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Local characteristics and the Covid-19 pandemic: an analysis focused on the municipalities from the Brazilian state of Minas Gerais *

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Abstract

In order to understand the reasons that led certain locations to face more/less difficulties in dealing with COVID-19, the effect of some municipal characteristics, on the main statistics related to the disease, was estimated. For this purpose, cross-section data (with cases/deaths accumulated up until April 21, 2021), on the municipalities of Minas Gerais were considered, and Ordinary Least Squares, Poisson and Negative Binomial estimators were used, in addition to the Extreme Bounds Analysis technique. Small towns, with a larger number of public health clinics (known in Brazil as "basic health units") and more young people would have fewer cases/deaths. Urban, hot, polluted locations with higher inequality, as well as greater economic activity and movement of employees, presented the greatest problems. Incidence/mortality would increase in hot cities, with greater economic activity and a history of comorbidity. However, mortality would decrease among the youngest/most educated people. Furthermore, lethality would be lower among the younger population and in sparsely populated (up to 150,000 inhabitants) and rainless cities.

Keywords: COVID-19, Regional policies, Socioeconomic determinants.

Resumo

Características locais e a pandemia de Covid-19: uma análise voltada aos municípios do Estado brasileiro de Minas Gerais

Visando compreender os motivos que levaram certas localidades a enfrentar mais/menos dificuldades no combate à COVID-19, estimou-se o efeito de determinadas características municipais sobre as principais estatísticas desta doença. Para tanto, consideraram-se dados *cross-section* (com casos/óbitos acumulados até 21 de abril/2021), sobre os municípios de Minas Gerais, e usaram-se os estimadores de Mínimos Quadrados Ordinários, Poisson e Binominal Negativo, além da técnica *Extreme Bounds Analysis*. Verificou-se que cidades pequenas, com mais unidades básicas de saúde e populações mais jovens, teriam menos casos/óbitos. Alternativamente, locais quentes, poluídos, tipicamente urbanos, desiguais, com maior atividade econômica e circulação de empregados, seriam mais problemáticos. A incidência e mortalidade aumentariam em municípios quentes, com maior atividade econômica e histórico de comorbidades. Todavia, a mortalidade diminuiria entre os mais educados e jovens. Ademais, a letalidade seria menor entre os jovens e em cidades com até 150 mil habitantes e poucas chuvas.

Palavras-chave: COVID-19; Políticas Regionais; Determinantes socioeconômicos.
JEL: I10, R58, C2.

Introduction

The COVID-19 pandemic, caused by the new coronavirus (SARS-CoV2)[1], started in Wuhan, China on December 31, 2019 (Khatib, 2020) and is already the most lethal virus in the

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(1) "(...) *it is a beta-coronavirus, of the same subgenus as the severe acute respiratory failure syndrome (SARS), which caused an epidemic in China in 2003, and the Middle East respiratory syndrome (MERS), which caused the same in the Middle East in 2012*." (Strabelli; UIP, 2020, p. 598 – free translation from Portuguese).

last 100 years (Arbix, 2020). Data from the Johns Hopkins University – JHU (2021) indicate that, 1 year and 4 months after the first case, there were already more than 140 million cases and about 3 million deaths worldwide.

As there is no effective treatment for COVID-19 symptoms, and vaccines were still not a reality for much of the population at this time, experts recommended measures of social distancing to reduce contagion and prevent the collapse of health systems (Pedersen; Favero, 2020). Such measures included the closing of non-essential establishments and schools, restrictions on national and international travel and the cancellation of parties, concerts, services and other activities that generate crowding (Nicola et al., 2020).

The economic impacts due to these distancing policies have generated debates between epidemiologists and economists (Khatib, 2020). While epidemiologists defend social isolation as the main way to stop contagion, economists are largely concerned with the socioeconomic impacts of this practice. According to Arbix (2020), the restrictions imposed by COVID-19 generate unemployment, income inequality, business failures and poverty in general. Furthermore, they can stimulate domestic violence (Mazza et al., 2020) and depression (Salari et al., 2020).

Given this dilemma, we sought to verify which local characteristics could affect the main statistics associated with COVID-19 (i.e., number of cases and deaths and incidence, mortality and lethality rates) and which of these could facilitate or hinder the fight against coronavirus. It is believed that the results collaborate with the adoption of specific and regionalized policies, in order to contain the contagion of the disease (including from new variants of the virus)[2] with the appropriate severity for each location, that is, with greater/lesser strictness where the disease is more/less harmful.

Therefore, to identify the effects of these local characteristics, models were estimated using *Ordinary Least Squares*, Poisson and Negative Binomial estimators, with cross-section data, referring to the municipalities from the Brazilian state of Minas Gerais and considering COVID-19 cases and deaths up until April 21, 2021[3]. As there is no well-defined specification to explain this pandemic, the variables suggested by the literature were evaluated not only by the aforementioned estimators, but also via Extreme Bounds Analysis – EBA (Levine and Renelt, 1992)[4]. Since most papers, in which the focus was to analyze the influence of local aspects on the fight against coronavirus (see section 2), have considered just one COVID-19 statistic (*e.g.*: cases, deaths, incidence, mortality or lethality rates) and have employed only one estimator (OLS, Poisson or Negative Binomial), without considering a robust procedure to select the explanatory variables (like EBA), the present research fills in gaps in the literature by applying different statistical methods to all the main statistics associated with COVID-19 and, therefore, providing greater statistical rigor to the results and inferences.

(2) Although the virus mutates and thus generates new epidemics, its form of contagion and basic symptoms usually remain the same. According to Stradelli and Uip (2020), the way in which SARS-CoV2 binds to cells is very similar to that of SARS (China/2003) and is 96.2% genetically similar to betaCoV/bat/Yunnan, found in bats.

(3) As this is an ecological study, based on secondary data (the unit of analysis of which are the municipalities and not the patients), individual aspects associated with COVID-19 were not included.

(4) "*Extreme bounds analysis is useful for testing whether minor changes in the list of examined variables can fundamentally alter the conclusions of empirical research studies. (...) EBA can identify explanatory variables that are most robustly associated with the outcome variable*" (Hlavac, 2016, p. 1-2).

The results showed that small towns, with a greater number of Basic Health Units (*Unidades Básicas de Saúde* – UBS) and a larger young population would have fewer COVID-19 cases and deaths. Alternatively, typically urban, hot, polluted places with higher inequality in addition to greater economic activity and movement of employees would face more problems related to coronavirus. Incidence and mortality would increase in hot cities, with greater economic activity and a history of comorbidities. However, mortality would decrease among young people and those with more education. Furthermore, lethality would be lower among young people and in cities with up to 150,000 inhabitants and little rain.

This paper is organized as follows: the next section provides a review of the possible determinants of COVID-19 cases and deaths. This is followed by the methodology and a description of the database used in the estimations. Finally, the results, final considerations and references are presented.

2 Regional choice and the local determinants of COVID-19

According to Neiva et al. (2020), Brazil is one of the epicenters of the COVID-19 pandemic, concentrating, on April 17, 2021, almost 10% of cases and just over 12% of deaths worldwide (JHU, 2021). Since the country has a continental dimension, with large socioeconomic and cultural disparities, the statistics on coronavirus may vary considerably across the Brazilian territory (*Ministério da Saúde* – MS, 2021). Therefore, this research focused on understanding the reasons that led certain Brazilian locations to face more/less difficulties in dealing with COVID-19.

Since the constitution of Brazil in 1988, there has been an "*intense process of political, administrative and fiscal decentralization, seeking to give municipalities greater autonomy for the formulation and implementation of public policies at the local level*" (Barroso et al., 2022, p. 2)[5]. Despite attempts from the federal government to define, alone, major actions to combat the pandemic (Gomes et al., 2020; Ramos et al., 2020; Silva, 2021), in order to delay/hinder open access to information about COVID-19 (Bosa; Maas, 2021) and encourage the use of medicines without proven efficacy (Santos-Pinto et al., 2021), the *Supremo Tribunal Federal* – STF (the last instance of the Brazilian judiciary system) decided that each federated entity could legislate and define its own rules to face this pandemic.

After this decision was made by the STF, Brazil's municipalities achieved greater autonomy to propose local measures against coronavirus and, therefore, became the target of this research. Firme and Simão Filho (2014, p. 683) stated that "(...) *due to the creation of new municipalities and precarious data collection in poorer regions, it is rarely possible to analyze all Brazilian municipalities*"[6]. Thus, our analysis focused on the 853 municipalities from the state of Minas Gerais[7].

There were technical advantages to making this regional cut (*i.e.*, in that it allowed us to consider and test more explanatory variables than would be possible in a study with all municipalities from Brazil) without a significant loss of socioeconomic heterogeneity. According to the *United Nations Development Programme* – UNDP (2022), the *Human Development Index*

(5) Free translation from Portuguese.

(6) Free translation from Portuguese.

(7)The first cases of COVID-19 in Brazil (MS, 2021) and in Minas Gerais – MG (*Secretaria de Saúde*, SS/MG, 2021 – the state's health department) occurred on February 26th and March 6th, 2020, respectively.

– HDI (base-year 2010) from Minas Gerais (0.731) is quite similar to Brazil's (0.727). In addition, some of the most developed and underdeveloped Brazilian municipalities are found in this state. While municipalities like São João das Missões, Araponga, Bonito de Minas, Catuji, Ladainha, Monte Formoso, Setubinha and Frei Lagonegro are among the 5% least developed in Brazil, with an average $HDI = 0.539$ (similar to countries like Pakistan, 0.538, Myanmar, 0.536, and Angola, 0.532), there are others among the 5% most developed, with an average $HDI = 0.778$ (comparable to countries like Malaysia, 0.779, Bulgaria, 0.782, and Uruguay, 0.793)[8].

Generally speaking, Minas Gerais: *i*) is a relatively heterogeneous region in socioeconomic terms, which allows us to analyze the effects of COVID-19 in markedly different locations (Perobelli; Ferreira; Faria, 2007; Amaral; Lemos; Chein, 2007; Cardoso; Ribeiro, 2015); *ii*) has the highest concentration of municipalities among the country's 26 states (about 15.3% of the Brazilian total), favoring the asymptotic properties of the estimators; *iii*) has a rich municipal database, with a low incidence of missing values, an essential attribute for empirical analyses (Firme; Simão Filho, 2014, p. 683). Furthermore, the state is economically representative (with the 3rd largest GDP in Brazil; IBGE, 2021) and has been responsible for approximately 9.2% of the cases and 8.1% of Brazilian deaths (*Ministério da Saúde* – MS, 2021). When comparing the data from the MS (2021) and the JHU (2021), the sample considered represents about 0.9% of the cases and 1% of deaths worldwide[9].

Once the geographical focus (municipalities) and regional cut-out (Minas Gerais) is defined, we must consult the literature about COVID-19 in order to specify which local factors could favor/hinder the control of the disease. As the first case of COVID-19 was announced less than 1.5 years ago[10], there are still few studies on which local aspects would explain the intensity of this disease in specific regions, especially in Brazil. In general, the prevalence of socioeconomic, demographic, climatic, pollution-related factors and some health indicators were observed, as described below:

a) ***Socioeconomic factors***: local per capita income is believed to be associated with the number of cases (Wadhera et al., 2020; Cole et al., 2020; Barros *et al.*, 2020) and COVID-19 deaths (Wadhera et al., 2020; Jinjarak *et al*., 2020; Cole et al., 2020). According to Stojkoski et al. (2020) and Ehlert et al. (2020), the spread of the virus would be intensified in places with a higher level of economic activity, where there would be a greater need for social interaction[11]. The same logic can be applied to the labor market, suggesting greater contagion in regions with intense movement of workers (Barros et al., 2020; Ehlert, 2020).

Moreover, Mollalo et al. (2020) found a positive association between income inequality and COVID-19 cases in the US. As inequality tends to be greater in large centers, it is possible that inequality indicates some type of urban agglomeration. In addition, Wadhera et al. (2020), when assessing New York neighborhoods, found that regions with lower educational rates had higher rates of COVID-19 hospitalization and death. Although Ehlert (2020) recognizes the importance of education, he states that its effect can be contradictory. As education and wealth

(8) Namely: Barbacena, Montes Claros, Timóteo, Ipatinga, Araxá, Uberaba, Araguari, Pouso Alegre, Viçosa, Itaú de Minas, Lagoa Santa, Juiz de Fora, Varginha, Poços de Caldas, Lavras, Itajubá, Uberlândia and Belo Horizonte.

(9) If Minas Gerais were a country, its cases (about 1.293 million) and deaths (more than 30,700) would rank it in the 22nd and 19th position worldwide, respectively (SS/MG, 2021; JHU, 2021).

(10) During the preparation of this research, the pandemic had been present/ongoing for 1 year and 4 months.

(11) "*A high level of economic activity is often based on networking (including physical networking), travel and social contacts (...)*" (Ehlert, 2020, p. 10-11).

are positively correlated, it is possible that individuals with more education have access to better hospitals, medical treatments and have informational advantages regarding the disease. However, as mentioned before, richer regions tend to have more COVID-19 cases and deaths. Therefore, there may be a difference between the impact of this variable at the individual and collective level.

b) ***Demographic factors***: studies suggest that population density and size could affect the number of COVID-19 cases and deaths (Stojkoski et al., 2020; Ehlert, 2020; Cole et al., 2020; Jinjarak et al., 2020). As the most severe cases of the disease require specialized monitoring and, at times, highly complex interventions, it is natural that the numbers are concentrated in larger cities, which have a better medical-hospital structure. Furthermore, Ehlert (2020) suggests that places with higher population density would be more prone to agglomeration and, thus, to the incidence of the virus. The results published by Jinjarak et al. (2020) indicate that population density would also affect the disease's mortality rates. The author also argues that urban regions, due to their higher risk of contagion, would typically have higher mortality rates.

There is evidence that cases and deaths are not randomly distributed among age groups. In general, the incidence of the virus tends to be higher among young people (possibly due to greater social interaction among this group), while mortality is higher among the elderly (Ehlert, 2020; Jinjarak et al., 2020; Lippi et al., 2020; Cole et al., 2020). Finally, Lippi et al. (2020) argue that the risk of death as a result of COVID-19 has been higher among men. Male predisposition to hypertension and cardiovascular and respiratory diseases (possibly due to the increased consumption of alcohol and tobacco) may explain this result (Gebhard et al., 2020).[12]

c) ***Pollution and climate factors****:* Wu et al. (2020) and Cole et al. (2020), when analyzing counties in the USA and the Netherlands, respectively, found that regions with more pollution would present more COVID-19 cases and deaths. Both suggest that long-term exposure to pollutants could weaken cardiac and respiratory capacity, aggravating symptoms associated with coronavirus.[13] The authors claim that such a scenario would lead to a greater number of cases, hospitalizations and deaths associated with coronavirus.

The effects of weather are still quite controversial. While some indicate that high temperatures and higher air humidity would increase COVID-19 cases and deaths (MA et al., 2020; Auler et al., 2020)[14] others suggest the opposite (Prata et al., 2020; Wang et al., 2020)[15]. In Brazil, which has a predominantly tropical climate, the hottest places could encourage individuals to leave their homes more frequently, increasing the contagion by the virus. On the other hand, Teixeira and Carvalho (2020) state that low temperatures and reduced air humidity favor the survival of SARS-CoV-2. Therefore, the issue regarding climate involves finding out which of these arguments would be more relevant in the place under analysis.

(12) "*Preliminary data indicate an association between comorbidities, such as chronic lung disease, hypertension, and cardiovascular disease, and severity of COVID-19. Worldwide, these morbidities are higher among men than women (...) smoking and drinking, may be contributing to the gender gaps*" (Gebhard et al., 2020, p. 7-8)

(13) "*It is well known that long-term exposure to pollutants such as nitrogen dioxide (NO2), sulfur dioxide (SO2), and fine particulate matter (PM2.5) contributes to cardiovascular disease, reduces lung function, and causes respiratory illness*" (Cole et al., 2020, p. 1)

(14) According to Auler et al. (2020), the contagion would be greater in Brazilian cities with high average temperatures (27.5 °C) and relative humidity (close to 80%). Ma et al. (2020) also found a positive association between coronavirus mortality and temperature in China.

(15) Prata et al. (2020) claim that higher temperatures would reduce cases in state capitals in Brazil, while Wang et al. (2020) suggested that higher temperature and relative humidity would reduce disease transmission in major Chinese cities.

d) ***Health indicators***: the medical-hospital condition of a region reveals its capacity to carry out mass diagnoses and deal with more severe epidemics. Although an adequate medical-hospital structure can reduce mortality associated with coronavirus, it is possible that the places with better health conditions present more COVID-19 cases, due to more testing in these regions (Stojkoski et al., 2020). As a larger number of cases tends to generate more deaths, the effect of the health infrastructure may diverge in aggregated (ecological) and individual studies (Ehlert, 2020). The variables used to measure the size and quality of this sector include health expenditure, the number of hospitals, doctors and nurses, and coverage of essential health services (Ehlert, 2020; Mollalo et al., 2020; Stojkoski et al., 2020).

Another relevant factor refers to pre-existing comorbidities, that is, chronic diseases and etiologically correlated with COVID-19. According to Gebhard et al., (2020), these diseases (e.g.: cancer, diabetes, hypertension, heart and respiratory problems) would aggravate the symptoms related to coronavirus, leading more individuals to undergo tests, seek hospital treatment and even die (Barros et al., 2020; Gebhard et al., 2020; Lippi et al., 2020).

3 Methodology and database

In this research, we sought to estimate the impact of the explanatory variables, suggested in Section 2, on the total number of COVID-19 cases and deaths and on the incidence, mortality and lethality rates of the disease. Thus, by grouping the k explanatory variables (including the constant)[16] in a matrix X_{nxk} and including the cases (or deaths, or any rates associated with SARS-CoV2) in a vector y_{nx1} (dependent variable), it is possible to estimate the impact ($\hat{\beta}_{kx1}$) of k elements of X_{nxk} on y_{nx1} by assuming that:

$$y_{nx1} = X_{nxk}\hat{\beta}_{kx1} + \varepsilon_{nx1} \tag{1}$$

Where: ε_{nx1}contains the residuals of $n = 853$ municipalities, which is supposed to be independent and identically distributed (*iid.*). Therefore, the Ordinary Least Squares Estimator (OLS) could be used to obtain vector $\hat{\beta}$ (Greene, 2002). Formally:

$$\hat{\beta}_{MQO} = (X'X)^{-1}X'y \tag{2}$$

OLS, although adequate to estimate incidence, mortality and lethality rates (whose values are continuous), would be problematic for cases and deaths, which assume a small number of integer and non-negative values (discrete variables) and would be unlikely to have a normal distribution. In these cases, the Poisson Regression Model (POI) is recommended (Greene, 2002); of which the conditional density function (CDF) of y, given the X explanatory variables, is:

$$f(y_i|X_i'\beta) = \left[e^{-exp(X_i'\beta)}exp(X_i'\beta)^{y_i}\right]/y_i! \tag{3}$$

Equation 3 is not linear and must be estimated by maximum likelihood (GREENE, 2002). Thus, to obtain β, the following Log-Likelihood function, $L(\beta) = \sum_{i=1}^{n=853}[-exp(X_i'\beta) + y_iX_i'\beta - lny_i!]$, must be maximized. Formally:

$$\frac{\partial lnL}{\partial \beta} = \sum_{i=1}^{n=853}\{[y_i - exp(X_i'\beta)]X_i\} = 0 \tag{4}$$

(16) Table 1 shows that $k = 32$, that is, 31 explanatory variables (based on section 2) plus the constant.

However, if $Var(y_i|X_i'\beta) > E(y_i|X_i'\beta)$, overdispersion would occur and the Poisson estimator (POI) would be inconsistent and inefficient.[17] In these cases, the Negative Binomial Estimator (NB), which controls the problem by including an additional term (ϵ_i) in the conditional mean ($X_i'\beta$) of the Poisson Estimator, becomes more appropriate. Thus, if $\lambda_i = exp(X_i'\beta)$ and $u_i = exp(\epsilon_i)$, the CDF of NB becomes Equation 5, and the other steps would be analogous to the Poisson Estimator (Greene, 2002).

$$f(y_i|X_i'\beta, u_i) = \left[e^{-\lambda_i u_i}(\lambda_i u_i)^{y_i}\right]/y_i! \tag{5}$$

As there is no well-defined specification to explain local COVID-19 outbreaks (i.e.: cases, deaths, incidence, mortality and lethality), the explanatory variables were evaluated not only via Equation 1, using OLS, Poisson (POI) and Negative Binomial (BN) estimators, but also based on Extreme Bounds Analysis (EBA) (Levine and Renelt, 1992). The EBA technique, by evaluating the coefficient (β_r) of any explanatory variable (r), in the presence of different combinations of the other explanatory variables (S), ends up reducing the uncertainty inherent in the models, reducing the possibility that "*different studies reach different conclusions depending on what combination of regressors the investigator chooses to put into his regression*." (Hoover; Perez, 2004, p. 766). Formally, the test consists of providing estimates, by OLS, similar to Equation 6:

$$\text{y} = a + F\beta_f + \beta_r r + S\beta_s + \varepsilon \tag{6}$$

where: y is the dependent variable; r is the tested variable, F is a fixed group of regressors (common to all regressions)[18] and S is a subset of three variables, extracted from the matrix X_{nxk^*} (Eq. 1), where $k^* = k - 2$ (it does not include the constant and the r tested variable). Thus, estimates are made for all combinations of S (3 by 3)[19].

Levine and Renelt (1992) call the variable r "robust" if its lower (lowest β_r estimated minus 2 standard deviations) and upper (highest β_r estimated plus 2 standard deviations) limits are significant (significance of 5%) and maintain the same sign. However, as this criterion is quite restrictive (Beugelsdijk et al., 2004),[20] a significance level of 15% and only 1 standard deviation were considered in the calculation of extreme values. This test was made available in the STATA software by Impávido (1998).

Operationally, the impact of any variable on the total number of COVID-19 cases and deaths was evaluated, via OLS, POI and NB estimators (unrestricted models)[21] and based on the EBA (restricted model). Given the continuous nature of Incidence, Mortality and Lethality rates, only OLS and EBA were considered.

3.1 Database

The total number of COVID-19 cases (CSE) and deaths (DTH), up until April 21, 2021, for each municipality in Minas Gerais (MG), was obtained from the Health Department of MG (*Secretaria de Saúde* – SS/MG, 2021). Thus, the incidence $[INC = (CSE/POP) * 100.000]$ and

(17) This hypothesis can be tested by regressing $(\varepsilon_t^2 - 1)$ against $\hat{y}_t$, after estimating the Poisson model, where $\hat{y}_i$ is the estimate of y_i e $\varepsilon_i^2 = (y_i - \hat{y}_i)^2$ (Wooldridge, 1996).

(18) In this research, fixed variables were not included in the EBA test. Therefore: $F = \{\emptyset\}$.

(19) Therefore, regressions will be performed $\{k^*!/[(k^* - 3)!\,3!]\}$ for each variable tested.

(20) "*The basic argument is that the EBA condition that a relationship should be significant as well as the same sign in each and every regression equation is too strict*" (Beugelsdijk et al., 2004, p. 122):

(21) Unlike the "unrestricted" models, the EBA does not allow the inclusion of all explanatory variables together.

mortality rates [$MRT = (DTH/POP) * 100.000$], per 100 thousand inhabitants, and the coronavirus' lethality [$LET = (DTH/CSE) * 100$] were calculated[22].

Based on local factors, associated with COVID-19 and described in section 2, the following explanatory variables were considered:[23]

a) ***Socioeconomic factors***:

- Level of economic activity: this variable refers to the current GDP per capita (GDP_{pc}), from 2018, calculated by the IBGE (FJP, 2021).

- Formal employment ($EMP.F$): number of formal workers divided by population – percentage values from 2019 (FJP, 2021).

- Inequality ($GINI$): the GINI index was used, calculated by the IBGE based on the per capita household income in the 2010 *census* (DATASUS, 2021).

- Education ($EDUC$): percentage of workers with university degree (or higher) in 2018, based on the Annual Social Information Report – *Relação Anual de Informações Sociais*, RAIS (2021).

b) ***Demographic factors***:

- Gender (GEN): percentage of men in the total population in 2018 (RAIS, 2021).

- Age group: percentage of the population up until 19 years old (reference), between 20-39 (AGE_{20-39}), 40-59 (AGE_{40-59}) and 60 or over (AGE_{60+}), in 2019 (FJP, 2021).

- Urban Population (URB): percentage of individuals who, in 2019, lived in urban areas (FJP, 2021).

- Population Density ($DEN.P$): refers to the 2019 population divided by the municipal geographic area (in Km^2), available in the FJP (2021).

- Municipal Size: dummies were included, based on the population size of 2019 (FJP, 2021), for municipalities with up to 10 thousand inhabitants (reference), 10-50 thousand (PS_{10-50}), 50-150 thousand (PS_{50-150}) and with a population greater than 150 thousand (PS_{150+}).

c) ***Pollution and climate factors***:

- Pollution: the vehicle density in 2019 ($DVEI$)[24] and the percentage of production from the industrial sector in 2018 (IND), both of which came from the FJP (2021).

- Climate: refers to average rainfall, in millimeters/month ($RAIN$) and temperature, in degree centigrade ($TEMP$), from the Climate Research Unit of the University of East Anglia, for December, 2011 (Ipeadata, 2020). Regarding the cases in which there was no available information, the information from the nearest municipality was used[25].

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(22) The 2019 municipal population was used, calculated by the *Instituto Brasileiro de Geografia e Estatística* (IBGE) and made available by the *João Pinheiro Foundation* – FJP (2021).

(23) As some of these factors may have a bi-causality relationship with the pandemic, only data prior to the pandemic were considered. Thus, only the effect of explanatory variables on the disease is expected to be evaluated, and not the other way around.

(24) Division of vehicles, registered in the National Traffic Department, by the municipal area (in Km2).

(25) For this purpose, the GEODA software was used, which, through a matrix of spatial weights, allows the identification of the closest neighbors of each location. For more information see Almeida (2012).

d) ***Health indicators***:

➢ Expenditure on Health: current public expenditure, per capita, on health and sanitation (EoH_{pc}) from 2019, of the National Treasury of Brazil (*Secretaria do Tesouro Nacional* – STN). When there was no data available, the value of the most recent year was used, updated to 2019 via IPCA (Ipeadata, 2021).

➢ Structure and Equipment: total number of public health clinices (usually known in Brazil as *unidades básicas de saúde* – UBS), emergency care units (known as *unidades de pronto atendimento/socorro* – PRS), hospitals ($HOSP$), hospital beds (BED)[26] and respirators ($RESP$), per 100 thousand inhabitants – values from December, 2019 (CNES – Datasus, 2020).

➢ Professionals in the area: total number of general physicians ($PHY.G$) and lung specialists ($PHY.L$) and nurses (with general formation – $NUR.G$ and specialists in intensive care – $NUR.IC$)[27] per 100,000 inhabitants. The average number of professionals, between the months of 2019, registered in the National Register of Health Establishments in Brazil (*Cadastro Nacional dos Estabelecimentos de Saúde* – CNES) was used (Datasus, 2021).

➢ Access to private healthcare: percentage of individuals with private health insurance (PHC). Data from the Primary Care System: Family Health, referring to December, 2015 (Datasus, 2021)[28].

➢ History of correlated diseases ($D.COR$): percentage of deaths from cancer, diabetes, circulatory and respiratory diseases[29] in relation to total municipal deaths (per residence) – average value between 2009 and 2019 (Datasus, 2021).

Table 1 contains the main descriptive statistics of the database used in this research.

Table 1
Descriptive statistics from database

	Variable	Acronym	Value	Average	Std. Dev.	Minimum	Maximum
COVID-19	Cases	CSE	Total	1516.89	7035.63	10.00	166187.00
	Deaths	DTH	Total	36.05	176.27	0.00	3967.00
	Incidence	INC	p/100,000 inhab.	4980.00	2676.83	83.81	22361.33
	Mortality	MRT	p/100,000 inhab.	109.28	74.26	0.00	416.44
	Lethality	LET	% of cases	2.30	1.43	0.00	10.00
Socioeconomic Factors							
	Economic Activity	GDP_{pc}	R$/2018: thousand	20.03	22.20	6.30	337.29
	Formal employment	$EMP.F$	% of population	14.87	8.95	3.14	96.46
	Inequality	$GINI$	Index: 0 to 100	48.12	5.37	32.88	78.32
	University Education	$EDUC$	% of population	16.25	5.87	2.49	45.59

To be continued…

(26) Hospital beds (inpatient and complementary) and emergency beds (rest and observation) were included.
(27) $NUR.G$ is equal to the total number of nurses minus $NUR.IC$.
(28) The 2015 population (FJP, 2021) was considered in the calculations.
(29) CID-10, Chapters II, IV (E10-E14), IX and X.

Table 1 – Continuation

Variable	Acronym	Value	Average	Std. Dev.	Minimum	Maximum
		Demographic Factors				
Gender	GEN	% of population	50.51	1.25	46.88	56.10
Age Group (AGE)	AGE_{19-}	% of population	26.87	1.11	23.33	32.29
	AGE_{20-39}	% of population	30.27	1.33	27.47	35.26
	AGE_{40-59}	% of population	25.65	0.59	23.65	27.65
	AGE_{60+}	% of population	17.21	1.28	11.55	20.04
Urban Population	URB	% of population	75.76	15.50	19.35	100.00
Population Density	$DEN.P$	Inhabitants/Km^2	71.54	339.58	1.32	7607.03
Population Size (PS)	PS_{10-}	Binary (0 or 1)	0.56	0.50	0.00	1.00
	PS_{10-50}	Binary (0 or 1)	0.36	0.48	0.00	1.00
	PS_{50-150}	Binary (0 or 1)	0.06	0.24	0.00	1.00
	PS_{150+}	Binary (0 or 1)	0.02	0.14	0.00	1.00
		Pollution and Climate Factors				
Vehicle Density	$DVEI$	Vehicles/Km^2	38.17	256.28	0.16	6902.97
Industrial Pollution	IND	Industrial GDP (%)	13.34	14.15	1.90	80.80
Temperature	$TEMP$	Degrees ºC	21.06	1.85	14.97	25.08
Rainfall	$RAIN$	Millimeters/month	113.39	18.74	64.91	152.57
		Health indicators				
Expenditure on Health	EoH_{pc}	R$ from 2019	953.08	385.72	417.71	3903.06
Basic Health Units	UBS	p/100 K people	50.42	27.97	6.53	256.08
Emergency Care Units	PRS	p/100 K people	0.73	2.77	0.00	42.68
Hospitals	$HOSP$	p/100 K people	3.07	5.19	0.00	60.64
Hospitals' beds	BED	p/100 K people	112.96	152.54	0.00	1030.93
Respirators	$RESP$	p/100 K people	7.68	15.47	0.00	162.64
General Physicians	$PHY.G$	p/100 K people	38.27	33.65	0.00	275.39
Lung Physicians	$PHY.L$	p/100 K people	0.12	0.77	0.00	15.45
General Nurses	$NUR.G$	p/100 K people	56.74	38.16	0.00	332.01
Intense Care Nurses	$NUR.IC$	p/100 K people	0.08	0.68	0.00	12.37
Private Healthcare	PHC	% of population	4.98	6.29	0.00	51.74
Correlated Diseases	$D.COR$	% of total deaths	58.93	7.35	37.21	76.53

Source: Authors' own elaboration.

4 Results

Unrestricted estimates, via OLS, reveal that the variables used have a low explanatory power on COVID-19 lethality rates ($R^2 \cong 0.08$), but improve when explaining mortality ($R^2 \cong 0.19$), incidence ($R^2 \cong 0.27$) and total cases and deaths (both with $R^2 \cong 0.78$). Considering all estimates, only the age group between 40-59 years (AGE_{40-59}) and the percentage of individuals with private healthcare (PHC) were not significant. However, in the case of AGE_{40-59}, this only implies that there is no relevant difference (in terms of cases, deaths, incidence, mortality and lethality) between this range and AGE_{60+} (Table 2).

Table 2

Unrestricted estimates of factors associated with COVID-19

	Cases						Deaths						Incidence		Mortality		Lethality	
	OLS$^{(1)}$	OLS$^{(2)}$	POI$^{(1)}$	POI$^{(2)}$	N. B. $^{(1)}$	N. B. $^{(2)}$	OLS$^{(1)}$	OLS$^{(2)}$	POI$^{(1)}$	POI$^{(2)}$	N. B. $^{(1)}$	N. B. $^{(2)}$	OLS$^{(1)}$	OLS$^{(2)}$	OLS$^{(1)}$	OLS$^{(2)}$	OLS$^{(1)}$	OLS$^{(2)}$
GDP_{pc}	0.0002	NS	3.5e-06**	3.5e-06**	3.1e-06*	2.8e-06*	-0.00002	NS	5.2e-06***	5.1e-06***	3.8e-6**	3.8E-06***	0.0207*	0.0225**	0.0004**	0.0004***	3.0e-06	3.1e-06
$EMP.F$	61.980**	73.153***	0.0167***	0.0167***	0.0112***	0.0112***	1.2528*	1.1274**	0.0048	0.049	-0.0009	NS	35.706*	39.366**	-0.4388	NS	-0.0293***	-0.0319***
$GINI$	3950.3***	3950.4**	0.8824	0.8814	0.7280*	0.7329*	112.97**	119.29***	0.9778	0.9416	1.0886**	1.0772**	-417.58	NS	21.303	NS	0.3088	NS
$EDUC$	24.972	31.000	0.0025	0.0025	-0.0054	-0.0057	0.3055	NS	-0.0039	-0.0041	-0.0196***	-0.0193***	-8.0938	NS	-1.5189***	-1.4979***	-0.0266***	-0.0251***
GEN	10.127	NS	-0.0399	-0.0398	-0.0408**	-0.0397**	-0.3012	NS	-0.0542	-0.0519	-0.0549**	-0.0545**	-90.032	NS	-3.6988	-3.6057	0.0070	NS
AGE_{19-}	-526.66**	-439.90**	-0.2466***	-0.2475**	0.0547	0.0545	-16.104**	-13.919**	-0.3810***	-0.3859***	-0.0891*	-0.0890*	26.856	NS	-13.284***	-14.169***	-0.3184***	-0.2951***
AGE_{20-39}	-103.23	NS	0.2699***	0.2697***	0.4158***	0.4201***	-3.1567	NS	0.3168***	0.3152***	0.4166***	0.4188***	129.32	NS	2.7632	NS	-0.0632	NS
AGE_{40-59}	-280.79	NS	0.0017	NS	-0.1118	-0.1226	-4.2131	NS	-0.0611	-0.0658	-0.1583	-0.1565	19.277	NS	-8.2304	-11.637	-0.2131	-01925
AGE_{60+}	EXC	EXC	EXC	EXC	EXC	EXC	EXC	EXC	EXC	EXC	EXC	EXC	EXC	EXC	EXC	EXC	EXC	EXC
URB	-17.050**	-13.398*	0.0057**	0.0058**	0.0046***	0.0045**	-0.5552***	-0.5770***	0.0022	0.0025	0.0034	0.0036*	21.998***	24.663***	0.2869	0.3686**	-0.0026	NS
$DEN.P$	0.8926	NS	-0.0001	-0.0001	0.0002*	0.0002*	0.0730	0.0725	0.0000	0.0000	0.0002**	0.0002*	-0.2716	NS	0.0027	NS	0.0002	0.0001*
PS_{10-}	-16115***	-16378***	-1.7256***	-1.7262***	-1.7570***	-1.7555***	-455.65***	-445.10***	-1.4860***	-1.4870***	-1.7950***	-1.8203***	171.77	NS	-19.702	-47.471***	-0.6756*	-0.3450
PS_{10-50}	-15523***	-15893***	-0.8836***	-0.8843***	-1.1711***	-1.1695***	-446.35***	-437.24***	-0.7811***	-0.7823***	-1.2317***	-1.2549***	326.55	NS	-18.714	-42.451***	-0.6982**	-0.4482*
PS_{50-150}	-13269**	-13769***	-0.5761***	-0.5759***	-0.4028	-0.4023	-414.52***	-410.93***	-0.6758***	-0.6753***	-0.6057***	-0.6170***	957.90	857.62**	-13.268	-24.635*	-0.5560*	-0.4833*
PS_{150+}	EXC	EXC	EXC	EXC	EXC	EXC	EXC	EXC	EXC	EXC	EXC	EXC	EXC	EXC	EXC	EXC	EXC	EXC
$DVEI$	16.697***	17.646***	0.0005***	0.0005***	0.0002**	0.0002**	0.3312***	0.3337***	0.0004***	0.0004***	0.0002**	0.0002**	0.2236	NS	-0.0003	NS	-0.0002	NS
IND	8.0902	NS	0.0023	0.0023	0.0043**	0.0042**	0.0797	NS	-0.0014	-0.0014	0.0027	0.0026	15.828	19.189**	0.2382	NS	0.0002	NS
$TEMP$	104.31	NS	0.0696**	0.0695**	0.0312*	0.0296*	4.4268**	4.2927***	0.1229***	0.1172***	0.0765***	0.0748***	136.94*	139.47*	7.6878***	6.1902***	0.0857**	0.0794**
$RAIN$	-15.752*	-20.879***	-0.0066**	-0.0066**	-0.0033	-0.0035*	-0.1705	-0.1897	0.0008	NS	0.0041*	0.0042*	-24.186***	-24.465***	0.2011	NS	0.0128**	0.0137***

To be continued…

Table 2 – Continuation

	Cases						Deaths						Incidence		Mortality		Lethality	
	OLS$^{(1)}$	OLS$^{(2)}$	POI$^{(1)}$	POI$^{(2)}$	N. B. $^{(1)}$	N. B. $^{(2)}$	OLS$^{(1)}$	OLS$^{(2)}$	POI$^{(1)}$	POI$^{(2)}$	N. B. $^{(1)}$	N. B. $^{(2)}$	OLS$^{(1)}$	OLS$^{(2)}$	OLS$^{(1)}$	OLS$^{(2)}$	OLS$^{(1)}$	OLS$^{(2)}$
EoH_{pc}	0.2406	NS	0.0001	0.0001	-0.0001	NS	-0.0040	NS	-0.0001	-0.0001	-0.0002	-0.0002	0.6398	NS	-0.0005	NS	-0.0004**	-0.0004**
UBS	-11.584**	-9.9621**	-0.0094***	-0.0094***	-0.0027**	-0.0028***	-0.2838***	-0.02793***	-0.0099***	-0.0100***	-0.0035***	-0.0036***	-4.9626	-4.4896	-0.0949	NS	-0.0009	NS
PRS	-91.405*	-91.450*	-0.0080	-0.0080	0.0011	NS	-1.8582*	-1.8792*	0.0065	0.0067	0.0067	NS	-15.132	NS	0.9186	NS	0.0342*	0.0327
$HOSP$	-24.039	-18.236*	0.0119	0.0119	-0.0095	-0.0092	-0.8203	-0.6916**	0.0078	0.0082	-0.0096	-0.0102**	-10.289	NS	0.0251	NS	0.0139	NS
BED	0.0933	NS	-0.0008*	-0.0008*	0.0004	0.0003	0.0080	NS	-0.0009*	-0.0009**	-0.0001	NS	0.2331	NS	-0.0520	-0.0433**	-0.0010*	-0.0006
$RESP$	30.452**	30.894**	0.0007	0.0007	0.0005	NS	0.8049**	0.8195**	0.0018	0.0018	0.0014	NS	-3.7753	NS	0.1014	NS	0.0018	NS
$PHY.G$	3.2289	3.9175	0.0015	0.0015	-0.0006	NS	0.1374*	0.1361*	0.0030**	0.0030**	0.0000	NS	-4.0221	NS	-0.0844	NS	-0.0009	NS
$PHY.L$	306.50	278.74	0.1021***	0.1021***	0.0466	0.0482	7.8986	7.9296	0.0860***	0.0863***	0.0328	NS	196.57*	188.40*	1.6585	NS	-0.0473	NS
$NUR.G$	2.9786	NS	-0.0001	-0.0001	0.0003	NS	0.1234	0.1232	0.0011	0.0011	0.0012	0.0013*	-1.2922	NS	0.1127	NS	0.0032	0.0031*
$NUR.IC$	107.45	NS	0.0069	0.0069	-0.0058	NS	0.6173	NS	-0.0024	NS	-0.0300	NS	26.200	NS	-0.6210	NS	-0.0472	-0.0643**
PHC	-10.544	NS	-0.0005	-0.0005	0.0019	NS	-0.5376	-0.5291	-0.0029	-0.0029	-0.0001	NS	14.294	NS	-0.0744	NS	-0.0022	NS
$D.COR$	9.093	NS	0.0049	0.0049	0.0139***	0.0140***	-0.0052	NS	0.0005	NS	0.0138***	0.0137***	103.14***	105.07***	2.1695***	2.2507***	0.0055	NS
Constant	37152.4	28469.6***	6.0739	6.1469*	-3.3446	-3.2131	1004.6	724.76***	5.4963	5.9133	-2.7104	-2.8027	-4761.0	-4384.4*	481.82	744.40***	16.178**	13.452**
R^2	0.783	0.782	0.944	0.944	0.151	0.151	0.778	0.778	0.916	0.916	0.239	0.239	0.272	0.264	0.189	0.180	0.080	0.076
AIC	16288.2	16267.7	235381.5	235379.7	11827.8	11815.5	10020.1	100001.1	9634.6	9630.2	5633.1	5620.1	15673.4	15645.1	9649.8	9625.0	3013.6	2991.7

Notes: a) *p*-value: * <0.10; ** <0.05; *** <0.01; b) White's robust matrix was used in all estimates; c) The overdispersion problem was detected in all Poisson models; d) NS = not significant and EXC = excluded variable (reference); e) cross-hatched cells indicate alternating significant signals (among the models).

Source: Authors' own elaboration based on STATA 14 software.

Given the discrete character of cases (CSE) and deaths (DTH) and the *overdispersion* problem verified in all Poisson models (POI), the use of Negative Binomial (NB) estimators is recommended in both cases. In addition, the least significant variables of each model were excluded to minimize the AIC criterion. This procedure improved the initial specifications and allowed for the identification of some relevant variables (e.g.: a greater number of hospital beds, BED, which did not seem to affect mortality in OLS$^{(1)}$, could reduce it in OLS$^{(2)}$).Therefore, considering the appropriate estimator for each case and the models with the smallest AIC, indicated by the superscript (2), it was found that (TABLE 2):

a) **Socioeconomic factors**: cities with greater economic activity (GDP_{pc}) would tend to have a higher number of COVID-19 cases, deaths, incidence rate and mortality. On the other hand, places with a high percentage of formal jobs ($EMP.F$) would have a high number of cases, incidence rate and lethality. Inequality ($GINI$) is associated with more cases and deaths, while education ($EDUC$) could reduce deaths, mortality and disease lethality.

This harmful effect of a greater GDP_{pc}, $EMP.F$ and $GINI$, on the main COVID-19 statistics, has been identified by several researchers (Williams; Cooper, 2020; Wadhera et al., 2020; Cole et al., 2020; Credit, 2020; Rafael et al., 2020; Barros et al., 2020; Jinjarak et al. 2020; Stojkoski et al., 2020; Ehlert et al., 2020; Mollalo et al., 2020) and suggests that the spread of coronavirus would be intensified in places prone to agglomeration (*i.e.*, with higher and unequal economic activity, which demands an intense movement of workers). As in Wadhera et al. (2020), it was verified that cities with better levels of education ($EDUC$) would be better equipped to deal with this pandemic. According to Ehlert (2020), a more educated person would have information advantages regarding the disease and would most likely have access to better hospitals and medical treatments.

b) **Demographic factors**: municipalities with a higher percentage of men (GEN) would tend to have fewer cases and deaths. Those with a predominantly younger population (AGE_{19-}), on the other hand, would have fewer deaths, mortality and lethality due to coronavirus. However, individuals between 20-39 years (AGE_{20-39}) would inflate the number of cases and deaths in their localities. Urban populations (URB) would typically face higher numbers of COVID-19 cases, deaths, incidence rate and mortality.[30] Population density ($DEN.P$) would also be harmful, increasing cases, deaths and disease lethality. Furthermore, cities with more than 150,000 inhabitants (PS_{150+}) would likely have more cases and deaths and would be affected by higher mortality and lethality rates.

The damaging impact of URB, $DEN.P$ and PS_{150+} is supported by the literature (Stojkoski et al., 2020; Ehlert, 2020; Cole *et al.*, 2020; Jinjarak et al., 2020) and reinforces the pernicious effect of agglomeration on COVID-19 statistics. As expected, the results indicated that adults (AGE_{20-39}), who tend to socialize more often than the youngest and oldest age groups, would boost the number of cases of coronavirus in their cities. Furthermore, the youngest age group (AGE_{19-}) seems to face fewer problems related to coronavirus (most likely due to the better health conditions, on average, of this age group). Contrary to Lippi *et al.* (2020), we verified that a higher concentration of men (GEN) would result in lower rates of the disease.

c) **Pollution and climate factors**: cities with greater vehicle pollution ($DVEI$) would possibly present more cases and deaths. On the other hand, locations with an industrial profile (IND) could also present high numbers of cases and incidence rate of COVID-19. Higher

(30) Although OLS estimates indicate a negative effect of URB on cases and deaths, it is emphasized that, in both cases, the Negative Binomial (BN) is the most adequate model, with positive coefficients.

temperatures ($TEMP$) were associated with more cases, deaths, incidence rate, mortality and lethality. Although the results indicate that rainy cities ($RAIN$) have fewer cases and a low incidence rate, this condition seems to lead to an increase in deaths and lethality.

The results associated with $DVEI$ and IND indicate that both vehicular as well as industrial pollution may worsen this pandemic. According to Wu et al. (2020) and Cole *et al.* (2020), places with high levels of pollution could present weaker cardiac and respiratory capacity in the populations, aggravating coronavirus symptoms and boosting the cases and deaths from the disease. As verified by Auler et al. (2020), we also found that higher temperatures ($TEMP$) may hinder the control of the virus. It is possible that it would be more difficult to maintain social distancing in the hottest areas of a region with a tropical climate. Since rainy cities ($RAIN$) can, naturally, help limit agglomeration, fewer cases and a low incidence of coronavirus is expected, as suggested by Wang et al. (2020). However, there is still a lack of information on the harmful effect of this variable on deaths and lethality.

d) **Health indicators**: locations that maintain higher public spending on health (EoH_{pc}) proved to be more effective in reducing the lethality of coronavirus. As for the structural issue, basic units (UBS) seem to contain cases and deaths, while hospitals ($HOSP$) reduce deaths. Furthermore, cities with more hospital beds (LTO) would face lower mortality rates. Although estimates indicate that places with more intensive care nurses ($NUR.IC$), would present a lower lethality from the disease, the other results, associated with the "health team", proved to be adverse. In general, cities with more lung specialists ($PHY.L$) showed higher mortality, while those with more nurses ($NUR.G$) would have more deaths and higher mortality. Finally, municipalities with a more severe history of diseases related to COVID-19 ($D.COR$) would present more cases, deaths, incidence rate and mortality.

The benefits of EoH_{pc}, UBS, $HOSP$ and LTO (on the main coronavirus statistics) reinforces the relevance of providing an adequate health infrastructure, as highlighted by Stojkoski et al. (2020). Nonetheless, it was found that municipalities with more health professionals ($PHY.L$ and $NUR.G$) would face more problems associated with COVID-19. Since the physicians and nurses tend to be concentrated in bigger cities, the variables $PHY.L$ and $NUR.G$ may be impacted by some kind of local agglomeration. Similar to Gebhard et al. (2020), Barro et al. (2020) and Lippi *et al.* (2020), our estimates on $D.COR$ reveal that places with a history of comorbidities would be more negatively affected by the pandemic.

As it is possible that some of the signs and significances, obtained in Table 2, change after the inclusion or exclusion of certain explanatory variables, we sought to ensure the validity of the previous inferences through Extreme Bounds Analysis, EBA (Table 3). After 1,540 estimations, for each explanatory variable considered[31], the EBA technique allowed for the identification of the non-significant (NS) ones and those with dubious signs (marked with "X"). As in Table 2, the EBA test (presented in Table 3) indicates that the emergency care units (PRS) would not be significant in any of the models considered. Alternatively, the effect of rainfall ($RAIN$) on incidence, which would be negative in Table 2, revealed itself unreliable in EBA (i.e., it would oscillate between positive or negative, according to the specification). Furthermore, the fact that only $RAIN$ explains COVID-19 lethality (LET) significantly reinforces the low explanatory power associated with this rate and encourages further studies on the subject.

(31) This research used 31 explanatory variables (TABLE 1). However, the age groups (AGE) and the *dummies* of population size (PS), whose sum is 1, were excluded (EXC) from the EBA test to avoid perfect co-linearity with the model's constant. Thus, 23 variables remained in the test. Therefore, $k^* = 22$ and there is a total of $\{22!/[(22-3)!\,3!]\} = 1540$ estimates for each variable r tested (see Eq. 6).

Table 3

Restricted analysis of variables associated with COVID-19: EBA test

	Cases – CSE		Deaths – DTH		Incidence – INC		Mortality – MRT		Lethality – LET	
	Signif. Test (Min. to Max.)	Signal Test (Min. to Máx.)	Signif. Test (Min. to Max.)	Signal Test (Min. to Máx.)	Signif. Test (Min. to Max.)	Signal Test (Min. to Máx.)	Signif. Test (Min. to Max.)	Signal Test (Min. to Máx.)	Signif. Test (Min. to Max.)	Signal Test (Min. to Máx.)
GDP_{pc}	0.027 to 0.047	0.009 to 0.066	0.0007 to 0.0008	0.0002 to 0.0013	0.0218 to 0.0457	0.0150 to 0.0525	0.0005 to 0.0006	0.0004 to 0.0007	NS	NS
$EMP.F$	66.46 to 318.50	18.07 to 366.89	1.836 to 7.702	0.606 to 8.932	57.940 to 122.800	41.775 to 138.965	1.229 to 1.859	0.938 to 2.150	NS	NS
$GINI$	11100.0 to 22500.0	7246.5 to 26353.5	284.40 to 540.80	188.98 to 636.22	NS	NS	NS	NS	NS	NS
$EDUC$	116.80 to 245.30	66.24 to 295.86	4.372 to 5.873	3.171 to 7.074	-91.640 to -63.550	-113.332 to -41.858	-2.721 to -1.775	-3.090 to -1.406	NS	NS
GEN	-1610.00 to -511.60	-1933.24 to -188.36	-40.440 to -12.840	-48.544 to -4.736	-460.00 to -278.40	-530.70 to -207.61	-11.160 to -8.213	-12.830 to -6.543	NS	NS
AGE_{19-}	EXC	EXC	EXC	EXC	EXC	EXC	EXC	EXC	EXC	EXC
AGE_{20-39}	EXC	EXC	EXC	EXC	EXC	EXC	EXC	EXC	EXC	EXC
AGE_{40-59}	EXC	EXC	EXC	EXC	EXC	EXC	EXC	EXC	EXC	EXC
AGE_{60+}	EXC	EXC	EXC	EXC	EXC	EXC	EXC	EXC	EXC	EXC
URB	41.08 to 119.10	15.22 to 144.96	1.054 to 2.943	0.408 to 3.589	26.440 to 57.920	19.683 to 64.677	0.799 to 1.337	0.694 to 1.442	NS	NS
$DEN.P$	5.747 to 15.740	2.800 to 18.687	0.2090 to 0.3980	0.1555 to 0.4515	NS	NS	NS	NS	NS	NS
PS_{10-}	EXC	EXC	EXC	EXC	EXC	EXC	EXC	EXC	EXC	EXC
PS_{10-50}	EXC	EXC	EXC	EXC	EXC	EXC	EXC	EXC	EXC	EXC
PS_{50-150}	EXC	EXC	EXC	EXC	EXC	EXC	EXC	EXC	EXC	EXC
PS_{150+}	EXC	EXC	EXC	EXC	EXC	EXC	EXC	EXC	EXC	EXC
$DVEI$	12.940 to 21.470	10.492 to 23.918	0.2310 to 0.5140	0.1455 to 0.5995	NS	NS	NS	NS	NS	NS
IND	41.510 to 80.480	22.566 to 99.424	1.138 to 1.317	0.685 to 1.770	28.250 to 64.250	16.898 to 75.602	0.738 to 1.009	0.580 to 1.167	NS	NS
$TEMP$	NS	NS	NS	NS	228.80 to 444.20	124.07 to 548.93	6.436 to 12.270	2.714 to 15.992	NS	NS
$RAIN$	84.980 to 92.690	63.619 to 114.051	1.752 to 2.405	1.218 to 2.939	-31.840 to 49.230	~~-45.874 to 63.264~~	0.573 to 1.594	0.215 to 1.952	0.0112 to 0.0212	0.0087 to 0.0237

To be continued…

Table 3 - Continuation

	Cases – CSE		Deaths – DTH		Incidence – INC		Mortality – MRT		Lethality – LET	
	Signif. Test (Min. to Max.)	Signal Test (Min. to Máx.)	Signif. Test (Min. to Max.)	Signal Test (Min. to Máx.)	Signif. Test (Min. to Max.)	Signal Test (Min. to Máx.)	Signif. Test (Min. to Max.)	Signal Test (Min. to Máx.)	Signif. Test (Min. to Max.)	Signal Test (Min. to Máx.)
EoH_{pc}	1.681 to 3.815	0.731 to 4765	0.0453 to 0.0897	0.0218 to 0.1132	0.928 to 1.916	0.488 to 2.356	0.030 to 0.035	0.022 to 0.043	NS	NS
UBS	-73.250 to -21.570	-86.419 to -8.401	-1.799 to -0.564	-2.126 to -0.237	-24.850 to -13.380	-29.342 to -8.888	-0.510 to -0.403	-0.601 to -0.312	NS	NS
PRS	NS	NS	NS	NS	NS	NS	NS	NS	NS	NS
$HOSP$	-398.00 to -189.70	-505.09 to -82.61	-9.988 to -4.723	-12.659 to -2.052	NS	NS	NS	NS	NS	NS
BED	4.022 to 18.580	~~-0.251 to 22.853~~	0.1080 to 0.4600	~~-0.0002 to 0.5682~~	2.475 to 4.198	1.699 to 4.974	NS	NS	NS	NS
$RESP$	76.16 to 179.50	52.30 to 203.36	1.906 to 4.525	1.308 to 5.123	24.150 to 32.250	17.519 to 38.881	0.679 to 0.779	0.535 to 0.923	NS	NS
$PHY.G$	18.660 to 51.430	8.883 to 61.207	0.511 to 1.279	0.265 to 1.525	11.240 to 15.150	7.681 to 18.709	NS	NS	NS	NS
$PHY.L$	845.90 to 1868.00	544.22 to 2169.68	20.640 to 47.260	13.034 to 54.866	NS	NS	NS	NS	NS	NS
$NUR.G$	18.140 to 49.620	9.944 to 57.816	0.441 to 1.282	0.237 to 1.486	NS	NS	0.274 to 0.302	0.230 to 0.346	NS	NS
$NUR.IC$	899.70 to 2756.00	317.15 to 3338.55	23.840 to 66.530	9.421 to 80.949	NS	NS	NS	NS	NS	NS
PHC	NS	NS	NS	NS	60.010 to 81.340	42.258 to 99.092	NS	NS	NS	NS
$D.COR$	NS	NS	NS	NS	47.38 to 110.30	31.21 to 126.47	1.652 to 3.340	1.305 to 3.687	NS	NS

Notes: a) Signif. Test → significance test of extreme values (only considering the coefficients with p-value $\leq$ 0.15); b) Signal test → extreme signal alternation test (it uses $\beta^{max} + 1SD$ and $\beta^{min} - 1SD$, where SD is the standard-deviation from all estimated β of each variable considered); c) NS = not significant (*i.e.*: p-valor > 0.15) and EXC = excluded variable; d) cross-hatched cells indicate signals change, when compared to Table 2.

Source: Authors' own elaboration based on STATA 14 software.

When comparing the restricted and unrestricted estimations, it is clear that the signals indicated in the EBA technique (Table 3) only diverged from the unrestricted models (Table 2) regarding the impact of Education ($EDUC$) on deaths and the effect of rainfall ($RAIN$) on COVID-19 cases. Therefore, with the exception of these two cases, the other analyses previously carried out remain valid. Even so, it is possible to increase the credibility of the inferences by compiling, in Table 4, the significant estimates and their signs, obtained via EBA and unrestricted models[32].

Table 4
Compilation of the main results on variables associated with COVID-19

	Cases			Deaths			Incidence			Mortality			Lethality		
	Sig. Test	Signal +	Signal -	Sig. Test	Signal +	Signal -	Sig. Test	Signal +	Signal -	Sig. Test	Signal +	Signal -	Sig. Test	Signal +	Signal -
GDP_{pc}	6/8	6/6	0/6	6/8	6/6	0/6	4/4	4/4	0/4	4/4	4/4	0/4	0/4	NS	NS
$EMP.F$	8/8	8/8	0/8	4/8	4/4	0/4	4/4	4/4	0/4	2/4	2/2	0/2	2/4	0/2	2/2
$GINI$	6/8	6/6	0/6	6/8	6/6	0/6	0/4	NS	NS	0/4	NS	NS	0/4	NS	NS
$EDUC$	2/8	2/2	0/2	4/8	2/4	2/4[(a)]	2/4	0/2	2/2	4/4	0/4	4/4	2/4	0/2	2/2
GEN	4/8	0/4	4/4	4/8	0/4	4/4	2/4	0/2	2/2	2/4	0/2	2/2	0/4	NS	NS
AGE_{19-}	4/6	0/4	4/4	6/6	0/6	6/6	0/2	NS	NS	2/2	0/2	2/2	2/2	0/2	2/2
AGE_{20-39}	4/6	4/4	0/4	4/6	4/4	0/4	0/2	NS	NS	0/2	NS	NS	0/2	NS	NS
AGE_{40-59}	0/6	NS	NS	0/6	NS	NS	0/2	NS	NS	0/2	NS	NS	0/2	NS	NS
AGE_{60+}	EXC	EXC	EXC	EXC	EXC	EXC	EXC	EXC	EXC	EXC	EXC	EXC	EXC	EXC	EXC
URB	8/8	6/8	2/8	5/8	3/5	2/5	4/4	4/4	0/4	3/4	3/3	0/3	0/4	NS	NS
$DEN.P$	4/8	4/4	0/4	4/8	4/4	0/4	0/4	NS	NS	0/4	NS	NS	1/4	1/1	0/1
PS_{10-}	6/6	0/6	6/6	6/6	0/6	6/6	0/2	NS	NS	1/2	0/1	1/1	1/2	0/1	1/1
PS_{10-50}	6/6	0/6	6/6	6/6	0/6	6/6	0/2	NS	NS	1/2	0/1	1/1	2/2	0/2	2/2
PS_{50-150}	4/6	0/4	4/4	6/6	0/6	6/6	1/2	1/1	0/1	1/2	0/1	1/1	2/2	0/2	2/2
PS_{150+}	EXC	EXC	EXC	EXC	EXC	EXC	EXC	EXC	EXC	EXC	EXC	EXC	EXC	EXC	EXC
$DVEI$	8/8	8/8	0/8	8/8	8/8	0/8	0/4	NS	NS	0/4	NS	NS	0/4	NS	NS
IND	4/8	4/4	0/4	2/8	2/2	0/2	3/4	3/3	0/3	2/4	2/2	0/2	0/4	NS	NS
$TEMP$	4/8	4/4	0/4	6/8	6/6	0/6	4/4	4/4	0/4	4/4	4/4	0/4	2/4	2/2	0/2
$RAIN$	7/8	2/8	5/8	4/8	4/4	0/4	4/4	1/4	3/4	2/4	2/2	0/2	4/4	4/4	0/4
EoH_{pc}	2/8	2/2	0/2	2/8	2/2	0/2	2/4	2/2	0/2	2/4	2/2	0/2	2/4	0/2	2/2
UBS	8/8	0/8	8/8	8/8	0/8	8/8	2/4	0/2	2/2	2/4	0/2	2/2	0/4	NS	NS
PRS	2/8	0/2	2/2	2/8	0/2	2/2	0/4	NS	NS	0/4	NS	NS	1/4	1/1	0/1
$HOSP$	3/8	0/3	3/3	4/8	0/4	4/4	0/4	NS	NS	0/4	NS	NS	0/4	NS	NS
BED	4/8	1/4	3/4	4/8	1/4	3/4	2/4	2/2	0/2	1/4	0/1	1/1	1/4	0/1	1/1
$RESP$	4/8	4/4	0/4	4/8	4/4	0/4	2/4	2/2	0/2	2/4	2/2	0/2	0/4	NS	NS
$PHY.G$	2/8	2/2	0/2	6/8	6/6	0/6	2/4	2/2	0/2	0/4	NS	NS	0/4	NS	NS
$PHY.L$	4/8	4/4	0/4	4/8	4/4	0/4	2/4	2/2	0/2	0/4	NS	NS	0/4	NS	NS
$NUR.G$	2/8	2/2	0/2	3/8	3/3	0/3	0/4	NS	NS	2/4	2/2	0/2	1/4	1/1	0/1
$NUR.IC$	2/8	2/2	0/2	2/8	2/2	0/2	0/4	NS	NS	0/4	NS	NS	1/4	0/1	1/1
PHC	0/8	NS	NS	0/8	NS	NS	2/4	2/2	0/2	0/4	NS	NS	0/4	NS	NS
$D.COR$	2/8	2/2	0/2	2/8	2/2	0/2	4/4	4/4	0/4	4/4	4/4	0/4	0/4	NS	NS

Notes: a) Sig. Test: reveals in how many estimates each variable was significant; b) Signal: among the significant coefficients, it shows how many had a negative/positive sign; c) NS = not significant and EXC = excluded (reference); d) cross-hatched cells indicate the majority signal.
Source: Authors' own elaboration based on Tables 2 and 3.

(32) Regarding cases and deaths, the 6 unrestricted estimates (Table 2), and the minimum and maximum coefficients obtained via EBA (Table 3), were considered. As for the rates, the 2 unrestricted estimates and the 2 coefficients (minimum and maximum) from EBA were used.

The results from Table 4 assure, with *high confidence*[33], that there would be fewer cases of COVID-19 in cities with up to 50,000 inhabitants (PS_{10-} and PS_{10-50}) or in those that have more basic health units (UBS). Thus, outbreaks of the disease would be concentrated in places with greater circulation of employees ($EMP.F$), typically urban populations (URB) and those with a high rate of vehicular pollution ($DVEI$). In addition, there is *a good chance* that rainy cities ($RAIN$) have fewer cases, while the more unequal ($GINI$) and with greater economic activity (GDP_{pc}) would have more cases.

With *high confidence*, deaths are believed to be less frequent in young populations (AGE_{19-}), in small and medium-sized cities (PS_{10-}, PS_{10-50} and PS_{50-150}) and in those with more basic health units (UBS). However, vehicular pollution ($DVEI$) would tend to increase deaths. In addition, there is a *good chance* that deaths are higher in municipalities with higher inequality ($GINI$), with greater economic activity (GDP_{pc}), hot climate ($TEMP$) and with a high concentration of general physicians ($PHY.G$).

As for the rates, there is *high confidence* that urban locations (*URB*) and places with a hot climate (*TEMP*), with greater economic activity (GDP_{pc}) and movement of employees ($EMP.F$), less rainfall ($RAIN$) and a more severe history of related diseases ($D.COR$) would have a higher incidence of COVID-19. Mortality, on the other hand, would be lower among young people (AGE_{19-}) and in places with a higher educational level ($EDUC$). However, it would tend to increase in hot cities (*TEMP*) with greater economic activity (GDP_{pc}), and with a history of related diseases ($D.COR$). As for lethality, the problem would be smaller in small and medium-sized cities (PS_{10-50} and PS_{50-150}) and among young people (AGE_{19-}), but it could increase in locations with more rain ($RAIN$). Finally, there is a *good chance* that the incidence and mortality rates are higher in regions with an industrial profile (IND) and typically urban (URB), respectively.

Conclusion

This research aimed to verify which local characteristics could affect the main statistics associated with COVID-19 (i.e., number of cases and deaths and incidence, mortality and lethality rates) and which one of these could facilitate or hinder the fight against coronavirus. In order to identify these effects, regression models, with cross-section data and different estimators, were estimated for the municipalities of Minas Gerais, considering the accumulated cases/deaths from COVID-19 up until April 21, 2021. As there is no well-defined specification to explain this pandemic, the explanatory variables were also evaluated through Extreme Bounds Analysis (EBA). The results from this paper suggest that:

Cases/Deaths: small towns, with a greater number of basic health units (UBS) and young populations would have fewer COVID-19 cases and deaths. On the other hand, locations subject to agglomeration, that is, those that are typically urban, unequal, with greater economic activity and movement of employees, would have more difficulty in controlling the pandemic.

Although vehicular pollution has also proved harmful to cases and deaths, the possibility that this variable captures some kind of local concentration must be considered. After all, cities with more vehicles per km^2 would naturally be more crowded. Therefore, further studies are necessary to ensure that the problem is associated with pollution, and not with the concentration

(33) The term "*high confidence*" was only assigned to variables that were significant in 100% of the estimates, while "*good chance*" refers to those that were significant between 75% and 99% of the cases.

itself. As for the proportion of physicians per inhabitant, which was positively associated with deaths, this characteristic is believed to be typical of larger cities, which have a greater concentration of individuals[34]. Alternatively, it is possible that a significant part of local deaths is associated with the "frontline" professionals in the fight against the coronavirus. Thus, the larger the health team, the greater the number of deaths.

The results also suggest that hot climate locations would be more likely to have coronavirus cases and deaths, while rainy cities would be subject to fewer cases but more deaths. Due to the tropical climate in Minas Gerais, we assume that maintaining social distancing would be harder in the hottest municipalities in this state, with harmful effects on cases and deaths in these areas. The opposite is true for rainy places, that could hinder agglomerations, thus reducing cases. The positive effect of precipitation on deaths requires further analysis.

Incidence: This rate is higher in urban and hot cities with less rain, which concentrate income and workers and have a more severe history of related diseases. Therefore, the concentration of individuals with more comorbidities in places that would possibly make it difficult to maintain social distancing, would tend to inflate the incidence of this disease.

Mortality: As expected, coronavirus mortality was lower among the younger and more educated population. It is likely that individuals with more education would have access to better hospitals, medical treatments and would benefit from informational advantages about the disease. Similar to incidence, the results showed that mortality would also tend to increase in hot cities, with a higher level of economic activity and a history of related diseases.

Lethality: The models associated with this statistic had low explanatory power (compared to the others), indicating the need for further research. The results however did indicate that COVID-19 lethality would be lower among young people and in small to medium-sized cities (up to 150 thousand inhabitants). However, similar to the number of deaths, this rate could also increase in rainy places.

By identifying which municipal characteristics would harm the control of this pandemic, it is believed that the results of this research can help the adoption of specific and regional policies in the fight against COVID-19, including in terms of how strict they are. Our results allow us to propose an elementary regional policy, but quite accessible, which consists of the following steps:

> a) select one statistic on COVID-19 (*e.g.*: mortality); b) choose a confidence degree – see footnote 36 (*e.g.*: high confidence); c) use Table 4 to verify which local aspects must be considered (*e.g.*: Young People – AGE_{19-}, Education Level – $EDUC$, Hot places – *TEMP*, economic activity – GDP_{pc} and history of comorbidities – $D.COR$) and their impacts on the selected variable (*i.e.*: negative/positive signal can be considered favorable/harmful to this disease control); d) define the maximum and minimum ranges (MAR and MIR), according to each local aspect considered, by adding/decreasing their respective standard deviations to their averages – see these values in Table 1 (*e.g.*: the ranges of TEMP are $21.06+1.85=22.91^oC$ and $21.06-1.85=19.21^oC$); e) calculate an index for each municipality by adding 1 whenever a harmful variable is above MAR or a favorable one is below MIR, and -1, when a harmful variable is below MIR or a favorable one is above MAR, otherwise, maintain the value at zero

(34) The 20 cities with the highest concentration of physicians include Belo Horizonte, Montes Claros and Juiz de Fora. These 3 cities, together, represent almost 16.5% of the total population of the state of MG.

(*e.g.*: considering *TEMP* alone and the fictional areas "a", "b" and "c", in which the temperatures are 24 ^oC, 21 ^oC and 18 ^oC, their indexes would be 1, 0 and -1, respectively).

Since the places with a higher index would likely face more problems related to coronavirus, the hypothetical area "a" should apply more restrictive measures to control the pandemic than "c" and even than "b". For practical reasons, this procedure was tested for the largest municipalities from Minas Gerais (*i.e.*: those with more than 150 thousand inhabitants). Considering the aforementioned steps, we were able to create an index that was 0.63 correlated with the mortality rate from these areas and correctly suggests that Uberlândia, Governador Valadares, Ipatinga, Juiz de Fora, Uberaba and Contagem would have the highest mortality rates among the biggest cities. However, the proposed index requires greater precision and needs to be improved for future research.

Despite the potential contributions to the local control of coronavirus, we must emphasize that the use of secondary data, which focuses on the municipalities (and not on the patient) constitutes a limitation of this work. Furthermore, the cross-section data does not allow us to implement certain adjustments that would be available in a panel approach, such as intertemporal analyses and the proper treatment of some unobserved effects, which are constant over the time-period and difficult to measure (*e.g.*: culture and preferences). Thus, given the recent nature of this research agenda, we feel that new studies, with different time horizons, regional cuts and methodological approaches are welcome and could help to corroborate or refute some of the results obtained here.

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