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8373
2020

June 2020

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Impressum:

CESifo Working Papers
ISSN 2364-1428 (electronic version)
Publisher and distributor: Munich Society for the Promotion of Economic Research - CESifo GmbH
The international platform of Ludwigs-Maximilians University's Center for Economic Studies and the ifo Institute
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Editor: Clemens Fuest
https://www.cesifo.org/en/wp
An electronic version of the paper may be downloaded
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CESifo *Working Paper No. 8373*

Measuring the Economic Risk of COVID-19

Abstract

We measure the economic risk of COVID-19 at a geo-spatially detailed resolution. In addition to data about the current prevalence of confirmed cases, we use data from 2014-2018 and a conceptual disaster risk model to compute measures for exposure, vulnerability, and resilience of the local economy to the shock of the epidemic. Using a battery of proxies for these four concepts, we calculate the hazard, the principal components of exposure and vulnerability to it, and of the economy's resilience (i.e., its ability of the recover rapidly from the shock). We find that the economic risk of this pandemic is particularly high in most of Sub-Saharan Africa, South Asia, and Southeast Asia. These results are consistent when comparing an ad-hoc equal weighting algorithm for the four components of the index, an algorithm that assumes equal hazard for all countries, and one based on estimated weights using previous aggregated Disability-Adjusted Life Years losses associated with communicable diseases.

JEL-Codes: I100.

Keywords: epidemic, COVID-19, risk measurement, economic impact.

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June 2020

1. Defining the Economic Risk

The economic risk of an epidemic, any epidemic, is very distinct from the its health (morbidity and mortality) risk. The basic framework that assesses disaster risk is typically constructed around four concepts: hazard, exposure, vulnerability, and resilience, and it is the interaction of these four that leads to the economic consequences. The hazard, in these frameworks, is the natural trigger. In the present circumstances, it is the SARS-Cov-2 virus which causes COVID-19. Since the economic risk is determined not only by the hazard, but also exposure, vulnerability, and resilience, this risk has plausibly very different spatial variability than the spread of the virus.

Even with a low case load or mortality associated with it, the epidemic can lead to very adverse changes inside and outside an affected economy that can lead to dramatic economic effects. In the most extreme cases, the economic risk might be high even if there are no confirmed cases of COVID-19 in the country; this is the case, for example, for some of the South Pacific Island countries (Doan and Noy, 2020).

Given the paucity of data on epidemic cases in the recent past (the period for which comprehensive economic and demographic records are available), and the unprecedented nature of this event, our aim here is not to precisely measure the likely consequence of this pandemic, but rather to comparatively evaluate where the economic risk of COVID-19 is currently concentrated using several algorithms.

An alternative approach is to calculate the actual risk for each country using structural modelling; see for example an estimate for the likely impact of pandemic influenza in Fan et al. (2016) and consequently the expected annual global impact of this influenza risk (evaluated therein at US$ 80B). This approach, in our view, cannot yet produce credible estimates given the paucity of our understanding of the economic impact of lockdown (shelter-in-place) policies and the impact of the rapid de-globalization these lockdowns have generated.

Once we have compared the economic risk across regions and countries, we can then identify many potentially important policy interventions and prioritise their implementation. For example, it seems to us that multilateral financial assistance should prioritise those countries in which the economic risk is higher, rather than the health risk. In contrast, funding from the World Health Organisation should target places where the health risk is high.

Our risk measure is premised on the observation that a disaster, including an epidemic, occurs when a hazard (in this case the disease) interacts with an exposed population that is vulnerable to this hazard, thus causing harm to people. Epidemics always arise out of a natural pathogen (very often zoonotic), but the pathogen by itself does not create the epidemic and definitely not its economic consequences. For that, the pathogen must encounter a society, people and an economy, that is both exposed and vulnerable to it. Resilience, in this framework, is conceptualized and quantified as the ability of the economy to bounce back given the magnitude of the shock that is generated by the intersection of the hazard, exposure, and vulnerability (an alternative term to 'resilience' is 'capacity,' but we prefer the term 'resilience' or 'socio-economic resilience' as defined by Hallegatte, 2014). The degree of resilience in an economy is thus determined by the speed in which the recovery process occurs, and when the system reverts back to its pre-shock level (i.e., full recovery is achieved).

2. A Method for Measuring the Economic Risk

As defined by UNDRR (2017), a disaster is "a serious disruption of the functioning of a community or a society at any scale due to hazardous events interacting with conditions of exposure, vulnerability and capacity, leading to one or more of the following: human, material, economic and environmental losses and impacts. The effect of the disaster can be immediate and localized, but is often widespread and could last for a long period of time."

Exposure in the UNDRR definition refers to the population and the economic activity that is located in areas that are being exposed to the pathogen or that is indirectly exposed to the changing behavior that is induced by the presence of this pathogen (e.g., Epstein, 2009). Vulnerability, in this case, refers to the ability of the pathogen to adversely affect the exposed economy. A higher degree of vulnerability will lead to a more adverse outcome for the economy, given the same exposure to the SARS-Cov-2 virus. It is important to note that these distinctions are always imperfect, and that is also the case for epidemics. Even the basic epidemiological parameter, R_0, is a function of the socio-economic environment – see Janes et al. (2012).

Over time, the economic losses will depend on the depth of the shock, and on the economy's resilience (its ability to bounce back). A more resilient economy, in this framework, is one that manages to minimize the post-shock cumulative loss of income during the recovery process for a given size of the shock (Hallegatte, 2014). As Prager et al. (2017) note, resilience policies are often not really plausible to pursue during the rapid phase of the spread of the epidemic. What is more plausible is to make up for lost production once the epidemic has abated, and potentially prepare the economy for the recovery period while the epidemic is still ongoing (as many governments are now trying to do). The ability to implement such policies, as determined by both financial and institutional capacity, is therefore an important determinant of economic resilience.

In a previous paper (Noy et al., 2019), we analysed the economic risk of a generic epidemic. Here, instead of focusing on a generic emerging infectious disease event, we focus on COVID-19 (Figure 1). SARS-Cov-2 fits perfectly the pattern of a zoonotic pathogen emerging from the interaction of a wild animal population with a food market that epidemiologists have been warning about (e.g. Allen et al., 2017). However, the economic characteristics of this unprecedented event are somewhat different. For example, while tourism collapses in individual countries had happened before (e.g., West Africa because of Ebola in 2014-2015, Korea because of MERS in 2015), the total collapse of all international tourism is unique. We therefore modified our risk analysis to fit the new experience with COVID-19.

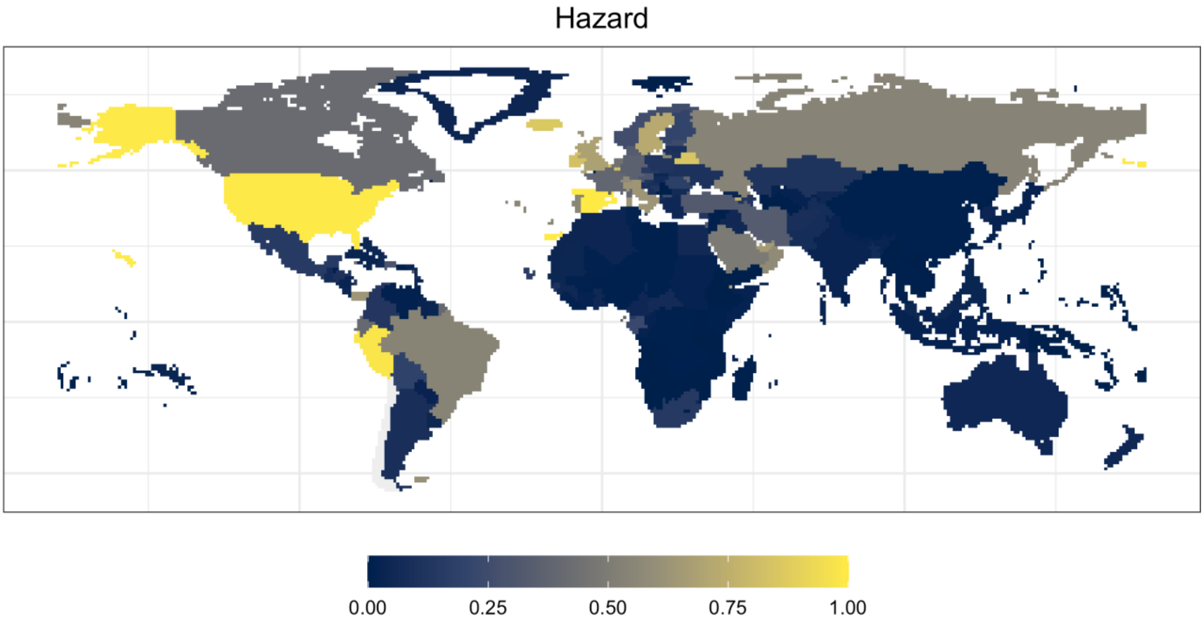

Fig. 1 COVID-19 hazard index map (calculated from the ratio of the number of confirmed cases to population). Data updated: 10 June 2020.

Measured at the level of grid cells, g, we model the risk associated with the economic impact of epidemics as a linear combination of hazard plus a local economy's exposure and vulnerability to it, minus its resilience or ability to bounce back:

$$\widehat{Risk}_g = \alpha_1 Hazard_g + \alpha_2 Exposure_g + \alpha_3 Vulnerability_g - \alpha_4 Resilience_g \qquad \text{(Eq. 1)}$$

We collect a large group of sub-national and national measures from recent years (2014-2018) to proxy for exposure, vulnerability, and economic resilience. The selection of variables is based on the literature measuring disaster risk, as reviewed in Yonson and Noy (2018), and on the current experience of COVID-19. We then use principal component analysis (PCA) to compute a standardized index for each exposure, vulnerability, and resilience. Using the first component of exposure, vulnerability, and resilience index, in addition to the number of confirmed cases of COVID-19, we compute a risk index in relation to the economic risk of epidemics. In our simplest specifications, we assume $\alpha_i = \alpha_j$ for all *i* and *j*; in an alternative algorithms, we assume $\alpha_1 = 0$ (the Hazard is equal for all countries).

In another alternative, we estimate the α_i based on a least-squares regression algorithm which estimates, as dependent variable, the Disability Adjusted Life Years (DALY) metric available from the Institute for Health Metrics and Evaluation. We calculate the average of DALY in the period 2012-2017 from three communicable causes: (i) Diarrhoea and common infectious diseases; (ii) Malaria and neglected tropical diseases; and (iii) other communicable diseases. We use this aggregate measure of DALY lost as an alternative proxy for the risk of epidemics. Since the DALY aggregates are calculated for each country, we merge the country-level data into grid cell data. The implied assumptions are that the current health situation and an ideal health status are identical in the different grid cells within each country. We then estimate the following model by Ordinary Least Squares (OLS):

$$DALY_g = \beta_0 + \beta_1 Hazard_g + \beta_2 Exposure_g + \beta_3 Vulnerability_g + \beta_4 Resilience_g + \varepsilon_g \qquad \text{(Eq. 2)}$$

where $Hazard_g$ is the prevalence of COVID-19 in grid g. $Exposure_g$, $Vulnerability_g$, and $Resilience_g$ is the first component of principal component analysis for exposure, vulnerability, and resilience in grid g.

3. Statistical Methods and Data

To compute a coherent index for exposure, vulnerability, and resilience separately, we use principal components analysis (PCA) - an algorithm whose aim is to compress a large set of variables while retaining most of the information in the initial larger set (Ringnér, 2008). Before going through the dimensionality reduction procedure to find the principal components, we standardize all variables.

Hazard and Exposure indicators

We use the number of COVID -19 confirmed cases per 1 million people. Data is updated on 10 June 2020. In terms of economic exposure, we use population and nighttime light density to measure human presence and economic activity. Nightlight data is used as a proxy for economic wealth; the data is described in Román et al. (2018). Transport density provides another relevant indicator for population density. An urban metropolitan area likely has a denser network of highways and air links. To get a coherent layer of transportation density, we use all types of transport as described in Lloyd et al. (2017). Transport databases from Open Street Map (OSM) include: Highway, waterway, railway network, railway station and airport. Last, we use the number of net incoming migrants to proxy for external economic exposure. Data for each variable to proxy for exposure are collected as raster format with higher resolution than data for hazard. Hence, we can plausibly merge with data about epidemic into grid 1 degree by 1 degree by WGS84 projection.

Vulnerability indicators

Likewise, we use a set of data on economic outcomes, human development, tourism, and health quality to measure vulnerability. Drake et al. (2012) argue that the vulnerability to infectious disease outbreak is much higher in low- and middle-income countries, especially the vulnerability to mortality and morbidity risk. The United Nations' Human Development Index (HDI) and total GDP in each grid cell, are collected from the data described in Kummu et al. (2018). Kummu et al. (2018) estimate Gross Grid-Cell Product by multiplying country-level GDP per capita (PPP) with 30 arc-sec population counts following the method pioneered by Nordhaus and Chen (2016). To get sub-national data on HDI, Kummu et al. (2018) develop scaling factors to combine sub-national and national data.

Tatem et al. (2012) survey the need and availability of sub-national detailed demographic data that might be useful in understanding disease exposure and vulnerability. They argue that for improvement in our understanding of disease transmission and control, we require detailed spatially-referenced demographic data (for example, distinguished by cohorts and gender). This data is only available in low frequency in countries that conduct a comprehensive census. We lack data on health quality at the sub-national level; except for spatially-detailed data on the old population density and infant mortality rate, we use country-level measures of healthcare spending and number of hospital beds per 1000 population. These data are from the World Bank Development Indicators (WDI) and World Health Organization (WHO). We merge the country-level data into the grid cell data by assigning the same value for all grid-cells within the same country.

Since the healthcare spending data might not be a perfect proxy for the robustness of the public health system, and its ability to prevent the spread of an epidemic, we also use two alternative proxies. One is the presence of a robust public-health systems (or lack thereof) – this International Health Regulations Score is available from the WHO. Another alternative is the Global Health Security Index that is available from Johns Hopkins School of Public Health. These results are available in the appendix.

Resilience indicators

Hallegatte et al. (2016) argue that early warning systems possibly reduce asset losses. We assume information about epidemics is accessed via the internet and mobile phones, so we associate higher penetration rates of these with higher resilience. We use data from the WDI and the International Telecommunication Union. Next, we assume that the capacity of government to implement economic relief policy, and household to access loans are positively associated with resilience. Last, we use data about ethnic and linguistic diversity to measure socio-cultural disparity (Alesina et al., 2003). We assume that the diversity plausibly affects the behaviour of individuals and communities in a hazard event.

4. The Measured Risk Index

Figure 2 shows descriptive information and PCA results of all variables we use to measure exposure, vulnerability, and resilience. The principal component index is the output of linear combination of the original variables. We use the first principal component for each exposure, vulnerability, and resilience index. As the first component accounts for most variation in the data and contribute the most explanation in the combining procedure. The proportion of eigenvalues indicates the explanatory importance of the factor, which are 4.0, 3.4, and 2.8 for exposure, vulnerability and resilience respectively. Economic activities, demographic measures, and infrastructure density all positively explain exposure. High income areas with better healthcare quality (as measured by lower infant mortality, health spending, hospital infrastructure) are related to less vulnerable areas. Tourism areas and high numbers of the elder are associated with higher vulnerability. For resilience, areas with higher social, and cultural disparity have a lower index. Countries having lower ratio of government debt and higher expenditure are more resilient.

We normalize all exposure, vulnerability, and resilience indices. Figure 3 presents the cumulative distribution of main results for: Hazard, exposure, vulnerability, resilience, and economic risk. For hazard, we use the number of confirmed cases of COVID-19 per 1 million people from the worldometer website, which has the most frequently updated data. We calculate the economic risk by an equal-weight linear combination of the four indices.

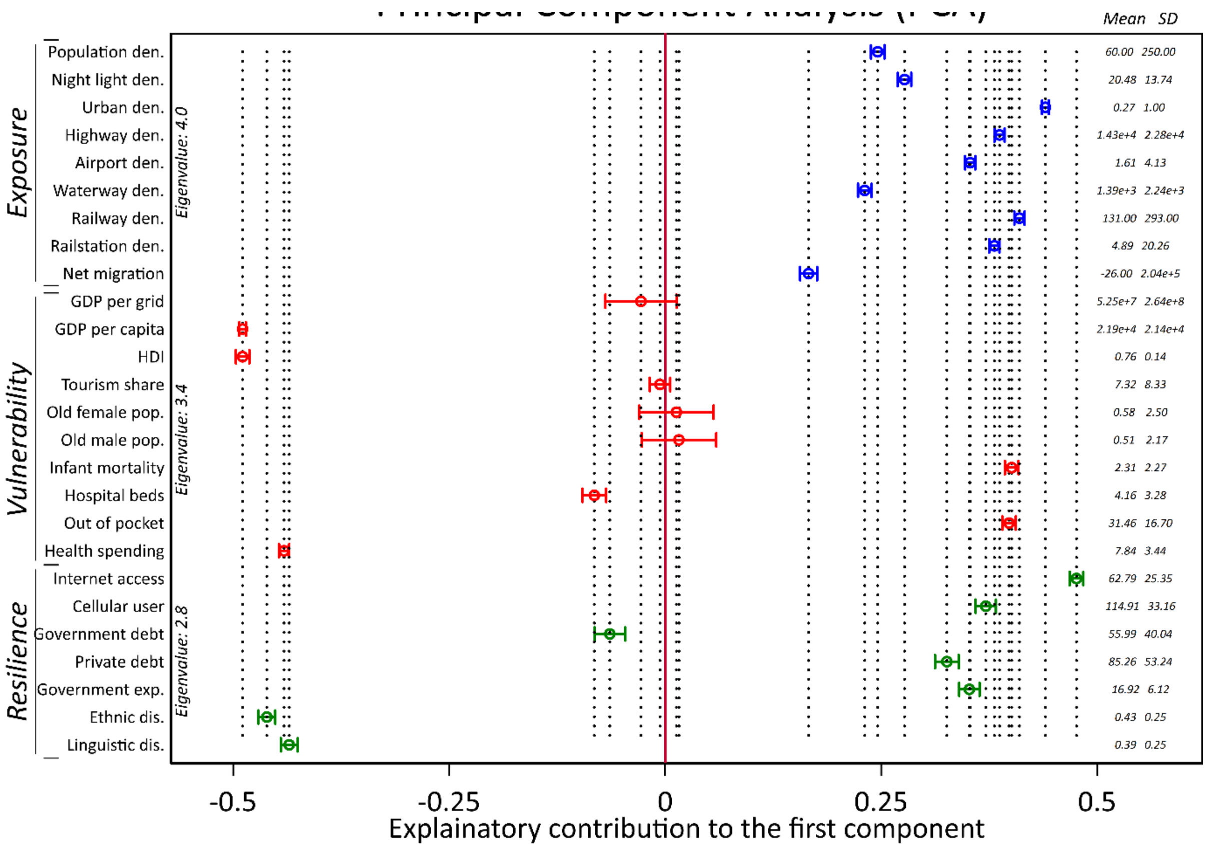

Fig. 2 Descriptive data and principal component analysis (PCA) results. The lower and upper caps represent standard errors of each variable in the first component.

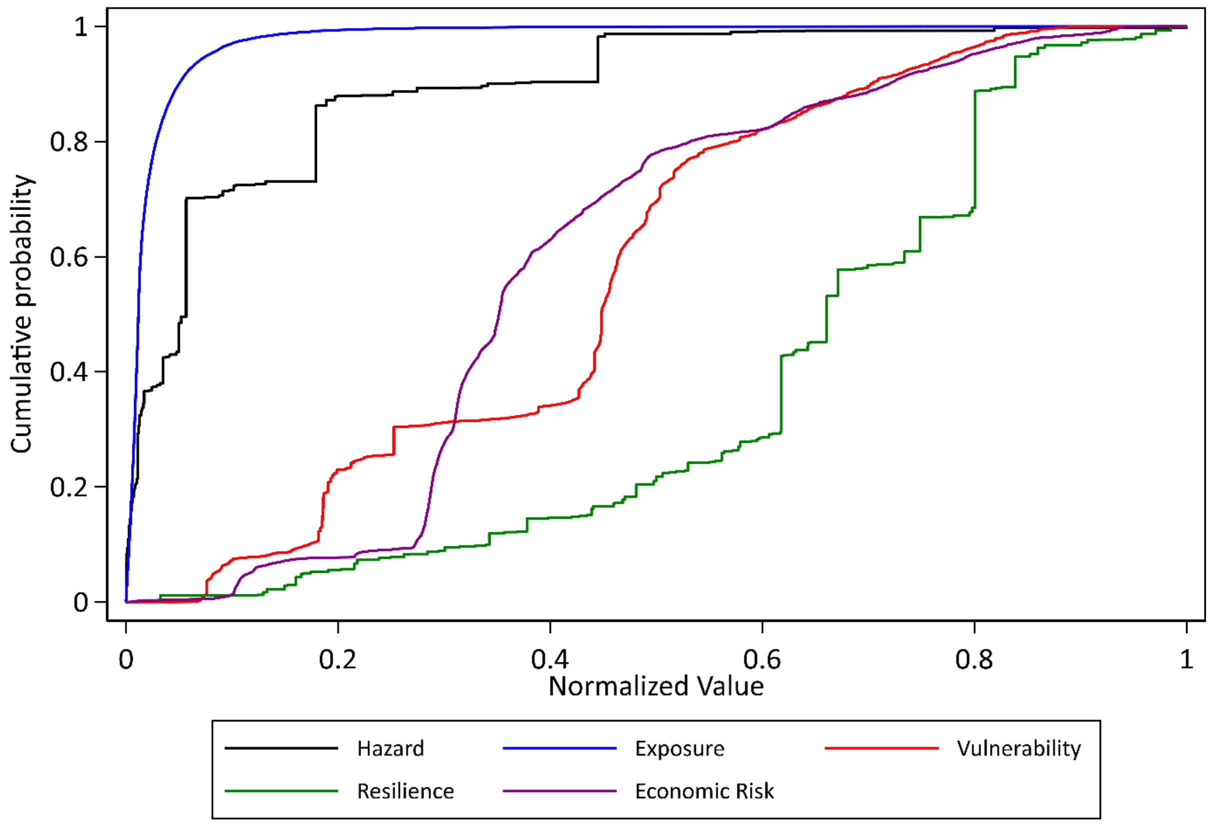

Fig.3 The cumulative distribution of the indices

We find that the economic risk of epidemics is especially high in much of Sub-Saharan Africa, South Asia, Iran, Afghanistan and much of Southeast Asia (Figure 4). Fundamentally, areas of the greatest vulnerability align with the high economic risk. The economic risk is high in Africa and Southeast Asia, as these are the most vulnerable areas with low income and healthcare quality. Resilience, intentionally or otherwise, plays a role in reducing the economic risk from epidemics. For example, in Southern Cone countries (Argentina and Chile) the resilience is higher than neighbourhood countries due to less fractionalized socio-cultural characteristics (lower ethnic and linguistic disparity) and higher incomes. Oil exporting countries face a vulnerability to global oil prices (which have collapsed in the first few months of the pandemic), while other commodity exporters have faced less volatility in the prices of their exports.

In Figure 5, we assume that the hazard (the presence of the virus) is identical to all countries. This can be motivated either by the expectation that eventually, the spread of the virus will reach epidemic levels in all countries, or because of the widely held view that differences in the testing regimes account for a lot of the differences in the number of confirmed cases (probably especially relevant for low-income countries). As such, the assessment of the economic risk that is caused by this virus should not be based on the present known spread of the virus, but on its global potential. Besides some expected differences, however, the results presented in Figure 5 (uniform spread of the virus) and Figure 4 (hazard based on the current spread of the virus) are very similar. The only slight difference is that the United States and the countries of Northern Europe that have very high official infection rates per population (e.g., Sweden and Iceland) are assessed to be a comparably lesser risk in Figure 5 (when we assume a uniform level of the hazard).

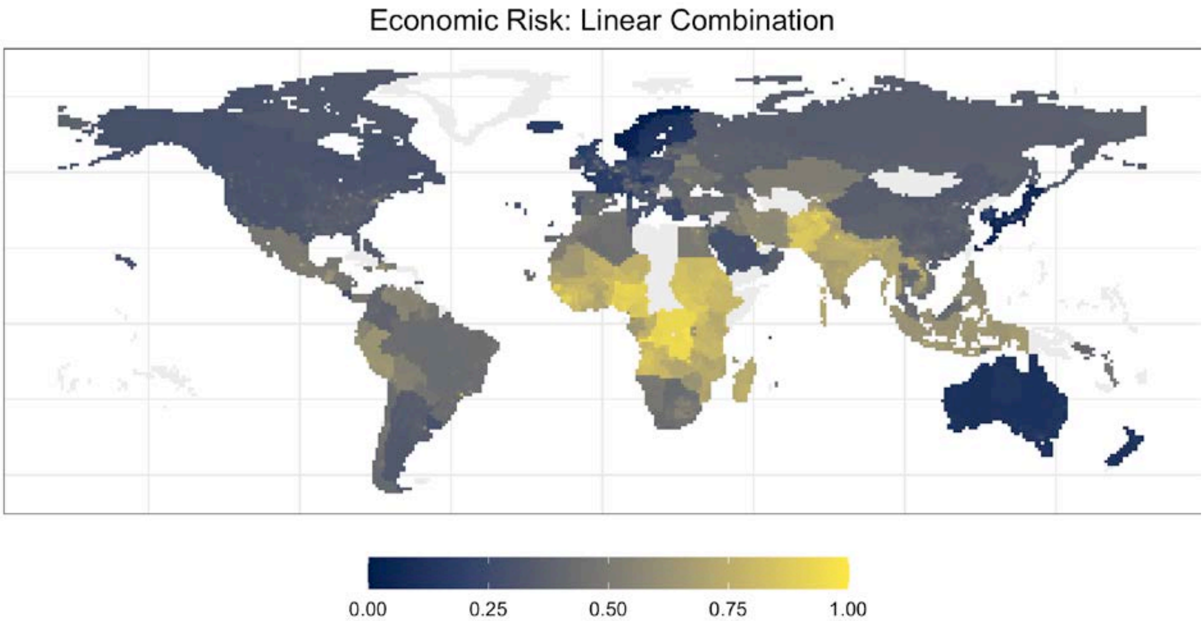

Fig. 4 Economic Risk of COVID-19 using equation (1) with equal weights.

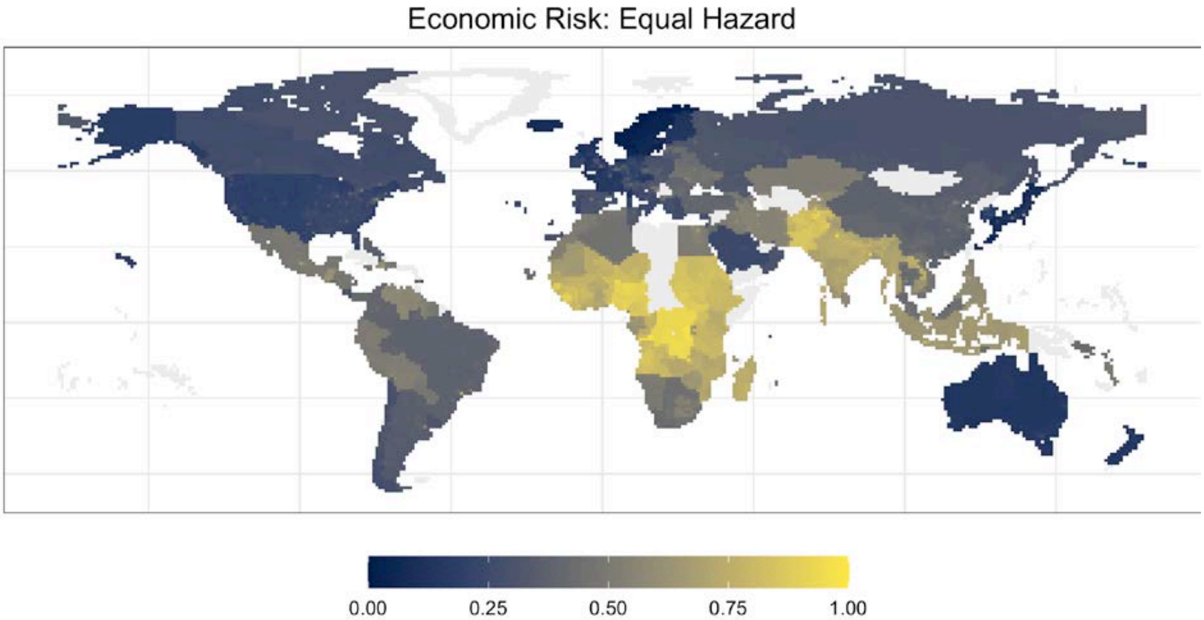

Fig. 5 Economic Risk of COVID-19 using a modified equation (1) with hazard calibrated so all countries have an equal hazard (all are susceptible to COVID-19).

A less ad-hoc weighting scheme, instead of equal-weights to the exposure, vulnerability and resilience indices - as in Figures 4 and 5, relies on the Disability-Adjusted Life Years (DALY) measure of overall disease burden. Since previous DALYs associated with communicable disease is the outcome of previous events, it could be a good source for understanding the interactions between the (mostly zoonotic) hazard and exposure, vulnerability, and resilience to it. DALYs are the sum of years lost due to ill-health, disability or premature death from communicable diseases. Weights for each of the four components are derived by Ordinary Least Squares regression with the country-level DALYs as the dependent variable, as in Eq. 2 (we assign the same DALY value for all grid cells within each country).

Table 1: Estimation results for National DALY

Hazard	20.956***	(5.371)
Exposure	495.018***	(46.726)
Vulnerability	169.309***	(5.878)
Resilience	-97.386***	(4.730)
_cons	19.318***	(3.974)
Obs.	16654	
R-squared	0.166	

Robust standard errors are in parenthesis. **** p<0.01, ** p<0.05, * p<0.10.*

Building on the regression results presented in Table 1, the alternative functional form to measuring economic risk uses the weights implied in the coefficients described therein. The weights are calculated by $\hat{\beta}_j(\sum_{j=0}^{4}|\hat{\beta}_j|)^{-1}$, then:

$$\widehat{WRisk}_g = 0.02 + 0.03Hazard_g + 0.62Exposure_g + 0.21Vulnerability_g - 0.12Resilience_g \quad \text{(Eq.3)}$$

The estimated weights are then plugged into the risk function (i.e., $\alpha_g = \beta_g$) which now places considerably more weight on exposure than on hazard, resilience, and vulnerability. The spatial patterns of the DALY-weighted risk map in Figure 6 are still, though, similar to those observed in the unweighted maps (Figures 4 and 5). As before, the areas at highest risk of economic losses from epidemics remain Sub-Saharan Africa and South and South-East Asia. But, some of Central Europe and East Coast of the United States are now considered more risky with this approach as these are densely populated. Besides, the Indian subcontinent, area that is both poor and densely populated, is much riskier.

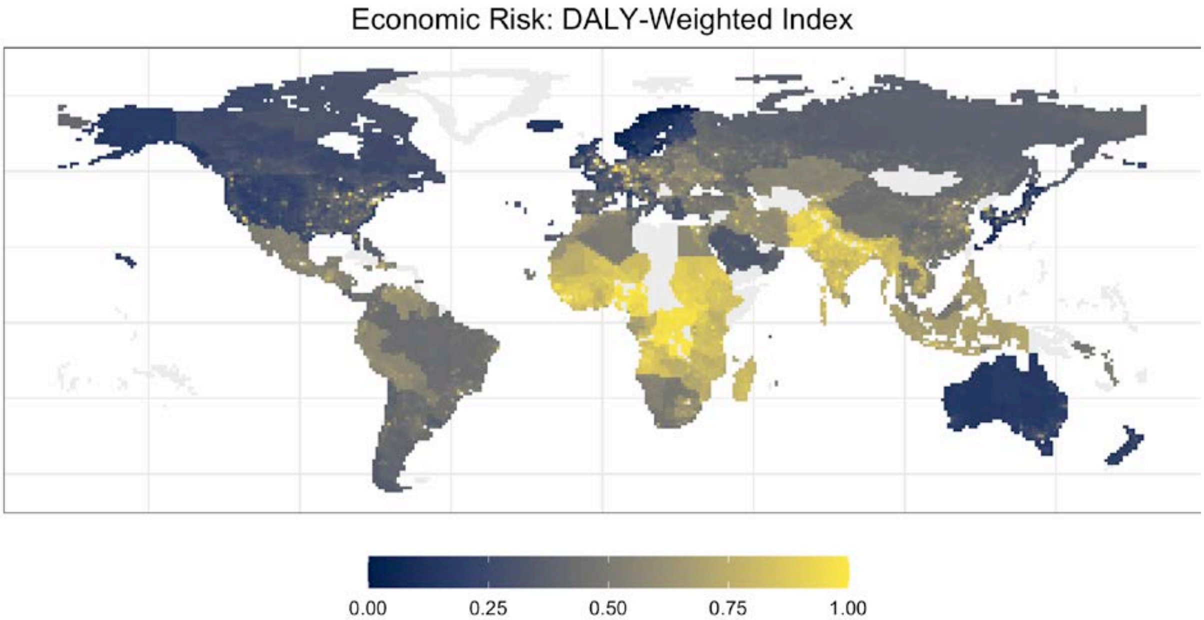

Fig. 6 Economic Risk of COVID-19 using the DALY-weighted index.

5. Discussion and Conclusions

We developed a measurement tool to estimate the economic risk of epidemics. This index of economic risk is based on pre-epidemic data, so it can readily be used in the initial stages of the epidemic. A substantial amount of recent research has already assessed the risk from the epidemic to financial markets, since high-frequency data for these markets is readily available (e.g., Al-Awadhi et al., 2020; Goodell, 2020; Sharif at al., 2020; and Zhang et al., 2020). Fewer papers, however, have examined the economic risk, as observed economic data for the second quarter of 2020 is not yet available (and even first quarter data is not uniformly available or reliable). Using structural macroeconomic modelling (sometimes coupled with epidemiological ones) several papers do attempt to qualitatively or quantitatively describe the likely economic impact and its determinants (e.g., Céspedes, et al., 2020; Ludvigson, et al., 2020; Lewis et al., 2020). Their emphasis is quantifying the risk for a specific country, for a specific point in time, and it relies on a significant body of assumptions regarding the relevant structural characteristics of the economy that is modelled. Our work attempts to compare the risk across countries, rather than evaluate the exact magnitude of the risk in a specific country.

The economic consequences of an epidemic, like any other natural hazard shock, can be delineated into damages, direct losses, and indirect losses (Noy, 2016). If measured through the standard statistical tools used by governments to evaluate the cost of life (the Value of Statistical Life – VSL), the direct costs of COVID-19 due to illness and mortality will probably turn out to be much smaller than the indirect losses. This is, of course, especially true for countries in which the epidemic has not yet spread indiscriminately, but that are very exposed to the global shock it created (for example, in tourism dependent economies). With growing globalisation of information, increasing inter-connectedness among far-flung populations and extensively longer supply-chains comes increased exposure to the indirect economic losses from epidemics, with potentially dire implications for many economies.

When we account for the ways an epidemic creates economic losses, we need to measure not only the direct reductions in economic activity that are attributable to changes in government policy (e.g., mandatory lockdowns), but also measure behavioural changes that are caused by changing subjective judgements about the risk of contraction among the still healthy population. These behavioural changes may be influenced not only by the characteristics of the epidemic contagion process and the disease virulence, but also by its media coverage and the fear it might generate. These, of course, are much more difficult to quantify than explicit government policies such as those recorded in Petherick et al. (2020).

As public health systems have improved over the past century, this pandemic's health impacts are unlikely to be of the magnitude of the 1918-19 Influenza pandemic, though it still will be of catastrophic scale (more than any other sudden-onset disaster in the past century). However, what remains equally salient is the pandemic's economic consequences. The exposure, vulnerability, and resilience to these economic consequences were not ameliorated as much when public health systems developed throughout the last century. In contrast, plausibly, globalisation of trade, increased tourism and labour flows, the advent of social media, and loss of trust in traditional sources of information (especially the 'old' media and government) are all likely to have amplified the economic losses, by creating additional vulnerabilities, and amplifying behavioural responses.

An example of the extensive behavioural reaction is the SARS crisis in 2003 (Shields and Noy, 2019). It could be typified as a high prevalence-elasticity response to a disease outbreak - i.e., when the public response to an epidemic results in large behavioural changes (Brahmbhatt and Dutta, 2008). The SARS case fits with the argument of Philipson (2000), that when private behaviour is strongly prevalence-elastic, the main economic cost of a disease outbreak is likely to arise out of preventative actions rather than directly from infections. This appears to be true for COVID-19, compared to previous epidemics, for reasons we are yet to fully understand. It is equally clear that with somewhat different basic parameters of the disease, this behaviour-prevalence elasticity could have been even higher. A similar virus that would have had high mortality associated with the younger than 5, rather than the older than 80, would have generated an even stronger behaviour reaction (from both governments and individuals).

A study by Perrings et al. (2014) highlights the importance of government intervention which targets the private costs and benefits of disease avoidance so that they induce individual behavioural responses which align with the overall interests of the wider society. This concerns the trade-off that individuals make regarding their respective costs and benefits from, for example, social distancing, in an epidemic situation, and internalises any externalities that are generated by either the prevention action or the infection itself.

If the benefits of social interactions for an individual are high (e.g., these are necessary to earn the income required to meet daily subsistence costs) then this could result in continued interaction during an epidemic and, while reducing the economic impact, can potentially increase the disease reproduction rate. This can also work in the opposite direction; if the individual costs of public avoidance are very low and benefits very high, then mass public avoidance in an epidemic, where the mortality and contagiousness are not significant enough to warrant such a response, will lead to unnecessarily large economic and welfare losses. Improved understanding of the dynamics of individual trade-offs could help to prioritise public health interventions beyond what is suggested from our measure of economic risk.

To summarise, what is most apparent from our analysis is that the economic risk from COVID-19 is not located in Italy or the United States, where much of the media and global public attention was concentrated. Rather, the most dire economic risks are in countries and regions that do not get much global attention in normal times (e.g. Sub-Saharan Africa) and get even less in the midst of the frantic reporting from what was, for a while, the immediate frontlines of the pandemic's spread in Bergamo or New York City. This lack of attention was further compounded by the inability of the press to move around globally. This is unfortunate, as the ultimately, the economic costs will be borne in places with little global media exposure, away from global public scrutiny and assistance.

These observations, and the description of the spatial distribution of the risk, should generate several conclusions about mitigation and prevention policy – focusing on mitigating the economic damage and loss, rather than that of the disease spread itself. We argue that since the economic and public health risks are distinct, evaluation and the design of policies to ameliorate these risks should be pursued separately. And using information from studies, such as ours, one can design better policies that specifically target the areas where the risk is higher.

In the long term, the main insight we gain from this analysis is that while it seems our public health systems have been caught by surprise, that is even more true for our social and economic policy institutions. There has been almost no economic analysis that has been devoted to understanding the economic risk of epidemics, before the COVID-19 crisis. This pandemic is not going to be the last one to hit us, even if we improve our public health institutions. We need to make sure that our economic policymaking mechanisms, including the Bretton Woods institutions and other international bodies, are prepared for the economic risk of future pandemics.

The framework of analysis we use also suggests that attempts to reduce the economic risk of epidemics should focus on reducing the exposure and vulnerability of our economies to this risk, and on increasing their resilience. Obviously, there will be many other co-benefits from pursing that as a goal, as these will also reduce other risks, and provide other social benefits.

Table 3: Details of variables

	Variable name	Description	Unit of measurement	Kind of indicators	Spatial availability	Year released/ updated	Data coverage by grid	Source
1	COVID-19	Number of confirmed cases per 1 million people	Number of people	Hazard	Country-level	10 June 2020	100%	Worldometer
2	Population density	Number of persons per square kilometre in 2015	Number of people per km^2	Exposure	Resolution: 0.5' (1 km)	2017	100%	(CIESIN, 2018)
3	Night-time lights	Night-time light intensity in 2016	Index	Exposure	Resolution: 1.5' (3 km)	2017	100%	Román et al. (2018)
4	Urban built-up	Human impact on land by urbanization activity	Index	Exposure	Resolution: 0.5' (1 km)	2014	100%	Tuanmu and Jetz (2014)
5	Transport networks in 2016	Highway density	Index	Exposure	Resolution: <1 km	2016	100%	Lloyd et al. (2017)
		Airport density						
		Waterway density						
		Railway network						
		Rail station density						
6	Net migration	Number of in-migrants minus out-migrants	Number of people	Exposure	Resolution: 0.5' (1 km)	2015	100%	de Sherbinin et al. (2015)
7	GDP	Gross Domestic Product (PPP) per grid in 2015 (constant 2011 USD).	USD	Vulnerability	Resolution: 0.5' (1 km)	2018	100%	Kummu et al. (2018)
8	GDP per capita	Gross Domestic Product per capita (PPP) per grid in 2015 (constant 2011 USD).	USD	Vulnerability	Resolution: 5' (10 km)	2018	98%	World Bank (WDI)
9	HDI	Human Development Index [0-1]	Index	Vulnerability	Resolution: 0.5' (1 km)	2018	100%	Kummu et al. (2018)
10	Tourism	Share of travel and tourism to GDP	Percent	Vulnerability	Country level	2018	94%	World Bank (WDI)
11	Old population density	Number of female/male aged 70 or more per square kilometre in 2020	Number of people per km^2	Vulnerability	Resolution: 0.5' (1 km)	2017	100%	WorldPop and CIESIN (2018)

12	Infant mortality rate	The number of children who die before their first birthday per 1,000 births in 2017	Proportion	Vulnerability	Resolution: 0.5’ (1 km)	2018	100%	(CIESIN, 2019)
13	Hospital beds	The number of hospital beds per 1,000 population	Number of beds	Vulnerability	Country level	2015	95%	World Health Organization (WHO)
14	Out-of-pocket	Share of Out-of-Pocket Expenditure on Healthcare	Percent	Vulnerability	Country level	2014	96%	World Bank (WDI)
15	Health spending	Total health care expenditure as GDP	Percent	Vulnerability	Country level	2014	96%	World Bank (WDI)
17	Internet access	Share of population using the Internet	Percent	Resilience	Country level	2017	99%	World Bank (WDI)
18	Cellular user	Mobile cellular subscriptions per 100 people	Numeric	Resilience	Country level	2017	99%	International Telecommunication Union (ITU)
19	Public and private debt	Ratio of central government debt to GDP	Percent	Resilience	Country level	2018	98%	IMF and WDI
		Ratio of domestic credit to private sectors to GDP						
20	Government expenditure	Ratio of government expenditure to GDP	Percent	Resilience	Country level	2018	98%	World Bank (WDI)
21	Socio - Cultural disparity	Ethnic disparity [0-1]	Index	Resilience	Country level	2016	99%	Alesina et al. (2003)
		Linguistic disparity [0-1]						

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Appendix

Figure A1. Map of Exposure, Vulnerability, and Resilience

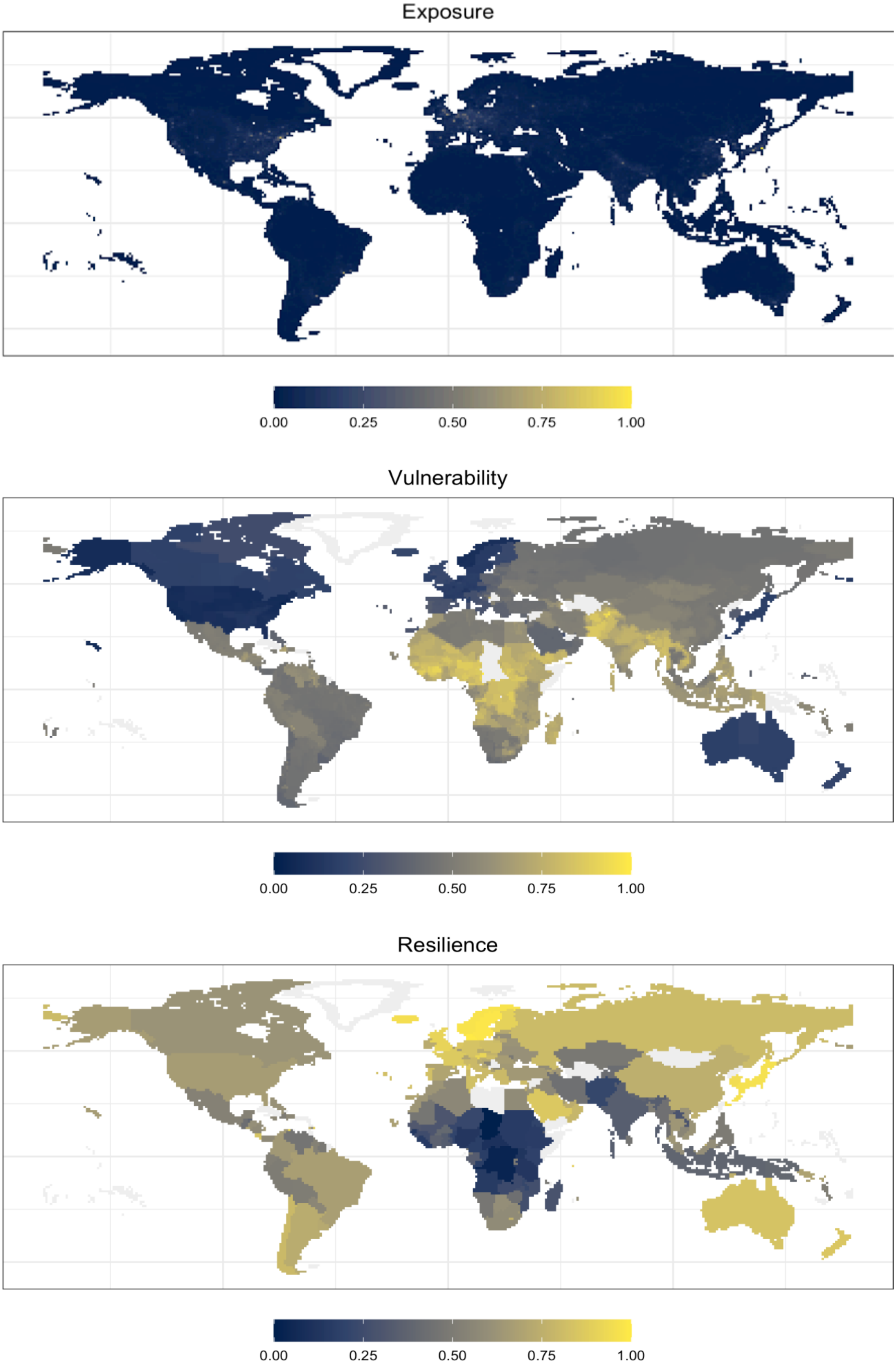
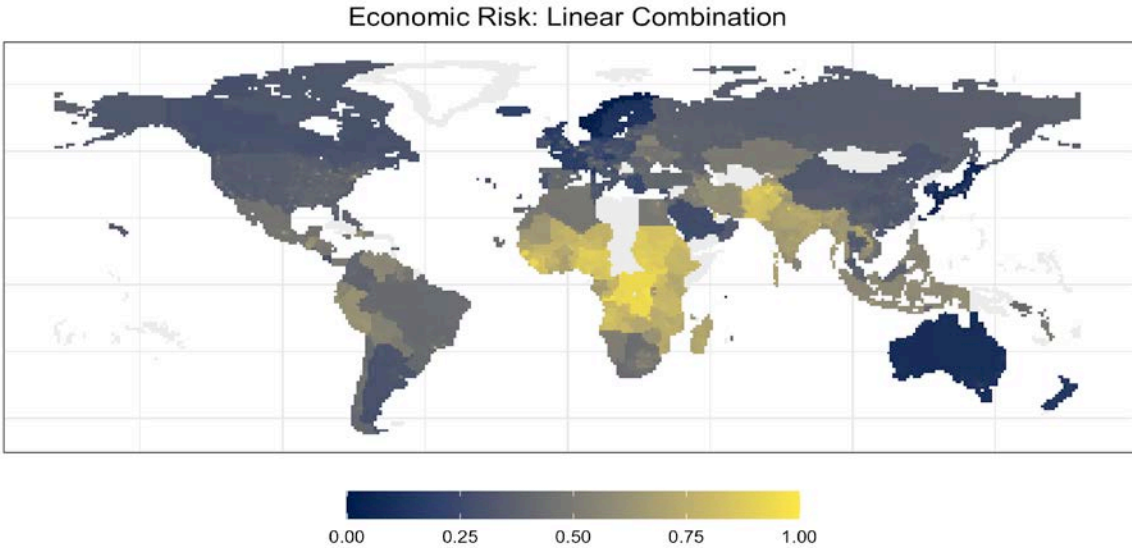
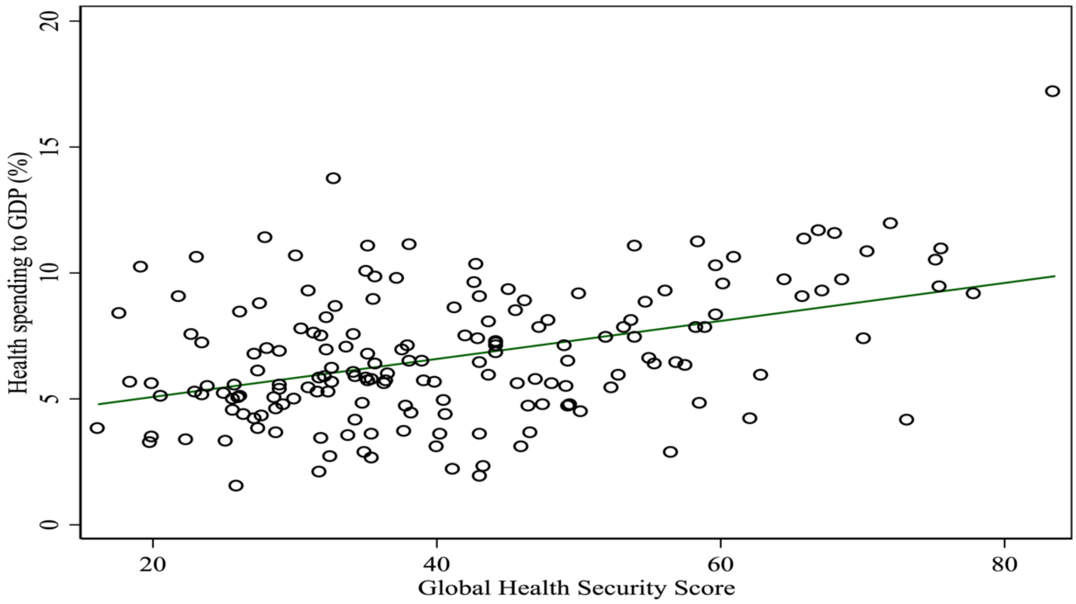


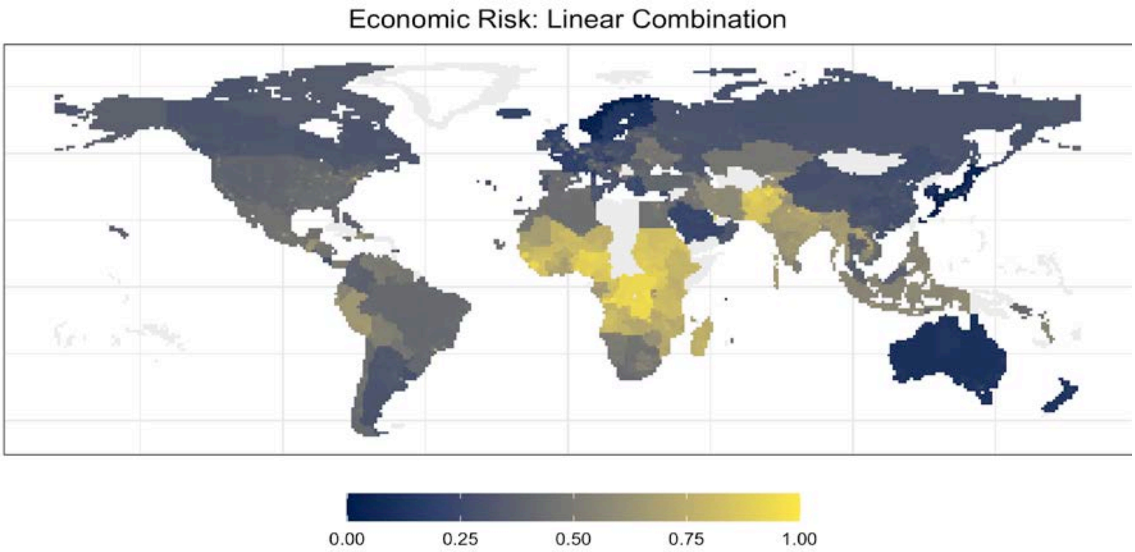
Figure A2. Global Health Security Score

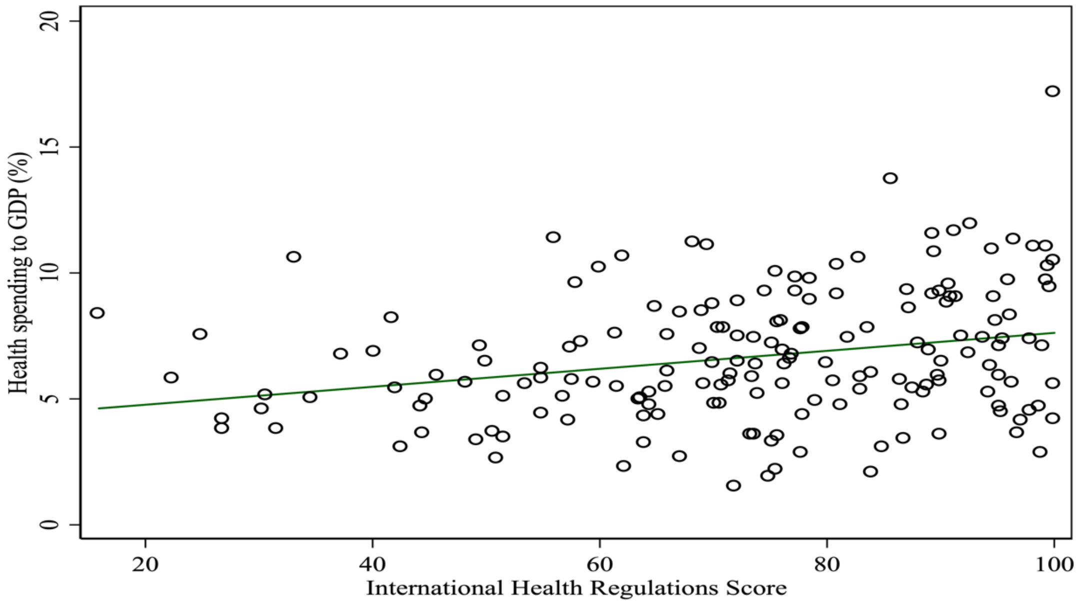




Instead of the ratio of health spending to GDP, we use the global health security score 2019 developed by Center for Health Security of John Hopkins university. Global health security score, ranged from 0 to 100, measures how prepared a country is for infectious disease outbreaks (higher score is more prepared). The global health security score is significantly correlated to the total healthcare spending. Using the global health security score as a proxy for vulnerability component index, the global economic risk is consistent to our main findings.

Figure A3. International Health Regulations Score





An alternative proxy is the international health regulations score from World Health Organization. The international health regulations score is the average of 13 core health capacities. The first capacity is about legislation, policy (e.g. universal health coverage), financing. The score is also significantly associated to the healthcare spending.