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# Lockdown strictness and mental health effects among older populations in Europe☆

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A B S T R A C T

This paper investigates whether lockdown policies aggravated mental health problems of older populations (50 and over) in Europe during the first COVID-19 wave. Using data from the Survey of Health, Ageing and Retirement in Europe (SHARE COVID-19 questionnaire) and from the Oxford COVID-19 Government Response Tracker for 17 countries, we estimate the causal effect of lockdown policies on mental health by combining cross-country variability in the strictness of the policies with cross-individual variability in face-to-face contacts prior to the pandemic. We find that lockdown policies worsened insomnia, anxiety, and depression by 5, 7.2 and 5.1 percentage points, respectively. This effect was stronger for women and those aged between 50 and 65. Interestingly, lockdown policies notably damaged the mental health of healthy populations. We close with a discussion of lockdown policies targeted at individuals above 65 and/or with pre-existing conditions.

## 1. Introduction

The COVID-19 pandemic declared by the World Health Organization (WHO) on March 11, 2020 led governments around the world to implement a wide range of response measures, including "stay at home" orders and closures of non-essential businesses, to restrict citizens' mobility and thereby reduce the transmission and incidence of the virus (Bu et al., 2020). While these unprecedented "social distancing" strategies have been crucial for limiting the spread of the virus and alleviating pressure on health systems (Mendiola et al., 2021; Soucy et al., 2020; Fang et al., 2020; Prem et al., 2020), they have had other adverse consequences for the well-being of affected populations (Giuntela et al., 2020).

In addition to their dramatic economic impact (business closures and joblessness), policies that restrict mobility and social contacts have had health consequences linked to social isolation and lack of freedom. Social relationships are central to human well-being (Steptoe et al., 2013), and it is well known that loneliness and isolation can cause substantial damage to mental health (Hwang et al., 2020; Brodeur et al., 2021; Henssler et al., 2021). In addition, the impact of lockdown measures on mental health may not have been evenly distributed across different population groups. The WHO has emphasized the risks of lockdown for older adults during the Covid-19 pandemic, as these populations are more vulnerable to social isolation than others (WHO, 2020). Face-to-face social interaction is considered a key factor for healthy aging (Ang and Chen, 2019), and some studies have indicated that lower frequency of in-person social contact with friends and family among older adults is a predictor of depression (Teo et al., 2015; Litwin and Levinsky, 2021).

The main goal of this paper is to investigate whether the COVID-19 lockdown policies implemented by governments during the first wave of the pandemic have caused mental health problems in senior and older Europeans. Lockdown policies have differed among European countries and this heterogeneity is not always linked to the incidence of COVID-19 (see Fig. 4).

We use microdata on anxiety, depression, and insomnia after the

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COVID-19 outbreak for 16 European countries and Israel. Data comes from the SHARE (Survey of Health, Ageing and Retirement in Europe) COVID-19 questionnaire, which took place between June and August 2020 and asked individuals about their COVID-19 living situation. We also use data on the relationship networks of individuals before the COVID-19 pandemic from Wave 6 of the SHARE survey, so we can impute social contacts from Wave 6 to individuals with similar characteristics interviewed by the COVID-19 survey. Our sample includes 40,501 respondents aged 50 and over. In addition, we use information from the Oxford COVID-19 Government Response Tracker (OxCGRT) to construct an index of containment strictness. Our index focuses exclusively on policies that restrict mobility and social contacts in order to slow down the spread of the COVID-19 epidemic. Hereafter we refer to these policies as lockdown policies.

The data clearly shows that mental health is a major problem for older populations in Europe. Of the COVID-19 survey respondents, 27% reported to have insomnia during the month before the interview, 30% reported that they suffered from anxiety and 28% reported depression. More importantly, many of these individuals declared that these mental problems were aggravated after the outbreak of the pandemic (34%, 73% and 63% for insomnia, anxiety and depression respectively). However, as there are many possible causes for psychological distress during a pandemic, our goal is to quantify the causal impact of lockdown policies, in particular those that restricted mobility and social contacts, in Europe on these measures of mental health.

We estimate three models for which our outcomes are binary variables indicating whether the respondents suffered a worsening of mental health (insomnia, anxiety and depression, respectively) during the first COVID-19 wave. We face the challenge of distinguishing the impact of lockdown policies on mental health from individual responses to the incidence of COVID-19 (e.g., anxiety about infection and voluntary lockdown). Thus, to quantify the causal impact of lockdown policies on mental health outcomes we combine differences across countries in the strictness of the lockdown policies with differences across individuals regarding their pre-COVID level of face-to-face social interactions in those countries. The latter differences allow us to define treatment and control groups (individuals with high and low frequency of face-to-face contacts before the outbreak of the corona, respectively), based on the assumption that individuals with high levels of face-to-face contacts prior to the outbreak will experience greater deterioration of mental health than individuals with low frequency of face-to-face contacts as a result of lockdown.

This approach assumes that there are no systematic differences in the way the pandemic impacted the behaviour of treatment versus control groups apart from those stemming from lockdown policies. Controlling for several individual observable socioeconomic characteristics allows us to relax this assumption. Interestingly, the fact that our results hold when we also control by individual exposure to the COVID illness and country-specific case fatality rates of COVID-19, gives support to our claim that the effects found are driven by the strictness of the government policies.

Our estimates suggest that lockdown policies increased the incidence of insomnia, anxiety, and depression by 5, 7.2, and 5.1 percentage points, respectively. That is, lockdown policies increase the incidence by 74.6%, 39.5% and 36.4% of insomnia, anxiety, and depression for individuals of the treatment group relative to a situation with less strict lockdown policies. In addition to controlling for individual exposure to COVID and case fatality rates, we validate our identification strategy and results by presenting a wide battery of robustness exercises that include alternative model specifications, different sample criteria, and alternative outcome variables among others.

We also explore whether the effect of lockdown policies is concentrated in particular population groups. Interestingly, the estimated causal effect is present in almost all types of individuals considered. The one noteworthy exception to this general finding is the differential effect related to gender, as the estimated causal effect for men is not statistically significant. Therefore, the worsening effect of lockdowns on mental health is clearly stronger for women. In addition, this effect is also clearly stronger for those aged between 50 and 65.

Our study adds to a fast-growing literature concerning the effects of the COVID-19 pandemic on mental health. Most studies have focused on the possibility of differential impacts on population groups distinguished by demographic and socioeconomic characteristics: working parents (Cheng et al., 2021), ethnic minorities, (Proto and Quintana-Domeque, 2021), age and gender (Etheridge and Spantig, 2020; Davillas and Jones, 2021; Banks and Xu, 2020; Pierce et al., 2020), household composition (Davillas and Jones, 2021; Pierce et al., 2020), social networks (Litwin and Levinsky, 2021; Bu et al., 2020), political affiliations (Zhou, MacGeorge and Myrick, 2020; Le and Nguyen, 2021), psychiatric patients and health care professionals (Pedrosa et al., 2020). However, fewer studies have investigated the reasons for the deterioration of mental health during the pandemic. Our paper aims to fill this gap in the literature by quantifying the causal impact of lockdown policies in Europe on older populations mental health.

Specifically, our study makes the following contributions. First, we show that the causal impact of lockdown policies on mental health is fairly large. Despite well-recognized correlations, most of the studies that document unfavorable mental health effects as a consequence of lockdown measures fail to account for causality (Devaraj and Patel, 2020; Atzendorf and Gruber, 2021). Secondly, we enlarge the geographic scope of previous causal studies (Serrano-Alarcon et al., 2021; Altindag et al., 2021) by using data on mental health after the outbreak of the pandemic for a large number of countries.[1] Third, we use high-quality survey data on mental health, while other causal studies are based on small samples or samples that are not representative of the population (Brodeur et al., 2021; Altindag et al., 2021), or fail to include validated clinical measures of mental health (Brodeur et al., 2021).[2] Fourth, we contribute to the debate about the decision to impose specific lockdown measures based on age and/or pre-existing conditions as a way to reduce the economic damage of lockdown (Acemoglu et al., 2020; Altindag et al., 2021). Fifth, differently to other causal studies that analyze lockdown impact during the first weeks of the pandemic, we focus on the entire first COVID-19 wave but with a mid-term perspective (our survey data was collected between June and August 2020). This is important because having more face-to-face contacts before the pandemic could act as a buffer, at least during the first weeks of the lockdown when individuals began to organize video "happy hours" as a substitute for their face-to-face social interactions (Folk et al., 2020). However, the detrimental effect of the pandemic on mental health probably worsened as the mobility restrictions and social distancing policies were prolonged (Folk et al., 2020; Shokrkon and Nicoladis, 2021).

The rest of the paper is organized as follows. In Section 2 we describe the data sources. In Section 3 we present our main variables. In Section 4 we explore the causal effect of lockdown policies on mental health. In Section 5 we present our main results and provide several robustness exercises and placebo tests that support our identification strategy. Section 6 concludes.

## 2. Data sources

The analysis of this study combines two types of data from two

[1] Serrano-Alarcon et al. (2021) exploit the different lockdown restriction levels in England and Scotland. Altindag et al. (2021) assess the effects of an age-specific lockdown order for adults aged 65 and older in Turkey.

[2] Brodeur et al. (2021)) evaluate the causal effects of lockdown across European countries and US states using google search data and compare the intensity of searching for mental health terms before and after a lockdown. In Altindag et al. (2021) data on mental outcomes is collected through phone interviews with 1909 individuals by a private firm.

primary sources: the Survey of Health, Ageing and Retirement in Europe (SHARE), and the Oxford COVID-19 Government Response Tracker (OxCGRT) database.

### *2.1. The Survey of Health, Ageing and Retirement in Europe (SHARE)*

Our first primary data source is the special "SHARE Corona" questionnaire of the Survey of Health, Ageing and Retirement in Europe (SHARE).

SHARE provides microdata about health and socio-economic living conditions of adults aged 50 and over in a large number of countries. The outbreak of COVID-19 coincided with the middle of SHARE's Wave 8 data collection. In response, SHARE suspended the regular face-to-face interviewing in all participating countries and instituted a computer-assisted telephone interview (CATI) using a special "SHARE Corona" questionnaire (see Scherpenzeel et al., 2020 for details on data collection). The data collected by this special Corona questionnaire was similar to that of the regular SHARE questionnaire but was shortened and targeted to the COVID-19 living situation of people aged 50 and over. From the CATI telephone survey a sample was selected by SHARE for each country. The CATI was executed in the summer between June and August of 2020.

In this paper, we draw from the SHARE COVID-19 questionnaire to collect data about individual mental health problems after the onset of the pandemic, as well as information about socioeconomic characteristics and physical health. Notice that all this data was collected once the pandemic and the subsequent lockdown had begun.

Moreover, we use data from Wave 6 (2015–2016) of the SHARE survey to characterize the social networks of individuals before the COVID-19 pandemic and predict the behavior of similar individuals in the sample from the special "SHARE Corona" survey.[3] Wave 6 includes the most recent social network module of the SHARE survey and includes 16 European countries and Israel. In this module, respondents report information about their frequency of contact and geographic proximity to social network members (mainly relatives and friends). As we will explain in Section 3, this data about social networks before the pandemic will be crucial for the design of our causal empirical strategy.

Our sample size includes 41,792 respondents residing in the following 17 countries: Belgium, Croatia, Czech Republic, Denmark, Estonia, France, Germany, Greece, Italy, Israel, Luxemburg, Poland, Portugal, Slovenia, Spain, Sweden and Switzerland.

### *2.2. The Oxford COVID-19 Government Response Tracker (OxCGRT) database*

Information about the strictness of lockdown policies comes from the Oxford COVID-19 Government Response Tracker (OxCGRT) database, which provides daily data on indicators of government response to COVID-19 epidemic at country-level for nearly all countries. We focus on eight containment indicators (C1-C8 in the OxCGRT database), all of which are aimed at restricting human mobility and social contacts to slow down the spread of COVID-19.

The selected indicators are ordinal and measure policies on a simple scale of intensity. The policies and corresponding strictness levels are as follows: (C1) closing of schools, (C2) closing of workplaces, (C3) cancellation of public events, (C4) restrictions on gathering size (no restrictions, restrictions on very large gatherings, gatherings limits of 1000 people, gathering limits of 100 people, gathering limits of 10 people or less), (C5) closing of public transportation, (C6) stay at home requirements (no measures, recommended not leaving house, require with some exceptions, require with minimal exceptions), (C7) restrictions on internal movement and (C8) restrictions on international travel (no measure, screening, quarantined arrivals from high-risk regions, ban on arrivals from high-risk regions, ban on all arrivals). Stringency levels for policies (C1), (C2), (C3), (C5), (C7) are: no measures, recommended closing or restriction, required closing or restriction.

## 3. Main variables

In this section we describe only the most important variables for our causal analysis. A complete list and description of all variables is provided in Appendix table A.1.

### *3.1. Mental health after the outbreak*

We include three mental health outcomes in our analysis: anxiety, depression and insomnia. Depression and anxiety are prototypical mental health disorders as they are among the most common health causes of days off work, unemployment, and years of life lived with disability. We also include insomnia because of its various associations with mental illness and because of the way it can exacerbate the symptoms of many mental conditions.[4] The self-reporting of insomnia has proved to be useful and reliable (Katic et al., 2015), while anxiety and depression are usually under-diagnosed because of low self-reporting (Katic et al., 2015), suggesting that our results for these two outcomes could be skewed downwards.

In the SHARE Corona questionnaire, individuals are asked about their mental health problems in the last month and whether these problems have been aggravated, improved, or remained the same since the beginning of the pandemic. Accordingly, we categorize the variable *insomnia* as a binary variable that takes value 1 if respondents answered that they experienced more sleeping problems and zero if these problems improved or remained the same. Similarly, the variable *anxiety* takes value 1 if respondents experienced more anxiety after the outbreak, and zero if they experienced less or about the same anxiety. Finally, the variable *depression* takes value 1 if respondents confirmed they suffered from more depression after the outbreak, and zero if they suffered from less depression or about the same. Note that all our outcome variables measure the worsening of mental health during the pandemic, not simply the existence or absence of symptoms.

### *3.2. Containment index*

We use the information from the Oxford COVID-19 Government Response Tracker (OxCGRT) database to build our containment index of COVID-19 policies. This index measures the strictness of the COVID-19 containment policies implemented in each country. Following Hale et al. (2020), we construct a daily simple additive unweighted index composed of the 8 government response indicators described above. Once the daily composite index was created, we used the monthly average of the containment index for the months April and May 2020.[5]

The average containment index for all 17 countries in our sample is 76.5 (with a standard deviation of 10 points). However, as Fig. 1 shows,

[3] Although SHARE is a panel study, the SHARE Corona survey had specific characteristics that prevented us from using longitudinal panel data for the same individuals and variables of interest over time.

[4] According to the National Alliance on Mental Illness (www.nami.org) approximately 50% of insomnia cases are related to depression, anxiety or psychological stress, and up to 80% of adults with depression experience sleep problems. Recent evidence from a cross-sectional analysis in the UK (the largest of this kind ever conducted) suggests that people with mental illness are more likely to have poor sleep quality (Wainberg et al., 2021).

[5] We chose April and May as reference months since those were the hardest months in terms of mobility restrictions in the countries of our sample. To check our results, we estimated alternative models (creating the Index using the average values per fortnight of April and May, the average of April and the average of May) and all the qualitative results hold.

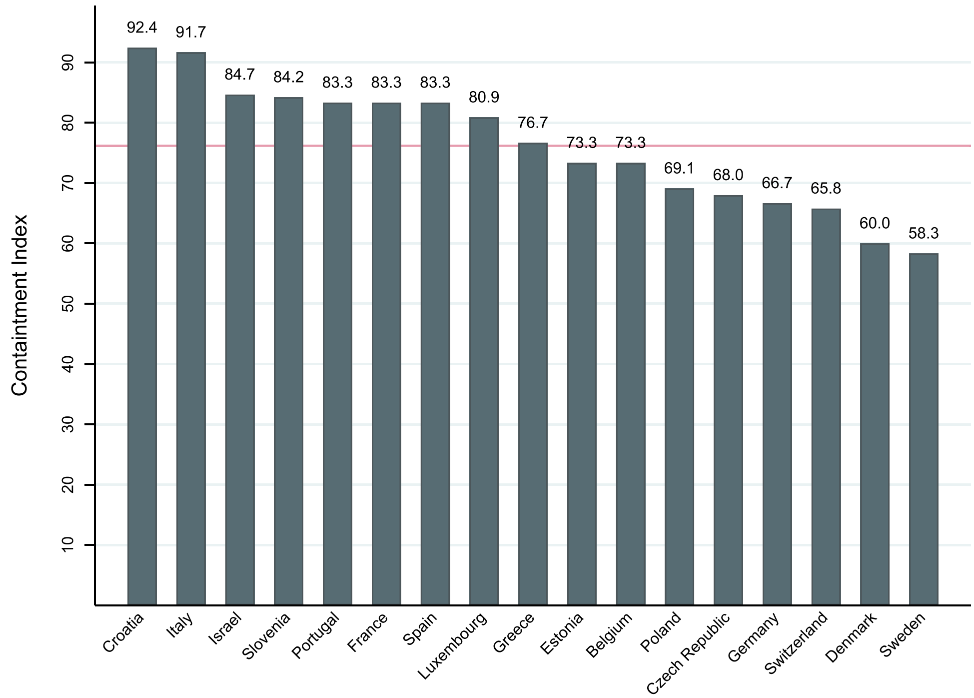


**Fig. 1.** Sample statistics: Containment Index cross country variability. Note: This Figure displays the Containment Index across the 17 countries used in the regression analysis. The Containment Index describes the mean of the index between April and May 2020. These are own calculations using Oxford COVID-19 Government Response Tracker (OxCGRT). The horizontal line refers to the median of the index distribution.

the index varies noticeably across countries. Using the median value, we divided the countries into two groups: "strict lockdown countries" where the containment index is above the median, and "less strict lockdown countries" where the containment index is below the median. Under this assignment rule, the strict lockdown countries in our sample are Greece (76), Luxembourg (80), France (83), Spain (83), Portugal (83), Slovenia (84), Israel (84), Italy (91) and Croatia (92). The less strict lockdown countries are Sweden (58), Denmark (60), Switzerland (65), Germany (66), Czech Republic (68), Poland (69), Estonia (73) and Belgium (73.3). This classification will be useful in our identification strategy as it will become clear in Section 4.

### 3.3. *Score for face-to-face social interactions*

Our causal analysis is based on the idea that individuals who had frequent pre-COVID face-to-face contacts will suffer more from strict lockdown policies than their counterparts in less strict countries. Because information on pre-COVID face-to-face contacts is not available for our COVID-19 SHARE sample (from the 2020 CATI survey), to construct our variables related to social contacts we use the information provided by Wave 6 (2015–2016) of the SHARE survey, which is the most recent wave that includes a social network module. In that module, individuals are asked about their frequency of contact with and geographic proximity to social network members.

We should note that the SHARE social network survey does not distinguish between different forms of contact with social network members—e.g., in person, by phone or mail, email or any other electronic means. Since there is evidence that face-to-face contact is strongly related to short distances and that the frequency of such contacts drops significantly over distance (Carrasco, Miller and Wellman, 2008; Mok, Wellman and Carrasco, 2010), we define our variable of frequency of pre-COVID face-to-face social interactions using those contacts that take place at least once a week within 25 kilometers of distance.[6] That is, we create a dummy variable for pre-COVID face to face contacts that takes value one when the social contact responds to the above-mentioned frequency and distance, and zero otherwise.[7] Using this variable, through a discrete choice econometric model we obtain the probability of having pre-COVID face-to-face contacts according to several socio-economic observed characteristics of the individuals in the SHARE social network survey—age (seven age intervals), gender, physical health (5 groups ranged from excellent to poor), household size (4 categories)—along with country of residence.[8]

As a second step, we use these socioeconomic characteristics to match individuals from the 2015–2016 SHARE social network survey with individuals from the 2020 COVID-19 survey, and impute to everyone in our COVID-19 sample the corresponding score for pre-COVID face-to-face contacts. Table A.2 in the Appendix provides the results of the Discrete Choice Model that predict our social scores. The mean value of pre-COVID face-to-face social interactions is 43%, with a minimum of 12% and a maximum of 71%. Using the median value, we divide individuals into two groups: those with high frequency of face-to-face social contacts (above the median), and those with low frequency of face-to-face social contacts (below the median). These two groups constitute the treatment and control groups in our identification strategy.

## 4. The empirical approach

Our objective is to identify the causal impact of lockdown restrictions implemented in 16 European countries and Israel during the spring of 2020 on health outcomes of anxiety, depression, and insomnia of senior

[6] Contacts with individuals living in the same household are not considered.

[7] In Section 5.2 we increase the distance to the social contact as a placebo test.

[8] We include all the socio-economic characteristics available both in the wave 6 of SHARE and in the SHARE COVID-19 survey that are unrelated to the COVID pandemic. Using these sets of pre-determined characteristics, we end up with 120 types of individuals for each country.

**Table 1**
Mental Health Variation and the DiD identification strategy.

| | Countries | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Total Mean | | Strict lockdown ($T_j = 1$) | | | | Less strict lockdown ($T_j = 0$) | | | |
| | | Mean | Mean | Mean | Diff | Mean | Mean | Mean | Diff | DiD |
| | | | Treated ($S_i = 1$) | Comparison ($S_i = 0$) | (pp.) | Mean | Treated ($S_i = 1$) | Comparison ($S_i = 0$) | (pp.) | pp |
| Outcomes | | | | | | | | | | |
| Insomnia | 9.9% | 11.8% | 12.6% | 11.2% | 1.5*** | 7.7% | 6.7% | 9.4% | -2.7*** | 4.2*** |
| Anxiety | 23.1% | 27.4% | 31.9% | 23.8% | 8.0*** | 17.5% | 18.2% | 16.6% | 1.7*** | 6.4*** |
| Depression | 18.7% | 22.2% | 24.4% | 20.4% | 4.0*** | 14.4% | 14.0% | 15.1% | -1.1*** | 5.1*** |

Notes: The table presents total means and the different means by subgroups of countries (strict versus less strict lockdown levels) and individuals (treated versus comparison) for each outcome variable. Also presents the differences of the mean between treated and control individuals (D*iff)* and the corresponding double difference (*DiD*). The statistical significance for Diff (pp) columns displays a two-sample t test. * 10% statistical significance level; ** 5% statistical significance level; *** 1% statistical.

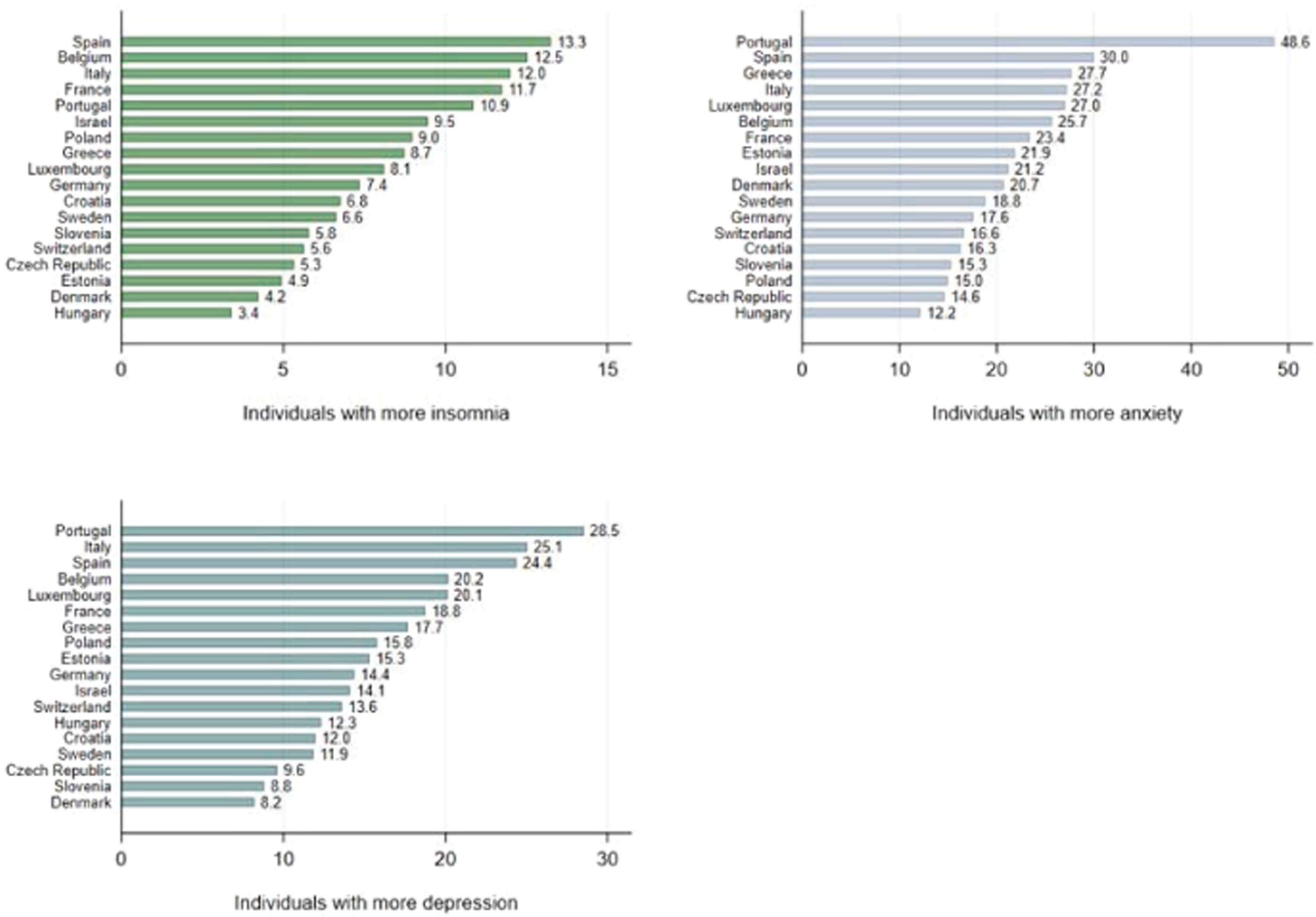


**Fig. 2.** Sample statistics main outcome variables: cross country variability. Note: This figure represents sample means by country for our main outcomes of mental health: insomnia, anxiety and depression. Own calculations based on SHARE-COVID-19 for the 17 countries used in the regression analysis. Survey sample weights are used.

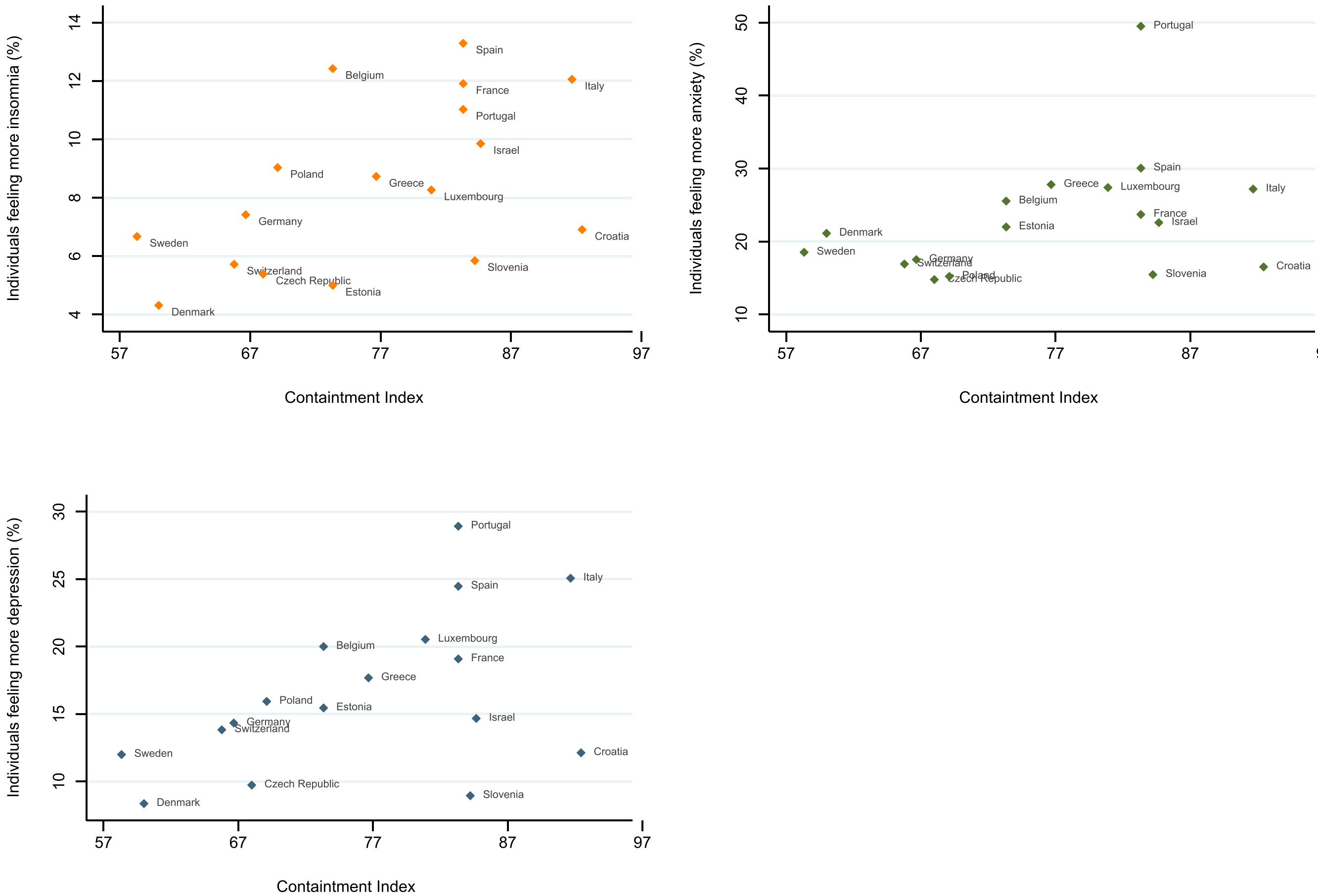


**Fig. 3.** Statistical Relation between mental health and Lockdown Policies. Note: This figure relates our main outcomes variables of mental health (Insomnia, depression and anxiety) with the Containment Index. The index level refers to the mean of the Containment Index between April and May 2020. Mental health outcomes are obtained from SHARE-COVID-19 using the corresponding survey sample weights.

and older adults. The importance of this goal is supported by high levels of deterioration in mental health in these populations, as shown by Figs. 2 and 3.[9]

Fig. 2 shows that, while on average insomnia increased for 9.9% of the respondents, this figure ranges from 4% in Denmark to more than three times that level in Spain (13%). A similarly broad range is found with the other two mental health outcomes. On average anxiety and depression increased by 23.1% and 18.7%, respectively, while figures range between 14.8% (Czech Republic) and 50% (Portugal) for anxiety, and from 8% (Denmark) to 28.9% (Portugal) for depression.[10] From this data, a simple statistical analysis (Fig. 3) shows that individuals living in countries with stricter lockdown policies suffered a larger deterioration in mental health.

### *4.1. Econometric model: double cross-sectional difference*

To estimate the effects of lockdown policies on mental health we rely on the approach of double differences. However, in contrast with the most common version of this approach that relies on differences between a treatment and a control group at two time periods, our estimation bases the double difference on a combination of cross-country differences in the strictness of lockdown policies with cross-individual differences regarding the potential effect these policies may have on their mental health within each country.[11] In our analysis, the treatment and control groups are constructed according to the frequency of individuals' pre-COVID face-to-face social interactions. The assignment rule for treatment and control groups is based on the distribution of the pre-COVID social score $\{Social_i\}$: individuals are assigned to the treatment group if their social score is above the median and to the control group if their social score is below the median. Our policy of interest is the lockdown imposed by countries, which is measured using the Oxford containment index. As already mentioned, strict lockdown countries are those with a containment index above the median value.[12] Using this approach, our strategy is to examine how differences in outcome between the treated and control individuals in strict lockdown countries

[9] Because our sample only includes individuals over 50, we cannot make comparisons with younger populations. Some studies of general populations have found that younger populations were the most affected by the pandemic or lockdown (Eurofound, 2020). Even so, as we discuss in the conclusion, a focus on older individuals is justified by their precarious level of health and ongoing debates about the need for policies targeted at specific age groups.

[10] These are sample statistics, using survey weights, for the 17 countries included in the causal approach analysis.

[11] The archetypical differences in differences study design has cross-sectional and time as the two common dimensions. But the differences in differences idea is much more general and instead of time one can group data by cross-sectional characteristics (see, for instance, Gruber and Madrian, 1994, Bleakley, 2010, Getler and Molyneaux, 1994, and Duflo, 2001).

[12] The median and mean value of the social score are 43% and 44%, respectively. The median and mean value of the index is 76.1 points and 76.66 points, respectively. Henceforth, there are not large differences in the estimates when using an assignment rule based on the mean instead of the median.

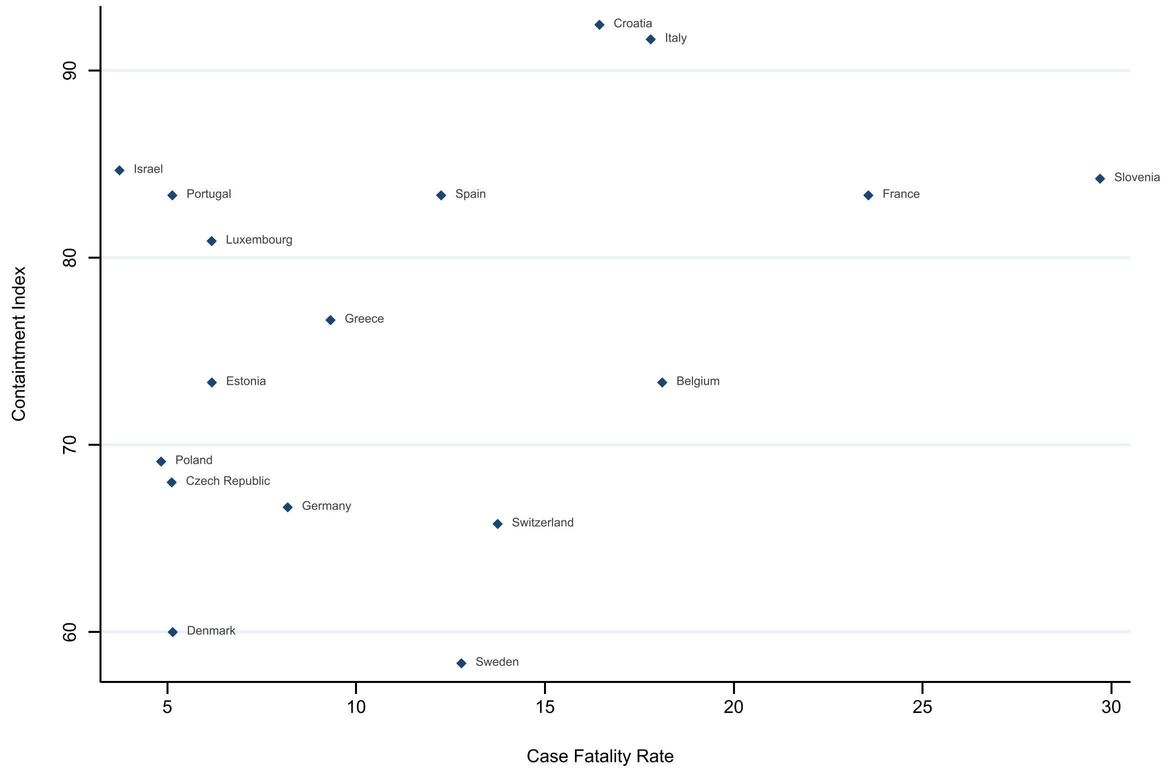


**Fig. 4.** Lockdown Policies and Country-specific Case Fatality Rates (CFR). Note: This figure relates the Containment Index with the country-specific case fatality rates of COVID-19. The index level refers to the mean of the Containment Index between April and May 2020. The country-specific case fatality rate is the mean of the case fatalities rates during April and May. Data on case facilities is provided by the European Centre for Disease Prevention and Control.

evolve, compared to differences in outcome between treated and control individuals in non-strict lockdown countries.

More precisely, the basic idea behind our identification strategy can be illustrated using the following simple regression model:

$$\Delta \mathrm{MH}_{ij}^{*} = \alpha + \beta_1 \mathrm{T_j} + \beta_2 S_{\mathrm{i}} + \beta_3 (S_i * T_j) + \mu_{\mathrm{j}} + \varepsilon_{\mathrm{ij}}, \quad (1)$$

where the subscript "i" refers to individuals and "j" to country of residence. The dependent variable $\Delta \mathrm{MH}_{ij}^{*}$ represents the change in individual mental health after the outbreak and corresponds to our three measures of mental health: anxiety, depression, and insomnia, presented in Section 3.1.[13] $\mathrm{T_j}$ is a dummy variable indicating whether individual "i" lives in a strict lockdown country "j", and zero otherwise. $S_{\mathrm{i}}$ is a dummy variable indicating whether the individual "i" belongs to the treatment group (high frequency of face-to-face contacts before the outbreak), and zero otherwise. The term $\mu_{\mathrm{j}}$ represents country fixed effects and $\varepsilon_{\mathrm{ij}}$ is the error term. The coefficient of interest $\beta_3$ measures the causal association between mental health deterioration and lockdown policies. Whenever these lockdown policies caused a worsening in individuals' mental health, the sign of the estimated coefficient $\beta_3$ should be positive. The other two parameters of the equation, $\beta_1$ and $\beta_2$, control for systematic differences in mental health between strict and less strict lockdown countries and between treatment and control groups, respectively. We estimate Eq. (1) with a linear probability model and standard errors are clustered at the country level using survey sample weights.[14]

The identification strategy in Eq. (1) is based on two main assumptions: (i) lockdown policies affect mental health of individuals differently depending on their pre-COVID level of face-to-face contacts; and (ii) there are no systematic differences in the way the pandemic affects the behaviour of treatment versus control groups apart from those stemming from lockdown policies.

In relation to the first assumption, a larger frequency of face-to-face contact usually requires more mobility and more social life outside the house. Thus, it is reasonable to assume that individuals who enjoyed a higher frequency of face-to-face social interactions before the outbreak suffered greater deterioration of mental health because of lockdown measures. In other words, although all kinds of individuals who live in strict lockdown countries should, on average, suffer a greater deterioration of mental health than those in less strict countries, the effect should be even greater for those who had a higher frequency of face-to-face contacts before the pandemic. In fact, there is evidence that shows how limiting the social contact of these individuals causes a larger decrease in mental well-being when compared with individuals with low frequency of face-to-face contacts whose social life is less affected by the pandemic (Wijngaards et al., 2020). This is especially relevant for older populations since the literature indicates that face-to-face interactions are more relevant for them than for populations in other periods of life (Teo et al., 2015; National Academic of Sciences, Engineering, and Medicine, 2020).

In relation to the second assumption, a possible objection is that individuals may act contrary to lockdown policies in ways that affect our results. For instance, individuals in strict lockdown countries may try to evade government restrictions, while individuals in less strict lockdown countries may decide to stay home out of fear. However, empirical evidence suggests that these behaviours, if they occurred, would be exceptional. Santamaria et al. (2020) show that individuals living in Europe comply to a large extent with the lockdown policies of their countries. In particular, by using the Oxford Stringency Index, they find

[13] Note that although we do not know individuals' mental health pre- and post-lockdown, we know whether their mental health has deteriorated since the outbreak of the pandemic.

[14] Since standard errors in our setting (only 17 clusters) can overstate estimation precision, in the results section we complement our analysis using wild bootstrapped standard errors and inference randomization.

**Table 2**
Sample composition: strict and less strict lockdown countries and treated and control individuals (Variables used in DID analysis).

| | Strict lockdown ($T_j = 1$) | | | Less strict lockdown ($T_j = 0$) | | | |
|---|---|---|---|---|---|---|---|
| | Treated ($S_i = 1$) | Control ($S_i = 0$) | Diff (pp) | Treated ($S_i = 1$) | Control ($S_i = 0$) | Diff (pp) | DiD (pp) |
| **Pre-COVID Socioeconomic Characteristics** | | | | | | | |
| Female | 67,8% | 42,6% | 25.2*** | 61,6% | 40,2% | 21.4*** | 3.7* |
| *Number members household* | | | | | | | |
| 1 | 12,0% | 33,1% | 21.1*** | 22,1% | 43,1% | 21.4*** | -0.1 |
| 2 | 62,1% | 34,4% | 27.7*** | 65,6% | 30,5% | -35.2*** | -7.5*** |
| *3–4* | 22,7% | 30,3% | -7.6** | 12,0% | 20,8% | -8.8*** | 1.1 |
| *>4* | 3,3% | 2,2% | 1.1 | 0,2% | 5,6% | -5.4*** | 6.5*** |
| *Pre-COVID Physical Health* | | | | | | | |
| Excellent | 5,0% | 7,2% | -2.1** | 10,0% | 3,9% | 6.1*** | -16,0*** |
| Very Good | 14,8% | 20,7% | -5.8*** | 20,4% | 17,8% | 2.5** | -10,6*** |
| Good | 45,8% | 46,4% | -0.6*** | 44,4% | 51,5% | 7.0*** | 6,3*** |
| Fair | 29,0% | 18,8% | 10.2*** | 20,8% | 18,9% | 1.8** | 10,0*** |
| Poor | 5,3% | 6,7% | -1.3** | 4,5% | 7,6% | -3.1* | 3,7*** |
| *Age* | | | | | | | |
| 50–55 | 0,3% | 5,1% | -4,7*** | 0,7% | 7,7% | -7,01*** | 2,2** |
| 56–59 | 14,6% | 27,8% | -13,2*** | 23,7% | 24,1% | -0,39 | -12,8*** |
| 60–64 | 31,6% | 18,5% | 13,0*** | 21,9% | 20,6% | 1,3 | 11,6*** |
| 65–69 | 12,8% | 11,1% | 1,7** | 14,3% | 14,8% | -0,46 | 2,2* |
| 70–75 | 13,7% | 11,4% | 2,2*** | 13,5% | 11,6% | 1,9* | 0,34 |
| 75–80 | 11,3% | 7,3% | 4,0*** | 11,6% | 4,8% | 6,8*** | -2,8*** |
| >80 | 15,8% | 18,8% | -3,0*** | 14,2% | 16,4% | -2,2** | -0,75 |
| **Social score** | 52.6% | 33.1% | 19.5*** | 53.0% | 34.6% | 18.4*** | 1.1*** |
| **Containment Index** | 84.5 | 84.5 | – | 66.8 | 66.8 | – | – |

*Notes:* The table displays means sample statistics for the covariates used in Eq. (2), expressed as a percentage for the different groups (countries and individuals) and the differences between the means for treated and control individuals expressed as percentage points. Diff (pp) and DiD (pp) columns display a two-sample t test. * 10% statistical significance level; ** 5% statistical significance level; *** 1% statistical significance level. All the variables are described in Appendix Table A.1.

that these measures explain up to 90 percentage points of the mobility data of Europeans during the lockdown. In addition, using information for three countries—Canada, USA and UK—with different levels of restrictions, Folk et al. (2020) find that individuals with a high frequency of social relations before the pandemic complied with the social distance policies during the pandemic similarly to those who had low frequency of contacts. These findings from the literature seem to justify our assumption that, for any given level of policy strictness, individuals with different frequencies of pre-COVID face-to-face contacts behave similarly and are thus equally exposed to the virus. Our study also confirms that individuals largely comply with lockdowns. When we explore the variation in the severity of lockdown enforcement in Europe using the Google Mobility Index (see subsection 5.2) we find that our causal results do not change.

To address potential bias derived from omitted variables, we expand the baseline model in Eq. (1) by including additional control variables. Firstly, we add the pre-COVID frequency of face-to-face contacts, ($Social_{ij}$), and its interaction with the group of individuals with high frequency of face-to-face contacts, ($Social_{ij} * S_i$). Secondly, we additionally control for a battery of pre-determined observable socioeconomic characteristics, known to be associated both with mental health and with the levels of face-to-face social contacts, $z_{ij}$. These characteristics correspond with those used to build the score for face-to-face social interactions described in Section 3.3: age-groups (seven groups), gender, household size (four categories) and physical health before the outbreak (five situations ranging from excellent to poor). Table A.3 in the Appendix presents sample statistics for all these variables.

$$\Delta MH^*_{ij} = \alpha + \beta_1 T_j + \beta_2 S_i + \beta_3 (S_i * T_j) + \beta_4 Social_{ij} + \beta_5 (Social_{ij} * S_i) + \gamma z_{ij} + \mu_j + \varepsilon_{ij} \tag{2}$$

As in Eq. (1), the coefficient of interest $\beta_3$ measures the causal association between mental health deterioration and lockdown policies but, in this extended model, net of any observed differences between treatment and control groups.

Nevertheless, in Section 5 we will carry out several sensitivity analyses to prove that our identification strategy is solid to potential confounders and alternative classifications of countries and treated and control groups.

### 4.2. Main sample statistics for the DID

Our final sample comprises 40,501 respondents.[15] In Table 1 we present main descriptive statistics of our sample selection. We observe that 9.9% of the respondents reported more insomnia after the outbreak, while 23.1% reported more anxiety and 18.7% reported more depression.

Among individuals living in strict lockdown countries ($T_j = 1$), 11.8% reported more insomnia, 27.4% reported more anxiety and 22.2% reported more depression. Moreover, of these individuals, 12.6%, 31.9% and 24.4% of those in the treatment group ($S_i = 1$) reported more insomnia, anxiety, and depression, respectively. In contrast, for individuals in the control group ($S_i = 0$) these figures decrease to 11.2%, 23.8% and 20.4%.

Among individuals who live in less strict lockdown countries ($T_j = 0$), 7.7%, 17.5% and 14.4% reported more insomnia, anxiety, and depression, respectively. Note that these figures are all lower than those presented for strict lockdown countries. In less strict lockdown countries, the mental health of treatment versus control groups also differs and these differences are statistically significant. Among individuals of the treatment group, 6.7%, 18.2% and 14% reported more insomnia, anxiety, and depression, respectively. Meanwhile, the corresponding figures for the control group are 9.4%, 16.6% and 15.1%.

This information allows us to offer a first approximation of our differences in differences estimator. The difference between the share of treated versus control individuals living in strict lockdown countries ($T_j = 1$) that reported more insomnia during the pandemic is 1.5 percentage points. The difference between the share of treated versus control individuals living in less strict lockdown countries ($T_j = 0$), is

[15] We end up with a sample of 40,501 (from an original total sample of 41,792) respondents, as some respondents were withdrawn because they were aged below 50 or were missing information in some relevant socioeconomic covariates such as age or mental health status.

2.7 percentage points. Thus, the double difference would be 4.2 percentage points. Following the same procedure for the cases of anxiety and depression, we find that the double difference stands at 6.4 and 5.1 percentage points, respectively. These three differences in differences are statistically significant at 1%.

These simple estimators suggest that the strictness of COVID-19 lockdown policies was the cause of greater deterioration of mental health, as measured by additional increases of insomnia, anxiety, and depression of 4.2, 6.4 and 5.1 percentage points, respectively. This statistical double difference can be interpreted as the causal effect of the strictness of the lockdown measures under the assumption that in the absence of those restrictions the variation in mental health among individuals of the treatment group would not have been systematically different between those living in strict lockdown countries versus those living in less strict lockdown countries.

Table 2 presents sample statistics for main socio-demographic characteristics (gender, age groups, household size, and physical health) for treated and control individuals in strict and less strict lockdown countries. It shows that there are observable differences. Columns 3 and 6 show that the differences in sample composition by pre-COVID socioeconomic characteristics between treated and control individuals exist for both strict and less strict lockdown countries and, apparently, they do not disappear with the double difference. Accordingly, these characteristics should be considered in the empirical analysis.

In the last two rows of Table 2 we present main sample statistics for the estimated pre-COVID social score and the containment index. The scores for treatment group individuals are around 18-19 percentage points higher than for the control group. Recall that the assignment rule used to define treatment and control groups, creates two groups of individuals that strongly differ in pre-COVID levels of face-to-face social interactions. For instance, in strict lockdown countries the percentage of individuals with high pre-COVID levels of face-to-face social interaction are 52.6% versus a percentage of 33.1% of individuals with low levels of the same, while in less strict lockdown countries these percentages are 53.0% versus 34.6%, respectively. Similarly, the main criterion for defining a strict versus less strict lockdown country is whether the containment index lies above or below the median. The containment index is measured at the national level. The value of the containment index in strict lockdown countries is 84.5 whereas it is 66.8 in less strict lockdown countries. Note that the difference between strict and less strict lockdown countries is around 20 points (twice that of the standard deviation of the index).

## 5. Results

The raw data suggests that mobility restrictions have contributed to a deterioration of mental health in older populations. In this section we present the results of our differences in differences empirical exercise, and we carry out sensitivity analyses to test the robustness of the results. Means sample statistics for all the variables we use to test the robustness of our results are included in Table A.5 in the Appendix.

### 5.1. Average effect of lockdown policies on the deterioration of mental health

Table 3 presents the main estimation results from our causal empirical exercise. Table 3 is organized as three panels (A, B and C), which present main estimation results for insomnia, anxiety, and depression. Each panel is further divided into five columns.

The first three columns present different model specifications. Col-

**Table 3**
Main results from double difference estimation: worsening in mental health.

| **Worsening in mental health** | (1) | (2) | (3) | (4) Bootstrap standard errors | (5) Randomization inference (p-value) |
|---|---|---|---|---|---|
| **Panel A: Insomnia** | | | | | |
| $\boldsymbol{\beta_3\ (S_i * T_j)}$ | **0.049**** | **0.059***** | **0.050***** | **0.050**** | **0.050***** |
| **s.e** | **(0.011)** | **(0.014)** | **(0.015)** | **(p-value 0.05)** | **(p-value 0.01)** |
| **Panel B: Anxiety** | | | | | |
| $\boldsymbol{\beta_3\ (S_i * T_j)}$ | **0.070***** | **0.094**** | **0.072***** | **0.072**** | **0.072***** |
| **s.e** | **(0.019)** | **(0.027)** | **(0.020)** | **(p-value 0.05)** | **(p-value 0.01)** |
| **Panel C: Depression** | | | | | |
| $\boldsymbol{\beta_3\ (S_i * T_j)}$ | **0.057**** | **0.075***** | **0.051**** | **0.051*** | **0.051***** |
| **s.e** | **(0.019)** | **(0.025)** | **(0.019)** | **(p-value 0.08)** | **p-value 0.04** |
| $\beta_1\ (T_j = 1)$ | X | X | X | X | X |
| $\beta_2 (S_i = 1)$ | X | X | X | X | X |
| $Social_i\ \&\ Social_{ih_s}$ | | X | X | X | X |
| Individual Socioeconomic Characteristics | | | X | X | X |
| Country FE | X | X | X | X | X |
| Observations | 40,501 | 40,501 | 40,501 | 40,501 | 40,501 |

*Notes*: The table displays the coefficient of the causal effect of interest $\{\beta_3\}$ and its corresponding cluster standard error considering survey sample weights (in parentheses). The dependent variable is a binary variable indicating whether the individual declared suffering more mental problems (Insomnia, Anxiety, Depression, respectively) and zero otherwise. * 10% statistical significance level; ** 5% statistical significance level; *** 1% statistical significance level. Individual socioeconomic pre-determined characteristics include age, gender, household composition and pre-COVID physical health. Column 4 reports results using bootstrap standard errors and survey weights. Column 5 reports the p-values based on a two-sided randomization inference test statistic that the placebo coefficients are larger than the actual. The p-values were computed based on 10,000 random draws. Detailed results for models of columns 1, 2 and 3 are shown in Appendix Table A.4. For the rest of the models, detailed results are provided upon request.

**Table 4**
Sensitivity analysis: alternative definitions for treated and control groups, and strict and less strict lockdown countries.

| | Alternative definitions for $T_i$ *and* $S_i$ : Sample restrictions: | | Alternative definitions for $S_i$ | | Alternative definitions for $T_i$ |
|---|---|---|---|---|---|
| | *Index*$_j$ | *Social*$_i$ | $S_i${proximity of social network members} | | $T_i${Google mobility index} |
| | ($Index_j > p60$ $Index_j < p40$) | ($Social_i > p60$ $Social_i < p40$) | 25–100 kms | $>$ 100 kms | |
| | (1) | (2) | (3) | (4) | (5) |
| **Panel A: Insomnia** | | | | | |
| $\beta_3$ ($S_i * T_j$) | 0.056** | 0.032** | 0.020 | -0.026 | 0.044*** |
| s.e | (0.02) | (0.02) | (0.02) | (0.02) | (0.02) |
| **Panel B: Anxiety** | | | | | |
| $\beta_3$ ($S_i * T_j$) | 0.085*** | 0.047** | 0.032 | -0.011 | 0.063*** |
| s.e | (0.02) | (0.02) | (0.03) | (0.03) | (0.02) |
| **Panel C: Depression** | | | | | |
| $\beta_3$ ($S_i * T_j$) | 0.059** | 0.067*** | 0.047 | -0.038* | 0.041** |
| s.e | (0.02) | (0.02) | (0.03) | (0.02) | (0.02) |
| Observations | 26,095 | 30,960 | 40,501 | 40,501 | 40,501 |

*Note*: The table displays the coefficient of the causal effect of interest $\{\beta_3\}$ and its corresponding robust standard error cluster at the country level and considering survey sample weights (in parentheses). The dependent variable is a binary variable indicating whether the individual declared suffering more mental problems (Insomnia, Anxiety, Depression) and zero otherwise. * 10% statistical significance level; ** 5% statistical significance level; *** 1% statistical significance level. Model specification from column 1–5 corresponds with our preferred model 3 of Table 3. Model in column 1 only contains observations from countries with containment indexes below percentile 40 of the index ($T_j$=0: $Index_j$ <p40) and above percentile 60 value of the index ($T_j = 1 : Index_j$ >p60). Model in column 2 only contains observations from individuals whose value of the Social score is below percentile 40 ($S_i = 0 : Social_i < p40$) or above percentile 60 value of this variable ($S_i = 1 : Social_i > p60$). Model in column 3 defines treatment using social interactions that take place at least once a week within a distance 25–100 kms. Model in column 4 defines treatment using social interactions that take place with the same frequency but within a distance > 100 kms. Model in column 5 uses Google Mobility index instead of the Oxford containment index to measure the strictness of the lockdown policies. Using the Google mobility index the only difference in the classification of countries comes from Belgium. This country belongs to the group of strict lockdown countries according to the Google Mobility index, but it is assigned to the group of less strict lockdown countries according to the Oxford containment index. Results displayed in Table 4 are robust to bootstrapped standard errors

umn 1 lists the coefficients from the baseline model according to Eq. (1). Column 2 shows the results of adding frequency of face-to-face interactions. Column 3 shows the results of additionally including individual socioeconomic characteristics and corresponds to the model in Eq. (2). For the sake of brevity, we present only the main parameter estimates of the causal effect $\{\beta_3\}$ of lockdown restrictions on mental health.

Estimates of $\beta_3$ across these three different specifications are all positive, of similar size and statistically significant, between 1% and 5%. Variations in the coefficient estimates for $\beta_3$ are not statistically significant, which suggests that observed individual characteristics barely affected the impact of lockdown policies on mental health outcomes.[16] In what follows, we will use the model presented in column 3 as our main reference model, as many of these individual characteristics are statistically significant. Table A.4 in the Appendix provides detailed results for this model and for models of columns 1 and 2.

According to the estimated value of $\beta_3$ shown in our reference model, lockdown policies caused a deterioration in mental health that would have not existed in the absence of these policies. More precisely, we find that lockdown policies aggravated insomnia problems by 5 percentage points (from 6.7% to 11.7% or by 74.6% in relative terms), anxiety problems by 7.2 percentage points (18.2% to 25.4%, or by 39.5% in relative terms) and depression by 5.1 percentage points (14.0% to 19.1%, or by 36.4% in relative terms).

Columns 4 and 5 complement the results presented in column 3. Column 4 presents same model estimation computing bootstrapped standard errors instead of clustering standard errors at the country level. In column 5 we provide p-values from a two-sided randomization inference test of zero treatment effects. This test consists of reassigning the treatment and control status in the sample and reestimating $\beta_3$using this placebo assignment multiple (10,000) times. Under the null hypothesis of zero treatment effects, the proportion of reestimated $\beta_3$ that are higher than the actual $\beta_3$ provides a p-value for this null hypothesis. In summary, columns 4 and 5 show the robustness of our standard errors and reinforce our results.

### *5.2. Sensitivity analysis: alternative definitions for treated and control groups, and strict and less strict lockdown countries*

In this subsection, we run a set of robustness tests in relation to different definitions of face-to-face social contacts and strict and less strict lockdown countries. Table 4 presents estimates from several different specifications using as a reference our preferred model in column 3 of Table 3.

First two columns of Table 4 provide new definitions for strict and less strict lockdown countries, and treated and control individuals, by restricting sample estimation. In column 1, we omit from the main sample those countries that are most similar in terms of the strictness of their lockdown policies.[17] That is, we define strict lockdown countries ($T_j = 1$) as those whose *index* is above percentile 60 of the index distribution, and less strict lockdown countries ($T_j = 0$) as those whose index is below percentile 40. Even though this reduces the sample size by 12% (the new sample contains 26,095 individuals), the causal effect is a bit higher than that of our preferred model and, more importantly, it remains statistically significant at 5%. Similarly, in column 2 we omit

[16] We have estimated additional models including other types of regressors. For instance, we included as a regressor the month in which the Corona survey interview took place (June, July or August), and covariates that describe the financial and employment situation of the individual at the outbreak. The estimated value of $\beta_3$ remains the same as in our preferred specification. For the sake of brevity, we opted not to include these results in the paper but they are available upon request.

[17] These countries are those whose containment index is located between percentile 60 and percentile 40 of the containment index distribution. The average value of the index for strict and less strict lockdown countries is now 86 and 62 respectively. Countries assigned to the group of strict lockdown countries, whose index values range between 78 and 92, are Greece, Lithuania and Malta. Countries assigned to the group of less strict lockdown countries, whose index values lie between 48 and 68 are Belgium, Poland and Estonia.

individuals who are similar in terms of their score of face-to-face social interactions.[18] That is, treated individuals ($S_i = 1$) are those whose score of face-to-face social interactions is above the percentile 60 of the score distribution, and control individuals ($S_i = 0$) are those whose score is below percentile 40. Estimates for $\beta_3$ are again positive and statistically significant at 5%, although the estimated effect is slightly lower.

Columns 3 and 4 of Table 4 provide alternative definitions for treated and control individuals, allowing us to test the plausibility of our assumption that the deterioration of mental health is related to the sudden drop of face-to-face social interactions caused by lockdown policies. More precisely, we conjecture that social interactions with social network members across larger geographic distances are not as likely to be affected by lockdown measures, as those contacts are generally maintained by phone, mail, e-mail, or other electronic means. Using geographical proximity as a proxy for face-to-face contact, we estimate an alternative model for which a social network score is calculated using larger geographic distances (distances between 25 and 100 km and more than 100 km). Thus, model estimation in column 3 defines treated individuals as those whose frequency of social contacts—at least once a week and within a distance of 25–100 kilometers—is above the median of the value of the corresponding score. Analogously, model estimation in column 4 defines treated individuals as those whose probability of being in contact with social network members—at least once a week and within a distance larger than 100 kilometers—is above the median. Estimated causal effects of $\beta_3$ presented in columns 3 and 4 of Table 4 are not statistically significant and the sign of the coefficient depends on the particular outcome. Thus, as we increase the geographical distance with social network members, the estimated value of $\beta_3$ loses its statistical significance and/or becomes negative. The fact that the causal effect of strict lockdown on mental health vanishes when pre-COVID 19 social contact was maintained with the same frequency, but mostly by phone, mail, or internet (rather than face-to-face interaction) also supports our main finding. Note that results from these columns 3 and 4 in Table 4 can be interpreted as a placebo exercise.

Finally, in column 5 we classify strict and less strict lockdown countries using the median value of the average Google Mobility Index for the months of April and May 2020. The Google Mobility Index shows how the movement of people worldwide has changed during the pandemic. This strategy allows us to measure the actual strictness of lockdowns by exploring variations in the severity of enforcement. Results in column 5 show that our estimates hardly change, and differences are not statistically significant.

Summing up, the set of robustness exercises presented in Table 4 supports our main result, that is, that lockdown policies contributed significantly to the worsening of mental health outcomes in older populations.

### 5.3. Potential confounders

Our identification strategy relies on the assumption that the worsening of mental health between treatment and control groups would have been the same if strict lockdown countries had applied the same policies as less strict lockdown countries. However, this assumption cannot be checked directly. Thus, in this subsection we perform a set of robustness exercises that indirectly test whether there might be confounding variables that could bias our estimates. If estimates of $\beta_3$ do not vary significantly across these specifications, we can rule out the existence of confounding factors.

**Table 5**
Robustness exercise: more control variables.

| | (1) | (2) |
|---|---|---|
| Panel A: Insomnia | | |
| $\beta_3$ ($S_i * T_j$) | 0.050*** | 0.050*** |
| s.e | (0.02) | (0.02) |
| Panel B: Anxiety | | |
| $\beta_3$ ($S_i * T_j$) | 0.071** | – |
| s.e | (0.02) | |
| Panel C: Depression | | |
| $\beta_3$ ($S_i * T_j$) | 0.051** | 0.051** |
| s.e | (0.02) | (0.02) |
| $\beta_1$ ($T_j = 1$) | X | X |
| $\beta_2$($S_i = 1$) | X | X |
| $Social_i$ & $Social_{ih_s}$ | X | X |
| Individual Characteristics | X | X |
| $Pre-COVID\ Mental\ health_i$ | | X |
| Exposure | X | |
| Fatality Rate | X | |
| Country FE | X | X |
| Observations | 40,501 | 40,501 |

*Notes*: The table displays the coefficient of the causal effect of interest $\{\beta_3\}$ and its corresponding robust standard errors clustered at the country level and considering survey sample weights (in parentheses). The dependent variable is a binary variable indicating whether the individual declared suffering more mental problems (Insomnia, Anxiety, Depression, respectively) and zero otherwise. * 10% statistical significance level; ** 5% statistical significance level; *** 1% statistical significance level. Detailed results are provided upon request. Individual socioeconomic pre-determined characteristics include age, gender, household composition and pre-COVID physical health.

#### 5.3.1. Fear of infection

A potential threat to our identifying strategy derives from the fact that mental health can also be affected by fear of infection. If individuals living in strict lockdown countries and with frequent pre-COVID face-to-face contacts were more exposed to the virus, then our estimates for $\beta_3$ could be biased. To assess the existence of this potential bias, we take two different approaches.

The first approach is to add to our preferred model (shown in column 3, Table 3) observable indicators of the severity of the pandemic, such as the exposure to the virus and the case fatality rate. Data on individual exposure to COVID-19 comes from the SHARE Corona questionnaire, while data on case fatality rates is provided by the European Centre for Disease Prevention and Control. The results of this new estimation are shown in column 1 of Table 5. As the effect of the lockdown policies remains the same, we conclude that differences in the expansion of the virus do not seem to be affecting our results.[19]

The second approach is to test whether there is a link between individual exposure to the virus and strictness of lockdown policies. To do

[18] Individuals whose face-to-face scores are between percentile 40 and 60 of the distribution of face-to-face social interactions are withdrawn from the estimation. In this sample, the average probability of pre-COVID face-to-face contact ranges from 4% to 38% for the control group, and from 46% to 71% for the treatment group.

[19] The estimated coefficient for the covariate COVID-19 exposure is positive and statistically significant for anxiety and depression at 5% (0.035, 0.067 and 0.035, for insomnia, anxiety, and depression respectively). That is, respondents who were exposed to cases or experiences of COVID among friends, neighbors or relatives were found to suffer more mental health problems. On the contrary, the estimated coefficient for the case fatality rate has a negative sign, when statistically significant, for anxiety and depression (but not for insomnia). The result for the case fatality rate must be interpreted as conditional on lockdown policies, country-fixed effects, socioeconomic characteristics of the individual and, more importantly, individual exposition to the virus. For instance, the estimated coefficient for the case fatality rate has positive sign and is statistically significant when adding it as a regressor to the baseline model in Eq. (1).

**Table 6**
Falsification analysis and potential confounders.

| | Outcome: COVID-19 Exposure | Outcome: Pre-COVID Mental Health | | Outcome: Same or Better Mental Health | | |
|---|---|---|---|---|---|---|
| | | Insomnia | Depression | Insomnia | Anxiety | Depression |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $\beta_3\ (S_i * T_j)$ | 0.005 | -0.010 | 0.020 | 0.003 | 0.001 | 0.008 |
| | (0.02) | (0.01) | (0.02) | (0.02) | (0.02) | (0.02) |
| Survey | SHARE-COVID19 | SHARE-Wave 6 | SHARE-Wave 6 | SHARE-COVID19 | SHARE-COVID19 | SHARE-COVID19 |
| Observations | 40,501 | 61,917 | 61,917 | 40,501 | 40,501 | 40,501 |

*Notes*: The table displays the coefficient of the causal effect of interest $\{\beta_3\}$ and its corresponding standard error clustered at the country level and considering survey sample weights (in parentheses). The dependent variable is a binary variable in all columns. Model estimated corresponds with the same model specification of column 3 of Table 3 but with a different outcome variable. In column 1, the binary variable takes value one when the individual declares having been exposed to COVID-19 and zero otherwise. In columns 2 and 3, model estimation uses Wave 6 of SHARE and the dependent variable refers to mental health before the pandemic. In columns from 4 to 6, we return to main sample estimation but the dependent variable takes value one when the individuals declared their mental health problems to improve or be about the same as before the outbreak of the corona and zero otherwise. * 10% statistical significance level; ** 5% statistical significance level; *** 1% statistical significance level.

this, we estimate the model in Eq. (2) using individual exposure to the virus as the outcome variable. If treated individuals in strict lockdown countries were more exposed to the virus, then $\beta_3$ should be positive and statistically significant. The result from this exercise is shown in Table 6, column 1. Given our result that $\beta_3$ is not statistically significant, we conclude that our estimated causal effects are not biased by fear of infection.

In summary, both approaches indicate that our identification strategy enables us to isolate the effect of lockdown policies on mental health from a possible fear of infection.

### 5.3.2. *Mental health before the pandemic*

The existence of unobserved confounders can be tested indirectly by examining mental health outcomes of treated and control groups before the pandemic. For instance, if countries with higher prevalence of mental disorders implemented strict lockdown policies, our estimate for $\beta_3$ could be affected.

For this exercise we benefit from information on mental health available in Wave 6 of SHARE (the same wave used to create our index for face-to-face social contacts). As before, we proceed in two ways. First, using Wave 6, we build a variable that measures the probability that the individual was mentally ill (suffering from depression or insomnia) during the pre-pandemic period. [20] Then, we include this probability as a control variable in Eq. (2). Results are presented in Table 5, column 2 and show that the estimated value of $\beta_3$ remains the same as in our preferred model specification.

In addition, we estimate our reference model using the observed pre-COVID mental health as the outcome variables. Note that this second estimation corresponds with a placebo test analysis and, as a result, we expect $\beta_3$ to be close to zero and non-statistically significant for all pre-COVID mental health outcomes. Results of this exercise are displayed in Table 6, columns 2 and 3 for pre-COVID levels of insomnia and depression respectively, and confirm that there are no systematic differences in mental health before the pandemic between treated and control individuals.

### 5.3.3. *Alternative definition of the mental health outcome variables*

To further investigate whether there might exist other unobserved confounders that could influence our causal estimation results, we propose another placebo test where we estimate Eq. (2) using an alternative coding of our mental health outcome variables.

In the SHARE corona survey, those individuals who declare having suffered mental health problems during the last month are asked whether these problems have been aggravated, improved, or remained

[20] Unfortunately, there is no information available for anxiety for the pre-pandemic period.

**Table 7**
Causal Effects of Lockdown Policies: Subgroup analysis.

| | Insomnia Model 3 | Anxiety Model 3 | Depression Model 3 |
|---|---|---|---|
| **Panel A: Age:** | | | |
| **50-65 years** (N=12,857) | | | |
| $\beta_3\ (S_i * T_j)$ | 0.061** | 0.094** | 0.071** |
| | (0.03) | (0.030) | (0.033) |
| **66-75 years** (N=21,662) | | | |
| $\beta_3\ (S_i * T_j)$ | 0.009 | 0.057** | 0.005 |
| | (0.013) | (0.023) | (0.022) |
| **>75 years** (N=6,994) | | | |
| $\beta_3\ (S_i * T_j)$ | 0.041 | 0.035 | 0.055 |
| | (0.026) | (0.026) | (0.033) |
| **Panel B: Physical Health** | | | |
| **Excellent, Very Good, Good** (N=27,647) | | | |
| $\beta_3\ (S_i * T_j)$ | 0.028** | 0.066** | 0.043** |
| | (0.013) | (0.026) | (0.019) |
| **Fair or less** (N=13,192) | | | |
| $\beta_3\ (S_i * T_j)$ | 0.074* | 0.082 | 0.068* |
| | (0.040) | (0.050) | (0.038) |
| **Panel C: Gender** | | | |
| **Women (N=23,291)** | | | |
| $\beta_3\ (S_i * T_j)$ | 0.054** | 0.070** | 0.047 |
| | (0.016) | (0.034) | (0.030) |
| **Men (N=17,210)** | | | |
| $\beta_3\ (S_i * T_j)$ | -0.021 | 0.043 | -0.026 |
| | (0.021) | (0.039) | (0.027) |
| **Panel D: Pre-Covid Labor Situation** | | | |
| **Employed (N=8,335)** | | | |
| $\beta_3\ (S_i * T_j)$ | 0.115** | 0.064** | 0.050 |
| | (0.029) | (0.030) | (0.031) |
| **Non-Employed (N=32,166)** | | | |
| $\beta_3\ (S_i * T_j)$ | 0.029 | 0.082*** | 0.058** |
| | (0.018) | (0.026) | (0.024) |
| **Panel E: Household Composition** | | | |
| **Alone** (N=10079) | | | |
| $\beta_3\ (S_i * T_j)$ | 0.098** | 0.076** | 0.050** |
| | (0.03) | (0.03) | (0.02) |
| **Cohabitation: > 1** (N=31043) | | | |
| $\beta_3\ (S_i * T_j)$ | 0.037** | 0.047** | 0.057* |
| | (0.02) | (0.02) | (0.03) |

Note: The table displays the coefficient of the causal effect of interest $\{\beta_3\}$ and its corresponding standard error clustered at the country level and considering survey sample weights (in parentheses). The dependent variable is a binary variable indicating whether the individual declared suffering more mental problems (Insomnia, Anxiety, Depression) and zero otherwise. * 10% statistical significance level; ** 5% statistical significance level; *** 1% statistical significance level. Model specifications used in estimates models of Table 7 correspond with our preferred model 3 of Table 3.

the same as before the outbreak of Corona. Thus, we re-estimate equation (2) using an outcome variable that takes value 1 when the individual declares that their mental health problems (insomnia, anxiety or depression) have improved or remained about the same as before the outbreak of corona, and zero otherwise. We expect $\beta_3$ to be close to zero and non-statistically significant for the new defined mental health outcomes.

Results of this additional robustness exercise are displayed in Table 6, columns 4 through 6. As expected, estimates of $\beta_3$ are close to zero and not statistically significant for the three outcomes of interest, which supports our results that mobility restrictions have contributed to a deterioration of population mental health.

### *5.4. Subgroup analysis: how does the lockdown impact different population groups?*

In this section we explore whether the estimated causal effect of lockdown policies on mental health differs according to individual characteristics.

Panels A, B C, D and E in Table 7 present the results of the heterogeneous causal effects by age (below 65/66–75/above 75), physical health before the pandemic (poor/fair/good), gender (female/male), labor situation at the outbreak (employed/non-employed), and household composition (living alone/cohabitation). Estimated results are displayed for our preferred Model (3) of Table 3.

This analysis shows that the estimated causal effect is present in almost all types of individuals considered. That is, we can say that lockdown policies restricting face-to-face social contacts is important for understanding the deterioration of mental health among senior and older Europeans, independently of age, household composition, labor status, or physical health. Our results are general in the sense that we find the sign of the estimated coefficient $\beta_3$ to be positive and statistically significant for almost all subgroups and health outcomes, with few exceptions.

However, a first notable result of this heterogeneous analysis is that the effect of lockdown policies on the worsening of mental health is found mainly in those individuals between 50 and 65 in the three outcomes analyzed. The lockdown seems to affect those between 65 and 75 only in respect of worsening anxiety (Panel A). For those above 75 years old the effects of lockdown are not statistically significant, although the coefficients are positive and large. A second important finding is that individuals with good physical health had a notable worsening of their mental health (Panel B).

These two findings are relevant to the debate over whether strict lockdown policies should target individuals over 65 and/or with conditions that make them more vulnerable, with the purpose of obtaining better health and economic outcomes (Acemoglu et al., 2020; Savulescu and Cameron, 2020; Joffe, 2021).[21] These two results give some support to this idea. However, the fact that anxiety worsened among Europeans between 65 and 75 years old, and that those with poor health also experienced a worsening of mental health calls for additional complementary policies such as increased mental health call centers and local support services for at risk-populations (Galea et al., 2002).

[21] The Turkish government imposed strict mobility restrictions during the first wave of the pandemics exclusively on senior citizens. This also happened in countries like Russia https://www.euronews.com/2020/04/21/coronavirus-lockdown-in-moscow-elderly-struggling-to-cope-with-covid-19-restrictions and the Philippines https://www.gmanetwork.com/news/news/nation/735791/urgesrelaxation-of-community-quarantine-rules-on-elderly/story/, 27 April 2020. Other countries like Italy discussed the possibility of strict lockdown just for individuals aged 70 and older. (ABC, 03/11/2020, Available at: https://www.abc.es/sociedad/abci-italia-reabre-debate-confinar-solo-mayores-70-anos-unos-66-millones-personas-espana-202011030233_noticia.html?ref=https%3A%2F%2Fwww.google.com%2F

Finally, the third notable finding is the differential effect related to gender. Specifically, we find that women show more deterioration in mental health as a result of lockdown policies (Panel C). For men, coefficient estimates are low, not statistically significant, and negative in the case of depression. Other studies also find a more severe deterioration of women's mental health during the pandemic (Pierce et al., 2020; Etheridge and Spantig, 2020; Adams-Prassl et al., 2021). Etheridge and Spantig (2020) do find some differences in family and caring responsibilities during the pandemic in the UK, while Adams-Prassl et al. (2021) do not find such differences in the US. Both studies point to the possibility that the bulk of the gender gap in mental health can be explained by social factors. Etheridge and Spantig (2020) find that women reported to have more close friends before the outbreak and that women also reported feeling more loneliness afterwards. This finding suggests that the greater reduction of social contact imposed by lockdowns on women is what explains the gender gap in mental health. Our results support this conclusion, as individuals in our treatment group (high frequency of pre-COVID-19 face-to-face contacts) were mostly women.

Finally, in the case of employment (PANEL D), both those employed and unemployed before the outbreak suffered a worsening in their mental health. Similarly, in the case of household composition (PANEL E) individuals who lived alone and those who cohabited suffered mental health deterioration. However, our findings indicate that those who lived alone were more strongly affected by the lockdown. This is aligned with other results in the literature (see for instance Fancourt et al., 2020 or Hendriksen et al., 2021).

## 6. Conclusions

As a result of the COVID-19 pandemic, all governments implemented lockdown policies with different degrees of strictness to control the spread of the virus. This paper analyses the causal effect of these policies on the mental health of a large sample of individuals over 50 in 17 countries.

Because policy interventions have not been randomized, we must rely on quasi-experimental strategies to identify causal effects. By including two cross-sectional dimensions, across countries and across individuals within countries, our empirical strategy provides important advantages over other methods such as before-and-after comparisons. In addition to this, we enlarge the geographic scope of previous causal studies and we combine high-quality survey data on mental health and individual characteristics with the Oxford COVID-19 Government Response Tracker database, which provides daily data on government responses to COVID-19.

Beyond the stresses inherent to the illness itself and other factors, in this study we find that lockdown restrictions imposed during COVID-19 pandemic have worsened the mental health of senior and older Europeans. The estimated causal effects are large and amount to 5 percentage points for insomnia, 7.2 percentage points for anxiety and 5.1 percentage points for depression. Our results are robust to: (i) alternative model specifications and (ii) the use of alternative definition of control and treated groups. Moreover, placebo tests suggest that our results are not due to systematic differences between the groups we study.

When we explore demographic heterogeneity in the treatment effects, we find that lockdown policies negatively impact mental health mainly to women and those aged between 50 and 65. In general, evaluating the impact of lockdown policies on mental health according to different group characteristics is critical to the design of policies that can be better tailored to such differences instead of the common "one size fits all" approach that was followed by policy makers at the outbreak of the pandemic. In this respect, our discovery of a gender gap in mental health is important and reveals the high costs of strict lockdown for certain populations.

The possibility of implementing targeted policies for certain age-groups has also been considered. However, our finding that individuals between 65 and 75 also suffered from more anxiety as a result of strict lockdown policies suggests that a policy targeting those above 65 years old would be recommendable only if additional support from health systems were in place. It is important to remember that those above 65 are more prone to suffer from depression and commit suicide than other age groups in the absence of pandemics and other disasters (Shah, 2007). Also, such a targeted policy could contribute to the stigmatizing of this age-group, with harmful effects (Sleap, 2020).

Our results also indicate that confining all groups of populations disregarding their health status can damage the mental health of the healthier populations. It is not surprising that in addition to the debate about confining those populations above 65 years old, there have been policy discussions about the need to confine only those individuals more vulnerable in terms of health, independently of their age. Countries like the UK discussed about implementing such a policy during the first months of the pandemic but finally decided to impose a general lockdown (McArdle, 2020). Other countries, like Turkey, not only imposed a lockdown on those individuals above 65 years old, but also on those with certain health conditions: autoimmune disorders, chronic pulmonary disease, asthma, cardiovascular disease, hypertension, renal, and liver-related diseases (Altindag et al., 2021). Based on our findings, it seems that a lockdown targeting individuals with pre-existing conditions could protect them from complications associated with the virus, even at the expense of a certain deterioration of their mental health, while minimizing effects on the mental health of healthy individuals who are not so vulnerable to the virus. This kind of targeted policy would also mitigate the economic costs of the lockdown.

In the light of the dramatic impact of lockdown policies on the mental health of older populations, it becomes clear that mental health costs need to be weighed against health risks related to COVID-19. Social isolation has effects not only on mental health but can also predict adult mortality similar to smoking, obesity, elevated blood pressure and high cholesterol (Pantell et al., 2013). Our results and discussion of policies can help to refine lockdown measures in the future. In any case, the increased of mental health problems related to the pandemic and the resulting lockdown has not been adequately addressed by existing mental health services (WHO, 2021). Governments must urgently address this need.

Finally, our approach highlights the importance that face-to-face social interactions have for some individuals. Future research should explore more directly not only the effects of reducing face-to-face social interactions on mental health but also the effects of substituting face-to-face social contacts by email, phone, and online platforms and the effects of such substitution in the long run.

## Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## Appendix A

See Table A1 to A5.

**Table A.1**
Variables description.

| Variables | Description |
|---|---|
| ***Mental health Outcomes*** | |
| *Insomnia* | It takes value 1 if respondents experienced more sleeping problems after the outbreak of Corona, and zero otherwise. |
| *Anxiety* | It takes value 1 if respondents confirmed they suffered from more anxiety after the outbreak of Corona, and zero otherwise. |
| *Depression* | It takes value 1 if respondents confirmed they suffered from more depression after the outbreak of Corona, and zero otherwise. |
| ***Variables*** | |
| **At the individual level** | |
| *Female* | Takes value “1” if the respondent is a female and “0” if the respondent is a male. |
| *Age* | *Age 50–54*: Takes value “1” if the respondent is aged between 50 and 54 years old and “0” otherwise. |
| | *Age 55–59:* Takes value “1” if the respondent is aged between 55 and 59 years old and “0” otherwise. |
| | *Age 60–64:* Takes value “1” if the respondent is aged between 60 and 64 years old and “0” otherwise. |
| | *Age 65–69:* Takes value “1” if the respondent is aged between 65 and 69 years old and “0” otherwise. |
| | *Age 70–74:* Takes value “1” if the respondent is aged between 70 and 74 years old and “0” otherwise. |
| | *Age 75–79:* Takes value “1” if the respondent is aged between 75 and 80 years old and “0” otherwise. |
| | *Age > 80:* Takes value “1” if the respondent is over 80 years old and “0” otherwise. |
| *Household size* | *Alone:* Takes value “1” if the household size is equal to 1, and “0” otherwise. |
| | *2:* Takes value “1” if there are two people residing in the house, and “0” otherwise. |
| | 3–4: Takes value “1” if there are three or four people residing in the house, and “0” otherwise. |
| | > 4: Takes value “1” if there are more than four people residing in the house, and “0” otherwise. |
| *Physical Health* | *Excellent*: Takes value “1” if the respondent reported excellent health before the outbreak of Corona, and “0” otherwise. |
| | *Very Good*: Takes value “1” if the respondent reported very good health before the outbreak of Corona, and “0” otherwise. |
| | *Good*: Takes value “1” if the respondent reported good health before the outbreak of Corona, and “0” otherwise. |
| | *Fair:* Takes value “1” if the respondent reported fair health before the outbreak of Corona, and “0” otherwise. |
| | *Poor:* Takes value “1” if the respondent reported poor health before the outbreak of Corona, and “0” otherwise, and “0” otherwise. |

**Table A.2**
Detailed Results Discrete Choice Model to Predict Social Scores {Logit Estimation}.

| Outcome: $S_i = 1$ if *Social* Interactions are at least once a week and within a distance of 25 km), and zero otherwise | | |
|---|---|---|
| | Female | 0.334*** |
| | | (0.04) |
| *Physical Health* | Excellent | 0.609*** |
| | | (0.10) |
| | Very good | 0.746*** |
| | | (0.08) |
| | Good | 0.656*** |
| | | (0.07) |
| | Fair | 0.608*** |
| | | (0.07) |
| *Age* | Age 55–59 | 1.566*** |
| | | (0.07) |
| | Age 60–64 | 2.113*** |
| | | (0.07) |
| | Age 65–69 | 2.250*** |
| | | (0.07) |
| | Age 70–74 | 2.131*** |
| | | (0.08) |
| | Age 75–79 | 2.145*** |
| | | (0.08) |
| | Age > 80 | 1.753*** |
| | | (0.08) |
| *Household size* | Two individuals | 0.942*** |
| | | (0.05) |
| | Three-Four Individuals | 0.965*** |
| | | (0.06) |
| | More than Four Individuals | 0.846*** |
| | | (0.10) |
| Country Fixed Effects | Yes | (0.15) |
| | Observations | 64,801 |

**Table A.3**
Mental Health by socioeconomic characteristics.

| | Insomnia | Anxiety | Depression |
|---|---|---|---|
| Female | 12,1% | 27,9% | 24,5% |
| *Male* | 7.5% | 17.3% | 12,0% |
| *Age* | | | |
| Age 50–54 | 12,6% | 23,7% | 20.2% |
| Age 55–59 | 10,9% | 23,8% | 17.3% |
| Age 60–64 | 11,7% | 24,6% | 17.8% |
| Age 65–69 | 7,1% | 21,5% | 17.3% |
| Age 70–75 | 8,7% | 22,1% | 18.8% |
| Age 76–79 | 9,4% | 23,4% | 19.5% |
| Age > 80 | 9,3% | 22,0% | 23.1% |
| *Household Size* | | | |
| 1 | 11,2% | 23,2% | 21,5% |
| 2 | 9,2% | 22,5% | 17,7% |
| *3–4* | 10,3% | 22,6% | 17,1% |
| *> 4* | 8,1% | 24,6% | 19,9% |
| *Pre-COVID Physical Health* | | | |
| Excellent | 5,6% | 14,9% | 12,8% |
| Very Good | 5,6% | 17,9% | 12,8% |
| Good | 9,1% | 21,3% | 16,5% |
| Fair | 14,8% | 30,8% | 26,1% |
| Poor | 20,5% | 35,5% | 34,6% |

*Notes*: The table displays means sample statistics taking survey weights for the outcomes of mental health for different socio-economic characteristics. These variables are described in Appendix Table A1.

**Table A.4**
Detailed Results from Double Difference estimation of some models from Table 3.

| | Insomnia | | | Anxiety | | | Depression | | |
|---|---|---|---|---|---|---|---|---|---|
| | Model 1 | Model 2 | Model 3 | Model 1 | Model 2 | Model 3 | Model 1 | Model 2 | Model 3 |
| $\beta_3$ $(S_i * T_j)$ | 0.049*** | 0.059*** | 0.050** | 0.070*** | 0.094*** | 0.071*** | 0.057*** | 0.075*** | 0.050** |
| | (0.011) | (0.014) | (0.015) | (0.018) | (0.026) | (0.020) | (0.018) | (0.025) | (0.019) |
| $\beta_2$ $(S_i = 1)$ | -0.025*** | -0.123 | -0.116 | 0.008 | -0.243* | -0.204* | 0.006 | -0.170 | -0.131 |
| | (0.011) | (0.082) | (0.08) | (0.008) | (0.135) | (0.11) | (0.01) | (0.131) | (0.100) |
| $\beta_1$ $(T_j = 1)$ | -0.050** | -0.065*** | -0.056** | -0.078*** | -0.118*** | -0.094*** | -0.079*** | -0.110*** | -0.083*** |
| | (0.011) | (0.021) | (0.021) | (0.017) | (0.013) | (0.02) | (0.02) | (0.023) | (0.018) |
| $Social_i$ | | 0.009 | 0.103** | | 0.064 | 0.273*** | | 0.133* | 0.290** |
| | | (0.112) | (0.040) | | (0.090) | (0.052) | | (0.071) | (0.102) |
| $Social_{ih}$ $(Social_i * S_i)$ | | 0.186 | 0.148 | | 0.464 | 0.343 | | 0.305 | 0.185 |
| | | (0.171) | (0.174) | | (0.271) | (0.220) | | (0.241) | (0.191) |
| Female | | | 0.033*** | | | 0.067*** | | | 0.088*** |
| | | | (0.014) | | | (0.006) | | | (0.011) |
| Age: | | | | | | | | | |
| 55–59 | | | -0.026 | | | -0.045 | | | -0.059 |
| | | | (0.023) | | | (0.054) | | | (0.037) |
| 60–65 | | | -0.026 | | | -0.060 | | | -0.078* |
| | | | (0.024) | | | (0.051) | | | (0.039) |
| 65–69 | | | -0.063*** | | | -0.098* | | | -0.085** |
| | | | (0.019) | | | (0.050) | | | (0.040) |
| 70–74 | | | -0.067*** | | | -0.104* | | | -0.088** |
| | | | (0.022) | | | (0.050) | | | (0.035) |
| 75–79 | | | -0.079*** | | | -0.128** | | | -0.105*** |
| | | | (0.021) | | | (0.045) | | | (0.034) |
| $> 80$ | | | -0.089*** | | | -0.138*** | | | -0.090*** |
| | | | (0.022) | | | (0.047) | | | (0.030) |
| Household Size | | | | | | | | | |
| 2 | | | -0.030** | | | -0.057*** | | | -0.061*** |
| | | | (0.014) | | | (0.015) | | | (0.016) |
| 3 | | | -0.028** | | | -0.065** | | | -0.066*** |
| | | | (0.013) | | | (0.024) | | | (0.016) |
| $> 4$ | | | -0.046*** | | | -0.020 | | | -0.035 |
| | | | (0.015) | | | (0.044) | | | (0.031) |
| Very Good-Health | | | -0.009 | | | 0.035** | | | 0.010 |
| | | | (0.014) | | | (0.021) | | | (0.010) |
| Good-Health | | | 0.038*** | | | 0.083*** | | | 0.042*** |
| | | | (0.012) | | | (0.022) | | | (0.014) |
| Fair health | | | 0.103*** | | | 0.165*** | | | 0.129*** |
| | | | (0.014) | | | (0.021) | | | (0.021) |
| Poor health | | | 0.167*** | | | 0.236*** | | | 0.234*** |
| | | | (0.012) | | | (0.031) | | | (0.017) |
| Constant | 0.095*** | 0.086* | 0.046** | 0.168*** | 0.129*** | 0.018 | 0.139*** | 0.075* | 0.013 |
| | (0.005) | (0.044) | (0.019) | (0.012) | (0.039) | (0.040) | (0.010) | (0.036) | (0.024) |
| R-squared | 0.005 | 0.035 | 0.039 | 0.029 | 0.057 | 0.061 | 0.019 | 0.064 | 0.065 |

*Note*: The table displays detailed results -the coefficient estimates, and their corresponding standard errors cluster at the country level and considering survey sample weights (in parentheses)- for models in columns 1, 2 and 3 of Table 3. Sample size is 40,501 and all models include country fixed effects. Model 3 is our preferred specification**.** The dependent variable is a binary variable indicating whether the individual declared suffering more mental problems (Insomnia, Anxiety, depression) and zero otherwise. The constant term refers to male, age below 55, living alone in a house and excellent health. We obtained coefficient estimates using a linear probability model. * 10% statistical significance level; ** 5% statistical significance level; *** 1% statistical significance level.

**Table A.5**
Sample means for variables used in the robustness analysis (Tables 4, 5 and 6).

| | Sample Means |
|---|---|
| Google Mobility Index | 25,2% |
| COVID-19 Exposure | 22.7% |
| Case Fatality Rate | 13.7% |
| Pre-pandemic Insomnia (SHARE Wave 6) | 33,7% |
| Pre-pandemic Depression (SHARE Wave 6) | 42,9% |
| Insomnia (same or better) | 17.4% |
| Anxiety (same or better) | 10.1% |
| Depression (same or better) | 7.8% |

*Notes*: The table displays means sample statistics for variables used in the robustness analysis expressed as a percentage. COVID19 Exposure Takes value "1" if the respondent has experienced in his network the COVID-19 virus in any of these four aspects: symptoms that could be attributed to the Covid illness, positive in a Corona virus test, hospitalized or death due to an infection from the Corona virus. The case fatality rate is the ratio between the final number of deaths and the number of confirmed COVID cases, for a given country. Pre-pandemic insomnia takes value one when the individual declares having insomnia problems in Wave 6 of SHARE. Pre-pandemic depression takes value one when the individual declares having depression problems in Wave 6 of SHARE. Insomnia (same or better) takes value "1" if the respondent declares his insomnia problems (anxiety, insomnia, or depression) to improve or be about the same as before the outbreak of corona. Similarly, anxiety (same or better) takes value "1" if the respondent declares his anxiety problems to improve or be about the same as before the outbreak of corona and finally, depression (same of better) takes value "1" if the respondent declares his depression to improve or be about the same as before the outbreak of corona.

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