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Robust and fragile determinants of the severity of COVID-19 in developing and developed countries: a comparative analysis

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Abstract

Purpose – The primary objective of this paper is to explore the robust determinants influencing the infection rate and case mortality rate of COVID-19 in both developing and developed economies. The analysis is conducted using a dataset encompassing 148 countries.

Design/methodology/approach – To achieve this goal, empirical testing utilizes the Sala-i-Martin version of extreme bounds analysis, a method grounded in the cumulative density function. This approach allows for a comprehensive exploration of potential determinants.

Findings – The analysis results reveal that, to a large extent, distinct factors contribute to the infection and mortality rates in developed and developing countries. Notwithstanding these differences, certain common factors emerge, such as the risk environment, the number of tests conducted per million people and the percentage of the population over 65.

Originality/value – Despite acknowledging the potential limitations inherent in official data, this study concludes that the presented results offer valuable insights. The identified determinants, both unique and common, contribute to understanding the dynamics of COVID-19 in diverse economic settings. The information gleaned from this research holds significance for decision-makers involved in combating the ongoing pandemic.

Keywords COVID-19, Infection rate, Case mortality rate, Extreme bounds analysis, Cumulative density function

Paper type Research paper

Introduction

The severity of the COVID-19 pandemic, in terms of infection and mortality rates, varies drastically across countries. Identifying all the factors contributing to these variations in infection rate (cases per million people) and case mortality rates (the ratio of deaths to cases) across countries is a complex task. Casual observation suggests that high infection rates and high mortality rates do not always correlate. A country may have a high incidence of infection, but a lower number of deaths compared to other countries with comparable infection rates. Conversely, countries with low infection rates might experience high mortality rates. It is intuitive to suggest that infections and mortality are influenced by a

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variety of factors acting simultaneously, making it challenging to explain cross-country differences based on one or a few factors alone.

The severity of COVID-19 is influenced by various factors, including the political system and economic development. The Lowy Institute (2021) suggests that the political system is relevant because it reflects actions taken by governments to encourage or compel citizens to comply with preventive measures such as lockdowns. Economic development, measured by gross domestic product (GDP) per capita, is another determining factor; wealthier countries (high GDP per capita) can allocate more resources to combat the pandemic than poorer countries (low GDP per capita). The Lowy Institute shows that, on average, developed countries have performed better than developing countries. However, this may vary depending on how the data are interpreted and the specific time frame considered, as the situation changes continuously.

The problem can be framed as whether factors can be identified to explain differences in the performance of developing and developed economies in containing the virus. Therefore, the objective of this paper is to use extreme bounds analysis (EBA) to identify the factors that determine infection and case mortality rates in both developing and developed countries. While separate hypotheses related to the impact of various factors on infection and mortality rates are tested, the main hypothesis tested in this paper pertains to whether the important factors in one group are the same or different than those in another country. It is expected that the factors determining infection and mortality rates in developed countries may differ, or at least not match one-to-one, even though some common factors may be found. This is due to differences in characteristics such as the availability of adequate financial resources, demographic factors, quality of healthcare systems, access to healthcare and the perception of trade-offs between lives and livelihoods. Some of these factors work in favor of developing countries, while others benefit developed countries [1].

The use of extreme bounds analysis (EBA) is a novelty of this paper because it produces results that are less subjective than those derived from studies based on the estimation of one or a few equations with a data-driven specification. In other words, the results obtained by using EBA are not subject to the model uncertainty problem. This study thus contributes to the literature, by resolving controversies over the effects of certain variables, such as population density, on infection and mortality. Practically speaking, the findings offer various policy suggestions that could aid in controlling future pandemics.

Identifying potential explanatory variables

The identification of potential explanatory variables is based primarily on a review of the literature and to a certain extent on theory and intuition. Pragmatism also plays a role in selecting these variables. In general, pinpointing all the factors that determine the severity of COVID-19 and understanding how these factors operate in developed and developing countries is challenging. Identifying and collecting data on all of the potential explanatory variables that explain cross-country differences in infection and case mortality rates is a monumental task.

Several factors dictated our choice of explanatory variables. First, some variables highlight disparities in how developed and developing countries manage and respond to a pandemic, such as public health infrastructure. These differences pertain to the following factors: (1) financial resources, (2) the presence or absence of busy airports that bring in large numbers of passengers, (3) experience and preparation for dealing with a pandemic, (4) attitudes towards government instructions, (5) the incidence of politicians setting poor examples or failing to provide leadership, (6) age profiles and demographic factors, (7) the incidence of affluence and contagious diseases, (8) the quality of healthcare systems and measures of health security and (9) trade-offs between lives and livelihoods. Some of these factors favor developing countries, while others favor developed countries.

The second factor influencing the choice of variables is the guidance provided by existing literature and the variables previously selected by other researchers. For example, we use population density as an explanatory variable following Barr and Tassier (2020a). Additionally, we include six variables that measure preparedness and the ability to deal with a pandemic, which are often overlooked by other researchers such as Barr and Tassier (2020a). Intuition suggests that measures of preparedness are not only relevant but also crucial.

The third factor is based on economic and epidemiological theory. Some explanatory variables, such as population density, are implied by the basic epidemiological model used to determine the reproduction rate. We start with the simple epidemiological model used by Barr and Tassier (2020a).

Finally, the availability of data dictates the choice of explanatory variables. Some important variables may be excluded due to the unavailability of data or lack of comparable data across several countries. Despite these challenges, we managed to collect comparable data for 148 countries.

The choice of explanatory variables is problematic for empirical work because the outcomes are often influenced by the selected set, and no single theoretical model can reliably identify them. This is the main reason for using extreme bounds analysis instead of the conventional approach of arbitrarily selecting the preferred regression equation. Barr and Tassier (2020a) start with a theoretical model of the determinants of the reproduction rate, R, because it determines how cases grow over time. The basic equation is:

$$Y_t = Y_0 R^t \tag{1}$$

where Y_t is the number of cases at time t and Y_0 is the number of cases at time 0. The reproduction rate is calculated as follows:

$$R = C \times T \times S \times D \tag{2}$$

where C is the contact rate (number of interactions per day), T is the transmission rate (the probability that an infected individual passes the disease to another one through contact), D is the duration (the time taken by an infected person to move from infection to recovery or death) and S is the susceptibility rate (the fraction of people who can get infected at any point in time). By assuming that T, S and D are constant and that $Y_0 = 1$, it follows that:

$$Y_t = (\beta_0 C)^t \tag{3}$$

where $\beta_0 = T \times S \times D$. The determining factors, therefore, are those that impact the contact rate, C. According to Barr and Tassier (2020a), the contact rate depends on population density, which is the variable of interest, along with some "control variables" [2]. In their empirical model, however, they do not include population density as one of the explanatory variables. Instead, they use separate explanatory variables: population, land area, GDP (as a proxy for economic density), the proximity of a major airport and various measures of time, including days since the reporting of the first case.

Following the approach of Barr and Tassier (2020a), we incorporate time since the first case and population density as explanatory variables. Barr and Tassier (2020b) observe that the reproduction rate does not fully capture the dynamics of infectious disease spread, as it impacts countries differently based on timing. It is logical to assume that, *ceteris paribus*, the time elapsed since the first identified case correlates with an increase in the number of cases. Population density, on the other hand, is a major determinant of the contact rate, the number of cases and consequently the number of deaths (for example, Hu *et al.*, 2013). By ignoring the *ceteris paribus* condition, Barr and Tassier (2020b) introduced the concept of the "density paradox", since the effect of population density does not materialize in isolation from the effects of other factors. For example, they question why Asian countries, which have high population densities, have successfully controlled the virus spread. The impact of population density on the spread of pandemics and epidemics has been studied by Maybery (1999), Tarwater and Martin (2001), Sumdani *et al.* (2014) and Li *et al.* (2018). Tarwater and Martin (2001) conclude that because density affects the contact rate, it has a "dramatic effect on the distribution of contacts over time, the magnitude of the outbreak, and, ultimately, the spread of disease". Li *et al.* (2018), however, argue that the evidence on the role of population density is inconclusive. Sumdani *et al.* (2014) propose that the transmission dynamics forecasted by epidemiological models are influenced by population density. In more recent studies, Sy *et al.* (2021) find that the contact rate is higher in dense areas. Likewise, Martins-Filho (2021) emphasizes the importance of population density by exploring its effect on the spread of the pandemic in Northeast Brazil, where a large concentration of highly vulnerable people can be found. Moosa and Khatatbeh (2021b) demonstrate that while population density significantly increases the number of cases, it does not affect the number of deaths, attributing this to varying levels of preparedness. They also reject the notion of the "density paradox".

Another population-related factor that pertains to population density is urban population, the concentration of people in urban centers (hence, "urban density"). It is considered a separate variable from population density because while the population density of a particular country might be low, concentration in urban centers might lead to a higher contact rate and consequently a higher infection rate. Florida (2020) states that "the very same clustering of people that makes our great cities more innovative and productive also makes them, and us, vulnerable to infectious disease". However, some observers disagree with Florida's proposition, arguing that while New York City faced severe challenges, crowded Asian cities (such as Singapore, Seoul and Shanghai) performed well. Fang and Wahba (2020) suggest that urban population density can be advantageous because a minimum level of density may be required for economies of scale to be effective, particularly regarding high-grade facilities and services. Desai (2020) emphasizes that while crowded urban centers may be sustainable in terms of economies of scale, they may be unable to cope with unprecedented disease outbreaks. Acuto (2020) highlights the importance of urban density by suggesting that the pandemic has "changed the face of many of our cities and questioned how we should manage urban life in the wake of a pandemic". Some recent studies dispute the role of urban density. McFarlane (2021) examines the effect of urban density on the spread of the pandemic, arguing that while density initially facilitated the spread of the virus, this view evolved over time. He contends that the perception of "density-as-pathology" shifted towards understanding urban aspects of the crisis, emphasizing factors like connectivity, spatial conditions, domestic overcrowding and poverty. Khan *et al.* (2021) argue that it is a fallacy to believe that urban density is the main cause of COVID-19 spread in cities. Instead, they suggest income inequality, provision of healthcare, living conditions and government responsiveness. On the other hand, Moosa and Khatatbeh (2021a) discover that the rate of infection is more closely associated with urban density than with general population density, while mortality rates are more influenced by the age composition of the population and overall population density than by urban density.

Important factors ignored by Barr and Tassier (2020a) include preparedness indicators and associated elements, such as the quality of healthcare systems. Therefore, we consider six key variables: prevention (the emergence or release of pathogens), speed of response (mitigation of spread), detection and reporting, quality of the healthcare system, compliance with international norms and the risk environment (a country's vulnerability disease outbreak). These factors have rarely been used in empirical studies on the determinants of the severity of COVID-19. Moosa and Khatatbeh (2020) find the risk environment to be a robust determinant of the population mortality rate and that prevention is a robust determinant of case mortality rates.

The demographic composition of a population, such as the proportion of individuals aged over 65, has a more significant impact on mortality rates than on infection rates. Dowda *et al.* (2020) emphasize the crucial influence of demographic factors and suggest that age structure might account for variations in mortality rates across countries. Bilgili *et al.* (2021) argue that a higher percentage of elderly individuals in the population markedly affect the pandemic's progression. Blyuss and Kyrychko (2021) implement an age-differentiated Susceptible-Exposed-Infectious-Recovered (SEIR) model that incorporates more precise age-specific hospitalization and COVID-related mortality data. Additionally, Monod *et al.* (2021) report that in the USA, adults between 20–34 and 35–49 years have played a considerable role in maintaining COVID-19 transmission, consistently recording reproduction numbers above one.

The final variable examined in this research is the number of tests conducted, which could have divergent impacts on both infection and mortality rates. Extensive testing followed by isolating those infected is expected to lower both infection rates and, subsequently, mortality. Conversely, increased testing tends to uncover more previously undetected cases. Razzak (2020), utilizing panel data, discovers "reasonable evidence" to suggest that virus testing contributes to a reduction in deaths. More specifically, he finds that, on average, a one percent increase in daily testing reduces the number of deaths by about 4 a day. Pilecco *et al.* (2021) find a low correlation between the number of tests and the mortality rate. Mercer and Salit (2021) argue that countries with high testing rates were able to control transmission effectively during the initial stages of the pandemic. Cohen and Leshem (2021) demonstrate that controlled testing in the case of small new outbreaks can prevent the widespread escalation of new waves.

Methodology

Consider a cross-sectional regression of the form:

$$Y = \alpha + \sum_{i=1}^{n} \delta_i X_i + \varepsilon \tag{4}$$

where n is the number of explanatory variables.

When a large number of explanatory variables are considered, be it for theoretical reasons or because the variables have been used in previous studies, a researcher is invariably tempted to indulge in a process of heavy data mining, trying various combinations by adding and deleting explanatory variables from the available pool. The objective of data mining is to obtain one, out of hundreds of regression equations, the one that tells a good story. Young and Holsteen (2017) examine the 'model uncertainty' problem and note that "theory can be tested in many different ways and modest differences in methods may have a large influence on the results" [3]. Likewise, Gilbert (1986) notes that the significant coefficients appearing in the selected regression equation "cannot be taken as evidence for or against the hypotheses under investigation", presumably because they appear significant by design (that is, by a deliberate choice of the explanatory variables and other variation). He also refers to "the other 999 regressions assigned to the bin" in reference to the tendency to estimate a large number of regression equations and report one or few that serve some purpose (i.e. confirming a prior belief).

To avoid this problem, Leamer (1983, 1985) proposes extreme bounds analysis (EBA) as a sensitivity analysis that enables the selection of explanatory variables by using an elaborate procedure. EBA involves the estimation of a series of regressions where each of the potential explanatory variables is treated in turn as the variable of interest. For each variable of interest, many regressions are run, with different combinations of h variables, such that $1 < h < n - 1$. For each variable of interest, m equations are estimated where:

$$m = (n-1)!/[h!(n-1-h)]! \tag{5}$$

If X_1 is the variable of interest, then for given values of n and h, the first equation contains the explanatory variables X_1, $X_2, \ldots X_{h+1}$, whereas the last equation contains the variables $X_1, X_{n-h+1}, \ldots X_{n-1}, X_n$. Inference is based on the estimated coefficient on the variable of interest, β, not from one estimated equation, but from the wide range of values obtained from the m estimated equations. A variable of interest is regarded as a robust determinant of the dependent variable if the estimated coefficient on that variable does not change sign and significance across the range of estimated equations. The emphasis, therefore, shifts from significance in one equation to robustness in m equations.

Leamer's EBA is excessively rigorous and overlooks the distribution of the estimated coefficient on the variable of interest, β [4]. This is what motivated Sala-i-Martin (1997) to come up with an alternative EBA test that involves the same procedure and number of regressions, but a different criterion for the determination of robustness. This test is based on the entire distribution of β, which is analyzed to determine the fraction of the cumulative distribution function (CDF) falling on each side of zero, CDF (0). If at least 95% of the CDF lies on either side, the variable is considered robust, otherwise, it is fragile.

This methodology is adequate for the issue under consideration. Firstly, we are not aiming to identify all potential explanatory variables. For example, a crucial variable involves measures such as lockdowns, social distancing, quarantine policies and border closures. However, finding a unified representation for these factors is challenging due to their variations in terms of form, severity and timing. Secondly, compiling an exhaustive list of potential explanatory variables is not feasible. For instance, Klees (2016) asserts that "all relevant variables that may affect the dependent variable can never be included". Similarly, Meng (2019) mentions "an unknown number of relevant factors", some of which may be unknown, making it impossible to claim that all relevant variables are included in the model. Instead, this methodology allows us to undertake two modest, yet practical and feasible tasks. First, we can rank the variables that affect the infection and mortality rates in both developing and developed countries in terms of importance. Second, we can ascertain whether common factors play a significant role in the determination of the severity of COVID-19 in both developing and developed countries [5].

Data and stylized facts

The empirical results are based on cross-sectional data covering 148 countries. The International Monetary Fund (IMF) classification is used to divide the sample into two sub-samples (developed countries (33) and developing countries (115)) [6]. The definitions of the variables and data sources are provided in Table 1. Data on the number of cases and deaths are recorded up to the end of August 2021. Two dependent variables are used: the infection rate (Y_1) and the case mortality rate (Y_2). The eleven explanatory variables are X_1, . . . and X_{11} as defined in Table 1. The correlation matrix indicates no sign of potential multicollinearity [7].

To start with, the data show that the infection rate and case mortality rate do not correlate directly. Table 2 contains examples of countries with high infection rates, but low mortality rates and vice versa. Out of 148 countries, Angola has the highest infection rate but ranks 25th in terms of mortality rate. Conversely, Niger has the lowest infection rate but ranks 133rd in terms of mortality rate.

Variable	Symbol	Units	Source	Link
Infection rate	Y_1	Cases per million	European Centre for Disease Prevention and Control	https://www.ecdc.europa.eu/en/publications-data/download-todays-data-geographic-distribution-covid-19-cases-worldwide
Mortality rate	Y_2	Deaths per case	European Centre for Disease Prevention and Control	https://www.ecdc.europa.eu/en/publications-data/download-todays-data-geographic-distribution-covid-19-cases-worldwide
Prevention	X_1	Index 0–100	GHSI	https://www.ghsindex.org/
Detection and reporting	X_2	Index 0–100	GHSI	https://www.ghsindex.org/
Rapid response	X_3	Index 0–100	GHSI	https://www.ghsindex.org/
Healthcare system	X_4	Index 0–100	GHSI	https://www.ghsindex.org/
Compliance with international norms	X_5	Index 0–100	GHSI	https://www.ghsindex.org/
Risk environment	X_6	Index 0–100	GHSI	https://www.ghsindex.org/
Population density	X_7	People/square kilometer	World Bank Development Indicators	https://data.worldbank.org/indicator/EN.POP.DNST
Population over 65	X_8	percent	World Bank Development Indicators	https://data.worldbank.org/indicator/SP.POP.65UP.TO.ZS
Urban population	X_9	percent	World Bank Development Indicators	https://data.worldbank.org/indicator/SP.URB.TOTL.IN.ZS
Time since first reported case	X_{10}	Days	European Centre for Disease Prevention and Control (ECDC); Our World in Data (OWID)	https://www.ecdc.europa.eu/en/publications-data/download-todays-data-geographic-distribution-covid-19-cases-worldwide; https://ourworldindata.org/coronavirus
Tests	X_{11}	per million	Worldmeters.com	https://www.worldometers.info/coronavirus/#countries

Source(s): Authors' own creation

Table 1.
Variable symbols, units and data sources

Country	Infection rate		Case mortality rate	
Andorra	Value	Rank	Value	Rank
Angola	194,094	148	0.009	25
Bahrain	1,372	6	0.025	113
Estonia	105,598	131	0.009	30
Haiti	1,798	7	0.028	123
Malawi	3,052	16	0.035	136
Maldives	147,765	143	0.003	6
Niger	231	1	0.034	133

Source(s): Authors' own creation

Table 2.
Infection and mortality rates for selected countries

Table 3 displays the means of the dependent and explanatory variables, along with the t-statistics for testing the null hypothesis that the means for developed and developing countries are equal. In all cases, the difference between means is statistically significant. Developed countries have a significantly higher infection rate while developing countries have a higher case mortality rate. Developed countries score higher on all measures of health security, including the quality of the healthcare system, which can be explained by the differences in available financial resources. Developed countries also have higher levels of population density, a larger proportion of the population over 65 and a higher urban population. Additionally, they conduct a significantly larger number of tests. These characteristics have implications for both the infection rate and mortality rate, as explained earlier.

Table 4 compares developed and developing countries in terms of infection rate, mortality rate and the eleven factors expected to determine these rates. The comparison is based on the numbers of developed and developing countries included in the lowest and highest ten for each variable. Most countries in the lowest ten for both infection and mortality rates are developing countries. However, 6 out of the 10 countries with the highest infection rate are developing countries, and 9 out of the 10 countries with the highest mortality rates are also developing countries. Figure 1 shows the individual countries in the lowest and highest ten for each variable. Developing countries predominantly fall into the lowest 10 for all explanatory variables, except population density.

Empirical results

The EBA results are presented in Table 5, which reports the percentage of the cumulative distribution function lying on one side of zero, CDF(0). For each variable of interest, we run 120 regressions, each containing a unique combination of the remaining explanatory variables. No free variable is employed because this is a new strand of research, as COVID-19 is still a new phenomenon [8]. For an explanatory variable to be a robust determinant of the dependent variable at the 5% significance level, the condition $CDF(0) \geq 95$ must be satisfied.

Variable	Mean (developed)	Mean (developing	t-statistic
Y_1	72,032	42,237	3.56
Y_2	0.0146	0.0206	−2.24
X_1	58.32	33.26	9.60
X_2	70.37	40.66	7.64
X_3	55.56	36.53	7.21
X_4	50.04	24.05	9.82
X_5	61.89	47.28	6.53
X_6	76.90	52.2	10.54
X_7	438.72	165.81	1.97
X_8	18.36	6.98	12.46
X_9	79.73	57.44	5.51
X_{10}	556.47	536.33	6.24
X_{11}	2,245,758	499,264	6.12

Note(s): Y_1 Infection Rate, Y_2 Case Mortality Rate, X_1 Prevention, X_2 Detection and Reporting, X_3 Rapid Response, X_4 Health System, X_5 Compliance with International Norms, X_6 Risk Environment, X_7 Population Density, X_8 Population Over 65, X_9 Urban Population, X_{10} Time since First Reported Case, X_{11} Tests (per million)
Source(s): Authors' own creation

Table 3. Mean values of dependent and explanatory variables

Variable	Lowest 10 Developed	Lowest 10 Developing	Highest 10 Developed	Highest 10 Developing
Y_1	2	8	4	6
Y_2	2	8	1	9
X_1	0	10	9	1
X_2	0	10	10	0
X_3	0	10	8	2
X_4	0	10	9	1
X_5	0	10	7	3
X_6	0	10	8	2
X_7	3	7	3	7
X_8	0	10	8	2
X_9	0	10	6	4
X_{10}	0	10	6	4
X_{11}	0	10	8	2

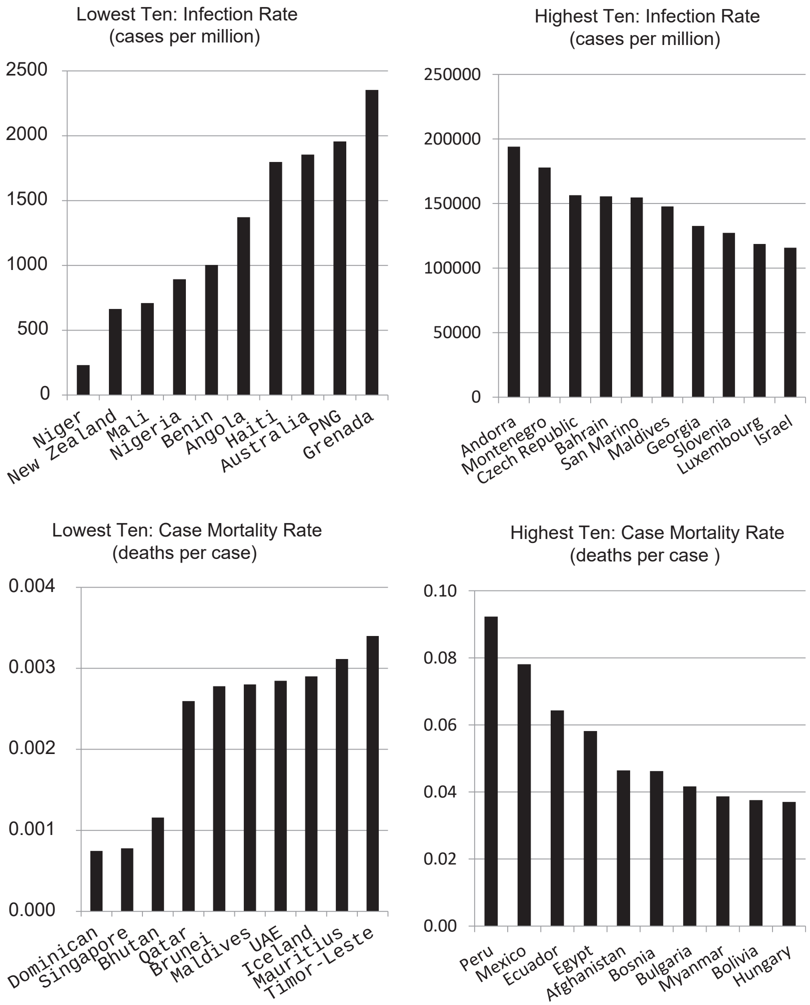
Note(s): Y_1 Infection Rate, Y_2 Case Mortality Rate, X_1 Prevention, X_2 Detection and Reporting, X_3 Rapid Response, X_4 Health System, X_5 Compliance with International Norms, X_6 Risk Environment, X_7 Population Density, X_8 Population Over 65, X_9 Urban Population, X_{10} Time since First Reported Case, X_{11} Tests (per million)
Source(s): Authors' own creation

Table 4. Developed and developing countries in the lowest and highest ten

For the first dependent variable, the infection rate, measured as cases per million of the population, the robust variables are the risk environment, population density and tests per million for developed countries and compliance with international norms, the risk environment, the population over 65, the urban population and the number of tests for developing countries. While different robust variables determine the infection rates in developed and developing countries, the two common factors are the risk environment and the number of tests per million. As for the mortality rate, the robust determinants are prevention, population density and population over 65 for developed countries and rapid response, population over 65, time since the first case and the number of tests for developing countries. The only common factor is the population over 65, which is logical given its significant impact on mortality.

Robust variables can be ranked in terms of their impact on infection and mortality rates. In Figure 2, we can see the 11 explanatory variables ranked according to CDF(0), with a dotted line at 95% to identify the robust variables. The most important determinant of the infection rate for developed countries is the number of tests and the least important is prevention. For developing countries, the most and least important determinants of the infection rate are urban population and prevention, respectively. As for the mortality rate, the most and least important determinants are population density and the risk environment, respectively for developed countries and population over 65 and detection and reporting, respectively for developing countries.

Overall, the infection and mortality rates depend on different factors in developed and developing countries, but two common factors for the infection rate are the risk environment and the number of tests. Population over 65 is the only common factor for the mortality rate. Some determinants of the infection rate are important for developing countries but not for developed ones, including compliance with international norms and urban population. This is likely because developed countries tend to be more compliant with international norms and because urban centers in developed countries are more equipped to handle a pandemic than those in developing countries. For the mortality rate,



Source(s): Authors' own creation

Figure 1.
Countries with lowest and highest infection and mortality rates

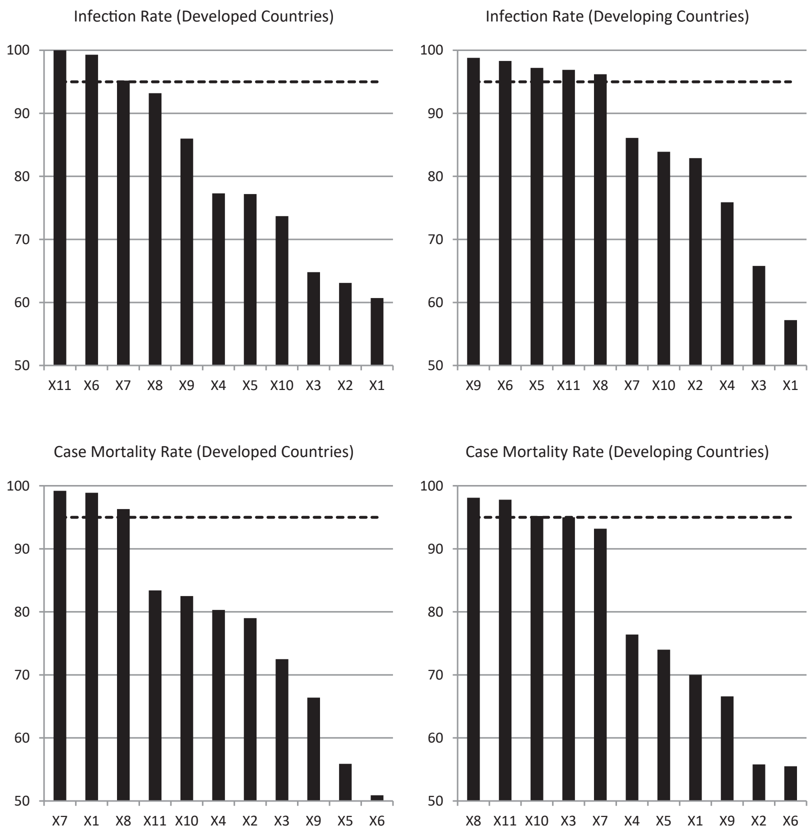
factors that appear robust in developing countries include only rapid response, time since the first reported case and tests per million.

How do these results compare with the limited literature surveyed earlier? Consider first the effect of population density. The literature shows that the effect of this factor is "dramatic" or "inconclusive". McFarlane (2021) and Khan *et al.* (2021) even dispute or dismiss the role of urban density in spreading the virus. The results obtained in this study indicate that population density is vital for determining the infection rate, in both developing and developed countries, but not the mortality rate in developed countries. It is important for the mortality rate in developing countries because more infected people die in developing than in developed countries due to differences in healthcare quality.

Variable	Y_1 Developed	Y_1 Developing	Y_2 Developed	Y_2 Developing
X_1	60.7	57.2	98.9	70.0
X_2	63.1	82.9	79.0	55.8
X_3	64.8	65.8	72.5	95.0
X_4	77.3	75.9	80.3	76.4
X_5	77.2	97.2	55.9	74.0
X_6	99.3	98.3	50.9	55.5
X_7	95.2	86.1	99.2	93.2
X_8	93.2	96.2	96.3	98.1
X_9	86.0	98.8	66.4	66.6
X_{10}	73.7	83.9	82.5	95.2
X_{11}	100.0	96.9	83.4	97.8

Table 5.
Estimated cumulative density function CDF(0)

Note(s): X_1 Prevention, X_2 Detection and Reporting, X_3 Rapid Response, X_4 Health System, X_5 Compliance with International Norms, X_6 Risk Environment, X_7 Population Density, X_8 Population Over 65, X_9 Urban Population, X_{10} Time since First Reported Case, X_{11} Tests (per million)
Source(s): Authors' own creation



Source(s): Authors' own creation

Figure 2.
Ranking of explanatory variables in terms of CDF(0)

The views and results also differ regarding the role of the urban population. This study shows that it is important to determine the mortality rate in developing countries but not in developed countries, again due to differences in healthcare quality and access. The finding on the effect of age structure is consistent with other studies, showing a significant effect on the mortality rate in both developing and developed countries. Similar to Razzak (2020), this study finds that the number of tests is closely related to the number of infections, not because testing causes infection but because it reveals more infections.

The variables that constitute the global health security index have rarely been used in other studies, which restricts direct comparisons. One of the earliest studies in this area, conducted by Barr and Tassier (2020a), overlooks measures of preparedness and associated factors. However, the confirmation that the risk environment is a critical factor aligns with the findings of Moosa and Khatatbeh (2020) regarding this variable.

Policy recommendations

Policy recommendations stemming from this study must address variables within the sphere of control of authorities, allowing for intervention of influence. It is prudent to focus on robust variables, which, for both developing and developed countries (and for both the infection and mortality rate), encompass aspects such as the risk environment, compliance with international norms, prevention measures, rapid response capabilities, population density, the proportion of individuals over 65, urbanization rates and the number of tests conducted per million people.

The first three variables are integral components of the global health security index, susceptible to policy actions and subject to financial constraints. The risk environment pertains to the country's vulnerability to biological threats, a concern that evolutionary biologists like Rob Wallace attribute to the encroachment on natural habitats. Wallace connects the frequent appearance of coronaviruses (such as SARS, MERS and COVID-19) to the intrusion of business enterprises into the habitat of these viruses (Wallace, 2020a, b). Wallace (2020a, b) refers to the "agroindustry's devastating impact on natural ecosystems" and highlights the "interplay between industrial production of food and a growing market for exotic wild food". In particular, Wallace (2020a) emphasizes deforestation and the push deeper into the remaining primary ecosystems as factors that have enabled the "spillover of previously boxed-in pathogens to human communities forced to breach the natural barrier between them while working". This becomes an issue of environmental regulation, requiring a balance between growth and environmental degradation.

Adhering to international standards involves enhancing national capabilities, funding initiatives to bridge deficiencies and following global norms. This is especially critical for developing nations that may face financial constraints. Official development assistance could support these efforts. Prevention focuses on preventing the emergence or dissemination of pathogens, including those posing significant public health risks, as defined by the criteria for a public health emergency of international concern. Rapid response relates to curbing the spread of an epidemic, which also demands sufficient financial resources.

Policy recommendations relating to these factors have been made in the report prepared by the Nuclear Threat Initiative (NTI) and Johns Hopkins Center for Health (2021). First, countries should allocate health security funds in national budgets to develop a national plan to identify risks and fill gaps. Second, international organizations should identify countries most needing additional support. Third, the private sector should look for opportunities to partner with governments. Finally, philanthropists and funders should develop new financing mechanisms to prioritize resources.

Whether anything can be done about demographic factors (population density, population over 65 and urban population) is debatable, but more careful urban planning can help. In developing countries, massive migration from the countryside to big urban centers can be slowed down by utilizing farm subsidies. Nothing practical can be done about the age structure of the population unless we consider the unethical Malthusian solution, which according to Al-Nakeeb (2022) was actually provided by Boris Johnson. Extending testing should be feasible if more resources are allocated to healthcare, as it should be. This would require a strong public sector and a departure from extreme neoliberal ideas of the absolute superiority of the private sector and militarism.

Taking these measures is important for the private sector, which was hit hard, particularly the hospitality and tourism sector. For example, Cadena and Laverde (2021) find that firms in operation for more than 3.5 years were most impacted due to a lack of innovation, technology backlog and low profitability. Accordingly, governments must consider policies that encourage and facilitate innovation in production processes, access to new technologies, processes and capital and the generation of knowledge-based firms.

Concluding remarks

The empirical analysis presented in this paper highlights that the differing characteristics of developed and developing countries result in variations in the factors determining the severity of COVID-19. Severity is measured by the infection rate (cases per million) and the case mortality rate (deaths per case). However, some common factors emerge, such as the risk environment the number of tests for the infection rate and the percentage of the population over 65 for the mortality rate.

The findings of this study are derived from EBA, which does not rely on a single regression model but rather uses numerous equations incorporating various systematically selected subsets of explanatory variables. The inference is drawn from the overall distribution of the coefficient on the variable of interest, with an emphasis on robustness as judged by the cumulative distribution function rather than on statistical significance as judged by t-statistics. This approach arguably makes the results more reliable and less subjective than those derived from a single regression equation. Conversely, the study may help resolve controversies regarding the effects of some variables on infection and mortality rates, such as population density. The results clearly illustrate the effects of density, dismissing the "density paradox", that occasionally appears in the literature.

On the practical side, the results offer several policy recommendations for containing the virus, not only for the current situation but also for dealing with and even reducing the probability of future pandemics resulting from the release of new pathogens. These recommendations are detailed in the policy section.

However, this research has limitations. Primarily, the classification of "developing countries" encompasses a broad and varied group compared to "developed countries." A more detailed categorization might yield more insightful findings, especially among the numerous developing nations. Additionally, significant concerns arise regarding data accuracy, such as confirmed cases and death counts. For instance, the UK government initially did not include fatalities in homes or care facilities in their counts. The noticeable discrepancies in mortality rates across even developed nations suggest data inaccuracies, possibly due to underreporting of COVID-19-related deaths. While data suppression might occur in certain countries, the study's findings still offer valuable insights that could support decision-making processes in the fight against the pandemic. Another potential improvement could be the incorporation of additional variables such as the duration of lockdowns, tourist numbers and vaccination rates.

These limitations can be addressed in future studies, with a particular emphasis on vaccination, which can be measured in various ways. Nonetheless, an important finding regarding vaccination provided in this study is that it is irrelevant to the infection rate, despite some claims made to the contrary.

Notes

1. Developed and developing countries differ not only in the severity of COVID-19 but also in various other aspects. For example, empirical research has identified a variety of factors that differently influence economic growth in developed and developing countries (see, for example, Batrancea, 2022; Batrancea *et al.*, 2021, 2022c).
2. The idea of "control variables" may seem unusual since the data are not derived from a controlled experiment. In an economy, data are generated by the simultaneous movement of all variables, none of which can be controlled.
3. The phrase "many different ways" may refer to the selected set of explanatory variables, measurement of the dependent and explanatory variables, model specification and estimation method (for example, linear versus long linear).
4. It is rigorous because if the coefficient on the variable of interest changes sign or significance in just one of the m regression equations, the variable is deemed to be fragile.
5. One of the earliest applications of EBA is determining the factors influencing economic growth, owing to the abundance of potential determinants. Alternatively, traditionally, this task is performed using straight cross-sectional or panel regression analysis, which is simpler because the analysis is based on the estimation of one or few equations, as opposed to the two million equations used in Sala-i-Martin (1997). For a comparison, consider the results of Sala-i-Martin (1997) with the results based on panel data as in Batrancea (2022, 2023) and Batrancea *et al.* (2021, 2022a, b, c, 2023a, b). Studies based on EBA tend to examine a much larger number of explanatory variables (Khatatbeh and Moosa, 2022; Khatatbeh and Abu-Alfoul, 2023).
6. Lists of developed and developing countries are provided in Appendix 1 and 2, respectively.
7. The correlation matrices and basic statistics are not reported here but the results can be obtained from the corresponding author upon request.
8. In EBA analysis, a free variable is an explanatory variable that appears in all regressions because it is deemed to be important according to theory and/or empirical evidence (Moosa and Khatatbeh, 2020; AbuAlfoul *et al.*, 2022).

References

AbuAlfoul, M., Khatatbeh, I. and Jamaani, F. (2022), "What determines the shadow economy? An extreme bounds analysis", *Sustainability*, Vol. 14 No. 10, p. 5761, doi: 10.3390/su14105761.

Acuto, M. (2020), "COVID-19: lessons for an urban(izing) world", *One Earth*, Vol. 2 No. 4, pp. 317-319, doi: 10.1016/j.oneear.2020.04.004.

Al-Nakeeb, B. (2022), *The Impact of Moral Economics: Improving Lives, Democracy and Humanity's Future*, Private Publication, New York.

Barr, J.M. and Tassier, T. (2020a), "Modeling the impact of density on the spread of the corona virus", Working Paper, 3 April, available at: https://buildingtheskyline.org/wp-content/uploads/2019/10/Theory-and-Empirical-Model-6April20.pdf

Barr, J.M. and Tassier, T. (2020b), "Escape from New York? Density and the coronavirus trajectory", 20 April, available at: https://buildingtheskyline.org/covid19-and-density/

Batrancea, L. (2022), "Determinants of economic growth across the European union: a panel data analysis on small and medium enterprises", *Sustainability*, Vol. 14 No. 8, pp. 1-17, doi: 10.3390/su14084797.

Batrancea, L. (2023), "The hard worker, the hard earner, the young and the educated: empirical study on economic growth across 11 CEE countries", *Sustainability*, Vol. 15 No. 22, 15996, (published online, 16 November), doi: 10.3390/su152215996.

Batrancea, L.M., Balcı, M.A., Akgüller, Ö. and Gaban, L. (2022c), "What drives economic growth across European countries? A multimodal approach", *Mathematics*, Vol. 10 No. 19, p. 3660, doi: 10.3390/math10193660.

Batrancea, L., Balcı, M.A., Chermezan, L., Akgüller, Ö., Masca, E.S. and Gaban, L. (2022a), "Sources of SMEs financing and their impact on economic growth across the European union: insights from a panel data study spanning sixteen years", *Sustainability*, Vol. 14 No. 22, 15318, doi: 10.3390/su142215318.

Batrancea, L., Rathnaswamy, M.M. and Batrancea, I. (2021), "A panel data analysis of economic growth determinants in 34 African countries", *Journal of Risk and Financial Management*, Vol. 14 No. 6, p. 260, doi: 10.3390/jrfm14060260.

Batrancea, L., Rathnaswamy, M.K. and Batrancea, I. (2022b), "A panel data analysis on determinants of economic growth in seven non-BCBS countries", *Journal of Knowledge Economy*, Vol. 13 No. 2, pp. 1651-1665, doi: 10.1007/s13132-021-00785-y.

Batrancea, L., Nichita, A., Balcı, M.A. and Akgüller, Ö. (2023a), "Empirical investigation on how wellbeing-related infrastructure shapes economic growth: evidence from the European union regions", *PLoS One*, Vol. 18 No. 4, e0283277, doi: 10.1371/journal.pone.0283277.

Batrancea, L.M., Rathnaswamy, M.M., Rus, M.I. and Tulai, H. (2023b), "Determinants of economic growth for the last half of century: a panel data analysis on 50 countries", *Journal of Knowledge Economy*, Vol. 14 No. 3, pp. 2578-2602, doi: 10.1007/s13132-022-00944-9.

Bilgili, F., Dundar, M., Kuşkaya, S., Lorente, D.B., Ünlü, F., Gençoğlu, P. and Muğaloğlu, E. (2021), "The age structure, stringency policy, income, and spread of coronavirus disease 2019: evidence from 209 countries", *Frontiers in Psychology*, Vol. 11, 12 February, doi: 10.3389/fpsyg.2020.632192.

Blyuss, K.B. and Kyrychko, Y.N. (2021), "Effects of latency and age structure on the dynamics and containment of COVID-19", *Journal of Theoretical Biology*, Vol. 513, (published online, 21 March), doi: 10.1016/j.jtbi.2021.110587.

Cadena, C.A.L. and Laverde, F.P. (2021), "Why companies and governments need to foster an entrepreneurial mindset and intrapreneurship", *Global Entrepreneurship Monitor*, 6 October.

Cohen, K. and Leshem, A. (2021), "Suppressing the impact of the COVID-19 pandemic using controlled testing and isolation", *Scientific Reports*, Vol. 11 No. 1, p. 6279, doi: 10.1038/s41598-021-85458-1.

Desai, D.D. (2020), "Urban densities and the covid-19 pandemic: upending the sustainability myth of global megacities", ORF Occasional Papers, Vol. 244.

Dowda, J.B., Andrianoa, L., Brazela, D.M., Rotondia, V., Blocka, P., Dinga, X., Millsa, M.C. and Mills, M.C. (2020), "Demographic science aids in understanding the spread and fatality rates of COVID-19", *PNAS*, Vol. 117 No. 18, pp. 9696-9698, 5 May, doi: 10.1073/pnas.2004911117, available at: https://www.pnas.org/content/117/18/9696

Fang, W. and Wahba, S. (2020), "Urban density is not an enemy in the coronavirus fight: evidence from China", World Bank Blogs, 20 April, available at: https://blogs.worldbank.org/sustainablecities/urban-density-not-enemy-coronavirus-fight-evidence-china

Florida, R. (2020), "The geography of coronavirus, 3 April", available at:, https://www.citylab.com/equity/2020/04/coronavirus-spread-map-city-urban-density-suburbs-rural-data/609394/

Gilbert, C.L. (1986), "Professor Hendry's econometric methodology", *Oxford Bulletin of Economics and Statistics*, Vol. 48 No. 3, pp. 283-307, doi: 10.1111/j.1468-0084.1986.mp48003007.x.

Hu, H., Nigmatulina, K. and Eckhoff, P. (2013), "The scaling of contact rates with population density for the infectious disease models", *Mathematical Biosciences*, Vol. 244 No. 2, pp. 125-134, doi: 10.1016/j.mbs.2013.04.013.

Khan, I., Iftikhar, M.N., Ali, S.H. and Khalid, S. (2021), "Cities and COVID-19: navigating the new normal", *Global Sustainability*, Vol. 4, e12, (published online, 9 March), doi: 10.1017/sus.2021.10.

Khatatbeh, I. and Abu-Alfoul, M. (2023), "The determinants of the hidden economy in developed and developing countries", *Applied Economics Letters*, pp. 1-5, doi: 10.1080/13504851.2023.2208331.

Khatatbeh, I. and Moosa, I. (2022), "Financialization and income inequality: an extreme bounds analysis", *The Journal of International Trade and Economic Development*, Vol. 31 No. 5, pp. 692-707, doi: 10.1080/09638199.2021.2005668.

Klees, S.J. (2016), "Inferences from regression analysis: are they valid?", *Real-World Economics Review*, Vol. 74, pp. 85-97.

Leamer, E. (1983), "Let's take the con out of econometrics", *American Economic Review*, Vol. 73, pp. 31-43.

Leamer, E. (1985), "Sensitivity analyses would help", *American Economic Review*, Vol. 75, pp. 308-313.

Li, R., Richmond, P. and Roehner, B. (2018), "Effect of population density on epidemics", *Physica A: Statistical Mechanics and Its Applications*, Vol. 510, pp. 713-724, doi: 10.1016/j.physa.2018.07.025.

Lowy Institute (2021), "Covid performance index: deconstructing pandemic responses", January, available at: https://interactives.lowyinstitute.org/features/covid-performance/

Martins-Filho, P.R. (2021), "Relationship between population density and COVID-19 incidence and mortality estimates: a county-level analysis", *Journal of Infection and Public Health*, Vol. 14 No. 8, pp. 1087-1088, doi: 10.1016/j.jiph.2021.06.018.

Maybery, P. (1999), "The effects of population density on the spread of disease", Texas Medical Center Dissertations, available at: https://digitalcommons.library.tmc.edu/dissertations/AAI9929469

McFarlane, C. (2021), "Repopulating density: COVID-19 and the politics of urban value", *Urban Studies*, Vol. 60, pp. 1548-1569, (published online, 9 June), doi: 10.1177/00420980211014810.

Meng, S. (2019), *Patentism Replacing Capitalism: A Prediction from Logical Economics*, Palgrave-Macmillan, New York.

Mercer, T.R. and Salit, M. (2021), "Testing at scale during the COVID-19 pandemic", *Nature Reviews Genetics*, Vol. 22 No. 7, pp. 415-426, doi: 10.1038/s41576-021-00360-w.

Monod, M., Blenkinsop, A., Xi, X., Hebert, D., Bershan, S., Tietze, S., Baguelin, M., Bradley, V.C., Chen, Y., Coupland, H., Filippi, S., Ish-Horowicz, J., McManus, M., Mellan, T., Gandy, A., Hutchinson, M., Unwin, H.J.T., van Elsland, S.L., Vollmer, M.A.C., Weber, S., Zhu, H., Bezancon, A., Ferguson, N.M., Mishra, S., Flaxman, S., Bhatt, S. and Ratmann, O. (2021), "Age groups that sustain resurging COVID-19 epidemics in the United States", *Science*, Vol. 371 No. 6536, 26 March, doi: 10.1126/science.abe8372.

Moosa, I.A. and Khatatbeh, I.N. (2020), "International tourist arrivals as a determinant of the severity of Covid-19: international cross-sectional evidence", *Journal of Policy Research in Tourism*, Vol. 13 No. 3, pp. 419-434, Leisure and Events (published online, 17 December), doi: 10.1080/19407963.2020.1859519.

Moosa, I.A. and Khatatbeh, I.N. (2021a), "Robust and fragile determinants of the infection and case fatality rates of Covid-19: international cross-sectional evidence", *Applied Economics*, Vol. 53 No. 11, pp. 1225-1234, doi: 10.1080/00036846.2020.1827139.

Moosa, I.A. and Khatatbeh, I.N. (2021b), "The density paradox: are densely-populated regions more vulnerable to Covid-19?", *International Journal of Health Planning and Management*, Vol. 36 No. 5, pp. 1575-1588, (published online, 18 May), doi: 10.1002/hpm.3189.

NTI and Johns Hopkins Center for Health (2021), "Global health security index: advancing collective action and accountability amid global crisis", December.

Pilecco, F.B., Coelho, C.G., Fernandes, Q.H.R.F., Silveira, I.H., Pescarini, J.M., Ortelan, N., Gabrielli, L., Aquino, E.M.L. and Barreto, M.L. (2021), "The effect of laboratory testing on COVID-19 monitoring indicators: an analysis of the 50 countries with the highest number of cases", *Epidemiol Serv Saude*, Vol. 30 No. 2, e2020722, doi: 10.1590/S1679-49742021000200002.

Razzak, W.A. (2020), *Does Testing for Coronavirus Reduce Deaths?*, Massey University, Discussion Papers, No 20.05, available at: https://www.massey.ac.nz/massey/learning/colleges/college-business/school-of-economics-and-finance/research/discussion-paper-series.cfm

Sala-i-Martin, X. (1997), "I just ran two million regressions", *American Economic Review*, Vol. 87, pp. 178-183.

Sumdani, H., Frickle, S., Le, M., Tran, M. and Zaleta, C.K. (2014), "Effects of population density on the spread of disease, technical report 2014-05", University of Texas at Arlington.

Sy, K.T.L., White, L.F. and Nichols, B.E. (2021), "Population density and basic reproductive number of COVID-19 across United States counties", *PLoS One*, Vol. 16 No. 4, e0249271, (published online, 21 April), doi: 10.1371/journal.pone.0249271.

Tarwater, P.M. and Martin, C.F. (2001), "Effects of population density on the spread of disease", *Complexity*, Vol. 6, pp. 29-36, doi: 10.1002/cplx.10003.

Wallace, R. (2020a), "Capitalist agriculture and Covid-19: a deadly combination", *Climate and Capitalism*, 11 March.

Wallace, R. (2020b), "Notes on a novel coronavirus", *Monthly Review*, 29 January.

Young, C. and Holsteen, K. (2017), "Model uncertainty and robustness: a computational framework for multimodel analysis", *Sociological Methods and Research*, Vol. 46 No. 1, pp. 3-40, doi: 10.1177/0049124115610347.

Appendix 1

Australia	Hungary	Netherlands
Austria	Iceland	New Zealand
Belgium	Ireland	Norway
Canada	Israel	Portugal
Czech Republic	Italy	Singapore
Denmark	Japan	Slovak Republic
Estonia	Korea	Slovenia
Finland	Latvia	Sweden
France	Lithuania	Switzerland
Germany	Luxembourg	United Kingdom
Greece	Malta	United States

Source(s): Authors' own creation

Table A1.
List of developed countries

Appendix 2

Afghanistan	Gabon	Pakistan
Albania	Gambia	Panama
Algeria	Georgia	Papua New Guinea
Andorra	Grenada	Paraguay
Angola	Guatemala	Peru
Antigua	Guinea-Bissau	Philippines
Argentina	Guyana	Poland
Armenia	Haiti	Qatar
Azerbaijan	Honduras	Romania
Bahamas	India	Russian Federation
Bahrain	Indonesia	Rwanda
Bangladesh	Iran	San Marino
Barbados	Iraq	Sao Tome and Principe
Belarus	Jamaica	Saudi Arabia
Belize	Jordan	Senegal

(*continued*)

Table A2.
List of developing countries

Benin	Kazakhstan	Serbia
Bhutan	Kenya	South Africa
Bolivia	Kyrgyz Republic	Sri Lanka
Bosnia	Lebanon	St. Vincent
Botswana	Libya	Suriname
Brazil	Liechtenstein	Thailand
Brunei	Malawi	Timor-Leste
Bulgaria	Malaysia	Togo
Cabo Verde	Maldives	Trinidad and Tobago
Cambodia	Mali	Tunisia
Chile	Mauritania	Turkey
Colombia	Mauritius	Uganda
Costa Rica	Mexico	Ukraine
Croatia	Moldova	United Arab Emirates
Cuba	Mongolia	Uruguay
Djibouti	Montenegro	Uzbekistan
Dominica	Morocco	Venezuela
Dominican Republic	Mozambique	Vietnam
Ecuador	Myanmar	Zambia
Egypt	Namibia	Zimbabwe
El Salvador	Nepal	
Equatorial Guinea	Niger	
Eswatini	Nigeria	
Ethiopia	North Macedonia	
Fiji	Oman	

Source(s): Authors' own creation

Table A2.

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