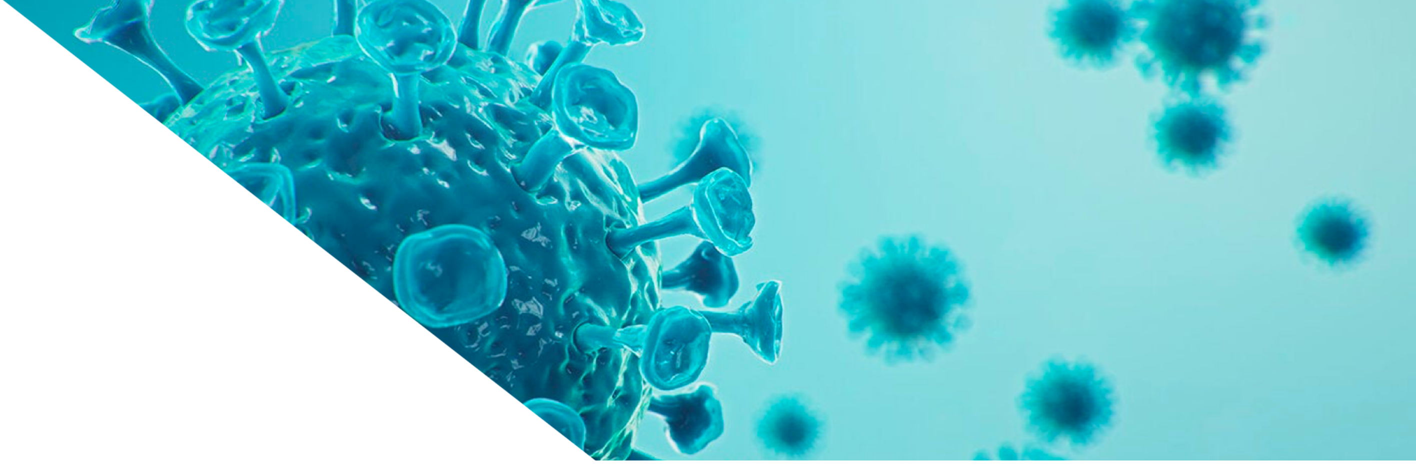

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The Causal Impact of COVID-19 Lockdown Policies on the Mental Health of Older Populations in Europe*

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August 3rd 2021

Abstract

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 the 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 increased insomnia, anxiety, and depression by 5.7, 5.6 and 5.3 percentage points, respectively, and we find that this effect is stronger for women, individuals employed at the outbreak of the pandemic, and those aged between 50 and 65.

Keywords: COVID-19, Mental Health, Lockdown, Confinement, Containment Index, Mobility Restrictions, Senior and Older Europeans, Causality.

JEL Codes: I18, I31

* We acknowledge financial support from Agencia Estatal de Investigación (Ministerio de Ciencia e Innovación), project PID2019-104452RB-I00, Fondo Europeo de Desarrollo Regional y Consejería de Transformación Económica, Industria, Conocimiento y Universidades, Junta de Andalucía, projects P18-RT-2135 and CV20-35470. The authors declare that no competing interests exist.

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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 the closure of all 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., 2020, 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 & 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 Figure 4).

We use microdata on anxiety, depression, and insomnia after the COVID-19 outbreak for 16 European countries and Israel. Data comes from the COVID-19 portion of the Wave 8 of the Survey of Health, Ageing and Retirement in Europe (SHARE), which interviewed respondents between June and August 2020 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. The fact that we control for 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, 5.6, and 5.3 percentage points, respectively. This is equivalent to an increase of 74%, 31% and 38% of insomnia, anxiety and depression for individuals of the treatment group who live in countries with strict lockdown policies relative to their counterparts in less strict countries. These results are robust to alternative model specifications, the severity of the pandemic and different sample criteria. Placebo exercises based on different definitions of social contacts and different classifications of strict versus less-strict lockdown countries and treated versus control individuals also support our results. The fact that the causal effect of strict lockdown on mental health vanishes when pre-COVID 19 social contact was maintained mostly by phone, mail, or internet (rather than face-to-face interaction) also supports our main finding.

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, that is, lockdown policies restricting face-to-face contacts caused mental health problems for senior and older Europeans, independently of their age or physical health. 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. To a lesser extent, individuals who were employed at the outbreak of the pandemic and individuals aged between 50 and 65 were more affected by lockdown policies.

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 & 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-Alarcón et al., 2021; Altinger 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 administrative 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., 2020; Altinger et al., 2021), or fail to include validated clinical measures of mental health (Brodeur et al., 2020).[2] Fourth, we contribute to the debate about the decision to impose age-specific lockdown measures as a way to reduce the economic damage of lockdown (Acemoglu et al., 2020). 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. Section 6 concludes.

[1] Serrano-Alarcón et al. (2021) exploit the different lockdown restriction levels in England and Scotland. Altinger et al. (2021) assess the effects of an age-specific lockdown order for adults aged 65 and older in Turkey.
[2] Brodeur et al. (2020) 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 Altinger et al. (2021) data on mental outcomes is collected through phone interviews with 1,909 individuals by a private firm.

2.- Data Sources

The analysis of this study combines two types of data from two 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 Survey of Health, Ageing and Retirement in Europe (SHARE). This is a social science panel study that provides microdata for the public health and socio-economic living conditions of adults aged 50 and over in a large number of countries. In particular, we draw from a SHARE COVID-19 questionnaire that was used to collect data on individual mental health problems after the onset of the pandemic, as well as information about socioeconomic characteristics and physical health. 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 for all of its panel respondents (Scherpenzeel et al., 2020). From the CATI telephone survey a sample was selected by SHARE for each country.[3] The CATI was executed in the summer between June and August of 2020 and amassed a total of 52,310 respondents.

We also 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. 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.

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

[3] The sample includes both panel members who had not been interviewed before the suspension of fieldwork, and panel members who had already been interviewed face-to-face in Wave 8.

(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 (not measure, 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: not measure, 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 A1.

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 (WHO, 2001). 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. Although insomnia can be assessed using various methods, self-reporting has proved to be useful and reliable (Katic et al. 2015). Regarding anxiety and depression, the literature on insomnia indicates that anxiety and depression are usually under-diagnosed because of low self-reporting (Katic et al. 2015), which means that our results might be biased 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 because of the pandemic. Thus, we categorize variable *insomnia* in a binary variable that takes value 1 if respondents answered that they experienced more sleeping problems after the outbreak, and zero otherwise. Similarly, the variable *anxiety* takes value 1 if respondents experienced more anxiety after the outbreak, and zero otherwise. Finally, the variable *depression* takes value 1 if respondents confirmed they suffered from more depression after the outbreak, and zero otherwise. 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.[4]

The average containment index for all 17 countries in our sample is 76.5 (with a standard deviation of 10 points). However, as Figure 1 shows, 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 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.[5] 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.[6] Using this variable, through a discrete choice econometric model we obtain the probability of having pre-COVID face-to-face contacts according to several socioeconomic observed characteristics of the individuals (all of them unrelated to the COVID pandemic) in the SHARE social network survey—age (six age intervals), gender, physical health (5 groups ranged from excellent to poor), household size (4 categories) — along with country of residence.[7]

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[4] 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.

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

[6] In the robustness section we increase the distance to the social contact as a placebo test.

[7] Using these sets of pre-determined characteristics, we end up with 120 types of individuals for each country.

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 A2 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 and older adults. The importance of this goal is supported by high levels of mental health problems in these populations, as shown by the descriptive data (see Table 1) and figures 2 and 3.

Figure 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.[8] From this data, a simple statistical analysis (Figure 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.[9] 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 described

[8] These are sample statistics, using survey weights, for the 17 countries included in the causal approach analysis.
[9] Similar identification approaches are commonly found in the literature of public finance and are also used in the literature of development economics (Gertler and Molyneaux, 1994, Duflo, 2001).

above $\{Index_j\}$. As already mentioned, strict lockdown countries are those with a containment index above the median value.[10]

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

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

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.[11] $\mathrm{T_j}$ is a dummy variable indicating whether individual "i" lives in a strict lockdown country "j", and zero otherwise. S_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 $\varepsilon_{\mathrm{ij}}$ is the error term. The coefficient of interest β_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 β_3 should be positive. The other two parameters of the equation, β_1 and β_2, control for systematic differences in mental health between strict and less strict lockdown countries and between treatment and control groups, respectively. We estimate equation (1) with a linear probability model and clustering standard errors at the country level using survey sample weights.[12]

The identification strategy in equation (1) is based on two assumptions: (i) lockdown policies affect 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 as a result 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. While some studies indicate that individuals who usually have frequent social interactions are more resilient (Shokron and Nicoladis, 2021), others find that 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). The fact that we are dealing with older populations implies that limiting their face-to-face network

[10] 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 when using an assignment rule based on the mean instead of the median.
[11] 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.
[12] As Bertrand, Duflo and Mullainathan (2004) point out, conventional standard errors often severely understate the standard deviation of the estimators.

contacts must have deteriorated their mental health as indicated in the literature (Litwin et al., 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. Mendiola et al. (2020) and Santamaria et al. (2020) show that individuals comply to a large extent with the lockdown policies of their countries.[13] In addition, using information for three countries—Canada, USA and UK—with different levels of restrictions, Folk et al. (2021) 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 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.

However, if individuals who live in countries with high COVID-19 mortality also have worse mental health, this variable might be confounded with the strictness of lockdown policy in those same countries. In section 5.1, we test for potential bias of our estimated parameter β_3 by adding to the model the covariates of case fatality rate and individual exposure to the virus, as well as individual financial and employment status. None of these potential confounders influence our causal estimation results.

In addition, in our final specification of the model, we control for a battery of pre-determined socioeconomic characteristics: age-group (three groups), gender, household size (number of people residing with the respondent in the same household, divided into four categories), physical health before the outbreak (five dummies of health status ranging from excellent to poor). Country-fixed effects are also included in all model estimations. The fact that we control for these individual observable socioeconomic characteristics makes identification assumptions be less demanding.

4.2. Main Sample Statistics for the DID

Our final sample comprises 40,501 respondents.[14] 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.

[13] Using google mobility data for 73 countries in 6 world regions, Mendiola et al. (2020) show that self-imposed mobility restrictions in response to the arrival of the pandemic account for up to 15 percentage points of the total observed reduction in mobility, while government-mandated measures account for a much larger part (up to 50 percentage points). Santamaria et al. (2020) use the Oxford Stringency Index and find that these measures explain up to 90 percentage points of the mobility data of individuals living in European countries during the lockdown.

[14] 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.

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 -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.

Table 2 also includes other covariates used in the sensitivity analysis, such as the month of the interview, the financial situation of the respondent after the outbreak, the employment status at the outbreak, individual exposure to COVID-19 and country-specific case fatality rate. Table 2 shows that, as expected, individuals with major financial problems and individuals exposed to COVID-19 are higher in strict lockdown countries than in less strict lockdown countries. Once the double difference is calculated, differences in the month of the interview between treated and control individuals disappear, but they remain for the financial variables, the labor status, and the individual exposure to COVID-19. The country-specific case fatality rate is higher in strict lockdown countries.

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 population mental health. In this section we present the results from our differences in differences empirical exercise, and we carry out some sensitivity analyses to test the robustness of the results.

5.1.- Estimating the causal effects of lockdown policies

Table 3 presents the main estimation results from our causal empirical exercise. Table 3 is structured in three Panels, A, B and C, which present main estimation results for insomnia, anxiety, and depression, respectively. For each Panel, Table 3 includes seven columns that correspond with different model specifications. For the sake of brevity, we present only the main parameter estimates of the causal effect $\{\beta_3\}$ of lockdown restrictions on mental health.[15] Column 1 of each Panel presents the baseline causal model according to equation (1) with country-fixed effects. Note that for this baseline model, the estimated parameter β_3 is positive and statistically significant at 1%-5% for the three outcomes of interest: 0.052 for insomnia, 0.056 for anxiety and 0.060 for depression.

To relax some of the main identification assumptions, we add control variables sequentially in columns (2), (3) and (4). Firstly, to exploit variation in treatment intensity we generalize

[15] With discrete outcomes, the linear probability model can lead to predictions outside the allowable range. These concerns have led researchers to consider non-linear transformations of an additive single index. However, the economic justification for the additivity assumptions required for difference in difference model may be tenuous in such cases. For this reason, we opted to estimate models using OLS methods instead of discrete choice estimation models. In addition, we estimated the different models using discrete choice methods (probit and logit estimators) and estimated marginal effects are quantitatively similar to those presented in Table 3.

the model in equation (1) by adding the value of the containment index ($Index_j$) and the value of the imputed individual score for face-to-face social interactions ($Social_i$). This is done in column (2). In column (3) we add main individual socioeconomic characteristics, such as age, gender, household composition and pre-COVID physical health.[16] Estimates in column (4) exploit variation in the intensity of face-to-face social interactions between treated and control individuals by adding as a regressor the social score for treated individuals ($Social_{iT}$= $Social_i$* S_i). Similarly, we add the value of the index for strict lockdown countries ($Index_{jT}$ = $Index_j$*T_j). This gives additional flexibility to the model as it relaxes some implicit model assumptions. For these reasons, we will use it as our main reference model.[17] Table A.4 in the Appendix provides detailed results for this model and also for models in columns 1 and 3.

Estimates across these four different specifications are all positive, of similar size and statistically significant at 1% in almost all models. According to estimated value of β_3 shown in baseline Model 4 of Table 3, lockdown restrictions have caused deterioration in mental health for individuals of the treatment group. That is, we find that insomnia have increased by 5.7 percentage points, anxiety problems by 5.6 percentage points and depression by 5.3 percentage points, all statistically significant at 5%. Estimates of β_3 for Models 1-3 remain similar to those shown in Model 4. Broadly speaking, these models show a small variation of coefficient estimates from 5.2 to 5.7 for insomnia, 4.2 to 6.4 for anxiety and 4.3 to 5.3 for depression.

In columns (5), (6) and (7) of Table 3 we provide a robustness exercise to the main model specification of column (4). Estimates in column fifth test whether heterogeneity in the dissemination of the virus could be driven by our causal estimates. For that purpose, we add the covariates of individual exposure to the virus and the case fatality rate. The estimated value of β_3 remains the same as in column (4), which gives support to our identification strategy because it confirms that our estimate of β_3 is not driven by other confounding factors such as the fear of being infected. Moreover, as expected, the estimated coefficient for the covariate *COVID-19 exposure* is positive and statistically significant for the three outcomes variables at 5% (0.043, 0.059 and 0.022, for insomnia, anxiety, and depression respectively). That is, respondents who were exposed to cases or experiences of COVID among friends, neighbours 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).[18] In column (6) we add as a regressor the month of interview (June, July or August) to test whether heterogeneity in the timing of the interview could bias our estimation. Again, the estimated value of β_3 does not change; the month of the interview is not statistically significant. Finally, in column (7) we add as regressors to main model specification of column (4) the covariates of financial situation and employment at the outbreak. Again, the estimated value

[16] All these covariates are statistically significant. Coefficients for physical health show that, given model specification, those individuals with worse health before the outbreak suffered more insomnia, anxiety, and depression problems during the pandemic.

[17] Detailed results from Table A.4. show that some of these additional interactions are statistically significant.

[18] Note that this 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 1.

of β_3 remains the same. As expected, the estimated coefficients for the *financial problem* covariates are positive and statistically significant for the three outcomes variables. We find that those respondents with severe or moderate financial problems since the outbreak suffer more mental health problems than those with minor financial problems.[19]

Summing up, estimates across these different specifications shown in Table 3 are all positive, of similar size, and statistically significant at the 1% or 5% level, except for some particular cases (anxiety, in column (3)). Moreover, all estimates confirm that lockdown policies lead to a significant deterioration of mental health of populations over 50.

5.2.- Robustness exercises and placebo tests.

We have estimated additional models to test for the robustness of our estimated causal effect in relation to different sample criteria, different definitions of face-to-face social contacts and different classifications of strict versus less-strict lockdown countries and treated versus control individuals. Main results from these exercises are shown in Table 4. Models from column 1 to column 4 in Table 4 use as a reference model the specification of our preferred model 4 in Table 3. In columns 5 and 6 the reference model used is Model 1 of Table 3. As before, we present main estimation results using three panels (A, B and C) that correspond to our three outcome variables.

First two columns of Table 4 restrict 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.[20] That is, we define strict lockdown countries ($T_{\mathrm{j}} = 1$) as those whose *index* is above the percentile 60 of the index distribution, and less strict lockdown countries ($T_{\mathrm{j}} = 0$) 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 Model 4 and, more importantly, it remains statistically significant at 5%. In column (2) we omit individuals who are similar in terms of their score of face-to-face social interactions.[21] 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 ($S_i = 0$) those whose score is below percentile 40. Estimates for β_3 are again positive and statistically significant at the 5%, though the estimated effect is slightly lower.

Methodologically, we have relied on the assumption that the deterioration of mental health is related to the sudden drop of face-to-face social interactions caused by lockdown policies. We conjecture that it is more likely that social interactions with social network members

[19] The estimated coefficients for *financial problems-major* are 0.121, 0.122 and 0.123 for insomnia, anxiety, and depression respectively (all of them significant at 1%). For *financial problems-moderate* we obtain 0.020, 0.035 and 0.032, statistically significant at 5% or 10%. The estimated coefficients for the covariate employed are close to zero and non-statistically significant.

[20] 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 78-92, are Greece, Lithuania and Malta. Countries assigned to the group of less strict lockdown countries, whose index values lie between 48-68 are Belgium, Poland and Estonia.

[21] 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.

across larger geographic distances will not be affected by lockdown measures, as those contacts are generally maintained by phone, mail, email or other electronic means. Columns 3 and 4 of Table 4 present exercises that test the plausibility of this assumption. Because we have proxied face-to-face contacts using the geographic proximity of the contact, we estimate an additional model for which the social network score is calculated using contacts within larger geographic distances (distances between 25-100 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 β_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 β_3 loses its statistical significance and/or becomes negative. Note that results from these last two columns in Table 4 can be interpreted as a placebo exercise. They show that individuals whose contacts were made with the same frequency, but mainly by mail or telephone, did not suffer a worsening in their mental health due to lockdown policies.

The last two columns of Table 4 present additional placebo exercises. In column 5 countries are randomly assigned to strict versus less strict lockdown countries (T_{j}). In column 6 individuals (S_i) are randomly assign to treatment and control groups. Again, estimated causal effects of β_3 presented both in columns 5 and 6 of Table 4 are not statistically significant and the coefficients are close to zero or become negative.

Summing up, 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.[22]

5.3.-Subgroup Analysis

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

Panels A, B C, D and E in Table 5 present the results of the heterogeneous causal effects by age (below 65/65-75/above 75), physical health before the pandemic (poor/fair/good),

[22] We have performed more robustness exercises but, for sake of brevity, they are not displayed in the current version of the paper. We have tested for robustness of the results to different types of standard errors (general robust standard errors or standard errors clustered by types of individuals given their level of social scores). There are small differences in the statistical significance of some regressors, but our estimated causal effect remains significant at the 1%-5% level. We have also used a discrete choice model, instead of a linear probability model, to estimate the different models presented in Table 3 and also found no important variation in the results. Finally, we have also estimated a multivariate probit model that allows for a joint estimation of the effect of lockdown policies on the three mental health outcomes. This last estimation approach reinforces the causal effect presented above. We have also used the value of the mean, instead of the median, in the assignment rule to classify treated versus control individuals. Nevertheless, given the high similarity between both measures in our sample there were no relevant differences.

gender (female/male), labor situation at the outbreak (employed/non-employed), and household composition (living alone/cohabitation). Estimation results are displayed for Model 1 and Model 4 - our preferred specification- of Table 3.

The key result of this analysis is 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 β_3 to be positive for almost all subgroups and health outcomes, although it is not always statistically significant. It is difficult to establish definite reasons for the lack of statistically significant coefficient estimates for certain cases (sample sizes might be the reason in some instances) and health outcomes, but it should be noted that the value of the coefficients do not deviate much from the general result presented in Table 4. Hence, lockdown policies undoubtedly caused a worsening in the mental health in populations over 50 in Europe for almost all types of individuals.

The one noteworthy exception to this general 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). Because only 20% of women in our sample were employed at the time of the outbreak of the COVID 19, the strong causal effect found for women cannot be linked exclusively to employment. 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, Adam-Prassl et al., 2021), but not through the expected channels: financial and work situation, health situation, and/or health behaviors. Etheridge and Spantig (2020) do find some differences in family and caring responsibilities during the pandemic in the UK, while Adam-Prassl et al. (2021) do not find such differences in the US. Both studies point at 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 pandemic than men, in addition to feeling more loneliness after the outbreak. Therefore, the reduction of social contact imposed by lockdowns seems to be the main mechanism that explains this gender gap. Our results also point to the same mechanism, as individuals in our treatment group (high frequency of pre-COVID-19 face-to-face contacts) were mostly women.

Secondly, the causal effect of lockdown policies is stronger for those individuals that were employed at the time of the outbreak (Panel D). This could happen because of anxiety about possible job and income losses, and/or because individuals had to work from home. The fact that heterogeneity of the financial situation did not bias our estimation results seems to point to isolation and stress associated with working from home as the main underlying mechanisms.

When we look at the causal effects of lockdown policies on mental health for individuals with good pre-COVID physical health versus those with fair or poor health (Panel B), there seems to be larger effects for individuals with poor or fair health, but the results for individuals with good health are also large and statistically significant. Finally, the size of the household does not seem to be a potential channel through which lockdowns policies negatively impact mental health. Although the coefficients for insomnia and anxiety are larger for individuals who live alone, lockdown policies cause more depression among individuals residing in households with more members (Panel E).

Finally, we find that the effect of lockdown policies on the worsening of mental health seems to decrease with age. Individuals between 50 and 65 are more affected by lockdown policies than those between 65 and 75, and these policies do not seem to affect those above 75 (Panel A).

There are some voices in the literature (Acemoglu et al., 2020, Savulescu and Cameron, 2020; Joffe, 2021) that recommend a targeted policy that applies strict lockdown only on individuals over 65 to obtain better health and economic outcomes.[23] Our results give some support to this idea because we find that the effects of lockdown policies on mental health were larger for those between 50 and 65, with this effect declining with age. These effects were also larger for those who were employed at the time of the outbreak. However, the fact that mental health also deteriorated among Europeans over 65 calls for additional complementary policies such as increasing the number of mental health call centers and local support services for at risk-populations (Galea et al., 2020).

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 administrative 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

[23] 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

health of senior and older Europeans. The estimated causal effects are large and amount to 5.7 percentage points for insomnia, 5.6 percentage points for anxiety and 5.3 percentage points for depression. When we explore demographic heterogeneity in the treatment effects, we find that lockdowns policies negatively impact mental health mainly to women, those who were employed at the outbreak of the pandemic 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, seeing that individuals between 65 and 75 also suffered a worsening of mental health 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).

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. 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.

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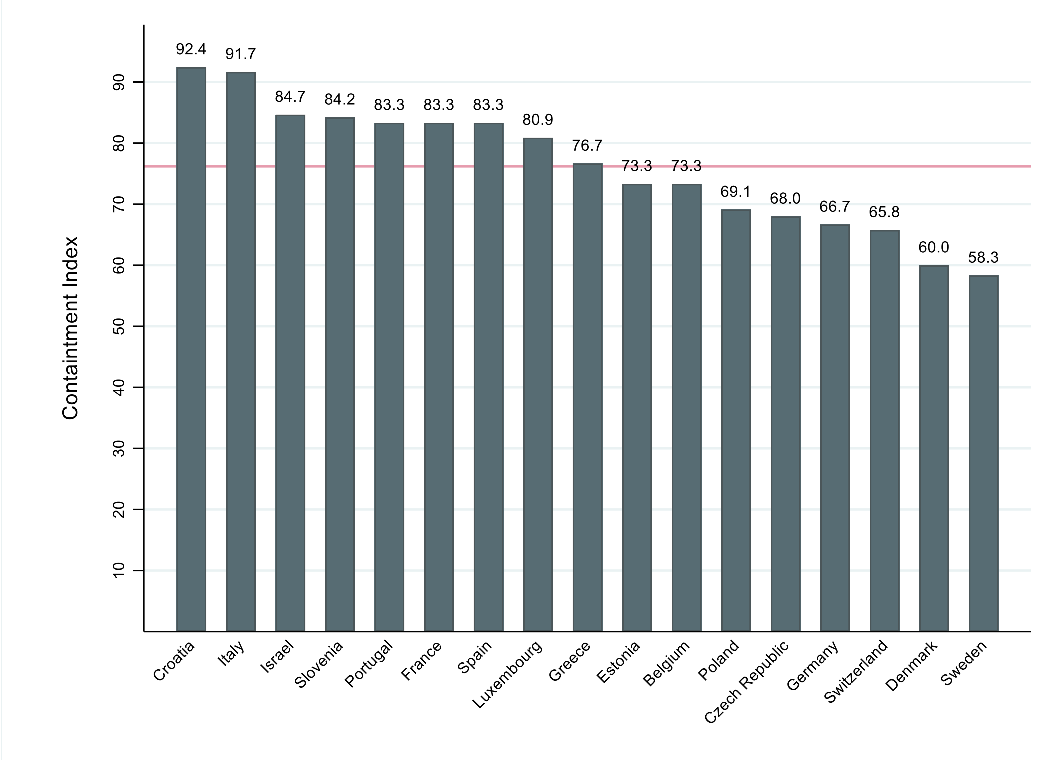
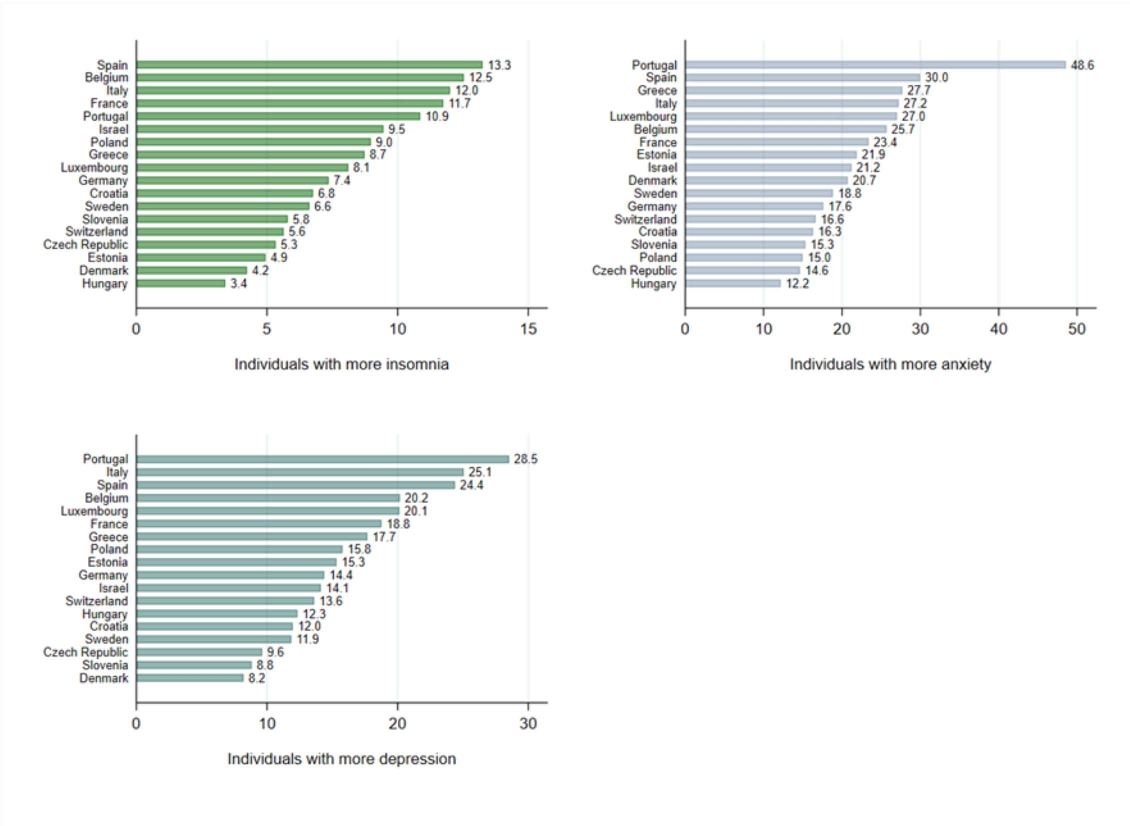
Tables and Figures

Figure 1: Sample statistics: Containment Index cross country variability



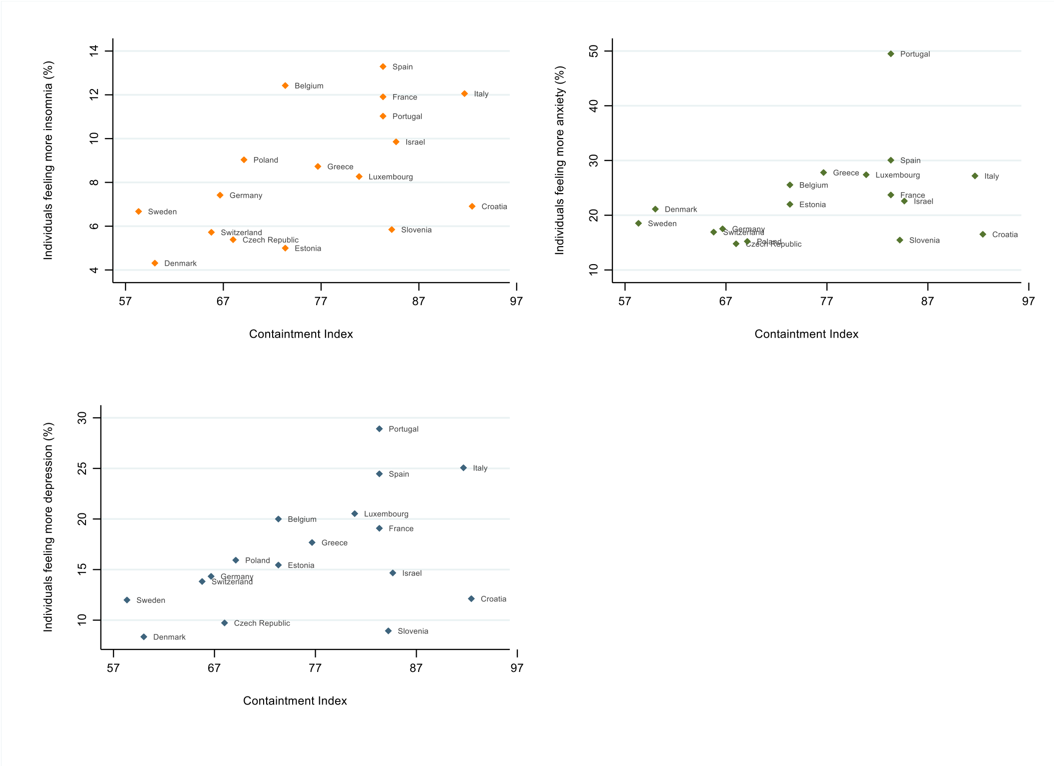
Note: This Figure displays the Containment Index across the 17 countries used in the regression analysis. The Containment Index describes the mean of the index between April and May 2020. These are own calculations using Oxford COVID-19 Government Response Tracker (OxCGRT). The horizontal line refers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

Figure 2: Sample statistics main outcome variables: cross country variability



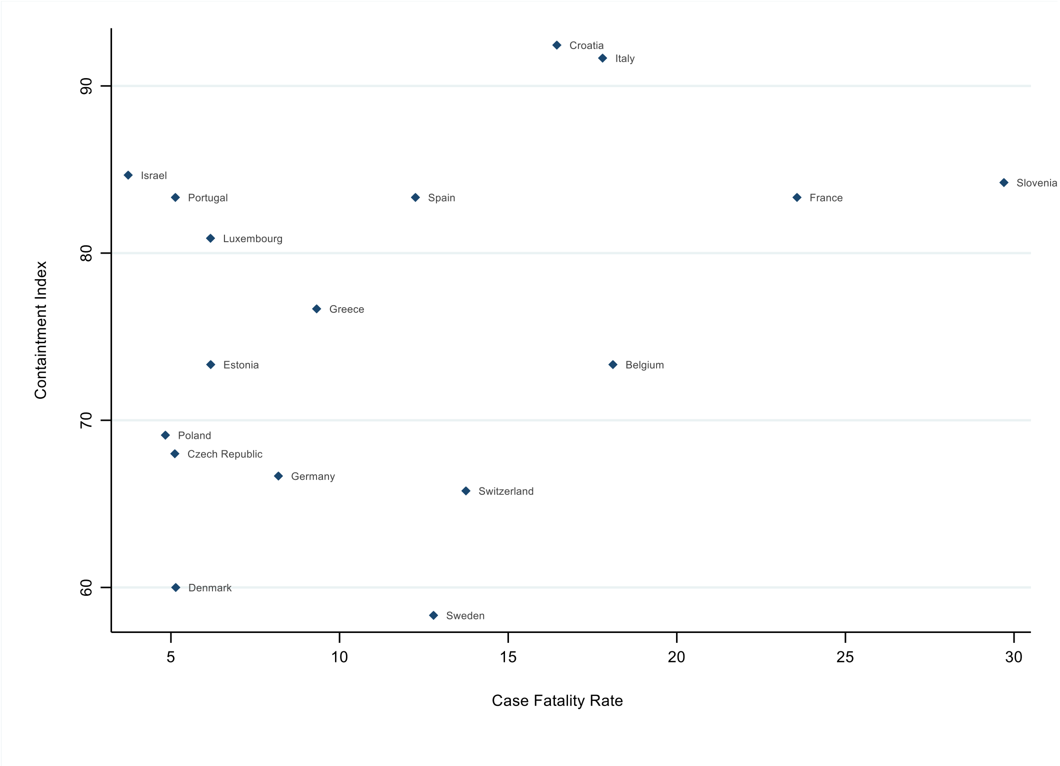
Note: Figure represents sample means by country for our main outcomes of mental health: insomnia, anxiety and depression. Own calculations based on SHARE-COVID-19 for the 17 countries used in the regression analysis. Survey sample weights are used.

Figure 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.

Figure 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.

Table 1. Mental Health and the DiD identification strategy.

	Total Mean	Strict lockdown ($T_j = 1$)				Less strict lockdown ($T_j = 0$)				DiD
		Mean	Mean	Mean	Mean Diff	Mean	Mean	Mean	Mean Diff	
			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 (*Mean diff)* and the corresponding double difference. The statistical significance for Diff (pp) columns displays a two-sample t test. Standard errors taking into account sample weights in parentheses. * 10% statistical significance level; ** 5% statistical significance level; *** 1% statistical.

Table 2. Sample composition: Strict and less strict lock down countries and Treated and Control Individuals (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-determined 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	5,3%	7,0%	-1.8	10,1%	4,3%	5.8***	7.5***
Very Good	15,7%	20,0%	-4.3**	20,3%	18,5%	1.7***	-6.0***
Good	66,3%	74,2%	-7.9***	75,4%	73,4%	2.0***	-9.9***
Fair	28,2%	19,5%	8.7***	20,6%	18,8%	1.8**	6.9***
Poor	5,5%	6,3%	-0.8***	4,0%	7,7%	-3.8 **	3.0***
Age							
Age <65	46,9%	51,7%	-4.8***	46.3%	53.2%	-6.9***	2.1**
Age 65-75	38,0%	29,8%	8.2***	39.9%	31.1%	8.8***	-0.7
Age >75	15,2%	18,5%	-3.3***	13.8%	15.7%	-1.9	1.4*
Other Covariates							
Month of the interview							
June	55,2%	53,8%	1.4	52,0%	51,1%	0.9	0.5
July	44,8%	46,2%	1.4	48,0%	48,9%	-0.9	-0.5
COVID-19 Exposure	22.7%	21.9%	0.8	18.8%	15.7%	3.1***	-2.3***
Financial Problems							
Major	7.4%	7.2%	0.2	1.6%	5.3%	-3.7***	3.9***
Moderate	19.0%	18.9%	-0.1	7.6%	20.6%	-13.1***	12.9***
Minor	73.7%	73.7%	-0.1	90.8%	74.1%	16.8***	-16.8***
Employed	22.2%	34.4%	-12.2***	39.3%	39.5%	-0.2	-11.9***
Case Fatality Rate	13.7	13.7	-	9.26	9.26	-	-
Variables for the double difference							
$Social_i$	52.6%	33.1%	19.5***	53.0%	34.6%	18.4***	1.1***
$Index_j$	84.5	84.5	-	66.8	66.8	-	-

Notes: The table displays means sample statistics for the covariates used in equation (1), 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) 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 A.

Table 3. Main results from Double Difference estimation:

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Insomnia							
$\boldsymbol{\beta_3}$ $(\boldsymbol{S_i} * \boldsymbol{T}_{\mathrm{j}})$	**0.057*** **	**0.058*** **	**0.052*** **	**0.057*** **	**0.057*** **	**0.057*** **	**0.057*** **
s.e	**(0.01)**	**(0.01)**	**(0.02)**	**(0.02)**	**(0.02)**	**(0.02)**	**(0.02)**
Panel B: Anxiety							
$\boldsymbol{\beta_3}$ $(\boldsymbol{S_i} * \boldsymbol{T}_{\mathrm{j}})$	**0.056** **	**0.058** **	**0.042* **	**0.056** **	**0.056** **	**0.056** **	**0.056** **
s.e	**(0.02)**	**(0.02)**	**(0.02)**	**(0.02)**	**(0.02)**	**(0.02)**	**(0.02)**
Panel C: Depression							
$\boldsymbol{\beta_3}$ $(\boldsymbol{S_i} * \boldsymbol{T}_{\mathrm{j}})$	**0.060** **	**0.062*** **	**0.043*** **	**0.053** **	**0.053** **	**0.053** **	**0.052*** **
s.e	**(0.01)**	**(0.01)**	**(0.01)**	**(0.02)**	**(0.02)**	**(0.02)**	**(0.01)**
β_1 $(T_{\mathrm{j}} = 1)$	X	X	X	X	X	X	X
$\beta_2(S_i = 1)$	X	X	X	X	X	X	X
$Social_i$		X	X	X	X	X	X
$Social_{\mathrm{iT}}$				X	X	X	X
$Index_{\mathrm{j}}$		X	X	X	X	X	X
$Index_{\mathrm{jT}}$				X	X	X	X
Individual Characteristics			X	X	X	X	X
COVID-19 Exposure					X		
Case Fatality Rate					X		
Month of the Interview						X	
Economic Problems & Employment							X
Country FE	X	X	X	X	X	X	X
Observations	40,501	40,501	40,501	40,501	40,501	40,501	40,501

Notes: The table displays the coefficient of the causal effect of interest $\{\boldsymbol{\beta_3}\}$ 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, respectively) and zero otherwise. * 10% statistical significance level; ** 5% statistical significance level; *** 1% statistical significance level. Detailed results for models of columns 1, 3 and 4 are shown in Appendix Table A.3. For the rest of the models, detailed results are provided upon request. Individual socioeconomic pre-determined characteristics include age, gender, household composition and pre-COVID physical health.

Table 4: Robustness Exercise: Additional sample restrictions to define treated and control individuals

	Sample restriction: $Index_j$	Sample restriction: $Social_i$	Proximity of social network members		Placebo: Random Assignment	
	($Index_j$ >p60) $Index_j$ <p40)	($Social_i > p60$ $Social_i < p40$)	25-100 kms	> 100 kms	to strict versus less strict lockdown country (T_j)	to treated versus control individual (S_i)
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Insomnia						
β_3 ($S_i * T_j$)	0.065**	0.045**	0.010	-0.023	0.001	-0.022
	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)
Panel B: Anxiety						
β_3 ($S_i * T_j$)	0.071**	0.037*	-0.023	0.044	0.001	-0.022
	(0.03)	(0.02)	(0.03)	(0.03)	(0.04)	(0.02)
Panel C: Depression						
β_3 ($S_i * T_j$)	0.062***	0.034*	0.023	-0.001	-0.008	-0.022
	(0.02)	(0.02)	(0.02)	(0.02)	(0.04)	(0.02)
Observations	26,095	30,960	40,501	40,501	40,501	40,501

Note: The table displays the coefficient of the causal effect of interest {$\boldsymbol{\beta_3}$} 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 specification from column 1 to 4 corresponds with our preferred model 4 of Table 3. Models in columns 5 and 6 take as a reference Model 1 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 randomly assigns countries to strict versus less strict lockdown countries. Model in column 6 randomly assigns individuals to treatment and control groups.

Table 5: Causal Effects of Lockdown Policies: Subgroup analysis by individual socioeconomic characteristics

	Insomnia Model 1	Insomnia Model 4	Anxiety Model 1	Anxiety Model 4	Depression Model 1	Depression Model 4
Panel A: Age:						
<65 years						
$\beta_3\ (S_i * T_j)$	0.083***	0.076*	0.061	0.060	0.079**	0.077*
	(0.02)	(0.04)	(0.04)	(0.05)	(0.03)	(0.05)
Observations	11,123	11,123	11,123	11,123	11,123	11,123
65-75 years						
$\beta_3\ (S_i * T_j)$	0.020	0.014	0.071***	0.076**	0.044*	0.031
	(0.01)	(0.02)	(0.02)	(0.03)	(0.02)	(0.03)
Observations	15,962	15,962	15,962	15,962	15,962	15,962
> 75 years						
$\beta_3\ (S_i * T_j)$	0.035	0.046*	0.031	0.033	0.034	0.025
	(0.02)	(0.03)	(0.03)	(0.04)	(0.03)	(0.04)
Observations	13,416	13,416	13,416	13,416	13,416	13,416
Panel B: Physical Health						
Good						
$\beta_3\ (S_i * T_j)$	0.034***	0.034	0.056	0.065**	0.048**	0.046*
	(0.01)	(0.02)	(0.03)	(0.03)	(0.02)	(0.03)
Observations	27,309	27,309	27,309	27,309	27,309	27,309
Fair or less						
$\beta_3\ (S_i * T_j)$	0.108**	0.094*	0.046	0.029	0.090*	0.076
	(0.05)	(0.05)	(0.04)	(0.05)	(0.04)	(0.05)
Observations	13,192	13,192	13,192	13,192	13,192	13,192
Panel C: Gender						
Women						
$\beta_3\ (S_i * T_j)$	0.028**	0.056**	0.037	0.070**	0.016	0.049*
	(0.01)	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)
Observations	23,291	23,291	23,291	23,291	23,291	23,291
Men						
$\beta_3\ (S_i * T_j)$	0.017	0.012	0.049	0.037	-0.017	-0.023
	(0.02)	(0.03)	(0.03)	(0.06)	(0.04)	(0.04)
Observations	17,210	17,210	17,210	17,210	17,210	17,210
Panel D: Pre-Covid Labor Situation						
Employed						
$\beta_3\ (S_i * T_j)$	0.143***	0.129**	0.088***	0.080	0.127***	0.107*
	(0.04)	(0.06)	(0.02)	(0.06)	(0.03)	(0.06)
Observations	8,335	8,335	8,335	8,335	8,335	32,195
Non-Employed						
$\beta_3\ (S_i * T_j)$	0.022	0.026	0.056**	0.060**	0.035*	0.034
	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)
Observations	32,166	32,166	32,166	32,166	32,166	32,166
Panel E: Household Composition						
Alone						
$\beta_3\ (S_i * T_j)$	0.086***	0.071	0.081	0.065	0.001	0.016
	(0.02)	(0.06)	(0.06)	(0.06)	(0.01)	(0.06)
Observations	9,695	9,695	9,695	9,695	9,695	9,695
Cohabitation						
$\beta_3\ (S_i * T_j)$	0.066*	0.056*	0.024	0.014	0.086*	0.065*
	(0.03)	(0.03)	(0.03)	(0.03)	(0.05)	(0.04)
Observations	30,806	30,806	30,806	30,806	30,806	30,806

Note: The table displays the coefficient of the causal effect of interest $\{\boldsymbol{\beta_3}\}$ 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 5 correspond with model 1 and our preferred model 4 of Table 3.

Appendix

Table A.1. Variables description

Variables	Description
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.
Covariates	
	At the country level
Case Fatality Rate	Ratio between the number of confirmed COVID cases and the final number of deaths, for a given country.
	At the individual level
Female	Takes value "1" if the respondent is a female and "0" if the respondent is a male.
Age	*Age <65:* Takes value "1" if the respondent is younger than 65 years old and "0" otherwise. *Age 66-75:* Takes value "1" if the respondent is aged between 66 and 75 years old and "0" otherwise. *Age >75:* Takes value "1" if the respondent is older than 75 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.
Financial Problems	Major: Takes value "1" if the respondent is able to make ends meet with great difficulty since the outbreak of Corona. Moderate: Takes value "1" if the respondent is able to make ends meet with some difficulty since the outbreak of Corona. Minor: Takes value "1" if the respondent is able to make ends meet easily or very easily since the outbreak of Corona.
Month of the Interview	*June:* Takes value "1" if the respondent has been interviewed in June. *July:* Takes value "1" if the respondent has been interviewed in July or August.

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

Note: The table displays estimated coefficients from the model used to build Pre-COVID level of social face-to-face interactions. The dependent variable is a binary variable indicating whether the individual had social contacts within a distance of 1-25 kilometers at least once a week, and zero otherwise. We use the Logit model to obtain parameters estimates. We select pre-determined covariates that minimize the rate of false positives and false negatives. Robust standard errors using survey weights and cluster at the country level are in parentheses. *** p<0.01, ** p<0.05, * p<0.1. The constant term contains men, aged below 55 years old, living alone and bad physical health.

Table A.3. Outcomes variable by socioeconomic characteristics

	Insomnia	Anxiety	Depression
Female	12,1%	27,9%	24,5%
Male	7.5%	17.3%	12,0%
Age			
Age <65	11,1%	23,8%	19.8%
Age 65-75	8,5%	21,9%	18.3%
Age >75	9,7%	23,0%	23.2%
Number members household			
1	11,2%	24,2%	17,5%
2	9,2%	22,5%	17,7%
3-4	10,3%	22,6%	17,1%
>4	9,1%	24,6%	18,9%
Pre-COVID Physical Health			
Excellent	5,9%	15,0%	12,0%
Very Good	5,1%	17,3%	12,5%
Good	7,7%	19,8%	15,1%
Fair	14,5%	30,5%	26,6%
Poor	20,8%	35,1%	34,1%

Notes: The table displays means sample statistics for the outcomes of mental health for different socioeconomic characteristics. These variables are described in Appendix A.1

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

	Insomnia			Anxiety			Depression		
	Model 1	Model 3	Model 4	Model 1	Model 3	Model 4	Model 1	Model 3	Model 4
$\boldsymbol{\beta_3\ (S_i * T_j)}$	**0.057*****	**0.052*****	**0.057*****	**0.056****	**0.043****	**0.056****	**0.060*****	**0.043*****	**0.053*****
	(0.01)	**(0.02)**	**(0.02)**	**(0.02)**	**(0.02)**	**(0.02)**	**(0.01)**	**(0.01)**	**(0.02)**
$\beta_2\ (S_i = 1)$	-0.029**	-0.039**	-0.090	0.026**	-0.007	-0.147	0.005	-0.037**	-0.130
	(0.01)	(0.02)	(0.06)	(0.01)	(0.02)	(0.11)	(0.01)	(0.02)	(0.08)
$\beta_1\ (T_j = 1)$	-0.057***	0.252**	-0.701*	-0.066***	-0.026	1.645**	-0.080***	0.207**	-0.102
		(0.09)	(0.36)		(0.13)	(0.57)		(0.09)	(0.42)
$Social_i$		-0.002	-0.076		-0.054	-0.239		-0.084	-0.197
		(0.16)	(0.14)		(0.29)	(0.27)		(0.17)	(0.12)
$Index_j$		-1.199***	-1.182***		-0.110	-0.382		-1.057***	-1.212***
		(0.28)	(0.30)		(0.53)	(0.49)		(0.35)	(0.35)
$Social_{iT}$		-	0.117		-	0.319		-	0.212
		-	(0.14)		-	(0.24)		-	(0.16)
$Index_{jT}$		-	1.022*		-	-1.657**		-	0.418
		-	(0.49)		-	(0.75)		-	(0.56)
Woman		0.047***	0.047**		0.104***	0.102***		0.128***	0.126***
		(0.02)	(0.02)		(0.02)	(0.02)		(0.02)	(0.01)
Age:									
65-75		-0.034***	-0.034***		-0.032*	-0.033*		-0.007	-0.006
		(0.01)	(0.01)		(0.02)	(0.02)		(0.01)	(0.01)
> 75		-0.056***	-0.053***		-0.067***	-0.064***		-0.013	-0.010
		(0.01)	(0.01)		(0.01)	(0.01)		(0.01)	(0.01)
Household Composition									
Alone		0.012	0.011		0.008	0.008		0.006	0.007
		(0.02)	(0.02)		(0.03)	(0.02)		(0.02)	(0.02)
2		-0.003	-0.003		-0.025	-0.022		-0.025***	-0.023***
		(0.02)	(0.02)		(0.02)	(0.02)		(0.00)	(0.00)
3-4		-0.027	-0.029		-0.014	-0.017		-0.028	-0.028
		(0.02)	(0.02)		(0.05)	(0.05)		(0.02)	(0.03)
Pre-COVID Physical Health									
Fair health		0.079***	0.078***		0.105***	0.102***		0.106***	0.105***
		(0.01)	(0.01)		(0.02)	(0.01)		(0.02)	(0.02)
Poor health		0.145***	0.145***		0.157***	0.157***		0.178***	0.179***
		(0.02)	(0.01)		(0.02)	(0.02)		(0.02)	(0.02)
Constant	0.077***	0.874***	0.886***	0.116***	0.214	0.542	0.139***	0.829**	1.017***
	(0.00)	(0.25)	(0.26)	(0.02)	(0.48)	(0.44)	(0.01)	(0.32)	(0.29)
Country FE.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	40,501	40,501	40,501	40,501	40,501	40,501	40,501	40,501	40,501
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 error clustered at the country level and considering survey sample weights (in parentheses)- for three models of Table 3, that of column 1, 3 and column 4. This last one 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. We obtained coefficient estimates using a linear probability model. * 10% statistical significance level; ** 5% statistical significance level; *** 1% statistical significance level.