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# The effect of COVID-19 confinement and economic support measures on the mental health of older population in Europe and Israel



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# ABSTRACT

This study focuses on the impact of confinement and economic support measures on the mental health of the older population (aged 50 and above) across twenty-five European countries and Israel. While studies evaluating the effect of confinement measures on mental health exist, they largely ignore the potentially offsetting effects of economic support measures. Moreover, previous findings on the effect of confinement measures are inconsistent, and many studies are based solely on cross-sectional designs. Using data from the Corona Survey wave (2020) of the Survey on Health, Ageing and Retirement in Europe (SHARE), we leverage the date of interview information to vary individual exposure to different policy contexts within countries. Overall, we do not find support for the negative effect of confinement measures on older adults' mental health. If anything, both confinement and euffects, however, are contingent on age, potentially indicating that younger people are more likely to be negatively affected by lockdowns.

# 1. Introduction

The COVID-19 pandemic has profoundly affected peoples' lives all across the globe. The dangerous and very contagious virus prompted governments in many countries to adopt unprecedented confinement measures to prevent the overload of public healthcare systems. Social distancing, restrictions on mobility and mass gatherings, the closure of schools, cafes, and restaurants, and other confinement measures caused profound disruptions in people's everyday routines. Such disruptions might be a source of great stress (Landa-Blanco et al., 2021) leading to lowered mental health.

Vast majority of earlier research align with this assumption. Several reviews that summarized this earlier research conclude that lockdown measures indeed have substantially harmed people's mental health (Luo et al., 2020; Salari et al., 2020; Singh et al., 2020; Vindegaard and Benros, 2020; Panchal et al., 2021). In a more recent review, however, Prati and Mancini (2021) fairly acknowledge that much of the earlier research suffers from methodological limitations due to cross-sectional designs and the absence of appropriate control groups. These limitations, in particular, make it difficult to disentangle the effect of the pandemic situation itself from that of the lockdown policies (also noted

by Richter et al., 2021). Prati & Mancini's meta-analysis of studies based on longitudinal and natural-experiment research designs reveals that lockdown effects on mental health are, in fact, relatively small and "that most people are psychologically resilient to their effects" (p. 201). They also "found no significant moderation effects for mean age, gender, continent, COVID-19 death rate, days of lockdown, publication status or study design" (Ibid). These conclusions thus underplay the conclusions from the reviews of earlier evidence.

Our study contributes to the current state of this knowledge in three important respects. Firstly, we revisit the conclusion of Prati & Mancini by focusing on the older populations of 25 European countries and Israel. We do so by combining data from the Corona Survey wave (2020) of the Survey on Health, Ageing and Retirement in Europe (SHARE) with the data from the Oxford Coronavirus Government Response Tracker (OxCGRT). We are not the first to use this combination of the data (Voss et al., 2021; Atzendorf and Gruber, 2021). A unique feature of our research design is that we link SHARE data to that of OxCGRT via the date of interview, with which we leverage both between- and within-country variance in respondents' mental health (SHARE) as well as pandemic and policy contexts (OxCGRT). This circumvents the problem recognized in previous reviews (Prati and Mancini, 2021;

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Received 21 June 2022; Received in revised form 6 October 2022; Accepted 8 October 2022 Available online 14 October 2022 0277-9536/© 2022 Elsevier Ltd. All rights reserved. Richter et al., 2021) by disentangling the effects of the pandemic itself from those of the policies implemented in different countries.

Secondly, by leveraging our research design we consider more nuances in COVID-19 policies in evaluating their overall effect on mental health. In particular, we consider not only the implementation and/or duration of lockdowns but also the varying degree of lockdown stringency, which many previous studies did not address (Prati and Mancini, 2021; Richter et al., 2021). In addition, we investigate the effect of economic support measures, which in many countries have been implemented alongside confinement measures and which may potentially countervail the negative effects of the latter. To our knowledge, only one study has considered such possibility in practice, but it has focused on life satisfaction and was limited to a handful of European countries (Clark and Lepinteur, 2021).

Thirdly, we pick up on Prati & Mancini's regret that their moderator analyses "were limited to gender and age, because characteristics such as socioeconomic status, education, and working status were not reported in some studies" (p. 209). Our analysis overcomes this limitation and explores how the effect of different policies varied by different subgroups of the elderly population such as those defined not just by gender and age, but also by socioeconomic characteristics, such as education and wealth.

The article is structured as follows. In the next section, we briefly review theoretical and empirical arguments linking COVID-19 policies to mental health, and their possible variations by gender, age and socioeconomic background. After that we introduce our pseudolongitudinal research design combining the SHARE and the OxGRT data. In the remaining part, we detail and discuss our findings. We conclude by reviewing the contributions and the practical implications of our study, its limitations, and by providing recommendations for future research.

#### 2. Theory and hypotheses

# 2.1. Confinement stringency and mental health

Confinement measures generally refer to the government interventions that limit physical interaction between people to contain the spread of the pandemic. During the COVID-19 pandemic national governments have implemented a variety of measures. Typically, they included restrictions on mobility and mass gatherings, the shift to homeoffice working arrangements, the closure of schools, cafes, and restaurants, curfews as well as quarantining and self-isolation measures for those who are under high risk of contracting COVID-19 with graver health consequences.

The common intuition is to expect such restrictive measures to negatively affect mental well-being. Numerous mechanisms can mediate this effect. For example, lockdowns confine social and physical contact, whereby people are deprived of an important source of socializing and moral support (e.g., Shir-Wise, 2021). They also reduce access to many usual entertainment opportunities, such as dining out, traveling and attending popular sites and events, which can make people feel bored and unhappy (Martinelli et al., 2021). Some may even regard this as a violation of their basic freedoms, causing disappointment with their governments and paradoxically instigating a sense of insecurity rather than protection (Cheung and Ip, 2020). Above all that, the lifestyles during a lockdown present a radical discontinuity with the usual lifestyles (such as switching to home-office and/or home-schooling arrangements, spending an unusually large amount of time with family members and so on) (De Haas, Faber and Hamersma, 2020; Navas-Martín et al., 2021), and adapting to those can be a source of great stress and frustration in itself (e.g., Abd El-Fatah et al., 2021).

But should the lockdown effects on mental health be exclusively negative? The explicit purpose of lockdowns is to protect people by decreasing their chance of getting sick with the dangerous disease and/ or receiving inadequate medical help due to overloaded healthcare system. As such, stricter lockdowns can also contribute to the sense of security and, with it, have a positive effect on mental health. Accordingly, this should be particularly the case for those people, who have the highest risk of suffering the most unpleasant consequences of the COVID-19, i.e., various health complications or death. Besides, we should not dismiss the possibility that people can, to a certain extent, overcome certain negative implications of restrictive measures. For example, the lack of physical social contact can partly be compensated for through telecommunication. Similarly, usual leisure opportunities can be substituted by the "new" ones, such as reading, watching TV shows, exercising at home, self-educating and many others.

The ultimate strength and the direction of the effect of lockdowns on mental health would thus be a combination of both negative and positive influences. This study focuses on the older people, for whom COVID-19 poses a greater danger (Lithander et al., 2020). It is therefore reasonable to expect the positive, i.e., protective, effects of lockdowns to offset the negative ones more effectively in older generations, when compared to the general population. On the other hand, more stringent lockdowns potentially contribute to social disengagement, which has been shown to have particularly detrimental effects on the mental health of older people (Luhmann and Hawkley, 2016). The ultimate influence is thus hard to predict with confidence, but below we contemplate on a number of more specific predictions when attending to more subtle variations by age.

#### 2.2. Economic support and mental health

COVID-19 lockdowns were not costless measures. They caused large disruptions in the national economies and put many people in a situation of unprecedented economic insecurity by leaving them unemployed (even if only temporarily). This prompted many governments to implement various measures of economic support, including those that directly target households, i.e., measures such as direct income support, debt relief programs, tax reductions and others. The sense of economic insecurity is a source of great stress (Odle-Dusseau, Matthews and Wayne, 2018) and, as such, it has a strong negative impact on mental health. It is therefore reasonable to expect the scope and extent of economic support to have a positive effect on mental health, particularly in those groups which are directly hit by the negative economic consequences of lockdowns and thus constitute the target groups for such programs.

Older people, however, are more likely to be immune to such measures than the general population on average for the following reasons. First of all, they are much less likely to be hit by the negative economic consequences of lockdowns because many of them are already retired and do not have large debts (Hansen et al., 2008). Besides, those who are not yet retired might be close to leaving the labor force and receiving the retirement benefits, which can also minimize the sense of insecurity stemming from the concerns about future unemployment. Older people are also usually not burdened by younger dependents, who, in situations of economic insecurity, can be a source of particularly great anxiety to younger parents (Nelson et al., 2014). Yet, the response of older people to economic support can be quite positive, without the measures directly affecting them. The extent and scope of such support can signal that the state has matters under control, instilling the sense of security. Besides, even if older people do not have younger dependents, their mental health might benefit from the support that might be potentially received by others, including adult children, other relatives and friends, as well as from generally more positive outlook on the national economy affairs, giving them less reasons for concern. Such positive effects, on the other hand, might be tempered if the intensity of state economic support is merely a response to financial and economic problems, which on their own can be a source of serious distress in the population.

#### 2.3. Variations by age

Older people are a group of relatively large age range, making their internal heterogeneity a non-negligible factor. Indeed, it is plausible to suggest that COVID-19 policies can have a varying effect on mental health, contingent on more specific individual age. As far as the effects of lockdowns are concerned, we contend that the balance of positive influences and negative influences would shift in a more favorable direction with age. Among the oldest old the imposition of restrictive measures possibly implies less radical departure with previous routines due to naturally higher levels of social disengagement typical of their age (Johnson and Barer, 1992). Thus, it should lead to fewer negative influences on their mental health. On the other hand, the consequences of COVID-19 get particularly dangerous with age, which implies that their protective effect also increases in relevance, leading to more positive influences.

As far as economic support measures are concerned, we expect their positive effect on the mental health of older people would decrease with age. Similar to the arguments already outlined above, fewer of them would potentially qualify for such measures due to being out of the labor force and/or having large debts, as well as fear the risk of unemployment.

#### 2.4. Variations by gender

Confinement experiences might also be gendered. Given that women are more at risk of psychological disturbances in general (ESE-MeD/MHEDEA 2000 et al., 2004), more prone to caregiver burden as primary caregivers (Barusch and Spaid, 1989), and more vulnerable to domestic violence (Roesch et al., 2020), it is reasonable expect their mental health to be more negatively affected by confinement stringency compared to that of men. Besides, given that COVID-19 is more dangerous to men (Brodin, 2021), they are less likely to appreciate the protective effect of confinement measures.

As far as the effect of economic support, is concerned one can expect men to benefit more because women are less likely to be the target of respective measures, due to their generally lower rates in labor force participation (Del Boca et al., 2020). On the other hand, one could think that, in couples, this argument might be irrelevant because if one partner can reckon with such support then the other would benefit also. In fact, there are good reasons to suggest that the mental well-being of women might benefit even more from economic support measures. Indeed, loss of employment and reduced income are factors known to increase the risk of domestic violence against women (Sharma and Borah, 2020). Therefore, the gender implications of the governmental support measures of countries are not that obvious as also pointed out by a few recent studies (Hidrobo et al., 2020).

#### 2.5. Variations by socioeconomic status

Social scientists uniformly agree that quality of life, in general, and health conditions, in particular, are positively associated with economic resources. That is, wealthier people and individuals of higher socioeconomic standing not only enjoy a higher standard of living than poor people, but they also tend to be healthier and to live longer (Maskileyson, 2014). Rich people have better access than poor people to high quality medical technologies, expensive treatment, healthy nutrition and preventive medicine. Hence, the rich are in a better position to prevent or delay illness, and to treat sickness when it occurs (Deaton, 2008). Therefore, we expect variations in the effect COVID-19 related measures on the mental health of older people by socioeconomic status. More socioeconomically advantaged individuals are more resourceful and therefore have greater adaptive capacity to withstand the negative effects of confinement. There are also least likely to suffer economic hardships as a result of it.

# 3. Data

We utilize data from the SHARE Corona Survey (release 1.0.0 as of June 23rd, 2020) (Börsch-Supan et al., 2013; Bergmann, 2019; Börsch-Supan, 2021; Börsch-Supan, 2022). The survey was carried out between June and August 2020 in 27 European countries and Israel as part of Wave 8 data collection program for the Survey of Health, Ageing and Retirement in Europe (SHARE). SHARE is a large-scale cross-national panel study collecting data on health, socioeconomic status, and social and family networks of people who are 50 years and older. The more specific Corona Survey was developed in response to the COVID-19 pandemic crisis and the prolonged lockdowns. The data were collected via Computer Assisted Telephone Interviews (CATI). The survey covered the same topics as the regular SHARE questionnaire but shortened and targeted to the COVID-19 situation (e.g., physical health and health related behavior, mental health, infections and healthcare, changes in work and economic situation, social networks). The complete questionnaire can be found online (SHARE COVID-19 questionnaire for telephone interviews, 2020) (for more detailed information on methodological adaptions and the innovations of this new questionnaire see Scherpenzeel et al., 2020).

We enhance the use of SHARE Corona Survey with the use of Additional COVID-19 Interview Date Data (release 1.0.0 as of June 23rd, 2020) (Börsch-Supan et al., 2013; Börsch-Supan, 2021; Börsch-Supan, 2022). Data collection periods varied for different countries participating in SHARE ranging between 41 days (in Luxembourg) and 78 days (in Belgium), with an average of 55.6 days for the 28 participant countries. Most of the collection period landed on June-July 2020, i.e., the summer period, in which various countries started to lift the COVID-19-related restrictions. The interview data thus provides a leverage, which allows us to contextualize the Corona Survey respondents in time and, accordingly, to assign them to various confinement (e.g., lockdown) and support (e.g., financial support) measures. Our analytical sample included 26 countries. We excluded Ireland because it did not participate in Wave 7 which we merged with Corona survey to attach general information on several variables and the Netherlands because information on the date of the interview essential for our analysis was missing.

The macro level data on response measures were obtained from the Oxford Coronavirus Government Response Tracker (OxCGRT). It provides continuously updated, readily useable and comparable information on policies related to closure and containment, health and economic policy for more than 180 countries (Hale et al., 2021). The data are collected and maintained by the Blavatnik School of Government and the University of Oxford. Policy responses in this dataset are recorded on ordinal or continuous scales for 19 policy areas, capturing variation in degree of response. In addition to these more specific indicators, the producers of OxCGRT offer four convenience indices that aggregate the data into a single number from 0 to 100: the Overall Government Response Index, the Containment and Health index, the Stringency Index, and the Economic Support Index. All these indices are simply normalized averages of different combinations of individual component indicators (more specifically, their ordinal versions, in which relevant policies are ranked on a simple numerical scale<sup>1</sup>). The detailed methodology for calculating the indices is available online (Covid-Policy--Tracker, 2020). OxCGRT tracks all its different indicators in a daily time-series format.

<sup>&</sup>lt;sup>1</sup> An example for school closing measures would be: "0" for no measures, "1" for the recommendation to close schools or have them open with some minor restrictions, "2" for selective mandatory closures and "3" for mandatory closure at all levels.

#### Table 1

Description of variables.

Variable	Description and measurement
OUTCOME VARIABLES	
Sleep problems	Source/variable: SHARE Corona Survey/camh007_
	"1" for respondents reporting having had trouble sleeping
Dennessian	recently or recent change in pattern, "0" otherwise
Depression	"1" for respondents reporting having felt pervous anxious
	or on edge in the last month. "0" otherwise
Anxiety	Source/variable: SHARE Corona Survey/cah020_
	"1" for respondents reporting having felt sad or depressed in
	the last month, "0" otherwise
INDEPENDENT VARIAE	LES OF INTEREST
stringency index	The index records the strictness of 'lockdown style' policies
	that primarily restrict people's behavior. It is calculated
	using all ordinal containment and closure policy indicators,
	plus an indicator recording public information campaigns. It
	ranges from 0 to 100 corresponding to minimum and
	maximum stringency accordingly. The end values are daily index values averaged over 14 days preceding the date of
	interview (see Methods section for more detail).
Economic Support	Source/variable: OxCGRT/Economic Support Index
Index	The index records measures such as income support and debt
	relief. It is calculated using all ordinal economic policies
	indicators. It ranges from 0 to 100 corresponding to
	are daily index values averaged over 14 days preceding the
	date of interview (see Methods section for more detail).
CONTROLS	
COVID-19 Cases	Source/variable: OxCGRT/Confirmed Cases
	We transformed the original variable to measure daily new
	as of 2020 (according to World Bank). The end values are
	daily index values averaged over 14 days preceding the date
	of interview (see Methods section for more detail).
COVID-19 Deaths	Source/variable: OxCGRT/Confirmed Deaths
Dava sinas	We applied similar transformation as above.
outbreak	Date Data/int year ca int month ca int day ca
outbroak	The number of days since the first reported COVID-19
	positive case in a country.
Gender	Source/variable: SHARE Corona Survey/cadn042_
4.00	"1" for female, "0" for male
Age	2020 minus year of respondent's birth
Subjective health	Source/variable: SHARE Corona Survey/caph003
•	Subjective health before outbreak: Before the outbreak of
	Corona, would you say your health was excellent, very good,
	good, fair, or poor? Measured on a 5-point scale with "1"
	health
COVID-19 Contact	Source/variable: SHARE Corona Survey/cac002_
	"1" for respondents reporting knowing anyone who had
	COVID-19 symptoms, "0" otherwise
Job loss	Source/variable: SHARE Corona Survey/caw002_
	"1" for respondents reporting being unemployed, laid off or closing business due to COVID 19. "0" otherwise
Education	Source/variable: SHARE wave 7/vedu (generated and
	imputed by SHARE from DN041 (in w1 based on
	International Standard Classification of Education (ISCED))
	Years of education, in years
Income	The end value is the value standardized by country.
meonie	imputed by SHARE from the question on monthly household
	income (HH017))
	Monthly total household income, in Euro
	The end value is calculated as ln (original value $+$ 3),
	standardized by country.

# 4. Method

To estimate the effect of government response (i.e., confinement and economic support) measures on different indicators of mental health, we adopt the following strategy. First, we link SHARE Corona Survey individual-level data to OxCGRT country-level time-varying data via the date of interview. This affords us a pseudo-longitudinal design, whereby respondents surveyed on different dates are treated as time series observations, representing different contexts of pandemic development and relevant government response measures. We then estimate a series of logistic regression models of the following general kind:

 $Outcome_{ict} (log odds) =$ 

$$= \underbrace{\beta_1 \overline{SI}_{ct} + \beta_2 \overline{ESI}_{ct}}_{variables of interest} + \underbrace{\beta_3 \overline{\Delta Cases}_{ct} + \beta_4 \overline{\Delta Deaths}_{ct} + \beta_5 Days_{ct}}_{pandemic context controls} + \underbrace{\beta_3 \overline{\Delta Cases}_{ct} + \beta_4 \overline{\Delta Deaths}_{ct} + \beta_5 Days_{ct}}_{pandemic context controls} + \underbrace{\beta_3 \overline{\Delta Cases}_{ct} + \beta_4 \overline{\Delta Deaths}_{ct} + \beta_5 Days_{ct}}_{pandemic context controls} + \underbrace{\beta_3 \overline{\Delta Cases}_{ct} + \beta_4 \overline{\Delta Deaths}_{ct} + \beta_5 Days_{ct}}_{pandemic context controls} + \underbrace{\beta_3 \overline{\Delta Cases}_{ct} + \beta_4 \overline{\Delta Deaths}_{ct} + \beta_5 Days_{ct}}_{pandemic context controls} + \underbrace{\beta_5 \overline{\Delta Cases}_{ct} + \beta_5 \overline{\Delta Cases}_{ct} + \beta_5 \overline{\Delta Cases}_{ct}}_{pandemic context controls} + \underbrace{\beta_5 \overline{\Delta Cases}_{ct} + \beta_5 \overline{\Delta Cases}_{ct}}_{pandemic context controls} + \underbrace{\beta_5 \overline{\Delta Cases}_{ct} + \beta_5 \overline{\Delta Cases}_{ct}}_{pandemic context controls} + \underbrace{\beta_5 \overline{\Delta Cases}_{ct} + \beta_5 \overline{\Delta Cases}_{ct}}_{pandemic context controls} + \underbrace{\beta_5 \overline{\Delta Cases}_{ct} + \beta_5 \overline{\Delta Cases}_{ct}}_{pandemic context controls} + \underbrace{\beta_5 \overline{\Delta Cases}_{ct} + \beta_5 \overline{\Delta Cases}_{ct}}_{pandemic context controls} + \underbrace{\beta_5 \overline{\Delta Cases}_{ct} + \beta_5 \overline{\Delta Cases}_{ct}}_{pandemic context controls} + \underbrace{\beta_5 \overline{\Delta Cases}_{ct} + \beta_5 \overline{\Delta Cases}_{ct}}_{pandemic context controls} + \underbrace{\beta_5 \overline{\Delta Cases}_{ct} + \beta_5 \overline{\Delta Cases}_{ct}}_{pandemic context controls} + \underbrace{\beta_5 \overline{\Delta Cases}_{ct} + \beta_5 \overline{\Delta Cases}_{ct}}_{pandemic context controls} + \underbrace{\beta_5 \overline{\Delta Cases}_{ct} + \beta_5 \overline{\Delta Cases}_{ct}}_{pandemic context controls} + \underbrace{\beta_5 \overline{\Delta Cases}_{ct} + \beta_5 \overline{\Delta Cases}_{ct}}_{pandemic context controls} + \underbrace{\beta_5 \overline{\Delta Cases}_{ct} + \beta_5 \overline{\Delta Cases}_{ct}}_{pandemic context controls} + \underbrace{\beta_5 \overline{\Delta Cases}_{ct} + \beta_5 \overline{\Delta Cases}_{ct}}_{pandemic context controls} + \underbrace{\beta_5 \overline{\Delta Cases}_{ct} + \beta_5 \overline{\Delta Cases}_{ct}}_{pandemic context controls} + \underbrace{\beta_5 \overline{\Delta Cases}_{ct} + \beta_5 \overline{\Delta Cases}_{ct}}_{pandemic context controls} + \underbrace{\beta_5 \overline{\Delta Cases}_{ct} + \beta_5 \overline{\Delta Cases}_{ct}}_{pandemic context con$$

 $+\beta_6 Contact_i + \beta_7 JobLoss_i + \beta_8 Gender_i + \beta_9 Age_i + \beta_{10} Health_i + \beta_8 Gender_i + \beta_9 Age_i + \beta_{10} Health_i + \beta_8 Gender_i + \beta$ 

$$+\beta_{11}Education_i + \beta_{12}Income_i + \gamma_c + \varepsilon_i \tag{1}$$

In the equation above, *Outcome*<sub>i</sub> represents the log-odds of whether a respondent *i* located in country *c* and at time *t* has reported any recent decrease in his or her mental health. We use three alternative indicators, estimating one separate model per each: whether a respondent (1) reported having "had trouble sleeping recently"<sup>2</sup> (*sleep problems*), or whether "in the last month" he or she (1) "felt nervous, anxious, or on edge" (*anxiety*) or (3) whether he or she has felt "sad or depressed" (*depression*).<sup>3</sup> Clearly, none of these experiences, as per exact formulations in the SHARE Corona Survey, are precisely identified in time. We deliberate on our solution to this problem shortly below.

Variables  $\overline{SI}_{ct}$  and  $\overline{ESI}_{ct}$  correspond to the values of OxGRT Stringency and Economic Support Indices respectively, with which we measure confinement stringency and the scale of economic support. Both are country- and time-specific, accordingly indexed with *c* and *t*. The parameters  $\beta_1$  and  $\beta_2$  represent the change in the outcome variable (i.e., the change in a given indicator of the mental health) associated with the change in respective index (Stringency or Economic Support) values, ceteris paribus. However, OxGRT reports daily values of SI and ESI for each country, which poses two challenges for identifying the respective measures' effects on respondents' mental health. The first is that immediate changes in confinement or economic support measures need not have an immediate effect on the mental health. Rather it takes some uncertain amount of time for these measures to accumulate and to take an effect. The second challenge has to do with the nature of our dependent variables, all of which are only roughly identified in time. To deal with this problem we did the following. First, we calculated several versions of the SI and ESI variables, averaging daily values over a certain number of days preceding the date t: one week (7 days), two weeks (14 days), three weeks (21 days), four weeks (28 days), one month (31 days)

<sup>&</sup>lt;sup>2</sup> We put relevant definitions in quotes to highlight precise formulations as per the original English version of the SHARE Corona Survey questionnaire.

<sup>&</sup>lt;sup>3</sup> Following one of the reviewers' invitation, in supplementary analyses, we have also considered other specifications of the mental health outcome ranging from less restrictive to more restrictive, namely: (1) a binary indicating if a respondent has experienced any of the three conditions (i.e., anxiety, depression or sleep problems); (2) a binary indicating the experience of either depression or anxiety (i.e., ignoring sleep problems due to their underdefined timing relative to that of the other two variables); (3) a binary indicating a situation of "mild" co-morbidity, i.e., the experience of any two conditions at once; and (4) a binary for a situation of "severe" co-morbidity, i.e., the experience of all three conditions at once. The general pattern of findings that we report remains the same. If anything, these supplementary analyses additionally suggest that for more pronounced. However, we do not find this for the effect of economic support measures. We present the estimates in Appendix 7.

#### Table 2

The estimates for the effects of confinement stringency and the scale of economic support on the mental health of older adults.

Models by dependent variables and policy measures	A. Sample mean value of B. Effect size per one- the dependent variable unit change Value of a policy measure		D. Effect proportion, i. e., equals  C./A.	E. Effect size per one-unit change from naïve models <sup>1</sup>	
Sleep problems					
Stringency Index	0.296	-0.00229** (0.00102)	-0.109** (0.048)	0.368	-0.000263 (0.000707)
Economic Support Index		-0.0023** -0.153** (0.0668) (0.000998)		0.516	-0.0000608 (0.000773)
Anxiety					
Stringency Index	0.308	-0.00198** (0.000949)	-0.0951** (0.0446)	0.309	0.00107* (0.000605)
Economic Support Index		-0.00111 (0.00119)	-0.0752 (0.0789)	0.244	0.00093*** (0.000251)
Depression					
Stringency Index Economic Support Index	0.275	-0.0328* (0.00197) -0.00126 (0.00151)	-0.154* (0.0918) -0.084 (0.0973)	0.559 0.305	0.00149*** (0.000474) -0.0001 (0.000811)

Notes: Clustered robust standard errors in parentheses.  $^{1}$  – models excluding country fixed effects. \*p < 0.1, \*\*p < 0.05, \*\*\*p < 0.01.

and the daily average ever since the outbreak in a given country. Averaging, in our view, better captures the cumulative nature of exposure to respective conditions. We then estimated models with alternative versions of these variables and identified the best fitting model. A visual comparison of model fit statistics, provided in Appendix 1, reveals that the best fitting version is the two-week average.

To control for the pandemic context, which can confound the association between government response measures and changes in mental health, we include the set of variables  $\overline{\Delta Cases}_{ct}$ ,  $\overline{\Delta Deaths}_{ct}$  and  $Days_{ct}$ . The latter is simply the number of days since the outbreak (which we count as the day, on which the first COVID-19 positive case was reported in a country). We tested for its non-linear relationship to the dependent variables, none of which substantially improved the model fit. The former two variables measure daily rates of change in the number of COVID-19 positive cases and COVID-19 related deaths (both adjusted for country population size in 2020) respectively. Similar to the values SI and ESI, we calculated different versions of these variables (i.e., averaging the rates over different periods to the date of interview) and decided to use two-week averages after comparing model fit statistics (Appendix 1).

All remaining controls are individual-specific and are detailed in Table 1 (along with the variables just described). The last constant, i.e.,



Fig. 1. Average marginal effects of confinement stringency and the scale of economic support on the mental health of older adults, decomposition by age.



Fig. 2. Average marginal effects of confinement stringency and the scale of economic support on the mental health of older adults, decomposition by gender.

 $\gamma_c$  for *country fixed effects*, represents the advantage of our estimation strategy, allowing us to control away the unobserved heterogeneity between countries that may be causing both their responses to the pandemic and their populations' mental health. In simple cross-sectional designs, there is hardly a solution to this problem, but by leveraging the date-of-interview information in SHARE Corona Survey we can exploit within-country variation in government response measures, holding constant unobserved heterogeneity between countries. One reasonable suspicion might be that this substantially reduces the variance of our key independent variables (i.e., SI and ESI). In Appendix 2, we provide an illustration proving that this suspicion is only partly warranted: in the majority of country-specific samples, we are left with decent variation in the values of Stringency Index, less so for the Economic Support Index.

Finally, to explore how the effect of confinement measures and economic support on mental health varies by age, gender and socioeconomic characteristics (among which we consider education and income), we extend Eq. (1) to include all relevant interactions. For estimating the models, we used the software program STATA 17.0.

We estimate all our models with standard errors clustered by country. However, given the relatively small country samples in SHARE, to detect statistically significant estimates in our analyses we use conventional alpha-levels alongside with a more relaxed criterion of 10%.

#### 5. Results

# 5.1. General findings

We present our findings in Table 2. Conventional effect size estimates in the form of average marginal effects, i.e., average probability differences in the value of dependent variables (*Sleep problems, Anxiety* and *Depression*) due to one-unit increase in the value of independent variables (*Stringency Index* and *Economic* Support *Index*), are contained in column B. These estimates are negative in all of our models for both Stringency and Economic Support indices. Substantively, negative estimates for Stringency Index can be interpreted as an improvement in the mental health associated with more stringent measures. Namely, the stricter the lockdowns the better the mental health. Accordingly, negative estimates for Economic Support Index can be interpreted as an improvement in the mental health associated with more generous measures. That is to say, more generous economic support is associated with better mental health. We provide full models for reference in Appendix 3.

The evidence for the negative relationship between confinement stringency and the experience of mental health declines is statistically significant at conventional levels (i.e., p < 0.05 and p < 0.01) for anxiety and sleep problems and at a more relaxed alpha-level (i.e., p < 0.1) for depression. That is, stricter lockdown measures are associated with less decline in mental health. This is less the case for economic support measures, for which we can report a statistically significant relationship only with one of the mental health indicators, i.e., sleeping problems. However, the direction of the relationship is robust across models, possibly indicating this is not a chance result. The statistical uncertainty is most likely due to low within-country variance of our indicator for the Economic Support Index (see Appendix 2 and 4 for summary statistics).

To provide a better sense of scale of the effects, we enhance Table 2 with additional information. In column A, we provide sample mean values of the dependent variables. The values can be interpreted as the average unconditional probabilities of experiencing respective mental health problems in the SHARE Corona Survey sample. They are unconditional in the sense that they are not attributed to any specific cause of mental health problems be it the severity of the pandemic context,



Fig. 3. Average marginal effects of confinement stringency and the scale of economic support on the mental health of older adults, decomposition by education.

sociodemographic factors or COVID-19 related state policies. In Column C, we report conditional (i.e., unconfounded) one-unit effect sizes (as per Column B) multiplied by the sample mea'n values of respective policy indices. The effect sizes are thus scaled to represent more meaningful average mental health changes that can be interpreted as average experiences due to respective policy changes. In Column D, we report the values in Column C divided by the values in Column A. The values can be interpreted roughly as the proportion of change in mental health problems in the sample that can be attributed to respective policy changes.

The ratios in Column D reveal that (if we were to trust the effect sizes are estimated precisely, i.e., to ignore the statistical uncertainty) they are, in fact, non-trivial. Consider, for instance, the *Sleep problems* indicator. The sample average of the *Stringency Index* indicator is 50.35 units (Appendix 4), which translates into an average marginal effect of 10.9 percentage points in the probability of experiencing sleep problems. Juxtaposed with the 29.6 percent of the respondents in the sample, who reported experiencing sleep problems, this makes a sizeable difference with a ratio of 0.368. Interpreting this estimate in a causal sense, one could say that the proportion of respondents reporting sleep problems would have been 36.8 percent (or 10.9 percentage points) higher if no lockdown measures were implemented at all. Hence, stricter lockdowns are more likely to increase sleep quality. All similar effect proportions in Table 2 range from 24.4 to 55.9 percent, which we consider sizeable differences.

In the last column of Table 2 (Column E), merely for the sake of comparison, we present estimates from naïve models, in which we deliberately neglect unobserved heterogeneity between countries by dropping country fixed effects. This would roughly correspond to the estimation strategy adopted by Voss et al. (2021), who used a similar combination of data to that of ours to investigate the relationship between mental health and lockdown measures. Naïve model estimates reveal a story which is at odds with the one revealed by the fixed effect model estimates. First, they suggest that higher lockdown stringency is associated with higher (not lower) likelihood of experiencing problems with mental wellbeing. Although this conforms to the common-sense causal argument that stringent measures provoke greater levels of stress, naïve models cannot rule out possible selection. The uneven prevalence of mental health disorders among the populations of European countries is well documented already before the pandemic (e.g., Organisation for Economic Co-operation and Development, 2018). For instance, it could be that in countries, where people were more predisposed to such disorders, the governments might have opted for more protective measures. This would underpin a spurious positive association between confinement stringency and mental health problems at the country level, even without any real causal relationship between the two. The logic can also be extended to economic support measures. In fact, one of the naïve models (Anxiety) reveals that the relationship between Economic Support index and mental health problems is positive. When interpreted causally, this suggests that more generous economic



Fig. 4. Average marginal effects of confinement stringency and the scale of economic support on the mental health of older adults, decomposition by income.

measures have a negative (rather than a positive) effect on the mental health, which seems like an absolutely counter-intuitive finding. It thus exemplifies the problem with causal interpretation of naïve estimates.

We now turn to group-specific analyses to investigate whether the effects reported above differ by subgroups. To obtain group-specific estimates we simply interact corresponding group variables (i.e., age, gender, education and income) with both of our policy measures.<sup>4</sup> We present the resulting effect size estimates in the form of average marginal effects in Fig. 1 through 4.

The results are largely mundane as most models do not reveal any significant variation in effects sizes by specific groups (also corroborated by formal statistical tests, see Appendix 5). This is in particular true for the effect of economic support measures, for which no statistically significant interaction has been reported with any of the group variables (even using the relaxed alpha level). One the other hand, we do find effect heterogeneity for the confinement stringency by age in at least two models (*Sleep problems* and *Depression*) and by education in at least one model (*Depression*). Specifically, the overall effect of confinement stringency on mental health appears to be statistically negligible for the younger old (i.e., those aged 50–60) and the higher educated. However, its effect is positive among the older and the lower educated respondents in the sample. These findings partly conform to our theoretical expectations, as we expected the positive influences of confinement stringency to overwhelm the negative ones with age. The positive effect of

confinement stringency on the mental health of the lower educated, however, appears somewhat surprising, since we expected them to be more (not less) discomforted by the lockdown measures.

# 6. Discussion and conclusions

In sum, our analysis does not corroborate the intuition that more stringent lockdown measures have negatively affected the mental health among older adults. Rather the opposite, we find that more stringent confinement was robustly associated with fewer mental health problems. We take these findings to be more in line with the evidence summarized by Prati and Mancini (2021), suggesting that lockdowns themselves must have had little to do with the surge of mental health problems in the course of the pandemic, and "that most people are psychologically resilient to their effects". Moreover, our supplementary analysis mimicking a more naïve approach to estimating such effects using cross-country comparisons shows how one can reach somewhat different conclusions by ignoring unobserved heterogeneity between countries (cf., Voss et al., 2021).

Furthermore, we find tentative evidence that the economic support measures, which in some countries were implemented along with lockdown measures and which have not been considered in previous research, may have additionally compensated for some of the declines in the mental well-being. Overall, this moderates some of the earlier

<sup>&</sup>lt;sup>4</sup> The interaction is applied to both the *Stringency Index* and the *Economic Support Index* at the same time but separately for each grouping variable.

alarmist claims regarding the large mental health cost of the government measures aiming to contain the spread of the COVID-19 pandemic (Luo et al., 2020; Salari et al., 2020; Singh et al., 2020; Vindegaard and Benros, 2020; Panchal et al., 2021).

Yet, we recognize that our findings generalize only to the older population and that the mental health cost of the COVID-19 restrictions to the younger population might as well have been different (e.g., Kang et al., 2020). Indeed, older people might more likely benefit from the protective measures because these people constitute a higher-risk group and therefore put security at a higher stake. At the same time, they must be least affected by the multiple negative consequences that come with such measures: i.e., limiting mobility, employment opportunities and social engagement, the need to combine work and childcare in the home-office setting, etc. In other words, one could reasonably expect the balance of benefits and costs of such measures to shift in a less favorable directions for younger adults. In fact, our results partly suggest this because even among the older generation we find an age gradient in the way mental health responds to confinement measures. The oldest old seem to benefit from the protective, i.e., soothing effects of those measures, but these effects fade out among the younger old. We thus cannot not exclude the possibility that among younger people (aged 50 and below) the overall effect of confinement on the mental health could have been negative, although available evidence does not seem to agree that such an age gradient seem to exist (Prati and Mancini, 2021). The results of this study can help policy makers developing evidence-based recommendations for adapting existing and developing new preventative measures targeting subgroups of population at risk of mental problems.

Apart from the age gradient we considered heterogeneity by gender and socioeconomic characteristics. However, contrary to our theoretical expectations, our analyses generally did not reveal any prominent and/ or theoretically substantiated patterns. The single surprising exception is the finding that more stringent confinement reduced the likelihood of depression for the less educated people, but this "positive" effect was less pronounced for the more educated ones. This finding is at odds with the intuition that the less educated people must generally find it harder to adapt their lifestyles under the confinement and bear with such measures as a necessary step for containing the pandemic. Still, since the existence of such gradient is not corroborated with regard to the other two indicators of the mental health under the study (sleep problems and anxiety), we would treat this evidence with caution.

The results of this study should be interpreted within the context of its limitations. First, even though we aimed to get hold of within-country variance in COVID-19 policy contexts using the interview date information, we were limited to a specific period of observations, i.e., the period between June and July 2020. Although we do end up with a reasonable amount variance in respective policy measures using the OxGRT data, the period might not be so ideal because it refers to the time when most sweeping measures have already been introduced (roughly in March–April 2020) and the first wave of the pandemic has already been well through. More specifically, our observational window covers the time when the lockdown measures were being relaxed rather than strengthened. Besides, the low variance of economic support measures remains a source of concern, limiting our ability to precisely estimate it impact (e.g., all our respective estimates are statistically non-significant according to any conventional threshold).

Second, we do not dismiss the possibility of a measurement error. The OxGRT indicators, which we use to measure the level of confinement stringency and the scale of economic support, summarize information on multiple specific policies in a way that makes them reasonably comparable across different countries and time periods. However, as any such synthetic measures they are not perfectly accurate. These appear in our analysis as constructs for the key independent variables of interest, thus potentially lending the respective estimates to the attenuation bias problem. Accordingly, all of our estimates might be partly understated.

Third, in addition to the health measures used in this study, it would also be beneficial to employ standard indexes of mental health (such as EURO-D scale for example) (e.g., Maskileyson et al., 2021) which were not available in the SHARE Corona Survey.

Finally, the study focuses on older population of economically developed countries (Europe and Israel) and its findings do not necessarily generalize to the rest of the world. Populations of the countries with less accessible healthcare systems, and less generous welfare states may have completely different experiences. Indeed, there is a plethora of research that recognize healthcare system (e.g., Maskileyson, 2014) and welfare state (Beckfield et al., 2015) as a major explanatory factor of health inequality. Therefore, inclusion of countries from a variety of geographic regions and levels of economic development would add to the depth of the analysis and generality of the findings. Similarly, cross-country differences in the extent to which people's mental health is affected by different policy measures – a question that can potentially be addressed using our combination of data but was not addressed in the current study – marks another interesting and potentially fruitful direction.

# Credit author statement

GY: research design conception, data preparation, analysis, interpretation of results, writing, and proofreading. DM: data preparation, interpretation of results, writing, and proofreading. Both authors had access to and verified the validity of the data and results, contributed to the article, and approved the submitted version.

#### Data availability

The authors do not have permission to share data.

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Appendix



Appendix 1. The comparison of fit statistics for different specifications of time-varying variables. *Legend*: 14, 21, 28, 31, 7 correspond to 14-, 21-, 28-, 31- and 7-day daily averages respectively. A – daily average since outbreak in a country (the day of the first positively tested case).



Appendix 2. SHARE Corona Survey observation density by date of interview and the variance of OxGRT policy indicators in different countries. *Legend*: red line – 14-day average Stringency Index (OxCGRT); green line – 14-day average Economic Support Index (OxCGRT); bars – observation density (SHARE Corona Survey). Country abbreviations: SVN, Slovenia; SVK, Slovakia; ROU, Romania; PRT, Portugal; POL, Poland; MLT, Malta; LVA, Latvia; LUX, Luxembourg; LTU, Lithuania; ITA, Italy; ISR, Israel; HUN, Hungary; HRV, Croatia; GRC, Greece; FRA, France; FIN, Finland; EST, Estonia; ESP, Spain; DNK, Denmark; DEU, Germany; CZE, Czech Republic; CYP, Cyprus; CHE, Switzerland; BGR, Bulgaria; BEL, Belgium; SWE, Sweden.



Appendix 2. (continued).

# Appendix 3. Full model statistics (logistic regression models)

	Sleep problems	Anxiety	Depression
Stringency Index	-0.0106**	-0.00905**	-0.0155*
	(0.00440)	(0.00406)	(0.00874)
Economic Support Index	-0.0104**	-0.00515	-0.00622
	(0.00432)	(0.00520)	(0.00684)
COVID-19 Cases	-0.191	0.966	-1.533
	(0.650)	(1.326)	(1.221)
COVID-19 Deaths	-151.8***	-53.65	-71.55
	(41.74)	(55.91)	(83.69)
Days since outbreak	-0.00689***	-0.00475***	-0.00867**
	(0.00155)	(0.00174)	(0.00361)
COVID-19 Contact	0.275***	0.285***	0.246***
	(0.0361)	(0.0422)	(0.0436)
Job loss	0.225***	0.306***	0.283***
	(0.0504)	(0.0429)	(0.0962)
Age	0.00496	-0.0118***	0.00318*
	(0.00315)	(0.00241)	(0.00162)
Gender	0.524***	0.560***	0.737***
	(0.0354)	(0.0425)	(0.0303)
Subjective health	-0.537***	-0.521***	-0.620***
-	(0.0290)	(0.0251)	(0.0258)
Education	-0.0161	-0.00159	-0.0183
	(0.0118)	(0.0140)	(0.0156)
Income	-0.0609***	-0.0194	-0.0813***
	(0.0164)	(0.0141)	(0.0178)
Constant	2.206***	2.305***	2.780**
	(0.583)	(0.709)	(1.271)
–2 Log Likelihood	35232.7	36220.0	33453.6
N	31350	31315	31293

Notes: Clustered standard errors in parentheses. All models include country fixed effects.

For the detailed description of variables see main text, Table 1.

<sup>°</sup> p < 0.10, ** p	0 < 0.05	*** p <	0.01
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# Appendix 4. Summary statistics

Variable	Mean	SD overall	SD between countries	SD within countries	Sample min value	Sample max value	Valid N
Sleep problems	0.297	0.457	0.072	0.451	0	1	31576
Depression	0.275	0.447	0.069	0.442	0	1	31514
Anxiety	0.308	0.462	0.078	0.457	0	1	31540
Stringency Index	50.4	11.3	10.9	4.29	25.9	75	31794
Economic Support Index	70.6	17.6	18.1	4.19	37.5	100	31794
COVID-19 cases	0.0108	0.0196	0.0205	0.0111	0.000141	0.186	31794
COVID-19 deaths	0.00031	0.000506	0.00482	0.000271	0	0.00344	31794
Days since outbreak	133.8	19.3	14.5	12.6	94	196	31794
Gender	0.618	0.486	0.0438	0.484	0	1	31672
Age	71.3	9.4	2.11	9.21	50	104	31566
Education*	11.1	4.2	1.76	3.86	0	38	31793
Income*	22750	26597	17246	21596	0	647657	31794
Health	2.86	0.984	0.339	0.925	1	5	31614
COVID-19 contact	0.111	0.314	0.069	0.442	0	1	31491
Job loss	0.0361	0.187	0.0179	0.186	0	1	31623

Notes: for the detailed description of variables see main text, Table 1.\* Income and education statistics as per original, i.e., untransformed and unstandardized variables.

# Appendix 5. Interaction effect statistics

	Sleep problems	Anxiety	Depression
Stringency Index $\times$ Age	-0.000446** (0.000208)	0.0000451 (0.000190)	-0.000223** (0.000104)
Economic Support Index $\times$ Age	-0.000064 (0.000169)	-0.0000718 (0.0000970)	-0.0000283 (0.0000723)
Stringency Index $\times$ Gender	-0.000505 (0.00298)	0.000669 (0.00354)	0.000435 (0.00286)
Economic Support Index $\times$ Gender	-0.00138 (0.00210)	-0.000489 (0.00229)	-0.000954 (0.00158)
Stringency Index × Education	0.000177 (0.00123)	-0.000571 (0.00129)	0.00231* (0.00139)
Economic Support Index $\times$ Education	0.00027 (0.000717)	-0.000959 (0.000842)	-0.00245 (0.00101)
Stringency Index $\times$ Income	-0.0000862 (0.00146)	-0.000601 (0.00141)	-0.000335 (0.00184)
Economic Support Index $\times$ Income	-0.000583 (0.000914)	-0.000842 (0.000917)	-0.000518 (0.00122)

Notes: Clustered standard errors in parentheses. \* p < 0.10, \*\* p < 0.05, \*\*\* p < 0.01

# Appendix 6. Correlations matrix

	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.	13.	14.
1. Sleep problems	1.00													
2. Depression	0.27***	1.00												
<ol><li>Anxiety</li></ol>	0.30***	0.48***	1.00											
4. COVID-19 contact	0.01	0.04***	0.02***	1.00										
5. Job loss	-0.01	0.02***	-0.00	0.05***	1.00									
6. Age	0.08***	0.01**	0.08***	-0.08***	-0.19***	1.00								
7. Gender	0.12***	0.12***	0.15***	0.00	-0.01	0.04***	1.00							
8. Health	-0.24***	-0.20***	-0.25***	0.07***	0.09***	-0.28***	-0.05***	1.00						
9. Education	-0.07***	-0.04***	-0.07***	0.07***	0.05***	-0.25***	-0.08***	0.19***	1.00					
10. Income	-0.07***	-0.04***	-0.09***	0.05***	0.06***	-0.24***	-0.09***	0.16***	0.24***	1.00				
11. COVID-19 cases	-0.03***	-0.00	-0.01**	0.11***	0.01	0.03***	-0.02***	0.07***	-0.01*	-0.00	1.00			
12. COVID-19 deaths	-0.03***	0.02***	0.02***	0.15***	0.00	0.06***	-0.02***	0.06***	-0.01**	-0.01	0.55***	1.00		
13. Days since	-0.05***	0.01*	0.00	0.12***	0.04***	-0.01**	-0.04***	0.06***	-0.01	0.01*	0.17***	0.20***	1.00	
outbreak														
14. Stringency Index	-0.03***	0.04***	0.04***	0.09***	0.02***	0.05***	-0.02***	0.05***	0.00	-0.00	0.08***	0.34***	0.25***	1.00
15. Economic	$-0.01^{**}$	0.04***	-0.00	0.03***	0.02***	-0.00	-0.00	0.05***	0.00	0.00	0.01	-0.04***	-0.02***	0.21***
Support Index														

Notes: \* p < 0.10, \*\* p < 0.05, \*\*\* p < 0.01

# Appendix 7. The estimates for the effects of confinement stringency and the scale of economic support on the mental health of older adults (i.e., Table 2 of the main text) using alternative definitions of the dependent variables

Models by dependent variables and policy measures	A. Sample mean value of the dependent variable	B. Effect size per one- unit change	C. Effect size per sample mean value of a policy measure	D. Effect proportion, i. e., equals  C./A.	E. Effect size per one-unit change from naïve models <sup>1</sup>				
Any one of three conditions									
Stringency Index		-0.00259***	-0.138*** (0.0405)	0.269	0.000617 (0.000618)				
Economic Support Index	0.512	(0.00068) -0.00192** (0.0008)	-0.144** (0.0691)	0.282	0.000162 (0.000816)				
Any one of two conditions									
Stringency Index	0.401	-0.00256***	-0.128*** (0.0497)	0.320	0.00149** (0.000674)				
Economic Support Index	0.101	-0.00113 (0.00113)	-0.0792 (0.0791)	0.198	0.000930 (0.000251)				
Minimum two conditions									
Stringency Index		-0.00297* (0.00162)	-0.139* (0.0742)	0.522	0.00113** (0.000446)				
Economic Support Index	0.266	-0.00168 (0.00151)	-0.110 (0.0966)	0.416	0.000416 (0.000465)				
All three conditions at once									
Stringency Index		-0.00166 (0.00154)	-0.0702 (0.0586)	0.667	0.000607*** (0.000168)				
Economic Support Index	0.105	-0.000469 (0.0012)	-0.0301 (0.0716)	0.286	0.000238 (0.000249)				
<i>lotes</i> : Clustered robust standard errors in parentheses. <sup>1</sup> – models excluding country fixed effects. * p<0.1, ** p<0.05, *** p<0.001									

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