LABOUR ECONOMICS
WORKING PAPERS

Working Paper Series
LEWP No. 13

The impact of COVID-19 lockdown on mental health in the elderly: a non-linear relationship

Sánchez-Daniel, A.
Malo, M.A.

December 25

AEET
ASOCIACIÓN ESPAÑOLA
ECONOMÍA DEL TRABAJO

The impact of COVID-19 lockdown on mental health in the elderly: a non-linear relationship

Ángel Sánchez-Daniel*[1], Miguel Á. Malo[1]

[1]Department of Economics & Economic History, Universidad de Salamanca

November 26, 2025

Abstract

This paper explores the causal effects of variations in COVID-19 lockdown strictness on mental health of adults over 50. We analyse changes in sleep problems, depression symptoms, and loneliness feelings, and an additive mental health index across 27 European countries and Israel during three waves of the Survey of Health, Ageing, and Retirement in Europe (SHARE). We adopt a Generalized Propensity Score (GPS) matching approach and include a lockdown strictness index from the Oxford COVID-19 Government Response Tracker (OxCGRT) as a continuous treatment. Our results show a deterioration in mental health compared to pre-pandemic values at high levels of restrictions. However, the dose-response functions show non-linear effects across the lockdown strictness distribution: loneliness is more prevalent in highly restricted countries, sleep problems are more common in less restricted countries, and depression symptoms peak under moderate lockdown measures. We suggest the existence of imperfect sample compliance due to mortality risk, as deceased individuals systematically reported worse mental health than survivors, introducing potential bias. This study concludes by discussing the potential drivers for these findings and their consequences.

JEL classification: I12, I18, I38, J14

Keywords: Mental health; Lockdown strictness; Continuous treatment; Generalized Propensity Score Matching; Dose-response function.

*Corresponding author: angelsd1998@usal.es. Á. Sánchez-Daniel is supported by the Junta de Castilla & León [Grant “Ayudas para financiar la contratación predoctoral de personal investigador (PREDOC), co-funded by the European Social Fund (FSE+) (2023)"]

1 Introduction

The objective of this study is to estimate the causal effect of variations in COVID-19 lockdown strictness on the mental health of people over 50. The COVID-19 pandemic, declared a public health emergency by the World Health Organization (WHO) in January 2020, has exacerbated mental health problems among the general population (WHO, 2020b). Rates of depression and anxiety are estimated to have increased by 25% during the pandemic (WHO, 2022). We analyse the effects on older people, who require more intensive medical attention. Lockdown policies protected against the virus, but affected mental health, especially in older people, a vulnerable group that faced poorer health and age-related digital exclusion (Hill et al., 2008; Zapletal et al., 2023).

While the impact of the COVID-19 pandemic on mental health has been widely studied (Aknin et al., 2022; Prati & Mancini, 2021), particularly among elderly people, results are mixed. Most research shows a negative impact of lockdown on mental health (García-Prado et al., 2022; Krendl & Perry, 2021; Luchetti et al., 2020), but some find positive relationships in certain aspects during the early stages of the pandemic (Recchi et al., 2020; Van Winkle et al., 2021). Previous studies often use unrealistic binary settings (high vs. low lockdown), ignoring the continuous spectrum of lockdown measures. This creates a limitation by classifying countries with similar intermediate restriction levels into opposing treatment/control categories based on arbitrary thresholds. A continuous treatment could therefore provide more reliable results and better capture this heterogeneity.

This paper follows a Generalized Propensity Score (GPS) matching approach to estimate dose-response functions for different lockdown dosages. In this context of observational data, GPS can measure causal effects extending beyond binary to continuous treatments (Hirano & Imbens, 2004; Rosenbaun & Rubin, 1983; Serrano-Domingo & Requena-Silvente, 2013). We model the impact of a continuous lockdown strictness index (treatment) on mental health outcomes (sleep problems, depression symptoms, loneliness feelings), and an additive index, controlling for socio-economic and health variables. This method involves matching the sample to ensure treatment independence from covariates, impose the balancing condition, and estimate the propensity score. Finally, we estimate the dose-response function which shows the response in mental health outcomes to different levels of lockdown strictness.

We analyse three waves of SHARE interviews (2019-2021) alongside the Oxford COVID-19 Government Response Tracker (OxCGRT) to create a panel dataset with country-specific lockdown strictness measures to compare outcomes before and after the pandemic. Our main contribution is the application of the GPS methodology with a continuous treatment to estimate dose-response functions. This approach identifies a non-linear causal deterioration of mental health in highly restricted countries. We find that deceased individuals systematically reported worse pre-pandemic mental health than survivors, which creates potential attrition that could underestimate negative mental health outcomes; we address these issues through various model specifications and robustness tests. Our findings provide insights for policymakers designing future containment measures for vulnerable populations.

2 Literature Review

Capturing certain subjective aspects of mental well-being, such as psychological distress, and mental disorders, is crucial for improving the understanding of mental health, especially during a pandemic (Layard & Clark, 2014; OECD, 2012) . However, challenges persist in the accuracy and harmonisation of data, and the analysis, which provide valuable tools for researchers and policymakers (OECD, 2012, 2023; WHO, 2022). Mental heath problems existed before the pandemic, but have been worsened in the last years, and have economic repercussions (UN, 2021). Mental disorders, which affect around 20% of the working-age population (WHO & ILO, 2022), are leading to a 3-4% reduction in the Gross Domestic Product (GDP) in the European Union (EU) (OECD, 2012). The relevance of psychological well-being to the economy has been reinforced by the responses to the COVID-19 pandemic, whose impacts differ by country and self-isolation or restrictions levels (WHO, 2020a). Estimations on rates of depression and anxiety symptoms have increased by over 25%, magnifying disruptions in mental health services (WHO, 2022). Within the labour market, the shift to remote working contributed to higher distress and isolation levels in the workplace (ILO & EUROFUND, 2017). While containment measures were critical to economic recovery, there is a need to address the escalating mental health problems exacerbated by the pandemic (OECD, 2012, 2020, 2023).

Economic life-cycle theories often model well-being through utility derived from consumption or income across the lifespan, with a constant level of satisfaction across life (López Ulloa et al., 2013; Modigliani & Brumberg, 1955). However, evidence tends to give more reliability to theories that propose an U-shaped relationship between well-being and age (Blanchflower & Oswald, 2008; Wilson et al., 2021). Empirical studies show that younger people tend to have more mental health problems, but when they appear in older adults they are more intense. However, during the pandemic, older adults reported more depression and anxiety symptoms than young people (Moreno et al., 2023), but little is written on the context of global shocks (Bruine de Bruin, 2021). Protective or moderating factors for mental health are being active in the labour market (Tejero Pérez & Doblytė, 2023), and age (Wilson et al., 2021). Loneliness specially affects older cohorts (Creese et al., 2021). Females and disabled tend to suffer more from mental health problems (Fernández Castro & Núñez de Prado Gordillo, 2023; Pagán & Malo, 2023), with higher levels of persistence.

Focusing on the impact of COVID-19 lockdown on mental health and well-being of elderly population, most studies report negative effects, with some positive results in some extents. García-Prado et al. (2022) used data from the SHARE (2015-2020) to study the effects of lockdown policies on mental health subjective reports. They constructed a containment index for the treatment variable using the OxCGRT. They followed a difference-in-differences approach, employing binary treatment groups (high/low restriction) based on pre-pandemic social interactions, finding a deterioration in sleep, depression and anxiety. Then, Van Winkle et al. (2021) used the SHARE to conclude the existence of an unexpected decline in feelings of depression in the older population. They explored sample responses during seven periods, using a fixed-effects model, with subjective depression responses as the outcome, to conclude an average reduction of 14.5%.

Other studies provide further insights into the relationship between the COVID-19 pandemic and mental health. Self-isolation and physical distancing were key drivers of negative mental health impacts, with stay-at-home orders linked to greater loneliness and depression (Krendl & Perry, 2021), and correlation between mental health problems (Dziedzic et al., 2021). Conversely, time spent outdoors and maintaining social contact acted as protective measures against negative emotions (Lades et al., 2020). Individual circumstances significantly exacerbated effects, including pre-existing mental, gender disparities, job losses (Paccagnella & Pongiglione, 2022), living alone, chronic health conditions (Luchetti et al., 2020), income loss (Martinez-Bravo & Sanz, 2021) or the use of anxiolytics (García-Fernández et al., 2020).

Previous studies assumed that the effect of lockdown on mental health is in most cases negative, linear, and binary, comparing high versus low lockdown levels, but in this article we follow a continuous approach. The purpose of this paper is to analyse the effects of different levels of lockdown on self-reported mental health, which may be non-linear and heterogeneous.

3 Data and methodology

3.1 Data

This research relies on the SHARE[1] database, a multidisciplinary, cross-national panel study conducted in 27 European countries and Israel. The SHARE interviews around 50,000 individuals aged 50 years[2] and older every two years since 2004 to analyse the effects of health, social, and economic policies over the life course of European citizens (Bergmann & Börsch-Supan, 2021). The SHARE follow the sample for as long as possible, allowing us to track individ-

[1]This paper uses data from SHARE Waves 8, Corona Survey 1, and Corona Survey 2, see Börsch-Supan (2024a, 2024b, 2024c) for methodological details (www.share-project.org for the full list of funding institutions).

[2]Spouses or partners of target individuals are also included in the sample regardless of their age, as are those in nursing homes and residential care

uals over time, and includes regular refreshment samples to deal with attrition, ensuring the longevity and representativeness of the sample. Its design ensures data comparability over time and across countries.

We use three SHARE waves (2019-2021), to exploit the longitudinal design and follow the mental health responses of the same sample of individuals. We include Wave 8, conducted between October 2019 and March 2020, which was interrupted by the pandemic outbreak and strategically captures the pre-lockdown period. We also include two Special Corona datasets: Wave 8 Special Corona 1 (June-September 2020) and Wave 9 Special Corona 2 (June-September 2021). This provides one pre-treatment and two post-treatment periods, allowing us to track the effects of lockdown policies. We use information on individual health, socio-economic status, and other control variables related to well-being to estimate the treatment effects of COVID-19 lockdown strictness levels on mental health across Europe.

This work analyses three self-reported mental health conditions: sleep problems, depression symptoms, and loneliness feelings. These are dummies (1 if the condition is reported, 0 otherwise) based on responses to SHARE questionnaire[3]. Additionally, we analyse an additive mental health index (ranging 0-3) comprising the three previous outcomes providing an overall measure of mental health. We finally generate four new variables comparing responses before and after the pandemic to assess changes over time in mental health, taking value of 1 if there is a deterioration, value -1 if there is an improvement and, and value 0 for no change.

Table 1 shows the prevalence of these mental health conditions between 2019 and 2021. There is a slightly decrease in sleep problems (36.5% to 31.5%) and depression symptoms (39% to 29.4%), while loneliness feelings increased (27% to 31.1%). The average mental health index also shows a slight overall decrease. Consistent with Van Winkle et al. (2021) we find an unexpected improvement in mental health outcomes in the first stage of the pandemic, and a return to pre-pandemic levels in 2021. We include demographic, socio-economic, and health-related control variables in our analysis (see Annex I).

We complement SHARE data with the OxCGRT to construct the continuous treatment variable, a lockdown strictness policy index, that varies in intensity rather than being binary or categorical. The OxCGRT provide systematically collected daily data on government policy responses to COVID-19 globally (containment/closure measures, economic policies, health systems, and vaccination policies) (Hale et al., 2021). In addition, the OxCGRT contains statistics on the number of COVID-19 cases, deaths, and vaccination rates, which we use as control variables of

[3]Sleep problems and depression symptoms are reported as the positive responses to the following questions, respectively: "Have you had trouble sleeping recently?" and "In the last month, have you been sad or depressed?". We consider loneliness feelings as the response "often" or "some of the time" to the question "How much time/How often do you feel lonely?".

Table 1: Mental health outcomes variables: 2019-2021. Longitudinal sample.

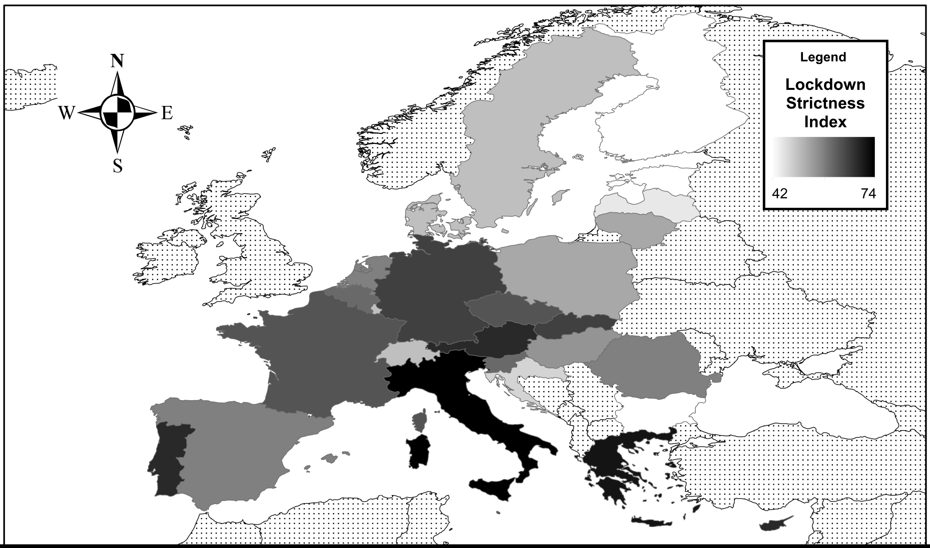
	2019	2020	2021	Average
Sleep problems	0.365	0.269	0.315	0.316
Depression symptoms	0.390	0.247	0.294	0.310
Loneliness feelings	0.270	0.282	0.311	0.288
Change in Sleep problems	.	.	-0.050	-0.050
Change in Depression symptoms	.	.	-0.096	-0.096
Change in Loneliness feelings	.	.	0.041	0.041
Mental Health Index	1.025	0.797	0.920	0.914
Change in Mental Health Index	.	.	-0.105	-0.105
Observations	31,060	31,060	31,060	93,180

Source: SHARE and own calculations.

country-specific context that address potential confounding factors.

Not all countries followed the same protocols to avoid the spread of COVID-19. Different levels of exposure to treatment may lead to variations in mental health outcomes, creating heterogeneous and non-linear effects. The daily policy tracking allows us to construct the continuous treatment to account for lockdown variability. We analyse the country-specific exposure to treatment in a quasi-experimental continuous setting rather than binary or categorical, which represents a methodological advancement. Treatment exposure have effects on mental health, and we assume that is country-specific and exogenous to the individual -assuming individuals did not choose their country during the pandemic-. The lockdown strictness index includes eight containment indicators and six health indicators[4] which values range from 0 to 100. The daily value of the index is the average value of these 14 indicators (equal weight to each policy measure). To create our treatment variable, we calculate the average value of this daily index from 1st April 2020 to 31st June 2021. This approach captures the cumulative exposure to restrictions that individuals experienced rather than point-in-time measures. Figure 1 shows the level of strictness by country, ranging from 74.0 in Italy, the most restrictive country, to 43.4 in Estonia, the least restrictive country. There was higher level of restrictions in southern European countries, and the lowest levels are found in Nordic and northern European countries. This geographic variation provides the treatment heterogeneity necessary for our identification strategy.

[4]Containment indicators: School closing, workplace closing, cancel public events, restrictions on gatherings, close public transport, stay-at-home requirements, restrictions on internal movements, and international travel controls. Health indicators: Public information campaigns, testing policy, contact tracing, facial coverings, vaccination policies, and protection of elderly people.



[redacted]

Figure 1: Average Lockdown Strictness Index: 1st April 2020 - 31st June 2021.
Source: OxCGRT.

3.2 Methodology

Many empirical economic questions address the causal effects of policies, but interventions often vary in intensity across different populations (Imbens & Wooldridge, 2009). This paper employs a quasi-experimental design adopting a GPS method, a generalisation of binary propensity score (Hirano & Imbens, 2004) given the variation in lockdown strictness, following Serrano-Domingo and Requena-Silvente (2013). Since randomization is impossible with observational data, the GPS method estimates causal effects by matching units on observed covariates to construct counterfactual comparisons. This creates comparable groups differing primarily in lockdown exposure, assuming treatment doses are randomly distributed conditional on these covariates. We estimate dose-response functions $\mu(t) = E[Y_i(t)]$ to identify average treatment effects and potential non-linear mental health outcomes across different lockdown strictness levels (Imbens, 2000; Rosenbaun & Rubin, 1983; Rubin, 1974). This approach allows identification of non-linear effects on mental health across different treatment levels.

The GPS works as follows, for each individual i we have a set of control variables X_i, the country-specific lockdown strictness index (the treatment) T_j, and the mental health outcome Y_{ij} (sleep problems, depression feelings, loneliness feelings, the mental health index, or the change from pre-COVID situation). In a binary approach $T_j = 0, 1$, while in this case T_j is an interval: the lockdown strictness index. Each potential outcome $Y_i(T)$ requires a continuous interval T. Adjusting for the GPS removes biases associated with differences in covariates Hirano and Imbens (2004). The dose-response function estimate $\mu(t) = E[Y_i(t)]$ across all individuals (Serrano-Domingo & Requena-Silvente, 2013), where $\mu(t)$ represents the value of the dose-response function at treatment level t. Comparing $\mu(t)$ with $\mu(t')$ reveals the causal effect of the change in the treatment. To establish causal effects, we need the unconfoundedness assumption for a continuous treatment, which requires treatment independence from the entire set of potential outcomes, $Y(t) \perp T | X$ (Rosenbaun & Rubin, 1983). We adopt the weak version of the unconfoundedness assumption from Imbens (2000), $Y(t) \perp T | X \ \forall t \in T$. This means that, conditional on covariates X, potential outcomes are independent of treatment level. Then, being $r(t,X)$ the conditional density of the treatment given the covariates, $r(t,X) = f_{X|T}(t|x)$, the GPS is defined as $R = r(T,X)$ (Hirano & Imbens, 2004). Within each treatment level, the GPS is independent of the covariates, so each lockdown strictness level translates into a unique propensity score.

For each individual and country, we observed a set of covariates X_{ij}, where i are the individuals and j are the countries, a given country-level of treatment T_j (the lockdown strictness index), the outcome Y_{ij} (sleep problems, depression symptoms, loneliness feelings, and the mental health index), which depends on the level of treatment received, and the error term ε_i:

$$Y_{ij} = \alpha(X_{ij}) + \beta(T_j) + \varepsilon_i \tag{1}$$

We use panel dataset integrating SHARE (pre- and post-treatment periods) and OxCGRT data. Control variables X_{ij} were selected based on previous literature. We followed these steps in our procedure: (1) we obtained the conditional level of the treatment T (conditional on covariates) $E(T)|X_{ij}$, via Ordinary Least Square (OLS) model to estimate the constant and slopes; (2) we estimated the GPS using a parametric approach from Hirano and Imbens (2004) and Serrano-Domingo and Requena-Silvente (2013):

$$\hat{R} = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{1}{2\sigma^2}\left(lnt - \hat{\beta}_0 - \hat{\beta}_1 X'\right)^2\right) \tag{2}$$

Finally, (3) we estimated the dose-response function across all individuals. We select the functional form using the Akaike Information Criteria (AIC), including the treatment variable, the GPS, and the interactions between them, and clustering standard errors at the country level.

The matching procedure ensures treatment assignment is independent of covariates conditional on the GPS and works as follows: (1) We stratified the sample into groups (quartiles), to make the treatment level assignment independent from covariates. (2) We estimated the GPS model using each group's median treatment, calculating GPS for individuals at that specific T level, and for control individuals at the other T levels. (3) We impose the common support condition removing observations outside overlapping GPS regions to ensure comparability. This ensures proper balance across groups and strengthens the independence of treatment assignment from covariates: covariates are statistically similar across treatment levels after matching. (4) We tested whether, conditional on the GPS, covariates are independent on treatment assignment to verify the balancing property of the GPS, examining t-statistics for mean differences across treatment strata after GPS adjustment. Finally, levels of treatment are independent on covariates so changes in outcome are due to changes in treatment, they are causal effects. For further methodological details, we refer the reader to Hirano and Imbens (2004) and Serrano-Domingo and Requena-Silvente (2013). For analysing continuous lockdown restrictions, GPS is preferable to binary methods, it reveals dose-response relationships between lockdown levels and mental health, and captures potentially non-linear effects often missed.

However, GPS has several limitations, when the treatment is continuous, non-parametric identification becomes more complex (Frölich & Sperlich, 2019), and estimates may be biased (Zhao et al., 2020). The GPS has been criticised regarding the potential confounding bias arising from the lack of randomisation, but with a large number of covariates, the assumption of unconfoundedness becomes more plausible (Gao et al., 2022). We assume that treatment levels are randomly assigned, which ignores the influence of government decisions on the implementation of closure measures. The presence of imperfect sample compliance and selection bias in older samples represent potential reduced representativeness (Gertler et al., 2011), potentially leading to an underestimation of negative impacts. Therefore, alternative model specifications are needed to address this issue. The following Section 4 show the results following the approach described here. Section 5 then present different robustness checks addressing these limitations, including alternative lockdown strictness index period, methods to account for mortality/self-selection bias and two-step procedures (Heckman, 1976), imputing values of deceased individuals, quantile analysis for reverse causality (Frölich & Sperlich, 2019), and control for health histories to account for unobserved characteristics (as done by Caliendo et al. (2017) with labour histories).

4 Results

4.1 Descriptive analysis

In this section, we present the descriptive analysis, focusing on the main summary statistics and the comparison between survivors and non-survivors. Our sample comprises 32,951 older adults followed over three years; 32,169 (97.6%) survived the follow-up, while 782 (2.4%) died during this period. Complete mental health data (sleep problems, depression symptoms, loneliness) is available for 31,060 individuals. Detailed summary statistics for all covariates are provided in Annex II: the proportion of females in the sample is 58.3%. The average age of the sample is 70.2 years. 14.6% of the sample reported having completed secondary education, and 6.9% reported having completed tertiary education. 91.4% report having at least one child. Regarding labour market status, most individuals (47.2%) are retired from work.

A critical methodological consideration is the potential for imperfect sample compliance due to mortality. This occurs when some observations are non-randomly lost during the study, there is a lack of adequate follow-up which can affect the results (Gertler et al., 2011). This is common in studies involving older populations, with high rates of mortality. When deaths are not random, particularly during a pandemic that disproportionately affected older adults, analysing only the survivors can bias causal estimates because the final sample is not representative of the initial population of interest. Specifically, excluding deceased participants, those with poorer pre-pandemic mental health, may bias our estimates of pandemic effects on mental health downwards, self-selecting survivors into the treatment and underestimating the true impact of lockdown measures. We address this potential selection bias in the robustness checks by using pre-death information to impute mental health outcomes for deceased individuals.

Table 2 confirms statistically significant pre-treatment differences between survivors and non-survivors. Those who died during follow-up were, on average, nearly a decade older (78.8 vs. 69.5 years) and predominantly male (65.6% vs. 41.3% of survivors). Finally, we observed differences in mental health outcomes between these groups. Individuals who deceased systematically reported worse pre-pandemic mental health across all three outcomes compared to survivors, with these differences being statistically significant ($p < 0.01$). Specifically, 44.9% of non-survivors reported sleep problems compared to 36.5% of survivors; 47.7% of non-survivors reported feeling depressed versus 39.1% of survivors; and 36.6% of the deceased report loneliness feelings compared to 27.1% of survivors. We implement several robustness checks in following sections to address this issue.

Table 2: Differences test: Survivors v. deceased. Pre-treatment period.

	Survivors	Deceased	Diff.	Std. Error
Percentage of males	0.413	0.656	-0.243***	0.018
Age of respondent	69.527	78.827	-9.301***	0.329
Sleep problems	0.365	0.449	-0.084***	0.019
Loneliness feelings	0.271	0.363	-0.092***	0.017
Depression symptoms	0.391	0.477	-0.086***	0.019

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Source: SHARE and own calculations.

4.2 Econometric analysis

Our analysis employs the GPS methodology described in Section 3.2. This approach constructs counterfactual scenarios by matching individual based on observed covariates to ensure a balanced sample with comparable groups across the continuous treatment. This quasi-experimental strategy allows us to explore the causal impact of different levels of lockdown strictness during the COVID-19 pandemic on individuals older than 50 years in Europe. The GPS coefficients and their standard errors, reported in Annex II, provide correlations between the treatment variable (lockdown strictness index) and the covariates. We observe that individuals with more social contacts tend to live in less restricted countries (negative correlation between the lockdown index and social contacts), which is consistent the idea that restrictions reduced social contacts. Being sick, disabled, or having a long-term illness was associated with lower lockdown strictness. Conversely, being a homemaker was associated with higher lockdown strictness. Countries with higher COVID-19 cases and larger populations tended to have less strict lockdowns (negative correlation). However, countries with higher vaccination rates had more strict lockdowns (positive correlation). We also find that as we increase the lockdown strictness index, there is a greater need for financial support. Age and birth cohort have less statistical effects.

We then impose the common support condition using histograms of the sample distribution, as mentioned in the matching procedure in Section 3.2. Figure 2 shows the overlapping of the propensity scores of our interval of interest and its respecting control interval. We drop all observations outside the common support condition to ensure that all individuals' covariates are independent of other treatment groups and sample is balanced (Dehejia & Wahba, 2002; Serrano-Domingo & Requena-Silvente, 2013). After the matching procedure, our final sample is restricted to 22,037 matched individuals.

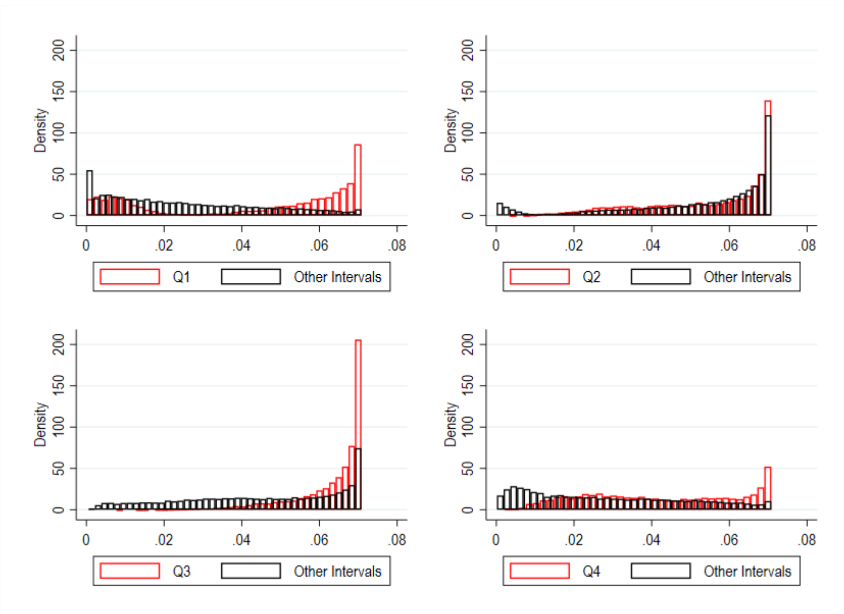
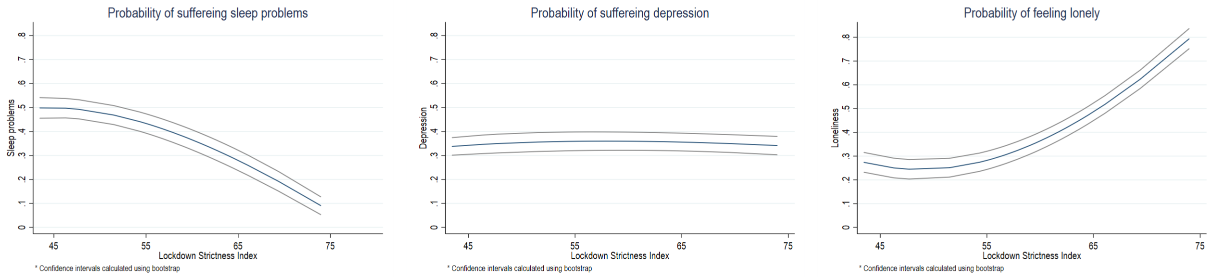


Figure 2: GPS support condition.
Source: SHARE, OxCGRT, and own calculations.

The dose-response functions represent the variation in mental health outcomes across the treatment spectrum. We examine dose-response functions for sleep problems, depression symptoms, loneliness feelings, both in levels (Figure 3) and as variations compared to pre-pandemic responses (Figure 4), plus a Mental Health Index (also in levels and variations) as a proposal to measure overall mental health (Figure 5). This dose-response relates each dosage of treatment (lockdown strictness index) to the post-treatment level of mental health. We selected the preferred functional form of the dose-response function taking into account the lockdown strictness, the GPS (both either in levels or log transformed and considering lineal or quadratic term), and the interaction between them, following the AIC and clustering standard errors at country level. Coefficients of the preferred specification are shown in Annex III.

Figure 3 shows the dose-response functions with the probability of reporting sleep problems, depression symptoms, and loneliness feelings across the treatment. Each mental health dimension follows a different pattern. For sleep problems (Figure 3a), individuals in countries with low levels of restriction suffered more from sleep problems, with almost 50% of them reporting poor sleep; a proportion that decreases to around 10% in more restrictive countries. The lowest values are found at the upper extreme of the distribution, in countries with high levels of restriction. For depression (Figure 3b), the highest probabilities appear in the middle of the treatment distribution in countries with lockdown strictness levels around the average (around 55 points on the lockdown strictness index), where almost 40% of the people reported feeling depressed, but there is less variation across the treatment. The lowest depression rates are observed at the extremes, with more intensity in less-restricted countries. At the lower and upper extreme of the lockdown strictness index, the depression rate was approximately 35%. The variation in depression is lower than in the case of sleep problems and loneliness feelings (Figure 3c), where the probability increases steadily throughout the distribution of lockdown stringency. It rises from almost 30% in the least restricted countries to approximately 80% in countries with strictest policies. The social isolation scenario and the advice to stay at home had their effects on the loneliness of older adults. The 95% confidence intervals of the dose-response functions were constructed using bootstrap.

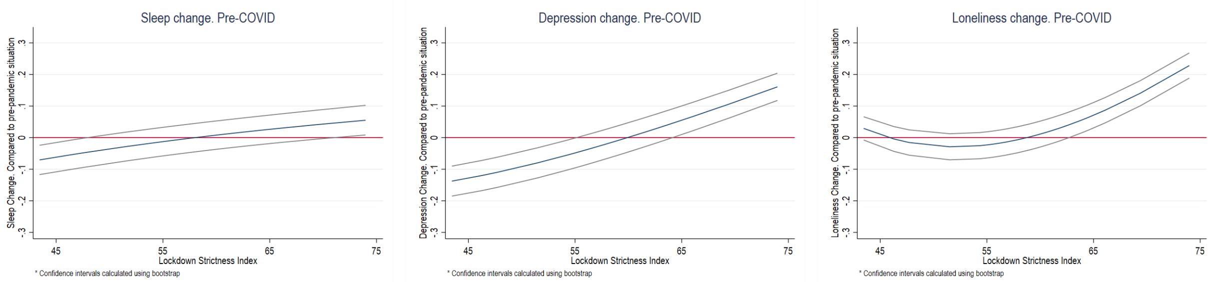
The probabilities of dealing with a mental health problem and the variations across the lockdown strictness index are different for each item considered: Less restricted countries have more sleep problems, more restricted countries have more loneliness feelings, and depression symptoms are more regularly distributed across the countries.



(a) Sleep problems (b) Depression symptoms (c) Loneliness feelings

Figure 3: Dose-response functions. Sleep problems, depression symptoms, loneliness feelings. *Source:* SHARE, OxCGRT, and own calculations.

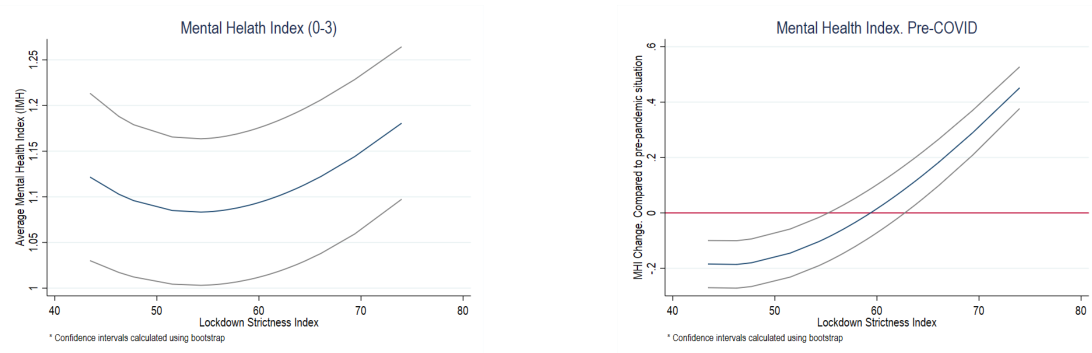
Figure 4 show changes in mental health responses compared to the pre-pandemic reports. Sleep problems (Figure 4a) slightly decreased in countries with lower restrictions, remained stable in countries with average restrictions, and increased in countries with stricter containment policies. As seen in the previous paragraph, in more restrictive countries sleep problems were less common, but they have increased around 5% compared with the pre-pandemic period. For depression symptoms (Figure 4b), individuals in less restrictive countries showed slight improvements, while those in more restrictive countries experienced 15% increases in depression. This suggests that only strict closure policies worsened depression symptoms, while mild and moderate policies had no effect. Following a similar pattern to the previous points, in Figure 4c loneliness worsened in the most restrictive countries, but in this case, we found no effect rather than an improvement in the less restrictive countries. Loneliness increased up to more than 20% at the top of the lockdown strictness index. We see worsening in mental health in the most restrictive countries for the three mental health dimensions, while just a slight improvement in depression in the less restricted countries.



(a) Sleep problems (b) Depression symptoms (c) Loneliness feelings

Figure 4: Dose-response functions. Sleep problems, depression symptoms, loneliness feelings. Change from pre-pandemic situation.
Source: SHARE, OxCGRT, and own calculations.

Finally, Figure 5 reports the effects of the lockdown strictness index on the additive mental health index, which ranges from 0 (no reported mental health problems) to 3 (all three problems reported). We find that the average mental illness in our matched sample varies from around 1.1 in less restricted countries to 1.2 in more restricted countries. This value reaches its maximum in highly restrictive countries. Comparing to pre-pandemic responses, we find a deterioration in mental health in the more restricted countries and a slight improvement in the less restricted countries, derived from depression, which is consistent with results using the individual mental health items in Figure 4 that are the ingredients used to construct the mental health index.



(a) Mental health index. Levels.

(b) Mental health index. Change to pre-COVID.

Figure 5: Dose response functions. Mental health index inlevels and compared to pre-COVID. *Source:* SHARE, OxCGRT, and own calculations.

Our findings show that variations in lockdown strictness produced distinct effects across mental health dimensions. The dose-response functions address our objective by showing that increased restrictions align with deterioration in sleep problems, depression symptoms, and feelings of loneliness. The patterns vary by specific condition: depression symptoms peaked at average restriction levels, sleep problems were most prevalent in less restrictive environments, and loneliness increased steadily with restriction intensity. However, when comparing to pre-pandemic baselines, all three conditions showed worsening trends as restriction levels increased, as well as the overall mental health index. This is consistent with previous findings by García-Prado et al. (2022), who found a negative effect of lockdown on mental health using binary difference-in-differences approaches. In next section we present results from alternative GPS specifications and complementary analyses, including alternative temporal definitions of the lockdown strictness index and estimating outcomes of deceased individuals. These extensions address potential methodological concerns regarding sample compliance, omitted variable bias, self-selection, and heterogeneity in treatment effects.

5 Robustness checks: alternative index, self-selection, and heterogeneity

Our results have shown a deterioration in mental health in highly restricted countries compared to pre-pandemic conditions, with distinct patterns in the probability of suffering mental health problems. However, several concerns regarding potential biases and measurement issues must be addressed to ensure robust causal inference. This section provides comprehensive robustness checks addressing: alternative lockdown index periods, attrition due to mortality, self-selection bias, and potential reverse causality through heterogeneity analysis. We also explored the possibility of conducting multilevel models at the country and regional levels to examine potential cluster-driven results, but Interclass Correlation Coefficients (ICC) show values lower than 5% for all mental health outcomes. Summary statistics of the Mental Health Index by country and European region are presented in Annexes VII and VIII.

5.1 Short-term lockdown strictness index

Table 3: GPS coefficients and standard errors.

	(1) GPS long-run (March 2020 - June 2021)		(2) GPS short-run (March 2021 - June 2021)	
Gender	-0.901***	0.073	-0.941***	0.083
Country	-0.124***	0.008	-0.222***	0.007
Language	0.164***	0.007	0.128***	0.007
Age	-0.220*	0.112	-0.237	0.129
Age^2	0.001	0.001	0.001	0.001
Secondary Education	-2.769***	0.092	-2.348***	0.106
Tertiary Education	-2.983***	0.123	-3.175***	0.143
Children	-1.495*	0.700	-2.687**	0.816
No children	-0.902	0.764	-1.784*	0.888
Retired	1.169***	0.132	1.057***	0.150
Unemployed	-0.466	0.356	-1.318**	0.423
Sick or disabled	-1.749***	0.335	-1.863***	0.366
Homemaker	3.105***	0.288	3.795***	0.352
Before 1930	1.649	0.930	1.216	1.068
1930-1940	1.858*	0.880	1.638	1.020
1940-1950	1.582	0.871	1.425	1.010
1950-1960	1.153	0.824	1.034	0.954
1960-1970	1.568*	0.758	1.510	0.880
Job status	0.395***	0.068	0.283***	0.082
Contact children	-0.598***	0.030	-0.593***	0.035
Contact relatives	-0.416***	0.042	-0.437***	0.048
Contact others	0.455***	0.031	0.586***	0.034
EContact children	-0.222***	0.034	-0.265***	0.039
EContact relatives	-0.203***	0.039	-0.336***	0.044
EContact others	-0.005	0.035	-0.024	0.040
Max COVID Cases	-0.000***	0.000	-0.000***	0.000
Max COVID Deaths	0.000***	0.000	0.000***	0.000
Pop vaccinated	0.190***	0.004	0.275***	0.004
Pop 2022	-0.000***	0.000	0.000***	0.000
Finantial support	1.174***	0.081	-0.659***	0.114
Long-term illness	-2.138***	0.069	-2.292***	0.080
Constant	62.878***	3.686	71.097***	4.309
Observations	27,157		27,157	
R-squared	0.443		0.417	

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Source: SHARE and own calculations.

Table 3 presents two alternative model specifications using different lockdown strictness indexes as treatment variables. The first shows the GPS coefficients from our baseline approach, using the average lockdown strictness index from 1st March 2020 to 31st June 2021, including the whole sample. The second incorporates a new lockdown strictness index, averaged from 1st March 2021 to 31st June 2021, capturing the second wave of the pandemic and the three previous months to the beginning of the last SHARE interviews. We observe that coefficients' signs, effect magnitudes, and significance levels remain remarkably consistent across both specifications. The dose-response functions (reported in Annex IV) maintain the same functional form as those obtained with the first specification in Section 4.2. This robustness check shows that countries change positions in the treatment distribution, which strengthens our argument that mental health effects are driven by lockdown strictness levels rather than country-specific characteristics or the choice of the specific time period to calculate the index.

5.2 Addressing attrition due to mortality and self-selection

Differences in mental health reports between survivors and deceased individuals led us to consider addressing potential attrition bias due to mortality. We address this issue by considering the different model specifications presented in Table 4. In model 1, we construct a model with fewer covariates and restrict the sample to individuals who survived 2021 from previous waves. Then, in model 2, we run a model in which we impute mental health values for deceased individuals using pre-treatment variables, to compare the results with the baseline model with survivors only.[5] We follow an approach similar to Gertler et al. (2014), where they impute outcome values to missing individuals to re-weight the data and avoid over-representation of some groups. Specifically, we fit a probit model estimating the probability of mental health outcomes (depression, sleep problems, and loneliness) in the post-treatment period for survivors, taking into account only pre-treatment variables. Using the resulting probit coefficients, we impute mental health outcomes for deceased individuals based on their pre-treatment characteristics. We assign a value of 1 to those with a predicted probability greater than 0.5, and 0 otherwise. The results of the probit models for depression, sleep problems, and loneliness feelings are reported in Annex V. The probit model is structured as follows:

$$Prob(Y_{it}) = \alpha + \beta(X_{t-2}) + \varepsilon_i \tag{3}$$

Where Y_{it} represents the probability of individual i of suffering the mental health symptom in the post-treatment period t, α is the constant, β are the coefficients associated with the covariates, X_{t-2} are the covariates in the pre-treatment period, and ε_i is the error term. So, the new mental health variable will be:

[5] Alternative stochastic imputation methods based on the predicted probabilities were also tested, yielding identical GPS coefficients as the GPS estimation is independent of the outcome variable.

If individual i is a survivor, $Y_{it} = Y_{it}^{obs}$
If individual i is deceased, Y_{it} is defined as:

$$Y_{it} = \begin{cases} 0 & \text{if } \mathrm{Prob}(Y_{it}) < 0.5 \\ 1 & \text{if } \mathrm{Prob}(Y_{it}) \geq 0.5 \end{cases} \tag{4}$$

Model 3 shows the model in which we first estimated the probability of survival for all individuals using pre-treatment variables and kept those with a probability above the 10% threshold, selected based on the distribution of estimated probabilities of survival. The probability of survival was estimated from a probit model, and the coefficients are reported in Annex VI. We then compute all mental health values according to Model 2 and compare the resulting estimates to assess consistency with the baseline model. Then, the GPS is run, and the coefficients are reported in Model 3. With this approach, we consider the part of the sample that was expected to survive before the pandemic and survived, and the deceased that reported a high probability of survival. As a result, we exclude deceased individuals and survivors whose estimated probability of survival before the pandemic was low.

Table 4: GPS coefficients and standard errors. Imputation models.

	(1) GPS Survivors		(2) GPS Imputation: Deceased		(3) GPS Expected survivors	
Gender	-0.303***	0.067	-0.279***	0.067	-0.330***	0.069
Country	-0.113***	0.007	-0.112***	0.007	-0.111***	0.007
Language	0.170***	0.007	0.169***	0.007	0.170***	0.007
Age	-0.032	0.097	-0.001	0.095	-0.011	0.105
Age^2	-0.000	0.001	-0.000	0.001	-0.000	0.001
Secondary Education	-3.045***	0.088	-3.011***	0.087	-3.012***	0.090
Tertiary Education	-3.566***	0.115	-3.553***	0.114	-3.599***	0.117
Children	-2.332***	0.603	-2.387***	0.585	-1.599	0.857
No children	-1.971**	0.613	-2.035***	0.595	-1.246	0.864
1930-1940	0.205	0.347	0.101	0.329	-0.098	0.404
1940-1950	0.190	0.436	0.072	0.418	-0.144	0.483
1950-1960	0.066	0.455	-0.038	0.438	-0.188	0.497
1960-1970	0.264	0.427	0.197	0.415	0.103	0.461
Max COVID Cases	-0.000***	0.000	-0.000***	0.000	-0.000***	0.000
Max COVID Deaths	0.000***	0.000	0.000***	0.000	0.000***	0.000
Pop vaccinated	0.200***	0.003	0.199***	0.003	0.200***	0.003
Pop 2022	-0.000***	0.000	-0.000***	0.000	-0.000***	0.000
Constant	53.939***	3.186	53.037***	3.115	52.447***	3.475
Observations	31,498		32,257		30,329	
R^2	0.3851		0.3845		0.3847	

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
Source: SHARE and own calculations.

Table 5 show two-step models to account for self-selection and different probabilities to be in the sample. Model 4 follows a two-step approach. First, we estimate the probability of survival during follow-up as in the previous model. Then, we include this probability as a covariate to re-weight the sample and to control for self-selection into treatment, reflecting both survival likelihood and exposure to lockdown policies (Heckman, 1976, 1990). This approach accounts for differential treatment probabilities across individuals.

Then, Model 5 and 6 implement extreme-case scenario analysis, assuming all survivors have positive mental health outcomes and all deceased have negative mental health outcomes. This approach tests the sensitivity of our results to the most extreme possible assumptions about the relationship between mortality and mental health outcomes:

$$\text{If individual } i \text{ is a survivor, } Y_{it} = 1$$
$$\text{If individual } i \text{ is a deceased, } Y_{it} = 0$$

The dose-response functions for these models are similar to the baseline approach. Model 6 includes probability of survival as a control variable. In Models 4 and 6, the coefficient for the probability of survival is positive and highly significant at the 0.1% level, indicating that higher pre-pandemic survival probability is associated with experiencing higher lockdown strictness levels. This finding suggests that highly restricted countries may have achieved better health outcomes, thereby increasing their citizens' survival probability. However, we find a low correlation coefficient (0.0348) between the lockdown strictness index and survival probability, suggesting that selection bias due to differential survival probability is unlikely to be a major confounder.

Table 5: GPS coefficients and standard errors. Self-selection models.

	(4) GPS prob. of survival		(5) GPS Extreme case (binary)		(6) GPS Extreme case + prob. of survival	
Gender	-0.785***	0.076	-0.279***	0.067	-0.819***	0.078
Country	-0.110***	0.007	-0.112***	0.007	-0.111***	0.007
Language	0.173***	0.007	0.169***	0.007	0.174***	0.007
Age	-0.239*	0.100	-0.001	0.095	-0.301**	0.102
Age^2	0.002*	0.001	-0.000	0.001	0.002**	0.001
Secondary Education	-2.769***	0.091	-3.011***	0.087	-2.784***	0.092
Tertiary Education	-3.405***	0.116	-3.553***	0.114	-3.410***	0.117
Children	-1.427	0.854	-2.387***	0.585	-1.502	0.862
No children	-1.133	0.861	-2.035***	0.595	-1.197	0.869
1930-1940	-0.397	0.345	0.101	0.329	-0.257	0.360
1940-1950	-0.403	0.436	0.072	0.418	-0.197	0.451
1950-1960	-0.251	0.455	-0.038	0.438	-0.046	0.469
1960-1970	0.008	0.429	0.197	0.415	0.160	0.439
Max COVID Cases	-0.000***	0.000	-0.000***	0.000	-0.000***	0.000
Max COVID Deaths	0.000***	0.000	0.000***	0.000	0.000***	0.000
Pop vaccinated	0.200***	0.003	0.199***	0.003	0.202***	0.003
Pop 2022	-0.000***	0.000	-0.000***	0.000	-0.000***	0.000
Prob. of survival	24.610***	1.920			26.450***	2.094
Constant	34.633***	3.633	53.037***	3.115	34.749***	3.746
Observations	31,195		32,257		30,583	
R^2	0.3869		0.3845		0.3874	

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Source: SHARE and own calculations.

Table 6 includes models with additional control variables. In Model 7 we include excess of mortality as an additional control variable to further explore potential endogeneity. This variable is calculated as average excess mortality from March 2020 to June 2021 using Eurostat data (Israel and Cyprus are excluded due to data limitations). The positive coefficient indicates that countries with higher excess mortality implemented stricter lockdown measures to control pandemic spread, confirming the expected policy response pattern. Finally, in Model 8 we include the year of the last job as a recall variable for labour market histories, aiming to control for unobserved characteristics Caliendo et al. (2017). As expected the sample size considerably reduce: individuals who have never work and those still in the labour market are excluded from the sample (additionally, some countries do not have this question in the SHARE database) but coefficients maintain size, sign, and significance.

Table 6: GPS coefficients and standard errors. Additional control variables.

	(7) GPS Control: Excess Mortality		(8) GPS Control: Recall variables	
Gender	-0.324***	0.067	-0.551***	0.116
Country	-0.113***	0.007	-0.066	0.039
Language	0.161***	0.006	0.299***	0.026
Age	-0.083	0.096	0.100	0.178
Age^2	0.000	0.001	-0.001	0.001
Secondary Education	-3.921***	0.081	-2.672***	0.240
Tertiary Education	-4.160***	0.106	-3.136***	0.261
Children	-1.967***	0.588	-2.872***	0.355
No children	-1.468*	0.598	-3.018***	0.409
1930-1940	0.282	0.346	-0.440	0.636
1940-1950	0.272	0.434	-0.715	0.798
1950-1960	0.167	0.452	-1.015	0.833
1960-1970	0.353	0.426	-1.401	0.806
Max COVID Cases	-0.000***	0.000	0.000***	0.000
Max COVID Deaths	0.000***	0.000	0.000**	0.000
Pop vaccinated	0.180***	0.003	0.170***	0.007
Pop 2022	0.000***	0.000	-0.000***	0.000
Excess of mortality	0.154***	0.005		
Long term illness			-0.914***	0.122
Year of last job			-0.014*	0.007
Constant	54.331***	3.159	79.685***	14.753
Observations	31,186		4,963	
R^2	0.4029		0.5897	

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Source: SHARE and own calculations.

5.3 Heterogeneity and quantile analysis

Heterogeneity across levels of treatment may mask the omission of significant unobserved variables, thereby violating the unconfoundedness assumption and making the causal estimates inconsistent. Figure 6 shows the lockdown strictness index by country. We observe high variability in the level of restrictions, from 43.4 in Estonia (least restrictive) to 74.0 in Italy (most restrictive). In addition, the variability in the index is found in the extremes of the distribution, while around the average, index levels are similar. We observe 19 countries falling between values of 55 and 65, but only 4 below 55 and 3 above 65.

As Frölich and Sperlich (2019) explains, non-parametric identification becomes complex when treatment is continuous, as heterogeneity may generate reverse causality and omitted variable bias. Causal effects cannot be identified when treatment variability is insufficient. We thus expect to find no causal effects when conditioning the model on sub-samples with homogenous treatment levels, and test conditioning the model on quantile distribution of treatment, dividing the sample in tertiles (Frölich & Sperlich, 2019). Under the unconfoundedness assumption, we expect to find no causal effects within these homogenous sub-samples as treatment variability becomes insufficient. This approach provides a powerful test against reverse causality.

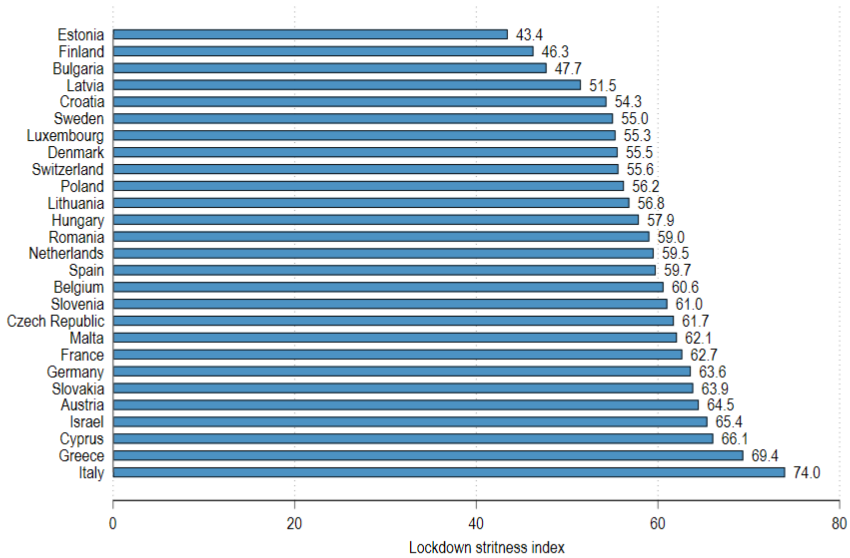


Figure 6: Lockdown strictness index by country.
Source: OxCGRT and own calculations.

We divided the country by their level of lockdown strictness into three groups: low restrictions, medium restrictions, and high restrictions. The first sample of countries, in the lower bound of the distribution ranging from Estonia (43.3) to Denmark (55.5). The second group in the middle of the distribution encompasses from Switzerland (55.6) to Slovenia (61.0), and finally, the third group of countries with the highest restrictions are from Czech Republic (61.7) to Italy (74.0). Due to reduced observations in each stratum, we employ three rather than four blocs to construct the stratification and the dose-response functions. We observe in Figure 7 that the treatment effect is null for two of the three groups, which is consistent with the hypothesis of unconfoundedness. The first cluster (low restrictions) still show significant effects, which may respond to the higher treatment variability remaining within that tertile. The group with medium restrictions show an effect indifferent from zero, and the group with high restrictions begins to show a positive effect at the lower end of the distribution, where is the higher variability.

Finally, the ICC reported in Annexes IX and X (consistently below 5%) justify our decision not to employ multilevel models. Frölich and Sperlich (2019) recommended ICC higher than 5% to employ clustered specifications. Additionally, Angrist and Pischke (2009) recommended a

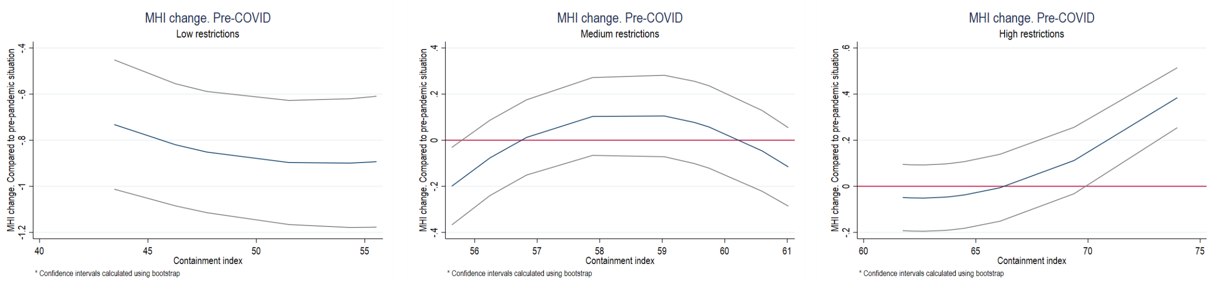


Figure 7: Dose-response functions by quantiles.
Source: SHARE, OxCGRT, and own calculations.

minimum of 42 clusters to properly address intra-groups correlation, and in this case we are working with 26 countries.

6 Discussion

Unlike previous studies using binary treatment classifications (García-Prado et al., 2022) or older baseline data (Van Winkle et al., 2021), our study employs a GPS methodology with a continuous treatment variable, using 2019 data as a more accurate pre-pandemic baseline. The COVID-19 pandemic significantly impacted older adults' mental health, with our findings confirming both overall deterioration and a slight improvement during the initial phase. This approach reveals non-linearities in lockdown impacts previously undetected, specifically showing that moderate lockdown measures produced less severe mental health impacts than very strict policies. Future policy evaluations should be based on continuous treatment settings rather than binary ones to capture the full dose-response relationship.

A critical insight concerns attrition bias due to mortality. Individuals who died during the follow-up systematically reported worse pre-death mental health than survivors. This pattern suggests mental health problems increase mortality risk, potentially creating downward bias in longitudinal assessments, as the most vulnerable individuals are lost from the sample. This makes this group a priority for mental health targeted policies. Our findings emphasizes the need to address mental health conditions early as mortality risk factors, to balance between physical and mental health. Lockdown policies during a pandemic should be focused to reduce the gap between the mental health reports of survivors and the deceased.

However, our approach has limitations. First, the data collection across three different periods creates potential temporal lags between policy implementation and observed effects. Second, the lack of continuous follow-up raised sample compliance concerns, though our complementary models suggest this bias is minimal. Third, we assume individual compliance to the treatment, and uniform treatment effects within countries may may mask individual variation, which can be affected by occupation or socio-economic status. A self-reported restriction index might improve results, but could introduce subjectivity bias. Finally, our three-wave design could be strengthened, the Special COVID datasets lack the full SHARE interview, limiting our available covariates.

External validity may be limited by different institutional frameworks, cultural attitudes towards mental health and healthcare systems, which our model may not fully capture, although we include country-level clustered standard errors. Other concurrent factors such as fear of infection, economic uncertainty, labour market status, socioeconomic level, or reduced access to healthcare also contributed to deteriorating mental health outcomes, not only lockdown restrictions. Future research should therefore focus on three areas: (1) the overlapping stressors that may have contributed to mental health deterioration during the pandemic, (2) the long-term persistence of the effects, and (3) identifying the individual resilience factors that protect mental health.

7 Conclusion

This article estimates the causal effects of COVID-19 lockdown policies on mental health of adults older than 50 years in Europe. We find a clear deterioration in mental health outcomes at high lockdown levels, consistent with the existing literature on the negative impact of lockdown measures on the sleep problems and depression symptoms (García-Prado et al., 2022; Krendl & Perry, 2021), and loneliness of the older population (Luchetti et al., 2020), and the positive impact on depression symptoms in the first stage of the pandemic (Van Winkle et al., 2021). However, we make two contributions previously unexplored, the non-linearities and heterogeneity, and the potential attrition due to mortality.

We employed a continuous approach for the treatment rather than the binary approach common in the literature. We construct a panel dataset using the SHARE and a continuous treatment variable (lockdown restriction index) using the OxCGRT. The GPS methodology based on Serrano-Domingo and Requena-Silvente (2013) allowed us to match the sample on pre-treatment variables and derive dose-response functions that reveal the non-linear relationships and heterogeneities between lockdown intensity and mental health outcomes. Additionally, we find that deceased individuals reported significantly worse pre-pandemic mental health, potentially biasing our results, and we address the implications of potential attrition due to mortality through imputation robustness models.

Our main finding is a statistically significant, non-linear deterioration in mental health concentrated in countries with the strictest lockdown policies. We find that sleep problems increased by approximately 5%, depression symptoms by 15%, and loneliness by 20% in most restrictive countries, while mental health remained stable or even improved in less restrictive countries in the case of depression. We also find the relationship is highly non-linear: in levels, mental health outcomes peak at different points in the treatment distribution. A critical challenge to this findings is the finding that individuals with poorer mental health have a higher mortality rate, and the difference in mental health is statistically significant. We address this potential imperfect sample compliance through alternative model specification and imputation methods, as well as alternative treatment variables and heterogeneity analysis as robustness checks that confirm our main findings.

Our finding on mental health worsening at high levels of lockdown restriction suggests a need for policies designed to mitigate the negative effects in future health crises. The non-linearities shown in levels suggest that generic policies focused on lockdown strictness levels are insufficient. There is a need for targeted policies for older adults, focusing on the specific mental health dimensions most affected by each level of restriction—such as loneliness in the strictest lockdowns. Finally, our article highlighted the difference in reported mental health between survivors and deceased, which goes beyond lockdown strictness policies: poor mental health may be a predictor for mortality, and health services should work on prevention measures that include mental health as a risk factor that can save lives.

Future research should first expand the scope of the analysis by including more countries with greater variability in mental health culture and lockdown strictness policies to improve external validity, implementing longer longitudinal designs to capture the long-term persistence of the effects, and incorporating additional mental health dimensions. Then, we should focus on other overlapping stressors —such as economic uncertainty or fear of infection— that likely contributed to mental health deterioration. Then, improving data availability with more waves could be helpful to incorporate other covariates such as labour histories. Finally, further work could develop alternative continuous estimators or better predict the behaviour of non-compliance.

Despite these limitations and plausible improvements, our study provides valuable evidence that strict lockdown policies significantly impacted mental health in older Europeans, with important non-linear patterns across restriction levels.

References

Aknin, L. B., De Neve, J.-E., Dunn, E. W., Fancourt, D. E., Goldberg, E., Helliwell, J. F., Jones, S. P., Karam, E., Layard, R., Lyubomirsky, S., Rzepa, A., Saxena, S., Thornton, E. M., VanderWeele, T. J., Whillans, A. V., Zaki, J., Karadag, O., & Ben Amor, Y. (2022). Mental Health During the First Year of the COVID-19 Pandemic: A Review and Recommendations for Moving Forward. *Perspectives on Psychological Science: A Journal of the Association for Psychological Science*, *17*(4), 915–936. https://doi.org/10.1177/17456916211029964

Angrist, J. D., & Pischke, J.-S. (2009). *Mostly Harmless Econometrics: An Empiricist's Companion*. Princeton University Press. https://doi.org/10.2307/j.ctvcm4j72

Bergmann, M., & Börsch-Supan, A. (2021). *SHARE wave 8 methodology: Collecting cross-national survey data in times of COVID-19*. MEA, Max Planck Institute for Social Law and Social Policy. https://share-eric.eu/data/data-documentation/waves-overview/wave-8

Blanchflower, D. G., & Oswald, A. J. (2008). Is well-being U-shaped over the life cycle? *Social Science & Medicine (1982)*, *66*(8), 1733–1749. https://doi.org/10.1016/j.socscimed.2008.01.030

Börsch-Supan, A. (2024a). *Survey of Health, Ageing and Retirement in Europe (SHARE) Corona Survey 1*. [Data set], SHARE-ERIC. https://doi.org/10.6103/SHARE.w8ca.900

Börsch-Supan, A. (2024b). *Survey of Health, Ageing and Retirement in Europe (SHARE) Corona Survey 2*. [Data set], SHARE-ERIC. https://doi.org/10.6103/SHARE.w9ca.900

Börsch-Supan, A. (2024c). *Survey of Health, Ageing and Retirement in Europe (SHARE) Wave 8*. [Data set], SHARE-ERIC. https://doi.org/10.6103/SHARE.w8.900

Bruine de Bruin, W. (2021). Age Differences in COVID-19 Risk Perceptions and Mental Health: Evidence From a National U.S. Survey Conducted in March 2020. *The Journals of Gerontology. Series B, Psychological Sciences and Social Sciences*, *76*(2), e24–e29. https://doi.org/10.1093/geronb/gbaa074

Caliendo, M., Mahlstedt, R., & Mitnik, O. A. (2017). Unobservable, but unimportant? The relevance of usually unobserved variables for the evaluation of labor market policies. *Labour Economics*, *46*, 14–25. https://doi.org/10.1016/j.labeco.2017.02.001

Creese, B., Khan, Z., Henley, W., O'Dwyer, S., Corbett, A., Vasconcelos Da Silva, M., Mills, K., Wright, N., Testad, I., Aarsland, D., & Ballard, C. (2021). Loneliness, physical activity, and mental health during COVID-19: A longitudinal analysis of depression and anxiety in adults over the age of 50 between 2015 and 2020. *International Psychogeriatrics*, *33*(5), 505–514. https://doi.org/10.1017/S1041610220004135

Dehejia, R. H., & Wahba, S. (2002). Propensity Score-Matching Methods for Nonexperimental Causal Studies. *The Review of Economics and Statistics*, *84*(1), 151–161. https://doi.org/10.1162/003465302317331982

Dziedzic, B., Idzik, A., Kobos, E., Sienkiewicz, Z., Kryczka, T., Fidecki, W., & Wysokiński, M. (2021). Loneliness and mental health among the elderly in Poland during the COVID-19 pandemic. *BMC Public Health*, *21*(1), 1976. https://doi.org/10.1186/s12889-021-12029-4

Fernández Castro, V., & Núñez de Prado Gordillo, M. (2023). *Dinámicas sociales en la explosión diagnóstica de la depresión* (Panorama Social No. 38). FUNCAS. https://dialnet.unirioja.es/servlet/articulo?codigo=9331954

Frölich, M., & Sperlich, S. (2019). *Impact Evaluation: Treatment Effects and Causal Analysis*. Cambridge University Press. https://doi.org/10.1017/9781107337008

Gao, Q., Zhang, Y., Sun, H., & Wang, T. (2022). Evaluation of propensity score methods for causal inference with high-dimensional covariates. *Briefings in Bioinformatics*, *23*(4), bbac227. https://doi.org/10.1093/bib/bbac227

García-Fernández, L., Romero-Ferreiro, V., López-Roldán, P. D., Padilla, S., & Rodriguez-Jimenez, R. (2020). Mental Health in Elderly Spanish People in Times of COVID-19 Outbreak. *The American Journal of Geriatric Psychiatry*, *28*(10), 1040–1045. https://doi.org/10.1016/j.jagp.2020.06.027

García-Prado, A., González, P., & Rebollo-Sanz, Y. F. (2022). Lockdown strictness and mental health effects among older populations in Europe. *Economics & Human Biology*, *45*, 101116. https://doi.org/10.1016/j.ehb.2022.101116

Gertler, P. J., Heckman, J., Pinto, R., Zanolini, A., Vermeersch, C., Walker, S., Chang, S. M., & Grantham-McGregor, S. (2014). Labor market returns to an early childhood stimulation intervention in Jamaica. *Science*, *344*(6187), 998–1001. https://doi.org/10.1126/science.1251178

Gertler, P. J., Martinez, S., Premand, P., Rawlings, L. B., & Vermeersch, C. M. J. (2011). *Impact Evaluation in Practice* (First Edition). World Bank. https://doi.org/10.1596/978-0-8213-8541-8

Hale, T., Angrist, N., Goldszmidt, R., Kira, B., Petherick, A., Phillips, T., Webster, S., Cameron-Blake, E., Hallas, L., Majumdar, S., & Tatlow, H. (2021). A global panel database of pandemic policies (Oxford COVID-19 Government Response Tracker). *Nature Human Behaviour*, *5*(4), 529–538. https://doi.org/10.1038/s41562-021-01079-8

Heckman, J. (1976). The Common Structure of Statistical Models of Truncation, Sample Selection and Limited Dependent Variables and a Simple Estimator for Such Models. *Annals of Economic and Social Measurement*, *5*(4), 475–492. http://www.nber.org/chapters/c10491

Heckman, J. (1990). Varieties of Selection Bias. *The American Economic Review*, *80*(2), 313–318. https://www.jstor.org/stable/2006591

Hill, R., Beynon-Davies, P., & Williams, M. D. (2008). Older people and internet engagement (M. Cushman & R. McLean, Eds.). *Information Technology & People*, *21*(3), 244–266. https://doi.org/10.1108/09593840810896019

Hirano, K., & Imbens, G. W. (2004). The Propensity Score with Continuous Treatments. In A. Gelman & X.-L. Meng (Eds.), *Applied Bayesian Modeling and Causal Inference from Incomplete-Data Perspectives* (Andrew Gelman, Xiao-Li Meng, pp. 73–84). John Wiley & Sons, Ltd. https://doi.org/10.1002/0470090456.ch7

ILO & EUROFUND. (2017). *Working anytime, anywhere: The effects on the world of work*. Publications Office of the European Union, and the International Labour Office. http://www.ilo.org/global/publications/books/WCMS_544138/lang--en/index.htm

Imbens, G. (2000). The Role of the Propensity Score in Estimating Dose-Response Functions. *Biometrika*, *87*(3), 706–710. https://www.jstor.org/stable/2673642

Imbens, G., & Wooldridge, J. M. (2009). Recent Developments in the Econometrics of Program Evaluation. *Journal of Economic Literature*, *47*(1), 5–86. https://doi.org/10.1257/jel.47.1.5

Krendl, A. C., & Perry, B. L. (2021). The Impact of Sheltering in Place During the COVID-19 Pandemic on Older Adults' Social and Mental Well-Being. *The Journals of Gerontology: Series B*, *76*(2), e53–e58. https://doi.org/10.1093/geronb/gbaa110

Lades, L. K., Laffan, K., Daly, M., & Delaney, L. (2020). Daily emotional well-being during the COVID-19 pandemic. *British Journal of Health Psychology*, *25*(4), 902–911. https://doi.org/10.1111/bjhp.12450

Layard, R., & Clark, D. M. (2014). *Thrive: How Better Mental Health Care Transforms Lives and Saves Money*. Princeton University Press. https://doi.org/10.2307/j.ctvc77595

López Ulloa, B. F., Møller, V., & Sousa-Poza, A. (2013). How Does Subjective Well-Being Evolve with Age? A Literature Review. *Journal of Population Ageing*, *6*(3), 227–246. https://doi.org/10.1007/s12062-013-9085-0

Luchetti, M., Lee, J. H., Aschwanden, D., Sesker, A., Strickhouser, J. E., Terracciano, A., & Sutin, A. R. (2020). The trajectory of loneliness in response to COVID-19. *American Psychologist*, *75*, 897–908. https://doi.org/10.1037/amp0000690

Martinez-Bravo, M., & Sanz, C. (2021). Inequality and psychological well-being in times of COVID-19: Evidence from Spain. *SERIEs*, *12*(4), 489–548. https://doi.org/10.1007/s13209-021-00255-3

Modigliani, F., & Brumberg, R. (1955). Utility analysis and the consumption function: An interpretation of cross-section data. *Post-Keynesian economics*. https://doi.org/10.7551/mitpress/1923.003.0004

Moreno, A., Lostao, L., & Regidor Poyatos, E. (2023). *Características sociodemográficas y tendencia de los problemas de salud mental en España en las dos primeras décadas del siglo XXI* (Panorama Social No. 38). FUNCAS. https://dialnet.unirioja.es/servlet/articulo?codigo=9331957

OECD. (2012). *Sick on the Job?: Myths and Realities about Mental Health and Work*. Organisation for Economic Co-operation and Development. https://doi.org/10.1787/9789264124523-en

OECD. (2020). *Job retention schemes during the COVID-19 lockdown and beyond* (OECD Contributions). OECD. https://doi.org/10.1787/0853ba1d-en

OECD. (2023). *Measuring Population Mental Health*. Organisation for Economic Co-operation and Development. https://doi.org/10.1787/5171eef8-en

Paccagnella, O., & Pongiglione, B. (2022). Depression deterioration of older adults during the first wave of the COVID-19 outbreak in Europe. *Social Science & Medicine*, *299*, 114828. https://doi.org/10.1016/j.socscimed.2022.114828

Pagán, R., & Malo, M. Á. (2023). *No todos sufrieron igual: efectos diferenciales de la pandemia en la salud mental de la población española* (Panorama Social No. 38). FUNCAS. https://dialnet.unirioja.es/servlet/articulo?codigo=9331958

Prati, G., & Mancini, A. D. (2021). The psychological impact of COVID-19 pandemic lockdowns: A review and meta-analysis of longitudinal studies and natural experiments. *Psychological Medicine*, *51*(2), 201–211. https://doi.org/10.1017/S0033291721000015

Recchi, E., Ferragina, E., Helmeid, E., Pauly, S., Safi, M., Sauger, N., & Schradie, J. (2020). The "Eye of the Hurricane" Paradox: An Unexpected and Unequal Rise of Well-Being During the Covid-19 Lockdown in France. *Research in Social Stratification and Mobility*, *68*, 100508. https://doi.org/10.1016/j.rssm.2020.100508

Rosenbaun, P. R., & Rubin, D. B. (1983). The central role of the propensity score in observational studies for causal effects. *Biometrika*, *70*(1), 41–55. https://doi.org/10.1093/biomet/70.1.41

Rubin, D. B. (1974). Estimating causal effects of treatments in randomized and nonrandomized studies. *Journal of Educational Psychology*, *66*(5), 688–701. https://doi.org/10.1037/h0037350

Serrano-Domingo, G., & Requena-Silvente, F. (2013). Re-examining the migration–trade link using province data: An application of the generalized propensity score. *Economic Modelling*, *32*, 247–261. https://doi.org/10.1016/j.econmod.2013.02.002

Tejero Pérez, A., & Doblytė, S. (2023). *La ventaja de trabajar: salud mental, pobreza y empleo en España* (Panorama Social No. 38). FUNCAS. https://dialnet.unirioja.es/servlet/articulo?codigo=9331959

UN. (2021). *The State of the World's Children 2021: On My Mind Promoting, Protecting and Caring for Children's Mental Health*. United Nations. https://doi.org/10.18356/9789210010580

Van Winkle, Z., Ferragina, E., & Recchi, E. (2021). The Unexpected Decline in Feelings of Depression among Adults Ages 50 and Older in 11 European Countries amid the COVID-19 Pandemic. *Socius: Sociological Research for a Dynamic World*, *7*, 23780231211032741. https://doi.org/10.1177/23780231211032741

WHO. (2020a). *The impact of COVID-19 on mental, neurological and substance use services: Results of a rapid assessment*. World Health Organization. https://www.who.int/publications/i/item/978924012455

WHO. (2020b). COVID 19 Public Health Emergency of International Concern (PHEIC). Global research and innovation forum: Towards a research roadmap. *R&DBlueprint*. https://www.who.int/publications/m/item/covid-19-public-health-emergency-of-international-concern-(pheic)-global-research-and-innovation-forum

WHO. (2022). *World Mental Health Report: Transforming Mental Health for All* (Report). World Health Organization. https://www.who.int/teams/mental-health-and-substance-use/world-mental-health-report

WHO & ILO. (2022). *Mental health at work: Policy Brief*. World Health Organization and International Labour Organization. https://www.ilo.org/global/topics/safety-and-health-at-work/areasofwork/workplace-health-promotion-and-well-being/WCMS_856976/lang--en/index.htm

Wilson, J. M., Lee, J., & Shook, N. J. (2021). COVID-19 worries and mental health: The moderating effect of age. *Aging & Mental Health*, *25*(7), 1289–1296. https://doi.org/10.1080/13607863.2020.1856778

Zapletal, A., Wells, T., Russell, E., & Skinner, M. W. (2023). On the triple exclusion of older adults during COVID-19: Technology, digital literacy and social isolation. *Social Sciences & Humanities Open*, *8*(1), 100511. https://doi.org/10.1016/j.ssaho.2023.100511

Zhao, S., van Dyk, D. A., & Imai, K. (2020). Propensity score-based methods for causal inference in observational studies with non-binary treatments. *Statistical Methods in Medical Research*, *29*(3), 709–727. https://doi.org/10.1177/0962280219888745

I Annex I

Table I.1: Variables.

Variable	Description
Outcome variables (Y_i):	
Sleep problems	Dummy. (1= respondent reported sleep problems in the last moth; 0= otherwise).
Depression symptoms	Dummy. (1= respondent reported symptoms of depression in the last moth; 0= otherwise).
Loneliness feelings	Dummy. (1= respondent reported feelings of loneliness in the last moth; 0= otherwise).
Change in Sleep problems	Dummy. (-1= Less sleep problems; 1= More sleep problems; 0= Same sleep problems).
Change in Depression symptoms	Dummy. (-1= Less depression; 1= More depression; 0= Same depression).
Change in Loneliness feelings	Dummy. (-1= Less loneliness feelings; 1= More loneliness feelings; 0= Same loneliness feelings).
Mental Health Index	Composite index 0-3. (0= No problems; 3= Sleep, depression and loneliness).
Change in Mental Health Index	Range (-3, 3). Higher: Worse MH than before pandemic. Lower: better MH than before the pandemic.
Treatment variable (T_i):	
Lockdown Strictness Index	Continuous treatment: Index of containment policies from OxCGRT (Country level).
Control variables (X_i):	
Gender	Dummy (0=Male, 1=Female).
Country	Dummy. Country of interview (1-27).
Language	Dummy. Language of interview (1-38).
Age	Numeric. Age of individuals at interview.
Age^2	Numeric. Squared age of individuals at interview.
Education:	
Secondary Education	Dummy. (1 = Secondary education, 0 = Other).
Tertiary Education	Dummy. (1 = Tertiary education, 0 = Other).
Children:	
Children	Dummy. (1 = 1 or more children, 0 = No children).
No Children	Dummy. (1 = No children, 0 = Other).
Labour market:	
Retired	Dummy. (1 = Retired, 0 = Other).
Unemployed	Dummy. (1 = Unemployed, 0 = Other).
Sick or disabled	Dummy. (1 = Sick or disabled, 0 = Other).
Homemaker	Dummy. (1 = Homemaker, 0 = Other).
Job status	Dummy. Different labour market status (1-6).
Cohort:	
Before 1930	Dummy. (1= Born before 1930, 0= Other).
1930-1940	Dummy. (1= Born between 1930 - 1940, 0= Other).
1940-1950	Dummy. (1= Born between 1940 - 1950, 0= Other).
1950-1960	Dummy. (1= Born between 1950 - 1960, 0= Other).
1960-1970	Dummy. (1= Born between 1960 - 1970, 0= Other).
Social Contacts:	
Contact Children	Dummy. Contact frequency with their children since COVID-19 outbreak (1-5).
Contact Relatives	Dummy. Contact frequency with relatives since COVID-19 outbreak (1-5).
Contact Others	Dummy. Contact frequency others since COVID-19 outbreak (1-5).
EContact child	Dummy. Electronic contact frequency with their children since COVID-19 outbreak (1-5).
EContact relatives	Dummy. Electronic contact frequency with relatives since COVID-19 outbreak (1-5).
EContact Others	Dummy. Electronic contact frequency with their children since COVID-19 outbreak (1-5).
Country-specific variables:	
Max COVID Cases	Numeric. Max confirmed positive COVID-19 cases in the country.
Max COVID Deaths	Numeric. Max confirmed COVID-19 related deaths in the country.
Pop Vaccinated	Numeric. Max population vaccinated in the country.
Pop 2022	Population of the country (2022).
Economic:	
Finantial Support	Dummy. (1= Received finantial support since COVID-19 outbreak; 0= No).
Health:	
Long-term illness	Dummy. (1= Long-term illness; 0= No).

Source: SHARE, OxCGRT.

II Annex II

Table II.1: Summary statistics and GPS coefficients.

	Summary statistics				GPS model	
	Mean	Std. Dev.	Max	Min	GPS coeff.	s.e.
Outcome variables						
Sleep problems	0.318	0.466	0.00	1.00		
Depression symptoms	0.314	0.464	0.00	1.00		
Loneliness feelings	0.291	0.454	0.00	1.00		
Change in Sleep problems	-0.049	0.524	-1.00	1.00		
Change in Depression feelings	-0.096	0.558	-1.00	1.00		
Change in Loneliness feelings	0.041	0.489	-1.00	1.00		
MHI	0.921	0.991	0.00	3.00		
MHI Change	-0.105	1.018	-3.00	3.00		
Treatment variable						
Containment index	59.265	7.519	43.44	73.98		
Control variables						
Gender	0.583	0.493	0.00	1.00	-0.901***	0.073
Country	13.748	7.751	1.00	27.00	-0.124***	0.008
Languauge	19.573	10.208	1.00	38.00	0.164***	0.007
Age	70.169	9.198	32.00	105.00	-0.220**	0.112
Age^2	5,008.340	1,311.648	1,024.00	11,025.00	0.001	0.001
Secondary education	0.146	0.353	0.00	1.00	-2.769***	0.092
Tertiary education	0.069	0.254	0.00	1.00	-2.983***	0.123
Children	0.914	0.280	0.00	1.00	-1.495**	0.700
No Children	0.081	0.273	0.00	1.00	-0.902	0.764
Retired	0.472	0.499	0.00	1.00	1.169***	0.132
Unemployed	0.010	0.100	0.00	1.00	-0.466	0.356
Sick or disabled	0.015	0.121	0.00	1.00	-1.749***	0.335
Homemaker	0.047	0.212	0.00	1.00	3.105***	0.288
Before 1930	0.022	0.145	0.00	1.00	1.649*	0.930
1930-1940	0.163	0.369	0.00	1.00	1.858**	0.880
1940-1950	0.342	0.475	0.00	1.00	1.582*	0.871
1950-1960	0.360	0.480	0.00	1.00	1.153	0.824
1960-1970	0.109	0.312	0.00	1.00	1.568**	0.758
Job status	2.109	1.968	0.00	5.00	0.395***	0.068
Contact children	2.707	1.300	1.00	5.00	-0.598***	0.030
Contact relatives	3.882	1.076	1.00	5.00	-0.416***	0.042
Contact others	3.291	1.270	1.00	5.00	0.455***	0.031
EContact children	2.068	1.107	1.00	5.00	-0.222***	0.034
EContact relatives	3.156	1.093	1.00	5.00	-0.203***	0.039
EContact others	3.125	1.155	1.00	5.00	-0.005	0.035
Max COVID Cases	1,427,632.087	1,638,096.163	30,623.00	5,863,138.00	-0.000***	0.000
Max COVID Deaths	32,373.008	39,399.954	375.00	127,566.00	0.000***	0.000
Pop vaccinated	33.112	8.361	5.85	61.11	0.190***	0.004
Pop 2022	20,003,991.350	24,633,845.633	520,971.00	83,237,124.00	-0.000***	0.000
Finantial support	0.132	0.339	0.00	1.00	1.174***	0.081
Long-term illness	0.548	0.498	0.00	1.00	-2.138***	0.069
Constant					62.878***	3.686
Observations	98,071				27,157	
R-squared					0.443	

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Source: SHARE, OxCGRT, and own calculations.

III Annex III

Table III.1: Estimated parameters of the conditional distribution of mental health outcomes given lockdown index and the GPS.

	(1) Depression Symptoms	(2) Sleep Problems	(3) Loneliness Feelings	(4) Mental Health Index	(5) Chage in Depression	(6) Change in Sleep	(7) Change in Loneliness	(8) Change in MHI
Lockdown index	0.648**	0.375	-0.065	1.055*	0.259	-0.092	-0.389**	-0.232
	(0.183)	(0.189)	(0.188)	(0.385)	(0.309)	(0.106)	(0.124)	(0.479)
Lockdown index^2	-0.011**	-0.006	0.001	-0.018*	-0.004	0.002	0.006**	0.004
	(0.003)	(0.003)	(0.003)	(0.007)	(0.005)	(0.002)	(0.002)	(0.008)
Lockdown index^3	0.000**	0.000	0.000	0.000*	0.000	-0.000	-0.000*	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
GPS	-14.599*	-21.489**	18.000*	-21.418	5.300	4.019	15.915***	25.975*
	(5.939)	(6.254)	(8.221)	(18.591)	(6.830)	(3.596)	(3.581)	(12.156)
GPS X Lockdown index	0.210*	0.338**	-0.331*	0.272	-0.124	-0.084	-0.257***	-0.476*
	(0.097)	(0.098)	(0.128)	(0.295)	(0.101)	(0.057)	(0.056)	(0.181)
Constant	-12.090**	-6.694	1.961	-18.647*	-5.152	1.539	7.798**	4.389
	(3.462)	(3.627)	(3.576)	(7.274)	(6.007)	(1.967)	(2.383)	(9.274)
Observations	21,966	22,073	21,992	21,943	21,767	21,819	21,753	21,676
AIC	27,485.84	28,335.54	27,316.01	61,934.56	36,058.87	33,483.01	29,755.54	61,859.52
R^2	0.0059	0.0154	0.0349	0.0110	0.0082	0.0023	0.0040	0.0091

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
Standard errors in parentheses

Source: SHARE, OxCGRT, and own calculations.

IV Annex IV

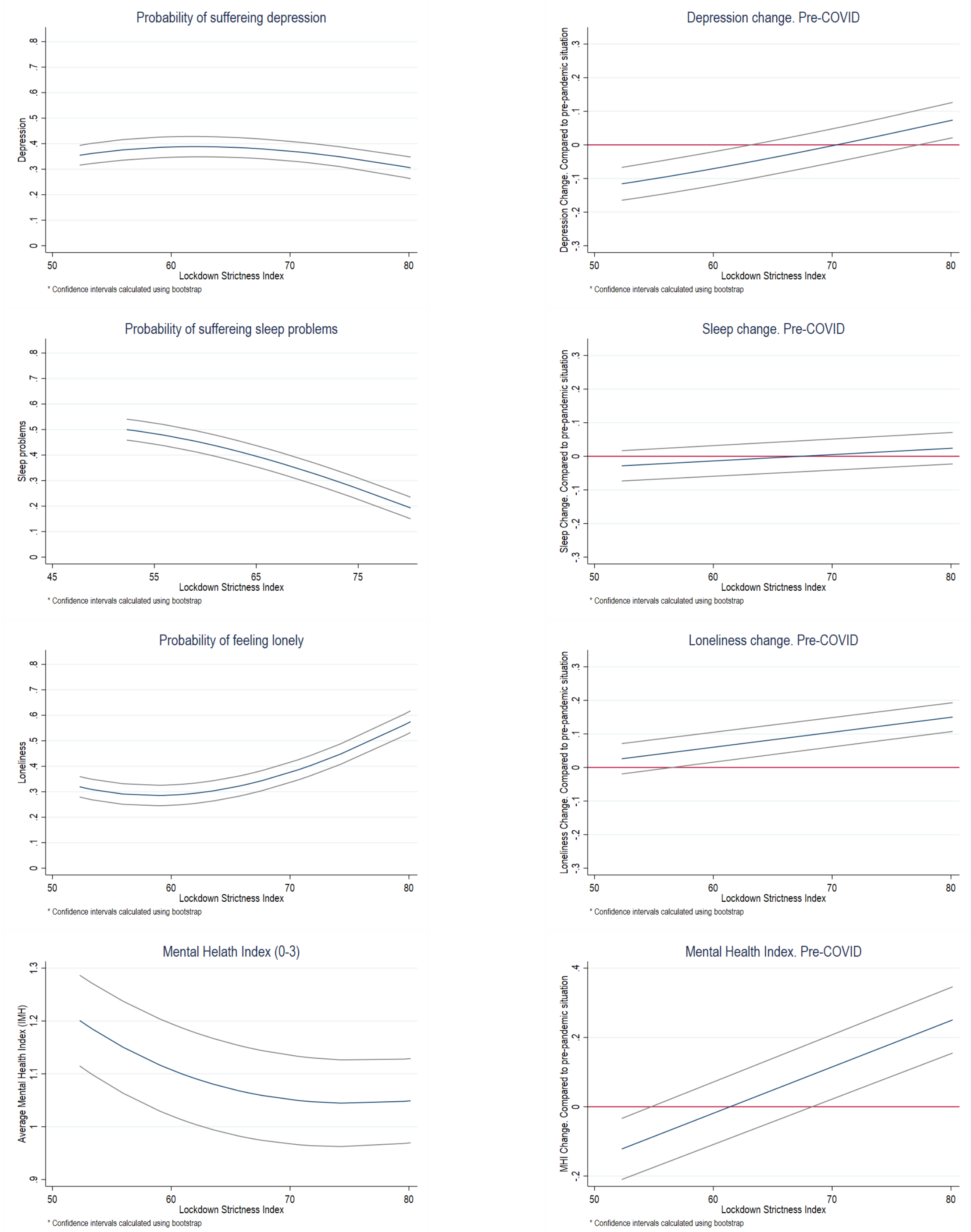


Figure IV.1: Dose-response functions. Lockdown strictness index from March 2021 to June 2021.
Source: SHARE, OxCGRT, and own calculations.

V Annex V

Table V.1: Probit model coefficients. Probability of depression, loneliness, and sleep problems.

	Depression		Sleep		Loneliness	
L2.Gender	0.250***	(0.0189)	0.178***	(0.0188)	0.226***	(0.0191)
L2.Age	0.004	(0.0202)	-0.016	(0.0201)	-0.024	(0.0204)
L2.Age^2	0.000	(0.0001)	0.000	(0.0001)	0.000*	(0.0001)
L2.Country	-0.005***	(0.0015)	-0.005***	(0.0015)	-0.011***	(0.0016)
L2.Languauge	0.003***	(0.0012)	0.002	(0.0012)	0.008***	(0.0012)
L2.Primary education	0.077	(0.0567)	0.074	(0.0579)	0.214***	(0.0571)
L2.Secondary education	0.063***	(0.0235)	0.115***	(0.0233)	0.077***	(0.0236)
L2.Tertiary education	0.071**	(0.0320)	0.130***	(0.0318)	0.055*	(0.0324)
L2.Children	-0.507***	(0.1444)	-0.445***	(0.1470)	-0.344**	(0.1504)
L2.No Children	-0.428***	(0.1467)	-0.436***	(0.1494)	-0.194	(0.1527)
L2.Before 1930	-0.103	(0.1262)	-0.111	(0.1269)	-0.270**	(0.1283)
L2.1930-1940	0.035	(0.0818)	-0.030	(0.0817)	-0.026	(0.0828)
L2.1940-1950	-0.016	(0.0619)	0.002	(0.0615)	-0.078	(0.0625)
L2.1950-1960	-0.042	(0.0429)	-0.002	(0.0427)	-0.058	(0.0433)
L2.Weight	0.000	(0.0006)	0.002***	(0.0006)	0.000	(0.0006)
L2.Long-term illness	0.138***	(0.0176)	0.174***	(0.0175)	-0.024	(0.0178)
L2.Trouble with pain	0.203***	(0.0173)	0.224***	(0.0172)	0.147***	(0.0176)
L2.Smoke daily	0.005	(0.0171)	-0.004	(0.0171)	-0.038**	(0.0173)
L2.Household size	0.030***	(0.0090)	-0.007	(0.0091)	-0.104***	(0.0095)
L2.Loneliness feelings	0.416***	(0.0180)	0.173***	(0.0184)	1.039***	(0.0180)
L2.Sleep problems	0.193***	(0.0171)	0.900***	(0.0168)	0.048***	(0.0177)
L2.Depression symptoms	0.575***	(0.0171)	0.145***	(0.0174)	0.243***	(0.0177)
Constant	-1.337*	(0.6996)	-0.566	(0.6982)	-0.111	(0.7061)
Observations	31,085		31,122		31,065	

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

t statistics in parentheses

Source: SHARE, OxCGRT, and own calculations.

VI Annex VI

Table VI.1: Probit model coefficients. Probability of survive.

	Probabillity of survive	
L2.Gender	0.4538***	(0.04)
L2.Age	0.0104	(0.05)
L2.Age^2	-0.0004	(0.00)
L2.Country	-0.0017	(0.00)
L2.Languauge	-0.0026	(0.00)
L2.Primary education	-0.2685***	(0.10)
L2.Secondary education	-0.2320***	(0.05)
L2.Tertiary education	-0.1983***	(0.07)
L2.Children	-0.1223	(0.42)
L2.No Children	-0.1460	(0.43)
L2.Before 1930	-0.1156	(0.26)
L2.1930-1940	-0.0569	(0.23)
L2.1940-1950	0.0079	(0.20)
L2.1950-1960	-0.0604	(0.15)
L2.Weight	-0.0007	(0.00)
L2.Long-term illness	-0.3275***	(0.04)
L2.Trouble with pain	-0.0126	(0.04)
L2.Smoke daily	-0.0811**	(0.04)
L2.Household size	-0.1114***	(0.02)
L2.Loneliness feelings	-0.0704*	(0.04)
L2.Sleep problems	-0.0622	(0.04)
L2.Depression symptoms	-0.0748*	(0.04)
Constant	3.9630**	(1.96)
Observations	31,803	

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

t statistics in parentheses

Source: SHARE, OxCGRT, and own calculations.

VII Annex VII

Table VII.1: MHI by European country and year.

	2019	2020	2021	Average
Austria	0.902	0.688	0.725	0.771
Belgium	1.033	0.797	0.851	0.894
Bulgaria	0.819	0.833	1.186	0.945
Croatia	1.071	0.918	1.125	1.038
Cyprus	0.877	0.744	0.789	0.805
Czech Republic	1.044	0.723	0.827	0.866
Denmark	0.742	0.402	0.474	0.541
Estonia	1.257	0.926	1.121	1.101
Finland	1.030	0.619	0.763	0.805
France	1.168	0.897	1.024	1.030
Germany	1.049	0.729	0.870	0.883
Greece	0.879	0.899	1.035	0.938
Hungary	0.907	0.901	1.138	0.980
Israel	1.137	0.857	1.112	1.034
Italy	1.122	1.063	1.126	1.103
Latvia	1.242	0.918	1.192	1.118
Lithuania	1.229	0.929	1.155	1.104
Luxembourg	1.003	0.787	0.860	0.883
Malta	0.933	0.792	0.872	0.866
Netherlands	0.948	0.560	0.553	0.689
Poland	1.247	1.017	1.073	1.113
Romania	1.211	0.893	0.891	1.000
Slovakia	0.900	0.908	1.034	0.948
Slovenia	0.941	0.667	0.775	0.793
Spain	0.974	0.882	0.878	0.912
Sweden	0.856	0.605	0.617	0.693
Switzerland	0.842	0.552	0.660	0.685
Total	1.031	0.809	0.924	0.921
Observations	32,338	32,253	31,896	96,487

Source: SHARE and own calculations.

VIII Annex VIII

Table VIII.1: MHI by European region and year.

	2019	2020	2021	Average
Balkans	1.077	0.891	1.043	1.003
Central Europe	0.995	0.749	0.853	0.866
Eastern Europe	1.247	0.925	1.141	1.104
Mediterranean	0.983	0.919	1.018	0.973
Nordic	0.865	0.529	0.604	0.667
Western Europe	1.069	0.806	0.883	0.920
Total	1.031	0.809	0.924	0.921
Observations	32,338	32,253	31,896	96,487

Note: Western Europe: France, Belgium, Netherlands, Luxembourg; Central Europe: Germany, Austria, Switzerland, Slovakia, Czech Republic, Poland, Hungary, Slovenia; Eastern Europe: Estonia, Latvia, Lithuania; Mediterranean: Spain, Italy, Greece, Malta, Israel; Balkans: Croatia, Romania, Bulgaria; Nordic: Finland, Sweden, Denmark

Source: SHARE and own calculations.

IX Annex IX

Table IX.1: Multilevel model ICC coefficients at country level.

Dependent Variable	ICC
Sleep problems	0.0208
Depression symptoms	0.0126
Loneliness feelings	0.0334
Change in Sleep problems	0.0117
Change in Depression symptoms	0.0235
Change in Loneliness feelings	0.0089
Mental Health Index	0.0224
Change in Mental Health Index	0.0259

Source: SHARE and own calculations.

X Annex X

Table X.1: Multilevel model ICC coefficients at European regional level.

Dependent Variable	ICC
Sleep problems	0.0184
Depression symptoms	0.0072
Loneliness feelings	0.0237
Change in Sleep problems	0.0034
Change in Depression symptoms	0.0052
Change in Loneliness feelings	0.0034
Mental Health Index	0.0185
Change in Mental Health Index	0.0086

Source: SHARE and own calculations.