Ricardo Puziol de Oliveira*, Jorge Alberto Achcar and Altacílio Aparecido Nunes

Modeling the incidence and death rates of COVID-19 pandemic in different regions of the world

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Abstract: This paper reports a broad study using epidemic-related counting data of COVID-19 disease caused by the novel coronavirus (SARS-CoV-2). The considered dataset refers to 119 countries' daily counts of reported cases and deaths in a fixed period. For the data analysis, it has been adopted a beta regression model assuming different regions of the world where it was possible to discover important economic, health and social factors affecting the behavior of the pandemic in different countries. The Bayesian method was applied to fit the proposed model. Some interesting conclusions were obtained in this study, which could be of great interest to epidemiologists, health authorities, and the general public in the face of the forthcoming hard times of the global pandemic.

Keywords: Bayesian methods; beta regression models; cases and deaths rates; COVID-19 counting data; SARS-CoV-2.

Introduction

An epidemic could be defined as the community occurrence of a group of illnesses of similar nature derived from a common or a propagated source (Gordis 2014), on the other hand, when an epidemic grows on a worldwide scale, then it is called a pandemic. In human history, epidemic diseases have killed millions of people at different times in varying speeds. Viruses have caused some of the worst registered epidemics, as smallpox (1896 to 1980), Spanish flu (1918 to 1919), measles (until 1963), AIDS (since 1981) and dengue over the last thirty years (World Health Organization 2020b). In 2009, cases of Influenza A (H1N1) were registered worldwide, and an outbreak of Ebola occurred between 2013 and 2016 in West Africa (see World Health Organization 2016). Over the last few years, the major epidemic diseases in Brazil were caused by Chikungunya (in 2013) and Zika (in 2015) viruses. These diseases had produced a vast international commotion as the number of new positive cases grew up considerably precisely when the country was about to host two of the most prominent sports events worldwide: 2014 FIFA World Cup and 2016 Summer Olympics Games.

Despite all the battles won against previous epidemics and pandemics, the world is currently experiencing one of the most significant challenges of the twenty-first century, the pandemic caused by the novel coronavirus. The COVID-19 disease is a viral infection of disruptive nature that is spreading quickly around the world since January 2020. The virus has emerged late in 2019 in the city of Wuhan, Hubei Province of China. According to the Situation Report 80 from the World Health Organization (WHO), the number of global cases reached 8,043,487 people until June 16, 2020, among which 439,487 died with COVID-19. Since December 2019, the pandemic of COVID-19 has spread to new areas and has increased considerably in the already affected areas. In the Situation Report 1 (January 21, 2020), there were only 282 confirmed cases in the region covering China, Japan, the Republic of Korea, and Thailand. However, in Situation Report 77 (April 06, 2020), there were

*Corresponding author: **Ricardo Puziol de Oliveira**, Universidade Estadual de Maringá, Av. Ângelo Moreira da Fonseca, 1800 - Parque Danielle, Umuarama, 87506-370, Brazil, E-mail: rpuziol.oliveira@gmail.com

Jorge Alberto Achcar and Altacílio Aparecido Nunes, Universidade de São Paulo Faculdade de Medicina de Ribeirão Preto, Ribeirão Preto, São Paulo, Brazil. <https://orcid.org/0000-0001-9934-920X> (A.A. Nunes)

1,210,956 confirmed cases and 67,594 deaths worldwide, being the South Sudan the last country to register cases of COVID-19. The disease initially called COVID-19 (**Coronavirus Disease 2019**) started to have the causative virus classified as SARS-CoV-2 by the International Virus Taxonomy Committee (Y. Chen et al. 2020). To track the virus, the WHO has updated the Laboratory Testing Strategy at March 21, 2020 (Lan et al. 2020) according to the different transmission scenarios: countries with no cases; countries with one or more cases (sporadic cases); countries experiencing a series of cases related to geographic location or common exposure (a group of cases); and countries experiencing massive outbreaks or sustained and pervasive local transmission (community transmission).

COVID-19 is a respiratory disease that affects different people in different ways, so that most people infected with the new coronavirus will experience mild to moderate respiratory illness, recovering without requiring specific treatments (World Health Organization 2020a). According to the WHO, the primary symptoms of COVID-19 are fever, tiredness, dry cough, shortness of breath, and sore throat, and very few people will report diarrhea, nausea, or runny nose. Older people and those with underlying medical conditions like cardiovascular disease, diabetes, chronic respiratory disease, and cancer are more likely to develop severe illness and death. The virus spreads primarily through droplets of saliva or discharge from the nose when an infected person coughs or sneezes. There are vaccines being developed and some are in the testing phase. There is no specific treatment for the disease and patients are treated according the symptoms they present, however, several ongoing clinical trials are being conducted to find potential treatments and drug repurposing opportunities. There are several vaccines under development, some already in phase III and others in the initial testing phase. Many researchers are putting great effort into the last months to better understand the behavior of the new coronavirus. It can be seen in the hundreds of scientific works being released in a short time (J.F.-W Chan 2020, K.-H. Chan 2020; Chen 2020; D. Chen et al. 2020; N. Chen et al. 2020; da Silva et al. 2020; Han et al. 2020; Huang et al. 2020; Kandel et al. 2020; Lai et al. 2020; Li et al. 2020; Lu et al. 2020; Lupia et al. 2020; Pung et al. 2020; Ribeiro et al. 2020; Shereen et al. 2020; Sohrabi et al. 2020; A. Wu et al. 2020; J. T. Wu et al. 2020; Zhao et al. 2020).

It is observed in the literature that countries in different regions could have different morbidity and mortality indicators such as Incidence Rate/100,000 (IR), Mortality Rate by cause/100,000 (MRC) and Case-Fatality Rate/100 (CFR), depending on the health structure, such as primary care units, specialized outpatient clinics and hospitals with and without intensive care units (ICU), as well as, number of diagnostic tests to detect coronavirus for the population, policy implemented in each country to isolate the population, that is, quarantine or total isolation and possibly other factors as ethical groups or climate differences that could affect the incidence and death rates. An important factor that affects the IR, MRC and CFR are underdiagnoses and/or under-notification, especially in the poorest countries of the world where there is great lack of hospitals, medical equipment and diagnostic tests to detect COVID-19, leading to very low and misleading rates related to the epidemic.

Thus, given the above, this article aims to analyze the correlations/associations between IR, MRC and CFR by COVID-19 with some variables described below, so in this study, 119 countries from different regions of the world were considered to compare such rates. The covariates assumed in this study for each country are:

- (1) **General information:** population/km².
- (2) **Economy:** GDP in million of current US\$ and GDP per capita in current US\$.
- (3) **Social indicators:** urban population (% of total population); infant mortality rate (deaths by 1,000 live births); physicians (number by 1,000 inhabitants) a health indicator and current expenditure in health (% of GDP on health spending) another health indicator.

This paper is organized as follows: Section 2 presents an overall description of the considered dataset and the proposed regression model for comparison of IR, MRC and CFR by COVID-19, notified from each country. The obtained results and the pertinent discussions are presented in Section 3. General comments and concluding remarks are addressed in Section 4.

Material and methods

Dataset

The data set consisted of the daily counting of new cases and daily deaths since until May 04, 2020 reported in the site European Union (EU) open data portal (<https://data.europa.eu/euodp/en/data/dataset/covid-19-coronavirus-data>). Moreover, some covariates associated to each country obtained from United Nations site (<https://data.un.org/>) relative for the year 2019, are considered in the data analysis assuming beta regression models under a Bayesian approach with responses given by IR, MRC and CFR to verify if there are significant effects of these covariates in the responses. The EU collects and manages data related to the COVID-19 pandemic involving daily counting of new cases and daily deaths. The SARS-CoV-2 has already infected the population since the beginning of the year 2020, especially in the northern hemisphere but in other countries, the infection only started in more recent months such as the southern hemisphere, leading a great heterogeneity of the data. For a better understanding of this behavior, the 119 countries considered in the study were selected from the world classified in 11 regions: East Asia, Central Asia, Asia Middle East, Europe, North America, Central America, South America, Oceania, Caribbean, North Africa and Sub Saharan Africa.

Beta regression model for the COVID-19 rates

Statistical modeling of daily and accumulated disease counting data can be considered under different approaches. Under a probabilistic point of view, the epidemic curves related to disease counting data could be modeled as a stochastic process (in the form of a counting process). Alternatively, one may consider the use of classical nonlinear models as those widely used to describe phenomena as population growth in ecology and demography or the individual body height or biomass (for growth analysis of subjects in physiology). Standard inference methods to obtain point and interval estimates for the parameters of growth models are well discussed within the nonlinear modeling literature (Bates and Watts 1980, 1988; Hazewinkel 2001; Ratkowsky 1983; Seber and Wild 2003).

Our approach in this paper is based on three univariate beta regression models for the responses $Y_1=IR$, $Y_2=MRC$ and $Y_3=CFR$ in presence of the following covariates: population/km², GDP (Gross Domestic Product of the country) in million of current US\$ in logarithmic scale, GDP per capita in current US\$ in logarithmic scale, urban population (% of total population), infant mortality rate (deaths by 1,000 live births), number of physicians by 1,000 inhabitants and % of GDP on health spending of each country in the study. In the regression model it is also considered categorical variables related to the 11 regions (use of dummy variables for categorical covariates regions where East Asia is considered as reference). Thus, since Y_1 , Y_2 and Y_3 are defined in the interval $[0, 1]$, it is assumed beta probability distributions for each random variable, given by the density probability function,

$$f(y|\alpha, \beta) = B(\alpha, \beta)y^{\alpha-1}(1-y)^{\beta-1}, 0 < y < 1, \quad (1)$$

where $B(\alpha, \beta)$ is a beta function defined by $B(\alpha, \beta) = \Gamma(\alpha + \beta)/\Gamma(\alpha)\Gamma(\beta)$ where $\Gamma(\kappa) = \int_0^\infty x^{\kappa-1}e^{-x} dx$. The Beta distribution is denoted by $Y \sim \text{Beta}(\alpha, \beta)$. The mean and variance of the beta distribution are given respectively by $\mu = \alpha/(\alpha + \beta)$ and $\sigma^2 = \alpha\beta/[(\alpha + \beta)^2(\alpha + \beta + 1)]$.

In presence of a vector of covariates associated to each unit, it is assumed a regression model considering a re-parametrized form for the beta distribution with density (1) given by, $\mu = \alpha/(\alpha + \beta)$ and $\Phi = \alpha + \beta$ (Ferrari and Cribari-Neto 2004; Jørgensen 1997). That is, $\alpha = \Phi\mu$, $\beta = (1 - \mu)\Phi$ with $E(Y) = \mu$ and $\text{var}(Y) = V(\mu)/(1 + \Phi)$ where $V(\mu) = \mu(1 - \mu)$, so that μ is the mean of the response variable and Φ can be interpreted as a precision parameter in the sense that, for fixed μ , the larger the value of Φ , the smaller the variance of Y . The density of the random variable Y can be written, in the new parameterization, as,

$$f(y|\mu, \Phi) = \frac{\Gamma(\Phi)}{\Gamma(\Phi\mu)\Gamma(\Phi(1-\mu))}y^{\Phi\mu-1}(1-y)^{\Phi(1-\mu)-1}, 0 < \mu < 1 \quad \text{and} \quad \Phi > 0. \quad (2)$$

Assuming the presence of a covariate vector $\mathbf{x} = (x_1, x_2, \dots, x_p)^T$ with p covariates associated to each COVID-19 rate, let us assume the following regression models (Cepeda-Cuervo et al. 2014),

$$\text{logit}(\mu) = \boldsymbol{\beta}^T \mathbf{x} \quad \text{and} \quad \log(\Phi) = \boldsymbol{\alpha}^T \mathbf{x} \quad (3)$$

where $\boldsymbol{\alpha} = (\alpha_1, \dots, \alpha_p)^T$ and $\boldsymbol{\beta} = (\beta_1, \dots, \beta_p)^T$ are vectors of regression parameters. To construct our regression model, we assumed besides the economic, social and health covariates (population/km², GDP in million of current US\$ in logarithmic scale, GDP per capita in current US\$ in logarithmic scale, urban population (% of total population), infant mortality rate (deaths by 1,000 live births), number of physicians by 1,000 inhabitants and % of GDP on health spending of each country in the study) some dummy variables related to the unordered categorical variables regions of the world (Asia Middle East; Central America; Central Asia; Caribbean; East Asia; Europe; North Africa; North America; Oceania; South America and Sub Saharan Africa). Asia East region is assumed as reference. In this way, the regression models are given by, $\text{logit}(\mu_{ri}) = g_1(\boldsymbol{\beta}_{ri}, x_i)$ and $\log(\Phi_{ri}) = g_2(\boldsymbol{\alpha}_{ri}, x_i)$ where,

$$\begin{aligned}
g_1(\beta_{ri}, x_i) = & \beta_{r0} + \beta_{r1} \text{urban.population}_i + \beta_{r2} \text{infant.mortality}_i \\
& + \beta_{r3} \text{physicians.1000}_i + \beta_{r4} \% \text{ of.GDP.health}_i + \beta_{r5} \log(\text{GDP})_i \\
& + \beta_{r6} \log(\text{GDP.capita})_i + \beta_{r7} \text{pop.density/km}_i^2 \\
& + \beta_{r8} \text{Sub.Saharan.Africa}_i + \beta_{r9} \text{Central.Asia}_i \\
& + \beta_{r10} \text{Asia.Middle.East}_i + \beta_{r11} \text{Central.America}_i + \beta_{r12} \text{Caribbean}_i \\
& + \beta_{r13} \text{Europe}_i + \beta_{r14} \text{North.Africa}_i + \beta_{r15} \text{North.America}_i \\
& + \beta_{r16} \text{Oceania}_i + \beta_{r17} \text{South.America}_i
\end{aligned}$$

and,

$$\begin{aligned}
g_2(\alpha_{ri}, x_i) = & \alpha_{r0} + \alpha_{r1} \text{urban.population}_i + \alpha_{r2} \text{infant.mortality}_i \\
& + \alpha_{r3} \text{physicians.1000}_i + \alpha_{r4} \% \text{ of.GDP.health}_i + \alpha_{r5} \log(\text{GDP})_i \\
& + \alpha_{r6} \log(\text{GDP.capita})_i + \alpha_{r7} \text{pop.density/km}_i^2 \\
& + \alpha_{r8} \text{Sub.Saharan.Africa}_i + \alpha_{r9} \text{Central.Asia}_i \\
& + \alpha_{r10} \text{Asia.Middle.East}_i + \alpha_{r11} \text{Central.America}_i + \alpha_{r12} \text{Caribbean}_i \\
& + \alpha_{r13} \text{Europe}_i + \alpha_{r14} \text{North.Africa}_i + \alpha_{r15} \text{North.America}_i \\
& + \alpha_{r16} \text{Oceania}_i + \alpha_{r17} \text{South.America}_i
\end{aligned}$$

where $r=1$ (IR), $r=2$ (MRC) and $r=3$ (CFR) for $i=1, \dots, 119$ (number of countries).

The beta regression approach based on (2) and (3) was proposed by Cepeda and Gamerman (2005) considering the joint modeling of the mean and variance or dispersion parameters in the bi-parametric exponential family, including joint modeling of the mean and dispersion parameters in the beta distribution, under a Bayesian approach. In our approach for COVID-19 rates, we present an analysis combining the joint prior distribution for the parameters of the model $\alpha = (\alpha_1, \dots, \alpha_p)^T$ and $\beta = (\beta_1, \dots, \beta_p)^T$ with the likelihood function based on the re-parametrized form of the beta density given by (2). The joint posterior distribution for all parameters is determined from the Bayes formula (Box and Tiao 2011) and the posterior summaries of interest are obtained using Markov Chain Monte Carlo (MCMC) methods (Chib and Greenberg 1995; Gelfand and Smith 1990).

Results and discussion

Figures 1, 2 and 3 show the box-plots of the rates (IR, MRC, CFR) where it is possible to see that countries in Europe and North America present larger IR and MRC when compared to countries of other regions of the world although these two regions present very high variability as compared to the other regions. It is important to point out that countries of these two regions have better health structures for the diagnostic of the infection, this is in line with the well-known and the close relationship between a higher case-fatality and mortality rate by COVID-19 and the worst structural health determinants (Bello-Chavolla et al. 2020). Also, it is observed that the MRC are very small for some regions of the world as East Asia, Oceania, North Africa and Sub Saharan Africa regions. It is important to highlight that countries in Oceania, such as Australia and New Zealand, managed to control the COVID-19 indicators with lower IR, MRC and CFR early, keeping the numbers constantly below those in other regions of the world (Cousins 2020; COVID-19 National Incident Room Surveillance Team and others 2020). However, the reasons for this better control are not fully clarified, while some authors point out climatic and geographical aspects (Chennakesavulu and Reddy, 2020), others highlight the role of demographic density (Ilardi et al. 2020; Rocklöv and Sjödin 2020) and some point to the cultural and socioeconomic characteristics, as well as political strategies employed in this region (Schulz et al. 2020; Varghese and Xu 2020).

On the other hand, it is important to point out that for the Sub Saharan region the epidemic is starting in the time of this study (data set until May 04, 2020), thus, it is expected that the infection/disease by COVID-19 in the countries of this region, can show its dynamics, which for some authors tends to be of lesser impact, for several reasons such as lower population mobility, for example. However, for many other authors, the epidemic has the potential to have a major impact on these populations, considering poverty, the greater agglomeration, as well as the poor conditions of health services (Lumu 2020; Ongole et al. 2020; Osseni 2020). Countries in North America region presents the larger MRC, perhaps partly explained by the high population density and differences in age and racial structures of countries in that region with the greatest weight in Mexico and United

Figure 1: Box-plots for the IR in different regions of the world (the numbers are based on the cumulative number of cases and deaths).

States (Holmes et al. 2020; Mendez-Dominguez et al. 2020) while the CFR show more variability among the 11 regions with larger values for the countries in North Africa region, certainly largely due to poor health service structures in the countries of that region, with little capacity to deal with good response to critically ill patients, due to the lack of ICU beds and trained medical personnel (Ohia et al., 2020).

Table 1 presents summary statistics (means, standard-deviations, minimum and maximum for the IR, MRC and CFR for each region (Asia Middle East; Central America; Central Asia; Caribbean; East Asia; Europe; North Africa; North America; Oceania; South America; Sub Saharan Africa). Figures 4, 5 and 6 show the plots of the rate means against each region, from where it is observed large IR for three regions: Asia Middle East, Europe and North America, explained in part by being regions with high demographic density, highly dynamic populations in terms of mobilization and with an age structure that favors greater contagion and transmissibility (Ilardi et al., 2020; Rocklöv and Sjödin, 2020), in addition, these regions have invested in mass testing for the diagnosis of disease infection/disease, and thus, there is a greater detection of cases, and consequently greater IR (Edson et al. 2020; Sunjaya and Sunjaya 2020).

Also, it is observed large means for CFR for six regions: Central America; Caribbean; Europe; North Africa; North America and South America, which is possibly attributed to the fragility of the health system in countries in some regions, as well as the presence of older populations, known to be at higher risk of death from SARS-CoV-2 (Miles et al., 2020). On the other hand, small means of CFR are observed for the regions Asia Middle East; Central Asia; East Asia; Oceania and Sub Saharan Africa.

Response: Y_1 (IR)

Using data from daily reported cases and deaths caused by COVID-19 in 119 countries until May 04, 2020, we have fitted the beta regression model assuming normal prior distributions $N(0, 1)$ for the parameters β_j and $N(0.0.01)$ priors for the parameters α_j , $j=0, 1, 2, \dots, 17$. The choice of these priors was considered to have approximately non-informative priors and good performance of the MCMC simulation algorithm (for the regression parameters α_j good convergence was obtained for a normal prior distribution with small variances). Some sensitivity analysis considering different hyperparameters was also considered leading very similar results. The statistical analysis was carried out in the R software (R Core Team 2019). The R2OpenBUGS and the coda packages were used to obtain and monitor the Bayesian estimates and the convergence of the MCMC

Figure 2: Box-plots for the MRC in different regions of the world (the numbers are based on the cumulative number of cases and deaths).

Figure 3: Box-plots for the CFR in different regions of the world (the numbers are based on the cumulative number of cases and deaths).

algorithm by usual time series plots for the simulated samples and Gelman and Rubin's methods (Brooks and Gelman 1998). Table 2 shows the posterior means (use of squared error loss function) for the regression parameters associated to each covariate, the posterior standard deviations (Std. Dev.) and 95% credible intervals for all parameters from where it is observed that the following covariates show significant effects (95% credible intervals do not contain the zero value for the respective regression parameters) associated to the proposed regression model on the mean μ and on the parameter Φ (related to the precision) assuming the response IR:

- Urban population (for both regression models on μ and on Φ , that is, parameters β_1 and α_1).
- Infant mortality rate (for both regression models on μ and on Φ , that is, parameters β_2 and α_2).
- $\log(\text{GDP-US\$ per capita})$ (for both regression models on μ and on Φ , that is, parameters β_6 and α_6).

Table 1: Means, standard-deviations (Std. Dev.), number of countries (N), minimum and maximum for the IR, MRC and CFR for each region (the numbers are based on the cumulative number of cases and deaths).

Rates	Regions	N	Mean	Std. Dev.	Minimum	Maximum
IR	Asia Middle East	12	128.6	154.6	4.6	559.1
	Central America	6	47.6	66.5	4.1	172.3
	Central Asia	6	29.5	44.2	6.5	119.1
	Caribbean	4	23.9	22.1	8.3	56.6
	East Asia	11	37.1	95	0.3	322.9
	Europe	42	221.6	308.2	15.8	1,722.7
	North Africa	4	9.88	2.98	6.57	13.61
	North America	3	177.7	168.3	18.6	354
	Oceania	2	25.24	2.79	23.27	27.21
	South America	10	53.6	63.3	1.2	172.9
	Sub Saharan Africa	19	11.47	26.1	0.12	115.96
MRC	Asia Middle East	12	0.958	1.221	0.088	4.127
	Central America	6	1.53	1.974	0.099	4.788
	Central Asia	6	1.39	3.03	0.03	7.58
	Caribbean	4	1.127	1.279	0.307	3.036
	East Asia	11	0.2773	0.1818	0	0.5691
	Europe	42	15.16	24.65	0.13	121.36
	North Africa	4	0.595	0.338	0.363	1.096
	North America	3	10.78	9.52	1.71	20.69
	Oceania	2	0.3947	0.0207	0.3801	0.4094
	South America	10	2.049	2.841	0.035	9.155
	Sub Saharan Africa	19	0.0976	0.0801	0.0027	0.2359
CFR	Asia Middle East	12	1465	1,329	77	4225
	Central America	6	3,355	2,421	812	7,773
	Central Asia	6	2,358	2,210	465	6,367
	Caribbean	4	4,561	2,108	1,919	6,897
	East Asia	11	3,096	2,496	0	7,550
	Europe	42	5,567	4,537	556	18,962
	North Africa	4	6,170	3,090	3,549	10,349
	North America	3	7,071	1,832	5,845	9,177
	Oceania	2	1,578	256	1,397	1,759
	South America	10	3,864	1,715	1,322	6,945
	Sub Saharan Africa	19	3,287	2,904	180	11,765

- $\log(\text{GDP})$ (for both regression models on μ and on Φ , that is, parameters β_5 and α_5).
- % GDP spent in health (for both regression models on μ and on Φ , that is, parameters β_4 and α_4).
- Population density by km^2 (for both regression models on μ and on Φ , that is, parameters β_7 and α_7).

It is observed that two of the covariates are linked to the economical situation of each country ($\log(\text{GDP-US\$ per capita})$ and $\log(\text{GDP})$); two covariates are linked to social situation of these countries (urban population and population density by km^2) and two covariates are linked to health structure and its consequences (positive or negative) of each country (Infant mortality rate and %GDP spent on health).

From the Monte Carlo estimates based on the simulated Gibbs samples for the posterior means (Table 2) of the regression parameters on μ , we observe that: β_1 (urban population), β_2 (infant mortality rate), β_4 (%GDP on health), β_6 ($\log(\text{GDP})$ per capita) are negative; while β_5 ($\log(\text{GDP})$), β_7 (population density by km^2) are positive. That is, the mean μ for the IR increases when the values of the covariates $\log(\text{GDP})$ and population density by km^2 increase. Possibly countries with larger GDP improves the diagnostic of the COVID-19 infection as showed by Lau et al. (2020). Countries with large population density by km^2 also increases the mean of the IR by COVID-19 as showed by Ilardi et al. (2020).

Figure 4: Plots of the means for the IR in different regions of the world (the numbers are based on the cumulative number of cases and deaths).

Figure 5: Plots of the means for the MRC in different regions of the world (the numbers are based on the cumulative number of cases and deaths).

In other direction, since the parameters $\beta_1, \beta_2, \beta_4$ and β_6 are estimated by negative values, it is possible to interpret that when there is increasing of urban population, infant mortality rate, %GDP spent on health and log(GDP) per capita there is a decreasing in the IR. The correlation founds in relation to the largest urban population, the highest infant mortality rate, as the lowest IR, needs to be better evaluated, considering that the opposite of this scenario would be expected, since it is known that the disease has spread more easily in urban areas, while so far, there is no association between IR and the infant mortality rate. The other covariates do not show significant effects on the means (95% credible intervals contain the zero value). Similar interpretations could be given for the parameters associated to the regression model for the precision parameter Φ . The regression parameters associated to the 11 regions of the world do not show significant differences.

Figure 6: Plots of the means for the CFR in different regions of the world (the numbers are based on the cumulative number of cases and deaths).

Response: Y_2 (MRC)

Table 3 shows the posterior summaries of interest, from where it is observed that the following covariates show significant effects (95% credible intervals do not contain the zero value for the respective regression parameters) assuming the response MRC:

- Urban population (for both regression models on μ and on Φ , that is, parameters β_1 and α_1).
- Infant mortality rate (for both regression models on μ and on Φ , that is, parameters β_2 and α_2).
- Physicians by 1,000 inhabitants (for both regression models on μ and on Φ , that is, parameters β_3 and α_3).
- % of GDP spent in health (only for regression model on Φ , that is, parameter α_4).
- $\log(\text{GDP-US\$ per capita})$ (for both regression models on μ and on Φ , that is, parameters β_6 and α_6).
- $\log(\text{GDP})$ (for both regression models on μ and on Φ , that is, parameters β_5 and α_5).
- Population density by km^2 (for both regression models on μ and on Φ , that is, parameters β_7 and α_7).
- Dummy covariate Europe (only for regression on ϕ , that is, parameter α_{13})

In this case, also it is observed that two of the covariates are linked to the economical situation of each country ($\log(\text{GDP-US\$ per capita})$ and $\log(\text{GDP})$); two covariates are linked to social situation of these countries (urban population and population density by km^2), three covariates are linked to health structure of each country (infant mortality rate, physicians by 1,000 inhabitants and % GDP spent on health) and one dummy covariate associate to region (Europe).

By observing the Monte Carlo estimates based on the simulated Gibbs samples for the posterior means (Table 3) for the regression parameters, it is possible to see the effect of each covariate: negative estimates for the regression parameters β_1 (urban population), β_2 (infant mortality rate), β_5 ($\log(\text{GDP})$), β_6 ($\log(\text{GDP capita})$), α_{13} (Europe), α_2 (infant mortality rate), α_3 (physicians by 1000 inhabitants), α_5 ($\log(\text{GDP})$), α_6 ($\log(\text{GDP capita})$), and α_7 (pop. density/ km^2); positive estimates for the regression parameters β_3 (physicians by 1000 inhabitants), β_7 (pop. density/ km^2), α_1 (urban population) and α_4 (% of GDP health).

Response: Y_3 (CFR)

Table 4 shows the posterior summaries of interest, from where it is observed that the following covariates show significant effects (95% credible intervals do not contain the zero value for the respective regression parameters) assuming the response CFR:

Table 2: Posterior summaries for the response IR ($r=1$) assuming a beta regression model for COVID-19 rates.

Parameters	Mean	Std. Dev.	95% Cred. Int.	
			Lower limit	Upper limit
α_0 (Intercept)	-0.01822	0.09490	-0.21220	0.16230
α_1 (Urban population)	-0.02986	0.00202	-0.03300	-0.02621
α_2 (Infant mortality rate)	-0.04162	0.00322	-0.04730	-0.03488
α_3 (Physicians/1000)	0.01477	0.05884	-0.10390	0.13780
α_4 (%GDP on health)	-0.21890	0.01457	-0.24470	-0.18970
α_5 (log(GDP))	0.16360	0.00887	0.14510	0.17920
α_6 (log(GDP per capita))	-0.08035	0.01179	-0.09908	-0.05968
α_7 (pop.density/km ²)	-0.04418	0.43000	-0.04502	-0.04333
α_8 (Sub-Saharan Africa)	0.02034	0.10130	-0.18040	0.21610
α_9 (Central Asia)	-0.25000	0.10060	-0.19860	0.19570
α_{10} (Asia Middle East)	-0.04493	0.09528	-0.23550	0.14270
α_{11} (Central America)	-0.02780	0.08610	-0.19320	0.15290
α_{12} (Caribbean)	-0.00182	0.09977	-0.19780	0.19260
α_{13} (Europe)	0.05176	0.08184	-0.09335	0.21520
α_{14} (North Africa)	-0.00151	0.10030	-0.19540	0.19140
α_{15} (North America)	-0.36300	0.09998	-0.20030	0.19500
α_{16} (Oceania)	-0.38700	0.10010	-0.19560	0.19760
α_{17} (South America)	-0.00103	0.09946	-0.19980	0.19380
β_0 (Intercept)	-2.42400	1.07400	-4.34400	-0.07547
β_1 (Urban population)	-0.20860	0.01978	-0.24800	-0.17220
β_2 (Infant mortality rate)	-0.11780	0.03105	-0.18700	-0.06574
β_3 (Physicians/1000)	0.20540	0.46010	-0.92170	0.72920
β_4 (%GDP on health)	0.59870	0.15060	0.38060	0.98240
β_5 (log(GDP))	-1.97200	0.08154	-2.12500	-1.81900
β_6 (log(GDP per capita))	-1.62200	0.13950	-1.92200	-1.41500
β_7 (pop.density/km ²)	0.25510	0.01343	0.23780	0.27550
β_8 (Sub-Saharan Africa)	0.26700	0.95360	-1.61000	2.11200
β_9 (Central Asia)	0.00394	1.00000	-1.95500	1.94600
β_{10} (Asia Middle East)	0.56550	0.78830	-0.92600	2.10800
β_{11} (Central America)	-0.55980	0.83730	-2.17800	1.07300
β_{12} (Caribbean)	7.94E-4	1.01300	-1.97300	1.99000
β_{13} (Europe)	-0.57340	0.73850	-2.01200	0.85680
β_{14} (North Africa)	-0.95800	1.00300	-1.97900	1.95500
β_{15} (North America)	-0.00735	1.00100	-1.98300	1.95800
β_{16} (Oceania)	-0.01301	0.99850	-1.95700	1.96800
β_{17} (South America)	0.00845	0.99840	-1.96200	1.94700

- Urban population (only for regression model on Φ , that is, parameter α_1).
- Infant mortality rate (only for regression model on μ , that is, parameter β_2).
- % of GDP spent in health (only for regression model on Φ , that is, parameter α_4).
- log(GDP-US\$ per capita) (for both regression models on μ and on Φ , that is, parameters β_6 and α_6).
- log(GDP) (only for regression model on Φ , that is, parameter α_5).
- Population density by km² (for both regression models on μ and on Φ , that is, parameters β_7 and α_7).

In this case, also it is observed that two of the covariates are linked to the economical situation of each country (log(GDP-US\$ per capita) and log(GDP)); two covariates are linked to social situation of these countries (urban population and population density by km²), two covariates are linked to health structure of each country (infant mortality rate and % GDP spent in health). By observing the Monte Carlo estimates based on the

Table 3: Posterior summaries for the response MRC ($r=2$) assuming a beta regression model for COVID-19 rates.

Parameters	Mean	Std. Dev.	95% Cred. Int.	
			Lower limit	Upper limit
α_0 (Intercept)	-0.05722	0.00991	-0.07446	-0.04754
α_1 (Urban population)	0.01819	0.08650	0.01801	0.01825
α_2 (Infant mortality rate)	-0.03296	0.00174	-0.03445	-0.03025
α_3 (Physicians/1000)	-0.02184	0.89300	-0.02347	-0.02041
α_4 (%GDP on health)	0.00175	0.27800	0.00106	0.00216
α_5 (log(GDP))	-0.02055	0.12600	-0.02072	-0.02017
α_6 (log(GDP per capita))	-0.01189	0.34800	-0.01257	-0.01140
α_7 (pop.density/km ²)	-0.13470	0.02340	-0.13480	-0.13470
α_8 (Sub-Saharan Africa)	-0.01117	0.08511	-0.18960	0.16510
α_9 (Central Asia)	0.75600	0.10080	-0.19980	0.20060
α_{10} (Asia Middle East)	0.06425	0.14560	-0.17830	0.27280
α_{11} (Central America)	0.00150	0.10020	-0.19680	0.19840
α_{12} (Caribbean)	-0.03279	0.08105	-0.14950	0.14850
α_{13} (Europe)	-0.06469	0.00396	-0.06891	-0.05644
α_{14} (North Africa)	0.07812	0.05067	-0.00398	0.20260
α_{15} (North America)	-0.00183	0.10040	-0.20070	0.19340
α_{16} (Oceania)	-0.00130	0.09966	-0.19930	0.19240
α_{17} (South America)	0.00127	0.09820	-0.19240	0.18930
β_0 (Intercept)	-1.99600	0.87750	-3.57400	-0.06685
β_1 (Urban population)	-0.46890	0.04046	-0.53090	-0.40180
β_2 (Infant mortality rate)	-0.10610	0.05338	-0.21760	-0.01399
β_3 (Physicians/1000)	1.18300	0.57800	0.36690	2.33100
β_4 (%GDP on health)	0.55330	0.56170	-0.32360	1.27200
β_5 (log(GDP))	-1.48400	0.17600	-1.74200	-1.04500
β_6 (log(GDP per capita))	-0.77480	0.19270	-1.24700	-0.47630
β_7 (pop.density/km ²)	0.42820	0.03068	0.37110	0.47060
β_8 (Sub-Saharan Africa)	-0.28360	1.00800	-2.27200	1.72100
β_9 (Central Asia)	-0.06732	0.98600	-1.97500	1.92200
β_{10} (Asia Middle East)	0.18180	1.06900	-1.92000	2.38200
β_{11} (Central America)	0.00871	0.98860	-1.92300	1.95500
β_{12} (Caribbean)	0.21730	1.03900	-1.86300	2.15800
β_{13} (Europe)	-0.10380	0.83920	-1.68300	1.53100
β_{14} (North Africa)	0.20600	0.93070	-1.63100	2.05800
β_{15} (North America)	0.01071	1.00400	-1.95600	1.98400
β_{16} (Oceania)	-0.01070	0.99630	-1.95600	1.96100
β_{17} (South America)	-0.02546	1.00200	-1.92900	1.93800

simulated Gibbs samples for the posterior means (Table 4) for the regression parameters it is possible to see the effect of each covariate: negative estimates for the regression parameters β_2 (infant mortality rate), β_6 (log(GDP per capita)), α_1 (urban population), α_4 (% GDP spent on health), α_5 (log(GDP)), α_6 (log(GDP per capita)); positive estimates for the regression parameters β_7 (pop. density/km²) and α_6 (% of GDP per capita).

From the obtained results of this study, using the proposed beta regression model, it is observed that the covariates affecting IR, MRC and CFR for COVID-19 pandemic based on the data of 119 countries could be summarized by:

- Urban population for both regression models on μ (mean) and on Φ (parameter linked to precision) for IR and for MRC, as well as, for CFR for the regression model on Φ .
- Infant mortality rate for both regression models on μ (mean) and on Φ (parameter linked to precision) for IR and MRC and for CFR for the regression model on μ (mean).

Table 4: Posterior summaries for the response CFR ($r=3$) assuming a beta regression model for COVID-19 rates.

Parameters	Mean	Std. Dev.	95% Cred. Int.	
			Lower limit	Upper limit
α_0 (Intercept)	-0.01124	0.08517	-0.18840	0.11630
α_1 (Urban population)	-0.03760	0.00346	-0.04221	-0.03090
α_2 (Infant mortality rate)	-0.00423	0.00289	-0.00967	0.00112
α_3 (Physicians/1,000)	0.02822	0.04732	-0.03621	0.12470
α_4 (%GDP on health)	-0.20010	0.01820	-0.23210	-0.17130
α_5 (log(GDP))	-0.14700	0.01054	-0.16780	-0.12830
α_6 (log(GDP per capita))	0.14120	0.03016	0.08804	0.17610
α_7 (pop.density/km ²)	-0.03791	0.20000	-0.03833	-0.03759
α_8 (Sub-Saharan Africa)	0.91200	0.09768	-0.19540	0.19400
α_9 (Central Asia)	0.00652	0.09339	-0.18270	0.18990
α_{10} (Asia Middle East)	0.03480	0.08566	-0.13290	0.20240
α_{11} (Central America)	-0.10230	0.08966	-0.27930	0.06621
α_{12} (Caribbean)	0.08596	0.06671	-0.03393	0.22310
α_{13} (Europe)	-0.02402	0.09117	-0.20860	0.14900
α_{14} (North Africa)	0.00265	0.10050	-0.20160	0.20060
α_{15} (North America)	-0.00275	0.10050	-0.20400	0.19580
α_{16} (Oceania)	-0.63500	0.10030	-0.19570	0.19740
α_{17} (South America)	4.1E-01	0.09845	-0.19910	0.19010
β_0 (Intercept)	-2.55700	1.01300	-4.52100	-0.56300
β_1 (Urban population)	0.03444	0.03757	-0.02483	0.12450
β_2 (Infant mortality rate)	-0.14540	0.06126	-0.25560	-0.00975
β_3 (Physicians/1000)	0.08384	0.58470	-1.12700	1.15500
β_4 (%GDP on health)	-0.04063	0.23290	-0.45060	0.43480
β_5 (log(GDP))	-0.13760	0.41790	-0.85350	0.53430
β_6 (log(GDP per capita))	-1.90400	0.63330	-2.69600	-0.63680
β_7 (pop.density/km ²)	0.09527	0.01494	0.07096	0.12440
β_8 (Sub-Saharan Africa)	-0.03485	0.98350	-2.00600	1.85300
β_9 (Central Asia)	0.04304	0.96380	-1.81800	1.98100
β_{10} (Asia Middle East)	-0.32040	0.86750	-2.01600	1.39900
β_{11} (Central America)	0.99750	0.90840	-0.77470	2.77100
β_{12} (Caribbean)	-1.06800	0.93810	-2.91800	0.72260
β_{13} (Europe)	0.41120	0.87380	-1.27100	2.06300
β_{14} (North Africa)	-0.03380	0.98310	-1.98900	1.82300
β_{15} (North America)	0.00444	0.99220	-1.95000	1.98500
β_{16} (Oceania)	-0.00749	1.00300	-2.00400	1.96700
β_{17} (South America)	-0.00591	0.99570	-1.86600	1.95300

- log(GDP-US\$ per capita) for the regression models on μ (mean) and on Φ (parameter linked to precision) for the IR, for MRC and for CFR.
- log(GDP) for the regression models on μ (mean) and on Φ (parameter linked to precision) for IR and for MRC and for the CFR only for the regression model on Φ .
- % GDP spent in health for the regression models on μ (mean) and on Φ (parameter linked to precision) for IR and for CFR and CFR only for the regression model on Φ .
- Population density by km² for the regression models on μ (mean) and on Φ (parameter linked to precision) for IR, for MRC and for CFR.
- Physicians by 1,000 inhabitants for the regression models on μ (mean) and on Φ (parameter linked to precision) for the MRC.
- Dummy covariate Europe only for regression on Φ for MRC.

In summary, from the results of this study some economic indicators (GDP-US\$ per capita, GDP), health indicators (infant mortality rate, % GDP spent on health, Physicians by 1000 inhabitants), sociodemographic indicators (urban population, Population density by km²) and some differences in regions are the most important factors which could impact in better or worse results for the COVID-19 pandemic in different countries of the world. However, all of these results must be considered with great caution, since the pandemic of COVID-19 has been shown to be extremely dynamic, with patterns of distribution, contagion, transmissibility among continents, and even often within the same country, where marked differences have been observed (Nepomuceno et al. 2020; Raciborski et al. 2020). It is important to note that, while writing this manuscript, we observed the interiorization and ruralization of COVID-19 in some countries (Joob and Wiwanitkit 2020; Sriwijitalai and Wiwanitkit 2020), which suggests that we know very little about the properties of SARS-CoV-2 and its interaction/ adaptation with the environment and the human beings K.-H. Chan (2020).

Other important aspects to consider in view of the results we found, as we use three main epidemiological indicators (IR, MRC and CFR) as responses, are the countries' ability to diagnose in a timely manner, as well as to report cases properly and accurately, avoiding underdiagnoses and underreporting of cases and deaths. These points are highly dependent on the massive testing capacity of symptomatic and/or asymptomatic infected people and their contacts, as well as on the structure responsible for the registration of cases and deaths. This is undoubtedly a major limitation of our study, since, when studying data from 119 countries, these points undergo great differences among them, considering the socioeconomic profile and the health infrastructure of each of them.

Concluding remarks

The main goal of this paper was try to understand the different epidemiological indicators of morbidity (IR) and mortality (MRC and CFR), among the coronavirus novel around the world, using a beta regression model. For that, it has been considered a beta regression structure based on logit and log links assuming a re-parametrized version of beta distribution to describe the respective rates derived from daily reported cases and deaths by COVID-19 until May 04, 2020, for 119 countries. The proposed methodology can be extended by using other factors, such as the daily rate of social isolation. When available, the inclusion of additional covariates may provide more accurate model fits, whose underlying results may offer suggestions on how fast the virus will spread in the short-term period. The proposed regression model has shown to accommodate well the nature of the epidemiological rates by COVID-19. Nevertheless, the present methodology can also be used to provide a comprehensive understanding the dynamics of the epidemic by SARS-CoV-2, which may alert authorities to keep restrictive strategies to control the advance of the pandemic, especially in more impoverished regions and with precarious health systems.

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Appendix 1

Table 5: Daily number of cases and deaths in May 04, 2020.

Country	Cases	Deaths	Population	Region
Burkina Faso	662	45	19,751,535	Sub Saharan Africa
Congo	229	10	5,244,363	Sub Saharan Africa
Cote d'Ivoire	1,398	17	25,069,229	Sub Saharan Africa
Democratic Republic Congo	684	34	84,068,091	Sub Saharan Africa
Djibouti	1,112	2	95,8920	Sub Saharan Africa
Equatorial Guinea	315	1	1,308,974	Sub Saharan Africa
Ethiopia	135	3	109,224,559	Sub Saharan Africa
Gabon	335	5	2,119,275	Sub Saharan Africa
Ghana	2,169	18	29,767,108	Sub Saharan Africa
Guinea	1,586	7	12,414,318	Sub Saharan Africa
Kenya	465	24	51,393,010	Sub Saharan Africa
Mali	563	27	19,077,690	Sub Saharan Africa
Nigeria	2,558	87	195,874,740	Sub Saharan Africa
Senegal	1,182	9	15,854,360	Sub Saharan Africa
South Africa	6,783	131	57,779,622	Sub Saharan Africa
Sudan	678	41	41,801,533	Sub Saharan Africa
United Republic Tanzania	480	16	56,318,348	Sub Saharan Africa
Zambia	124	3	17,351,822	Sub Saharan Africa
Zimbabwe	34	4	14,439,018	Sub Saharan Africa
Afghanistan	2,704	85	37,172,386	Central Asia
Iran	97,424	6203	81,800,269	Central Asia
Kazakhstan	3,964	27	18,276,499	Central Asia
Kyrgyzstan	830	10	6,315,800	Central Asia
Pakistan	20,186	462	212,215,030	Central Asia
Uzbekistan	2,149	10	32,955,400	Central Asia
Bahrain	3,383	8	1,569,439	Asia Middle East
Iraq	2,296	97	38,433,600	Asia Middle East
Israel	16,208	232	8,883,800	Asia Middle East
Jordan	461	9	9,956,011	Asia Middle East
Kuwait	4,983	38	4,137,309	Asia Middle East
Lebanon	737	25	6,848,925	Asia Middle East
Oman	2,568	12	4,829,483	Asia Middle East
Palestine	522	4	4,569,087	Asia Middle East
Qatar	15,551	12	2,781,677	Asia Middle East
Saudi Arabia	27,011	184	33,699,947	Asia Middle East
Turkey	126,045	3,397	82,319,724	Asia Middle East
United Arab Emirates	14,163	126	9,630,959	Asia Middle East
Costa Rica	739	6	4,999,441	Central America
Dominican Republic	7,954	333	10,627,165	Central America
El Salvador	555	12	6,420,744	Central America
Guatemala	703	17	17,247,807	Central America
Honduras	1,055	82	9,587,522	Central America
Panama	7,197	200	4,176,873	Central America
Cuba	1,649	67	11,338,138	Caribbean
Jamaica	469	9	2,934,855	Caribbean
Puerto Rico	1,808	97	3,195,153	Caribbean
Trinidad and Tobago	116	8	1,389,858	Caribbean
Bangladesh	9,455	177	161,356,039	East Asia
China	83,964	4,637	1,392,730,000	East Asia
India	42,533	1,373	1,352,617,328	East Asia
Indonesia	11,192	845	267,663,435	East Asia

Table 5: (continued)

Country	Cases	Deaths	Population	Region
Japan	15,057	510	126,529,100	East Asia
Malaysia	6,298	105	31,528,585	East Asia
Philippines	9,223	607	106,651,922	East Asia
Singapore	18,205	18	5,638,676	East Asia
South Korea	10,801	252	51,635,256	East Asia
Thailand	2,969	54	69,428,524	East Asia
Vietnam	271	0	95,540,395	East Asia
Albania	795	31	2,866,376	Europe
Andorra	748	45	77,006	Europe
Armenia	2,386	35	2,951,776	Europe
Austria	15,597	598	8,847,037	Europe
Azerbaijan	1932	25	9942334	Europe
Belarus	16,705	99	9,485,386	Europe
Belgium	49,906	7,844	11,422,068	Europe
Bosnia-Herzegovina	1,857	77	3,323,929	Europe
Bulgaria	1,618	73	7,024,216	Europe
Croatia	2,096	79	4,089,400	Europe
Cyprus	872	20	1,189,265	Europe
Czechia	7,781	248	10,625,695	Europe
Denmark	9,523	484	5,797,446	Europe
Estonia	1,700	55	1,320,884	Europe
Finland	5,254	230	5,518,050	Europe
France	131,287	24,895	66,987,244	Europe
Georgia	589	5	3,731,000	Europe
Germany	163,175	6,692	82,927,922	Europe
Greece	2,626	144	10,727,668	Europe
Hungary	3,035	351	9,768,785	Europe
Iceland	1,799	10	353,574	Europe
Ireland	21,506	1303	4,853,506	Europe
Italy	210,717	28,884	60,431,283	Europe
Lithuania	1,410	46	2,789,533	Europe
Luxembourg	3,824	96	607,728	Europe
Moldova	4,121	125	3,545,883	Europe
Netherlands	40,571	5,056	17,231,017	Europe
North Macedonia	1,511	84	2,082,958	Europe
Norway	7,809	208	5,314,336	Europe
Poland	13,693	678	37,978,548	Europe
Portugal	25,282	1,043	10,281,762	Europe
Romania	13,163	780	19,473,936	Europe
Russia	134,687	1,280	144,478,050	Europe
San Marino	582	41	33,785	Europe
Serbia	9,464	193	6,982,084	Europe
Slovakia	1,408	24	5,447,011	Europe
Slovenia	1,439	96	2,067,372	Europe
Spain	217,466	25,264	46,723,749	Europe
Sweden	22,317	2,679	10,183,175	Europe
Switzerland	29,822	1,472	8,516,543	Europe
Ukraine	11,913	288	44,622,516	Europe
United Kingdom	186,599	28,446	66,488,991	Europe
Algeria	4,474	463	42,228,429	North Africa
Egypt	6,465	429	98,423,595	North Africa
Morocco	4,903	174	36,029,138	North Africa
Tunisia	1,013	42	11,565,204	North Africa
Canada	59,474	3682	37,058,856	North America
Mexico	23,471	2,154	126,190,788	North America

Table 5: (continued)

Country	Cases	Deaths	Population	Region
United States of America	1,158,041	67,682	327,167,434	North America
Australia	6,801	95	24,992,369	Oceania
New Zealand	1,137	20	4,885,500	Oceania
Argentina	4,770	246	44,494,502	South America
Bolivia	1,594	76	11,353,142	South America
Brazil	101,147	7,025	209,469,333	South America
Chile	19,663	260	18,729,160	South America
Colombia	7,668	340	49,648,685	South America
Ecuador	29,538	1,564	17,084,357	South America
Paraguay	396	10	6,956,071	South America
Peru	45,928	1,286	31,989,256	South America
Uruguay	655	17	3,449,299	South America
Venezuela	357	10	28,870,195	South America

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