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Abstract

This paper studies the effectiveness of the non-pharmaceutical measures adopted by governments in order to control the evolution of the COVID-19 pandemic. To that end, we estimate a Panel VAR model for 50 countries and test for causality between the 7 day cumulative incidence, the mortality rate and a stringency index that measures government actions. The use of Granger-type statistics provides evidence that the evolution of the COVID-19 pandemic caused the measures taken by governments; however, we cannot find evidence of the reverse situation. This result suggests that the government measures were not very effective in controlling the pandemic. This does not necessarily imply that the government responses were useless. However, our results show a considerable lack of effectiveness, a lesson that governments should learn and correct if similar events occur again.

Keywords: Government response index; stringency indexes; Granger causality; incidence, SARS-CoV-2 infection, COVID-19.

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1. Introduction

The COVID-19 pandemic has become one of the most important events of the 21st century so far. Since March 11th, 2020, when the World Health Organization (WHO) declared the pandemic situation, its outbreak has led to serious human losses (by June 2022, 534 million cases and 6.31 million deaths have been recorded worldwide) and has also generated one of the largest economic crises known to date. According to the World Bank Data[1], the worldwide Gross Domestic Product decreased by 3.4% in 2020 while that of the Eurozone decreased by 6.4%. Brodeur et al (2021) and Bloom et al (2022) present an interesting perspective on the economic consequences of COVID-19, comparing it with other modern infectious diseases. It should also be pointed out that the pandemic has had a significant social impact in many areas, affecting all segments of the population but being particularly detrimental to the most disadvantaged groups, as noted by Bhattacharya (2020). The situation continues to evolve and some of the problems related to the pandemic have not yet fully emerged.

Faced with this avalanche of health and socio-economic effects, governments were forced to take quick measures to control the pandemic. State and local governments imposed a wide array of restrictions on activity, easing or tightening them as the transmission evolved. Moreover, these restrictions were quite similar in all countries, as reported by Alfano et al (2022)[2]. Some of the restrictions included stay-at-home requirements, the closing of schools and workplaces, shutting down international traffic, and limits on the size of public gatherings. Other more long-term measures encouraged the use of pharmaceutical interventions. The Oxford COVID-19 Government Response Tracker (OxCGRT) provides a systematic method of tracking government responses to COVID-19 across countries (Hale et al, 2020). It classifies measures aimed at containing the pandemic into three main dimensions: containment and closure policies, health system policies, and vaccination policies. The analysis of all these measures has become the focus of a number of recent papers. The conclusions that can be drawn from these studies are varied and often contradictory.

Much of this research has focused on the analysis of the social and health implications of certain specific measures. In this regard, we can cite the paper by Alfano and Ercolano

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[1] https://www.worldbank.org/en/publication/global-economic-prospects (2022)

[2] We should note that these authors consider the first wave of COVID-19. Consequently, the sample size is shorter than the one used here.

(2020), who state that lockdown measures were effective in reducing the number of new cases in the countries that implemented them, and their subsequent paper in which they draw a similar conclusion for school closures (Alfano and Ercolano (2022)). Elgin et al (2020) focused on the economic policies adopted by national governments, whilst Brauner et al (2021) studied the effectiveness of non-pharmaceutical interventions for a sample of 41 countries. Alfano (2022) examined the relevance of the work ethics in the containment of COVID-19 for a sample of 30 European countries. Despite the interest of these articles, they offer a partial view on the effects of the different measures adopted during the pandemic. We consider that it is not possible to analyze the effect of an isolated measure. Rather, it is better to have an overall view of the decisions taken in order to measure the real effectiveness of the response of governments. This could be done by summarizing the different actions in a single measure or index.

In fact, the development of the above mentioned indexes has been another important line of work in the analysis of the implications of governmental actions during the pandemic. The indexes elaborated by the Oxford COVID-19 Government Response Tracker are obtained by combining the evolution of some indicators of the measures taken by different governments into a single measure and are used to describe the variation in public responses. Among the different works that use this type of index for a wide group of countries, we can highlight those of Liu et al (2021), Alfano et al (2021), Alfano et al (2022) Sun et al (2022) and Caselli et al (2022). These works show that lockdown policies that restricted internal movement substantially reduced COVID-19 cases, especially when they were introduced early in a country's epidemic. However, these results have been questioned by many scholars who find that there is no clear negative correlation between the degree of lockdown and fatalities due to the COVID-19 pandemic. This is the case of Chaudry et al (2020) or Bjørnskov (2021), amongst others, who consider a large sample of international countries. The reviews of the literature by Allen (2022) or Herby et al (2022) show that the evidence fails to confirm that lockdowns had a significant effect in reducing COVID-19 mortality.

Today, it remains an open question whether lockdowns have had a large, significant effect on containing the pandemic. Moreover, they have imposed enormous economic and social costs where they have been adopted, reducing economic activity, raising unemployment, reducing schooling and undermining liberal democracy. As a consequence, their use as a pandemic policy instrument is clearly questioned, given the great socioeconomic cost[3].

The origin of the controversy about the results of governmental actions during the pandemic may reside in the methodologies applied to date. Most of the work has focused on the search for correlations, but not on the causality analysis. This is a fundamental question in this framework, given that the direction of the causality provides information on the consequences of the decision taken by governments on the evolution of the pandemic. Therefore, it seems quite interesting to apply the causality concept developed by Granger (1969) in this scenario[4]. Following this author, a variable X is said to cause (or Granger-cause) a variable Y if it can be shown that those values of X provide statistically significant information about the future values of Y. Most often, this is done by using a vector autoregressive model (VAR) and testing whether the lagged estimates of the variable X are significantly different from 0. In this context, an analysis of the causality between the measures taken by the government and the mortality rate may provide additional information to help clarify whether these measures are effective or not.

Against this background, we should note that this study aims to fill this gap by analyzing the effectiveness of the measures adopted by different governments to control the evolution of the COVID-19 pandemic by testing the null hypothesis of non-causality. To that end, we will estimate a panel VAR which includes two variables that can capture the evolution of the pandemic, namely the 7-day cumulative incidence and the death rate, and an index of the response of governments that collects systematic information on policy measures that governments have taken to tackle the pandemic.

The rest of the paper is organized as follows. Section 2 provides a discussion on the data and explains the methodology applied. The main results are reported in Section 3 and discussed and analyzed in Section 4. The main conclusions are presented in Section 5.

2. Data and methods

2.1. Database

The variables considered in this analysis are the following: the 7 day cumulative incidence (CI7) of the pandemic, the death rate (MR), and an index that reflects the response of

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[3] In this regard, we can cite Dergiades et al (2022).

[4] We are aware of some papers where the use of the Granger causality methodology is criticized. See Stokes and Purdon (2017) and Barnett et al (2018) in this regard. However, we consider that this is the best procedure to analyze causality in a framework such the one considered in this paper.

governments. CI7 and MR have been obtained from the database organized by Johns Hopkins University[5].

In order to measure the response of governments to the pandemic, we have employed a set of indexes compiled by the Oxford COVID-19 Government Response Tracker (OxCGRT) that provides a systematic set of cross-national, longitudinal measures of government responses. OxCGRT calculates simple indices that combine information to provide an overall measure of the intensity of government response in a particular domain. The basic index is the Stringency Index (SI, hereafter) which is a comprehensive measure based on the evolution of nine different indicators: school closures; workplace closures; cancellation of public events; restrictions on public gatherings; closures of public transport; stay-at-home requirements; public information campaigns; restrictions on internal movements; and international travel controls.

This institution also offers a second index, called the Containment and Health Index (CHI, hereafter). CHI includes the information related to the lockdown policies that primarily restricted people's behavior contained in the Stringency Index and combines it with measures such as the testing policy and contact tracing, short term investment in healthcare, as well investments in vaccines.

Finally, there is a third index, called the Government Response Index (GRI). This is the most general one and collects publicly available information on several[6] indicators of government responses, spanning containment and closure policies (such as school closures and restrictions on movement), economic policies, and health system policies (such as testing regimes).

These three indexes quantify the intensity of government response and range from 0 to 100. The closer to 100, the more stringent the government response to the COVID-19 pandemic. Further details on these three indexes can be found in Petherick et al (2020) and Hale et al (2021). Finally, we should note that the results presented here are obtained by using the GRI index. We can consider that GRI nests the rest of the indexes and, consequently, it reflects the evolution of government response better than the other indexes.

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[5] The data were collected from the webpage https://coronavirus.jhu.edu/

[6] The number of indicators considered has varied across time. This paper is based on the version that considers 17 indicators.

We have considered the following list of countries: Argentina, Australia, Austria, Belgium, Brazil, Bulgaria, Canada, Chile, China, Colombia, Costa Rica, Croatia, Cyprus, Czechia, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, India, Indonesia, Ireland, Israel, Italy, Japan, Latvia, Lithuania, Luxembourg, Mexico, Netherlands, New Zealand, Norway, Poland, Portugal, Romania, Russia, Saudi Arabia, Slovakia, Slovenia, South Africa, South Korea, Spain, Sweden, Switzerland, Turkey, the United Kingdom and the United States. This set of data constitutes to some extent a somewhat homogeneous group of countries. This is a necessary property given the econometric techniques that we will employ, which do not work well in the presence of serious problems of heterogeneity. This could be the case of Yang et al (2021) who perform a similar analysis but including a set of 118 countries. The differences in the group of countries considered as well as the size of the sample justify this analysis and explain the difference in the results between the two papers.

The sample covers the weekly data from March 22nd, 2020 to August 29th, 2021. Then the data are previous to the appearance of the Omicron variant. The daily data have been transformed into weekly in order to smooth the variability of the data, remove the influence of some lack of data and avoid the existence of possible measurement errors.

2.2. Methodology

The aim of the paper is to analyze the Granger causality between the two measures of the evolution of the COVID-19 pandemic (confirmed cases and death rate) and the government responses to it, measured by the GRI index presented in the previous Section. To that end, the use of time series analysis offers an excellent framework to carry out this study. More precisely, we want to estimate a Panel VAR and, subsequently, test the null hypothesis of Granger causality. The estimation of the panel VAR requires the variables employed to be stationary. We will take advantage of the advances on panel unit root inference to do this, although the selection of the most appropriate statistic depends on the possible existence of cross-sectional dependence.

The following subsections present the set of statistics that will be employed, all of them aimed to guarantee the appropriateness of the panel VAR estimation.

2.2.1. Testing for cross-sectional dependence

We first need to analyze the possible presence of cross-sectional dependence to determine the most appropriate panel data unit root tests. If the null hypothesis of no cross-sectional dependence is not rejected, then the statistics proposed by Im et al (2003) can be used. However, the existence of cross-sectional dependence distorts the behavior of these statistics and, consequently, it must be taken into account.

There are various statistics to test for cross-sectional dependence. The most commonly used is the one in Pesaran (2015), which is defined as follows:

$$CD_P = \sqrt{\frac{2T}{N(N-1)}}\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\hat{\rho}_{ij} \overset{As}{\rightarrow} N(0,1)$$

With $\hat{\rho}_{ij}$ being the pair-wise correlation coefficient.

2.2.2. Testing panel data unit root tests

If we can prove the existence of cross-sectional dependence, as can be expected, then we should employ panel data unit root statistics that take it into account. We have several possibilities, but the one developed by Pesaran (2007) seems to be a good choice. This author extends the standard statistic by including some extra regressors that take into account the cross-sectional dependence. More precisely, the statistic is obtained by estimating the following equation:

$$\Delta y_{it} = \alpha_i y_{it-1} + \gamma_i \overline{\Delta y_{it}} + \delta_i \overline{y_{it-1}} + \mu_i + f(t)\delta_i + \varepsilon_{it}$$

where y_{it} reflects the vector of the variables included in the analysis and f(t) is a function of t. We should note that this regression extends the individual ADF regressions with the cross-sectional means of the lagged levels ($\overline{y_{it-1}}$) and the first difference of the variables under analysis ($\overline{\Delta y_{it}}$), capturing the effect of the non-observable factors. In order to test the null hypothesis $H_o{:}\alpha_i=0$ (i=1,2,..,N) versus the alternative that $H_A{:}\alpha_i<0$ for some (i=1,2,…,m), with m<N, Pesaran (2007) defines the following statistic:

$CIPS = \sum_{i=1}^{N} t_i$, with $t_i = \hat{\alpha}_i/\hat{\sigma}_{\hat{\alpha}_i}$

The critical values are reported in Pesaran (2007). This author also designs a truncated version (CIPS*) of this statistic that removes the influence of extreme values. The threshold values and the critical values of this alternative version are also presented in the cited paper.

2.2.3. Panel VAR estimation and testing for causality

After proving the absence of unit roots, we can then estimate a panel VAR. This model is an interesting extension of the standard VAR first introduced by Sims (1980). The panel VAR can be stated as follows:

$$Y_{it} = Y_{it-1} A_1 + Y_{it-2} A_2 + \dots + Y_{it-p} A_p + X_{it} B + u_i + e_{it} \qquad (1)$$

i=1,2,…N, t = 1,2, … T, where Y_{it} is a (1xk) vector of dependent variables, X_{it} is a (1xℓ) vector of exogenous explanatory variables, u_i is a (1xk) vector of dependent variable-specific panel fixed effects, and e_{it} is a (1xk) vector of idiosyncratic errors, such as $E(e_{it})=0$, $E(e_{it}'e_{it})=\Sigma$, and $E(e_{it}'e_{is})=0$ for all t>s. Finally, A_j (j=1,2,…p) is a kxk matrix of parameters, whilst B is a ℓxk matrix of parameters.

The estimation of this model is not straightforward, given that the presence of lagged dependent variables makes the standard methods (ordinary least squares, for instance) biased, as Nickel (1981) noted. Then, we should employ alternative methods to obtain estimators with good properties. To obtain consistent and efficient estimates under this condition, Arellano and Bond (1991) developed a generalized method of moment (GMM), which was later improved by the refinement of Blundell and Bond (1998), who developed the system-generalized method of moment (System-GMM). This uses the lagged differences of the dependent variable as instruments for equations in levels and also includes the lagged levels of the dependent variable as instruments for equations in first differences[7].

Once we have estimated the system of equations, causality inference is straightforward. Following Granger (1969), testing for Granger causality implies analyzing the hypothesis that all coefficients on the lag of variable m are jointly zero in the equation for variable n. This can be carried out by employing Wald tests implemented based on the GMM estimation of the matrix A and its covariance matrix.

Finally, panel VAR analysis is carried out by selecting the optimal lag order in both the panel VAR specification and moment condition. To that end, we have considered the results of Andrews and Lu (2001) who proposed an optimal moment and model selection criteria (MMSC) for GMM models based on Hansen's (1982) J statistic of overidentifying restrictions. This statistic is analogous to various commonly used maximum likelihood-based model-selection criteria, namely, the Akaike information criteria (AIC), developed

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[7] See Abrigo and Love (2006) in this regard.

in Akaike (1969), and the Bayesian information criteria (BIC) proposed in Schwarz (1978).

3. Results

3.1. Cross-sectional dependence tests

The results of the cross-sectional dependence tests are presented in Table 1. As one can observe, the null hypothesis of no cross-sectional correlation is rejected by using the statistic proposed in Pesaran (2015).

This result has consequences in the subsequent steps, given that we should apply panel data unit root tests that take into account this fact, as is the case of the CADF statistics proposed by Pesaran (2007) and presented in the methodological section.

3.2. Panel data unit root tests

The results of the panel data unit root tests are presented in Table 2. According to the analysis, the evidence against the null hypothesis of unit root is overwhelming. Consequently, we cannot consider that the variables are first-order integrated and the use of cointegration techniques is not appropriate, contrary to what was observed in Yang et al (2021). To understand the differences, we should take into account that the samples differ in the number of countries, the type of data employed and, especially, the sample size. Sample size is of particular importance, given that we should note that all the variables will tend to decline at the end of the pandemic, all of them moving towards 0. Therefore, we cannot consider these variables are I(1), although their behavior can be similar to this type of variable for some periods of time. However, they should hopefully be considered as I(0) in the long-run.

The results obtained are very relevant given that they determine the econometric tools that should be employed. Since no evidence in favor of the presence of unit roots has been found, then “standard” econometric techniques can be used. In our case, we have opted for the use of the panel VAR approach.

3.3. *Panel VAR and testing for* Granger causality

Table 3 presents the results of the estimation of model (1) with $Y_{it}=(GRI_{it}, CI7_{it}, MR_{it})$, considering that the application of the statistics for selecting the appropriate number of lags suggests p=3 and where the inclusion of the matrix X_{it} of exogenous variables is discarded. The analysis of this table provides a number of very interesting insights. If we begin by considering the CI7 equation, we can observe that the only estimations that are statistically different from 0 are the CI7 lags, whilst the lags of MR and GRI are not. Moreover, the estimation of the parameter of the CI7 lags reveals the existence of a very high amount of persistence in this variable, although this variable is not integrated. As a consequence, the reversion towards the expected values of this variable is very slow.

The results of the estimation of the MR equation are somewhat different. The lags of the MR variable are statistically different to 0 and also denote a large amount of persistence. We can also observe that the estimations of some lags of the CI7 variable are different from 0. By contrast, the lags of the GRI variable are not statistically different from 0. This implies that the evolution of the CI7 is very important for understanding that of the MR, whilst the effect of the GRI is not statistically different from 0, as occurred in the CI7 equation.

The results of the GRI equation are also very interesting. The lags of this variable are statistically different from 0 and, even more relevant, they once more show a great amount of persistence. We can also appreciate a significant impact of the lags of the CI7 and MR on the evolution of the GRI variable. Then, it seems that the response of governments depended on the evolution of the pandemic, and the worse the pandemic evolution, the more restrictive the measures taken by governments.

If the sample is divided by country groups, the results for the EU countries are qualitatively similar to those obtained for the total sample. The most relevant difference is the fact that the influence of the CI7 and MR lags in the GRI equation is higher than that observed for the total sample. However, the analysis of the results for the EU countries leads us to very similar conclusions to those obtained for the total sample.

The results of the panel VAR estimation reveal the scant relevance of the lags of the different stringency indexes on the evolution of the COVID-19 measures, which suggests that there is not causality. However, this is not the appropriate procedure for analyzing this, it being more appropriate to explicitly test for the non-causality hypothesis. Table 4 presents the Granger statistics.

First, we can observe the very clear rejection of the null hypothesis of non-causality between CI7 and MR for both considered samples. This null hypothesis is also robustly rejected when we analyze causality from pandemic variables to GRI. But, focusing on the effect of these measures on the COVID-19 variables, the rejection of the null hypothesis of non-causality is not so evident.

Therefore, we should conclude that the effect of the responses offered by the different governments was not especially fruitful in the control of the COVID-19 propagation. Rather, the evolution of the pandemic marked the path of these responses, which turned governments into mere followers of the pandemic, exhibiting a rather poor capacity to anticipate and to influence its evolution.

4. Discussion

The main insight that emerges from our results is the very well-known fact that correlation does not mean causality. We have previously reported on some papers where a strong correlation is found between government responses and the evolution of the COVID-19 pandemic. However, these papers do not explicitly test for causality, except for Yang et al (2021). Our results reveal that causality from government responses to the pandemic evolution is scant. By contrast, there exists robust evidence in the reverse direction.

In any case, it is important to note that the results obtained do not imply that the measures taken were useless, as they made it possible to control the epidemiological situation, especially at the beginning of the pandemic. This fact is supported by the results of Alfano and Ercolano (2020, 2022) for a sample of international countries, Alfano et (2021) in Italy, and Rees et al (2022) in Canada. Moreover, our results do not show the counterfactual situation, therefore it is not possible to say what would have happened if these lockdown measures had not been implemented.

However, we should recognize that the results presented in these papers show that governments may have exhibited some degree of overreaction, as Pingle (2022) notes. Some other authors, such as Frijter et al (2021) and Chaudhuri (2022), also support this point. Therefore, it is possible that less severe restrictions would have been as effective as those taken and with less damaging socio-economic consequences. The lockdown measures adopted in all countries have led to far-reaching social and economic changes, resulting in economic crisis and recession, a reduced workforce across all economic sectors, social distancing, self-isolation, an increase in poverty, hunger, and inequalities, as Schippers et al (2022) note.

In any event, we cannot consider that government responses were inadequate, especially if we bear in mind the behavior of the virus was totally unknown. However, our results do question their effectiveness. Some factors, such as inappropriate behavior by some members of the public, the inadequate use of facemasks, and the existence of a certain disdain for citizens' compliance with the regulations, could help to explain this lack of effectiveness. Some previous papers also suggest this. For instance, Alfano et al (2022) study a sample of 34 countries and show that corruption in politicians and public officials is directly correlated to the COVID-19 cases, perhaps connecting the mistrust of the public with the lack of effectiveness in the application of the previously mentioned measures. Park et al (2021) study the case of South Korea and conclude that an improvement in individual preventive measures by the public might have reduced the need for more restrictive measures, such as quarantine, isolation, or contact screening. A similar conclusion is reached by Huang et al (2022) for the USA case. Similarly, Spiliopulos (2022) concludes that the maximum effectiveness of non-pharmaceutical restrictions is attainable with interventions associated with lower values of the GRI. These papers, and others like those of Haug et al (2020), BenDavid et al (2021) and Vickers et al (2022), suggest that governments might have overreacted to the evolution of the pandemic in the sense that more severe restrictions were not significantly more effective than less restrictive policies.

Therefore, we consider that adopting very severe measures has a very high economic and social cost, and public policies should take this into consideration in order to improve the effectiveness of their implementation in the event that a situation similar to that of the COVID-19 pandemic would have to be faced. The best antidote to that end is the continuous evaluation of these public policies.

5. Conclusions

This paper analyzes the effectiveness of government responses to the outbreak of the COVID-19 pandemic in 50 countries. For this purpose, a panel VAR has been estimated that includes as variables the cumulative 7-day incidence, mortality and a measure of the responses of governments to the pandemic. This measure is based on the set of indexes compiled by the Oxford COVID-19 Government Response Tracker at the Blavatnik School of Government. This institution publishes the GRI index that provides very useful information to assess the evolution of the different decisions taken by governments. The sample used covers weekly data from March 22nd, 2020 to August 29th, 2021, which reflects the evolution of the pandemic before the arrival of the omicron variant and the mass vaccination of individuals. Based on the estimation of the aforementioned panel

VAR, we have tested the null hypothesis of non-causality to determine the direction of the relationship between the variables included in the VAR specification.

The results obtained show that, first, the pandemic variables (MR and CI7) are very persistent, but not integrated. Therefore, they have a very slow reversion towards their natural value, which in the long term should tend to 0. Secondly, the existence of causality between these two variables is observed. There is also evidence of causality from these variables to the GRI index, which indicates that decisions were taken based on their evolution. However, there is no clear evidence that these government responses caused changes in the evolution of the pandemic. This result can be partially explained by the aforementioned persistence of MR and CI7, but it also suggests a certain lack of effectiveness of the measures. Therefore, no evidence of causality in the direction from government responses to the pandemic is found either for the total sample or for the subset of EU countries included in the sample.

The overall conclusion is that the measures of government responses were of very limited effectiveness. However, we should interpret this with some caution as the results do not prejudge the adequacy of the responses. These policies were the best that could have been applied, especially in the initial situation, given the dramatic epidemiological circumstances and the absence of pharmaceutical solutions, which have played a crucial role in this regard. However, it can be deduced from our results that the responses may have generated a certain degree of overreaction. Additionally, it seems that the way in which these measures were applied may not have been the most appropriate. These lessons have to be taken into account in the, hopefully unlikely, event that governments are faced with situations similar to those that led to the outbreak of the COVID-19 pandemic.

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Table 1. Cross-Sectional dependence tests

Variable	CD
Part I. All countries	
GRI	298.7***
CI7	186.5***
MR	169.9***
Part II. EU countries	
GRI	148.9***
CI7	113.4***
MR	107.9***

This table presents the values of the CD statistic designed in Pesaran (2015) for testing the null hypothesis of weak cross-sectional independence. The statistic asymptotically goes towards a standard N(0,1) distribution. Part I and Part II consider the 50 countries included in our sample and the EU countries, respectively.

*** means 1% rejection

Table 2. Panel data unit root tests

	I. No-trend			II. trend		
Variable	MW	CIPS*	CIPS	MW	CIPS*	CIPS
		Panel A. 50 countries				
GRI	344.2^{***}	-2.93^{***}	-2.17^{**}	196.6^{***}	1.34	-2.19
CI7	149.8^{**}	-4.29^{***}	-2.35^{***}	128.61^{**}	-4.21^{***}	-2.87^{***}
MR	255.6^{***}	-10.3^{***}	-3.14^{***}	183.3^{***}	-8.43^{***}	-3.37^{***}
		Panel B. EU countries				
GRI	187.8^{***}	-4.53^{***}	-2.62^{***}	114.9^{***}	-1.90^{**}	-2.67^{**}
CI7	149.8^{***}	-4.29^{***}	-2.35^{***}	128.6^{***}	-4.21^{***}	-2.87^{***}
MR	308.6^{***}	-10.97^{***}	-3.22^{***}	210.8^{***}	-8.79^{***}	-3.42^{***}

This table presents the CIPS and the CIPS* statistics developed in Pesaran (2007) for testing the panel data unit root null hypothesis. Panel II considers the presence of a deterministic trend in the specification, whilst this is excluded in the results presented in panel I.

***, ** and * mean 1%, 5% and 10% rejection, respectively.

Table 3. Panel VAR estimation.

Lag Var.\Equation	CI7	MR	GRI
		Panel A. 50 countries	
L.CI7	1.65	0.005	0.002
	(0.06)	(0.001)	(0.002)
L^2.CI7	-0.90	-0.001	-0.006
	(0.08)	(0.001)	(0.003)
L^3.CI7	0.16	-0.002	0.005
	(0.04)	(0.001)	(0.002)
L.MR	0.78	1.19	-0.06
	(2.06)	(0.06)	(0.09)
L^2.MR	0.26	-0.27	0.14
	(2.41)	(0.07)	(0.14)
L^3.MR	0.01	-0.03	-0.16
	(1.25)	(0.03)	(0.08)
L.GRI	-0.23	-0.000	0.91
	(0.19)	(0.003)	(0.03)
L^2.GRI	0.31	0.002	-0.00
	(0.25)	(0.004)	(0.03)
L^3.GRI	-0.19	0.002	-0.00
	(0.16)	(0.004))	(0.01)
		Panel B. EU countries	
L.CI7	1.61	0.005	0.003
	(0.07)	(0.001)	(0.002)
L^2.CI7	-0.83	-0.001	-0.008
	(0.09)	(0.001)	(0.003)
L^3.CI7	0.13	-0.002	0.007
	(0.05)	(0.0001)	(0.002)
L.MR	-0.37	1.25	-0.08
	(2.06)	(0.67)	(0.10)
L^2.MR	0.05	-0.33	0.06
	(2.52)	(0.08)	(0.15)
L^3.MR	0.52	-0.016	-0.09
	(1.37)	(0.04)	(0.08)
L.GRI	-0.25	-0.007	0.74
	(0.40)	(0.007)	(0.05)
L^2.GRI	0.24	0.008	0.10
	(0.53)	(0.008)	(0.04)
L^3.GRI	-0.22	0.008	0.02
	(0.34))	(0.007)	(0.02)

This table reflects the estimation of the model (1) when the specification includes the variables CI7, MR and GRI. The values in parenthesis are the estimations of the standard errors of the different estimators. Part A includes all the considered countries, whilst the results of part B are related to the EU countries exclusively.

L means the lag operator.

Table 4. Granger Causality

Equation\excluded var.	CI7	MR	GRI
	Panel A. 50 Countries		
CI7	-	2.55	2.31
MR	176.75***	-	2.55
GR	7.18*	8.50**	
	Panel B. European Union		
CI7	-	0.57	0.69
MR	125.26***	-	5.48
GR	13.01***	9.83**	

This table presents the Wald-type tests for testing the null hypothesis of no Granger causality. The first column reflects the equation of the system, whilst the first row is associated to the excluded lags.

CI7, MR and GRI are the 7 days cumulative incidence, the mortality rate and the GRI index that measures the responses of governments to COVID-19. Panel A presents the results for the 50 countries considered in our sample , whilst Panel B focuses on the EU countries exclusively.

***, ** and * mean 1%, 5% and 10% rejection, respectively.