

A Country Pandemic Risk Exposure Measurement Model

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Purpose: The purpose of this study is to develop a Pandemic Risk Exposure Measurement (PREM) model to determine the factors that affect a country's prospective vulnerability to a pandemic risk exposure also considering the current COVID-19 pandemic.

Methods: To develop the model, drew up an inventory of possible factor variables that might expose a country's vulnerability to a pandemic such as COVID-19. This model was based on the analysis of existing literature and consultations with some experts and associations. To support the inventory of selected possible factor variables, we have conducted a survey with participants sampled from people working in a risk management environment carrying out a risk management function. The data were subjected to statistical analysis, specifically exploratory factor analysis and Cronbach Alpha to determine and group these factor variables and determine their reliability, respectively. This enabled the development of the PREM model. To eliminate possible bias, hierarchical regression analysis was carried out to examine the effect of the "Level of Experienced Hazard of the Participant (LEH)" considering also the "Level of Expertise and Knowledge about Risk and Risk Management (LEK)".

Results: Exploratory factor analysis loaded best on four factors from 19 variables: Demographic Features, Country's Activity Features, Economic Exposure and Societal Vulnerability (i.e. the PREM Model). This model explains 65.5% of the variance in the level of experienced hazard (LEH). Additionally, we determined that LEK explains only about 2% of the variance in LEH.

Conclusion: The developed PREM model shows that monitoring of Demographic Features, Country's Activity Features, Economic Exposure and Societal Vulnerability can help a country to identify the possible impact of pandemic risk exposure and develop policies, strategies, regulations, etc., to help a country strengthen its capacity to meet the economic, social and in turn healthcare demands due to pandemic hazards such as COVID-19.

Keywords: COVID-19, pandemic risk, risk measurement model, hazard, exposure

Introduction

The Coronavirus or, as it is better known, COVID-19 has disrupted life as we knew it. This virus is causing a national disaster of epidemic nature with considerable economic and social impact. The United Nations (UN) defines disaster as 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.¹ The Centre for Research on the Epidemiology of Disasters (CRED) identifies a disaster if at least one of the following criteria is met:

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10 or more people are reported killed;
100 people are reported affected;
a state of emergency is declared;

a call for international assistance is issued.² The pandemic COVID-19 meets all these criteria.

A pandemic is defined as “an epidemic occurring worldwide, or over a very wide area, crossing international boundaries and usually affecting a large number of people”.³ On the other hand, a pandemic can be defined as a natural event that causes a disruption in the functioning of the economic system that has a significant negative impact on assets, production factors, output, employment or consumption, etc.⁴

When a hazard arises, such as that of a pandemic, it leads to the loss of life and damage to infrastructure, emphasizing the reality that society and its assets are vulnerable to such events. According to the Sendai Framework for Disaster Risk Reduction 2015–2030, a hazard is a process, phenomenon or human activity that may cause loss of life, injury or other health impacts, property damage, social and economic disruption or environmental degradation.¹ COVID-19 can be characterised as a biological hazard, since biological hazards are of organic origin or conveyed by biological vectors, including pathogenic microorganisms, toxins and bioactive substances. Examples are bacteria, viruses or parasites, as well as venomous wildlife and insects, poisonous plants and mosquitoes carrying disease-causing agents.

The COVID-19 pandemic outbreak so far, during March to June 2020 has substantially influenced the majority of the countries in the world, besides, according to the Research Note of German Deutsche Bank, experts already speak about the second wave of the virus, and highlight that during the next ten years the world can face a much more serious pandemic than COVID-19.⁵

Therefore, there is a need to understand the objective factors that indicate the experienced level of hazard that a country may be faced with, if or when pandemics such as COVID-19 or similar outbreaks strike.

The purpose of this study is to develop a Pandemic Risk Exposure Measurement (PREM) model to determine the factors that affect a country’s prospective vulnerability to a pandemic risk exposure such as COVID-19. These factors can be indirectly and directly affected by different factors on each other and similarly have a direct and indirect effect on vulnerability. The idea is to answer the following a priori research questions:

RQ1 – What are the factors that enable the measurement of a country’s vulnerability to a pandemic risk exposure such as COVID-19?

RQ2 – Do the factors vary according to the Level of Experienced Hazard of a country (LEH)?

RQ3 – Do the factors vary according to Level of expertise and knowledge of the respondents (LEK)?

The questions above and the forecasts noted above increase the importance of developing such a model, which can be used as a checklist for determining the status of a country in terms of possible vulnerabilities, which can later develop into hazards. It is useful for risk managers and policymakers to proactively identify the factors that make the country more vulnerable to the pandemic risk and if necessary, manage them and/or set tolerance limits, policies, regulations, rules, standards, etc. PREM could also serve as a guide for businesses in developing their business continuity plans and insurance policy documents. Insurance underwriters can also utilise this model to set the correct policy wording and premiums when underwriting risks.

Although there are various studies that have indicated factor variables that are important for addressing and measuring the vulnerability of countries, the COVID-19 pandemic has indicated a serious need to go back to the drawing board. It is important to understand the areas or functions that have been missed and to develop a tool that is flexible enough to help national risk managers and policymakers proactively identify and determine the risk vulnerabilities of their country; and devise a continuity plan that improves the measure of vulnerability of a country. This is important so as to determine when to take action or flag the problem, based on a present tolerance level.

To develop this inventory of factor variables we consulted literature on pandemics such as the COVID-19 and identified variables that might not have yet been considered. Therefore, the case of the COVID-19 pandemic was used to help add value to current measures, by updating the model with new important factor variables that might not have been seen as important until now.

Methods

For the purpose of this study, a purposely built semi-structured survey was designed by creating an inventory of factor variables that can be used to measure a country’s exposure to a pandemic risk such as COVID-19. To develop such an inventory we participated in various online forums,

talks, webinars and sub-groups related to risk management during disruptions of infectious diseases such as that of COVID-19 and asked other participants and colleagues (who worked in a risk management function) to provide us with those aspects that in their opinion safeguarded or hindered a country's preparedness against infectious diseases. This information together with that gathered from the research literature and using a thematic approach⁶ resulted in the construction of an initial set of 25 variables and 2 additional data measurements that reflect vulnerability of a country for a pandemic (see Table 1).

There exists a variety of studies on different aspects of country's development. Some studies⁸ suggest such factor variables as "Population Density" measured by the number of persons per square kilometre, "Night-time Light Intensity" measured by the night light development index.^{9,11,12} As well as "the Ecological Footprint Index,"¹³ "Transport Network Density"^{14,15,52} and "Net Migration Rate".^{16,53,54}

Various studies suggest using "Human Development Index (HDI)" as a composite index of life expectancy, education, and per capita income indicators⁵⁵ and "Tourism".²⁴ Recent studies suggest population age structure related indicators as 'Population over/below 65'^{25,26,48} in conjunction with gender.⁵⁶

Studies on population health measures commonly use "The Infant Mortality Rate (IMR)".^{27,28} Healthcare system capacity studies emphasize the "Hospital beds available per capita",^{29,30,35,57} "Out-of-pocket expenditure (OOPs)",^{31,32,58} and "Health care expenditure % to GDP".^{30,34-36,57,59,60}

There is a variety of widely used economic factor variables that influence country's vulnerability as 'Gross Domestic Product'¹⁸ and "GDP per capita",^{19,61} "Public and private debt to GDP"^{38,39} and "Government expenditure to GDP",^{40,41} "Inflation Rate"⁷ and "Unemployment rate"^{45,46} as well as "Current Account Balance to GDP".⁴⁷

Table 1 Factor Variables Identified

Nr.	Factor Variables	Literature Support
Q1	Level of expertise and knowledge (LEK)	Bezzina & Grima, 2012 ⁷
Q2	Population density	Calka et al, 2017; ⁸ Noy et al, 2020; ⁹ Jakovljevic et al, 2017 ¹⁰
Q3	Night-time light intensity	Noy et al, 2020; ⁹ Florida et al, 2012; ¹¹ Mellander et al, 2015 ¹²
Q4	Ecological footprint	GFN, 2020 ¹³
Q5	Transport network density	Luke & Rodrigue, 2008; ¹⁴ Inglesby & Adalja, 2019 ¹⁵
Q6	Net migration	Ivakhnyuk, 2020; ¹⁶ Jakovljevic et al, 2018 ¹⁷
Q7	Gross Domestic Product (GDP)	Dynan & Sheiner, 2018 ¹⁸
Q8	Gross Domestic Product per capita	Bruederl & Hodler, 2018; ¹⁹ Pe' rez-Velasco, 2012; ²⁰ Jakovljevic & Getzen, 2016 ²¹
Q9	Human Development Index (HDI)	Abdul-Fadi & Sarhan, 2020; ²² WEF, 2020 ²³
Q10	Tourism	Zeng et al, 2005 ²⁴
Q11	Old population male over 65	Acemoglu & Restrepo, 2017; ²⁵ Rupeika-Apoga et al, 2018 ²⁶
Q12	Old population female over 65	Acemoglu & Restrepo, 2017; ²⁵ Rupeika-Apoga et al, 2018 ²⁶
Q13	Infant Mortality Rate (IMR)	Reidpath & Allotey, 2003; ²⁷ Stockwell et al, 1987 ²⁸
Q14	Hospital beds available per capita	Keegan et al., 2019; ²⁹ Dieleman et al., 2017 ³⁰
Q15	Out-of-pocket expenditure (OOPs)	WHO, 2020; ³¹ WB, 2020; ³² Grima et al, 2018 ³³
Q16	Health care expenditure % to GDP	Xu et al, 2011; ³⁴ Dieleman et al., 2017 B; ³⁵ Jakovljevic & Ogura, 2016 ³⁶
Q17	Telecommunication	Oliver et al, 2020 ³⁷
Q18	Public and private debt to GDP	Bohn, 1988; ³⁸ Missale, 1999 ³⁹
Q19	Government expenditure to GDP	Gounder & Saha, 2007; ⁴⁰ Moradbeigi & Law, 2014 ⁴¹
Q20	Socio-cultural disparity	Alesina, et al, 2003 ⁴²
Q21	Inflation rate	Bezzina & Grima, 2012; ⁷ Treaty on the European Union; ⁴³ Eurostat ⁴⁴
Q22	Unemployment rate	OECD, 2020; ⁴⁵ Di Maggio & Kermani, 2016 ⁴⁶
Q23	Current Account Balance to GDP	Edwards, 2007 ⁴⁷
Q24	Population of Males below 65	Acemoglu & Restrepo, 2017; ²⁵ Rupeika-Apoga et al, 2019 ⁴⁸
Q25	Population of Females below 65	Acemoglu & Restrepo, 2017; ²⁵ Rupeika-Apoga et al, 2019 ⁴⁸
Q26	Gender	Maestas et al, 2016 ⁴⁹
Q27	Level of experienced hazard (LEH)	Bezzina & Grima, 2012 ^{7,50,51}

Taking into account the specifics of the recent COVID-19 outbreak such indicators as ‘Socio-cultural disparity’⁴² and use of “Telecommunication” tools³⁷ became important.

Although at the time of writing, studies on the COVID-19 pandemic and its effect on a country’s economic, social and health vulnerability measures were still limited, we were still able to uncover studies on COVID-19 and others based on similar infectious diseases and pandemics such as Severe Acute Respiratory Syndrome (SARS), the Human Immunodeficiency Viruses (HIV), etc., which helped us build the inventory laid out in [Table 1](#).

The survey was administered as an online survey via weblink on Qualtrics to contacts of the authors on social media, namely LinkedIn, Facebook and Twitter, who worked in a risk management function (Non-probability purposive sampling). Moreover, respondents were also invited using direct emails and were also asked to send this link to others working in the risk management function (non-probability snowballing sampling). Responses were collected through Qualtrics. The URL was set to limit only one response per computer, but respondents had the option of going back to edit or update their answers until they finished. Confidentiality of responses was guaranteed. A total of 2831 completed surveys were received between May and June of 2020.

The survey consisted of three sections. The first section consisted of 2 questions, wherein Question 1 we asked the participants to state whether they are working in a risk management function, which was the main filter to allow participants to continue with the survey only in the event of a positive response, and then in Question 2 (Q1), we asked them to indicate on a Likert scale of ‘1’- being the lowest LEK and ‘5’- being the highest LEK of the participant, their LEK. This was done to understand whether the Level of Expertise and knowledge (LEK) affected the scores provided by participants (who worked in a risk management function) in the development of the model.

In the next section, which consisted of 1 main question (Question 2), the participants were required to indicate on a 5-point scale their level of agreement with each of the 25 inventory items (Q2 to Q26) developed as described above. These items were individually operationalized via a five-point Likert scale ranging from “1” for strongly disagree to “5” for strongly agree.

The final section, Question 4 and Q27 in our proposed inventory we asked participants to provide us with an indication of their country of residence to enable us to determine their country’s exposure to the hazard/disruption

and asked them to add any comments they would like to express about the subject.

We then determined “The level of Experienced Hazard of the participant (LEH)”, Q27, through the number of Coronavirus (COVID-19) cases per 1 million population as of the 9th June 2020 of their country of residence provided by the participant. The data were determined from the Worldometer website.⁶² We used the following scale: a score of “1”- for the lowest risk with under 499 Cases; “2” - between 500 and 999 cases; “3” - between 1000 and 1999 cases; “4” - between 2000 and 2999 cases; and “5” – for the highest risk with over 3000 cases per 1 million population. Participants with the lowest risk experience, i.e. Level 1–9.9%, Level 2–0%, Level 3–14.5%, Level 4–12.8% and Level 5 – the highest level of risk exposure 62.8%.

We then loaded all the data in a quantitative format onto IBM SPSS V26 software package through which we carried out all our statistical analysis. As a next step, to answer research question 1 (RQ1) we selected the variables and developed the PREM model using exploratory factor analysis. Exploratory factor analysis, via principal components extraction with Orthogonal rotation (Varimax with Kaiser Normalization), was used to assess the construct validity of the Country Risk Exposure Index while internal-consistency reliability was assessed by computing Cronbach’s alpha coefficients. This further supported continuance of factor analysis and so the analysis proceeded. Cronbach’s alpha reliability coefficient was 0.789, KMO value was 0.712, and Bartlett test was found to be 24352.006, df 171 $p < 0.001$.

We used Varimax rotation because the factor variables are interrelated and we reduced them to 4 grouped factors consisting of 19-factor variables. Hierarchical regression analysis was carried out to see the effect of 4 factors on “Level of Expertise and Knowledge (LEK)” and on “The level of Experienced Hazard of the participant (LEH)” to enable us to provide an answer to research question 2 and 3 – (RQ2) and (RQ3).

The hierarchical regression analysis was carried out with the obtained data in two steps. In the hierarchical regression analysis, “LEH” was used as the dependent variable. In the first stage of analysis (Model 1), the 4 obtained factors as a result of factor analysis were used as independent variables. In the second stage (Model 2), the analysis was repeated by adding the “LEK” variable to the four factors in the first stage. Thus, the effects of both 4 factors and LEK on “LEH” were measured.

Results

Analysing the completed surveys, we conclude, that 9.3% of the participants stated that their LEK was 1; 20.4% stated that their level was 2, 41.6% stated that their level was 3; 22.9% stated that their level was 4 and 5.8% stated that their level was 5.

Using exploratory factor analysis, we determined that 6-factor variables were eliminated from the model, Q6 – “Net Immigration”, Q7 – “Gross Domestic Product”, Q16-“Health Care Expenditure % to GDP”, Q26 - “Gender”, Q24 - “Population of Males below 65 years” and Q25 - “Population of Females below 65 years”. This was because these variables explained too little of the variance and this made them unstable and often unreliable because they were defined by other variables.⁶³ This left us with the 19-factor variables included in the PREM model and exhibited in Table 2. All factors have been carefully interpreted and omitted scientifically. The factor variable Q18 –“Public and Private Debt to GDP,” which is highly related to one of two factors (Factor 3 and 4), but lower to factor 4, was attached to Factor 3.

Based on the analysis made, we have identified four factors indicating vulnerability of the country: Factor 1 ‘Country’s Activity Features’, Factor 2 ‘Demographic Features’, Factor 3 ‘Societal Vulnerability’, and Factor 4 ‘Economic Exposure’.

These factors affect a country’s prospective vulnerability to pandemic risk exposure.

Table 3 shows the factors and reliability values of the four identified factors. Cronbach’s alpha coefficient of these factors varies between 0.688 and 0.861. Of the four factors, the total variance in the survey explained 59.03%, while the factor common variances were observed to vary between 0.235 and 0.851.

The results of the hierarchical regression analysis are shown in Table 4. Results show that the 4 factors composing the PREM model [Factor 1 (Country’s Activity Features), Factor 2 (Demographic Features), Factor 3 (Societal Vulnerability), and Factor 4 (Economic Exposure)] explained 64% of the change in LEH with a high level of statistical significance ($p < 0.001$).

When the LEK variable was included in the analysis in the second stage, the rate of the total variance increased from 64% to approximately 66%. Therefore, we can conclude that the LEK variable helped to explain only another 2% with a high level of statistical significance ($p < 0.05$).

As noted in Table 2, the exploratory factor analysis loaded best under four factors. Factor 1 includes population density (Q2), night-time light intensity (Q3), ecological footprint (Q4) and transport network density (Q5).

Table 2 Factors

	Factor 1	Factor 2	Factor 3	Factor 4
Q11. Old population male over 65		0.809		
Q12. Old population female over 65		0.804		
Q10. Tourism (Contribution of tourism to GDP)		0.801		
Q14. Hospital beds available per capita		0.730		
Q9. Human Development Index		0.659		
Q13. Infant Mortality Rate		0.606		
Q8. Gross Domestic Product per capita		0.524		
Q15. Out-of-Pocket expenditure (OOPs)		0.420		
Q3. Night-time light intensity	0.812			
Q5. Transport network density (road, airport, railroad, waterway)	0.790			
Q4. Ecological footprint (human demand on natural capital)	0.746			
Q2. Population density	0.669			
Q21. Inflation rate				0.907
Q22. Unemployment rate				0.850
Q23. Current account balance to GDP				0.839
Q19. Government expenditure to GDP			0.870	
Q18. Public and private debt to GDP			0.697	0.338
Q17. Telecommunication (use of the internet and mobile phones)			0.615	
Q20. Socio-cultural disparity			0.584	

Table 3 Factors and Reliability Values

Factors	Number of Question	Cronbach's Alpha	Eigen Values	% of Variance Explained
Factor 1 [Q2+Q3+Q4+Q5]/4	4	0.765	2.836	14.929
Factor 2[Q8+Q9+Q10+Q11+Q12+Q13+Q14+Q15]/8	8	0.828	4.281	22.534
Factor 3 [Q17+Q18+Q19+Q20]/4	4	0.688	1.482	7.799
Factor 4 [Q21+Q22+Q23]/3	3	0.861	2.616	13.769

There is a variety of factor variables that can promote the spread of diseases, such as high population density and economic activity, ubiquitous air travel and with fast transportation comes a quick and extensive diffusion of a communicable disease.¹⁴ Many studies have shown that light at night and population density can be used as indicators of economic activity.^{11,12} Population density is one of the key parameters for assessing the magnitude of the population exposed to risk.⁸ The increase in human population density and the growth in transportation networks of roads, container ships, and airways that has now linked the global population presents more rapid and robust pathways for infectious pathogens.¹⁵ Whereas ecological footprint as a measure of human impact on the land by urbanization shows country exposure to the pandemic risk.⁹ Summing up, we label Factor 1, as Country's Activity Features, as it represents the people's activity features and infrastructure located in hazard-prone areas.

Factor 2 includes GDP per capita (Q8), HDI (Q9), Tourism (Q10), old population male over 65 (Q11), old population female over 65 (Q12), IMR (Q13), Hospital beds available per capita (Q14) and OOPs (Q15). GDP per capita is a commonly used indicator for economic and human development²¹ and as poverty measure^{20,64}. HDI is a statistic composite index of life expectancy, education, and per capita income indicators, ranking countries in human development.²² Cities with robust governance and health infrastructure are in a better position to manage pandemics and have lower case fatality rates and excess mortality than those that do not.²³ Meanwhile, the infant mortality rate (IMR) is a commonly used measure of population health. IMR is associated with other factor variables affecting the health status of an entire population, such as its economic development, general living conditions, social well-being, incidence rate and environmental quality.^{27,28} Also, COVID-19 statistics show that the older population is, the more vulnerable to the virus it is. In many countries, an ageing population is challenging the healthcare system,

social security, fiscal system.^{25,26,48} One of the proxies for healthcare system capacity is the number of hospital beds available per capita.²⁹ This variable has become critical because of COVID-19, as availability of excess beds means more lives are saved.³⁵ Out-of-pocket payments (OOPs) signify spending on health directly out of pocket by households in each country. Dependence on OOPs varies widely around the world, but there is a very strong correlation between the level of OOPs and the incidence of catastrophic and impoverished health expenditures. These two indicators are determined by the extent to which OOPs absorb a household's financial resources.³¹⁻³³ Besides, the current situation with COVID-19 has shown that countries with a high level of tourism, such as Italy, are more vulnerable to pandemics due to population flows. In this paper, we label Factor 2 as Demographic Features, because it represents variables that increase a person's and in turn the country's vulnerability to the effects of hazards.

Factor 3 includes telecommunication (Q17), public and private debt to GDP (Q18), government expenditure to GDP (Q19), and socio-cultural disparity (Q20). The modern economy is characterized by the increased use of telecommunication tools. During the recent COVID-19 outbreak, mobile phone data were actively used to tackle the pandemic and Internet provided timely informing and warning of population.³⁷ Meanwhile, debt has an important role in ensuring the resilience of the country to macro-economic and other shocks.^{38,39} We believe that lower level of public and private debt in case of pandemic enables the country to provide timely financial support of the economy, providing external and internal access to finance.³⁰ Government expenditure to GDP indicates total government consumption, investment and transfer payments as a share of the country's GDP. This indicator is seen as a factor of a country's fiscal behaviour⁴⁰ and the determinant of output volatility,⁴¹ whereas increasing government expenditure allows for reducing the negative effects of output volatility. Besides, higher government

Table 4 Hierarchical Regression Analysis

Model	Independent Variables	R	R ²	Adjusted R ²	F	df	B	β	p
1	Constant	0.802	0.643	0.642	1271.04	4/2825	-.434	0.760	0.000
	F1						1.219	0.045	0.000
	F2						0.074	0.056	0.000
	F3						0.108	-0.176	0.000
	F4						-0.245		
2	Constant	0.809	0.655	0.655	1072.85	5/2824	-.466	0.715	0.000
	F1						1.147	0.026	0.025
	F2						0.043	-0.163	0.000
	F3						-0.227	0.124	0.000
	F4						0.156	0.044	0.000
	LEK						0.085		

expenditure is increasing disaster mitigation capability of the country. According to Alesina et al,⁴² the socio-cultural disparity has an impact on the behaviour of individuals and the community as a whole especially in the case of a hazard. The contribution of the socio-cultural disparity to the pandemic risk exposure is not unambiguous. Factor 3 we label as Societal Vulnerability due to the variables indicating vulnerability of society to pandemics.

Factor 4 includes inflation rate (Q21), unemployment rate (Q22), current account balance to GDP (Q23). The inflation rate is one of the fundamental indicators of a country's macroeconomic conditions. However, the contribution of the inflation rate to the country's exposure to pandemic risk is not uniform. Moderate inflation stimulates economic growth making the country less vulnerable to the risk, whereas high inflation rate implies rising prices good and services, including healthcare expenditures, increasing out-of-pocket payments and making the country more vulnerable to pandemic risk. The unemployment rate is one of the fundamental macroeconomic indicators showing the number of unemployed people as a share of the labour force.⁴⁵ Given a higher unemployment rate, the total output is more sensitive to demand shocks,⁴⁶ making countries more vulnerable to pandemic risk. The current account balance to GDP is one of the measures of a country's external imbalances. It indicates the level of the international competitiveness of the country. High current account deficit increases the probability of capital flow contraction⁴⁷ increasing the country's vulnerability to external shocks and more vulnerable to pandemic risk. Factor 4 we label as Economic Exposure following the economic nature of the included variables.

To the knowledge of the authors, it is the first paper, which provides a Pandemic Exposure Measurement Risk model to

determine the factors that affect a country's prospective vulnerability to a pandemic risk exposure such as COVID-19.

Before the COVID-19 pandemic, the Global Health Security Index (GHSI) was used as a measure of the country's pandemic preparedness.⁶⁵ The more developed and prosperous countries are better equipped to deal with pandemics, according to GHSI. In practice, it is better to benchmark countries during a pandemic in ways that allow information on outcomes and performance to be obtained, analysed, reported, and used in real-time.⁶⁶

The recent study of measuring the economic risk of COVID-19 has computed measures for exposure (population, night-time light and transport density), vulnerability (data on economic outcomes, human development, tourism, and health quality) and resilience (Internet access, public and private debt, government expenditure, socio-cultural disparity) of the local economy to the shock of the epidemic. The study concludes that the highest economic risks are in countries and regions that do not get much global attention in normal times (such as sub-Saharan Africa) and get even less during pandemic's spread.⁹

Another study used 16 independent variables, such as hospital, mosque, ATM, bank, fuel, attraction, city, footprint, road, and village, to model and map the risk of COVID-19.⁶⁷

Based on the analysis of existing literature, including literature on COVID-19, consultations with experts and associations and survey conducted with risk managers we have identified the unaddressed factor variables for determining the vulnerability of countries to the pandemic.

Conclusion

With this study we aimed to develop a Pandemic Risk Exposure Measurement (PREM) model to determine the

factors that affect a country's prospective vulnerability to a pandemic risk exposure such as COVID-19. Given the current COVID-19 pandemic landscape worldwide it is important to understand several consequences. Although unpredicted by the most national and transnational level authorities, it has put to the test health financing capabilities.⁶⁸ This event has revealed the limits of extension of the national hospital and intensive care unit capacities in scenarios of sudden exceptional demand for medical care. The comprehensive burden was exposed to the mature post-industrial societies and Emerging markets⁶⁹ and other LMICs countries alike. Due to a variety of distinctively different historical legacies of national health system establishments, they all responded with an array of adaptive strategies. Despite the burden, efficient responses came from India, China, Russia⁷⁰ and few other non-OECD economies.⁷¹ Another side of the equation was the unstable response burdened with several core inefficiencies in the traditional Western European high-income societies such as Italy, Spain⁷² and few others. Thus, COVID-19 has revealed huge mutual interconnectivity among the distant economic hubs of the modern-day world. Proper risk assessments and the development of effective coping strategies might be highly valuable for the public health challenges of the future. Besides, supranational actions might be needed to build up both public and private capacity to deal with pandemics.⁷³

The developed PREM model consists of Factor 1 (Country's Activity Features), Factor 2 (Demographic features), Factor 3 (Societal Vulnerability), and Factor 4 (Economic Exposure), and explains 65.5% of the variance in "The level of Experienced Hazard of the participant (LEH)". We also found that "The level of Experience and Knowledge of the participant" (LEH) explains only approximately 2% of LEH.

Our developed PREM model is useful for risk managers and policymakers to proactively identify the factors that make the country more vulnerable to the pandemic risk and if necessary, manage them and/or set tolerance limits, policies, regulations, rules, standards, etc.

It is not the intention with this study to design a one size fits all model but to provide policymakers and risk managers with a list of factors to enable the identification of country exposure and thereby enable proactive management and the development of a business continuity plan.

Moreover, as noted in the methodology section the study analysis is based mainly on self-reported responses to an

online survey. This was built after consultation of the literature and case studies and deliberation with experts in the area of Risk Management. Despite known weaknesses of this methodology, such as participant bias due to personal experiences; may result in classification error and underestimation or overestimation of measures.⁷⁴ The case studies used, deliberation with peers and the literature review was carried out before choosing the measures, to limit this and provide a robust list of measures.³⁶ Moreover, hierarchical regression analysis showed that the difference in the explanation of variances when Q1 – "The level of Experience and Knowledge of the participant" was added was of only approximately 2%.

Therefore, we can conclude that monitoring of these factors can help a country manage the change in their LEH and devise policies to ensure that the country strengthens its capacity to meet demands for healthcare brought about by pandemic hazards such as COVID-19. That is, to flatten the curve of healthcare, social and economic demands below the capacity and thus provide to this demand over some time. This is a flexible model which can be adjusted to the specificities of the relevant countries since the aim is to provide a way to measure vulnerability without considering the tolerance level and the controls put in place, which is dependent on the country itself. Therefore, only when the latter two variables are considered can a country give value to the PREM measure and prepare an accurate plan to ensure continuity of the norm (the variables to be considered by each country in addition to the PREM model are tolerance and the controls in place).

Research Code of Practice and Ethics Review Procedure

We declare that we have abided by the Research Ethics Review Procedures of the University of Malta, Faculty of Economics, Management and Accountancy, Malta Ethics Committee and GDPR Directive – Research and Data Protection Unique Form ID: 5581_31052020, Submitted by Professor Simon Grima to the Faculty of Economics, Management and Accountancy Ethics Committee (FREC). Since there were no ethical issues or personal data collected we were provided with an automated ethical clearance and the clearance was submitted for filing with FREC.

The survey was administered as an online survey via weblink on Qualtrics to contacts of the authors on social media, namely LinkedIn, Facebook and Twitter, who

worked in a risk management function (Non-probability purposive sampling). Moreover, respondents were also invited using direct emails and were also asked to send this link to others working in the risk management function (non-probability snowballing sampling). Responses were collected through Qualtrics, no personal data were collected and/or maintained (anonymous response) and participants participated on a voluntary basis. The only filters, were that participants had to tick a box noting that they worked within a risk management function and that they consent (an informed consent) that we use the information collected for the analysis purposes of our study, before they could continue to answer the survey. An introductory paragraph describing the study was also provided at the beginning of the survey.

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Disclosure

The authors report no conflicts of interest in this work.

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