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Confinement policies: controlling contagion without compromising mental health

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Confinement policies: controlling contagion without compromising mental health*

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Abstract

A growing literature shows that confinement policies used by governments to slow COVID-19 transmission have negative impacts on mental health, but the differential effects of individual policies on mental health remain poorly understood. We used data from the COVID-19 questionnaire of the Survey of Health, Ageing and Retirement in Europe (SHARE), which focuses on populations aged 50 and older, and the Oxford COVID-19 Government Response Tracker for 28 countries to estimate the effects of eight different confinement policies on three outcomes of mental health: insomnia, anxiety and depression. We applied robust machine learning methods to estimate the effects of interest. Our results indicate that closure of schools and public transportation, restrictions on domestic and international travel, and gathering restrictions did not worsen the mental health of older populations in Europe. In contrast, stay at home policies and workplace closures aggravated the three health outcomes analyzed. Based on these findings, we close with a discussion of which policies should be implemented, intensified, or relaxed to control the spread of the virus without compromising the mental health of older populations.

Keywords: COVID-19, mental health, confinement policies, older populations, Europe, robust machine learning methods.

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1.- Introduction

In response to the rapid spread of COVID-19, governments around the world imposed a variety of confinement policies and preventive measures to limit virus transmission and reduce pressure on health care systems. Since then, a number of studies have analyzed the effectiveness of confinement policies for reducing virus expansion. Some of these studies analyze the impact of confinement policies as a whole on virus transmission [1-6], while other studies focus on the impact of individual measures [7-12]. For example, one study finds evidence that travel restrictions in Wuhan reduced the spread of the contagion by about half in the two weeks following the introduction of restrictions [9], while another finds that the use of masks in Canada reduced the expansion of the virus about 22% per week [10]. Similarly, cross-country evidence shows that school closures were effective in reducing the number of COVID-19 infections in Europe [11]. However, other measures, such as the use of masks outdoors, have been found to be ineffective [12]. These studies are relevant because, given the dramatic economic impact of confinement measures, there is a clear and urgent need to determine which are most effective in reducing the spread of the virus.

The relevant literature also includes studies that focus on compliance with confinement policies, highlighting the importance of social capital and the quality of institutions as factors that influence the efficacy of these policies [13]. At the same time, studies suggest that it is important to avoid the demotivation of citizens and prevent so-called "pandemic fatigue" [12,14]. Finally, in addition to the economic problems and non-compliance, it is crucial to highlight the dramatic increase in mental health problems that can result from such policies. In particular, it has been shown that the social isolation and lack of freedom associated with confinement policies has led to the deterioration of mental health in society overall [15-16] and in particular groups [17-19]. All these studies focus on the effect of confinement on different mental health-related variables.

Few studies, however, have focused on the potentially different effects of the various confinement measures on mental health. Some studies [20,21] used online surveys to show that the stay-at-home policy is associated with increased depression. A study that took place in Japan [22] found that school closures deteriorated parents' mental health, once this effect was isolated from other policies. Another study found that small business closure increased anxiety and/or depression in the US [23]. However, although these studies focus on individual policies, they are limited by small subsets of countries or by samples that are not representative of the population. In addition, these studies do not compare the effect of each of these confinement policies to see which ones are more damaging for the mental health of individuals. This is an unattended and yet important and urgent policy question because implies a better understanding of which policies can effectively control spread of COVID-19 without overly compromising the mental health of the population.

In this paper, we investigate the relationships between several COVID-19 confinement policies and mental health problems of older populations in Europe. The World Health Organization (WHO) has emphasized the risks of confinement policies for older adults during the Covid-19 pandemic, as these populations are more vulnerable to social isolation than others [24]. In fact, face-to-face social interaction is considered a key factor for healthy aging [25]. In particular, we use cross-country microdata on anxiety, depression, and insomnia after the COVID-19 outbreak in 27 European countries and Israel. These data come from the COVID-19 questionnaire of the Survey of Health, Ageing and Retirement in Europe (SHARE), which provides microdata for the COVID-19 living situation of people aged 50 and over in a large number of countries. We also use information from the Oxford COVID-19 Government Response Tracker (OxCGRT) on eight confinement measures implemented to restrict mobility and social contacts (measures C1 to C8 in the OxCGRT database). These measures include closure of workplaces, cancellation of public events, restrictions on large gatherings and stay at home rules, among others.

To answer our research question concerning the effects of confinement policies on the mental health of older adults, we used a fully data-driven empirical estimation based on machine learning methods. The motivation behind this empirical approach was to avoid model misspecification, thus yielding more accurate results and more reliable conclusions. Machine learning methods have become increasingly popular in economics. Recent literature has developed statistical models and methods specifically designed to facilitate inference using a variety of machine learning methods in a semi-parametric setting [26, 27]. The empirical methods employed in this paper rely on the theoretical findings by Chernozhukov et al. [27] and Kennedy et al. [28]. In particular, we use these robust machine learning estimators to analyze the influence of a composite confinement index (that includes all measures C1 to C8), and of each confinement policy taken separately, on the worsening in mental health.

General results show that confinement policies are positively correlated with the worsening of mental health for the three mental health outcomes analyzed: insomnia, anxiety and depression. This is in line with previous findings in the literature [29, 30].

Regarding particular policies, we find that closure of public transportation and restrictions on domestic and international travel do not seem to have worsened the mental health of older populations in Europe. Similarly, restrictions on gathering size do not seem to have negatively affected mental health. The only measures that seem to have led to mental health deterioration are stay-at-home rules and workplace closures, which we found to have impacted the three mental health outcomes of insomnia, anxiety and depression.

This paper complements a previous study [19], where we estimated the causal effect of lockdown policies (constructing a composite confinement index) 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 across 17 European countries. In the current study, we forego this causal approach. Instead, we expand the range of countries studied to 28 (from the previous 17) and examine the effect of each of the diverse policies that have been implemented (using individual confinement indicators) to identify which policies have had the most detrimental effect on the mental health of citizens. Our results contribute to efforts to understand the effect of individual confinement policies on mental health, complementing previous work on the effects of these policies on virus transmission. Our more fine-grained analysis will help policy-makers to decide which policies should be implemented, intensified or relaxed, to control the spread of the virus while minimizing impact on population mental health.

2. Materials and Methods

2.1. Data

This study combines two different data sources: the SHARE (Survey of Health, Ageing and Retirement in Europe) corona survey, and the Oxford COVID-19 Government Response Tracker (OxCGRT) database.

After the outbreak of COVID-19, SHARE distributed a special "SHARE CORONA" questionnaire to a subsample of SHARE wave 8 respondents targeted to the COVID-19 living situation of people aged 50 and over. The survey was conducted between June and August of 2020 by means of a computer assisted telephone interview (CATI) with a total of 52,310 respondents from different countries [32]. Countries participating in the survey include 27 European countries (Germany, Sweden, the Netherlands, Spain, Italy, France, Denmark, Greece, Switzerland, Belgium, Czech Republic, Poland, Portugal, Luxembourg, Hungary, Slovenia, Estonia, Croatia, Lithuania, Bulgaria, Cyprus, Finland, Latvia, Romania, Slovakia, and Malta) and Israel.

In this paper, we draw from this 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.[1]

We also use data from Oxford COVID-19 Government Response Tracker (OxCGRT) to gather information about the strictness of lockdown policies in Europe. The OxCGRT is a database that collects daily information on the type and intensity of government responses to COVID-19 in a large number of countries. Thus, it provides an objective measure of the degree and reach of several COVID-19 policy measures. As it will be explained afterwards, we focus on those confinement measures available in OxCGRT that aim at restricting mobility and social contacts.

2.2. Variable Definition

Mental Health Outcomes

Our dependent variable is the worsening in mental health of the population. We include three mental health outcomes in our analysis: anxiety, depression, and insomnia. Depression and anxiety are common mental health disorders, while insomnia prevalence

[1] Note that although SHARE is a panel study, the SHARE Corona survey has specific characteristics that prevent us from using longitudinal panel data for the same individuals and variables of interest over time.

has been found to be associated with measurements of worse physical and mental health [33, 34].

In the SHARE Corona questionnaire, individuals are asked about their mental health problems in the last month and whether there had been a worsening on these conditions since the beginning of the pandemic. Accordingly, we categorize these variables as binary variables that take value 1 if respondents answered that they experienced mental health deterioration after the outbreak, and zero if mental problems improved or remained the same.

COVID-19 confinement indicators

Our main explanatory variable is the strictness of several COVID-19 confinement indicators. We focus on eight policies or measures available in OxCGRT, all of them aimed at restricting mobility and social contacts: (C1) closure of schools, (C2) closure of workplaces, (C3) cancellation of public events, (C4) restrictions on gathering size, (C5) closure of public transportation, (C6) stay at home requirements, (C7) restrictions on domestic travel, and (C8) restrictions on international travel. For a given country and day, OxCGRT gives an integer value between 0 and 4 for all the indicators (measures or "confinement policies"), depending on the strictness of the policy, where 0 means no measure applied and 4 means that the maximum level of enforcement was applied. Following Hale et al. and García-Prado et al. [35, 19], we construct daily indicators for each measure. These daily indicators are rescaled (by their maximum value) to create a score between 0 and 100. We also build an additive unweighted composite index that includes all eight measures C1-C8. The index on any given day is calculated as the mean score of the eight individual policy response indicators, each taking a value between 0 and 100. Once the daily measures are created, we use their monthly average for April and May 2020 -the hardest months in terms of mobility restrictions in the countries of our sample- and apply these averages to the analysis of our sample.[2]

Potential Covariates

In the empirical analysis we additionally control for a battery of observable demographic and socioeconomic characteristics that are available in the SHARE COVID-19 survey and might be related with mental health. Demographic variables comprise gender, age and household size at the time of interview. Age was measured according to three groups: 50-65, 66-75 and 75+. Household size was categorized according to household size equal to one person, two people, three/four people or more than four people. Because socioeconomic hardships suffered during the pandemic may affect mental health, we analyze the economic situation of the respondent according to financial distress, which is

[2] We estimated alternative models: creating the index by using the average values per fortnight of April and May and the average of April and the average of May, and all the qualitative and quantitative results hold.

measured as individuals' capacity to make ends meet with great difficulty, some difficulty, or very easily since the outbreak of Corona.

Moreover, we also include as a regressor the month in which the Corona survey interview took place (June or July), which may have influenced the answers given by the interviewees (according to length of time that passed since lockdown).

To control for health-related covariates, we consider physical health and categorize respondents according to their reports of excellent, very good, good, fair, or poor physical health before the outbreak of Corona. Additionally, in order to distinguish those who experienced COVID-19 infection in their network from those who did not, we include the variable COVID 19 exposure that takes value 1 if the respondent, or anyone close to him (family, neighbors, or friends), has experienced symptoms, has been positive in a corona virus test, or has been hospitalized or death due to an infection from the coronavirus.

At the country level, we include in the estimations the average fatality rate, provided by the European Centre for Disease Prevention and Control, which measures the ratio between the final number of deaths and the number of confirmed COVID cases in our countries of study. Also, since estimates of fatality rates were not very accurate in many countries during the first wave of the pandemic, we include as covariate the *COVID19 Aggregate Exposure,* computed as the percentage of the respondents in each country, grouped by cohort of gender and age, that has been exposed to the Corona illness in his/her network (family, neighbors, or friends). These two variables allow us to control for the fear of the virus as indicators of the severity of the pandemic. Finally, we control for the economic differences between countries by adding the *GDP* per capita in the year before the pandemic, 2019. Data on annual GDP per capita is provided by the World Bank.

Table 1 provides a summary list and complete description of all variables in the model.

2.3. Empirical Strategy

To examine the extent to which the strictness of the different government responses influences the worsening in mental health of individuals following the COVID-19 outbreak, we define the following model on the full sample for each health mental health outcome,

$$\Delta \mathrm{MH}_{ij}^{*} = \beta_k \mathrm{C(k)_j} + \gamma \mathrm{z_{ij}} + \theta \mathrm{x}_j + \varepsilon_{\mathrm{ij}}, \qquad (1)$$

where the subscripts i, j refer to the individual and country, respectively, and k refers to the particular indicator of confinement (C1-C8).

The outcome variable $\Delta \mathrm{MH}_{ij}^{*}$ represents the worsening in mental health after the outbreak for three different outcomes of mental health: insomnia, anxiety, and depression, all of which are constructed as binary variables that take value one in cases of mental health deterioration (insomnia, anxiety or depression), and zero otherwise, as explained in previous subsection.

Our main explanatory variable, $C(k)_j$, is the COVID-19 confinement measure contemplated at OxCGRT and explained above. The value and statistical significance of each β_k inform us about the importance of the association between each confinement policy and the deterioration of mental health. We first estimate equation (1) with the composite index ($C(k)_j = \text{Index}_j$) that includes all eight measures in OXCGRT. Next, we estimate the individual effect of each confinement indicator ($C(k)_j$, from C1 to C8) on mental health. The term z_{ij} refers to the set of individual health and socioeconomic characteristics of the respondents and the term x_j refers to covariates that control for national characteristics.

From a conceptual point of view, it is difficult for researchers to select the control variables to be included in Equation (1). This challenge is further complicated by the fact that our small sample comprises individuals from 28 countries. Including too few controls may result in omitted variable bias, while incorporating too many controls, particularly if they are unrelated to impact on mental health, can risk overfitting the model.

Thus, to identify the parsimonious set of controls, we used a Lasso regularized lineal regression. It is important to note that regularized regression methods alone, such as Lasso, do not yield estimates that can be interpreted as causal. Therefore, in this context, we turn to recently developed estimators designed to provide reliable inference for the variable of interest—in this case, confinement policies. We use Lasso-based covariate selection to determine which variables should be included in the set of controls. These modern estimation approaches are designed to avoid estimation bias and enable causal inference within a semi-parametric framework [20]. Specifically, we consider double selection Lasso linear regression (using the 'dsregress' STATA command), partialling-out (with the 'poregress' STATA command), and cross-fit partialling-out --also named as double robust-- (via the 'xporegress' STATA command) linear regressions.[3]

Throughout the paper, we have used regularized linear regression methods for ease of interpretation, but our main results (Tables 3 and 4 below) hold under regularized logistic regression methods (see table A.4 in the online Appendix).

3. Results

3.1 Sample Characteristics

Table 2 displays summary statistics for our sample of SHARE-COVID19 survey's respondents. All sample statistics take sample weights into account. After removing respondents who were below 50 or were missing relevant data, we ended up with a sample of 51,353 respondents.

[3] These commands estimate coefficients, standard errors and confidence intervals, and perform tests for variables of interest, while using lassos to select the variables to be included in equation (1) from among potential control variables. The plug-in method was fully designed for variable selection within this inferential framework and boasts robust theoretical underpinnings.

Our sample of survey respondents is 54% female. Respondents are aged between 50 and 104 years old: 48% are aged between 50-65, nearly 36% are aged between 66-75, and nearly 16% are 76 and older. Respondents that live in households with just one member represent 27% percent of the sample. Respondents that live in households with two, three and four (or more) members are 48%, 21% and 3.2% of the sample, respectively. Regarding pre-COVID physical health characteristics, 7% of the individuals reported to have excellent health before the outbreak of the Corona. The figures for those who reported very good health, good health, fair health or poor health are 17%, 47%, 22% and nearly 6% respectively. Moreover, of our sample, 18.7% of the respondents have been exposed to the coronavirus. Regarding household financial situation, 6.3% of respondents are able to make ends meet with great difficulty since the outbreak of Corona, nearly 17% are able to make ends meet with some difficulty, and nearly 77% are able to do it easily or very easily. Regarding the month of the interview, 52.2% of the respondents were interviewed in June (or May) and 47.8% in July (or August).

At the country level, the percentage of respondents in each country --grouped by cohort of gender and age--, that has been exposed to the Corona illness in his/her network amounts to 18.7%. The average fatality rate in our countries of study during April and May 2020 raises at 9.79. Finally, mean GDP per capita, in 2019, in our countries of interest is about 32,150 euros.

Table 2 also shows that 9.4% of the respondents reported to experience more sleeping problems after the outbreak of Corona, 22% reported to suffer more anxiety and 17.9% reported to suffer more depression. Moreover, figure 1 shows wide variation across countries. While on average insomnia increased for 9.4% of the respondents, the figures range from 3.4% (Hungary) to nearly four times that level (13.3% in Spain). A similar range is found for the other two mental health outcomes: figures range from 11.1% (Slovakia) to 48.6% (Portugal) for anxiety, and from 8.2% (Denmark) to 28.5% (Portugal) for depression.

Table 2 also presents main statistics of all the confinement indicators (mean and standard deviation) and shows differences in the indicators' variability across countries. These differences range from (C5) closure of public transportation and (C7) restrictions on domestic travel, where heterogeneity across countries is quite high, up to (C3) cancellation of public events, that displays a particularly small relative standard deviation.

Figure 2 shows that the average of our composite confinement index stands at 80 (with a standard deviation of 9.1 points), but it varies noticeably across countries. Figure 3 shows variation across countries for each of the individual indicators C1-C8 separately. Notice that (C3) cancellation of public events does not only show low variability across countries, as mentioned above, but also all its variability comes from very few countries. Therefore, we will not include (C3) cancellation of public events in the individual estimation. Finally, a simple statistical analysis such as the one presented in Figure 4 shows that individuals living in countries with higher composite confinement index suffered a larger deterioration in mental health.

3.2 Regression analysis

We use inferential lasso models to set our reference model estimation. The three machine learning algorithms used (double selection, partialling-out and cross-fit-partialling out) allow us to obtain a coefficient estimate of β that is robust to the model-selection, while using lassos to select the variables to be included in equation (1) from among potential control variables.

Notice that under the machine learning approach only the coefficient of the covariate of interest is estimated because covariate selection methods do not produce estimates for the coefficients of the control covariates. For our purposes, however, this does not present a problem, as our primary aim is to estimate the impact of the composite confinement index and various individual confinement indicators on the deterioration of mental health.

Table 3 presents the results from estimating model (1) when $C(k)_j$ refers to the composite confinement index, $Index_j$. Panels A, B and C in Table 3 present main estimation results for insomnia, anxiety, and depression, respectively. Column (1) in each panel presents the double-selection (DS) estimators, while columns (2) and (3) show the partialling-out (PO) and the cross-fit-partialling-out (XPO) estimators respectively. Table 3 also includes the controls that were selected by our double machine learning approach from the list of potential control variables and were therefore included in the estimation of model (1).

Table 3 indicates a positive correlation between the confinement index and the deterioration of mental health across the three considered outcomes. The estimator of the composite confinement index is statistically significant and exhibits a similar magnitude across the three afore-mentioned machine learning algorithms. In particular, a 10-point increase in the composite confinement index (close to one standard deviation of the Index) increases the probability of worsened insomnia about 2.0 percentage points (21.27% in relative terms), worsened anxiety about 2.26-2.27 percentage points (10.27%-10.31% in relative terms), and worsened depression by 2.29 percentage points (12.79% in relative terms).[4]

Table 4 presents the results from estimating model (1), where $C(k)_j$ refers to each of the confinement indicators (C1-C8), separately. As before, Panels A, B and C present main estimation results for insomnia, anxiety, and depression, respectively. Additionally, column (1) in each panel presents the double-robust (DS) estimators, while columns (2) and (3) show the partialling-out (PO) and the cross-fit-partialling-out (XPO) estimators respectively. Results are consistent and robust across the three machine learning methods used. Interestingly, our estimates in all panels and columns show that (C5) closure of public transportation, (C7) restrictions on domestic travel and (C8) restrictions on

[4] Table A.1 in the Appendix presents the results of a traditional OLS analysis, using all the covariates selected by the three machine learning methods used in the paper. These results align with the findings obtained through the machine learning approach. Table A.1 also includes post-OLS machine learning estimations for the remaining variables of interest.

international travel did not worsen the mental health of older Europeans. (C1) Closure of schools and (C4) restrictions on gathering size did not worsen mental health either. In contrast, (C2) closure of workplaces and (C6) stay-at-home requirements are positively correlated with deterioration of our three mental health outcomes. In particular, a 10-point increase in the extent and/or strictness of workplace closures (C2), increases the probability of worsened insomnia by 1.3 percentage points (13.8% in relative terms), worsened anxiety about 2.3-2.4 percentage points (10.45%-10.9% in relative terms), and worsened depression about 2.0-2.4 percentage points (11.17%-13.4% in relative terms). Similarly, a 10-point increase in the extent and/or strictness of stay-at home requirements (C6), increases the probability of worsened insomnia by 1.2 percentage points (12.7% in relative terms), worsened anxiety by 3.0 percentage points (13.6% in relative terms), and worsened depression by 2.4 percentage points (13.4% in relative terms).[5]

Note that our findings in Tables 3 and 4 hold under machine learning robust estimators in logistic regressions (see Table A.4 in the online Appendix).

4. Discussion

Based on a large representative sample of older adults in Europe, we present two main results. First, we use a composite index to show how confinement policies aimed at restricting mobility and social contacts had an overall exacerbating effect on the mental health of older populations in Europe. Second, we examine individual confinement policies to determine how each one relates to the worsening of mental health of these populations.

While the former results are aligned with previous studies [19, 29-31], the latter contribute to an underexplored area of research that calls for more investigation, as it is crucial to choose policies that effectively reduce virus transmission without compromising mental health. Understanding the impact of different confinement measures on mental health is essential for public health authorities and policymakers as it will help them make informed decisions about implementing and adjusting lockdowns or other restrictive measures during public health crises like pandemics.

The closure of schools, public transportation and restrictions on domestic and international travel do not seem to have a problematic effect on the mental health of older populations in Europe. In contrast, stay-at-home policies and work and business closures do seem to be related to the deterioration of mental health in older populations. These findings are noteworthy, as recent empirical evidence shows that the additional effect of stay-at-home orders on the virus transmission is small in comparison with other confinement measures such as school closures, limiting gatherings to under 10 people, closure face-to-face businesses or working from home [7, 8]. Accordingly, if stay-at-home policies do not add much to other measures in relative terms and largely contribute

[5] Tables A.2 and A.3 in the Appendix present more detailed results for the indicators (C2) closure of workplaces and (C6) stay-at-home requirements, respectively.

to mental health deterioration, a policy targeting older populations should omit or soften stay-at-home restrictions. Regarding business closures, although they also have a detrimental effect on mental health, they can be modulated so as to minimize this negative effect. Our results also show that gathering restrictions do not seem to have worsened mental health of older European populations. This is a relevant finding, as there is evidence that restricting gatherings to less than 10 people and even to less than 100 people is effective in reducing virus transmission [7-10].

Since our analysis focuses on populations over 50, future research should consider the varying effectiveness of each confinement measure on different population groups. There is evidence, for instance, that school closures led to the deterioration of parents' mental health in Japan [22] and to the deterioration of adolescents' mental health in Finland [36] and Germany [37]. Further, the effect of similar containment measures on reducing virus transmission can vary widely across countries [8] and regions [13]. The effectiveness of the same containment measures can be conditioned by factors such as the quality of institutions, the level of trust in government, the capacity of the government to enforce its policies, as well as the public response [13, 37]. These findings suggest that the effects of confinement measures on mental health should also be studied on a country-by-country basis.

Our results also indicate that containment measures that worsen mental health need to be accompanied by adequate support from public mental health services. This is necessary even if such measures are carefully modulated as suggested above. The COVID-19 pandemic has revealed the chronically underfunded state of mental health services in European countries and the US [38, 39]. Greater investment in mental health services is needed not only for dealing with the current mental health epidemic, but also for dealing with effects that linger long after the pandemic has subsided [40].

Finally, an alternative to the top-down imposition of confinement measures is to allow for individuals to engage voluntarily in avoidance behavior, such as washing hands or wearing masks, once they fully perceive the risks of contagion [41, 42]. This voluntary approach could be less harmful for the mental health of the population. However, although there is evidence of the effectiveness of indoor mask usage and hand washing to reduce virus transmission [43, 44], other studies indicate that removing or relaxing business closures would erase the gains obtained by other means [10]. Further research on these trade-offs is needed.

This study has several limitations. First, because our mental health variables were self-reported, they may have been affected by subjective biases. However, insomnia self-reporting has proved to be reliable [45]. Anxiety and depression are often under-reported [45], which implies that our results for those two outcomes might be biased downwards. Second, at the beginning of the pandemic there was a surprising degree of commonality in the policies implemented by European countries, with remarkable clustering of policy measures within a 2-week period around mid-March 2020. However, later on, starting in April 2020, there was more variation with some policies being discontinued and others reapplied in the fall of 2020 [35]. Table 5 shows, in fact, that correlations among confinement policies across countries are moderate in our period of analysis, ranging from 1.3% to 49%. Third, as discussed above, the small sample of 28 countries made the choice of controls for our estimation challenging. To overcome this challenge and avoid model misspecification, we have followed a robust machine learning approach that has allowed us to select the set of control variables in a systematic manner, providing more accurate and reliable results.

In summary, despite these limitations, we believe that the findings of this study have important implications for policy making. Together with other findings in the literature, our results contribute to the discussion on which policies should be implemented, intensified, or relaxed to effectively control the spread of the virus without compromising the mental well-being of our aging populations.

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Availability of data and material (data transparency): All data are gathered from public sources reported in the text.
Code availability (software application or custom code): The author can provide all details upon request.

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Tables and Figures

Table 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
Aggregate COVID-19 Exposure	Percentage of respondents per country, grouped by cohort of gender and age, that has been exposed to the Corona illness in his/her network (family, neighbours, or friends), in any of the following 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.
Country-case fatality rate	Mean of the case fatalities rates (ratio between the final number of deaths and the number of confirmed COVID cases, for a given country) during April and May 2020.
GDP per capita, 2019	GDP per capita in 2019.
	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.
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.
Pre-COVID 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.
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.
Month of the Interview	*June:* Takes value "1" if the respondent has been interviewed in May or June. *July:* Takes value "1" if the respondent has been interviewed in July or August.

Table 2. Sample statistics main outcome and explanatory variables.

	Mean	Sd
Mental Health Outcomes		
Insomnia	0.094	(0.292)
Anxiety	0.220	(0.414)
Depression	0.179	(0.383)
Confinement indicators		
Closure of schools (C1)	87.00	20.22
Closure of workplaces (C2)	71.01	22.30
Cancellation of public events (C3)	96.81	12.21
Restrictions on gathering size (C4)	87.37	22.11
Closure of public transportation (C5)	40.83	31.48
Stay at home requirements (C6)	48.37	19.61
Restrictions on domestic travel (C7)	68.15	35.56
Restrictions on international travel (C8)	83.59	21.35
Covariates		
Female	0.539	(0.498)
Male	0.460	(0.498)
Number members household		
1	0.270	(0.442)
2	0.484	(0.478)
3-4	0.213	(0.409)
>4	0.032	(0.176)
Pre-COVID Physical Health		
Excellent	0.072	(0.434)
Very Good	0.172	(0.434)
Good	0.466	(0.499)
Fair	0.219	(0.413)
Poor	0.059	(0.236)
Age		
Age <65	0.483	(0.499)
Age 65-75	0.356	(0.479)
Age >75	0.159	(0.366)
Month of the interview		
June	0.522	(0.499)
July	0.478	(0.499)
COVID19 Exposure (Individual)	0.187	(0.389)
Aggregate COVID19 Exposure (cells by age-gender-country)	0.187	(0.133)
Country-case fatality rate (national level)	9.79	(6.7)
GDP per capita (2019, ten thousand)	3.215	(1.977)
Financial problems		
Major	0.063	(0.242)
Moderate	0.169	(0.374)
Minor	0.769	(0.422)

Note. Mental health outcomes and individual socioeconomic characteristics are obtained from SHARE-COVID-19. Calibrated individual weights are used to compute sample means. Confinement indicators are based on own computations using the Oxford COVID-19 Government Response Tracker (OxCGRT). The mean refers to the mean of the confinement indicators between April and May 2020 across the 28 countries used in the regression analysis. 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 3. Effects of confinement policies (composite confinement index) on mental health.

	Panel A: Insomnia			Panel B: Anxiety			Panel C: Depression		
	(1) DS	(2) PO	(3) XPO	(1) DS	(2) PO	(3) XPO	(1) DS	(2) PO	(3) XPO
Index	0.1994^{**}	0.1994^{**}	0.1994^{**}	0.2768^{**}	0.2768^{**}	0.2684^{**}	0.2905^{***}	0.2905^{***}	0.2905^{***}
	(0.074)	(0.074)	(0.074)	(0.126)	(0.126)	(0.124)	(0.101)	(0.101)	(0.101)
Age <65						x			
Female	x	x	x	x	x	x	x	x	x
Excellent health	x	x	x				x	x	x
Very good health	x	x	x			x	x	x	x
Fair health	x	x	x	x	x	x	x	x	x
Poor health	x	x	x	x	x	x	x	x	x
COVID19 Exposure				x	x	x	x	x	x
Major financial problems	x	x	x	x	x	x	x	x	x
N	51983	51983	51983	51983	51983	51983	51983	51983	51983
adj. R^2	0.032	0.032	0.032	0.047	0.043	0.045	0.055	0.055	0.055

Note: Panels A, B and C refer to Insomnia, Anxiety and Depression respectively. Variable Insomnia takes value 1 if respondents experienced more sleeping problems after the outbreak of Corona, and zero otherwise, Anxiety takes value 1 if respondents answered they experienced more anxiety after the outbreak of Corona, and zero otherwise, and Depression takes value 1 if respondents reported they suffered from more depression after the outbreak of Corona, and zero otherwise. Column (1) in each panel presents the double-robust (DS) estimators, while columns (2) and (3) show the partialling-out (PO) and the cross-fit-partialling-out (XPO) estimators respectively. Standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4. Effects of individual confinement indicators on mental health.

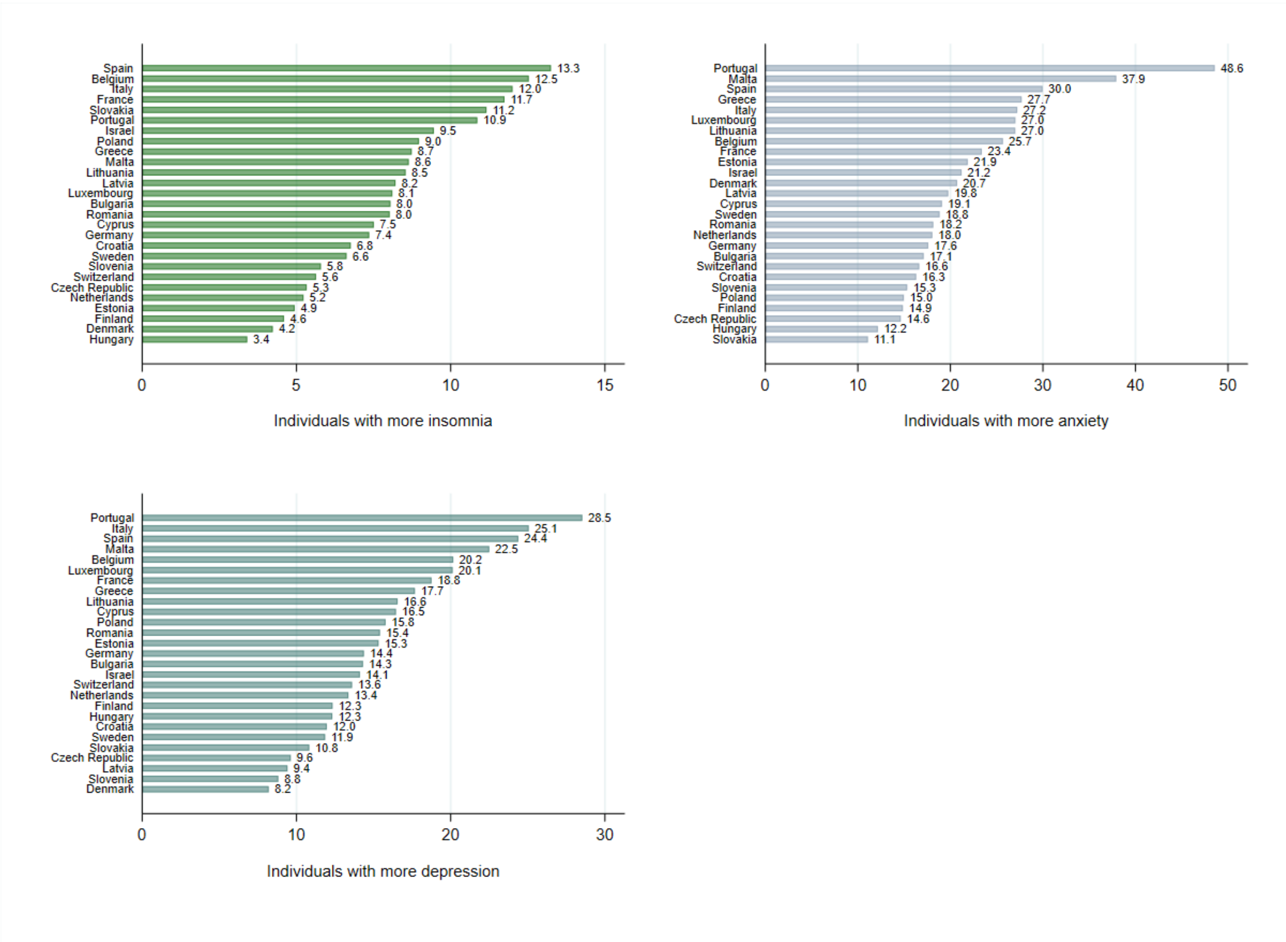
	Panel A: Insomnia			Panel B: Anxiety			Panel C: Depression		
	(1) DS	(2) PO	(3) XPO	(1) DS	(2) PO	(3) XPO	(1) DS	(2) PO	(3) XPO
C1	0.0424	0.0424	0.0424	0.0884	0.0884	0.0994	0.1672	0.1672	0.1672
Closure of schools	(0.057)	(0.057)	(0.057)	(0.109)	(0.109)	(0.110)	(0.113)	(0.113)	(0.113)
C2	0.1323***	0.1323***	0.1323***	0.2378***	0.2378***	0.2416***	0.2416***	0.2416***	0.2085***
Closure of workplaces	(0.037)	(0.037)	(0.037)	(0.070)	(0.070)	(0.070)	(0.070)	(0.070)	(0.045)
C4	0.0568	0.0568	0.0568	0.0621	0.0621	0.0640	0.0204	0.0204	0.0204
Gathering restrictions	(0.046)	(0.046)	(0.046)	(0.087)	(0.087)	(0.088)	(0.086)	(0.086)	(0.086)
C5	0.0294	0.0294	0.0296	0.0768*	0.0768*	0.0773*	0.0535	0.0535	0.0535
Closure of public transportation	(0.022)	(0.022)	(0.022)	(0.037)	(0.037)	(0.037)	(0.033)	(0.033)	(0.033)
C6	0.1237***	0.1237***	0.1237***	0.3017****	0.3017***	0.3037***	0.2399***	0.2399***	0.2399***
Stay at home requirements	(0.036)	(0.036)	(0.036)	(0.063)	(0.063)	(0.064)	(0.063)	(0.063)	(0.063)
C7	0.0101	0.0101	0.0098	-0.0395	-0.0395	-0.0401	0.0076	0.0076	0.0076
Restrictions on domestic travel	(0.030)	(0.030)	(0.030)	(0.055)	(0.055)	(0.056)	(0.046)	(0.046)	(0.046)
C8	-0.0550	-0.0550	-0.0554	-0.1747	-0.1747	-0.1689	-0.1451	-0.1451	-0.1451
Restrictions on international travel	(0.059)	(0.059)	(0.058)	(0.113)	(0.113)	(0.116)	(0.110)	(0.110)	(0.110)
N	51983	51983	51983	51983	51983	51983	51983	51983	51983

Note: Panels A, B and C refer to Insomnia, Anxiety and Depression respectively. Variable Insomnia takes value 1 if respondents experienced more sleeping problems after the outbreak of Corona, and zero otherwise, Anxiety takes value 1 if respondents answered they experienced more anxiety after the outbreak of Corona, and zero otherwise, and Depression takes value 1 if respondents reported they suffered from more depression after the outbreak of Corona, and zero otherwise. Column (1) in each panel presents the double-robust (DS) estimators, while columns (2) and (3) show the partialling-out (PO) and the cross-fit-partialling-out (XPO) estimators respectively. Standard errors in parentheses: * p < 0.10, ** p < 0.05, *** p < 0.01

Table 5. Correlation between individual confinement indicators (cross-country variability).

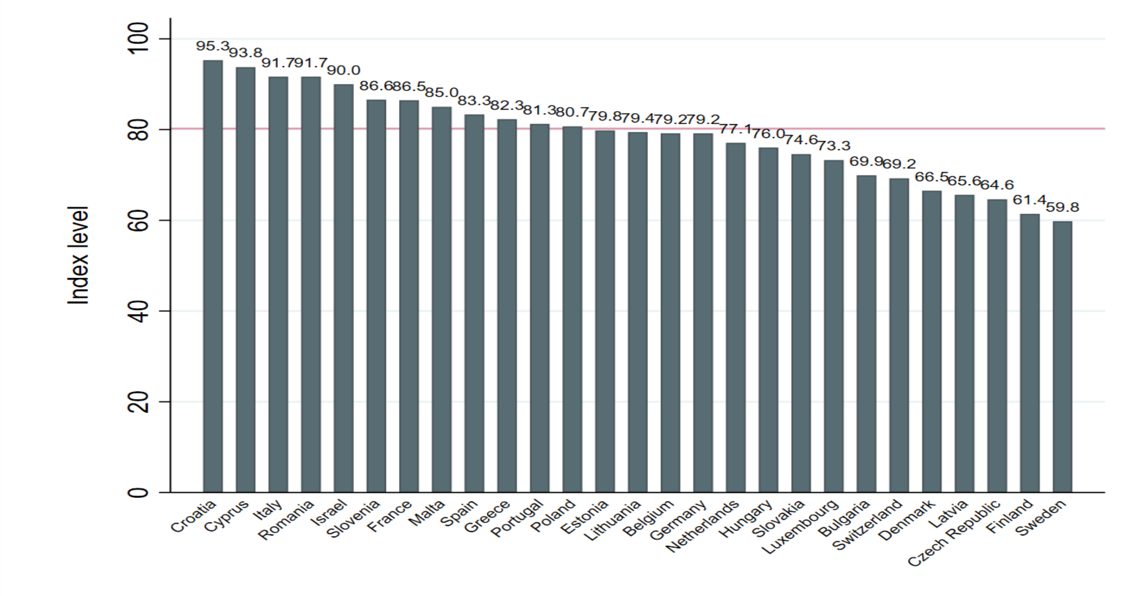
	C1	C2	C4	C5	C6	C7	C8
C1	1.00						
C2	0.3395	1.0000					
C4	0.3395	0.2549	1.0000				
C5	0.1933	0.1736	0.0805	1.0000			
C6	0.3233	0.4290	-0.0405	0.1075	1.0000		
C7	0.4113	0.1824	0.2128	0.2431	0.4910	1.0000	
C8	0.2282	0.0129	0.2835	0.2125	0.1470	0.1664	1.0000

Figure 1. Sample statistics main outcome variables: cross country variability



Note: Figure 1 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 28 countries used in the regression analysis. Survey sample weights are used.

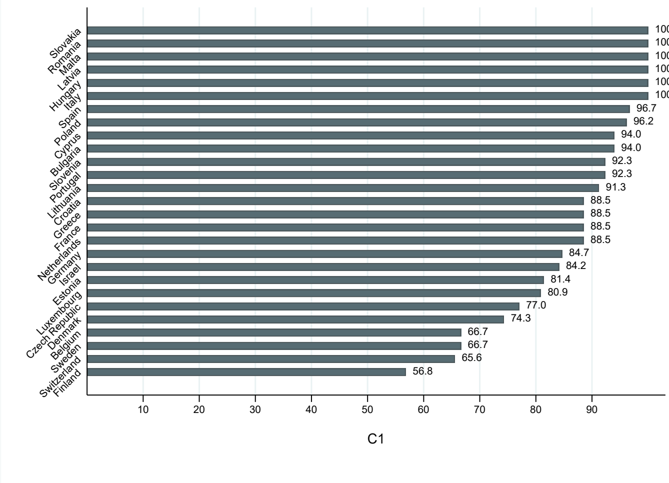
Figure 2. Confinement Index cross-country variability



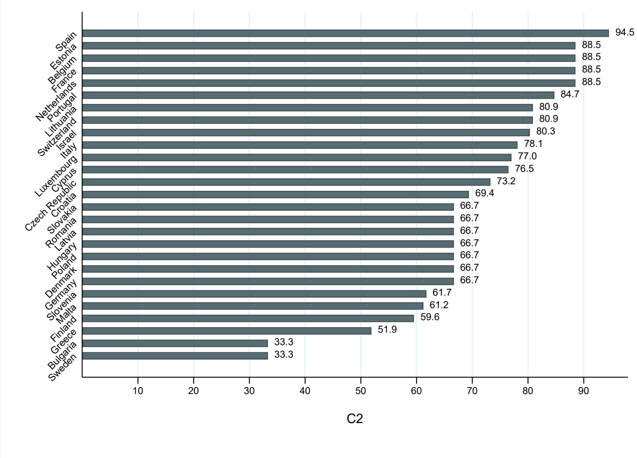
Note: This Figure displays the Confinement Index across the 28 countries used in the regression analysis. The Confinement Index describes the mean of the index between April and May 2020. These are own calculations using Oxford COVID-19 Government Response Tracker (OxCGRT).

*Figure 3. Individual confinement indicators and cross-country variability**

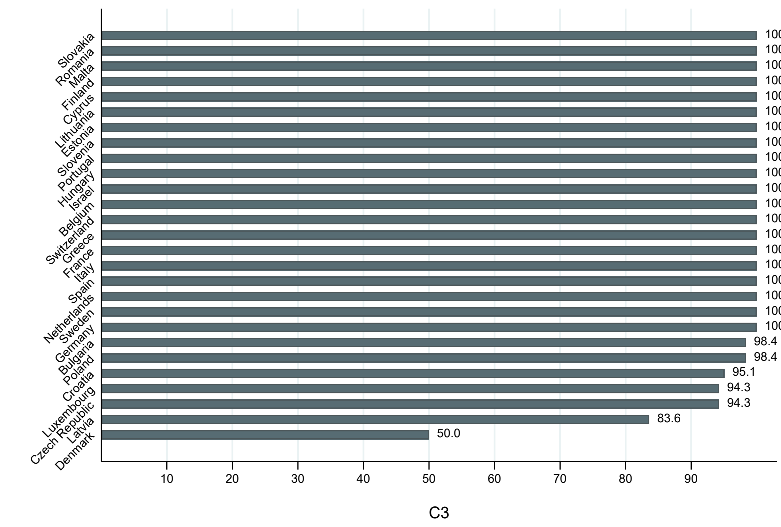
Closure of schools (C1): Cross-country variability



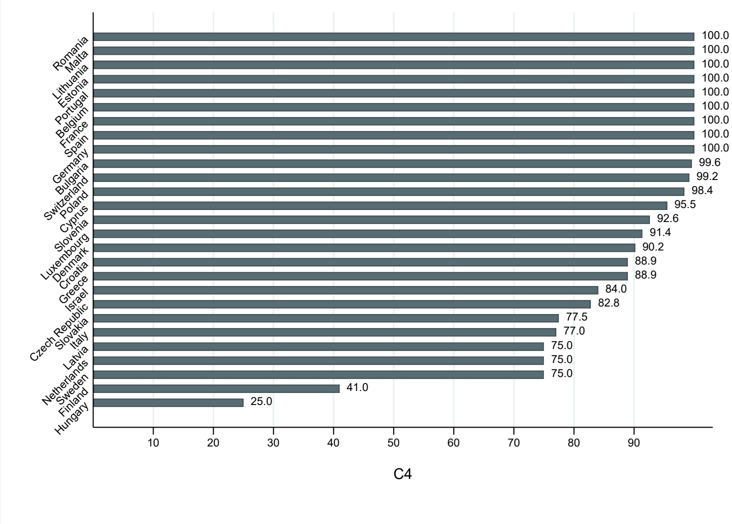
Closure of workplaces (C2): Cross-country variability



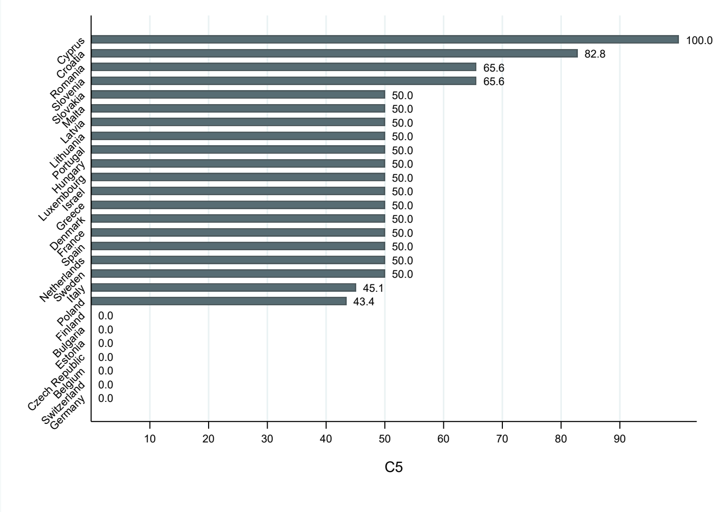
Cancellation of public events (C3): Cross-country variability



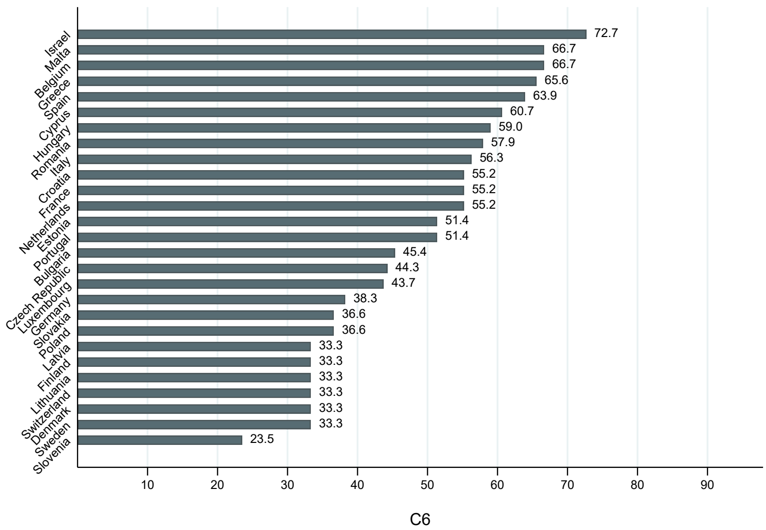
Restrictions on gathering size (C4): cross-country variability



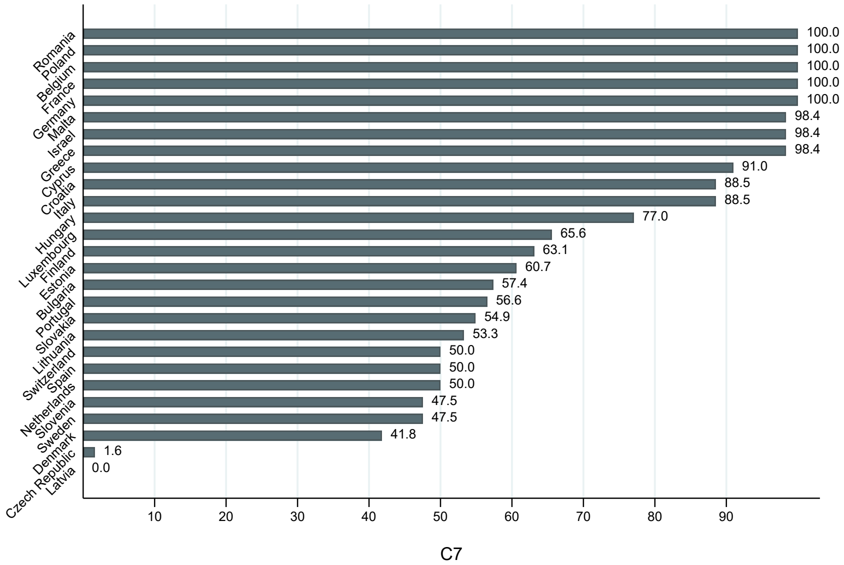
Closure of public transportation (C5): Cross-country variability



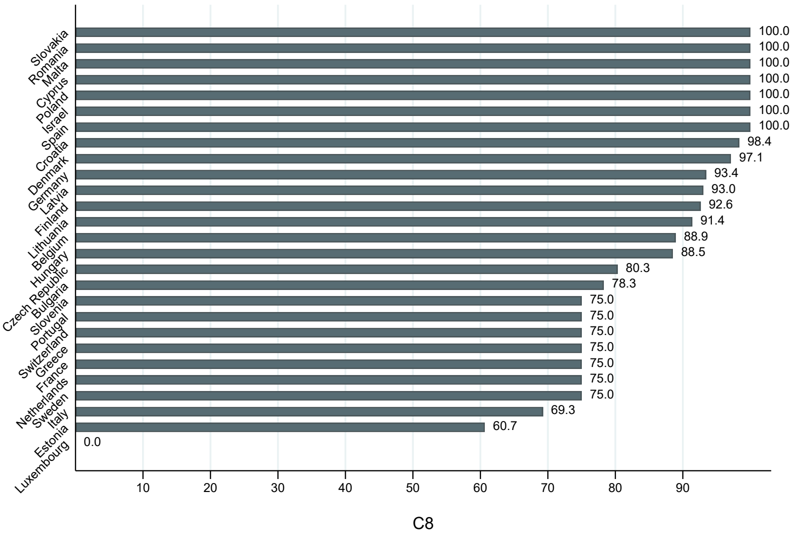
Stay at home requirements (C6): Cross-country variability



Restrictions on domestic travel (C7): Cross-country variability

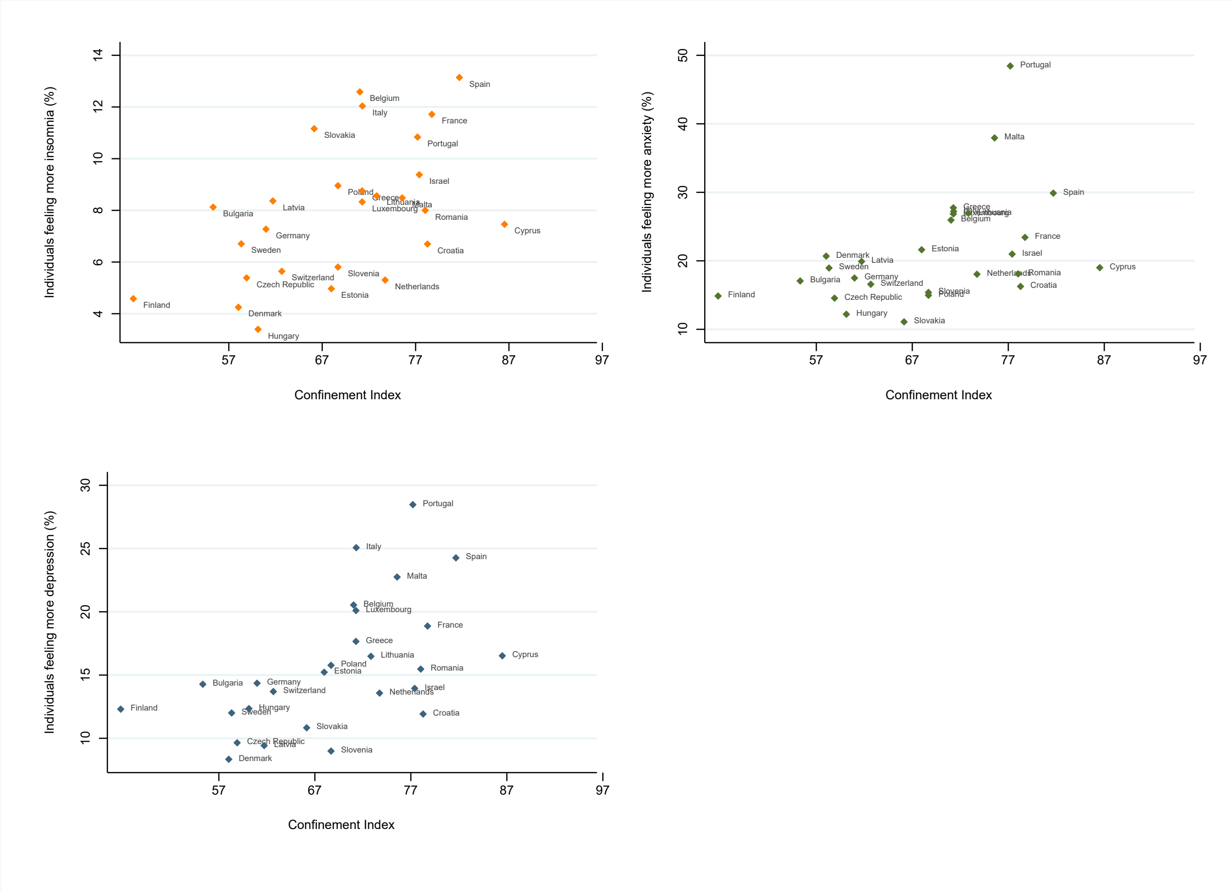


Restrictions on international travel (C8): Cross-country variability



*Note that each of the following figures reflects the strictness of each confinement indicator by country. These are all based on own calculations using the Oxford COVID-19 Government Response Tracker (OxCGRT). The horizontal line refers to the mean of the indicator during April and May 2020.

Figure 4. Statistical Relation between mental health and the composite confinement Index



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

Table A.1. Effects of confinement policies on mental health (composite confinement index)

	Panel A: Insomnia				Panel B: Anxiety				Panel C: Depression			
	(1) DS	(2) PO	(3) XPO	(4) OLS	(1) DS	(2) PO	(3) XPO	(4) OLS	(1) DS	(2) PO	(3) XPO	(4) OLS
Index	0.1994**	0.1994**	0.1994**	0.1882***	0.2768**	0.2768**	0.2684**	0.2427*	0.2905***	0.2905***	0.2905***	0.2895***
	(0.074)	(0.074)	(0.074)	(0.061)	(0.126)	(0.126)	(0.124)	(0.125)	(0.101)	(0.101)	(0.101)	(0.100)
Age 50-65				0.0332***			0.0374***	0.0402***				0.0036
				(0.007)			(0.008)	(0.008)				(0.006)
Female	0.0366***	0.0366***	0.0366**	0.0379***	0.0927***	0.0927***	0.0949***	0.0947***	0.1058***	0.1058***	0.1058***	0.1060***
	(0.012)	(0.012)	(0.012)	(0.013)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.013)
Excellent health	-0.0216***	-0.0216**	-0.0216**	-0.0300***				-0.0696***	-0.0380***	-0.0380***	-0.0380***	-0.0385***
	(0.007)	(0.007)	(0.007)	(0.007)				(0.018)	(0.010)	(0.010)	(0.010)	(0.009)
Very good health	-0.0315***	-0.0315***	-0.0315***	-0.0385***	-0.0266	-0.0266	-0.0318*	-0.0416**	-0.0288**	-0.0288**	-0.0288**	-0.0294**
	(0.006)	(0.006)	(0.006)	(0.006)	(0.015)	(0.015)	(0.014)	(0.016)	(0.010)	(0.010)	(0.010)	(0.010)
Fair good health	0.0497***	0.0497***	0.0497***	0.0549***	0.0889***	0.0889***	0.0956***	0.0870***	0.0894***	0.0894***	0.0894***	0.0900***
	(0.012)	(0.012)	(0.012)	(0.013)	(0.019)	(0.019)	(0.019)	(0.020)	(0.012)	(0.012)	(0.012)	(0.012)
Poor health	0.1038***	0.1038***	0.1038***	0.1130***	0.1372***	0.1372***	0.1454***	0.1373***	0.1651***	0.1651***	0.1651***	0.1658***
	(0.013)	(0.013)	(0.013)	(0.013)	(0.014)	(0.014)	(0.015)	(0.017)	(0.013)	(0.013)	(0.013)	(0.013)
COVID19 Exposure				0.0521**	0.0847***	0.0847***	0.0807***	0.0821***	0.0446***	0.0446***	0.0446***	0.0442***
				(0.017)	(0.018)	(0.018)	(0.018)	(0.018)	(0.010)	(0.010)	(0.010)	(0.011)
Major financial problems	0.0918***	0.0918***	0.0918***	0.0917***	0.1139***	0.1139***	0.1098***	0.1088***	0.1049***	0.1049***	0.1049***	0.1045***
	(0.020)	(0.020)	(0.020)	(0.019)	(0.017)	(0.017)	(0.017)	(0.017)	(0.025)	(0.025)	(0.025)	(0.025)
Cte	-0.0928	-0.0928	-0.0928	-0.1107**	-0.0861	-0.0861	-0.0990	-0.0717	-0.1350*	-0.1350*	-0.1350*	-0.1360*
	(0.055)	(0.055)	(0.055)	(0.048)	(0.093)	(0.093)	(0.093)	(0.094)	(0.075)	(0.075)	(0.075)	(0.075)
adj. R^2	0.032	0.032	0.032	0.040	0.043	0.043	0.045	0.047	0.055	0.055	0.055	0.055

Note: In each panel, columns (1), (2) and (3) present OLS estimations using the selected covariates of each of the three machine learning methods: double-selection (DS), partialling-out (PO) and the cross-fit-partialling-out (XPO, double robust) estimators, respectively. Column (4) in each panel presents traditional OLS estimation using all the covariates selected by the three machine learning methods.

Table A.2. Effects of individual confinement indicators on mental health (Closure of workplaces)

	Panel A: Insomnia			Panel B: Anxiety			Panel C: Anxiety		
	(1) DS	(2) PO	(3) XPO	(1) DS	(2) PO	(3) XPO	(1) DS	(2) PO	(3) XPO
C2	0.1323^{***}	0.1323^{***}	0.1323^{***}	0.2416^{***}	0.2416^{***}	0.2378^{***}	0.2416^{***}	0.2416^{***}	0.2085^{***}
Closure of workplaces	(0.037)	(0.037)	(0.037)	(0.070)	(0.070)	(0.070)	(0.070)	(0.070)	(0.045)
Age <65						x			
Female	x	x	x	x	x	x	x	x	x
Excellent health	x	x	x						x
Very good health	x	x	x	x	x	x	x	x	x
Fair health	x	x	x	x	x	x	x	x	x
Poor health	x	x	x	x	x	x	x	x	x
COVID19 Exposure				x	x	x	x	x	x
Major financial problems	x	x	x	x	x	x	x	x	x
N	51983	51983	51983	51983	51983	51983	51983	51983	51983
adj. R^2	0.041	0.033	0.033	0.051	0.047	0.049	0.058	0.047	0.058

Note: Column (1) in each panel presents the double-selection (DS) estimators, while columns (2) and (3) show the partialling-out (PO) and the cross-fit-partialling-out (XPO) estimators respectively. Standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.3. Effects of individual confinement indicators on mental health (Stay at home requirements)

	Panel A: Insomnia			Panel B: Anxiety			Panel C: Anxiety		
	(1) DS	(2) PO	(3) XPO	(1) DS	(2) PO	(3) XPO	(1) DS	(2) PO	(3) XPO
C6	0.1237**	0.1237***	0.1237***	0.3037***	0.3037***	0.3017***	0.3037***	0.3037***	0.2399***
Stay at home requirements	(0.036)	(0.036)	(0.036)	(0.064)	(0.064)	(0.063)	(0.064)	(0.064)	(0.063)
Age <65						x			
Female	x	x	x	x	x	x	x	x	x
Excellent health	x	x	x	x					x
Very good health	x	x	x	x	x	x	x	x	x
Fair good health	x	x	x	x	x	x	x	x	x
Poor good health	x	x	x	x	x	x	x	x	x
COVID19 Exposure				x	x	x	x	x	x
Major financial problems	x	x	x	x	x	x	x	x	x
N	51983	51983	51983	51983	51983	51983	51983	51983	51983
adj. R^2	0.040	0.032	0.032	0.051	0.048	0.049	0.057	0.057	0.057

Note: Column (1) in each panel presents the double-selection (DS) estimators, while columns (2) and (3) show the partialling-out (PO) and the cross-fit-partialling-out (XPO) estimators respectively. Standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.4. **Effects of *composite confinement index* and *individual confinement indicators* on mental health (Regularized logistic regression methods)**

	Panel A: Insomnia			Panel B: Anxiety			Panel C: Anxiety		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
	DS	PO	XPO	DS	PO	XPO	DS	PO	XPO
Index	2.7780***	2.7780***	2.7780***	1.7371**	1.7371**	1.7371**	2.2682***	2.2682***	2.2682***
	(1.049)	(1.049)	(1.049)	(0.796)	(0.796)	(0.796)	(0.789)	(0.789)	(0.789)
C1	0.586	0.586	0.586	0.578	0.578	0.597	1.311	1.311	1.311
Closure of schools	(0.78)	(0.78)	(0.78)	(0.70)	(0.70)	(0.71)	(0.88)	(0.88)	(0.88)
C2	1.757***	1.757***	1.757***	1.514***	1.514***	1.514***	1.596***	1.596***	1.596***
Closure of workplaces	(0.39)	(0.39)	(0.39)	(0.44)	(0.44)	(0.44)	(0.29)	(0.29)	(0.29)
C4	0.756	0.756	0.756	0.406	0.406	0.379	0.152	0.152	0.152
Gathering restrictions	(0.68)	(0.68)	(0.68)	(0.58)	(0.58)	(0.58)	(0.64)	(0.64)	(0.64)
C5	0.377	0.377	0.377	0.492**	0.492**	0.492**	0.400	0.400	0.400
Closure of public transportation	(0.27)	(0.27)	(0.27)	(0.23)	(0.23)	(0.23)	(0.24)	(0.24)	(0.24)
C6	1.569***	1.569***	1.569***	1.859***	1.859***	1.859***	1.769***	1.769***	1.769***
Stay at home requirements	(0.41)	(0.41)	(0.41)	(0.37)	(0.37)	(0.36)	(0.41)	(0.41)	(0.41)
C7	0.133	0.133	0.133	-0.236	-0.236	-0.236	0.059	0.059	0.059
Restrictions on domestic travel	(0.39)	(0.39)	(0.39)	(0.33)	(0.33)	(0.33)	(0.34)	(0.34)	(0.34)
C8	-0.639	-0.639	-0.639	-1.051	-1.051	-1.051	-1.020	-1.020	-1.020
Restrictions on international travel	(0.69)	(0.69)	(0.69)	(0.70)	(0.70)	(0.70)	(0.77)	(0.77)	(0.77)
N	51983	51983	51983	51983	51983	51983	51983	51983	51983

Note: Column (1) in each panel presents the double-selection (DS) estimators, while columns (2) and (3) show the partialling-out (PO) and the cross-fit-partialling-out (XPO) estimators respectively. Standard errors in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.