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The influence of underlying conditions of countries on the COVID-19 lethality rate

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Abstract. The management of the COVID-19 pandemic not only depends on the stringency measures established by governments but more importantly on the underlying capacity of territories in economic, health and sanitary infrastructure. This study aims to identify how the underlying conditions of countries influence their COVID-19 lethality rate. To do so, a classification of countries is first developed by the k-means partitioning method, using COVID-19-related variables such as the lethality rate, the contagion growth rate and the number of days with respect to China. Based on the resulting groups of countries of the first stage, Tobit and Ordinary Least Squares regressions are estimated to determine the effect of the underlying characteristics of countries on their COVID-19 lethality rate. Risks factors which increase the lethality rate in countries are the contagion growth rate, the trade flow with China, the age composition of the population and, to a lesser extent, the population density. Factors that help reduce the lethality rate are the government effectiveness, the health infrastructure (hospital beds) and, to a lesser extent, the economic growth rate.

JEL classification: H50, O10

Key words: COVID-19, underlying conditions, clustering analysis, Tobit, OLS

1 Introduction

In January 2020, the outbreak of the novel coronavirus, known as COVID-19, was declared a Public Health Emergency of International Concern (PHEIC). Governments took action and established regulations to mitigate the negative effects of the pandemic related to the spread of the virus and therefore, the lethality. The measures ranged from travel to lockdown restrictions. However, the management of the pandemic not only depended on the stringency measures, but also on the pre-existing conditions at the territorial level. For instance, the health capacity of countries was an important factor to manage the pandemic. Countries with historically high spending in health would perform better with respect to countries with historically low spending. According to the World Health Organization (WHO 2022), the health expenditure per capita in high-income countries ($2,525.11) is 11 and 26 times higher than that of medium- low-income countries ($219.15) and low-income countries ($94.53). Accordingly, this study aims to determine how the underlying conditions of countries' health infrastructure, economic resources and demographic structures influenced their COVID-19 lethality rate.

The capacity and the quality of health and care services affect the impact of a pandemic disease. The virus can have a moderate effect on morbidity in countries with an effective organization of health systems and at the same time can be devastating in countries where health systems are deficient (WHO 2009). In the context of the COVID-19 pandemic, existing studies display mixed results about the effect of health expenditure on the lethality rate. Jeanne et al. (2023) indicated that the number of doctors corresponds with a higher number of infected people and deaths. This result is explained by the notion that more developed countries were affected more rapidly and the demand for health escalated in such a way that even the positive conditions of their health systems were insufficient. On the other hand, Perone (2021), despite finding that higher health expenditure increases the lethality rate, they concluded that the health system performance reduced the case fatality rate in Italy.

One of our research questions is: what is the effect of pre-existing health capacity and infrastructure and other underlying socioeconomic characteristics on the COVID-19 lethality rate of countries? Answers to this question are crucial for public policy actions because they give valuable information about critical underlying factors that increase the lethality rate in countries. These results create knowledge, especially for developing countries with limited economic resources, as to where to allocate resources to face shocks such as the COVID-19 pandemic.

To determine such an effect, it is important to consider that the role of underlying characteristics to face the pandemic will depend on the degree of the COVID-19 affectation of countries, which in turn depends on the time the pandemic was declared in each country. Therefore, a specific objective of this study is to determine groups of countries with similar characteristics related to the COVID-19 pandemic. Using clustering techniques, countries are first classified in function of COVID-19 variables such as the lethality rate, the contagion growth and the number of days that elapsed until the country registered the first case with respect to China. It allows the researchers to determine comparable groups of countries with similar COVID-19 measures. For this reason, this study provides an econometric analysis that shows comparable results across countries. To the best of our knowledge, it is the first time that comparable countries in terms of COVID-19 affectations have been analyzed. Previous analyses have built clusters of countries considering socioeconomic and demographic variables (Perone 2021, Guevara-Rosero 2022), which distorts the real COVID-19 risk. The resulting groups follow a geographical distribution in terms of velocity and affectation of the COVID-19 pandemic. We used COVID-19 information corresponding to the period of 360 days from the first registered COVID-19 confirmed case to determine the clusters. Tobit models or Multiple linear regression models were estimated on the identified clusters according to whether the dependent variable is limited or not to estimate the effects of underlying characteristics on the lethality rate associated with COVID-19.

The article follows a logical organizational structure. Section 2 describes the existing literature on the incidence of underlying conditions of countries on the dynamics of pandemics. Section 3 displays worldwide statistics about the COVID-19 pandemic. Section 4 describes the data and the methodology. Section 5 discusses the results and Section 6 provides a conclusion.

2 Literature review

There are two sets of factors that can determine the number of deaths from COVID-19. The first set of factors is related to the pandemic itself, that is, aspects that arise from the development of the disease such as the spread of the disease and government measures to prevent further spread and, in turn, deaths. Those measures ranged from travel restrictions, closure of businesses to total lockdowns. The second set of factors are related to the underlying characteristics of countries such as demographics, economics, health capacity and governmental effectiveness.

Regarding the variables related to the pandemic itself, the Pan American Health Organization (PAHO 2022) mentioned that the transmission rate of the virus identifies the severity of the disease and its influence on the lethality of the population. Several studies have considered this factor to explain the lethality rate. Peralta et al. (2020) concludes that a high rate of contagion by COVID-19 implies that many infected people simultaneously cause the collapse of the health system and make it difficult for seriously ill cases to access to it. Saturation of the health system was analyzed by Perone (2021) through the ratio prevalence/ ordinary beds, which explained 86% of the case fatality rate in Italy. Another factor associated with the pandemic was the stringency measures implemented by governments to curb the transmission of the coronavirus SARS-CoV-2 and reduce mortality. Chaudhry et al. (2020) and Chisadza et al. (2021) highlight that less stringent measures increase the number of deaths from COVID-19. Jinjarak et al. (2020) concludes that strict policies to curb the spread of the virus were associated with lower mortality growth rates. Sorci et al. (2020) deduces that a higher case fatality rate is reached for intermediate values of the stringency index.

Pertaining to the underlying characteristics of countries, an important characteristic that influences their lethality level is the age composition of the population. This is due to the risk of hospitalization or death from COVID-19 increasing for people older than 60 years old by reason of the existence of more factors that make them prone to severe illness (Centers for Disease Control and Prevention 2021). For Promislow, Anderson (2020) and King et al. (2020), the health risks related to the virus increase with age. Regarding the fatality rate, Rubino et al. (2020) performs a comparative analysis for the first weeks of the pandemic and shows the Italian case fatality rate is 10.6% due to the fact it is a country with a large elderly population. The average age of death from COVID-19 was 81 years in Italy.

Generally, residing in a densely populated area is a contagion risk factor for SARS-CoV-2 (de Lusignan et al. 2020) as the physical proximity of infected people in urban centers facilitates the transmission (Waltenburg et al. 2020, Rocklöv, Sjödin 2021). Likewise, Ilardi et al. (2021) identifies a significant positive linear relationship between population density and case fatality rate. Some studies highlight a negative or a non-significant relationship between population density and deaths from COVID-19, indicating that population density is not a risk factor for lethality. Places with higher density are more likely to have considerable resources to respond to the pandemic and reduce the number of deaths (Fang, Wahba 2020).

The medical equipment and staff are also factors that explain the number of deaths from COVID-19 (Ilardi et al. 2021). A low number of hospital beds causes the collapse of the health system and therefore increases deaths (Acosta 2020, Park, Cha 2020). Chaudhry et al. (2020) and Asfahan et al. (2020) obtain that the number of doctors per 10,000 inhabitants has an inverse relationship with the fatality rate. Given this, Khan et al. (2020) suggests that building an effective multidimensional healthcare capacity is the means to mitigate deaths from future cases. Although a large number of doctors assumingly decreases the lethality rate, Jeanne et al. (2023) demonstrate a larger number of doctors was associated with a higher number of infected cases and deaths at the beginning of the pandemic. This indicates that in the case of European countries, the positive healthcare system was not sufficient to face the pandemic waves.

Regarding the economic level of countries, measures such as GDP or health spending are used in the literature. Asfahan et al. (2020) used a univariate regression to find that GDP per capita is negatively correlated with the case fatality rate from COVID-19. In the study by Chaudhry et al. (2020), countries with a higher GDP per capita recorded a higher number of deaths per million inhabitants. This reflects more widespread testing in those countries and greater transparency in reporting, as well as increased accessibility to air travel and international vacations in wealthier countries. It is worth mentioning that, during the first months, the burden of the pandemic was mainly focused on high and middle-income countries in Asia, Europe and North America (Chisadza et al. 2021) as they were most connected to China (Jeanne et al. 2023). In other words, countries with better conditions suffer a greater impact from the virus (Zevallos, Lescano 2020). Although the pandemic quickly reached countries with a high economic level, the consequences were more severe for less developed countries. The report presented by the Imperial University of London on the evaluation of the impacts of the pandemic on disadvantaged and vulnerable populations highlighted that the risk of death from

COVID-19 increases with poverty (Winskill et al. 2020). As for health spending, Khan et al. (2020) conclude that this variable did not reach statistical significance but was positively associated with fatal cases at the global level. For the Italian case, Perone (2021) deduced that the average public health expenditure per capita increases the death rate in Italian regions. While unexpected, the author explains that this variable is only one dimension of health system performance that globally was significant and negative for the death rate.

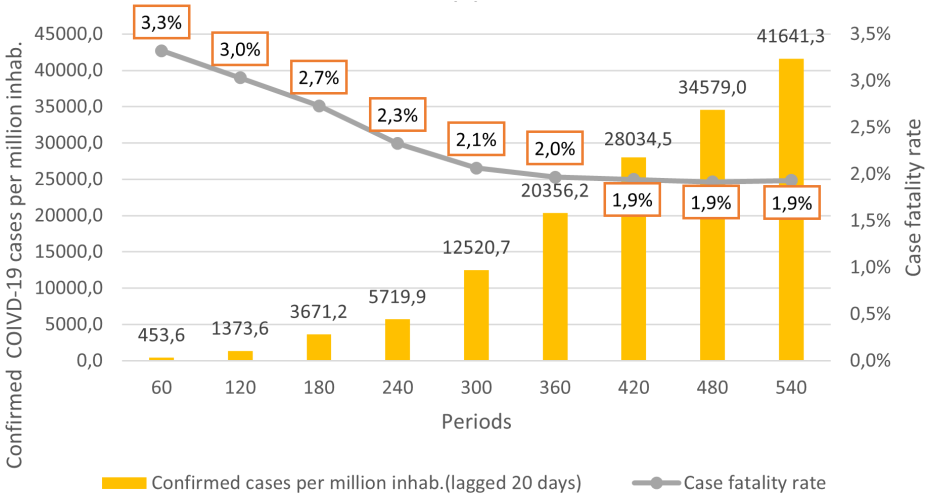
Trade flows and human capital mobility between countries are vital to understand the pandemic. Nations are strongly interconnected as a result of globalization, raising the potential of the pandemic spread (Opertti, Mesquita-Moreira 2020, Spyrou et al. 2016). Globalization contributed to the importation of cases (Abellán et al. 2020). However, just as global value chains were the main transmission channel for the first countries infected by the disease, they were also the main transmission channel for the effects of COVID-19 on world trade (Comisión Económica para América Latina y el Caribe; Naciones Unidas 2020).

Aside from inadequate health infrastructure, poor governance significantly complicates outbreak preparedness and response. It limits the state's ability to act effectively, which has devastating consequences for loss of human life, economic destabilization and social chaos (GPMB 2019). Liang et al. (2020) demonstrates that for a short-term crisis like the COVID-19 outbreak, government effectiveness is critical to respond efficiently and ensure effective policies that reduce case fatality rates (Serikbayeva et al. 2021). By contrast, Toshkov et al. (2021) conclude, based on robust models, that highly perceived capacity for government effectiveness provides false confidence that results in higher infections and deaths.

3 Pandemic Statistics

There are examples among positive COVID-19 cases in which the illness follows its course and ends with recovery, but there are other cases which get worse, requiring hospitalization, potentially resulting in death. A strategy to contain the spread of COVID-19 that had been used by many governments was the lockdown. This approach restricted face-to-face contacts among people. Once stringency measures were in place, people reduced contact with others (five days are considered in this study). Once a person became infected, the illness lasted approximately 15 days, but if it worsened, it could last longer until death (Javed 2020) (20 days are considered in this study). On this basis, the statistics illustrated in Figure 1 highlight the number of COVID-19 infections per million inhabitants at day t-20 and the case fatality rate at day t. The graph is specified by periods, namely, 60, 120, 180, 240, 300, 360, 420, 480 and 540 days from the first registered COVID-19 case in each country. The numbers are cumulative. On average, the worldwide cumulative fatality rate at the 60th day was 3.3% and decreased with time until reaching 2% at the 360th day. From this period to 540 days, the fatality rate had been stable at 1.9%. By contrast, the cumulative number of infection cases per million inhabitants had been increasing from 453.6 confirmed cases at the beginning of the pandemic to 41,641 infected people per million inhabitants at 540 days.

These COVID-19 statistics vary between countries which were rapidly infected (less than 75 days with respect to the first COVID-19 case registered in China) and slowly infected countries (more than 75 days with respect to the first COVID-19 case registered in China). The period of 75 days is the average number of days that elapsed between the first COVID-19 case in China and the first registered COVID-19 case in other countries. 146 countries registered the first COVID-19 case before the average of 75 days (hereafter, named as rapidly infected countries) and 67 countries that registered the first COVID-19 case after the average of 75 days (hereafter, named as slowly infected countries). Figure 2 shows a significant difference of COVID-19 confirmed cases per million inhabitants between rapidly and slowly infected countries in all periods. At the beginning of the COVID-19 pandemic (60-day period), the number of COVID-19 cases in rapidly infected countries was on average 535 per million inhabitants meanwhile it was 280 confirmed cases per million inhabitants in slowly infected countries. Rapidly infected countries



Source: European Center for Disease Prevention and Control (ECDC)
Notes: Own elaboration (March 2023)

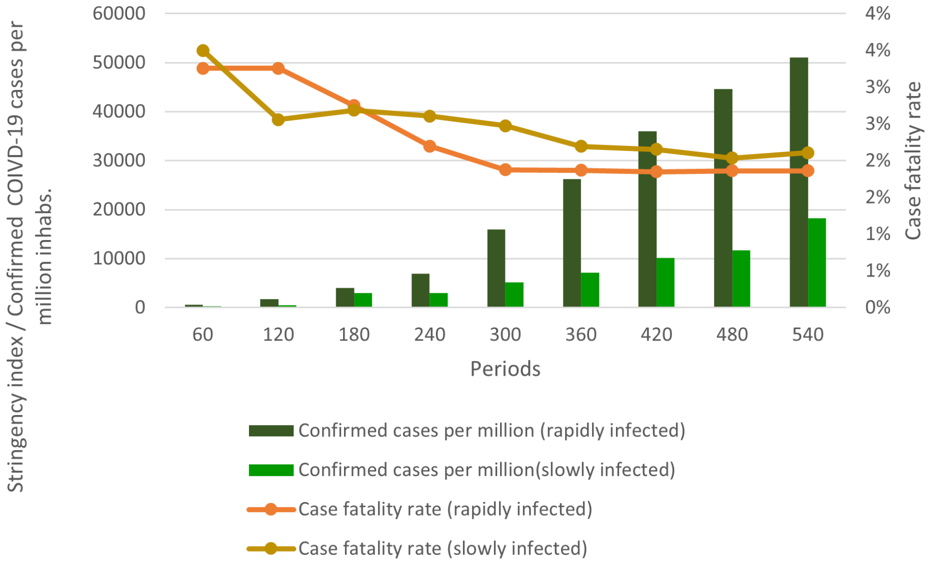
Figure 1: COVID-19 fatality rate, confirmed cases and the stringency index by periods

with the highest value of cumulative number of COVID-19 cases per million inhabitants at the 60th day were Vatican, San Marino, Andorra, Luxembourg and Iceland. Those with the lowest value for rapidly infected countries were Russia, Cambodia, Sri Lanka, India and Nepal. Slowly infected countries with the highest value of cumulative number of COVID-19 cases per million inhabitants at the 60th day were the Falkland Islands, Isle of Man, Montserrat, Bermuda and Sao Tome and Principe and those with the lowest value for slowly infected countries were Nicaragua, Uganda, Burundi, Papua New Guinea and Angola. The cumulative number of COVID-19 cases per million inhabitants at the 540th day was 51,097 in rapidly infected countries whereas it was only 18,241 in slowly infected countries. Rapidly infected countries with the highest value of cumulative number of COVID-19 cases per million inhabitants at the 540th day were Seychelles, Andorra, Czechia, Bahrain, Gibraltar and San Marino and those with the lowest number for rapidly infected countries were Macao, Vietnam, New Zealand and the Democratic Republic of Congo. Slowly infected countries with the highest value of cumulative number of COVID-19 cases per million inhabitants at the 540th day were Montenegro, British Virgin Islands, Isle of Man, the Bonaire, Sint Eustatius and Saba islands (BES) and the Turks and Caicos Islands. Those with the lowest number were Tanzania, Niger, Yemen, Chad and New Caledonia. However, slowly infected countries recorded a higher lethality rate than rapidly infected countries, except for the period of 120 days. Therefore, countries with fewer days of preparation had a lower case-fatality rate than those with more time to face the health crisis This can be explained by a higher level of development of rapidly infected countries with respect to slowly infected countries. A decreasing trend in the fatality rate from COVID-19 after 180 days of the pandemic is observed in both cases.

3.1 Pandemic statistics per period

Figure 3 shows the number of COVID-19 confirmed cases by periods. Countries that became infected later, with respect to China, report a lower number of COVID-19 cases for all periods of time, except for the 61–180-day period. The number of COVID-19 cases in rapidly infected countries increased emphatically from the periods of 61–180 days to 181-360 days and remains around 25000 cases per million inhabitants for the 361-540 day period. Whereas the number of COVID-19 cases per million inhabitants in slowly infected countries increased over time.

The case-fatality rate shown in Figure 4 indicates that the lethality rate starts at high levels (3.3%) and decreases to 1.8% after one and a half years since the beginning of



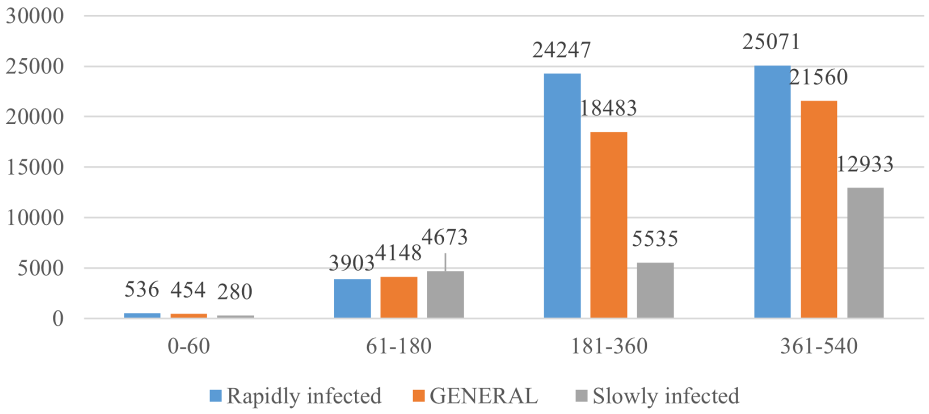
Source: European Center for Disease Prevention and Control (ECDC)
Notes: Own elaboration (March 2023)

Figure 2: COVID-19 fatality rate, confirmed cases and the stringency index by periods and types of countries

the pandemic, recording a reduction of 45%. This reduction of the lethality rate can be explained by the rollout of vaccines in 2021. Although the COVID-19 pandemic arrived later to certain countries (slowly infected countries), they recorded a higher case fatality rate (3.5%) during all periods of the pandemic except for the period of 61 to 180 days.,

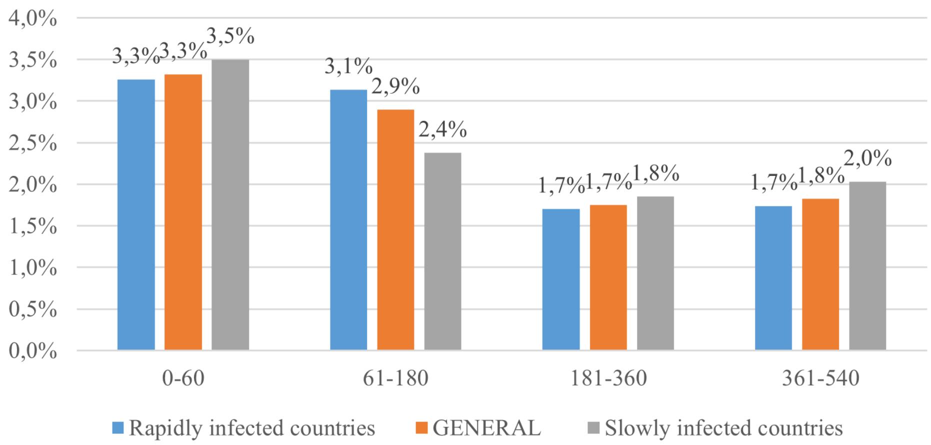
Table 1 displays the average number of COVID-19 confirmed cases per million inhabitants, the growth rate of contagion, the fatality rate and the number of days with respect to China for each continent for different periods. The first two variables are analyzed by periods (0 to 60 days; 61 to 180 days;181 days to 360 days;361 days to 540 days), while accumulated data is presented for the variables case fatality rate and days with respect to China.

The regions that registered the first COVID-19 confirmed case very rapidly with respect to China were North America (50 days), Asia (54 days) and Europe (57 days). They had less than two months to prepare for the pandemic. Africa and Latin America were the last regions to register the first COVID-19 case (78 days and 74 days, respec-



Source: European Center for Disease Prevention and Control (ECDC)
Notes: Own elaboration (March 2023)

Figure 3: COVID-19 cases per million inhabitants per periods



Source: European Center for Disease Prevention and Control (ECDC)
Notes: Own elaboration (March 2023)

Figure 4: Case fatality rate by COVID-19 per periods

tively)[1]. Regarding the number of confirmed cases per million inhabitants, Europe was the region that registered the highest number of confirmed cases for the 0–60-day period, roughly four times that of North America, the region with the second most infections. The number of infected people grew drastically between periods in all regions. The average growth rate between all periods was 341.8% for Africa, 441.45% for LAC, 790.6% for Oceania, 459.4% for Asia, 518.7% for Europe and 337.4% for North America. However, the growth rate of the number of infected people between the 180–360-day period and 360–540-day period is lower than the growth rate between previous periods. The growth rate between the last periods was 153.2% for Africa, 94.4% for LAC, 199% for Oceania, 69.9% for Asia, -33.6% for Europe and 15.56% for North America[2].

Regarding the average of daily growth rates of confirmed cases within periods (column 2), Europe recorded the highest daily growth rate in the first period, followed by Asia. Although the SARS-CoV-2 virus appeared to/in Africa last, this region recorded a higher daily growth rate than Latin America. The daily growth rate of infected people decreased across periods for all regions. Although the number of confirmed cases grew as time progressed, the contagion rate decreased. Most regions (except Oceania) registered contagion rates greater than 10% for the period from 0 to 60 days. The figure declined so that the contagion growth rate did not exceed 1.05% for the period of 361 to 540 days.

The most affected region for fatality rate in most periods is Latin America and the Caribbean (LAC). During the first two months, the region registered the highest fatality rate (5.40%) despite the contagion level and growth rate not being the highest. The regions of Europe and North America registered the highest fatality rate on average for the 180-day period. However, by 360 days and 540 days, Africa recorded the highest lethality rate despite the low rate of spread. This could be explained by their development level (Winskill et al. 2020, Sanmartín-Durango et al. 2019).

4 Data and methodology

The European Center for Disease Prevention and Control (ECDC) and the Blavatnik School of Government in Oxford are the main data sources used in this study. Data regarding the underlying conditions of countries in terms of health infrastructure, demographics and economics were sourced from the World Bank (WB), the World Health Organization (WHO) and the Global Innovation Index (GII). Across-sectional database was obtained with this information. Three types of variables were considered: i. COVID-19

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[1] It is worth noting that Latin America and Africa are regions where testing was not enough so there could be an under-registration of cases.

[2] Growth rate of the number of infected people between periods is calculated as $\frac{\text{final value}}{\text{initial value}} - 1$.

Table 1: COVID-19 statistics by continent

Continent	COVID-19 confirmed cases per million	Daily growth rate of confirmed cases	Case fatality rate	Days respect to China
	0-60 days		60 days	
Africa	155.78	13.34%	3.28%	77.56
Latin America & Caribbean (LAC)	467.34	11.94%	5.40%	74.07
Oceania	115.97	8.55%	0.29%	66
Asia	351.18	15.91%	2.13%	54.33
Europa	2165.73	17.99%	4.09%	56.96
North America	599.53	12.6%	2.68%	50
	0-180 days		180 days	
Africa	1192.03	2.29%	2.26%	77.56
Latin America & Caribbean	5431.44	2.40%	2.47%	74.07
Oceania	529.81	1.46%	1.62%	66
Asia	4327.32	2.30%	2.15%	54.33
Europa	2949.19	1.09%	4.20%	56.96
North America	3782.37	1.93%	4.22%	50
	0-360 days		360 days	
Africa	3659.7	0.67%	2.13%	77.56
Latin America & Caribbean	14545.09	0.86%	2.13%	74.07
Oceania	10627.81	0.74%	1.53%	66
Asia	11940.44	0.86%	1.80%	54.33
Europa	48761.99	1.41%	1.90%	56.96
North America	21397.86	0.84%	1.50%	50
	0-540 days		540 days	
Africa	9265.57	0.43%	2.18%	77.56
Latin America & Caribbean	28269.13	0.69%	2.16%	74.07
Oceania	22208.66	1.04%	1.24%	66
Asia	20291.41	0.77%	1.92%	54.33
Europa	32399.34	0.29%	1.74%	56.96
North America	24727.97	0.72%	1.17%	50

Notes: Elaborated by the authors

related variables such as the contagion growth rate and the stringency index; ii. structural variables such as the Government Effectiveness Index, GDP per capita growth, health expenditure as a percentage of GDP; iii. conjunctural variables such as the population aged more than 65 years, population density, hospital beds, doctors and trade flows with China. An average over the last five available years is used for the former. For the latter, the data of the last available year is used. We considered the day at which the first COVID-19 confirmed case was registered in each country by reason that the SARS-CoV-2 virus arrived in each country at different times. Therefore, the cross-country analysis is comparable. The database consists of 211 countries for the clustering analysis and 128 countries for the econometric analysis due to the limited availability of some variables for some countries.

4.1 Method

This study was conducted in two phases. In the first phase, clusters of countries based on COVID-19 variables were determined. The clusters of countries with similar characteristics related to the COVID-19 pandemic were used for estimations in the second phase. This allowed determining the effect of underlying socioeconomic characteristics on countries with similar affectations derived from the pandemic. Tobit and Ordinary Least Squares regressions were estimated. The choice of the Tobit models corresponded to the existence of a limited dependent variable (VDL). The lethality rate in many countries was zero at the beginning of the COVID-19 pandemic. Therefore, the dependent variable was limited since it maintained the zero-limit, and some observations hit this limit. The censored sample is representative of our group of countries and since many values record zero, the mean tends to be low. The OLS selection is derived from the non-existent zero lethality rates cases in some groups of countries.

4.1.1 First phase: Clustering analysis

To determine the clusters of countries in relation to their evolution in terms of the pandemic, the k-means method clustering technique was employed. The k-means method was developed by MacQueen (1967) and Lloyd (1982). It partitions the database of n objects in k clusters, such that the sum of square distances (see equation 1) between the observation, p, and the centroid of the cluster, c_i, is minimized.

$$E = \sum_{i=1}^{k} \sum_{p \in C_i} (p - c_1)^2 \tag{1}$$

The k-means algorithm first partitions objects into k nonempty subsets. It then calculates the clusters' centroids (mean point) of the current partitioning. Third, it assigns each object to the cluster with the nearest centroid. And last, it stops when the assignment is stable so that clusters do not change (Han et al. 2022, p. 451).

We used a set of 211 countries to determine the clusters. The data for 360 days was then applied for the variables: lethality rate, contagion growth rate and number of days with respect to China. The number of clusters was chosen based on the Elbow method that displays the intra-class variance according to the number of clusters. The optimal number of clusters is identified given a threshold at which the intra-class variance does not significantly decrease. The study employed the Elbow method, which indicated that the intra-class variance did not significantly decrease after three clusters.

4.1.2 Second phase: Estimation models

Models were estimated for each cluster (group A and group B[3]) and each period (60 days, 180 days, 360 days and 540 days). Tobit models and OLS models were estimated. The Tobit Model was used when the dependent variable, y, was zero for a non-trivial fraction of the population and when the OLS predictions were negative. This model had an approximately continuous distribution through positive values (Gujarati, Porter 2010, Woolridge 2010). The Tobit model for corner solution responses is estimated by Maximum Likelihood Method. This model involves non-negative predicted values that have sensible partial effects on the range of independent variables. The observed response, y, is expressed in terms of an underlying latent variable as shown in equation (2).

$$\begin{aligned} y^* &= \beta_0 + \mathbf{X}\boldsymbol{\beta} + u \\ y &= \max(0, y^*) \\ u|x &\sim N(0, \sigma^2) \end{aligned} \tag{2}$$

where y^* satisfies the assumptions of the classic linear model and has a normal and homoscedastic distribution with a linear conditional mean. In our case, y_i is the lethality rate, which is calculated as the number of deaths from the disease divided by the total number of cases in a specific period (Moreno et al. 2020). This measure represents the severity of which COVID-19 affected the population. X is a vector of explanatory variables, which are described in Table 2.

A multiple linear regression model was used for groups of countries that did not have a limited dependent variable. The specification is

$$Y_i = \beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + \ldots + \beta_p X_{ip} + \epsilon_i \tag{3}$$

where Y_i is the COVID-19 lethality rate as in the Tobit model, ϵ_i is the random error term.

Descriptive statistics of variables concerning the underlying conditions of countries and COVID-19 related variables are displayed in Table 3. According to these statistics,

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[3] Group C has insufficient observations (7) to run a model.

Table 2: Description of independent variables and expected results

Independent variable	Description	Exp. sign	Supporting literature
Contagion growth rate at t-20 days	Average of the daily growth rates at a certain period (60 days, 180 days, 360 days and 540 days). The daily growth rate is calculated as $\frac{\text{cases}_i - \text{cases}_{i-1}}{\text{cases}_{i-1}}$ and lagged by 25 days.	(+)	Peralta et al. (2020)
Stringency index at t-25 days	A 0-100 scale index (100 = strictest), based on nine response indicators including school closures, workplace closures, and travel bans. This variable is lagged in 25 days.	(-)	Jinjarak et al. (2020), Chisadza et al. (2021)
Government effectiveness index	The index reflects the population perception of the quality of public services, the quality of the civil service, the degree of governmental independence from political pressures, the quality of policy formulation and implementation, and the credibility of the government's commitment to such policies. This index is averaged for the last five available years.	(-)	Liang et al. (2020), Toshkov et al. (2021)
Population density	Calculated by dividing the total population of a country i by the surface in square kilometers, for the last available year	(ambiguous)	Chaudhry et al. (2020)
Percentage of the population older than 65 years old	Percentage of the population older than 65 years, for the last available year	(-)	de Lusignan et al. (2020)
GDP growth rate	Average of the GDP growth rate for the last 5 years	(-)	Asfahan et al. (2020), Chaudhry et al. (2020)
Health spending as a percentage of GDP	Average percentage of GDP allocated to Health Expenditure for the last 5 years	(-) / no significant	Asfahan et al. (2020), Khan et al. (2020)
Exports from China	Exports between China and country i in thousands of dollars for the last available year, in logarithm.	(+)	Abellán et al. (2020)
Hospital beds per 10000 inhabitants	Number of hospital beds per 10,000 inhabitants, for the last available year.	(-)	Park, Cha (2020), Acosta (2020)
Number of doctors per 10000 inhabitants	Number of doctors per 10,000 inhabitants, for the last available year	(-)	Chaudhry et al. (2020), Asfahan et al. (2020)

the contagion growth rate decreases over time. During the first period (60 days), the daily average contagion growth rate is 18%. It decreases to 2.6% during the last period (540 days). The high contagion rate at the beginning was caused by the ignorance about the forms of contagion and the dynamics of the virus spread. For instance, at the beginning, recommendations suggest the use of face masks only for ill people. The average stringency index reduced over time. The average of the government effectiveness is 47.45 points out of a maximum of 100 points. There is a high dispersion of this variable, indicating high heterogeneity between countries. the standard deviation (1507.008) of population density is greater than the mean (332.013). The average percentage of population older than 65 years old is 9.20%. The average number of doctors per 10,000 inhabitants is 21.19 and the average number of hospital beds per 10,000 inhabitants is 27.6. There is high dispersion in these measures, reflecting high disparity across countries. The average percentage of the population that has access to drinking water is 87.53%. On average, the annual GDP growth rate for the last five years was 2.868%. However, the dispersion is high since it ranges from -10.793% to 10.076%. The percentage of GDP allocated to health spending is 2.868%, and the standard deviation is low. China's exports to each country are on average 1.2 billion dollars.

Table 3: Descriptive statistics independent variables

Variable	Obs.	Min.	Max.	Std. Dev.	Mean
Lagged contagion growth rate at 60 days $(t-20)$	215	0	0.65	0.104	0.18
Lagged contagion growth rate at 180 days $(t-20)$	214	0	0.1879	0.028	0.065
Lagged contagion growth rate at 360 days $(t-20)$	211	0	0.091	0.013	0.036
Lagged contagion growth rate at 540 days $(t-20)$	205	0.001	0.061	0.0076	0.026
Lagged stringency index at 60 days $(t-25)$	181	0	100	25.87	70.91
Lagged stringency index at 180 days $(t-25)$	180	11.11	94.44	19.44	57.42
Stringency index at 360 days $(t-25)$	179	2.78	90.74	19.99	57.03
Stringency index at 540 days $(t-25)$	177	2.78	93.52	17.6	51.46
Government effectiveness	141	0.00	99.583	23.356	47.447
Percentage of population older than 65 years old	182	1.157	28.002	6.496	9.1965
Population density	196	0.137	19196	1507.008	332.013
GDP growth (average of the 5 last years)	190	-10.793	10.076	2.731	2.868
Current health expenditure (average of the 5 last years)	177	1.725	17.41	2.563	6.447
Hospital beds per 10000 inhabitants	172	1	129.8	22.875	27.6
Number of doctors per 10000 inhabitants	161	0.23	82.95	18.912	21.193
Logarithm of Chinese exports to each country i in thousands of dollars for the last available year	211	6.03	418584249.5	3.96e+07	1.20e+07

Source: Data from the World Bank, World Health Organization, Global Innovation Index, the Blavatnik School of Government in Oxford and the European Center for Disease Prevention and Control.
Notes: Own elaboration

The assumptions of the classic Gauss model were tested for robustness and valid interpretation of the estimations (Gujarati, Porter 2010, p. 61), and their results are shown in Table 4. According to the homoscedasticity test (White), the null hypothesis, that variance of errors is constant, was not rejected for all models. According to the Jarque-Bera test, all models presented normal residuals, except for the model of the 180-day period. For such a model, the normality was corrected by eliminating outlier observations (8 observations were eliminated). The Ramsey test results indicate there is no problem of omitted variable bias for most of the models, except for the models at 180 days. However, since the rest of the models have the same variables, the omitted variable bias in the 180-day models does not constitute a problem. According to the VIF (which is lower than 10), there is no multicollinearity in any model.

5 Results

5.1 Cluster analysis

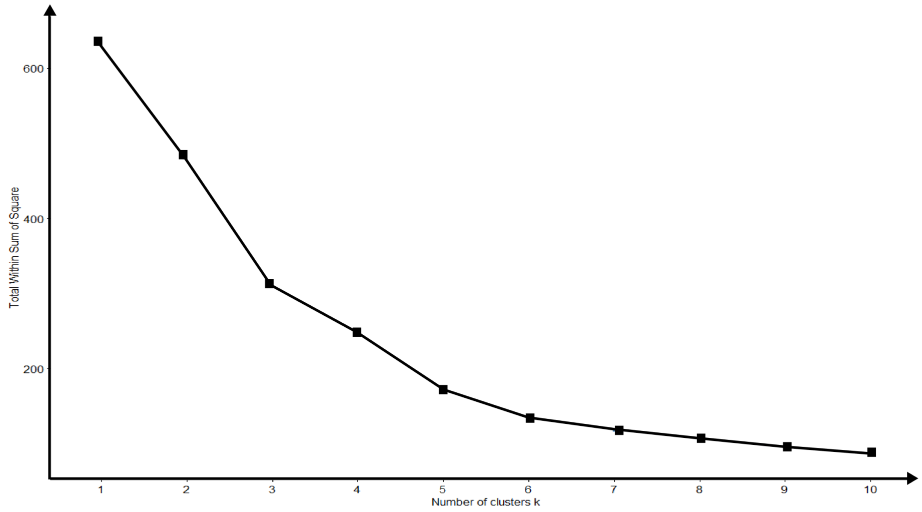
COVID-19 related variables were used for the clustering analysis of countries, namely the COVID-19 lethality rate, the contagion growth rate at t-20 and the number of days that elapsed before the first confirmed case with respect to China. The clustering analysis was based on the 360-day period (360 days after the first confirmed case in each country). The Elbow method represented in Figure 5 indicates the total within sum of square as a function of the number of clusters. The optimal number of clusters is three because this is when the total within sum of squares begins to level off. This is the number of clusters that allowed for similar observations within clusters and different observations between clusters.

Figure 6 and Table 3 displays the resulting clusters using the k-means partition method for the 360-day period. This indicates the standardized mean for each variable by group. Clusters are distributed geographically (shown in Figure 7).

From these results, three clusters were obtained:

Table 4: Model validation

MODEL	VIF	White Test	Normality Test	Ramsey test	Method
GROUP A					
60 days	2.35	0.2557	0.6116	0.5208	TOBIT
180 days	2.37 → 2.32	0.4210 → 0.2675	0.0294 → 0.0504	0.0183	TOBIT
360 days	2.34	0.4417	0.2696	0.0640	TOBIT
540 days	2.37	0.4596	0.2399	0.0616	TOBIT
GROUP B					
60 days	2.40	0.4334	0.3136	0.0634	TOBIT
180 days	2.28	0.4334	0.3874	0.0225	TOBIT
360 days	2.26	0.4334	0.1343	0.1008	OLS
540 days	2.21	0.4334	0.5524	0.2359	OLS
GENERAL MODEL					
60 days	2.26	0.0716	0.3370	0.0503	TOBIT
180 days	2.30 → 2.28	0.5684 → 0.3225	0.0033 → 0.1160	0.0000	TOBIT
360 days	2.31	0.8641	0.2780	0.5819	TOBIT
540 days	2.25	0.9169	0.2987	0.4612	TOBIT



Notes: Own elaboration

Figure 5: Optimal cluster number using the Elbow Method

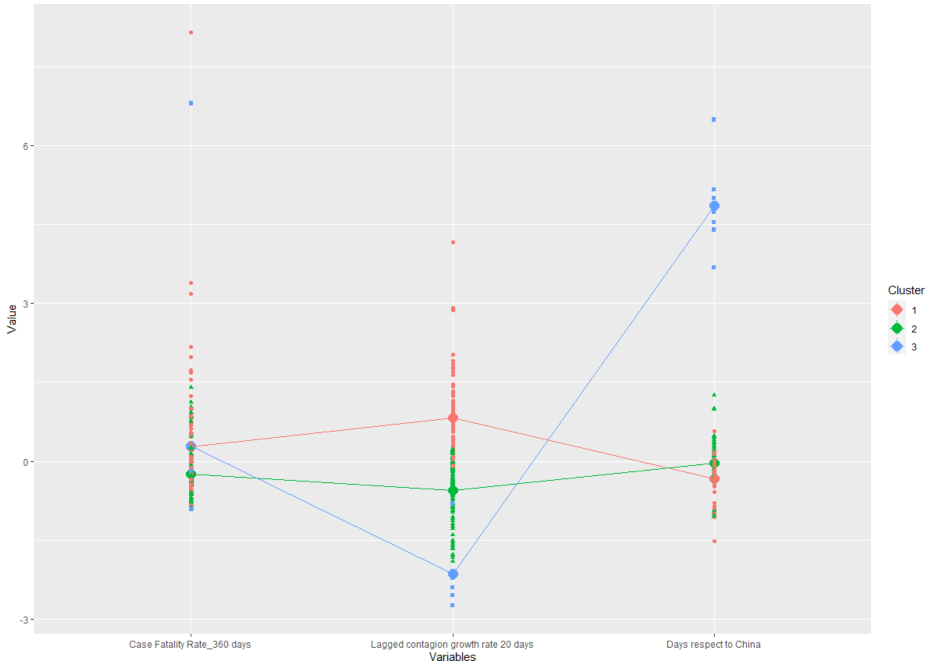
CLUSTER A: Rapidly infected countries with high lethality rate and high contagion growth rate

CLUSTER B: Less rapidly infected countries with very low lethality rate and moderate contagion growth rate

CLUSTER C: Slowly infected countries with very high lethality rate and very low contagion growth rate

Countries of Cluster A are mainly located in Europe, Asia and the Americas, except for the Caribbean. Countries of Cluster B are mainly located in Africa, Oceania and the Caribbean. Countries of Cluster C are mainly distant islands.

Cluster A encompasses 93 countries (see Appendix A), distributed around the world: Europe (36), Asia (24), Africa (15), North America (3, including Mexico), South America (9), Central America and the Caribbean (6). On average, these countries registered COVID-19 confirmed cases 58 days after the first case in China. They had less than two months to prepare themselves to face the pandemic. They register the highest contagion growth rate (4.02%) for this reason. The rapid arrival of the pandemic to these countries can be explained by their proximity to China in geographical and trade



Notes: Own elaborations

Figure 6: Graphic description of characteristics of clusters for 360 days

Table 5: Standardized means of COVID-19 variables by clusters

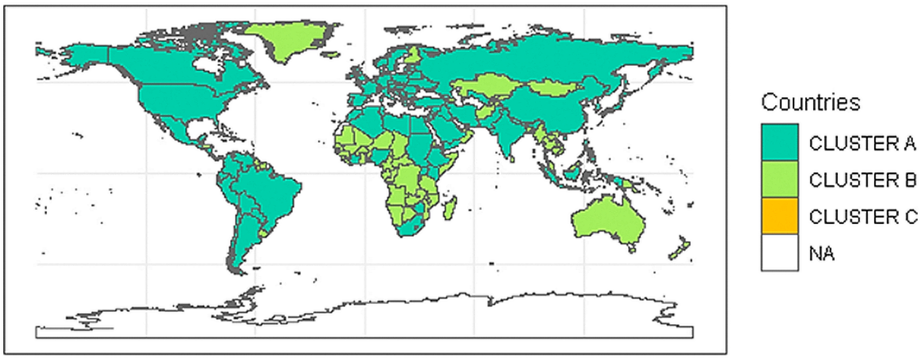
Cluster	Case Fatality Rate	Lagged contagion growth rate	Days with respect to China
Cluster 1 (A)	0,27	0,82	-0,33
Cluster 2 (B)	-0,25	-0,55	-0,03
Cluster 3 (C)	0,29	-2,14	4,85

terms. Trade openness and human mobility were important drivers of the COVID-19 worldwide spread. As a result of globalization, all nations are strongly interconnected, which worsened the spread of COVID-19 (Opertti, Mesquita-Moreira 2020, Spyrou et al. 2016). Another characteristic of countries in cluster A is the high lethality rate (2.5%). Cluster A encompasses countries from all continents. This indicates that COVID-19 dynamics tend to be similar across countries after a year following the first confirmed case in each country. Different dynamics are observed across countries when analyzing only a month after the first confirmed case was registered in each country, as revealed by Guevara-Rosero (2022).

Cluster B encompasses 111 countries (see Appendix A) from Africa (39), South America (4: Falkland Islands, Guyana, Suriname & Uruguay), Central America and the Caribbean (22), Asia (22), Europe (13), North America (2) and Oceania (6). On average, the SARS-CoV-2 virus arrived 71 days after the first registered case in China. The average lethality rate was 1.04%, whereas the contagion growth rate was 2.89%. Most countries in this group are not very interconnected with China in terms of human mobility or trade.

Cluster C encompasses only seven islands: in Oceania (Micronesia, Marshall Islands, Solomon Islands, Vanuatu, Wallis and Futuna & Samoa) and in Africa (Saint Helena). Due to their distant geographical position and low accessibility, these were the last countries that registered COVID-19 cases, on average, 308 days after China. They had more than 10 months to prepare themselves.

It is worth noting that the resulting groups do not follow a geographical pattern by continents; they are clustered by function of underlying mechanisms such as inter-



Notes: Own elaboration

Figure 7: Geographical distribution of clusters

connectedness with China and their response to the pandemic. To better understand the distinctions between clusters, socioeconomic and demographic characteristics were analyzed. Appendix B identifies those countries of Cluster A recorded a higher average government effectiveness index (49.7) than countries in Cluster B (44.7). In terms of demographic characteristics, countries in Cluster A recorded a higher percentage of population older than 65 years (11.4%), compared to countries in Cluster B (6.8%) and in Cluster C (4%). The average of the last five years of GDP growth was quite similar across clusters (2.8% in Cluster A; 2.9% in Cluster B and 3.03% in Cluster C). Regarding the health sector, countries in Cluster A recorded a higher average of the number of hospital beds per 10000 inhabitants and number of doctors per 10000 inhabitants (32 and 27) than countries in Cluster B (22 and 14) and C (12 and 4). Countries in Cluster A recorded a higher level of Chinese imports (US$ 18,000 million) with respect to countries in Cluster B (US$ 7,000 million) and C (US$ 444 million). The three clusters recorded similar percentages of health expenditure over GDP (7% in Cluster A, 6% in Cluster B and 8.6% in Cluster C). The resulting clusters are more related to the closeness to China, rather than to the economic development characteristics of countries.

5.2 Estimation results about the COVID-19 lethality rate

Table 5 presents the Tobit estimation results for all countries in different periods, namely, 60, 180, 360 and 540 days after the first occurrence of the virus in the territory. Tables 6 and 7 present the results for countries of Cluster A and countries of Cluster B[4]. As Tobit and OLS models were applied, Appendix C displays Tobit models for the last periods for comparison purposes. Table 5 presents the general estimation and shows that Cluster A countries recorded a higher lethality rate by 0.007% and 0.006% with respect to Cluster B countries, at 360 and 540 days. The former are those countries that registered COVID-19 cases more rapidly than Cluster B countries. It is worth noting that the difference in the lethality rate between Cluster A and B countries is not significant for the first time periods of 60 and 180 days. While rapidly infected countries registered higher contagion rates than slowly infected countries at the beginning of the pandemic; the lethality rate was only significantly higher later during the pandemic.

It is worth noting that the COVID-19 related variables were time lagged with respect to the lethality rate. The contagion growth rate is lagged by 20 days since once a person became infected, the illness lasted approximately 15 days but longer if conditions worsened (five more days are considered) until death. The stringency index is lagged by 25 days with respect to the lethality rate since once stringency measures were in place, people reduced contact with others. Therefore, we considered that the lethality rate at time t was influenced by stringency measures established at t-25. Our results

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[4] For the model of countries in Cluster A, it is worth mentioning that 72 countries out of 78 were considered since six outlier countries were eliminated (Belgium, France, Hungary, Mexico, Peru and Sudan).

Table 6: Estimation of demographic and economic factors affecting the case fatality rate from COVID-19 worldwide

Estimation	TOBIT (marginal effects)			
Variables	60 days	180 days	360 days	540 days
Average lagged contagion growth rate 20 days	0.0535 (0.037)	0.165** (0.08)	-0.192 (0.152)	-0.310 (0.231)
Lagged stringency index 25 days	-9.93e-05 (0.0001)	-2.50e-05 (7.19e-05)	6.32e-05 (6.29e-05)	2.78e-05 (5.94e-05)
Average Government effectiveness index for the last 5 years.	-0.0005*** (0.0002)	-5.61e-05 (8.92e-05)	-0.0002*** (7.20e-05)	-0.0003** (6.72e-05)
Population density for the last available year	-1.32e-06 (3.67e-06)	-4.16e-06** (1.72e-06)	-1.30e-06 (1.52e-06)	-1.10e-06 (1.43e-06)
Percentage of the population over 65 years of age for the last available year	0.0023*** (0.0009)	0.0017*** (0.0004)	0.0007* (0.0003)	0.0008** (0.0003)
Average GDP growth rate for the last 5 years	-0.0025* (0.0015)	-0.0004 (0.0007)	-0.0012* (0.0006)	-0.001* (0.0006)
Average percentage of GDP allocated to health in the last 5 years	0.0019 (0.0016)	0.0019** (0.0008)	0.0004 (0.0006)	0.0003 (0.0006)
Number of hospital beds per 10000 inhabitants for the last available year	-0.0005*** (0.0001)	-0.0003*** (7.40e-05)	-0.0002*** (5.95e-05)	-0.0001** (5.63e-05)
Number of doctors per 10000 inhabitants for the last available year	-0.0001 (0.0002)	-0.0003** (0.0001)	-4.40e-05 (9.54e-05)	-2.43e-05 (8.91e-05)
Logarithm of trade flow (exports) in thousands of dollars between China and its trading partners for the last available year	0.0015 (0.0017)	0.0016** (0.0008)	0.0013* (0.0006)	0.0015** (0.0006)
Group 1 countries	0.0118 (0.0072)	0.002 (0.0037)	0.0073** (0.0034)	0.0058* (0.0031)
Observations	128	120	128	128

Notes: Own elaboration, standard errors in parentheses: ***p<0.01, **p<0.05, *p<0.1

indicate that the contagion growth rate at t-20 significantly increased the lethality rate at time t for the second period (180 day-period) by 0.16%. However, the contagion growth rate was no longer significant for the 360-day and 540-day periods. This also occurred for Clusters A (rapidly infected) and B (slowly infected). The diminished effect of the contagion on the lethality rate reflects the impact of vaccination rollout. During 2020, clinical trials to develop COVID-19 vaccines were in process. By 2021, several vaccines were approved by the Food and Drug Administration (FDA) and they were distributed in developed countries first and then in developing countries. Vaccination marks an important milestone in the worldwide COVID-19 dynamics. An increase of the contagion growth rate did not lead to higher lethality rates a year after the beginning of the pandemic. People were still infected even with the presence of vaccines, but they protected against death. As the World Health Organization (WHO) states, vaccines provide protection against severe illness, hospitalization and death. In addition, the WHO indicates that some evidence shows that vaccines make people less infectious (WHO 2023). Another reason for the lower impact of contagion growth rate on the lethality rate was that the first population segment to get vaccinated were older people, who were recording the higher lethality rates. In general, the stringency index at t-25, although negative for the first periods, did not explain the lethality rate.

An economic variable related to COVID-19 is the trade flow with China. This variable captures the flow of people between China and other countries and therefore the spread of the virus across the globe. Our results show that an increase of the trade flow with China by 1% corresponds to an increase of 0.0014 in the fatality rate from COVID-19 at the global level and in the last three periods for countries in Cluster A. It is not significant for countries in Cluster B since their trade and human mobility relationship is not very strong.

The government effectiveness index measures the perception of the population about government performance and corresponds to a reduction of the lethality rate in both rapidly and slowly infected countries throughout three phases by roughly 0.0004, mean-

Table 7: Estimation of demographic and economic factors affecting the case fatality rate from COVID-19 for Group A countries

Estimation	TOBIT (marginal effects)			
Variables	60 days	180 days	360 days	540 days
Average lagged contagion growth rate 20 days	0.0609 (0.0586)	0.228* (0.121)	-0.225 (0.246)	-0.292 (0.365)
Lagged stringency index 25 days	-0.0003 (0.0002)	3.61e-06 (0.0001)	0.0001 (0.0001)	0.0001 (0.0001)
Average Government effectiveness index for the last 5 years	-0.0007* (0.0003)	-0.0002 (0.0001)	-0.0003** (0.0001)	-0.0004*** (0.0001)
Population density for the last available year	-1.70e-05 (1.81e-05)	0.0028*** (0.0006)	-7.11e-06 (7.56e-06)	-4.99e-06 (7.34e-06)
Percentage of the population over 65 years of age for the last available year	0.0029** (0.0013)	-1.07e-05 (8.68e-06)	0.0009* (0.0005)	0.0011** (0.0005)
Average GDP growth rate for the last 5 years	-0.0016 (0.0024)	-0.0004 (0.0011)	-0.0018** (0.0009)	-0.0012 (0.0009)
Average percentage of GDP allocated to health spending in the last 5 years	0.0033 (0.0027)	0.0019 (0.0012)	-0.0003 (0.001)	-0.0005 (0.001)
Number of hospital beds per 10000 inhabitants for the last available year	-0.0006*** (0.0002)	-0.0005** (0.0001)	-0.0002** (8.33e-05)	-0.0001* (7.95e-05)
Number of doctors per 10000 inhabitants for the last available year	-0.0003 (0.0003)	-0.0002 (0.0002)	-8.35e-05 (0.0001)	-4.49e-05 (0.0001)
Logarithm of trade flow (exports) in thousands of dollars between China and its trading partners for the last available year	0.003 (0.0028)	0.0036*** (0.0013)	0.002* (0.001)	0.0018* (0.0011)
Observations	78	72	78	78

Notes: Own elaboration, standard errors in parentheses: ***$p<0.01$, **$p<0.05$, *$p<0.1$

ing 4 deaths in 10,000 infected people. Liang et al. (2020) obtained that mortality and lethality rate are negatively correlated with government effectiveness. However, the estimated effect of government effectiveness in slowly infected countries was not significant at the beginning of the pandemic. This indicates that the government capacity to establish policies to reduce the effects of the COVID-19 pandemic was not adequate in slowly infected countries. Another explanation could be that effective governments promote an excessive confidence by people, increasing the number of infected people (Toshkov et al. 2021). However, this explanation is discarded as the effect of the average Government effectiveness index for the last 5 year is always associated with a reduction of the lethality rate.

Population density had a limited effect on the worldwide lethality rate, even being non-significant for slowly infected countries. It is negative and significant but still small in magnitude (0.0028) for rapidly infected countries during the second phase. A positively correlated relationship was expected because higher population density is supposed to worsen the spread of the virus, and therefore, the case fatality rate (de Lusignan et al. 2020). Nevertheless, Rodríguez-Pose, Burlina (2021), who also revealed a marginal negative effect of population density, highlight that agglomeration factors are irrelevant to explain excess mortality. They state that excess mortality might be more connected to the interaction and behavior of people, rather than density. Carozzi et al. (2020), state that density might have an immediate influence on outbreaks but have less of an influence on mortality over time.

The main factor that supports the reduction of the COVID-19 lethality rate is the number of hospital beds per 10000 inhabitants. This variable is significant for most models, with exception of Cluster Bat the 360-day period. An increase of 1 bed per 10000 inhabitants reduced the lethality rate, on average, by 0.0003 (3 deaths per 10000 infected people) across periods. This result is in line with the previous literature, indicating that the preexisting sanitary capacity is relevant to control the growth of cases (Rodríguez-Zúñiga et al. 2020, Acosta 2020). Moreover, our results display that the influence of the hospital beds per 10000 inhabitants reduces over time for both rapidly and slowly

Table 8: Estimation of demographic and economic factors affecting the case fatality rate from COVID-19 for Group B countries

Estimation	TOBIT (marginal effects)		OLS	
Variables	60 days	180 days	360 days	540 days
Average lagged contagion growth rate 20 days	0.125***	0.279*	0.0115	0.166
	(0.0413)	(0.144)	(0.275)	(0.473)
Lagged stringency index 25 days	3.49e-05	-0.0002	-2.61e-06	-3.02e-05
	(0.0001)	(9.93e-05)	(9.10e-05)	(8.06e-05)
Average Government effectiveness index for the last 5 years	-0.0002	-0.0003**	-0.0002	-0.0003**
	(0.0002)	(0.0001)	(0.0001)	(0.0001)
Population density for the last available year	-2.12e-08	-1.35e-06	-8.86e-07	-4.71e-07
	(2.04e-06)	(1.68e-06)	(1.54e-06)	(1.38e-06)
Percentage of the population over 65 years of age for the last available year	0.0006	0.0011*	0.0004	0.0004
	(0.0008)	(0.0006)	(0.0006)	(0.0005)
Average GDP growth rate for the last 5 years	-0.0026*	-0.001	-0.0002	-0.0005
	(0.0014)	(0.001)	(0.001)	(0.0009)
Average percentage of GDP allocated to health spending in the last 5 years	0.0002	-0.0003	0.0009	0.001
	(0.0013)	(0.001)	(0.001)	(0.0009)
Number of hospital beds per 10000 inhabitants for the last available year	-0.0005**	-0.0003**	-0.0002	-0.0002*
	(0.0002)	(0.0002)	(0.0001)	(0.0001)
Number of doctors per 10000 inhabitants for the last available year	0.0002	0.0002	2.96e-05	0.0001
	(0.0003)	(0.0002)	(0.0002)	(0.0002)
Logarithm of trade flow (exports) in thousands of dollars between China and its trading partners for the last available year	-0.0002	-0.0002	0.0006	0.0009
	(0.0015)	(0.001)	(0.0009)	(0.0008)
Constants			0.0115	0.0102
			(0.015)	(0.0156)
Observations	50	50	50	50
R- squared	—	—	0.193	0.333

Notes: Own elaboration, standard errors in parentheses: ***p<0.01, **p<0.05, *p<0.1

infected countries. The reduction of the lethality rate via hospital beds in the first 60-day period is 0.05% worldwide, 0.06% for rapidly infected countries and 0.05% for slowly infected countries. This reduction decreases over time, to 0.01%, worldwide, 0.01% for rapidly infected countries (Cluster A) and 0.02% for slowly infected countries (Cluster B). These results indicate that the preexisting sanitary capacity was more influential at the beginning of the pandemic.

The percentage of population older than 65 years old is significantly and positively associated to the fatality rate of COVID-19. This result is consistent with King et al. (2020) and Promislow, Anderson (2020), who published that the health risks posed by the virus increase with age. However, its influence on the lethality rate decreases over time from 0.23% at 60 days to 0.08% at 540 days. The percentage of population older than 65 years in Cluster A countries explains their lethality rate in most periods. For Cluster B countries, this variable is significant in only one period. This difference can be explained by the age composition in these countries. On average, the percentage of the population over 65 years of age for Cluster A is 11.35%, while Cluster B, mainly composed of African countries and Caribbean islands, averages 6.79%.

An increase in the average GDP growth over the last five years is associated to a lower lethality rate in most periods of the pandemic. Its effect decreases over time. In the first period, a 1% increase of the GDP growth correlated toa reduction in the lethality rate by 0.25%, whereas the reduction was only 0.1% in the last period. For Cluster A (rapidly infected countries), economic growth corresponds to a reduction of the lethality rate only until the end of the first year of the pandemic. The effect of the economic growth is not significant at the beginning of the pandemic since these rapidly infected countries experienced high rates of infection that potentially contributed to high lethality rates. Other studies conclude a positive relationship between the number of deaths and GDP per capita (Jeanne et al. 2023) because more developed countries are more connected to China and were more affected. In our case, an opposed effect of GDP was obtained since we analyzed different variables; the GDP growth and the lethality rate (number of death cases divided by number of infected people). Rodríguez-Pose, Burlina (2021) conclude that wealthier regions recorded excess mortality because wealthier regions were more accessible by road. The economic growth for countries of Cluster B was significantly associated with lower lethality rates only in the first period of the pandemic. The average percentage of GDP allocated to health spending does not explain the lethality rate in most periods, as obtained also by Khan et al. (2020). The effect of health spending is only significant but positive for the 180-day period. The positive unexpected effect may be explained by the notion that countries with the highest level of contagion and lethality were developed countries with high health spending. Revealed by Chaudhry et al. (2020), it could be explained by more testing and transparency in reporting fatal cases. The correlation rate between the case fatality rate and health spending is 0.1033 for the first period. This correlation coefficient is 0.1331, -0.0137 and 0.0536, for the following periods.

6 Conclusion

By employing Tobit and OLS estimations, this study determined how the underlying conditions of countries in terms of health infrastructure, economic resources and demographic structures influenced theCOVID-19 lethality rate. The results show that both COVID-19 related variables and underlying conditions of countries explain the lethality rate. Risk factors that increase the lethality rate in countries are the contagion growth rate, trade flows with China, the age composition of the population and, to a lesser extent, the population density. Factors that help to reduce the lethality rate are the government effectiveness, the health infrastructure (hospital beds) and, to a lesser extent, the economic growth rate. The contagion growth rate increases the lethality rate, but its influence reduces over time, which may reflect the impact of vaccination. People were still infected once vaccines became more readily available, but the vaccines prevented symptoms from getting worse and causing death. The existing government capacity and structural effectiveness are more important than the conjunctural stringency measures that governments established to reduce the lethality rate. Another structural variable that proved to be an influential factor for the management of the pandemic and reducing the lethality rate is the number of hospital beds per 10000 inhabitants.

It is concluded from the COVID-19 pandemic statistics that while the number of infected people had been increasing across periods, the lethality rate across periods had been decreasing, indicating an improvement in the management of the pandemic by health staff and the role of vaccines. The spread of the virus was not uniform worldwide as some countries registered COVID-19 cases before others. Although the COVID-19 pandemic arrived later to certain countries (slowly infected countries), in most periods, they recorded a higher case fatality rate with respect to rapidly infected countries. While Europe, North America, Oceania and Asia recorded high contagion levels, they recorded lower lethality rates than Latin America and Africa, which recorded low contagion levels and growth.

Using the COVID-19 lethality rate, the contagion growth rate and the number of days that elapsed to register the first confirmed case with respect to China, three clusters of countries are defined: i. Cluster A: Rapidly infected countries with high lethality rate and moderate contagion growth rate, ii. Cluster B: Less rapidly infected countries with very low lethality rate and moderate contagion growth rate, and iii. Cluster C: Slowly infected countries with very high lethality rate and very low contagion growth rate.

Some limitations arose when conducting this research. First, the measurement of confirmed cases and lethal cases records registration problems as some people were asymptomatic (Aliseda 2020) or there was a lack of Polymerase chain reaction (PCR) tests in some territories (Rubino et al. 2020). Regarding the fatal cases, some deaths were registered as severe respiratory infections and not precisely the virus (Parra Saiani et al. 2021). Despite these problems, data from the Blavatnik School of Government in Oxford are available for all countries and correspond to official statistics sent by national governments. For future research, it would be interesting to deeper explore the effect of vaccinations by including the percentage of people with a complete scheme of vaccinations.

Policy implications can be derived from our results. Since the number of doctors per capita had a significant negative correlation with the lethality rate, it is crucial for countries to improve their health system, focusing on health personnel. This action, however, should not be conjunctural, but structural, so the system would be resilient to negative shocks such as the COVID-19 pandemic. In addition, good governance is a key element that facilitates public actions and their effectiveness. Good governance to achieve effectiveness is also a structural feature that must be built constantly, emphasizing on the citizen participation and commonwealth.

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Appendix A

Table A.1: Countries Cluster 1

Country	Contagion Rate	Days respect China	CFR	Country	Contagion Rate	Days respect China	CFR
Albania	4,03%	69	1,70%	South Korea	4,24%	22	1,73%
Andorra	7,47%	62	1,02%	Kuwait	6,06%	55	0,57%
Argentina	5,11%	63	2,47%	Lebanon	4,22%	52	1,18%
Armenia	4,46%	61	1,86%	Libya	4,10%	84	1,65%
Austria	4,23%	56	1,89%	Lithuania	4,14%	60	1,64%
Belgium	5,07%	35	2,98%	Latvia	3,86%	62	1,89%
Bulgaria	3,77%	68	4,11%	Morocco	4,36%	62	1,78%
Bahrain	9,11%	55	0,36%	Moldova	4,22%	68	2,13%
Bosnia and Herzegovina	3,58%	65	3,87%	Mexico	5,11%	59	8,83%
Belarus	5,05%	59	0,69%	North Macedonia	4,02%	57	3,08%
Bolivia	3,95%	71	4,65%	Nigeria	4,03%	59	1,22%
Brazil	5,77%	57	2,43%	Nicaragua	5,11%	79	2,68%
Brunei	4,13%	69	1,60%	Netherlands	5,48%	58	1,43%
Canada	4,00%	23	2,68%	Norway	4,68%	57	0,89%
Switzerland	5,87%	56	1,81%	Nepal	4,09%	25	0,73%
Chile	4,72%	54	2,51%	Pakistan	4,43%	56	2,20%
China	7,41%	0	5,33%	Panama	5,56%	70	1,72%
Cote d'Ivoire	4,22%	71	0,57%	Peru	5,51%	66	9,28%
Colombia	5,13%	66	2,65%	Philippines	4,42%	30	1,99%
Costa Rica	4,54%	66	1,37%	Poland	5,31%	64	2,57%
Czechia	4,23%	61	1,66%	Portugal	4,43%	62	2,02%
Germany	5,26%	27	2,41%	Paraguay	4,34%	68	1,99%
Denmark	4,65%	58	1,13%	Qatar	6,30%	60	0,16%
Dominican Republic	4,41%	61	1,29%	Romania	4,67%	57	2,55%
Algeria	4,06%	56	2,65%	Russia	4,88%	31	1,86%
Ecuador	3,69%	61	5,61%	Saudi Arabia	4,99%	62	1,72%
Egypt	4,78%	45	5,70%	Sudan	3,49%	74	6,24%
Spain	5,37%	32	2,16%	El Salvador	3,75%	79	3,13%
Estonia	4,40%	58	0,93%	San Marino	4,23%	60	2,06%
Ethiopia	4,37%	73	1,46%	Serbia	4,94%	66	0,96%
France	4,86%	24	2,39%	Slovakia	4,47%	66	1,23%
United Kingdom	4,97%	31	2,68%	Slovenia	4,13%	65	2,02%
Georgia	4,38%	57	1,28%	Sweden	4,72%	32	2,02%
Greece	4,47%	57	3,51%	Eswatini	3,51%	74	3,83%
Guatemala	4,07%	74	3,62%	Syria	3,72%	82	6,68%
Croatia	4,18%	56	2,26%	Togo	4,36%	66	1,23%
Hungary	3,94%	64	3,51%	Tunisia	4,20%	64	3,43%
Indonesia	4,57%	62	2,70%	Turkey	6,14%	71	1,05%
India	5,98%	30	1,44%	Uganda	5,03%	81	0,82%
Ireland	4,57%	60	1,93%	Ukraine	4,95%	63	1,97%
Iran	4,96%	50	3,90%	United States	5,79%	22	1,68%
Iraq	4,89%	55	2,01%	Uzbekistan	4,51%	75	0,77%
Israel	4,58%	52	0,74%	Venezuela	4,22%	74	0,98%
Italy	5,94%	31	3,47%	Yemen	3,48%	101	19,57%
Jordan	5,52%	63	1,21%	South Africa	4,97%	65	3,30%
Japan	3,74%	22	1,38%	Zimbabwe	3,67%	80	4,12%
Kenya	4,05%	73	1,72%				

Table A.2: Countries Cluster 2

Country	Contagion Rate	Days respect China	CFR	Country	Contagion Rate	Days respect China	CFR
Aruba	2,74%	73	0,95%	Laos	1,10%	84	0,00%
Afghanistan	3,03%	55	4,37%	Liberia	2,12%	77	4,20%
Angola	3,18%	80	2,43%	Saint Lucia	2,78%	74	1,18%
Anguilla	0,75%	88	0,00%	Liechtenstein	2,74%	64	2,08%
United Arab Emirates	3,50%	29	0,29%	Sri Lanka	3,75%	27	0,49%
Antigua and Barbuda	2,45%	73	2,48%	Lesotho	3,47%	134	2,96%
Australia	2,90%	26	3,16%	Luxembourg	3,91%	60	1,16%
Azerbaijan	3,63%	61	1,37%	Macao	1,44%	22	0,00%
Burundi	2,48%	91	0,23%	Monaco	2,80%	60	1,21%
Benin	3,17%	76	1,25%	Madagascar	3,20%	80	1,55%
Bonaire Sint Eustatius and Saba	1,52%	93	1,53%	Maldives	2,69%	68	0,31%
Burkina Faso	3,73%	70	1,18%	Mali	2,89%	85	3,96%
Bangladesh	3,90%	68	1,54%	Malta	2,85%	67	1,39%
Bahamas	3,12%	76	2,14%	Myanmar	3,06%	87	2,25%
Belize	3,09%	83	2,55%	Montenegro	3,93%	77	1,35%
Bermuda	2,18%	79	1,63%	Mongolia	2,99%	70	0,06%
Barbados	2,53%	77	1,09%	Mozambique	3,70%	82	1,12%
Bhutan	2,23%	66	0,12%	Mauritania	3,29%	74	2,55%
Botswana	3,13%	90	1,32%	Montserrat	1,63%	78	5,00%
Central African Republic	3,39%	75	1,25%	Mauritius	1,92%	78	1,45%
Cameroon	3,68%	66	1,54%	Malawi	3,02%	93	3,33%
Democratic Republic of Congo	3,59%	71	2,69%	Malaysia	3,29%	25	0,37%
Congo	3,86%	75	1,40%	Namibia	3,13%	74	1,10%
Comoros	3,37%	121	3,81%	New Caledonia	1,20%	79	0,00%
Cape Verde	3,90%	80	0,97%	Niger	3,15%	80	3,74%
Cuba	3,04%	72	0,62%	New Zealand	2,88%	59	1,10%
Curacao	2,88%	74	0,46%	Oman	3,64%	55	1,12%
Cayman Islands	2,21%	73	0,44%	Kosovo	3,58%	74	2,24%
Cyprus	3,41%	70	0,64%	Papua New Guinea	2,68%	80	1,15%
Djibouti	3,45%	78	1,01%	Palestine	3,44%	65	1,11%
Dominica	1,99%	82	0,00%	French Polynesia	2,96%	73	0,76%
Eritrea	3,07%	81	0,23%	Rwanda	3,83%	74	1,37%
Finland	3,54%	29	1,61%	Senegal	3,61%	62	2,53%
Fiji	1,42%	79	3,03%	Singapore	3,70%	23	0,05%
Falkland Islands	1,60%	95	0,00%	Sierra Leone	2,79%	91	1,99%
Faeroe Islands	2,57%	64	0,15%	Somalia	3,07%	76	3,83%
Gabon	3,37%	74	0,57%	Saint Pierre and Miquelon	1,20%	96	0,00%
Ghana	3,44%	74	0,76%	South Sudan	3,88%	96	1,07%
Gibraltar	3,09%	64	2,19%	Sao Tome and Principe	3,39%	97	1,52%
Guinea	3,38%	73	0,57%	Suriname	3,38%	74	1,95%
Gambia	2,89%	77	3,10%	Seychelles	2,23%	75	0,47%
Guinea-Bissau	3,09%	85	1,55%	Turks and Caicos Islands	2,04%	88	0,74%
Equatorial Guinea	3,54%	75	1,51%	Chad	2,97%	79	3,57%
Grenada	2,75%	82	0,65%	Thailand	2,40%	22	0,60%

Country	Contagion Rate	Days respect China	CFR	Country	Contagion Rate	Days respect China	CFR
Greenland	1,26%	76	0,00%	Tajikistan	2,45%	122	0,66%
Guyana	3,75%	72	2,28%	Timor	1,76%	82	0,00%
Hong Kong	2,77%	23	1,70%	Trinidad and Tobago	3,42%	74	1,81%
Honduras	3,71%	71	2,45%	Taiwan	2,37%	22	0,82%
Haiti	3,12%	80	1,98%	Tanzania	2,49%	76	4,13%
Isle of Man	2,83%	80	1,99%	Uruguay	3,35%	73	1,02%
Iceland	3,24%	59	0,48%	Vatican	1,54%	66	0,00%
Jamaica	3,61%	71	1,76%	Saint Vincent and the Grenadines	2,55%	74	0,48%
Kazakhstan	3,84%	73	1,29%	British Virgin Islands	1,49%	88	0,65%
Kyrgyzstan	3,63%	78	1,70%	Vietnam	2,33%	23	2,28%
Cambodia	2,63%	27	0,00%	Zambia	3,82%	78	1,36%
Saint Kitts and Nevis	1,28%	85	0,00%				

Table A.3: Countries Cluster 3

Country	Contagion Rate	Days respect China	CFR	Country	Contagion Rate	Days respect China	CFR
Micronesia (country)	0,00%	387	0,00%	Vanuatu	0,69%	315	16,67%
Marshall Islands	0,74%	302	0,00%	Wallis and Futuna	2,55%	293	1,54%
Saint Helena	0,25%	251	0,00%	Samoa	0,44%	323	0,00%
Solomon Islands	0,86%	286	0,00%				

Appendix B

Table B.1: Descriptive statistics by clusters

	Cluster A				Cluster B				Cluster C			
Variable	Min.	Max.	Std. Dev	Mean	Min.	Max.	Std. Dev	Mean	Min.	Max.	Std. Dev	Mean
Case fatality rate	0.0	0.2	0.02	0.02	0	0.1	0.01	0.02	0.0	0.0	0.0	0.0
Lagged contagion growth rate at 540 days (t-20)	0.0	0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Stringency index at 540 days (t-25)	2.8	86.1	16.8	51.4	11.1	93.5	18.4	51.5	0.0	0.0	0.0	0.0
Government effectiveness	0.0	95.0	22.8	49.7	7.5	99.6	24.1	44.7	0.0	0.0	0.0	0.0
Percentage of population older than 65 years old	1.5	28.0	6.8	11.4	1.2	22.1	5.0	6.8	3.6	4.9	0.5	4.1
Population density	3.8	2017.3	236.0	154.4	0.1	20777.5	2951.0	757.0	23.3	324.5	113.7	120.4
GDP growth (average of the 5 last years)	-10.4	10.1	2.5	2.9	-10.8	7.4	2.9	3.0	1.9	3.6	0.6	3.0
Current health expenditure (average of the 5 last years)	2.4	16.9	2.4	7.1	1.7	17.4	2.5	5.8	3.3	17.2	5.3	8.7
Hospital beds per 10000 inhabitants	3.0	129.8	26.2	32.9	1.0	80.0	16.5	21.8	10.0	14.0	2.0	12.0
Number of doctors per 10000 inhabitants	0.8	79.3	18.2	26.9	0.2	83.0	17.3	14.3	1.8	5.8	1.8	3.6
Chinese exports to each country i in billions of dollars for the last available year	2.4	418584.2	48763.0	18422.8	0.006	279616.8	30447.2	7298.5	0.7	2384.7	868.4	444.6

Appendix C

Table C.1: TOBIT estimation of demographic and economic factors affecting the case fatality rate from COVID-19 for the countries of Group 2 for 360 and 540 days

	TOBIT (marginal effects)	
Variables	360 days	540 days
Average lagged contagion growth rate 20 days	0.0628 (0.231)	0.153 (0.384)
Lagged stringency index 25 days	-3.00e-06 (7.53e-05)	-2.78e-05 (6.54e-05)
Average Government effectiveness index for the last 5 years	-0.0002* (9.38e-05)	-0.0003*** (8.21e-05)
Percentage of the population over 65 years of age for the last available year	0.0004 (0.0005)	0.0003 (0.0004)
Population density for the last available year	-7.92e-07 (1.27e-06)	-4.34e-07 (1.12e-06)
Average GDP growth rate for the last 5 years	-0.0003 (0.0008)	-0.0005 (0.0007)
Average percentage of GDP allocated to health spending in the last 5 years	0.0008 (0.0008)	0.001 (0.0007)
Number of hospital beds per 10000 inhabitants for the last available year	-0.0002 (0.0001)	-0.0002** (9.77e-05)
Number of doctors per 10000 inhabitants for the last available year	1.59e-05 (0.0002)	0.0001 (0.0002)
Logarithm of trade flow (exports) in thousands of dollars between China and its trading partners for the last available year	0.0005 (0.0007)	0.0008 (0.0006)
Observations	50	50