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Abstract

"Awareness" about the occurrence of viral infectious (or other) tail risks can influence their socioeconomic inter-temporal impacts. A branch of the literature finds that prior lifetime exposure to signicant shocks can affect people and societies, i.e. by changing their perceived probability about the occurrence of an extreme, negative shock in the future. In this paper we proxy "awareness" by historical exposure of a country to epidemics, and other catastrophic events. We show that in a large cross-section of more than 150 countries, more "aware" societies suffered a less intense impact of the COVID-19 disease, in terms of loss of lives and, to some extent, economic damage.

Keywords: socioeconomic impact of pandemics, global health crises.

JEL classification: E43, F41, N10, N30, N40.

Resumen

La conciencia de los individuos y las sociedades sobre el alcance de las infecciones víricas y otros riesgos de cola puede influir en el impacto socioeconómico que estas dejan a lo largo del tiempo. La literatura muestra que la exposición a episodios negativos o extremos durante la trayectoria vital de las personas puede continuar afectándoles sustancialmente más adelante, ya que su percepción de la probabilidad de que estos eventos ocurran en el futuro se ve alterada. Este artículo utiliza la exposición histórica de un país a epidemias y otros eventos catastróficos como un instrumento de la conciencia de experiencias previas. Los resultados, utilizando una sección cruzada de más de 150 países, sugieren que en aquellas sociedades que se han mostrado «más conscientes», el COVID-19 ha tenido un menor impacto en términos de coste humano y, hasta cierto punto, también económico.

Palabras clave: impacto socioeconómico de las pandemias, crisis sanitarias globales.

Códigos JEL: E43, F41, N10, N30, N40.

1 Introduction

The severe acute respiratory syndrome coronavirus-2 (SARS-CoV-2, the virus that causes COVID-19) came as a surprise for many individuals and nations, but not for others. Some governments and individuals were more "aware" of the possibility of a pandemic outburst of this sort than others, for at least two reasons. First, a big part of the scientific community had been warning for at least a decade with increasing intensity about the likely appearance of "disease X" (see WHO, 2017; Daszah, 2020; de Bolle, 2021). On the other hand, some countries or regions had been more affected over the past decades by infectious diseases (like, SARS in 2002, MERS in 2012, or Ebola in 2014)[1] and/or other extreme natural events with very low frequency of impacting a given community (like earthquakes, volcano eruptions or tsunamis). Such phenomena have become more widespread in the recent past (see Figure 1). Societies more prone to the occurrence of these type of events, or that have been subject to them in a not-so-distant past, may be more prepared to identify a new episode -or a recurrent wave of an ongoing one (in case of biological events)- in an early fashion, or might have developed more resilient and forward-looking policy tools and institutions to mitigate their impact.

The literature has highlighted some channels through which the degree of "awareness" determines the social and economic inter-temporal impact of a pandemic.[2] In Economics, Kozlowski, Veldkamp and Venkateswaran (2020) show that the main economic costs of a pandemic could arise from changes in agents' behaviour long after the immediate health crisis is settled. [3] Indeed, Jordà, Singh and Taylor (2020) provide empirical evidence based on a wealth of historical episodes that pandemics do have long-run economic consequences. In turn, the epidemiological literature shows that individual (human) awareness is a relevant factor to account for the spreading of an epidemic, by stressing the interplay between awareness and disease outbreak (see, among others, Granell et al., 2013; Wu et al., 2012; Samantal and Chattopadhyay, 2014; or Wang et al., 2020).

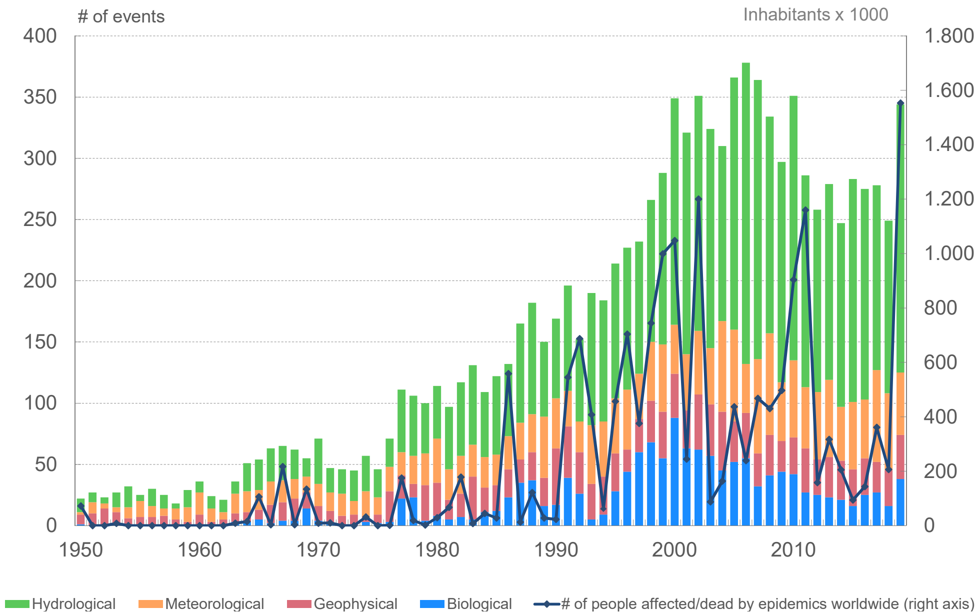
Against this background, in this paper we test to what extent more "aware" societies suffered a less intense impact (both human and economic) of the COVID-19 disease spread. Our aim is to shed some light in understanding the striking heterogeneity among countries in the incidence

[1] Just to quote the most prominent examples of the past 20 years, as noted in WHO (2017): the Severe Acute Respiratory Syndrome (SARS) appeared for the first time in 2002, and spread across hemispheres in just six months; the Middle East Respiratory Syndrome (MERS), identified in 2012, spread to 26 countries in three years and is still active; the Ebola outbreak that erupted in the spring of 2014 spread through the whole region of West Africa in a matter of weeks; to date, and in particular since 2015 a total of 86 countries and territories have reported evidence of mosquito-transmitted Zika-virus infection.

[2] Infectious diseases, in particular those that turn into pandemics, lead to significant human and socioeconomic costs. For historical evidence see, among others, Bloom et al. (2018), or Smith et al. (2019). For the COVID-19 crisis, see IMF (2020) or Sapir (2020).

[3] On related grounds, Lin and Meissner (2020), when studying the link between public health performance in the early days of the COVID-19 pandemic and those during the Spanish Influenza pandemic of 1918-20, find that experience with SARS is associated with lower mortality today, in a sample of 33 countries worldwide.

Figure 1: World-wide biological and other natural, extreme events, 1950-2020



Source: EM-DAT database: `https://www.emdat.be/`.

of the pandemic and its economic costs. To test the hypothesis at hand we take the following steps. First, we construct indicators of awareness, using measures of historical exposure to virual outbreaks, and other catastrophic events. Next, we build measures of the incidence of the COVID-19 pandemic, both from the human and economic points of view. Finally, we estimate spatial econometric models linking both sets of indicators using a cross-section of about 150 countries across the world. The spatial econometric framework allows us to control for the proximity among countries, a direct amplifier of spillovers from countries more exposed to the pandemic to the others. We also include other geographical and socioeconomic controls, including lockdown and curfew-type measures adopted by governments, a key element identified in the literature (see e.g. Ferraresi et al., 2020).

The rest of the paper is organized as follows. In Section 2, we outline the econometric methodology and describe the data used. In Section 3 we discuss the main results of the paper, and in Section 4 we draw some policy implications.

2 Methodology and data

Methodology We regress, for a large cross-section of over 150 countries, an indicator of the incidence of the pandemic (S) on an indicator of awareness (E), and a number of control variables (X), including a "spacial lag". For country i and time unit t the model takes the form:

$$S_{i,t} = \theta W S_{i,t} + \beta_0 E_{i,t} + \sum_{k=1}^{K} \phi_k X_{k,i,t} \epsilon_{i,t} \tag{1}$$

where $\theta WS_{i,t}$ captures the autocorrelation of the effects of the pandemic between close countries through the spatial weighting matrix W. For N countries, this object contains N^2 elements where the element w_{i_1,i_2} captures the distance from country i_1 to country i_2. The main diagonal is filled with zeros. Accounting for the proximity among countries is key, given that the health situations of closer geographies are likely to be more connected. While the concept of distance can refer to a variety of economic, social or geographical attributes, we adopt the latter in our analysis. We use two alternative approaches: (i) a more traditional contiguity approach, whereby only adjacent countries affect each other; (ii) another one whereby spillover effects are proportional to the inverse of the distance between all countries in the sample[4].

Indicators of awareness We proxy "awareness" with exposure in the past to epidemic outbreaks, and natural disasters. To identify relevant past disasters and epidemiological episodes we resort to the Emergency Events Database (EM-DAT, `https://www.emdat.be/`), constructed by the Center for Research on the Epidemiology of Disasters (CRED). The database logs details on more than 20,000 disasters that occurred since 1950, and covers most countries around the globe. The categorization of events is very rich, consisting of natural disasters (among which geophysical, meteorological, hydrological, climatological, biological and extra-terrestrial) and technological disasters (among which industrial accident; miscellaneous accident; transport accident). An event is included in the database if at least one of the following criteria are met: there are 100 or more affected people, more than 10 casualties, or the disaster has prompted the declaration of a state of emergency in a country. Epidemic diseases are grouped within natural disasters (biological).

We combine information in EM-DAT with population statistics from the World Bank and construct the following measures of disaster awareness by country: (i) number of epidemic episodes affecting more than 100 people; (ii) within the previous measure, focus on outbreaks linked to respiratory diseases (such as MERS and SARS, among others), and, more specifically, on SARS-CoV-1; (iii) number of natural disasters affecting more than 0.1% of the country's population. We restrict our sample and focus on events that occurred in the period 2000-2019.[5]

Indicators of incidence of the pandemic First, as regards the direct human incidence, we focus on the fatality rates of COVID-19.[6] We compute the accumulated number of deaths at a given reference date in a given country as a fraction of the number of inhabitants, to allow

[4]For our benchmark specifications and results, we use the contiguity approach, but all results using the other measure are available upon request.

[5]Results for related measures constructed different thresholds for the affected population are available upon request and provide very similar results. In addition, if awareness is linked to preparedness, there are indices that proxy the latter. One is the Global Health Security Index (GHS Index: see `https://www.ghsindex.org/about/`) developed by the Nuclear Threat Initiative, the Johns Hopkins Center for Health Security and The Economist Intelligence Unit. The GHS Index is a quantitative indicator on health security and related capabilities across 195 countries. Results using this index are available upon request, and show no robust link between GHS and pandemic incidence.

[6]Source: Johns Hopkins Coronavirus Resource Center: `https://coronavirus.jhu.edu/`.

for cross-country comparability. We show results for three reference dates: 1-month after the pandemic outbreak (proxied by the date at which the 10^{th} death was reported), 3-months after the same date, and the cumulative number of cases as of 31 December 2020. Looking at the results using different reference dates allows us to account for the fact that, as the pandemic developed worldwide, governments and individual citizens took social distancing measures and actions. Thus, as regards our hypothesis of pre-existing "awareness", an assumed advantage may have weakened over time.

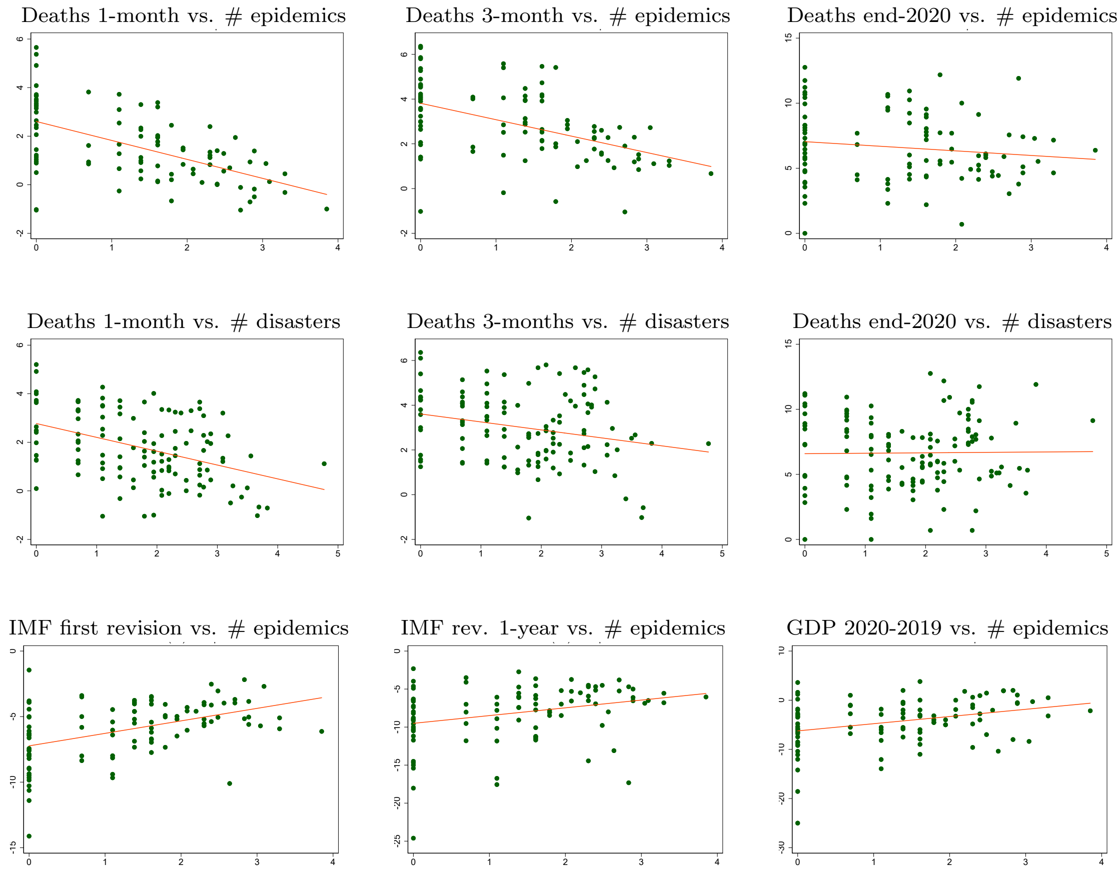
Second, regarding economic incidence, we look at indicators based on economic losses for the whole of 2020. This is motivated by the fact that the use of higher frequency data (either monthly or quarterly) would severely reduce our sample of countries, to between 40 and 70 countries (depending also on available control variables, presented later), with a marked bias towards advanced economies. Resorting to annual data allows us to include in our analysis some 150 countries, with a fair representation of advanced and emerging market economies (see Table A1). More specifically, we use the following measures of economic losses: (i) Annual growth rate of GDP in 2020; (ii) Revisions to 2020 GDP growth forecasts by the International Monetary Fund (IMF) with respect to the pre-pandemic outlook, proxied by the forecasts published by the IMF in November 2019. We take the projections from IMF's flagship publication *World Economic Outlook*. Specifically, the April 2020 vintage, that can be seen as an initial estimate of the incidence of the pandemic, based on limited within-the-year information, and the November 2020 one.[7]

Control variables To control for factors potentially affecting the evolution of the pandemic other than "awareness", we include the following variables in the analysis: urban population as a percentage of total population in 2019; the average temperature between 1991 and 2016; the average household size in 2019; gross national income per capita, PPP (current US dollars). In addition, via dummy variables, we control for the geographical location of each country within a continental group (Africa, Oceania, North America, South-Central America, Asia, Europe), and distinguish between emerging markets versus advanced economies, and small versus large countries (a dummy that takes value 1 if the population is above the median of all countries in the sample).

In addition, we control for the incidence of policy decisions, as measured by the widely-used Non Pharmaceutical Intervention indicator (NPIs), the Oxford COVID-19 Government Response Tracker of Hale et al. (2020). The indicator is available for a large set of countries. More stringent containment policies (e.g. more stringent lockdowns or curfews) entail an increase in the index. Ex ante, one may think that more "awareness" might be associated with the implementation of more effective health policies. Nonetheless, it is unclear whether "more aware" countries were more prone to the implementation of policies in the spirit of those captured by the index, or they rather

[7]In all case we trim the upper and lower 5% of the forecasts' distribution to prevent distortion from outliers.

Figure 2: COVID-19 incidence (Y-axis) and "awareness" (X-axis).



Notes: Human incidence indicators (in logs): "Deaths 1-month" refers to the number of COVID-19 casualties per million inhabitants in the 1^{st} month after the 10^{th} casualty was registered; "Deaths 3-months", three months after the 10^{th} casualty; "Deaths end-2020", as of 31 December 2020. Economic incidence indicators: "IMF 1^{st} revision" refers to the difference in GDP growth forecasts for 2020 between the April-2020 and October-2019 IMF World Economic Outlook reports; "IMF rev. 1-year" refers to the forecast differences between the October-2020 and October-2019 IMF WEO reports. As regards indicators of "awareness": "# epidemics" refers to the number of epidemic episodes suffered by a country between 2000 and 2019 that affected more than 100 people; "# disasters" refers to the number of biological and other natural disasters suffered by a country between 2000 and 2019 that affected more that 0.1% of its population.

resorted to other alternatives -such as intensive testing and contact tracing- that allowed them not to follow the stringent lockdown approach. With the available data we cannot test either hypothesis. Nevertheless, to account for potential endogeneity concerns with our empirical approach we explore the link between indicators of awareness and the NPI indicator in a very simple way, by regressing one on the other, i.e. we compute a simple correlation coefficient. For that purpose, we calculate the average value of the stringency index one month and three months after the 10^{th} death was notified in each country, as well as the average for the full year 2020. As shown in Table A2 in the Annex, the correlation between fatalities and stringency indicators is statistically not significantly different from zero for most of the indicators used. For the regression analysis, we extract the residuals of the previous regressions and include them as an additional control in the human incidence variables' specifications. These residuals capture the part of the stringency policies that are not associated to awareness.

3 Results

We provide some initial descriptive evidence in Figure 2, were we display scatterplots relating our indicators of COVID-19 human incidence (number of casualties per million inhabitant one/three months after the 10th case, and for the whole 2020) and economic incidence (revisions in IMF forecasts and 2020 GDP fall), against some measures of "awareness". The simple (unconditional) correlations show the expected signs. First, more exposure in the past to epidemics/disasters is negatively related to human losses, i.e. countries more exposed in the past to such events tend to show a lower death toll from the current pandemic, that seems to be more pronounced (higher negative slope) for the 1- and 3-month horizons. Second, the revision to macroeconomic projections (IMF indicators) and the output loss are less pronounced for countries that experienced in the past more epidemic/disaster events in the past. These are only unconditional correlations, that do not control for potential confounding factors. We show our regression results in Tables 1 and 2 for social-human incidence, and in Tables 3 and A3 for economic incidence. The columns in these Tables

Table 1: Social-human incidence of COVID-19 and number of epidemics in the past

Dependent variable: COVID-19 deaths per million, period after death 10

	1 month	1 month	1 month	3 month	3 month	3 month	end-2020	end-2020	end-2020
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]
# epidemics	-0.305***	-0.285***	-0.249***	-0.235***	-0.167*	-0.169*	-0.257***	-0.195**	-0.180***
	(0.000)	(0.000)	(0.008)	(0.004)	(0.097)	(0.081)	(0.000)	(0.014)	(0.008)
Spatial lag	0.195*	0.199*	0.173	0.265**	0.356***	0.306***	0.306***	0.372***	0.312***
	(0.083)	(0.067)	(0.134)	(0.019)	(0.002)	(0.007)	(0.000)	(0.000)	(0.000)
NPIs index		-0.024		0.189***		0.177***	0.283***		0.311***
		(0.661)		(0.002)		(0.006)	(0.000)		(0.000)
Urban			-0.020		0.033	0.067		0.082	0.135*
			(0.835)		(0.748)	(0.518)		(0.282)	(0.061)
Temperature			0.098		-0.063	-0.112		0.103	-0.092
			(0.298)		(0.535)	(0.252)		(0.129)	(0.183)
Household size			0.129		0.213*	0.163		0.119	0.133*
			(0.227)		(0.062)	(0.148)		(0.184)	(0.086)
GNI per capita			0.252*		0.209	0.135		0.129	0.013
			(0.074)		(0.166)	(0.373)		(0.278)	(0.905)
Africa	0.704***	0.676***	0.476*	0.096	-0.112	0.001	-0.125	-0.325	-0.099
	(0.003)	(0.007)	(0.072)	(0.725)	(0.695)	(0.996)	(0.526)	(0.140)	(0.628)
Oceania	-0.616	-0.637	-0.762	-1.076**	-1.338***	-1.202**	-0.831**	-1.422***	-0.811**
	(0.183)	(0.164)	(0.102)	(0.031)	(0.007)	(0.012)	(0.017)	(0.000)	(0.016)
North America	1.096***	1.035***	0.700	1.389***	1.139**	1.177**	0.845***	0.909**	0.923**
	(0.006)	(0.009)	(0.164)	(0.001)	(0.035)	(0.023)	(0.005)	(0.036)	(0.011)
Central-South	0.851***	0.897***	0.643**	0.655**	0.532*	0.575*	0.456**	0.501**	0.557**
America	(0.001)	(0.001)	(0.031)	(0.020)	(0.097)	(0.066)	(0.021)	(0.046)	(0.011)
Asia	0.254	0.236	-0.063	-0.121	-0.413	-0.379	-0.066	-0.146	-0.058
	(0.293)	(0.341)	(0.823)	(0.652)	(0.170)	(0.201)	(0.727)	(0.535)	(0.781)
Europe	0.979***	0.945***	0.952***	0.582***	0.460*	0.424*	0.688***	0.649***	0.751***
	(0.000)	(0.000)	(0.000)	(0.001)	(0.052)	(0.061)	(0.000)	(0.001)	(0.000)
EME	-0.618***	-0.690***	-0.506**	-0.342	-0.191	-0.323	-0.135	-0.191	-0.263
	(0.002)	(0.001)	(0.037)	(0.137)	(0.463)	(0.213)	(0.403)	(0.343)	(0.149)
Large country	-0.322***	-0.254**	-0.178	-0.052	0.090	0.114	-0.013	0.168	0.029
	(0.008)	(0.041)	(0.175)	(0.697)	(0.524)	(0.409)	(0.893)	(0.131)	(0.765)
Observations	150	143	126	143	126	123	143	132	123
R-squared	0.573	0.584	0.607	0.509	0.506	0.558	0.723	0.700	0.773

Notes: $*$ ($**$) [$***$] denotes statistical significance at 10% (5%) [1%]. Robust p-values in parentheses. Spatial regressions based on contiguity. All non-dummy variables are in logs and standardized. See main text of the paper for the definition of the variables.

show estimated versions of model (1) for different sets of indicators of “awareness”, incidence, and control variables. All variables are in logs (when applicable) and normalised, so that estimated parameters can be interpreted as correlation coefficients.

Turning to Table 1, some results are worth highlighting. First and foremost, we find a strong and robust negative association between the number of past epidemics, our preferred measure of awareness, and human incidence. The result holds for all the empirical specifications shown, and is robust to increasing number of control variables. In particular to the introduction of the stringency index, NPI (columns [2], [4], [6], [7] and [9]). Second, the statistical significance of the spatial lag indicates that proximity (contiguity) to countries affected by the pandemic has some bearing

Table 2: Social-human incidence of COVID-19: other indicators of “awareness”

Dependent variable: COVID-19 deaths per million, period after death 10

	1 month	1 month	1 month	1 month	3 months	end-2020	end-2020	end-2020	end-2020
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]
# epidemics	-0.252***				-0.158*	-0.179**			
	(0.003)				(0.087)	(0.016)			
# SARS-CoV-1	0.081	0.013			-0.065	-0.194***	-0.245***		
	(0.362)	(0.887)			(0.507)	(0.002)	(0.000)		
# respiratory ep.			-0.016					-0.121**	
			(0.812)					(0.021)	
# disasters	-0.139*			-0.226***	-0.192**	-0.020			-0.088
	(0.085)			(0.003)	(0.031)	(0.784)			(0.140)
Spatial lag	0.170	0.274**	0.277**	0.242**	0.303***	0.374***	0.379***	0.371***	0.370***
	(0.137)	(0.012)	(0.011)	(0.027)	(0.010)	(0.000)	(0.000)	(0.000)	(0.000)
NPIs index		-0.037	-0.037	-0.041			0.311***	0.296***	0.288***
		(0.514)	(0.515)	(0.457)			(0.000)	(0.000)	(0.000)
Additional controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	150	143	143	143	150	160	143	143	143
R-squared	0.586	0.535	0.534	0.564	0.477	0.631	0.713	0.692	0.686

Notes: $*$ $(**)$ $[***]$ denotes statistical significance at 10% (5%) [1%]. Robust p-values in parentheses. Spatial regressions based on contiguity. All non-dummy variables are in logs and standardized. “# SARS-COV-1” number of people affected by the disease in each country; “# respiratory ep.” number of respiratory epidemic episodes suffered by a country between 2000 and 2019; “# disasters” number of biological and other natural disasters suffered by a country between 2000 and 2019 that affected more that 0.1% of its population. Additional control variables: Continent; EME; “Large country”. For details on the controls and other variables see footnote to Table 1.

on cases, as expected. Third, countries more affected by COVID-19 put in place more stringent containment measures, as of the 3^{rd} month after the 10^{th} case, and overall when looking at the whole 2020 period. Fourth, countries in America and Europe were more severely affected by the disease in statistically significant terms than the average, while those in Oceania displayed a significantly lower incidence. Finally, even though on impact emerging market economies and large countries (countries with a population size above the median of the sample) suffered more (specifications [1] to [3]), this differential adverse effect vanished as the pandemic developed.

For the sake of robustness, in Table 2 we show empirical estimates for regressions that relate other indicators of awareness and human incidence. In particular, we look at exposure to SARS-CoV-1, exposure to respiratory epidemics, and incidence of a broader measure of catastrophic events (disasters refers to the number of biological and other natural disasters suffered by a country). When included in the model along with than the number of epidemics, the main result of Table 1 still holds, namely, the relevance of the indicator of past exposure to epidemics, while at the same time other indicators show a statistically significant correlation (columns [1], [5] and [6]). When looking at one-indicator-at-a-time regressions, exposure to SARS-CoV-1 seems to have induced some learning, when considering the experience with all the pandemic waves for the whole 2020

Table 3: Economic incidence of COVID-19 and number of epidemics in the past

	IMF first revision [1]	IMF first revision [2]	IMF first revision [3]	IMF 1-year revision [4]	IMF 1-year revision [5]	IMF 1-year revision [6]	GDP 2020 vs. 2019 [7]	GDP 2020 vs. 2019 [8]	GDP 2020 vs. 2019 [9]
# epidemics	0.173**	0.159**	0.007	0.113	0.096	-0.057	0.174**	0.130*	-0.020
	(0.019)	(0.028)	(0.945)	(0.171)	(0.245)	(0.575)	(0.015)	(0.058)	(0.813)
Spatial lag	0.060	0.002	-0.062	0.058	0.059	-0.099	0.060	0.106	-0.012
	(0.666)	(0.986)	(0.666)	(0.700)	(0.683)	(0.533)	(0.683)	(0.453)	(0.937)
NPIs index		-0.100*	-0.112*		-0.257***	-0.259***		-0.179***	-0.186***
		(0.084)	(0.080)		(0.000)	(0.000)		(0.001)	(0.001)
Urban			-0.078			-0.119			-0.054
			(0.457)			(0.266)			(0.557)
Temperature			0.039			-0.067			-0.056
			(0.688)			(0.514)			(0.550)
Household size			0.026			-0.215*			0.060
			(0.808)			(0.066)			(0.546)
GNI per capita			-0.151			-0.241			-0.211
			(0.312)			(0.127)			(0.111)
Tourism share			-0.159**			-0.275***			-0.231***
			(0.031)			(0.000)			(0.000)
Additional controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	161	138	118	162	140	119	161	137	117
R-squared	0.432	0.502	0.550	0.183	0.235	0.359	0.293	0.307	0.425

Notes: $*$ $(**)$ $[***]$ denotes statistical significance at 10% (5%) [1%]. Robust p-values in parentheses. Spatial regressions based on contiguity. Regressands standardized; regressors in logs and standardized. Additional control variables: Continent; EME; "Large country". For details on controls and other variables see footnote to Table 1.

year (columns [6] and [7]). Also, prior incidence of disasters, using the broad measure, shows the expected negative sign, with statistically significant results for the initial phases of the pandemic.

Finally, in Table 3 we provide some results on the association between awareness and economic incidence of the COVID-19 induced health crisis. This is a more demanding exercise, as a number of additional factors may be affecting the theoretical channel between epidemic/disaster memories and economic outcomes, most notably economic and health policies adopted since the outburst of the pandemic, and the heterogeneous economic structure of countries. We try to proxy some of these factors with a number of control variables. Results in the most basic regressions for the initial impact (columns [1] and [2]) and the overall output loss in 2020 (columns [7] and [8]) display a positive and statistically significant coefficient, that is robust to the inclusion of the NPI stringency index. Nevertheless, the inclusion of additional, plausible, control variables dissipates this finding, which is evidence of lack of robustness. In addition, when looking at alternative awareness indicators (see Table A3 in the Annex) we do not find significant correlations.

4 Policy implications

In this paper, we provide some suggestive evidence that more "aware" societies suffered a less intense human impact of the COVID-19 disease spread in terms of death toll, even after accounting for the heterogeneity across countries in non-pharmaceutical policy reactions, and other socioeconomic characteristics. We also find a weak link of past experience with epidemics and a lower economic toll, even though these findings do not hold when including socioeconomic controls and alternative awareness indicators.

From a normative point of view, awareness and, eventually, margin-building, save lives and reduces economic costs. Looking forward, thus, policy makers should look even beyond the current pandemic, and think as well about the next one, to reduce or even avoid the enormous costs of a new infectious disease reaching the global level. This might call, in particular, for greater investment in health systems and services. With extensive international travel and trade, infectious diseases in one country or region can elicit economic shock waves far beyond the realm of traditional health sectors and the original geographical range of a pathogen. Thus, a second policy implication is that prevention exceeds the national frontiers, and belongs also to the international domain, assigning a key role to multilateral bodies like the WHO.

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A Annex: additional tables

Table A1: Countries included in the analysis

ABW	*Aruba*	DNK	Denmark	KOR	Korea, Rep.	PRT	Portugal
AFG	Afghanistan	DOM	Dominican Rep.	KWT	Kuwait	PRY	Paraguay
AGO	Angola	DZA	Algeria	*LAO*	*Lao PDR*	QAT	Qatar
ALB	Albania	ECU	Ecuador	*LBN*	*Lebanon*	ROU	Romania
ARG	Argentina	EGY	Egypt, Arab Rep.	LBR	Liberia	RUS	Russian Federation
ARM	Armenia	ERI	Eritrea	LCA	St. Lucia	RWA	Rwanda
AUS	Australia	ESP	Spain	LKA	Sri Lanka	SDN	Sudan
AUT	Austria	EST	Estonia	LSO	Lesotho	SEN	Senegal
AZE	Azerbaijan	ETH	Ethiopia	LTU	Lithuania	SGP	Singapore
BDI	Burundi	FIN	Finland	LUX	Luxembourg	SLE	Sierra Leone
BEL	Belgium	FJI	Fiji	LVA	Latvia	SLV	El Salvador
BEN	Benin	FRA	France	MAR	Morocco	SOM	Somalia
BFA	Burkina Faso	GAB	Gabon	MDA	Moldova	SRB	Serbia
BGD	Bangladesh	GBR	United Kingdom	MDG	Madagascar	STP	Sao Tome and Pr.
BGR	Bulgaria	GEO	Georgia	*MDV*	*Maldives*	SUR	Suriname
BHR	Bahrain	GHA	Ghana	MEX	Mexico	SVK	Slovak Republic
BHS	Bahamas, The	GIN	Guinea	MKD	North Macedonia	SVN	Slovenia
BIH	Bosnia and Herzegovina	GMB	Gambia, The	MLI	Mali	SWE	Sweden
BLR	Belarus	GNB	Guinea-Bissau	MLT	Malta	SWZ	Eswatini
BLZ	Belize	GNQ	Eq. Guinea	MMR	Myanmar	TCD	Chad
BOL	Bolivia	GRC	Greece	MNE	Montenegro	TGO	Togo
BRA	Brazil	*GRD*	*Grenada*	MNG	Mongolia	THA	Thailand
BRB	Barbados	GTM	Guatemala	MOZ	Mozambique	TJK	Tajikistan
BRN	Brunei Darussalam	*HKG*	*Hong Kong*	MRT	Mauritania	*TLS*	*Timor-Leste*
BTN	*Bhutan*	HND	Honduras	MUS	Mauritius	TTO	Trinidad and Tobago
BWA	Botswana	HRV	Croatia	MWI	Malawi	TUN	Tunisia
CAF	Central African Rep.	HTI	Haiti	MYS	Malaysia	TUR	Turkey
CAN	Canada	HUN	Hungary	NAM	Namibia	TZA	Tanzania
CHE	Switzerland	IDN	Indonesia	NER	Niger	UGA	Uganda
CHL	Chile	IND	India	NGA	Nigeria	UKR	Ukraine
CHN	China	IRL	Ireland	NIC	Nicaragua	URY	Uruguay
CIV	Cote d'Ivoire	IRN	Iran, Islamic Rep.	NLD	Netherlands	USA	United States
CMR	Cameroon	IRQ	Iraq	NOR	Norway	UZB	Uzbekistan
COD	Congo, Dem. Rep.	ISL	Iceland	NPL	Nepal	*VCT*	*St. Vincent & the Gr.*
COG	Congo, Rep.	ISR	Israel	NZL	New Zealand	VEN	Venezuela, RB
COL	Colombia	ITA	Italy	OMN	Oman	VNM	Vietnam
COM	Comoros	JAM	Jamaica	PAK	Pakistan	YEM	Yemen, Rep.
CPV	Cabo Verde	JOR	Jordan	PAN	Panama	ZAF	South Africa
CRI	Costa Rica	JPN	Japan	PER	Peru	ZMB	Zambia
CYP	Cyprus	KAZ	Kazakhstan	PHL	Philippines	ZWE	Zimbabwe
CZE	Czech Republic	KEN	Kenya	PNG	Papua New Guinea		
DEU	Germany	KGZ	Kyrgyz Republic	POL	Poland		
DJI	Djibouti	*KHM*	*Cambodia*	*PRI*	*Puerto Rico*		

Notes: For countries in italics, either economic or human incidence data are unavailable.

Table A2: Non-Pharmaceutical interventions and "awareness"

Dependent variable: Non Pharmaceutical Intervention indicator COVID-19 Government Response Tracker

	1 month [1]	3 months [2]	3 months [3]	end-2020 [4]	end-2020 [5]	end-2020 [6]	end-2020 [7]	end-2020 [8]
# epidemics	0.0577	0.0308	0.0589	-0.146	-0.0313			
	(0.611)	(0.775)	(0.459)	(0.156)	(0.688)			
# SARS-COV-1						0.0757		
						(0.535)		
# respiratory ep.							-0.0629	
							(0.494)	
# disasters								-0.200**
								(0.0470)
Spatial lag	-0.0149	0.0205	0.244*	0.0534	0.338**	0.0609	0.0597	0.0648
	(0.923)	(0.890)	(0.0901)	(0.709)	(0.0129)	(0.676)	(0.676)	(0.645)
Additional controls	Yes	Yes	No	Yes	No	Yes	Yes	Yes
Observations	143	143	143	143	143	143	143	143
R-squared	0.0607	0.154	0.00108	0.231	0.00324	0.222	0.222	0.240

Notes: $*$ $(**)$ $[***]$ denotes statistical significance at 10% (5%) [1%]. Robust p-values in parentheses. Spatial regressions based on contiguity, assuming that adjacent counties affect each other. All non-dummy variables are in logs and standardized. Additional control variables included in all the regressions are: Continent; EME; "Large country".

Table A3: Economic incidence of COVID-19: other indicators of "awareness"

	IMF first revision [1]	IMF 1-year revision [2]	GDP 2020 vs. 2019 [3]	IMF first revision [4]	IMF 1-year revision [5]	GDP 2020 vs. 2019 [6]	IMF first revision [7]	IMF 1-year revision [8]	GDP 2020 vs. 2019 [9]
# SARS-CoV-1	0.104	-0.067	-0.075						
	(0.217)	(0.488)	(0.355)						
# respiratory ep.				0.023	-0.008	0.012			
				(0.718)	(0.915)	(0.849)			
# disasters							0.054	-0.048	-0.045
							(0.456)	(0.568)	(0.529)
Spatial lag	0.085	0.090	0.151	0.069	0.092	0.156	0.051	0.092	0.159
	(0.501)	(0.527)	(0.278)	(0.590)	(0.517)	(0.263)	(0.692)	(0.520)	(0.253)
NPIs index	-0.115**	-0.263***	-0.188***	-0.109*	-0.264***	-0.189***	-0.103*	-0.268***	-0.194***
	(0.048)	(0.000)	(0.001)	(0.060)	(0.000)	(0.001)	(0.079)	(0.000)	(0.001)
Additional controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	138	140	138	138	140	138	138	140	138
R-squared	0.498	0.233	0.307	0.493	0.233	0.307	0.495	0.233	0.308

Notes: $*$ $(**)$ $[***]$ denotes statistical significance at 10% (5%) [1%]. Robust p-values in parentheses. Spatial regressions based on contiguity, assuming that adjacent counties affect each other. Regressands standardized; regressors in logs and standardized. Additional control variables included in all the regressions are: Continent; EME; "Large country".

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