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The Economic Risk of COVID-19 in Developing Countries: Where is it Highest?

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Abstract. We measure the economic risk of COVID-19 in developing countries using pre-pandemic data sources. Following the standard conceptual model of disasters, we use data from 2014-2018 to compute measures for exposure, vulnerability, and resilience of the local economy to the economic shock of the epidemic. Using a battery of proxies for these three concepts, we calculate the principal components of exposure and vulnerability to it, and of the economy's resilience (i.e., its ability to recover rapidly from the shock). We find that the economic risk of this pandemic is particularly high in the poorer parts of the developing world. The economic risk from COVID-19 is not located in particular in China, where the virus originated, nor where most of the confirmed cases are currently found – in the United States and Western Europe. Rather, the highest economic risks are in Sub-Saharan Africa, and the poorest parts of South Asia, regions that do not get much global attention in normal times, and get even less when the media's interest is turned to the tragedies happening in places like Bergamo and New York City. Our spatial index of these economic risks is similar when comparing an ad-hoc equal weighting algorithm for the three components of the index (an algorithm that assumes equal hazard for all countries), and one based on an estimated weights using previous aggregated Disability-Adjusted Life Years losses associated with communicable diseases.

Key Words: Epidemic, COVID-19, risk measurement, developing countries, economic impact
JEL: I1, Q54
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Data access. All data is publicly available (see data appendix).

Introduction

The economic risk of COVID-19 is distinct from its health risk – in some instances, the two might even be orthogonal. In fact, even in countries or regions with no significant case load or associated mortality the economic risk associated with the pandemic may be very high. Seychelles and Fiji, for example, both have fewer than 20 reported cases and no mortality, but both are heavily reliant on tourism receipts and have fairly limited fiscal space for battling the ensuing recession. Other countries with more significant but still easily manageable caseload also find that they have access to very few resources to prop-up struggling firms, to extend the safety nets that are required to support their vulnerable populations during lockdowns, and to prevent deeper and longer-lasting recessions

Many of the current attempts to estimate the likely economic impact of the epidemic rely on epidemiological modelling coupled with macroeconomic models of the economy. These productively replicate the same modelling approach used in the economics of climate change literature – the Integrated Assessment Models (IAM) that couple global climate models with macroeconomic models. In these IAMs, the connection between the climate and economic models is usually stipulated to be between temperature (the climate) and productivity (the macroeconomy). In the new Pandemic-IAMs, the causal link can be on the supply-side, because of the lockdown policies enacted, on productivity because of the disease impact, or on demand by consumers (either because of the disease, or because of the lockdowns) – e.g., Baqaee and Farhi (2020); Çakmaklı et al. (2020); McKibbin and Fernando (2020).

Especially in a pandemic with wide-reaching and global impacts as this coronavirus, it is likely that the shock will lead to deep (even if temporary) structural changes inside and outside all affected economies, so that the structural parameters are unlikely to remain the same and equilibrium models might not provide a good dynamic representation of the economy. Another approach would be to use dis-equilibrium models (e.g., Mandel and Veetil, 2020), but these still require reliance on constant input-output data.

Another potential approach to assess the pandemic's likely impact is to extrapolate from the impact of similar past events. The two most notable comparisons that are frequently being made are SARS, a very similar coronavirus that hit several countries in Asia in 2003, and the global 1918-1919 Pandemic Flu. SARS, however, was a much more limited event that hit only a few countries and disappeared as quickly as it appeared (Shields and Noy, 2019), and the 1918-19 pandemic was taking place in a world just emerging from a debilitating World War, a world significantly less globalised, and with a much more limited and diminished ability to provide public health services. It is therefore not clear how much we can learn from these two comparisons.

Consequently, we take a different approach, and in order to estimate the likely magnitude of the economic risk facing different countries, we use a disaster risk modelling framework. As defined by the United Nations Disaster Risk Reduction Office (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."

The basic framework we use is taken from this UNDRR framework. It assesses disaster risk as constructed around four concepts: hazard, exposure, vulnerability, and resilience, and it is the interaction of these four that leads to the disaster's economic consequences. The hazard, in these frameworks, is the natural trigger, in the present circumstances, it is the SARS-Cov-2 virus which causes the COVID-19 infectious disease.

However, we hypothesize that in the case of the COVID-19 pandemic, and especially in developing countries where the pandemic has, for now, not grown explosively as in a few temperate climate wealthy countries, the economic risk is almost completely decoupled from the hazard (infection) risk. It is mostly determined by exposure, vulnerability, and resilience, and therefore this risk has very different spatial variability than the spread of the virus. In contrast, in most of the Pandemic-IAMs, the hazard component is an important link; and so it was in the 1918-19 Flu Pandemic (Shields and Noy, 2019, argue that this decoupling is also present, to a lesser extent, during SARS).

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.

Resilience, in this framework, is conceptualized as the ability of the economy to bounce back given the magnitude of the shock (generated by the intersection of the hazard, exposure, and vulnerability). The degree of resilience in a system (in this case, the economy) is thus determined by the speed in which the recovery process occurs, and when the system reverts back to its pre-shock level or arrives at a new steady-state (a new economy). 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 plausible to pursue during the rapid phase of the spread of the epidemic. More likely is to make up for lost production once the epidemic has abated, and prepare the economy for the recovery period while the epidemic is still ongoing (as many governments are trying to do now for COVID-19). The ability to implement such policies, as determined by both financial and institutional capacity, is therefore an important determinant of economic resilience.

Our aim here is not to precisely measure the likely consequence of this pandemic. Rather, we aim to comparatively evaluate where the economic risk of COVID-19 is currently concentrated in the developing world – defined as all countries that the World Bank categorised, in 2019, as middle-income or low-income.

In a previous paper (Noy et al., 2019), we analysed the economic risk of a generic epidemic, while in Noy et al. (2020a), we made global comparisons of the risk associated with COVID-

19. Here, instead of focusing on a generic emerging infectious disease event, or on the global comparisons, we focus on developing countries. The main motivation for this focus on a narrower sample is the realisation that while much of the current spread of the disease is in the high-income countries, much of the economic risk is in the developing world (Noy et al., 2020b).

In Figure 1, we show the comparative current spread of the disease—i.e. the hazard—in the developing countries sample we analyse. This is a current measure of the hazard; and given the discussion above, we will not be using it in the analysis that follows. Another reason for not using these case counts is that these are known to depend, to a very large extent, on the testing regime in place. We therefore doubt the comparability of these figures. It is worth noting that, suspiciously, the available data suggests that the virus has been slower to spread among some of the poorest countries – for example, most of Sub-Saharan Africa, Laos, Myanmar, North Korea, Venezuela, Syria, and Papua New Guinea.

In the following sections, however, we show that the economic risk, as we measure it, is actually most pronounced in the very poorest parts of the world, and especially in Sub-Saharan Africa and some parts of South and South-West Asia – all areas that currently seem to be only moderately exposed to the disease itself.

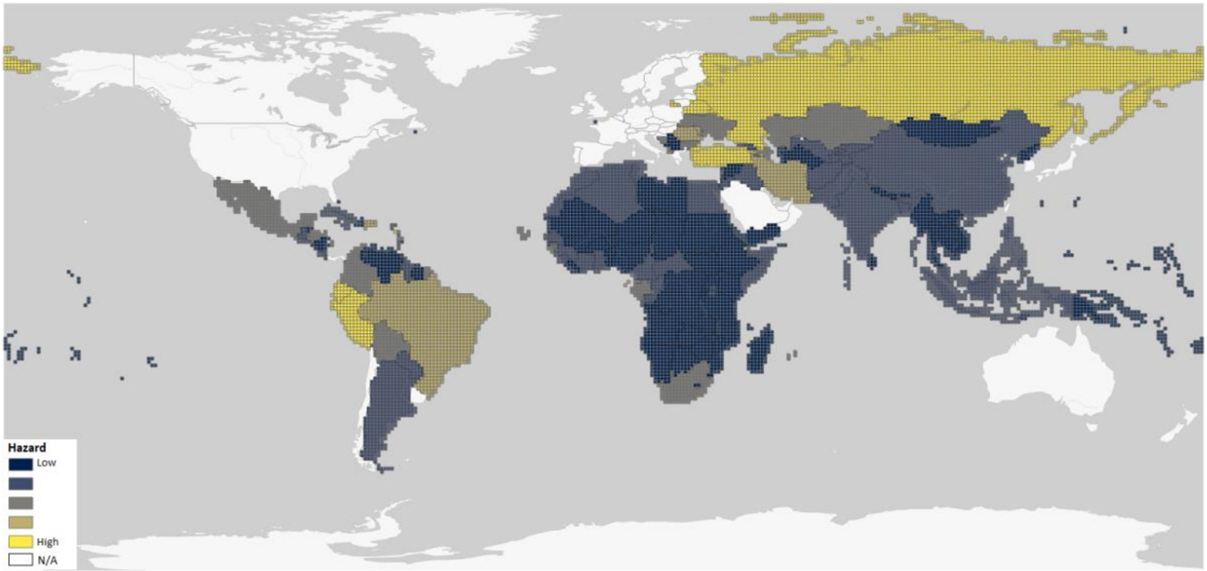

Fig. 1 COVID-19 hazard map in developing countries
(calculated as the ratio of the number of confirmed cases to population). Data updated: 17 May 2020.

Methodology

All of our analysis below is done at the grid-cell, rather than at the country level, but some of the data we use are only available at the country detail. Where available, we use the more spatially detailed grid-cell level data. Measured at the level of grid cells, g, we model the risk associated with the economic impact of the pandemic as a linear combination of a local economy's exposure and vulnerability to it, minus its resilience:

$$\widehat{Risk}_g = \alpha + \beta_1 Exposure_g + \beta_2 Vulnerability_g - \beta_3 Resilience_g \qquad \text{(Eq.1)}$$

We collect a 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 our observations of the current experience with 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 the exposure, vulnerability, and resilience indices, we compute a comprehensive risk index in relation to the economic risk of epidemics. In our simplest specifications, we assume equal weights ($\beta_i = \beta_j$; for all *i* and *j*); in alternative algorithms, we estimate the β_i based on a regression algorithm, using the number of Disability Adjusted Life Years (DALY) lost due to communicable diseases, in each country, in the last year for which this data is available.

Results

Figure 2 shows the 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).

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 elders 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.

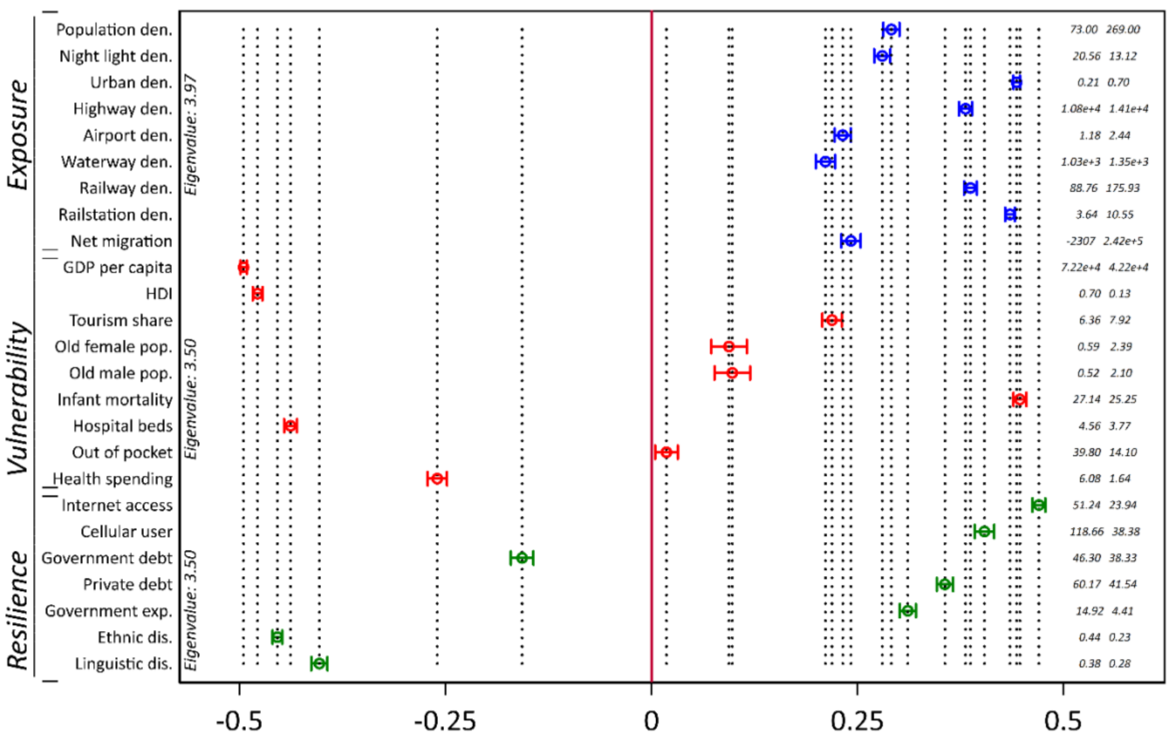

Fig. 2 Descriptive data and principal component analysis (PCA) results.

The lower and upper caps represent standard errors of each variable in the first component. The two columns on the right represent the mean and standard deviation of each variable.

We normalize all exposure, vulnerability, and resilience indices from the first component of the PCA in Figure 2. We calculate the economic risk by an equal-weight linear combination of the three indices: exposure, hazard and resilience.

We find, in Figure 3, that the economic risk of epidemics is especially high in most of Africa, South Asia (especially Pakistan and Nepal and some areas in India), and Laos. Interestingly, areas of the greatest exposure to the prevalence of COVID-19 are not where the economic risks are highest (Peru, Russia, Turkey). The economic risk is high in Africa and South Asia, as these are the most vulnerable areas, with low income and healthcare quality. Resilience, intentionally or otherwise, also plays a role in reducing the economic risk from epidemics. For example, in East Asia (China and Vietnam) the resilience is high due to less fractionalized socio-cultural characteristics (lower ethnic and linguistic disparity) and high capacity for policy mobilization associated with a high ratio of domestic credit to private sector (to GDP) and high levels of government expenditure (as share of GDP). While Brazil, the Mercosur countries, Turkey, China and Russia are estimated to have lower economic risks because their domestic economies are focussed on larger amount of exports, and are less reliant on the most vulnerable sectors like tourism.

In Figure 4, we restrict our analysis to all low and lower-middle income countries. This allows us to focus on those countries where the risk is highest. Not surprisingly, the bigger country with the highest risk is the Democratic Republic of the Congo (DRC), and the other highest concentrations of economic risk associated with the pandemic are in much of the rest of Central Africa, and besides some expected differences, however, the results presented in Figure 3 and Figure 4 are very similar. Low-income countries in Central Africa and South-West Asia remains among the highest risk areas.

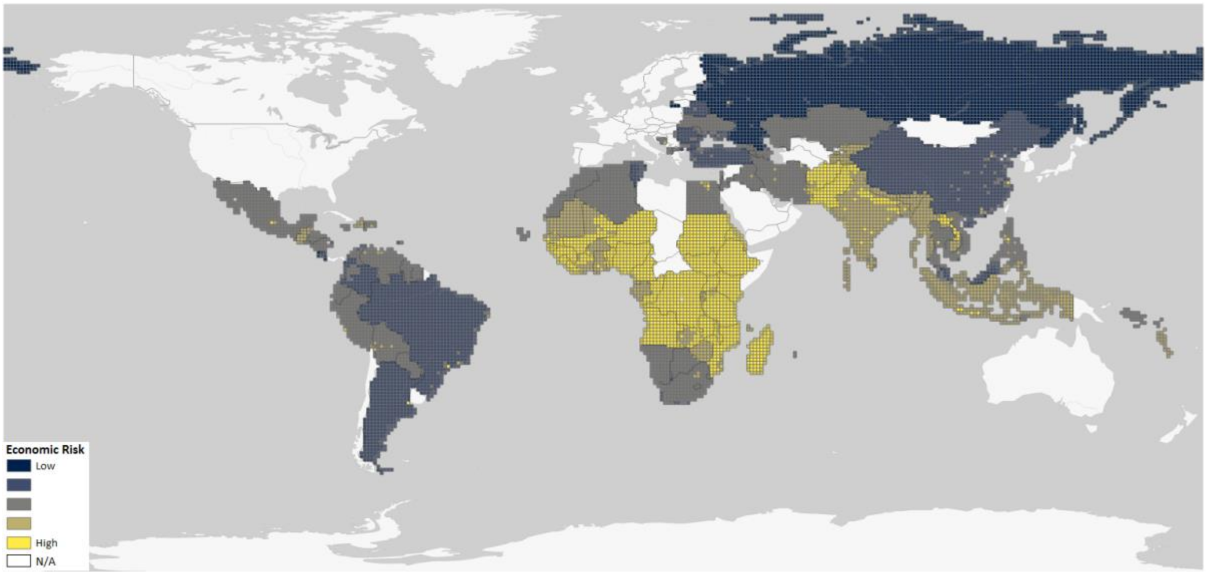

Fig. 3 Economic Risk of COVID-19 using equation (1).
Observations are divided into five classes by Jenks natural breaks classification method which optimally minimizes the average deviation from each class and maximizes the deviation across classes.

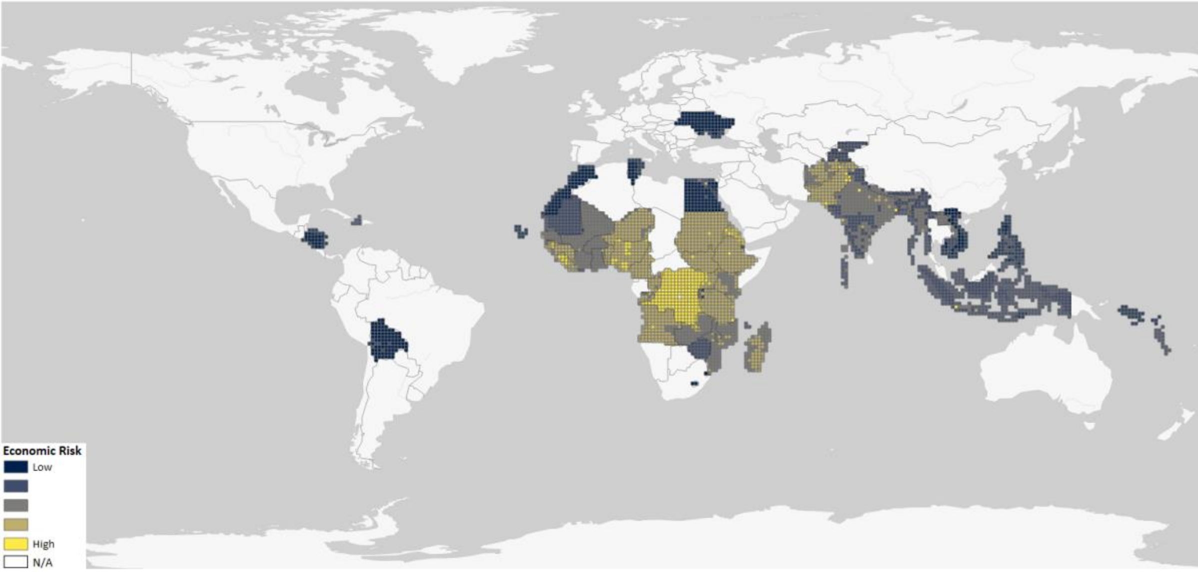

Fig. 4 Economic Risk of COVID-19 for low and lower-middle income countries.

A less ad-hoc weighting scheme, instead of the equal-weights assumption in Figures 3 and 4, relies on the Disability-Adjusted Life Years (DALY) measure of overall disease burden as collected by the WHO. 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 three dimension components are derived by OLS 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):

$$DALY_g = \alpha + \beta_1 Exposure_g + \beta_2 Vulnerability_g + \beta_3 Resilience_i + \varepsilon_g \qquad \text{(Eq. 2)}$$

The estimated weights and the constant are then plugged into the risk function, which now places considerably more weight on exposure than on resilience and vulnerability:

$$\widehat{WRisk}_g = 0.02 + 0.74 Exposure_g + 0.20 Vulnerability_g - 0.04 Resilience_g \qquad \text{(Eq. 3)}$$

The spatial patterns of the DALY-weighted risk map in Figure 5 are somewhat similar to those observed in the unweighted maps (Figures 3 and 4). As before, the areas at highest risk of economic losses from epidemics remain Sub-Saharan Africa and South Asia. But, much of Central Asia, and South East Asia are considered less risky with this approach, as are other areas that are relatively poor, but not so densely populated (as is Central America, for example). The other distinctive difference is that the diversity of the economic risk by grid-cells. With this DALY-based index, much of the weight comes from spatially-detailed exposure index, so the risks can now be identified with a better spatial resolution, and are found to be especially high in densely populated grids (e.g. East China, South Europe).

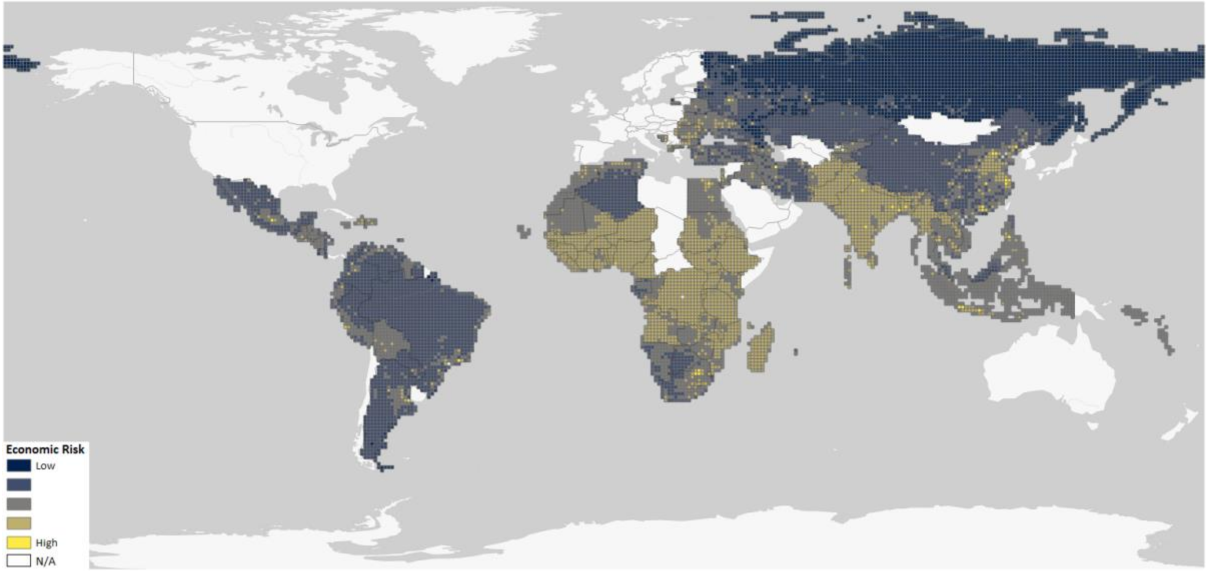

Fig. 5 Economic Risk of COVID-19 using the DALY-weighted index.

Discussion and Conclusions

The economic consequences of an epidemic, like any other natural hazard shock, can be delineated into damages, direct losses, and indirect losses (Noy, 2016). Direct losses included lost income and output due to death and symptomatic illness as well as increased healthcare costs. If measured through the standard statistical tools used by governments to evaluate the cost of life (the Value of Statistical Life – VSL), the experienced direct costs of the COVID-19 pandemic due to illness and mortality are probably smaller than the indirect losses caused by it. This is, of course, especially true now for countries in which the epidemic has not yet spread indiscriminately, but that are very exposed to the global shock it created (for example, tourism dependent economies like Fiji).

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 may still be of catastrophic scale. Especially worrying are those countries in which public health systems have not developed enough in the last century. However, what may be more salient is the pandemic's economic consequences. The exposure, vulnerability, and resilience to these economic consequences were not ameliorated as much even when public health systems are at their best.

Globalised trade and investment, increased tourism and labour flows, and the more recent advent of social media, are all likely to have amplified behavioural responses, and created additional vulnerabilities, thus potentially exacerbating the economic losses that will be experienced before this pandemic is over, and making it a much bigger economic event than the 1918-1919 Influenza Pandemic.

Besides the measurable differences we are able to control for, like public health, there are also distinctions within the developing world that may be important. Even within countries with similar level of incomes, there are differences that may make the epidemic and its consequences worse. Economic informality is one such distinction that is most likely important (but is not measured here). Bosio and Djankov (2020), for example, describe the ways in which informality makes it much more difficult for governments to intervene productively and reduce the duration or depth of the COVID-19 economic downturn.

Another difference that is difficult to measure, but is well known to be important in determining recovery, is social capital (Aldrich, 2012). There are several ways in which social capital may reduce both the health toll and the economic cost of this crisis – one example is that in societies with higher degrees of bonding social capital, mutual assistance is likely to ameliorate some of the more damaging distributional consequences of the shock.

To summarise, what is most apparent from our analysis is that the economic risk from COVID-19 is not located mostly in China, where the virus originated and spread first. Nor, as we found in Noy et al. (2020a), is it where most of the confirmed cases are currently found – in the United States and Western Europe. Rather, the highest economic risks are in countries and regions that do not get much global attention in normal times and get even less in the midst of the frantic reporting from the immediate frontlines of the pandemic's spread. This is unfortunate, as the ultimately, the economic costs will be borne there, away from the public eye.

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	17 May 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 Airport density Waterway density Railway network Rail station density	Index	Exposure	Resolution: <1 km	2016	100%	Lloyd et al. (2017)
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 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)
8	HDI	Human Development Index [0-1]	Index	Vulnerability	Resolution: 0.5’ (1 km)	2018	100%	Kummu et al. (2018)
9	Tourism	Share of travel and tourism to GDP	Percent	Vulnerability	Country level	2018	94%	World Bank (WDI)
10	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)
11	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)

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

References

Abdi, H., and Williams, L. J. (2010). Principal component analysis. *Wiley interdisciplinary reviews: computational statistics*, 2(4), 433-459.

Aldrich, D. (2012). *Building Resilience: Social Capital in Post-Disaster Recovery*. University of Chicago Press.

Alesina, A., Devleeschauwer, A., Easterly, W., Kurlat, S., and Wacziarg, R. (2003). Fractionalization. *Journal of Economic growth*, 8(2), 155-194.

Allen, T., Murray, K. A., Zambrana-Torrelio, C., Morse, S. S., Rondinini, C., Di Marco, M., Breit, N., Olival, K. J., and Daszak, P. (2017). Global hotspots and correlates of emerging zoonotic diseases. *Nature communications*, 8(1), 1124.

Baqaee, David and Emmanuel Farhi, 2020. Supply and Demand in Disaggregated Keynesian Economies with an Application to the Covid-19 Crisis. *NBER Working Paper No. 27152*.

Bosio and Djankov (2020), When economic informality is high, cash transfers may be the best Covid response. https://blogs.lse.ac.uk/businessreview/2020/05/19/when-economic-informality-is-high-cash-transfers-may-be-the-best-covid-response/.

Çakmaklı, Cem, Selva Demiralp, Şebnem Kalemli-Özcan, Sevcan Yesiltas, and Muhammed A. Yildirim, 2020. COVID-19 and Emerging Markets: An Epidemiological Multi-Sector Model for a Small Open Economy with an Application to Turkey. *NBER Working Paper No. 27191*.

CIESIN. (2018). Center for International Earth Science Information Network, Columbia University. Gridded Population of the World, Version 4 (GPWv4): Population Density Adjusted to Match 2015 Revision UN WPP Country Totals, Revision 11. Retrieved from: https://doi.org/10.7927/H4F47M65

CIESIN. (2019). Center for International Earth Science Information Network, Columbia University: Global Subnational Infant Mortality Rates, Version 2. Retrieved from: https://doi.org/10.7927/H4PN93JJ

de Sherbinin, A., Levy, M., Adamo, S., MacManus, K., Yetman, G., Mara, V., Razafindrazay, L., Goodrich, B., Srebotnjak, T., Aichele, C., and Pistolesi, L. (2015). Global Estimated Net Migration Grids by Decade: 1970-2000. Retrieved from: https://doi.org/10.7927/H4319SVC

Drake, T. L., Chalabi, Z., and Coker, R. (2012). Cost-effectiveness analysis of pandemic influenza preparedness: what's missing? *Bulletin of the World Health Organization*, 90, 940-941.

Epstein, J. (2009). Modelling to contain pandemics. *Nature* 460, 687.

Hallegatte, S. (2014). Economic Resilience: Definition and Measurement. *World Bank Policy Research Working Paper* 6852.

Hallegatte, S., Bangalore, M., and Vogt-Schilb, A. (2016). Assessing socioeconomic resilience to floods in 90 countries: The World Bank.

Janes, C. R., Corbett, K. K., Jones, J. H., and Trostle, J. (2012). Emerging infectious diseases: the role of social sciences. *The Lancet*, 380(9857), 1884-1886.

Kummu, M., Taka, M., and Guillaume, J. H. (2018). Gridded global datasets for gross domestic product and Human Development Index over 1990–2015. *Scientific data*, 5, 180004.

Lloyd, C. T., Sorichetta, A., and Tatem, A. J. (2017). High resolution global gridded data for use in population studies. *Scientific data*, 4, 170001.

McKibbin, Warwick and Roshen Fernando, 2020. The Global Macroeconomic Impacts of COVID-19: Seven Scenarios. *Brookings Institution Working Paper*.

Nordhaus, W., and Chen, X. (2016). Global gridded geographically based economic data (G-econ), version 4. In NASA Socioeconomic Data and Applications Center (SEDAC).

Noy, I. (2016). Tropical storms: The socio-economics of cyclones. *Nature Climate Change*, 6(4), 343.

Noy, I., Doan N., Ferrarini B., and Park, D. (2019). Measuring the Economic Risk of Epidemics. *CESifo Working Paper 8016.*

Noy, I., Doan N., Ferrarini B., and Park, D. (2020a). Measuring the Economic Risk of COVID-19. *Covid Economics* 3, 103-118.

Noy, I., Doan N., Ferrarini B., and Park, D. (2020b). “The Economic Risk from COVID-19 Is Not Where COVID-19 Is.” *VoxEU column* (May).

Noy, I., and Shields, S. (2019). The 2003 Severe Acute Respiratory Syndrome Epidemic: A Retroactive Examination of Economic Costs. *Asian Development Bank Working Paper*.

Perrings, C., Castillo-Chavez, C., Chowell, G., Daszak, P., Fenichel, E. P., Finnoff, D., Horan, R. D., Kilpatrick, A. M., Kinzig, A. P., and Kuminoff, N. V. (2014). Merging economics and epidemiology to improve the prediction and management of infectious disease. *EcoHealth*, 11(4), 464-475.

Philipson, T. (2000). Economic epidemiology and infectious diseases. *Handbook of health economics*, 1, 1761-1799.

Prager, F., Wei, D., and Rose, A. (2017). Total economic consequences of an influenza outbreak in the United States. *Risk Analysis*, 37(1), 4-19.

Ringnér, M. (2008). What is principal component analysis? *Nature biotechnology*, 26(3), 303.

Román, M. O., Wang, Z., Sun, Q., Kalb, V., Miller, S. D., Molthan, A., Schultz, L., Bell, J., Stokes, E. C., and Pandey, B. (2018). NASA's Black Marble nighttime lights product suite. *Remote Sensing of Environment*, 210, 113-143.

Tatem, A. J., Adamo, S., Bharti, N., Burgert, C. R., Castro, M., Dorelien, A., Fink, G., Linard, C., John, M., and Montana, L. (2012). Mapping populations at risk: improving spatial demographic data for infectious disease modeling and metric derivation. *Population health metrics*, 10(1), 8.

Tuanmu, M. N., and Jetz, W. (2014). A global 1-km consensus land-cover product for biodiversity and ecosystem modelling. *Global Ecology and Biogeography*, 23(9), 1031-1045.

UNDRR. (2017). *Terminology on Disaster Risk Reduction*, UNDRR. https://www.unisdr.org/we/inform/terminology.

WHO. (2018). *WHO methods and data sources for global burden of disease estimates 2000-2016*. World Health Organisation, Geneva.

WorldPop (www.worldpop.org - School of Geography and Environmental Science, University of Southampton; Department of Geography and Geosciences, University of Louisville; Departement de Geographie, Universite de Namur) and Center for International Earth Science Information Network (CIESIN), Columbia University (2018). Global High Resolution Population Denominators Project - Funded by The Bill and Melinda Gates Foundation (OPP1134076). https://dx.doi.org/10.5258/SOTON/WP00646

Yonson, R., and I. Noy (2018). Economic Vulnerability and Resilience to Natural Hazards: Concepts and Measurements. *Sustainability*, 10, 2850.