The causal impact of remote working on depression during the first wave of the Covid-19 pandemic

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Abstract

We use longitudinal data from the SHARE survey to estimate the effect of remote working during the Covid-19 pandemic on depression in senior Europeans. There are potential endogeneity concerns both for the probability of remaining employed during the pandemic and, conditional on employment, for the choice of work arrangements. Our research design overcomes these problems by exploiting the occupational variations in the technical feasibility of remote working and sectoral differences in the legal restrictions on in-presence work. We find that remote working increases the probability of reporting feelings of sadness or depression. This effect is larger for women, respondents with children at home, and singles, as well as in regions with more restrictive containment policies and low excess death rates. Our results should alert policy makers to the potential adverse consequences of remote working for mental health in the post-pandemic situation.

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1 Introduction

Mental health is a key to subjective well-being, a potential factor of risk for future health and a driver of choices, behavior and outcomes. One of the important challenges of the Covid-19 pandemic involves its effects on mental health (Banks et al., 2021; Pfefferbaum and North, 2020; Holmes et al., 2020).

According to Banks et al. (2021), several aspects of the pandemic may affect mental health in the short and the long run. First, anxiety stemming from the direct and indirect effect of being infected and hospitalized is particularly troublesome for senior individuals, who are at greater risk of serious health consequences. Second, the pandemic has caused financial problems for households whose members were employed in sectors affected by the crisis. Third, domestic and family arrangements may also have played a role: a blurred working environment may aggravate tensions when work has to be combined with family duties. In addition, space limitations or an insufficient number of PCs and devices may be a problem in a family where both parents work remotely, and children are engaged in remote schooling. Moreover, being forced to spend practically all one's time with other family members may be bothersome where pre-existing household tensions are present. Fourth, workers faced an unprecedented challenge in adapting to remote working arrangements. For instance, the need to learn new IT skills in order to work from home may have been a source of mental stress, especially for older workers. Finally, the loss of otherwise fulfilling activities and social contacts constitutes another threat to mental health, especially for the older population, who may be less familiar with digital communication (Cavapozzi and Dal Bianco, 2021).

When the pandemic struck in the spring of 2020, many private companies and government entities had to resort to working-from-home arrangements. Whereas remote working was relatively uncommon before the pandemic (according to data from the 2018 European Labour Force Survey, 10% of employees and 30% of self-employed workers worked from home at least part of the time), with the pandemic it became the prevalent work arrangement for a large fraction of the working population: Eurofound (2020) reports that 48% of employees worked remotely at least part of the time in 2020. The shift was uneven, however: the extent to which each firm adopted remote working arrangements varies by industry (Barbieri et al., 2020; Dingel and Neiman, 2020).

Understanding the relationship between remote working and mental health is important because the share of people working from home is likely to persist at a high level: Barrero et al. (2021) estimate that in the U.S. roughly 20% of total work time will be performed from home after the pandemic ends. Given the growing importance of alternative work arrangements, the possible public health implications are of special concern. On the one hand, remote working could help women in particular to reconcile work with family life and reduce stress (Angelici and Profeta, 2020; Mas and Pallais, 2017), with a mechanism similar to maternity leave (Avendano et al., 2015). On the other hand, while remote working may increase productivity, it can still have an adverse effect on career prospects (Bloom et al., 2015). What is more, it may accentuate isolation and heighten family tensions, especially where both partners work from home (Douglas et al., 2020).

Our paper contributes to the growing literature on mental health trajectories during the Covid-19 pandemic (Adams-Prassl et al., 2022; Banks et al., 2021; Barili et al., 2021; Cheng et al., 2021; Garcia-Prado et al., 2022; Giuntella et al., 2021; Koch and Park, 2022; Mendez-Lopez et al., 2022; Paccagnella and Pongiglione, 2022, among others), focusing on a specific and relatively under-investigated group, namely older workers. To date, the relevant literature for this population group is quite scanty (Oakman et al., 2020, reviews the pre-Covid literature), and in general they lack a research design for the identification of a causal impact on mental health (e.g. Perelman et al., 2021; Rinsky et al., 2021, with data collected during the pandemic).

In this study we exploit longitudinal data from the Survey of Health, Ageing and Retirement in Europe (SHARE), which interviewed a representative sample of Europeans aged 50 and up immediately before and after the first wave of the pandemic to investigate whether the shift to working from home affected reported feelings of sadness or depression. A priori, the effect is ambiguous: safety considerations could undermine the mental health of people working at their regular office or plant, while protracted home working could induce feelings of isolation, loneliness and stress.

While Covid-19 constituted a universal, unexpected shock, the circumstances faced by individuals in coping with the pandemic, such as remote working, cannot be considered to be randomly assigned. As a result, we need a careful research design to tackle the multiple sources of endogeneity arising in our context. First, there is unobserved heterogeneity: those who worked remotely may differ from the others with respect to unobservable predictors of depression. Second, self-selection into remote working may also play a role: expected risk of depression under different work arrangements may determine whether individuals chose to work from home or not. Finally, sample selection is also relevant: we compare individuals working from home with those that continued to work at their usual workplace, yet the probability of working during the first wave of the pandemic may depend on their depression rate and their willingness/feasibility to work remotely.

We address these endogeneity concerns by exploiting two sources of variability during the first wave of the pandemic. The first is the variability across sectors in the legal restrictions on in-presence work. The second is the variability in the attitude of a job to be performed remotely. Crucially, we provide evidence that prior to the pandemic the groups of workers defined by sector and degree of teleworkability had comparable sadness or depression trends. This confirms the exogeneity of these sources of variability and corroborates our identification strategy. To the best of our knowledge, this is the first paper that develops a research design to uncover a causal relation between remote working and mental health.

We estimate that, on average, feelings of sadness or depression increased more among those working remotely than those continuing at their regular workplace. This adverse effect was larger in magnitude for women, respondents with cohabiting children, and singles. Moreover, remote working was more detrimental in regions where the pandemic was relatively mild (measured by the excess death rate during the SHARE fieldwork period) and the public policy response was more stringent (measured by the Oxford Covid-19 Government Response Tracker). Our findings have important implications for the debate on the future of remote work and should alert policy makers to the need to temper work flexibility so as to address the threats to mental health, especially for women.

The remainder of the paper is organized as follows. In section 2 we describe the data and provide descriptive evidence on the key variables. The econometric specification is set out in section 3 and the results are discussed in 4. Section 5 assesses the robustness of our findings with respect to a number of alternative modelling assumptions, and section 6 draws the conclusions and policy implications.

2 Data and descriptive statistics

We combine longitudinal individual survey data with aggregate information on job characteristics and gauges of pandemic severity and the government response. The individual data come from the SHARE, an international panel survey on the health, employment and social conditions of a representative sample of the European population aged 50 and up. The survey began in 2004 and since then has been conducted biannually in an increasing number of countries. From 2018 it covers all 28 EU countries plus Israel and Switzerland.[1]

The fieldwork for Wave 8 of SHARE began in October 2019 and was interrupted by the pandemic; it had to be suspended in all participating countries in March 2020 when some 70% of the panel respondents across Europe had already been interviewed. In response, SHARE developed a special questionnaire covering the same topics as the regular survey, but considerably shortened and targeted to the circumstances of people aged 50 and above during the pandemic. This SHARE Corona Survey was conducted by telephone interview (CATI methodology) mostly between June and July 2020; for more on the survey methodology, see Börsch-Supan (2022) and Scherpenzeel et al. (2020). This approach means that we observe a sample of the over-50 population in Europe immediately before and after the first wave of the Covid-19 pandemic.

Our empirical analysis of mental health trajectories during the pandemic is based on the information provided by respondents participating in both Wave 8 and SHARE Corona. To validate our identification strategy, we also need to investigate their mental health trends between Wave 8 and at least one previous data collection wave. Therefore, we had

[1]More details on survey methodology of regular SHARE waves can be found in Börsch-Supan et al. (2013).

to exclude countries that participated in SHARE for the first time in Wave 7, as in that Wave information on mental health was not collected for those respondents (they were given a retrospective questionnaire). We also exclude Portugal, which was not present in Wave 8, and the Netherlands, where information on occupations - that is crucial to identify teleworkable jobs - was not collected in Waves 6 and 7. The individuals considered were employed at the outbreak of Covid-19 and aged between 50 and the statutory retirement age in each country (taken from the MISSOC tables and reported in Table A1 in the Appendix). Our sample thus includes 2,860 observations for the following 17 countries: Austria, Belgium, Croatia, Czech Republic, Denmark, Estonia, France, Germany, Greece, Israel, Italy, Luxembourg, Poland, Slovenia, Spain, Sweden, and Switzerland.

2.1 Depression

In the regular SHARE waves, the EURO-D scale serves as a validated measure of depressive symptoms (Prince et al., 1999). Unfortunately, only three of the EURO-D items were part of the SHARE Corona questionnaire, namely feelings of sadness or depression, loneliness, and sleep patterns. Lacking data on a validated scale for depressive symptoms, we focus on the direct question about feelings of sadness or depression, which reads: (*camh002*) "In the last month have you been sad or depressed?" and must be answered either Yes or No. [2] The same question was asked in Wave 8 as well as in the most recent previous wave. [3]

Our dependent variable ΔDEP captures the changes in depressive feelings between two SHARE interviews, $t-1$ and t; and takes value -1 if the respondent did not report depressive feelings at $t-1$ but did at t; 0 if the status has not changed; and $+1$ if the respondent reported sadness or depression at $t-1$ but not at t. Descriptive statistics on all the variables described in this section are given in Table 1, together with other economic and demographic control variables. Figure 1 shows the density plots of ΔDEP between SHARE Corona (Covid) and Wave 8 (left panel), and between Wave 8 and the closest available previous interview (hereafter, we will refer to this as Wave 7 for brevity). The unconditional distribution of the changes in sadness or depression suggests that depressive feelings diminished during the first wave of the pandemic relative to the previous period. ΔDEP improved between Wave 8 and SHARE Corona for roughly 25% of respondents and deteriorated for 7.4%. The comparable data for Wave 7 and Wave 8 were 17.4% and

[2] After the question, respondents who answer positively are also asked, retrospectively, whether they feel more or less sad/depressed than before the pandemic; the same goes for sleep patterns and loneliness. However, we cannot use this information to assess the variation in mental health for the whole sample because the questions were not put to those who answered that they had not been sad or depressed in the last month before the interview.

[3] Depression was not elicited in Wave 7 for respondents who had not yet answered the retrospective questionnaire addressed to SHARE respondents in Wave 3. For these individuals, we retrieve depression from previous waves (Wave 6 or Wave 5). In the end, we used Wave 5 data for 4% of the sample, Wave 6 data for 91%, and Wave 7 data for 5%.

14.8%. This result is in line with Atzendorf and Gruber (2021) and Van Winkle et al. (2021).

2.2 Employment status during the first wave of the pandemic and remote working

In the SHARE Corona survey, respondents are asked a series of questions to elicit labour market participation and work arrangements during the first wave of the pandemic. The first question is whether they were employed or self-employed at the outbreak of Covid-19 (*caep805*). Conditional on a positive answer, respondents were then asked if they became unemployed, were laid off or had to close their business because of the pandemic (*caw002*). After this set of questions, *caw010* asks "Since the outbreak of Corona, some people worked at home, some at their usual workplace outside their home, some both. How would you describe your situation?", with four possible answers: "Worked at home only", "Worked at the usual workplace", "Worked from home and at the usual workplace", "None of these (furloughed, did not work at all)". We use these responses to identify three groups of respondents: (i) those who continued at their usual workplace, (ii) those who worked from home at least part of the time, and (iii) those who lost their job or ceased work but retained their employment status (in many countries there were public policies to limit or avoid job losses, workers being furloughed and subsidized though general taxation). As reported in Table 1, roughly 75% continued to be employed during the first wave of the pandemic. Of those who remained employed, close to 40% worked from home for at least part of the time, while 60% worked only at the usual place.

2.3 Instrumental variables

The endogeneity concerns discussed in the introduction suggested an instrumental variables strategy to correct for endogenous selection into employment during the pandemic and for the choice of remote working.

As regards the former, we exploit the distinction between "essential" and "non-essential" workers. The governmental mobility restrictions resulting in lay-offs or furloughs did not apply to all workers: those employed in sectors considered to be "essential" could keep working, while mobility restrictions and home confinement applied to "non-essential" workers. The first country to furnish a list of essential and non-essential sectors was Italy: just as the pandemic broke out first in Italy, so containment policies developed there first. This list was issued in the Prime Ministerial Decree of 22 March 2020; sectors were divided into essential and non-essential by and large at the 2-digit NACE level: agriculture, hunting, mining, quarrying, utilities, transport and storage, public administration, education and health were classified as essential, while manufacturing, construction, wholesale and retail trade, hotels and restaurants, financial intermediation, real estate, and community services were non-essential. Almost the same distinction was later adopted by most European governments (Fana et al., 2020). The 2-digit NACE coding is available in Wave 8 of SHARE data, so each respondent can be classified as essential or non-essential.[4] Concerning the second issue, an exogenous determinant of the probability of eventually working remotely can be found in Sostero et al. (2020), namely the authors' index of technical teleworkability of jobs based on the 3-digit ISCO occupational codes. The index gauges the "technical possibility of providing labor input remotely": if a job has a significant amount of task content that requires the physical manipulation of objects or people, it is classified as not teleworkable. The construction relies on the Italian *Indagine Campionaria delle Professioni* or survey of occupations (ICP), collected by *Istituto Nazionale per l'Analisi delle Politiche Pubbliche* (INAPP), and on the European Working Conditions Survey (EWCS), collected by Eurofound. Starting from Wave 6, respondents' occupations are retrieved in SHARE by means of a "job coder", a survey tool that automatically maps self-reported occupations into 4-digit ISCO codes (Brugiavini et al., 2017). This feature of the data allows us to match each worker's occupation precisely with its teleworkability index value from Sostero et al. (2020). Figure 2 highlights the cross-country heterogeneity in shares both of essential sectors and of teleworkable jobs. Details on the construction of the two instruments on the basis of these data are in Section 3.

2.4 Covid-19 severity and containment policies

The extent to which work arrangements affect mental health is likely to depend also on the risk of contagion. We account for the local severity of Covid-19 by observing the peak in the excess death rate in the respondent's region between January 2020 and the week of the interview. We computed the excess mortality in region r and week w as the percentage difference between the number of deaths in 2020 and the average number of deaths in the same week w in 2016-2019:[5]

$$P - score_{r,w} = \frac{Deaths_{r,w,2020} - \frac{1}{4}\sum_{t=2016}^{2019} Deaths_{r,w,t}}{\frac{1}{4}\sum_{t=2016}^{2019} Deaths_{r,w,t}} * 100. \tag{1}$$

A *P-score* of 100% means the death count for that week was twice as high as the average

[4]the Decree specified some distinction at a finer detail than 2-digit NACE. As an example, within wholesale and retail, cars spare parts selling was considered essential. Since that was the only essential subsector in wholesale and retail, we considered the whole 2-digit NACE as non-essential.

[5]For EU countries, this information is available at NUTS2 to NUTS0 level from Eurostat. For Israel it is available at NUTS0 level from Statistics Israel. The regional aggregation level available in SHARE also differs by country. We used NUTS2 regions whenever possible, and otherwise NUTS1 or NUTS0. In detail, we use NUTS2 regions for Austria, Sweden, Spain, France, Italy, Greece, Switzerland, Belgium, Czech Republic, and Poland; NUTS1 regions for Germany; and the NUTS0 country level for Denmark, Luxembourg, Israel, Croatia, Slovenia and Estonia. In each country, we dropped respondents for whom information on region of residence was not available at this level.

death count in the same week over the previous four years. Finally, as proxy for the severity of the pandemic, we take the highest *P-score* in the respondent's region in 2020 up to the end of the SHARE fieldwork. Figure 3 displays the substantial differences in Covid-19 mortality faced by Europeans in different regions in the first half of 2020.

During the first wave of the pandemic, respondents in different countries were subjected to a variety of containment policies: restrictions on social activities, school closures, shutdowns of economic activities, even confinement at home. Most of these are compiled and organized in an internationally comparable way in the Oxford Covid-19 Government Response Tracker database, which also aggregates information into a number of policy indices (Hale et al., 2021). Our starting point is the "Stringency index" which measures the strictness of policies restricting conduct using nine ordinal containment and closure policy indicators including school closures, workplace closures, and travel bans, plus an indicator recording public information campaigns. It is then rescaled to a value from 0 to 100 (100 = strictest). We look at the overall distribution of the stringency index across countries and over the period between the Wave 8 and the SHARE Corona survey, defining as days in "strict lockdown" those in the top tertile of the index, i.e. over 59.72. Then, for each country, we counted the number of days of high stringency: Figure 4 highlights the heterogeneity in this measure across countries.

3 Econometric specification

Our outcome variable ΔDEP takes values $\{-1, 0, 1\}$ where depressive feelings of individual i in country c, region r interviewed in week w respectively worsened, held unchanged, or improved between Wave 8 and SHARE Corona. Given the discrete and ordinal nature of this variable, we analyze it using an ordered probit model, which considers it as the discrete counterpart of the latent variable ΔDEP^* defined as follows:

$$\Delta DEP^*_{i,c,r,w} = \beta_{1;1} RW_{i,c,r} + \boldsymbol{x}'_{i,c,r} \boldsymbol{\beta}_{X;1} + \delta_{1,c;1} + \delta_{2,c;1} iw_w + \varepsilon_{i,c,r,w;1} \tag{2}$$

The key regressor is a dummy $RW_{i,c,r}$ that takes value 1 if individual i in country c, region r worked remotely at least part of the time during the first wave of the pandemic and 0 if the individual kept going to the usual workplace. Control variables $\boldsymbol{x}_{i,c,r}$ include the log peak excess death rate by region, age, gender, and a dummy for a tertiary education degree; a dummy for living with a partner in the household; a dummy for not having children; household wealth tertiles (the lowest tertile is the omitted category); public employee dummy; and a self-employment dummy (private sector employee is the excluded category). All demographic characteristics in $\boldsymbol{x}_{i,c,r}$ are reported as observed during the interview in Wave 8. Finally, we include a vector of country dummies, $\delta_{1,c;1}$, and a vector of country-specific slopes in the week of the SHARE Corona interview, $\delta_{2,c;1}$. Conditional on the right-hand-side variables, the error term ϵ follows a standard normal distribution.

The latent outcome ΔDEP^* defines its discrete observed counterpart ΔDEP according to the transformation:

$$\Delta DEP = \begin{cases} -1 & \text{if} & & \beta_{1;1} RW_{i,c,r} + \boldsymbol{x}'_{i,c,r}\boldsymbol{\beta}_{X;1} + \delta_{1,c;1} + \delta_{2,c;1} iw_w + \varepsilon_{i,c,r,w;1} & \leq \alpha_{-1} \\ 0 & \text{if} & \alpha_{-1} < & \beta_{1;1} RW_{i,c,r} + \boldsymbol{x}'_{i,c,r}\boldsymbol{\beta}_{X;1} + \delta_{1,c;1} + \delta_{2,c;1} iw_w + \varepsilon_{i,c,r,w;1} & \leq \alpha_1 \\ 1 & \text{if} & \alpha_1 < & \beta_{1;1} RW_{i,c,r} + \boldsymbol{x}'_{i,c,r}\boldsymbol{\beta}_{X;1} + \delta_{1,c;1} + \delta_{2,c;1} iw_w + \varepsilon_{i,c,r,w;1} & \end{cases} \tag{3}$$

As noted above, to properly estimate the differential effects of remote versus in-presence working on sadness and depression, we must adjust for endogenous selection by individuals who continued working during the pandemic. We do so by adding a sample selection equation. The exclusion restriction, i.e. the variable that affects the probability of work being uncorrelated with mental health trajectories, is $IV1_{i,c,r}$, a dummy that takes value 1 if at the beginning of the pandemic individual i was in a non-essential sector and a non-teleworkable occupation (teleworkability index of 0). As shown in Table 1, 18% of workers in our sample had non-essential, non-teleworkable jobs ($IV1 = 1$). Figure 5 is a graphical representation of the role of $IV1$: the green circle represents the mass of non-essential, non-teleworkable individuals. Their employment rate is clearly lower than the average for the teleworkable and also lower than that of non-teleworkable but essential workers. We define the binary outcome $Demp_{i,c,r,w,s}$ as a dummy equal to 1 for individuals who keep on working during the pandemic and 0 for those who do not.

The second threat to identification of the causal impact of remote working on sadness and depression stems from reverse causality and omitted variable bias. A deterioration in mental health may itself increase the propensity to work from home, while unobservable factors (say, subjective perception of the risk of contagion) may affect both sadness and depression feelings, and the propensity to work remotely. Accordingly, we instrument the binary variable RW with $IV2_{i,c,r}$, a dummy that takes value 1 if individual i is in a teleworkable sector (technical teleworkability index greater than 0) at the outbreak of the pandemic, whether essential or not. Table 1 shows that this was the case for roughly 65% of the workers in our sample. Again, before going to the econometric specification, we provide a graphical intuition of the role of this instrument in the sample that excludes the non-essential, non-teleworkable individuals - for whom $IV1 = 1$ - in Figure 6: unsurprisingly, the probability of working remotely is substantially lower for the non-teleworkable.

We model the binary variables $Demp$ and RW using the following probit models:

$$Demp_{i,c,r,w,s} = 1(\boldsymbol{x}'_{i,c,r}\boldsymbol{\beta}_{X;2} + \beta_{2;2} IV1_{i,c,r} + \beta_{3;2} IV2_{i,c,r} + \delta_{1,c;2} + \delta_{2,c;2} iw_w + \varepsilon_{i,c,r,w;2} > 0) \tag{4}$$

$$RW_{i,c,r,t,s} = 1(\boldsymbol{x}'_{i,c,r}\boldsymbol{\beta}_{X;3} + \beta_{3,3} IV2_{i,c,r} + \delta_{1,c;3} + \delta_{2,c;3} iw_w + \varepsilon_{i,c,r,w;3} > 0) \tag{5}$$

The error terms in equations (3), (4) and (5) are standardized to have mean of 0 and variance of 1 and are allowed to be correlated. Their variance and covariance matrix is:

$$\mathbf{\Sigma} = \begin{bmatrix} 1 & \rho_{\Delta DEP,Demp} & \rho_{\Delta DEP,RW} \\ \rho_{\Delta DEP,Demp} & 1 & \rho_{Demp,RW} \\ \rho_{\Delta DEP,RW} & \rho_{Demp,RW} & 1 \end{bmatrix}$$

The coefficients in equations (3), (4) and (5), the thresholds α_{-1}, α_1 and the non-diagonal elements in the variance and covariance matrix Σ are jointly estimated by maximum likelihood, exploiting the triangular nature of the system (Roodman, 2011). As our system of equations is non-linear, the estimates of the coefficients are not the marginal effects. We then exploit the coefficient estimates and the estimated variance and covariance matrix to compute the Average Marginal Effects.[6]

Identification of the model requires that the instruments can be treated as exogenous (as good as random) as well as two exclusion restrictions. As regards exogeneity, the classification of sectors as essential or non-essential was decided suddenly by governments in response to the pandemic, and workers had practically no voice in it, nor time to react. The distinction between teleworkable and non-teleworkable jobs is trickier, however, as it basically depends on workers' occupational choices, which while pre-determined may nevertheless depend on their expected mental health benefits from working remotely. We offer empirical evidence of the exogeneity of this instrument, demonstrating that prior to the pandemic the trends in depression among workers in teleworkable and non-teleworkable occupations were comparable. They only started to diverge during the pandemic, when remote working became prevalent. Our model also requires two exclusion restrictions. First, unlike working in an essential but non-teleworkable sector, working in a non-essential and non-teleworkable sector ($IV1$) or in a teleworkable sector ($IV2$) does not affect depression during the pandemic directly but only through its effect on the probability of working (for $IV1$) and of remote working conditional on employment (for $IV2$). Although they are not testable, we consider these assumptions to be plausible.

4 Results

Table 2 reports the baseline estimates of the model described in section 3. Column (1) gives the estimates of equation 4: the excluded instrument $IV1$ is significant at the 1% level, confirming the descriptive evidence of Figure 5. With respect to individuals in essential sectors and non-teleworkable jobs, those in non-essential sectors and non-teleworkable jobs are 12 percentage points (p.p.) less likely to continue working during the first wave of the pandemic. This marginal effect is also strongly significant. Contrarily, the

[6] We compute the Average Marginal Effects on ΔDEP based on the Average Structural Function (Blundell and Powell, 2003). To compute the probabilities of interest, the set of conditioning factors is augmented with the products of the error term of every other regression multiplied by a term proportional to the covariance between the same error term and the one in the equation (3). This procedure holds all observable and unobservable covariates fixed while computing the marginal effect of interest.

effect of $IV2$ is much smaller in absolute value. Column (2) reports the probit estimate of equation 5. Again, the estimation results confirm the relevance of the instrument chosen: the effect of $IV2$ is positive and significant at the 1% level. Conditional on being at work during the first wave of the pandemic, having a teleworkable job (regardless of whether the sector is essential or not) increased the probability of working remotely of roughly 26-p.p.. Column (3) reports the ordered probit estimation of equation (3): the causal effect of remote working on sadness and depression is adverse and highly significant. By comparison with those going to their regular workplace, individuals working remotely at least part of the time had a 12.5-p.p. lower probability of an improvement in sadness or depressive feelings and a 6-p.p. and 7-p.p. higher chance of reporting no change or a worsening of sadness or depression, respectively. Considering that in the full sample the shares of those reporting better, constant and worse depression are respectively 24.6%, 68%, and 7.4%, these are very large effects.

At this stage, an obvious concern is whether this result is actually a change with respect to the trajectories in sadness and depression before the pandemic. Columns (4), (5) and (6) of Table 2 report the estimates when the dependent variable is the difference in depression between Wave 8 and the latest available previous wave. There is no evidence of any significant marginal effect of remote working on trends in sadness and depression prior to the pandemic: the coefficient is not significant and is precisely estimated (standard error of 0.04, as against 0.056 in the baseline regression). This placebo test indicates that there was no pre-existing systematic difference in depressive feelings between respondents who ended up working remotely and those who continued to go to their regular workplace during the pandemic, once we account for the potential endogeneity of such choices. These results offer corroboration of our identification strategy.

A relevant question is whether the effect of remote working on depression shown in Table 2 may not conceal heterogeneous effects. Table 3 reports estimates produced by splitting the sample according to some individual characteristics: columns (1) and (2) show the estimates by gender: no significant effect of remote working on depression for men, but an adverse effect for women, significant at the 1% level. Next, we investigate whether family composition matters. Column (3) estimates the model for respondents with children at home (both men and women), column (4) for those without children. We find a particularly large worsening in reported depression among respondents with children at home, significant at the 1% level. The change among respondents without children at home is three to four times smaller, and again precisely estimated. Finally, columns (5) and (6) show that respondents both with and without a partner at home reported a significant worsening of depression, but the magnitude of the coefficient and of the relative marginal effects is much greater for singles and widows/widowers. Angelici and Profeta (2020) find that, before the pandemic, working at home one day a week improved the well-being and work-life balance for women more than for men. The results reported in columns (1) and (2) seem to contradict this finding, but as columns (3) and (4) indicate, the presence of children was an appreciable burden for people working from home; Zamarro and Prados (2021) find that women shouldered most of the childcare burden while still working during the pandemic.[7]

Finally, we consider whether the effect of remote working differs according to regional and national factors related to the severity of the pandemic and to containment policies. Columns (1) and (2) of Table 4 divide the sample into regions above and below the median peak excess death rate, and in columns (3) and (4) into countries above and below the median of 73 days of strict lockdown. Remote working has a significant adverse effect in regions below the median peak excess death rate, but not in those above the median. Where the death rate was relatively low, remote working significantly increased the probability of reporting depressive feelings and reduced both that of improvement and that of no change. As regards containment measures, in countries with above-median days in strict lockdown, working remotely increased the probability of reporting sadness or depression and reduced the likelihood of an improvement. In countries below the median again we estimate an adverse effect of remote working on depression, but a considerably smaller one. To examine these differences more closely, we combined our proxies for Covid-19 severity and containment stringency and divided the pool of regions into four groups. In column (1) of Table 5, both excess death rate and days of strict lockdown are above the median: in these regions the coefficient is negative and significant at the 10% level, while the marginal effects are not significant. Where excess death rate is below median and lockdown stringency above it (column (2)), then the effect is statistically significant at the 1% level, and so are all the marginal effects: in these regions, respondents have a 17.1-p.p. greater probability of reporting worse depression, a 10.1-p.p chance of reporting no change, and a 6.9-p.p reduction in the likelihood of reporting an improvement. There is no significant effect in either of the groups with below-median stringency. Since the causal impact on depression is led by the subgroup of persons subjected to harsh containment measures while facing a relatively low risk of infection, our interpretation is that remote working has a detrimental depressive effect when the worker does not perceive a substantial benefit of home working in terms of diminished health risk.

5 Robustness

An obvious concern is whether our findings depend on our modelling choices. Since our outcome variable is discrete and ordinal, we have adopted a non-linear model and a normality assumption for the error term. Our sample-selection equation also depends on a normality assumption and on the validity of the exclusion restriction for $IV1$. To assuage these concerns we run several robustness checks. First, in Table A2 we show that all the results set out in Table 2 still hold even when no adjustment is made for the endogeneity

[7] We also sought to estimate the effect of remote working on depression in the four groups defined by respondent's gender and presence of children. The results are as expected, but the sample is severely reduced, raising problems for the recursive algorithm to solve the ML equations.

of sample selection into employment during the first wave of Covid-19 and equation 4 is dropped. Second, in Panel A of Table A3 we show that our baseline findings also hold qualitatively, but are imprecisely estimated, when a linear specification for the outcome is used. This choice neglects the ordinal nature of the dependent variable but avoids the normality assumption for the error term. We either include or exclude the sample selection equation and the first stage equation, which is tantamount to treating remote work as exogenous. In Panel B of Table A3 we stack the data by individual and wave and use a linear Difference-in-Differences (DiD) model estimated for the sub-sample of persons who continued to work during the first wave of the pandemic. The outcome is coded as a dummy equal to 1 if the individual reports feeling sad or depressed in the given wave and 0 otherwise, which factors out individual-level positive or negative changes between survey waves. As we observe remote working only in the SHARE Corona survey, we focus on the reduced form of our IV estimates, and compare trends in depression before and after Covid between persons who had teleworkable and non-teleworkable jobs before Covid. Hence, our specification includes $IV2$ (Teleworkability), a dummy for the post-Covid survey wave and the interaction between the two. The results, in column (1), show a positive and statistically significant effect of $IV2 \times Post$ on the probability of being sad or depressed. Column (2) fictitiously anticipates the onset of Covid from the SHARE Corona survey to Wave 8, to serve as a placebo test for parallel trends. As expected, the placebo effect is small and not statistically significant, again corroborating our identification strategy. Finally, in column (3) we replicate the specification in column (1) using a post double selection Lasso method (Belloni et al., 2014) for choosing the covariates to include among the ones that are present in our baseline specification (see Table 2). This method suggests including only Denmark and Germany as country dummies, plus a female dummy. The results are wholly comparable to those in column (1). Finally, ΔDEP could be a questionable proxy for changes in depression status. As is explained in section 2, the question on which this variable is based is one of the items used in regular SHARE waves to construct EURO-D, a validated scale measuring depression. The SHARE Corona questionnaire includes two other questions that are also EURO-D items: one on loneliness and one on sleeplessness. Table A4 reports the effects when our dependent variable is replaced by changes in sleep patterns (column (1)) and loneliness (column (2)). The definition of the dependent variables and the interpretation of the effects are the same as in Table 2. The estimated coefficients in columns (1) and (2) are both different from that of the baseline regression, confirming that ΔDEP captures differences in depression and not other dimensions of mental health. We also observe that while remote working did not alter sleep patterns, it did have a significant adverse effect on loneliness.

6 Conclusions

We estimate the effect of working from home on depression in older workers during the first wave of the Covid-19 pandemic, on the basis of surveys that interviewed the same workers immediately before and immediately after the outbreak of the pandemic. To gauge the causal impact, we exploit differences between countries and industries in exposure to Covid-19 and in containment policies. We find that on average working from home had a detrimental effect on depression compared to continuing to go to the usual workplace. On closer examination, we find this effect to be heterogeneous among subpopulations. The impact on depression during the first wave of Covid-19 was nil for men and limited for remote-working respondents without children at home; depression worsened among working women, and among remote-working respondents with children at home. Further, respondents living in regions with low exposure to Covid-19 but strict containment measures experienced an aggravation of depression. If - as expected - remote working remains a common arrangement even once the pandemic has passed, these findings raise public health concerns and need to be considered carefully by policy makers. First, working from home is hard to reconcile with the homemaking duties that typically still fall disproportionally on women. Thus, the health consequences of a massive shift to remote working are likely to be gender-biased. Second, the evidence indicates that containment measures must be proportionate to the actual health risks that individuals face.

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Tables and figures

Table 1: Descriptive Statistics

	Mean	Standard Deviation	Observations
Dependent variables			
Δ *Depression Covid - Wave 8*			
Worse Depression	0.074	0.262	2860
Same Depression	0.680	0.467	2860
Improved Depression	0.246	0.431	2860
Δ *Depression Wave 8 - Wave 7*			
Worse Depression	0.148	0.355	2860
Same Depression	0.678	0.467	2860
Improved Depression	0.174	0.380	2860
Endogenous variables			
Employed during COVID	0.747	0.435	2860
Remote working - employed only	0.408	0.491	2137
Instrumental variables			
Non-essential, Non-teleworkable job (*IV1*)	0.180	0.384	2860
Teleworkable job (*IV2*)	0.655	0.476	2860
Control variables			
Age	60.01	3.05	2860
Female	0.554	0.497	2860
Has a partner	0.787	0.410	2860
Tertiary education degree	0.374	0.484	2860
Has no children	0.099	0.298	2860
Employed as civil servant at COVID outbreak	0.322	0.467	2860
Self-employed at COVID outbreak	0.140	0.347	2860
log(Peak excess death rate) - by region	3.26	0.82	2860

Table 2: Main results. The effect of remote work on depression changes during the pandemic and pre-pandemic placebo tests.

	(1)	(2)	(3)	(4)	(5)	(6)
Time frame		Covid-Wave 8			Wave 8 - Wave 7	
Dependent variable	Employed	Remote work	ΔDEP	Employed	Remote work	ΔDEP
Coefficients						
IV1	-0.396***			-0.397***		
	(0.034)			(0.033)		
IV2	-0.113**	0.927***		-0.103*	0.944***	
	(0.054)	(0.078)		(0.058)	(0.084)	
Remote work			-0.441***			-0.066
			(0.056)			(0.040)
Observations	2,860	2,860	2,860	2,860	2,860	2,860
Clusters	98	98	98	98	98	98
Selected observations		2,137	2,137		2,137	2,137
Selected Clusters		94	94		94	94
Marginal effects						
Pr(Employed = 1)	-0.120***			-0.121***		
for IV1	(0.012)			(0.011)		
Pr(Employed = 1)	-0.031**			-0.029*		
for IV2	(0.016)			(0.017)		
Pr(Remote work= 1)		0.256***			0.260***	
for IV2		(0.028)			(0.029)	
Pr(ΔDEP = -1)			0.070***			0.015
for Remote Work			(0.011)			(0.009)
Pr(ΔDEP = 0)			0.055***			0.002
for Remote Work			(0.006)			(0.001)
Pr(ΔDEP = 1)			-0.125***			-0.016
for Remote Work			(0.015)			(0.010)

Notes: IV1 is a dummy for being employed in a non-essential and non-teleworkable job. IV2 is a dummy for being employed in a teleworkable job. The omitted category is employment in an essential and non-teleworkable job. All models control for country dummies, country-specific linear trends in the week of interview at the SHARE Corona Survey, age, gender, presence of partner, tertiary education degree, not having children, sector of employment at the outbreak of Covid-19 (public employee, private employee, self-employed), the log peak excess death rate by region. Standard errors are clustered by cells defined on the basis of essentiality and teleworkability. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 3: The heterogeneous effect of remote work on changes in depression by individual characteristics.

	(1)	(2)	(3)	(4)	(5)	(6)
Heterogeneity by	Gender		Children at home		Partner	
	Male	Female	Yes	No	Yes	No
Dependent variable	ΔDEP	ΔDEP	ΔDEP	ΔDEP	ΔDEP	ΔDEP
Coefficients						
Remote work	-0.030	-0.643***	-0.699***	-0.210***	-0.346***	-0.810***
	(0.073)	(0.065)	(0.118)	(0.058)	(0.068)	(0.123)
Observations	1,275	1,585	850	2,008	2,250	610
Clusters	90	92	80	96	94	78
Selected observations	944	1,193	610	1,525	1,687	450
Selected clusters	85	87	72	91	90	68
Marginal effects						
Pr(ΔDEP = -1)	0.003	0.118***	0.082***	0.034***	0.050***	0.145***
for Remote Work	(0.007)	(0.017)	(0.016)	(0.010)	(0.011)	(0.038)
Pr($\Delta DEP = 0$)	0.005	0.071***	0.119***	0.025***	0.047***	0.095***
for Remote Work	(0.013)	(0.008)	(0.022)	(0.006)	(0.008)	(0.017)
Pr($\Delta DEP = 1$)	-0.008	-0.190***	-0.201***	-0.059***	-0.097***	-0.240***
for Remote Work	(0.020)	(0.017)	(0.031)	(0.016)	(0.018)	(0.032)

Notes: see Table 2

Table 4: The heterogeneous effect of remote work on changes in depression by country and regional level factors.

	(1)	(2)	(3)	(4)
Heterogeneity by	Peak excess death rate		Stringency index	
	Above median	Below median	Above median	Below median
Dependent variable	ΔDEP	ΔDEP	ΔDEP	ΔDEP
Coefficients				
Remote work	-0.153	-0.398***	-0.452***	-0.154**
	(0.161)	(0.058)	(0.077)	(0.080)
Observations	828	2,032	1,681	1,179
Clusters	79	96	93	88
Selected observations	552	1,585	1,213	924
Selected clusters	66	93	84	85
Marginal effects				
Pr(ΔDEP=-1)	0.017	0.060***	0.071***	0.024*
for Remote Work	(0.019)	(0.009)	(0.016)	(0.013)
Pr(ΔDEP=0)	0.029	0.059***	0.055***	0.021**
for Remote Work	(0.031)	(0.009)	(0.007)	(0.010)
Pr(ΔDEP=1)	-0.046	-0.119***	-0.126***	-0.045**
for Remote Work	(0.050)	(0.017)	(0.022)	(0.023)

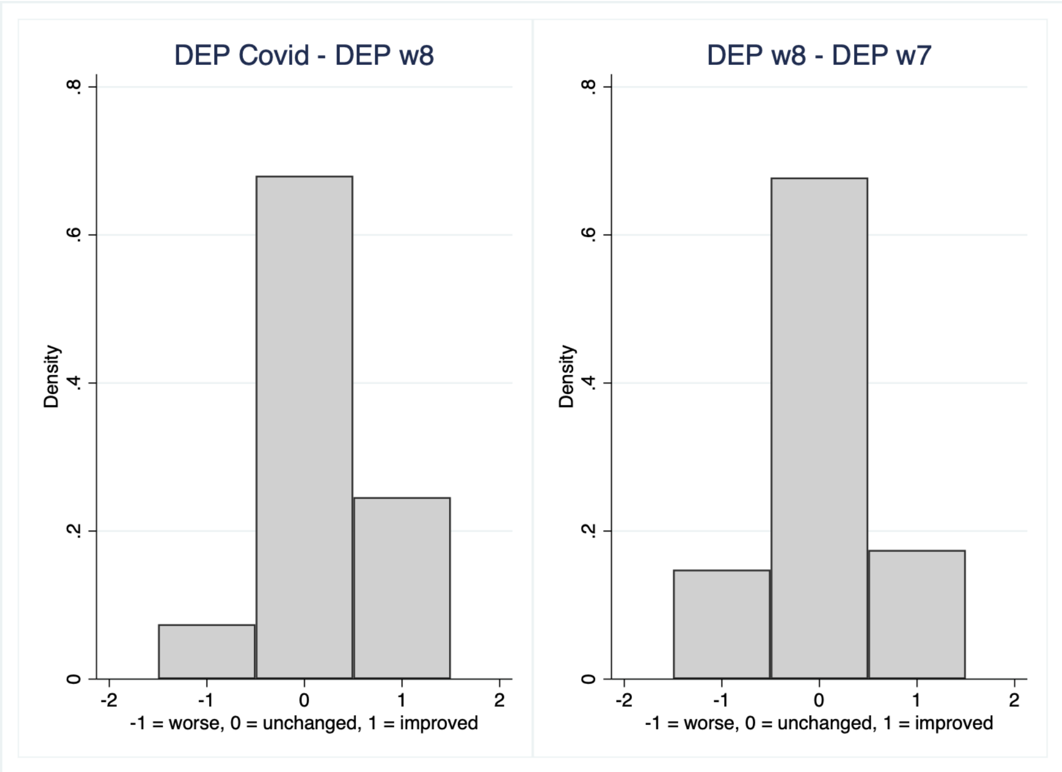
Notes: see Table 2

Table 5: The heterogeneous effect of remote work on changes in depression by interacted regional country-level factors.

	(1)	(2)	(3)	(4)
Peak excess death	Above median	Below median	Above median	Below median
Stringency index	Above median	Above median	Below median	Below median
Dependent variable	ΔDEP	ΔDEP	ΔDEP	ΔDEP
Coefficients				
Remote work	-0.370*	-0.533***	-0.220	-0.089
	(0.221)	(0.068)	(0.238)	(0.101)
Observations	599	1,082	229	950
Clusters	75	88	57	84
Selected observations	380	833	172	752
Selected clusters	59	79	52	81
Marginal effects				
Pr(ΔDEP=-1)	0.054	0.069***	0.029	0.013
for Remote Work	(0.035)	(0.012)	(0.034)	(0.015)
Pr(ΔDEP=0)	0.031	0.101***	0.033	0.013
for Remote Work	(0.020)	(0.013)	(0.033)	(0.014)
Pr(ΔDEP=1)	-0.085	-0.171***	-0.062	-0.026
for Remote Work	(0.054)	(0.021)	(0.066)	(0.029)

Notes: see Table 2

Figure 1: Depression - changes across survey waves



Notes: Individuals' depression worsens if they did not report sadness or depression at the baseline survey but do report it at the endline, and conversely for improvement. Individuals who continued to report/not report sadness or depression feelings are in the "unchanged" category.

Figure 2: Essential and teleworkable workers by country

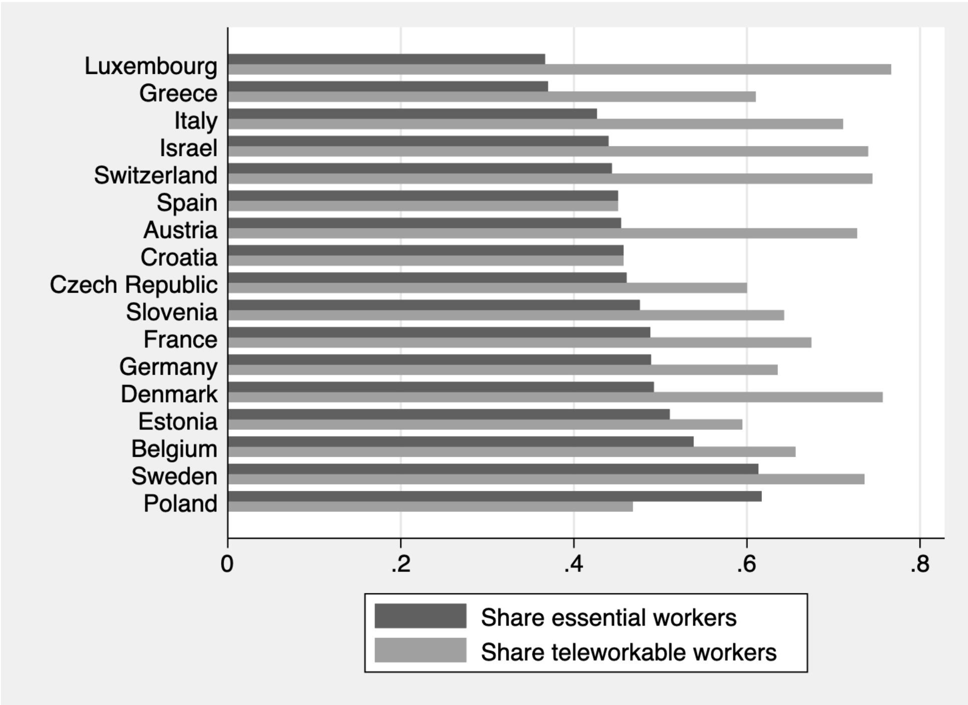
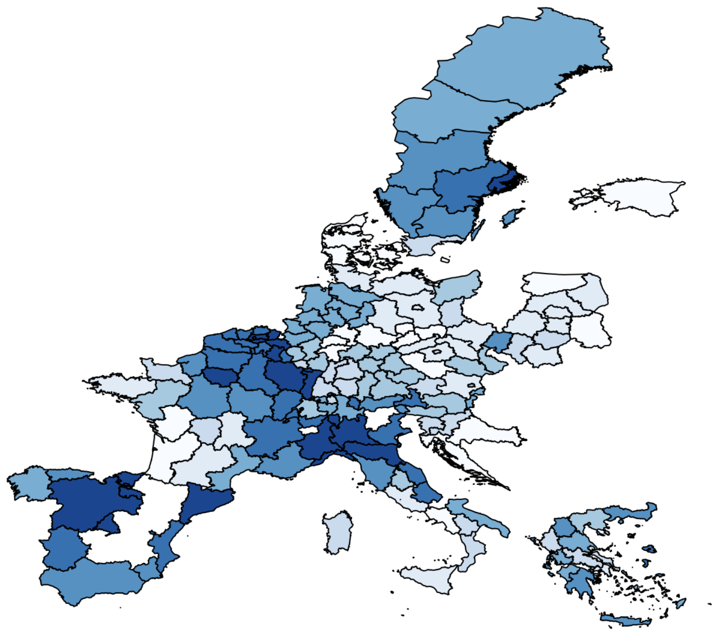
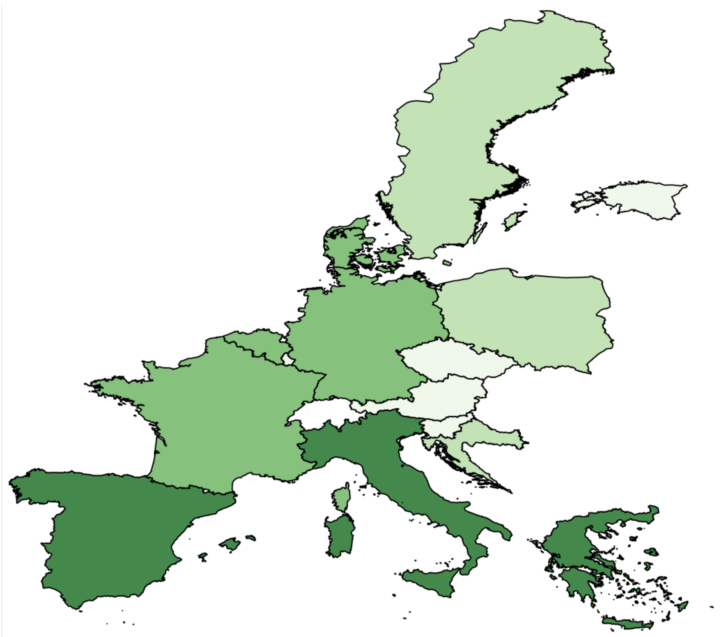


Figure 3: Peak weekly excess death rate by region



The figure depicts the highest weekly excess death rate in weeks 1-37 of 2020. Boundaries are defined at the NUTS 2 level. Darker (lighter) blue regions indicate higher (lower) values of the weekly excess death rate. Regions with no observations available are left white.

Figure 4: Stringency index by country



The figure depicts the number of days of strict lockdown during weeks 1-37 of 2020 (number of days with a value in the top tertile of the stringency index). Darker (lighter) green regions indicate more (fewer) days in strict lockdown. Regions with no observations available are left white.

Figure 5: Teleworkability, essential workers and employment probability

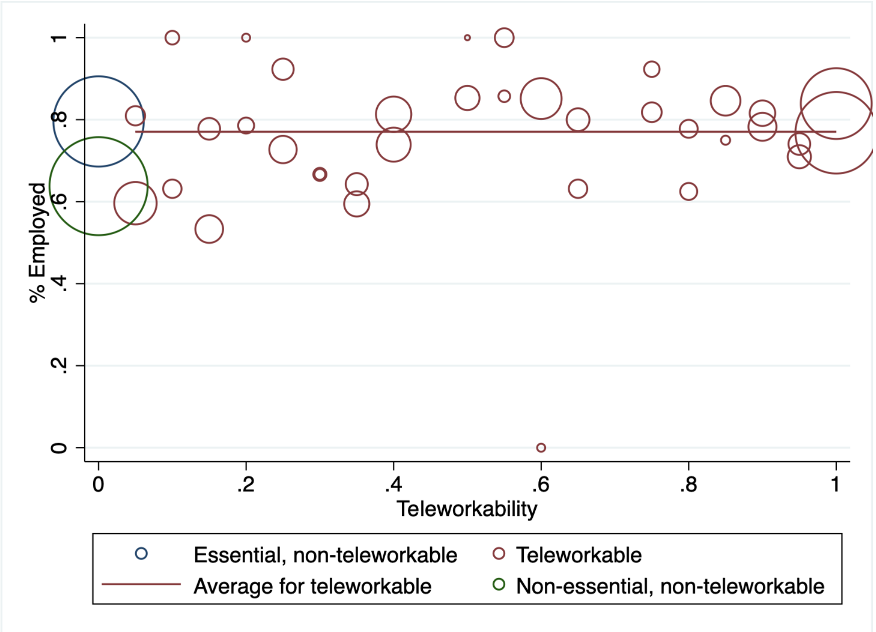
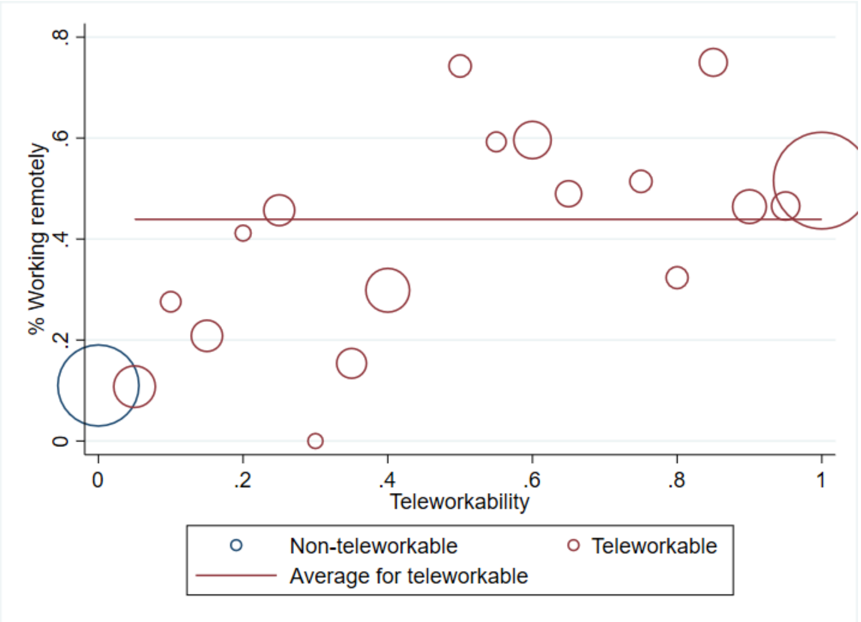


Figure 6: Teleworkability and remote working



The sample excludes non-essential, non-teleworkable individuals.

Appendix

Table A1: Minum retirement age by country

Country	Minimum Retirement Age
Austria	Female: 60
	Male : 65
Belgium	65
Croatia	Female: 63
	Male : 65
Czech Republic	Female with no children: 64
	Female with 1 child: 63
	Female with 2 children: 62
	Female with 3 children: 61
	Female with 4 children: 61
	Female with 5 children or more: 60
	Male: 64
Denmark	66
Estonia	64
France	62
Germany	66
Greece	67
Israel	Female: 62
	Male: 67
Italy	67
Luxembourg	65
Poland	Female: 60
	Male: 65
Slovenia	65
Spain	65
Sweden	65
Switzerland	Female: 64
	Male: 65

Source: MISSOC Comparative Tables (https://www.missoc.org/missoc-database/comparative-tables/)

Table A2: The effect of remote work on depression changes during the pandemic and pre-pandemic placebo tests. Ordered probit models allowing for the endogeneity of remote work and estimated on individuals who have worked continously during the panedemic.

	(1)	(2)	(3)	(4)
Time frame	Covid-Wave 8		Wave 8 - Wave 7	
Dependent variable	Remote work	ΔDEP	Remote work	ΔDEP
Coefficients				
IV2	1.066***		1.071***	
	(0.108)		(0.102)	
Remote work		-0.392**		-0.006
		(0.198)		(0.164)
Observations	2,860	2,860	2,860	2,860
Clusters	94	94	94	94
Marginal effects				
Pr(Remote work= 1)	0.318***		0.320***	
for IV2	(0.036)		(0.035)	
Pr(ΔDEP = -1)		0.053*		0.001
for Remote Work		(0.031)		(0.037)
Pr(ΔDEP = 0)		0.063**		0.000
for Remote Work		(0.026)		(0.004)
Pr(ΔDEP = 1)		-0.116**		-0.002
for Remote Work		(0.056)		(0.041)

Notes: IV2 is a dummy for being employed in a teleworkable job. All models control for country dummies, country-specific linear trends in the week of interview at the SHARE Corona Survey, age, gender, presence of partner, tertiary education degree, not having children, sector of employment at the outbreak of Covid-19 (public employee, private employee, self-employed), the log peak excess death rate by region. Standard errors are clustered by cells defined on the basis of essentiality and teleworkability of the job. *** p<0.01, ** p<0.05, * p<0.1.

Table A3: Alternative identification strategies based on linear specifications.

Panel A	(1)	(2)	(3)
Dependent variable	ΔDEP	ΔDEP	ΔDEP
Endogeneity of remote work	Yes	Yes	No
Endogeneity of sample selection	Yes	No	No
Remote work	-0.092	-0.094	-0.019
	(0.133)	(0.067)	(0.025)
Observations	2,860	2,860	2,860
Clusters	98	94	94
Panel B	(1)	(2)	(3)
Dependent variable	Depression (0/1) DiD	Depression (0/1) DiD placebo	Depression (0/1) DiD Lasso
Teleworkability×Post	0.032**		0.032**
	(0.015)		(0.015)
Teleworkability×Pre		0.015	
		(0.013)	
Observations	6,411	6,411	6,411
Clusters	94	94	94

Notes: **Panel A**. Column (1) reports the coefficient on remote work in a linear equation estimated by maximum likelihood allowing for the endogeneity of remote work and of the sample selection. Standard errors are based on 2,000 bootstrap replications to allow for the non-normality of the error term in the main equation. Column (2) reports the coefficient of remote work in a linear equation estimated by 2SLS allowing for the endogeneity of remote work. Column (3) reports the coefficient of remote work in a linear equation estimated by OLS. Equations in columns (2) and (3) are estimated in the selected sample including only individuals who continued to work during the pandemic. In the models of all columns ΔDEP is the dependent variable, and the covariates and instruments are those used in the main specification. Standard errors allow for correlation within cells defined on the basis of essentiality and teleworkability. **Panel B**. The dependent variable is defined as a dummy equal to 1 if the respondent reports being sad or depressed in the SHARE Corona Survey. Column (1) shows DiD estimates of the effect on depression of working in a teleworkable job. Column (2) anticipates the treatment to Wave 8. Column (3) reports DiD estimates selecting controls through Double-Lasso regression. Models are run only on individuals who continue to work after the Covid-19 outbreak. Standard errors are clustered by cells defined on the basis of essentiality and teleworkability. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A4: The effect of remote work on changes in sleep and loneliness.

	(1)	(2)
Time frame	Covid-Wave 8	
Dependent variable	ΔSleep	ΔLonely
Coefficients		
Remote work	0.012	-0.391***
	(0.051)	(0.060)
Observations	2,860	2,860
Selected observations	2,137	2,137
Clusters	98	98
Marginal effects		
Pr(ΔDEP=-1)	-0.001	0.058***
for Remote Work	(0.006)	(0.010)
Pr(ΔDEP=0)	-0.002	-0.000
for Remote Work	(0.010)	(0.003)
Pr(ΔDEP=1)	0.004	-0.058***
for Remote Work	(0.015)	(0.009)

Notes: see Table 2.