in fact, their mental health appears to improve relative to men in non-teleworkable occupations as measured by the SF12 index. Regarding GHQ12 caseness and Anxiety and Depression for women, 2019 now appears to be an unusually good mental health year for those in teleworkable occupations, casting doubt on whether the relative adverse shock to mental health in 2020 is really due to changes in remote work (or even COVID).

In view of some observable deviations from parallel trends in the pre-treatment period, the unusual behavior of mental health during the height of the pandemic, and the effect of including controls on event studies, we conclude that it is unlikely that a strict parallel trends assumption holds. This observation forms the basis for our using the Synthetic Differences-in-Differences estimator, which we present in the next subsection.

4.2. Synthetic Differences-in-Differences estimator

The previous exercise suggests that there may be systematic differences between workers in teleworkable occupations and non-teleworkable occupations over time, violating the parallel trends assumption. To account for the possibility of non-parallel trends in the basic event-study design, we also implement the synthetic difference-in-differences (SDD) method in Arkhangelsky et al. (2021). Arkhangelsky et al. (2021) propose an estimator with two sets of weights: the first of these (the individual weights on control units) approximately equate average outcomes in the pre-treatment period for control units with average outcomes for the treated units, up to a constant (i.e., the weights are used to approximate the trend in outcomes between treated and control groups).[8] The purpose of these individual unit weights is to construct a synthetic control group which trends in a way which is most similar to the treatment group. Control units whose behavior is most similar to that of the treatment groups receive higher weights. The second set of weights (on time periods)

[8] Their proposed estimator uses a shrinkage parameter when calculating unit weights, which penalizes deviations from equal weights. The inclusion of this estimator prevents overfitting, and in practice will mean that some (small) deviations from parallel pre-trends are preserved.

weights the pre-treatment periods in order to place a higher weight on the pre-treatment periods which are most similar to the post-treatment period for the control group.

A standard difference-in-differences (DD) estimator could be obtained from the following equation:

$$y_{it} = \alpha + \beta_{DD} \cdot tele_i \cdot post_t + \gamma_i + \delta_t + \epsilon_{it}, \tag{2}$$

where $post_t$ takes a value of "1" in the years 2020 and after (and zero otherwise). Note that the level effects associated with $tele_i$ and $post_t$ are absorbed by individual and year fixed effects, respectively. The SDD estimator β_{SDD} is obtained by simply running a weighted version of the regression equation (2). We report estimates of β_{DD} as well as β_{SDD} in the next section. Because obtaining β_{SDD} requires a balanced panel, we estimate β_{DD} on both unbalanced and balanced panels. To estimate the standard errors, we use a jackknife estimator that sequentially omits the data of each unit and then re-estimates the model to obtain a distribution of estimated parameters.

To assess how effective the unit weights are in delivering parallel trends, in Figure 5, we show the difference between unweighted outcomes (the β_t's in equation (1)) and weighted remote working rates, where the weights are chosen for control units to approximately mimic the pre-treatment trend in outcomes among the treated units. Because the question about using the option to work remotely is only asked in even waves of the Understanding Society survey, we aggregate years into two-year bins and define a balanced panel to be all those who answered the question about remote working exactly once in each two-year period. Following Arkhangelsky et al.'s (2021) recommendation, the sample used in this figure is a balanced panel, so all individuals in the sample have non-missing information for each survey period. The weighted differences in remote working rates are very small in the pre-treatment period (by construction), but the post-treatment (2020-21) difference is very similar to the unweighted difference. The pattern of results in Figure 6 for mental-health outcomes is similar in that weighted differences are smaller than unweighted ones in the pre-treatment period while differences in the post-treatment period are generally comparable; however, in the case of “loss of confidence” for men and the SF-12 index for both genders, weighted post-treatment differences are notably somewhat smaller (in absolute value) than unweighted ones.[9]

5. Results

One may be concerned that differential trends in mental health around the pandemic may be driven by differential labor-market trends by occupational characteristics other than propensity to work remotely. For example, certain occupations may be more likely to experience lay-offs during the pandemic and this effect might explain any estimates of the effect on mental health. We test this by regressing a dummy variable for employment on year dummies, person fixed effects and an interaction between having a teleworkable occupation in 2019 and the year being after 2019. Table 3 presents the results. For both men and women, the difference in the change in the propensity to work between those in teleworkable and non-teleworkable jobs is less than one percentage point and not statistically significant. This result suggests that employment outcomes *per se* are unlikely to drive our results.

Table 4 presents differences-in-difference estimators for the relative effect of the work-from-home revolution on the propensity to work remotely for people in teleworkable occupations in 2019 versus people in non-teleworkable occupations in 2019. In column (1), we present the two-way-fixed effect estimator comparing propensity to remote work in the years 2020 and onward to the years 2011 to 2019. In column (2), we restrict this to the years we use for the SDD estimator

[9] Arkhangelsky et al. (2021) assess the effectiveness of unit weights in reducing pre-trends by comparing the mean weighted outcome for the treatment group and the control group in each year. In the Appendix, we conduct the same exercise. Results are consistent with the event studies plots.

(from 2014 only). In column (3), we additionally restrict our data to a balanced panel. In column (4), we use SDD weights to reduce deviations from parallel trends and to compare post periods to their most similar pre periods. Although the sample restrictions and weights reduce the magnitude of the effect, in all estimates there is a statistically significant increase in remote working for those who worked in teleworkable occupations in 2019 compared to those who did not work in teleworkable occupations in 2019. The magnitude of these effects is also fairly consistent. The group of workers who were in teleworkable occupations in 2019 see a relative increase in their propensity to work from home of between 5 and 7 percentage points.

In Tables 5 and 6, we repeat this exercise for our mental health measures for men and women, respectively. Column 1 in each table displays simple DD estimates with only person and year fixed effects. Estimates from this column appear to indicate that the mental health of those in teleworkable occupations declined relative to those outside those occupations with the onset of COVID. This is true for both men and women according to the GHQ12 indices and sub-indices and the SF12 index (though a few individual coefficients are not statistically significant at normal levels).

In column 2 of each table, we estimate Equation (2) with additional controls for job level in 2019, having children in 2019, owning a home in 2019 and education in 2019, all interacted with year dummies. The inclusion of controls is sufficient to drive the estimated effects on mental health to be statistically insignificantly different to zero in all cases, even though standard errors do not significantly increase. This stylized result suggests that initial findings about a differential effect of the work-from-home revolution on mental health by occupational teleworkability may in large part be explained by differential trends in the mental health of different groups within the population which are correlated with occupation teleworkability.

Columns 3 and 4 present estimates from the same model as column 1 but only using data from 2015 on (column 3) and using data from 2015 on with a balanced panel (column 4). We note three key stylized facts: firstly, the reduction in sample size in moving to a balanced panel is significantly larger for the mental health variables than for the remote work variable. The large reduction in sample size is because mental health variables are observed in each wave, and we therefore require all units included in the balanced panel to have a measure of mental health exactly once in each year. This more demanding requirement involves discarding a larger number of observations.

Secondly, sample restrictions and weights have a much larger effect on the estimates when it comes to mental-health outcomes than with take-up of remote work. The majority of statistically significant effects in column 1 do not survive the sample restriction to the year 2015 and beyond (column 3). Once we restrict the sample to a balanced panel (column 4), there are no statistically significant effects. When we implement our synthetic difference-in-differences estimator in column 5, estimates magnitudes are largely similar to or smaller than (in absolute value) those in column 4. The lack of statistical significance in columns 4 and 5 is partially due to the large increase in standard errors as the sample size decreases. However, it is also notable that for the GHQ12 caseness (men and women), Anxiety and Depression (men), Loss of Confidence (men and women), Social Dysfunction (women) and the SF12 (men and women), the reduction in the magnitude of the effect going from column (1) to column (5) is large enough that the result would be statistically insignificant even if the standard error did not increase.

We conclude that it is likely that any observable differences in the evolution of mental health between workers who (in 2019) worked in teleworkable jobs and workers who (in 2019) worked in non-teleworkable jobs in 2020 and beyond is highly sensitive to which pre-treatment years are used as comparison as well as the inclusion of controls. Therefore, the finding that working from home has effects on mental health found in column 1 of each table may reflect deviations from the parallel trends assumption.

One concern about our synthetic differences-in-differences results is that the stringent balanced-panel restrictions for mental health outcomes might drive the differences between our synthetic differences-in-differences estimates and the unweighted differences-in-differences estimates. We therefore develop an additional estimator which groups individuals by the occupation they worked in in 2019 and estimates differences-in-differences in average mental health in an occupation between teleworkable occupations and non-teleworkable occupations. Specifically, we estimate Equation (3):

$$y_{ot} = \alpha + \beta_{DD} \cdot tele_o \cdot post_t + \gamma_o + \delta_t + \epsilon_{ot}, \tag{3}$$

Here y_{ot} is the average mental health of a person who worked in occupation o in 2019 in year t. γ_o is a 2019 occupation fixed effect and $tele_o$ an indicator for whether that occupation is teleworkable. We calculate synthetic differences-in-differences weights for control units by choosing weights on 2019 occupations to minimize pre-trends with a shrinkage parameter and choosing time weights to minimize the weighted average difference between pre-2020 non-teleworkable occupations and post-2020 non-teleworkable occupations. Standard errors are estimated using a block bootstrap, i.e., sampling unique individuals with replacement and then recalculating average mental health by 2019 occupation.

The advantage of this approach is that we can define sample balance in terms of 2019 occupations; that is, the sample is balanced if each 2019 occupation has an average mental health estimate in each year. As a result, the reduction in sample size as we move to a balanced sample is much smaller.

In Figure 7, we plot the results of TWFE event studies using a sample balanced as described above, with and without synthetic control weights. The unusual behavior of mental health in 2019 is present in these event studies for women's GHQ12 caseness score, symptoms of Anxiety and Depression, Loss of Confidence and Social Dysfunction when pre-periods are not weighted. However, occupation weights are effective at reducing the extent of pre-trends.

Turning to differences-in-differences results, we present estimates of the differential effect of the work-from-home revolution on remote working and mental health between those who worked in teleworkable occupations in 2019 and those who worked in non-teleworkable occupations in 2019 for men (Table 7) and women (Table 8). We present the results from 2011 onwards (column 1), from 2015 onwards (column 2), from 2015 onwards in a balanced sample (column 3), and from 2015 onwards in a balanced sample using synthetic differences-in-differences weights (column 4). Note that moving to a balanced sample leads to much smaller reductions in the sample defined in terms of 2019 occupation-year pairs than when our results were estimated at the individual level.

Our results are mostly consistent with our previous findings. There is a consistent statistically significant effect of the work-from-home revolution on the propensity to work remotely that affects those in teleworkable jobs more than those in non-teleworkable jobs. In these results, the effect is of a somewhat larger magnitude (as high as 8 percentage points for men and 11 percentage points for women). This difference from our previous results likely reflects the different weightings given to individuals when we aggregate to an occupation level: using individual-level data puts a more equal weight on individuals, whereas using occupation-level data puts a more equal weight on occupations.

Turning to mental health outcomes, there is some evidence of an adverse effect of the work-from-home revolution on those in teleworkable occupations versus those in non-teleworkable occupations—Social Dysfunction and the SF12 for men; Anxiety and Depression and the SF12 for women—however, again these results are not robust to using synthetic differences-in-differences weights, with the exception of the effect on the SF12 for men. This fact is consistent with initial evidence of an adverse effect being due to violations of the parallel trends assumption. Referring to the event studies, this single significant point estimate looks to be driven by the year 2022.

Overall, the results of aggregating dependent variables to the occupation level are consistent with our initial differences-in-differences results: while occupation in 2019 robustly predicts a person's propensity to remote-work in subsequent years, the evidence that this change in working conditions drove differential mental health outcomes is not robust to changes in specification. Estimates that more plausibly impose parallel trends tend to find null results.

6. Conclusion

Since the covid-19 pandemic, many countries have seen a large increase in the propensity to remote work. Many researchers have raised concerns about the potentially adverse effect of remote working on mental health (e.g., Bertoni et al. 2022; Nguyen, 2023).

In this paper we compare two groups who are differentially affected by the work-from-home revolution: those in teleworkable occupations in 2019 and those in non-teleworkable occupations in 2019. We show that their propensity to remote work diverged significantly and persistently after 2019. On the other hand, we find little effect of a persistent, robust divergence in the groups' mental health outcomes. The observed worsening of mental health for those in teleworkable occupations during the pandemic is not robust to the inclusion of controls, small changes in comparison years, or weighting schemes which eliminate pre-trends. We therefore conclude that it is unlikely that working from home caused large changes in mental health outcomes. Our results suggest that policymakers and employers should not be overly concerned about large population-level adverse mental health outcomes from the work-from-home revolution.

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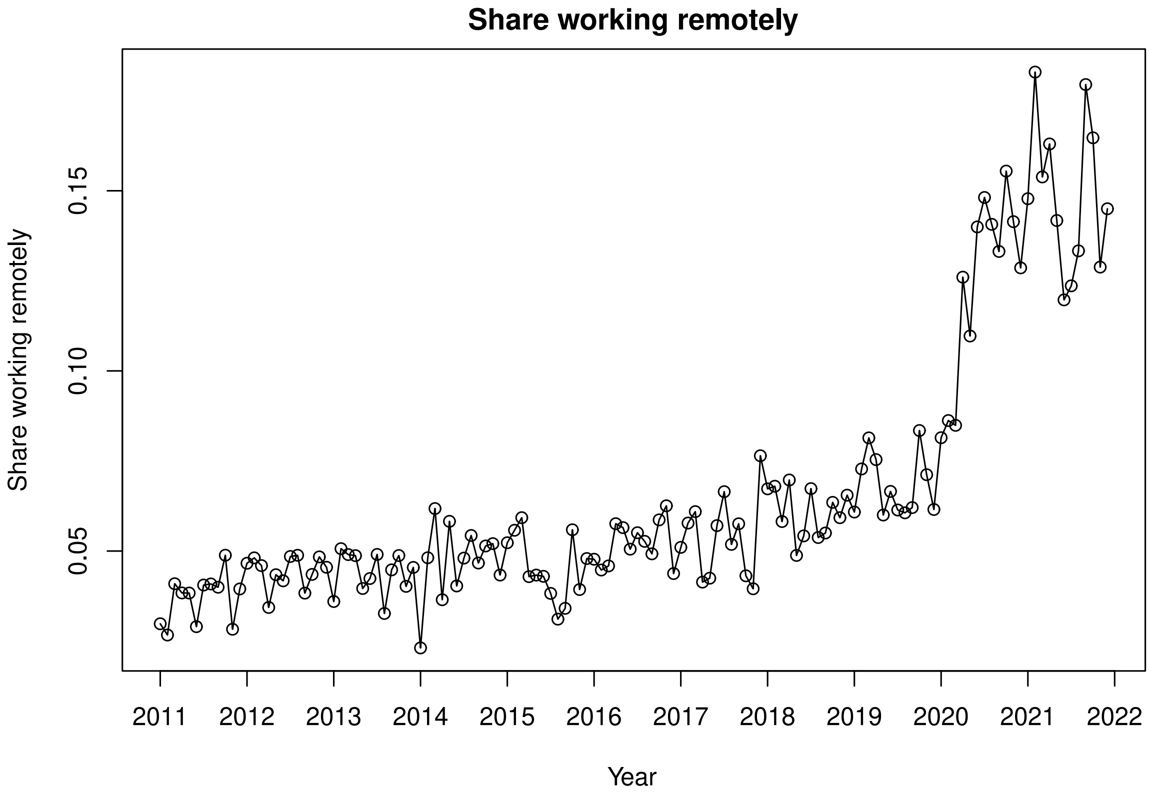
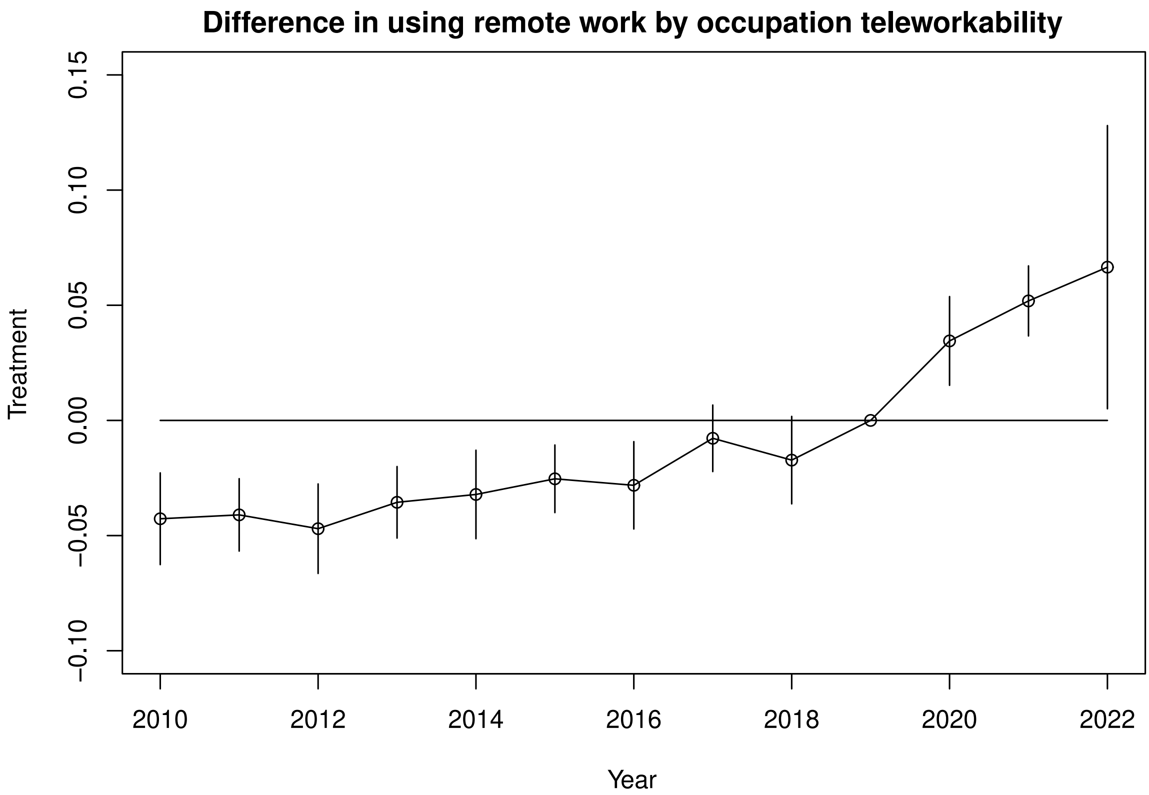
1 Figures

Figure 1: The share of workers who work remotely over time



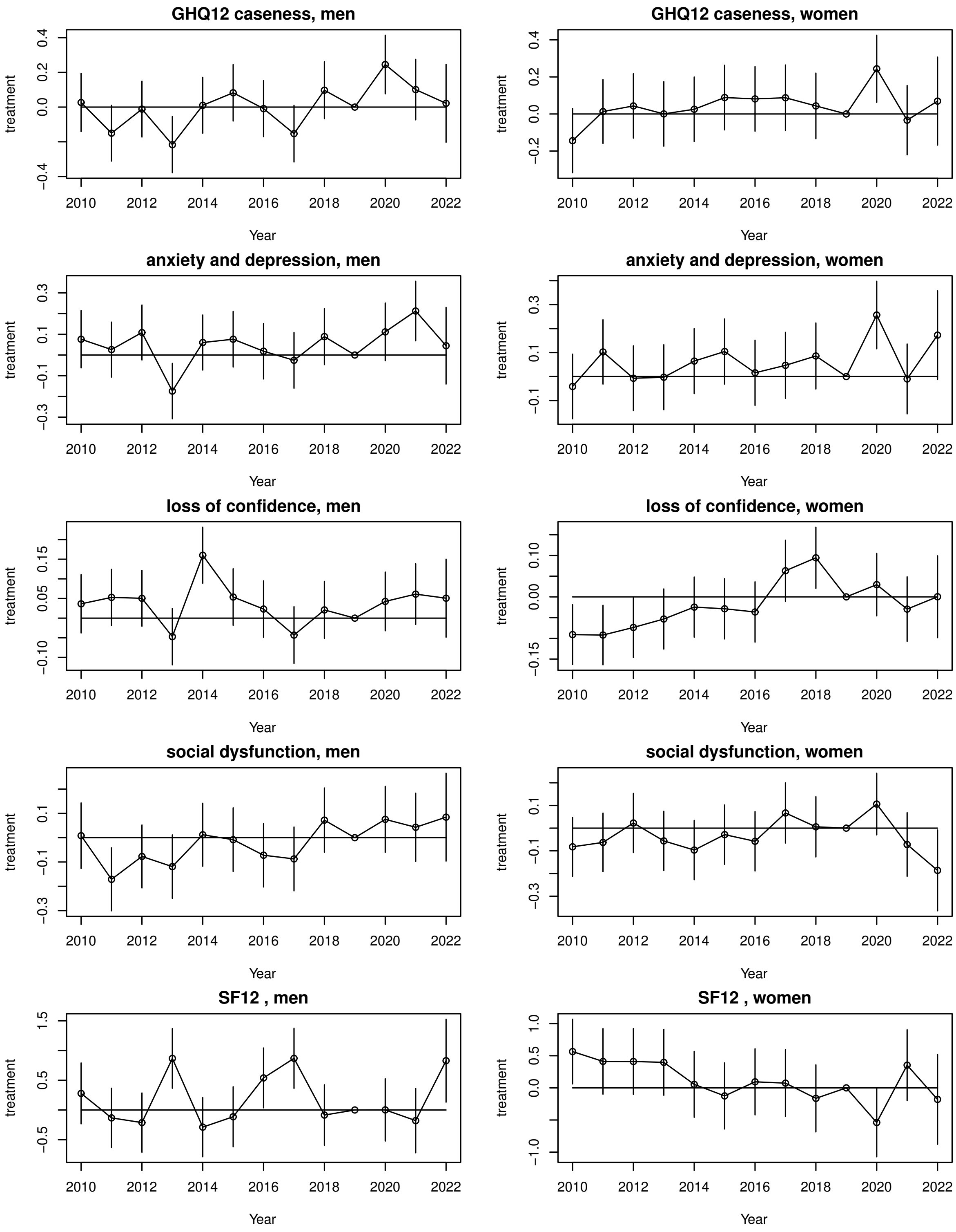
Notes: the Figure shows the percentage of respondents interviewed in each month who report working who use the option to work remotely. Data are from Understanding Society.

Figure 2: Event study using the offer to work remotely



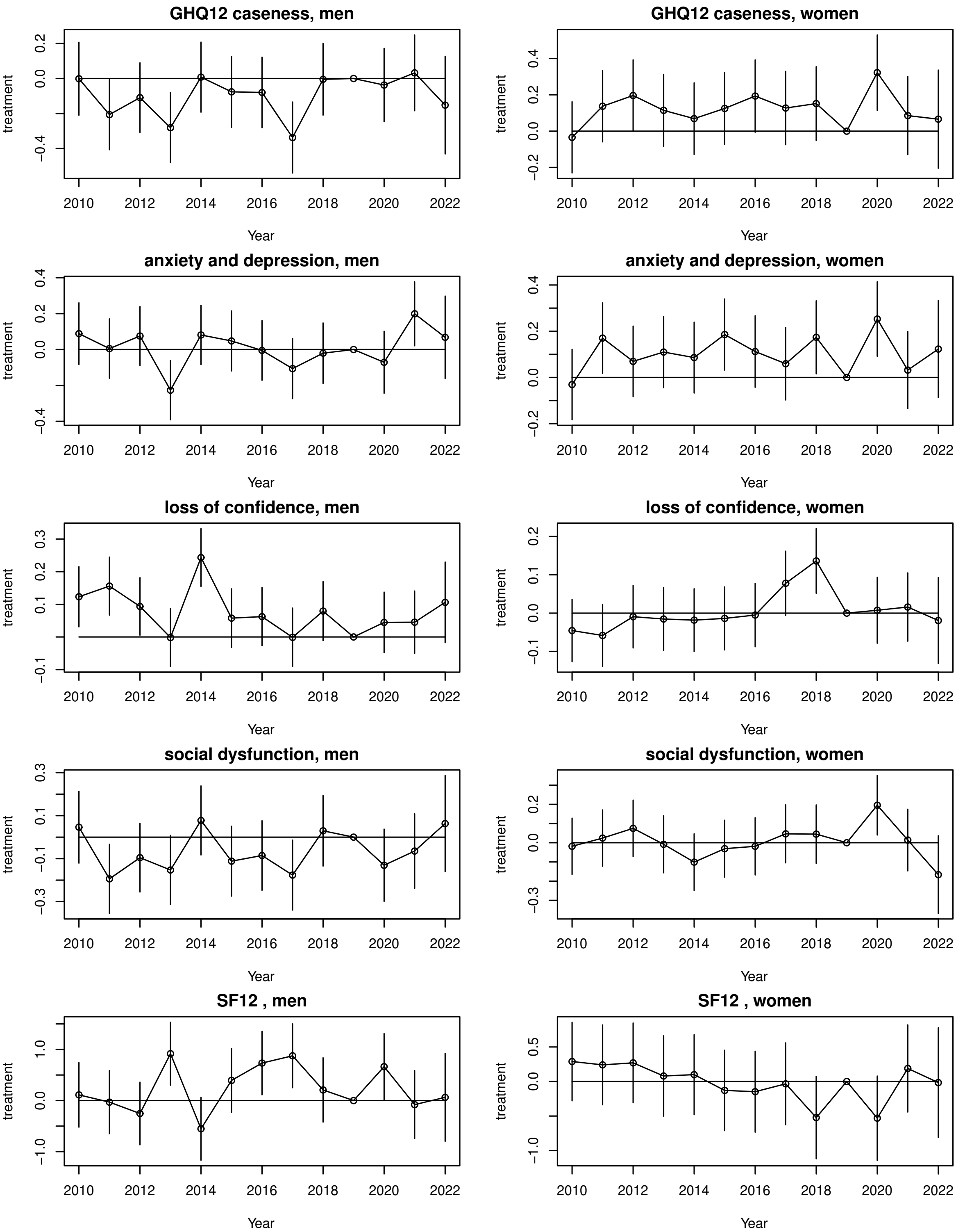
Notes: the Figure shows event studies for working remotely and being offered the option to work remotely. We estimate event studies using a two-way fixed effect estimator, where the treatment group is respondents who are observed worked in an occupation which is teleworkable in 2019 and the control group is respondents who are observed working in an occupation which is not teleworkable in 2019. We control for person fixed effects. We define Teleworkability using Dingel and Neiman's (2020) measure. Standard errors are clustered at the individual level.

Figure 3: Event studies for mental health outcomes



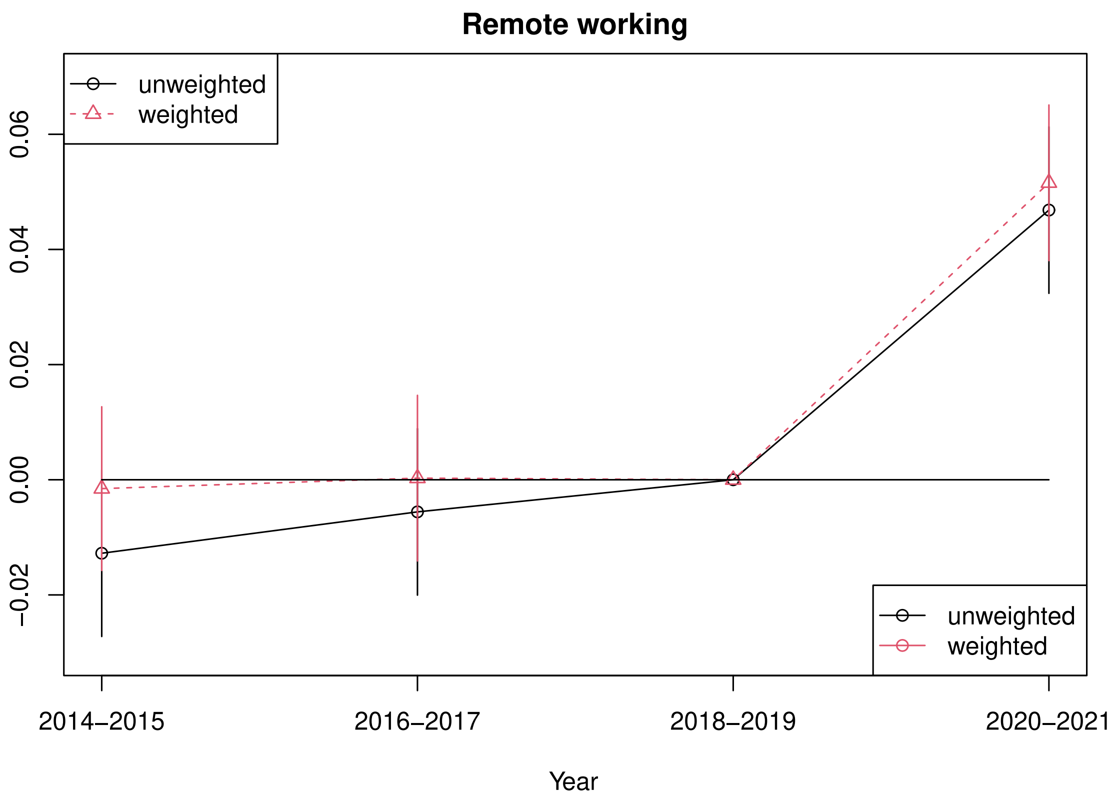
Notes: the Figure shows event studies for working remotely and being offered the option to work remotely. We describe the event study specification in the note to Figure 2. The GHQ12 caseness is the total number of adverse mental health symptoms a person has, from a possible 12. Anxiety and depression, loss of confidence and social dysfunction are subindices of the GHQ12 and measure the severity of symptoms of that kind. The SF12 is a measure of overall mental health, with higher numbers indicating better mental health.

Figure 4: Event studies for mental health outcomes with controls



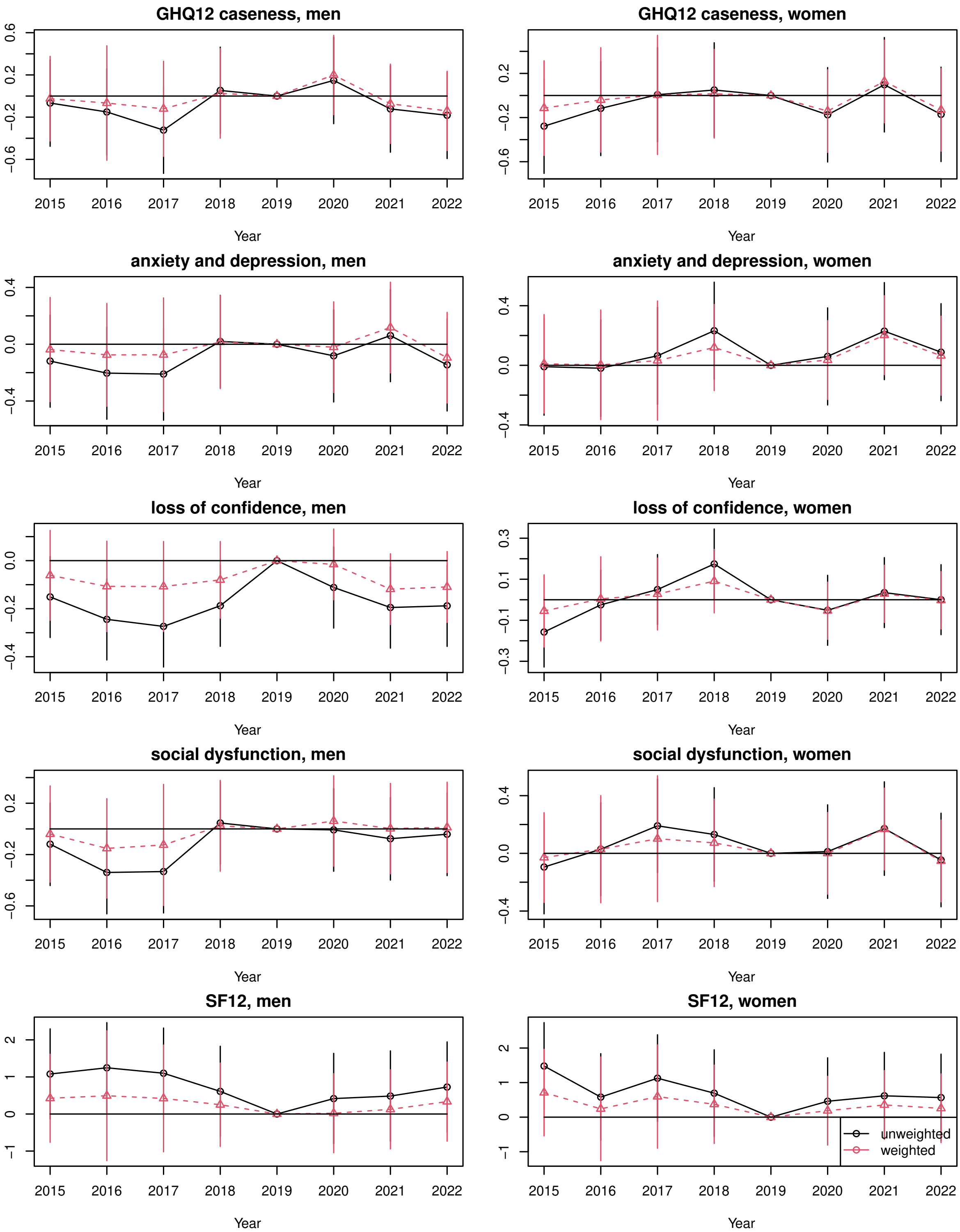
Notes: the Figure shows event studies for working remotely and being offered the option to work remotely (as in Figure 3), with additional controls. We additionally control for dummies for the following variables interacted with year dummies: the highest qualification received, job level in 2019, home ownership in 2019, having children in 2019.

Figure 5: TWFE event studies, remote work, weighted and unweighted



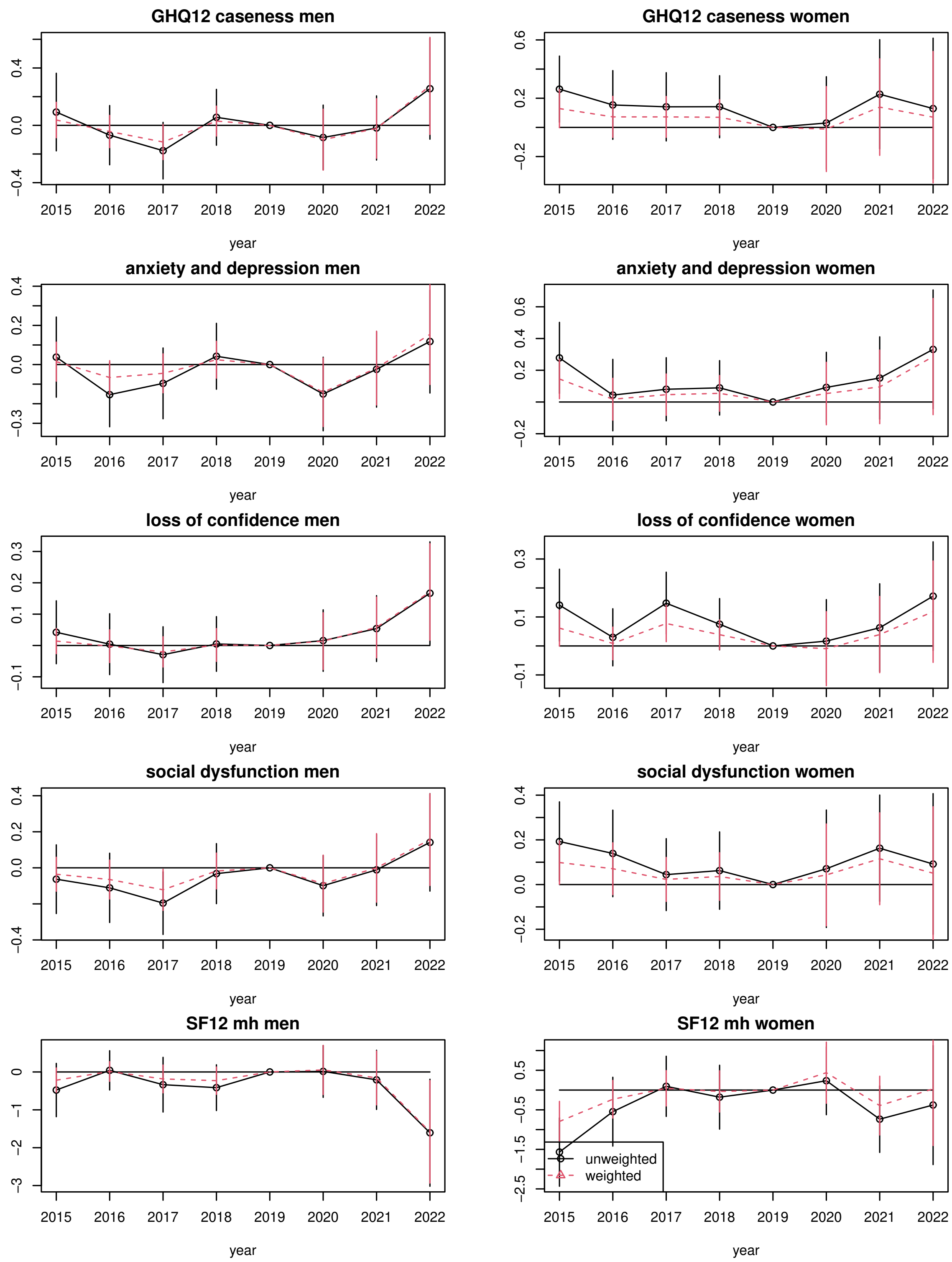
Notes: the Figure shows two-way fixed effects event studies for the differential effect of the expansion of remote working on those in teleworkable versus non-teleworkable occupations in 2019. The weighted two-way fixed effects estimator uses unit weights which solve the minimization problem in Equation 4 in Arkhangelsky, Athey, Hirshberg, Imbens, and Wager (2021). The sample is balanced in calendar time.

Figure 6: Event studies for mental health, balanced samples with and without weights



Notes: the Figure shows two-way fixed effects event studies for the differential effect of the expansion of remote working on those in teleworkable versus non-teleworkable occupations in 2019. The weighted two-way fixed effects estimators use unit weights which solve the minimization problem in Equation 5 in Arkhangelsky, Athey, Hirshberg, Imbens, and Wager (2021). The samples are balanced in calendar time. Mental health variables are defined in the note to Table 3.

Figure 7: Event studies for occupation-level mental health, weighted and unweighted



Notes: the Figure shows two-way fixed effects event studies for the differential effect of the expansion of remote working on those in teleworkable versus non-teleworkable occupations in 2019. In this estimator we aggregate mental health outcomes in each year by the occupation a person worked in in 2019. Each unit in this estimation is therefore a year-2019 occupation pair. The weighted two-way fixed effects estimators use unit weights which solve the minimization problem in Equation 5 in Arkhangelsky, Athey, Hirshberg, Imbens, and Wager (2021). The samples are balanced in calendar time. Mental health variables are defined in the note to Table 3. Standard errors are estimated using a block-bootstrap

2 Tables

Table 1: Sample summary statistics

Statistic	N	Mean	St. Dev.	Min	Max
Age	169,612	42.340	13.020	15	91
Female	169,618	0.531	0.499	0	1
Paid work	169,288	0.857	0.350	0	1
Use remote work	80,453	0.065	0.246	0	1
Occupation teleworkability in 2019	169,620	0.469	0.499	0	1
GHQ12 caseness	158,148	1.660	2.873	0	12
Anxiety and depression	158,541	7.471	2.459	4	16
Loss of confidence	158,694	3.111	1.322	2	8
Social dysfunction	158,375	12.391	2.122	6	24
SF12 mental health	157,520	48.875	9.536	0.000	77.090
SF12 physical health	157,520	53.019	7.936	4.620	76.290
Has children	164,825	0.210	0.407	0	1

Notes: the Table shows summary statistics for our sample. Our sample is of respondents who report working in 2019 in occupation to which teleworkability can be assigned. Paid work is a dummy variable for if a person does paid work. “Use remote work” is a dummy variable which is equal to 1 if a person uses the opportunity to work remotely. We assume that if a person does not work in a workplace which offers remote working they do not work. Occupation teleworkability in 2019 is a dummy variable which takes the value 1 if a person’s occupation in 2019 was teleworkable as measured by Dingel and Neiman (2020). The GHQ12 caseness is the number of symptoms of mental illness from a possible 12 that a person experiences. Anxiety and Depression, Loss of Confidence and Social Dysfunction measure the severity of symptoms of these types. SF12 indices are constructed from weighted responses to 12 health-related questions. They are scored from 100 (best) to 0 (worst). “Has children” a dummy variable equal to 1 if a person has biological children.

Table 2: Characteristics of workers in teleworkable and non-teleworkable occupations in 2019

	Non-teleworkable	Teleworkable
Age	43.262	44.227
Female	0.470	0.595
White	0.808	0.830
Has children	0.151	0.211
Married	0.533	0.598
Owns home	0.710	0.820
Mental Health		
GHQ12 caseness	1.572	1.687
Anxiety and depression	7.421	7.582
Loss of confidence	3.179	3.188
Social dysfunction	12.369	12.436
SF12 mental health	48.285	47.742
Job Characteristics		
Commute time	17.921	23.582
Working hours	32.149	33.358
Monthly labor income	1,999.051	2,760.420
Works remotely	0.031	0.121
Education		
Degree or equivalent	0.374	0.636
A-level or GCSE	0.488	0.312
Other/No qualification	0.118	0.043
Job level		
Management and professional	0.264	0.653
Intermediate	0.212	0.257
Routine	0.524	0.087
Region		
London	0.036	0.030
Southeast	0.105	0.101
Southwest	0.094	0.075
East	0.077	0.063
East Midlands	0.086	0.080
West Midlands	0.083	0.094
North West	0.112	0.155
Yorkshire and the Humber	0.108	0.139
North East	0.082	0.082
Wales	0.068	0.055
Scotland	0.087	0.074
Northern Ireland	0.061	0.052

Notes: the Table shows the average values of key variables in 2019 for those working in teleworkable occupations and occupations which are not teleworkable. See note to Table 1 for a description of mental health variables and how we define occupation teleworkability. Commute time is in minutes. Working hours is the usual number of hours worked per week. Monthly labor income is expressed in 2015 GBP. Education variables are the highest qualification obtained. Job level is defined at the occupation level.

Table 3: Differential effects on employment by occupation teleworkability

	Dependent variable:	
	Employed	
	(1)	(2)
Effect of changes in working from home on employment	−0.0001	0.001
	(0.007)	(0.007)
Observations	23,731	28,071
Men	Y	N

Notes: the table shows differences-in-differences estimates comparing changes in the probability of being employed in years after 2019 for those in teleworkable occupations in 2019 versus those in non-teleworkable occupations in 2019. We regress a dummy variable for being employed on year fixed effects, person fixed effects and the interaction between the year being after 2019 and the teleworkability of their 2019 occupation (the reported effect). *p<0.1; **p<0.05; ***p<0.01

Table 4: Effect of expansion of remote work on propensity to remote work for those in teleworkable occupations

	(1)	(2)	(3)	(4)
	Unbalanced panel	Unbalanced panel (from 2014 only)	Balanced panel	Synthetic DD
	0.069***	0.061***	0.053***	0.052***
	(0.004)	(0.004)	(0.006)	(0.007)
Obs	71,076	46,163	28,522	28,522
Pre-treatment mean	0.053	0.057	0.068	0.071

Notes: the Table shows differences-in-differences estimates. We compare changes in propensity to remote work in years after 2020 for those in teleworkable occupations in 2019 to changes in propensity to remote work in the years after 2020 for those in occupations which are not teleworkable in 2019. In column (1), we present the differences-in-differences estimator in the full sample of people who work in an occupation in 2019. In column (2), we restrict the sample to the years 2014 to 2022. In column (3) we limit the sample to those who are reported in every year pair from 2014-2015 to 2020-2021. In column (4) we present the synthetic differences-in-differences estimator (Arkhangelsky et al. 2021). Standard errors are clustered at the person level, except for the synthetic differences-in-differences estimator where we use the Jackknife estimator proposed by Arkhangelsky et al. (2021). *p<0.1; **p<0.05; ***p<0.01

Table 5: Effect of expansion of remote work on mental health for those in teleworkable occupations (men)

		(1) Unbalanced panel	(2) Unbalanced panel controls	(3) Unbalanced panel (2015 onwards)	(4) Balanced panel	(5) Synthetic DD
GHQ12 Casness	Estimate	0.165***	0.066	0.113***	0.045	0.023
	Standard error	(0.042)	(0.052)	(0.044)	(0.108)	(0.127)
	Obs	76, 033	76, 033	49, 034	6, 280	6, 280
	Pre-treatment mean	1.322	1.322	1.285	1.155	1.182
Anxiety and Depression	Estimate	0.087**	0.014	0.052	0.047	0.027
	Standard error	(0.035)	(0.043)	(0.036)	(0.086)	(0.104)
	Obs	76, 224	76, 224	49, 191	6, 392	6, 392
	Pre-treatment mean	7.176	7.176	7.153	7.057	7.089
Loss of confidence	Estimate	0.053***	0.015	0.006	0.006	-0.021
	Standard error	(0.018)	(0.023)	(0.019)	(0.045)	(0.053)
	Obs	76, 295	76, 295	49, 243	6, 408	6, 408
	Pre-treatment mean	2.932	2.932	2.949	2.890	2.917
Social dysfunction	Estimate	0.120***	0.030	0.090***	0.107	0.069
	Standard error	(0.033)	(0.041)	(0.035)	(0.085)	(0.099)
	Obs	76, 129	76, 129	49, 103	6, 288	6, 288
	Pre-treatment mean	12.158	12.158	12.187	12.130	12.152
SF12	Estimate	-0.149	-0.073	-0.140	-0.265	-0.090
	Standard error	(0.130)	(0.159)	(0.139)	(0.321)	(0.407)
	Obs	75, 719	75, 719	48, 374	6, 128	6, 128
	Pre-treatment mean	50.284	50.284	49.846	50.528	50.345

Notes: the Table shows differences-in-differences estimates for men. We compare changes in mental health outcomes in years after 2020 for those in teleworkable occupations in 2019 to changes in propensity to remote work in the years after 2020 for those in occupations which are not teleworkable in 2019. In column (1) we present the differences-in-differences estimator in the full sample of people who work in an occupation in 2019. In column (2) we additionally include controls for owning a home in 2019, having biological children in 2019, education in 2019, and job level in 2019, interacted with year dummies. In column (3), we restrict the sample to people observed in the years 2015 to 2022. In column (4) we limit the sample to those who are reported in every year from 2015 to 2022. In column (5) we present the synthetic differences-in-differences estimator (Arkhangelsky et al. 2021). Standard errors are clustered at the person level, except for the synthetic differences-in-differences estimator where we use the Jackknife estimator proposed by Arkhangelsky et al. (2021). Mental health measures are defined in the note to Table 1. *p<0.1; **p<0.05; ***p<0.01

Table 6: Effect of expansion of remote work on mental health for those in teleworkable occupations (women)

		(1) Unbalanced panel	(2) Unbalanced panel controls	(3) Unbalanced panel (2015 onwards)	(4) Balanced panel	(5) Synthetic DD
GHQ12 Casness	Estimate	0.107**	0.004	0.073	-0.015	-0.023
	Standard error	(0.045)	(0.049)	(0.048)	(0.113)	(0.139)
	Obs	91, 907	91, 907	58, 607	8, 216	8, 216
	Pre-treatment mean	1.852	1.852	1.856	1.698	1.702
Anxiety and Depression	Estimate	0.095**	0.019	0.084**	0.072	0.066
	Standard error	(0.035)	(0.038)	(0.037)	(0.086)	(0.103)
	Obs	92, 134	92, 134	58, 791	8, 328	8, 328
	Pre-treatment mean	7.661	7.661	7.669	7.537	7.547
Loss of confidence	Estimate	0.042**	0.008	0.014	-0.014	-0.026
	Standard error	(0.019)	(0.020)	(0.020)	(0.045)	(0.053)
	Obs	92, 225	92, 225	58, 852	8, 368	8, 368
	Pre-treatment mean	3.221	3.221	3.256	3.187	3.207
Social dysfunction	Estimate	0.031	-0.014	0.005	-0.005	0.014
	Standard error	(0.034)	(0.037)	(0.037)	(0.085)	(0.103)
	Obs	92, 058	92, 058	58, 716	8, 256	8, 256
	Pre-treatment mean	12.429	12.429	12.458	12.423	12.431
SF12	Estimate	-0.388***	-0.165	-0.163	-0.228	-0.016
	Standard error	(0.131)	(0.142)	(0.140)	(0.331)	(0.420)
	Obs	91, 500	91, 500	57, 934	8, 016	8, 016
	Pre-treatment mean	48.215	48.215	47.620	48.309	48.127

Notes: the Table shows differences-in-differences estimates for women. We compare changes in mental health outcomes in years after 2020 for those in teleworkable occupations in 2019 to changes in propensity to remote work in the years after 2020 for those in occupations which are not teleworkable in 2019. In column (1) we present the differences-in-differences estimator in the full sample of people who work in an occupation in 2019. In column (2) we additionally include controls for owning a home in 2019, having biological children in 2019, education in 2019, and job level in 2019, interacted with year dummies. In column (3), we restrict the sample to people observed in the years 2015 to 2022. In column (4) we limit the sample to those who are reported in every year from 2015 to 2022. In column (5) we present the synthetic differences-in-differences estimator (Arkhangelsky et al. 2021). Standard errors are clustered at the person level, except for the synthetic differences-in-differences estimator where we use the Jackknife estimator proposed by Arkhangelsky et al. (2021). Mental health measures are defined in the note to Table 1. *p<0.1; **p<0.05; ***p<0.01

Table 7: The effect of the expansion of remote work on mental health for those in teleworkable occupations, men, data aggregated at the occupation level.

		(1) Unbalanced panel	(2) Unbalanced panel (2015 onwards)	(3) Balanced panel	(4) Synthetic DD
Use remote work	Estimate	0.084***	0.065***	0.083***	0.073***
	Standard error	(0.013)	(0.013)	(0.023)	(0.024)
	N year-occupation pairs	3187	1865	536	536
GHQ12 Caseness	Estimate	0.027	-0.012	0.070	0.060
	Standard error	(0.082)	(0.081)	(0.102)	(0.108)
	N year-occupation pairs	3187	1865	1608	1608
Anxiety and Depression	Estimate	0.006	-0.002	0.015	0.011
	Standard error	(0.082)	(0.081)	(0.102)	(0.108)
	N year-occupation pairs	3187	1865	1608	1608
Loss of Confidence	Estimate	0.085	0.080	0.074	0.088
	Standard error	(0.070)	(0.065)	(0.078)	(0.079)
	N year-occupation pairs	3187	1865	1608	1608
Social Dysfunction	Estimate	0.088**	0.061	0.091**	0.041
	Standard error	(0.043)	(0.040)	(0.045)	(0.045)
	N year-occupation pairs	3187	1865	1608	1608
SF12	Estimate	-0.289***	-0.197***	-0.362***	-0.519***
	Standard error	(0.077)	(0.071)	(0.090)	(0.100)
	N year-occupation pairs	3187	1865	1608	1608

Notes: the Table shows differences-in-difference estimators for those in teleworkable and non-teleworkable occupations in 2019, estimated on men. We average mental health to the year-2019 occupation level, and regress the average mental health of a 2019 occupation in a given year on dummies for the 2019 occupation, the year, and an interaction between the year being after 2019 and whether the 2019 occupation is teleworkable. The latter is our variable of interest. The number of occupation-year pairs is the number of unique 2019 occupation-year pairs, and the number of balanced occupation year pairs is the number of unique 2019 occupation-year pairs when we only include 2019 occupations for which we have data in each year. Standard errors are estimated using a block-bootstrap. In column (1), we estimate an unweighted regression using data from 2011 for every 2019 occupation-year pair for which we have data. In column (2), we additionally restrict the data to run from 2015. In column (3), we additionally restrict the sample to be balanced in calendar time in terms of 2019 occupation-year pairs. In column (4), we use synthetic differences-in-differences weights (Arkhangelsky et al. 2021).

Table 8: The effect of the expansion of remote work on mental health for those in teleworkable occupations, women, data aggregated at the occupation level

		(1) Unbalanced panel	(2) Unbalanced panel (2015 onwards)	(3) Balanced panel	(4) Synthetic DD
Use remote work	Estimate	0.094***	0.075***	0.110***	0.101***
	Standard error	(0.004)	(0.004)	(0.006)	(0.006)
	N year-occupation pairs	2652	1562	440	440
GHQ12 Caseness	Estimate	0.200*	0.162	-0.011	0.004
	Standard error	(0.116)	(0.115)	(0.113)	(0.115)
	N year-occupation pairs	2652	1562	1312	1312
Anxiety and Depression	Estimate	0.199**	0.209***	0.093	0.091
	Standard error	(0.080)	(0.076)	(0.077)	(0.083)
	N year-occupation pairs	2652	1562	1312	1312
Loss of Confidence	Estimate	0.069	0.057	0.005	0.018
	Standard error	(0.044)	(0.044)	(0.046)	(0.049)
	N year-occupation pairs	2652	1562	1312	1312
Social Dysfunction	Estimate	0.130	0.118	0.021	0.027
	Standard error	(0.082)	(0.082)	(0.073)	(0.081)
	N year-occupation pairs	2652	1562	1312	1312
SF12	Estimate	-0.435	-0.285	0.148	0.327
	Standard error	(0.334)	(0.316)	(0.328)	(0.395)
	N year-occupation pairs	2652	1562	1312	1312

Notes: the Table shows differences-in-difference estimators for those in teleworkable and non-teleworkable occupations in 2019, estimated on women. We average mental health to the year-2019 occupation level, and regress the average mental health of a 2019 occupation in a given year on dummies for the 2019 occupation, the year, and an interaction between the year being after 2019 and whether the 2019 occupation is teleworkable. The latter is our variable of interest. The number of occupation-year pairs is the number of unique 2019 occupation-year pairs, and the number of balanced occupation year pairs is the number of unique 2019 occupation-year pairs when we only include 2019 occupations for which we have data in each year. Standard errors are estimated using a block-bootstrap. In column (1), we estimate an unweighted regression using data from 2011 for every 2019 occupation-year pair for which we have data. In column (2), we additionally restrict the data to run from 2015. In column (3), we additionally restrict the sample to be balanced in calendar time in terms of 2019 occupation-year pairs. In column (4), we use synthetic differences-in-differences weights (Arkhangelsky et al. 2021).

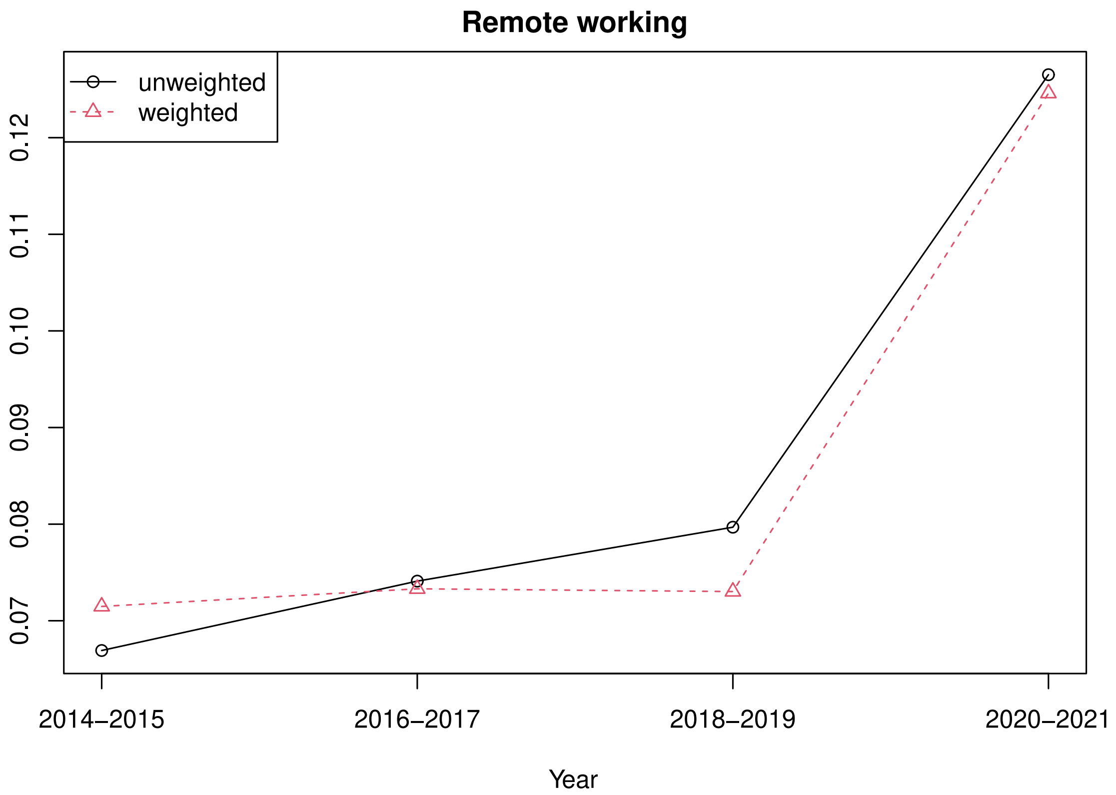
3 Appendix figures/tables

Table 9: Attrition in 2020 as a function of 2019 variables

	Dependent variable:
	Attrit in 2020
GHQ12 caseness in 2019	0.003***
	(0.001)
Teleworkable job in 2019	−0.024***
	(0.005)
GHQ12 caseness in 2019 × Teleworkable job in 2019	−0.0003
	(0.002)
Observations	16,989

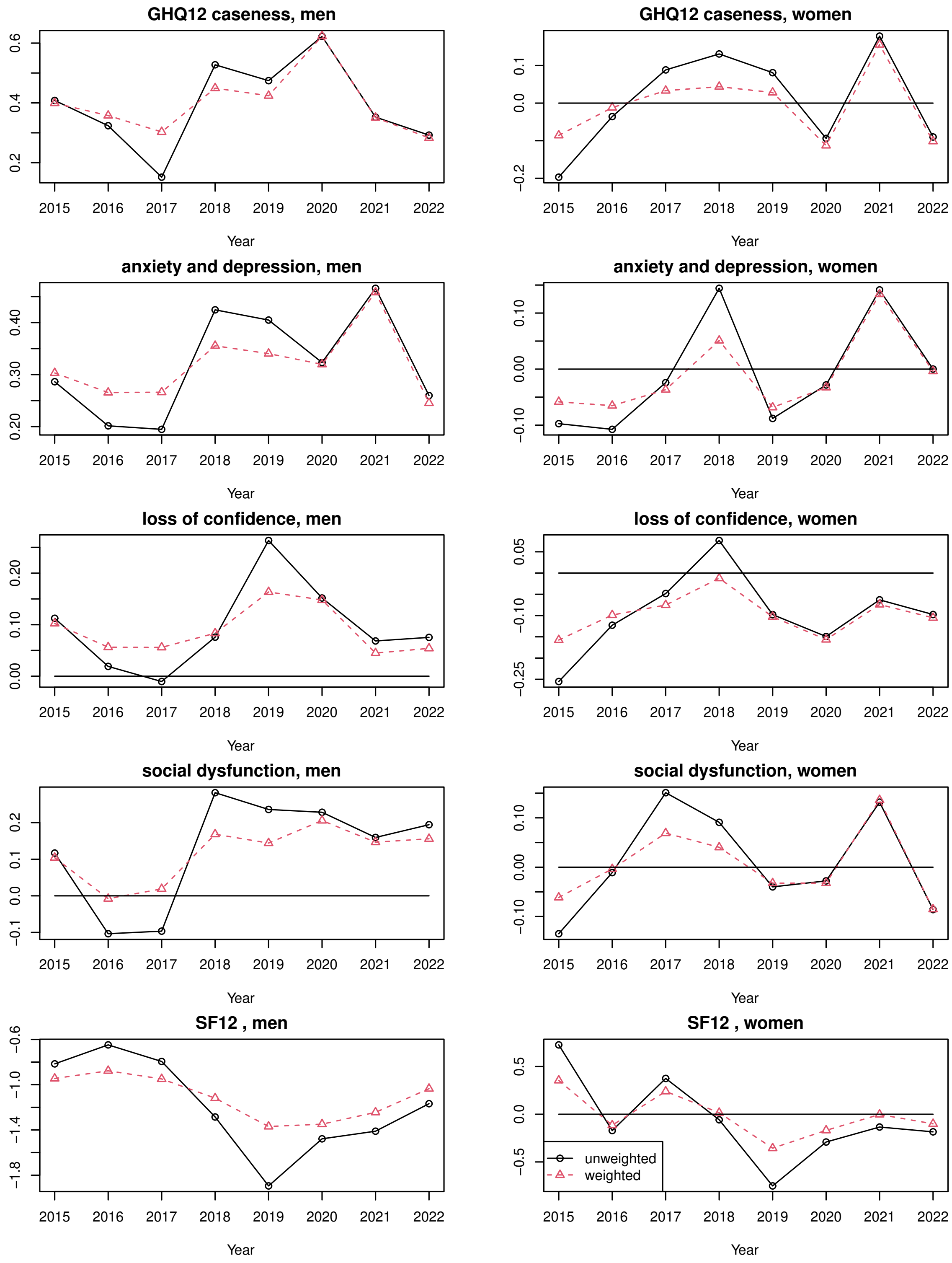
Notes: the Table shows the results of regressing a dummy for attriting in 2020 on a person's occupational teleworkability in 2019 interacted with their mental health. Mental health measures are defined in the note to Table 1. *p<0.1; **p<0.05; ***p<0.01

Figure 8: Mean weighted difference in propensity to work remotely between treatment and control groups



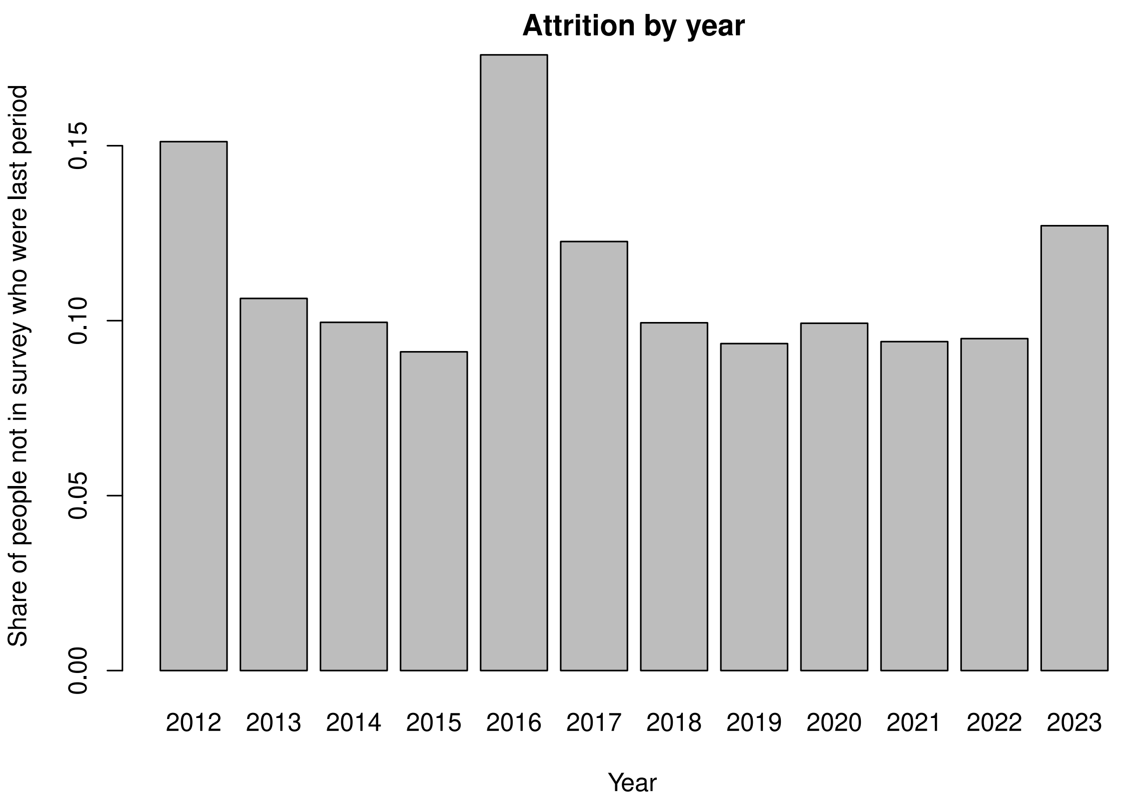
Notes: the Figure shows the mean difference in mental health between the treatment and control groups in a panel balanced in calendar years from 2015 to 2022. The black line with circular points is the mean difference in outcomes. The red line with triangular points weights control units in order to more closely match the pre-treatment trends between the groups. These weights solve the minimization problem in Equation 5 in Arkhangelsky, Athey, Hirshberg, Imbens, and Wager (2021).

Figure 9: Mean weighted difference in mental health between treatment and control groups



Notes: the Figure shows the mean difference in remote working between the treatment and control groups in a panel balanced in calendar year pairs from 2014-2015 to 2020-2021. The black line with circular points is the mean difference in outcomes. The red line with triangular points weights control units in order to more closely match the pre-treatment trends between the groups. These weights solve the minimization problem in Equation 5 in Arkhangelsky, Athey, Hirshberg, Imbens, and Wager (2021).

Figure 10: The share of respondents who attrit in each year



Notes: the Figure shows the share of people each year who attrit from the survey (do not appear in the survey but were present in the previous wave. NB: around 77% of attritors appear in at least one subsequent wave.