Scandinavian Journal of Public Health, 2023; 51: 682–691

ORIGINAL ARTICLE

Government interventions and control policies to contain the first COVID-19 outbreak: An analysis of evidence

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Abstract
Background: The overarching aim of this study was to evaluate the effectiveness over time of government interventions and policy restrictions and the impact of determinants on spread and mortality during the first-wave of the COVID-19 pandemic, globally, regionally and by country-income level, up to 18 May 2020. *Methods:* We created a global database merging World Health Organization daily case reports (from 218 countries/territories) with other socio-demographic and population health measures from 21 January to 18 May 2020. A four-level government policy interventions score (low to very high) was created based on the Oxford Stringency Index. *Results:* Our results support the use of very high government interventions to suppress both COVID-19 spread and mortality effectively during wave one globally compared to other policy levels of control. Similar trends in virus propagation and mortality were observed in all country-income levels and specific regions. ***Conclusions:* Rapid implementation of government interventions was needed to contain the first wave of the COVID-19 outbreak and to reduce COVID-19-related mortality.**

Keywords: *COVID-19, global, mortality, propagation, interventions*

Introduction

On 11 March 2020, the World Health Organization (WHO) declared the current novel coronavirus disease 2019 (COVID-19) as a public health emergency of international concern and later characterised it as a pandemic [1,2]. On 21 January 2020, the WHO published the first situation report, announcing the first cases of pneumonia of unknown aetiology detected in Wuhan City, China, on 31 December 2019 [3]. Extended local transmission outside China was reported among various European Union (EU) countries (e.g. France, Germany, Italy and Spain) and in the USA [4,5].

By 18 May 2020, more than 200 countries had reported confirmed cases of COVID-19 [6]. Several measures had already been implemented to prevent and contain the alarming propagation of COVID-19 [7]. Each country has applied its own disease control measures, which varied by specific policy

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Date received 23 July 2021; reviewed 10 January 2023; accepted 26 January 2023

DOI: 10.1177/14034948231156969
journals.sagepub.com/home/sjp
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and implementation timing. Some countries initially implemented 'softer' measures, whereas others adopted 'stricter' ones. These government health policies evolved rapidly based on local COVID-19 transmission. Policies ranged from temperature checks and medical screening for travellers at each country's entry point, public school closures and restrictions on movement, including the closure of most places of business, to an entire country's quarantine, physical distancing and limiting contacts, increasing testing and protecting essential workers, among others [8]. The EU adopted the policy of open borders for a specific period. However, after the alarming increase of COVID-19 cases in Italy (last week of February) and emerging virus transmission in Spain, France and Germany (beginning of March), travel restrictions were applied in the EU on 18 March 2020. Similarly, the USA blocked entry of non-US citizens for 30 days and implemented similar restrictions in mobility to US citizens (with certain exceptions) as those implemented in the EU.

Although the WHO has published relevant recommendations for COVID-19 from previous experiences of infectious disease outbreaks [9], this planning was not followed by most countries, posing considerable challenges [10]. The collective effectiveness of these interventions is empirically unknown, particularly in regions with different reasons for and levels of population vulnerability [11] (e.g. older adult populations, poverty, health infrastructure, etc.). Several studies so far have been based on modelling [12,13] in a certain number of regions [14–16]. Estimation of COVID-19 spread, over time and by each government's interventions and policies could help to identify which interventions and control policies (at country level) are effective and with what impact towards COVID-19 propagation and mortality evolution. Given the absence of the knowledge of effective medical treatment and vaccine schemes at the beginning of 2021 and taking into account the delays in delivery among countries, estimation of the effect of government interventions to combat COVID-19 could make a substantial contribution to the field facilitating the translation of knowledge and implementation of evidence into COVID-19 practice and policy [17]. In addition, it could guide authorities to establish early and effective decision making for the containment of the outbreak as well as when the control policies can be phased out [18,19]. Thus, the overarching aim of this study was to evaluate the effectiveness over time of government interventions, measurements and policy restrictions and the impact of determinants on COVID-19 spread and mortality, globally, regionally and by country-income level, from 21 January to 18 May 2020.

Methods

Study design

We conducted a retrospective, observational, longitudinal study. We obtained data on COVID-19 propagation and mortality, and related determinants from 218 countries. We compiled a data set of COVID-19 daily cases and deaths spanning the period 21 January–18 May 2020 based on the most recent publicly available population-level information (by country), as reported by the WHO (https://www.who.int/emergencies/diseases/novel-coronavirus-2019/situation-reports/). The current study was approved by Parc Sanitari's Sant Joan de Déu Ethics Committee (PIC-67-20, Barcelona, Spain) and conformed to the ethical guidelines of the 1975 Declaration of Helsinki.

COVID-19 international data

The WHO daily situation reports from 21 January to 18 May 2020 were used to assess disease transmission internationally [3]. Data on daily confirmed cases, total confirmed cases, daily confirmed deaths, total confirmed deaths, transmission classification and time since the last reported case were compiled for each of 218 countries/territories. Case classifications were based on WHO case definitions for COVID-19. Transmission was classified into three distinct groups to capture changes in the classification that the WHO applied during these four months: community transmission, transmission under investigation and sporadic-cluster transmission (includes sporadic transmission, clusters and local transmission) [3]. Cases identified on cruise ships were excluded from the analysis, and cases among China's provinces were grouped together. Based on the WHO database, Puerto Rico was classified separately from the USA as well as other territories.

Country's government interventions, health policy and restriction measures

The Oxford COVID-19 Government Response Tracker is an existing reliable online data set that also assesses government response [20]. From this data set, we specifically used the Oxford Stringency Index (ranged from 0 to 100) which includes information regarding containment and closure policies (such as schools, public transportation and workplace closures; restrictions on gatherings; cancelation of public events; cancellation of internal and international travel/movement; and stay-at-home orders) combining them with information on COVID-19 governmental public information campaigns. Thus, higher values on the Oxford Stringency Index indicate that the implemented COVID-19 government policies were more stringent. The indicators used to calculate the final index are presented in detail elsewhere [21] and cover interventions such as international travel controls, school closures and stay-at-home orders, among others.

We classified the Oxford Stringency Index into quartiles (quartile 1: low interventions; quartile 2: intermediate interventions; quartile 3: high interventions; and quartile 4: very high interventions) to obtain a four-level health and government policy interventions/measures score during wave one.

Other baseline assessments by country

Information regarding threat detection and risk assessment were obtained from the Index for Risk Management (INFORM) Epidemic Risk Index [22], developed by the EU Joint Research Centre in collaboration with the WHO. This information was used as a measure of each country's epidemic preparedness. The INFORM Index ranged from 0 to 10, and higher scores corresponded to lower epidemic preparedness risk of a country. More detail about the development of this index can be found elsewhere [22].

The World Bank income classification system was also used to classify each of the 218 countries based on income (high-income countries (HICs), upper-income countries (UMICs), lower middle-income countries (LMICs) and low-income countries (LICs)) [23]. Population density per square kilometre of land area was also assessed by country and was obtained from the World Bank [24].

The proportion of the population aged $\geqslant$70 years was also included using the publicly available information from the latest Global Burden of Disease (GBD) 2017 repository. Population summary health estimates using disability-adjusted life years (DALYs) for specific diseases such as for cardiovascular diseases (CVDs), respiratory infections, tuberculosis, respiratory disorders, neoplasms, diabetes and kidney diseases were also obtained from the GBD 2017 study. Briefly, DALYs are estimated as the sum of years of life lost and years lived with a disability for each cause, location, age group, sex and year [25]. Finally, information about the number of available acute care units (acute care beds per 100,000 population) for the latest available year and for each country was obtained from the publicly available WHO data set [26] and as published in Phua et al. [27].

Of the 218 countries, 179 had complete data and were selected for the adjusted analysis (regression modelling). The entire sample was used for the unadjusted analysis.

Statistical analysis

Normally distributed continuous variables (e.g. number of days) are presented as mean$\pm$standard deviation. Non-normally distributed values (e.g. mean rate values) were compared using the Kruskal–Wallis test to assess differences between government intervention levels.

Based on the literature review, government interventions did not have an instant effect on COVID-19 spread and mortality. For this reason, we considered their scheduling in respect to $t0$ with the addition of relevant lag times of seven days, following previous literature methodologies, [28], to correspond with the approximate virus incubation period [29]. All the analyses presented below considered those time-lag effects.

Bayesian spatiotemporal analysis. For each country, we recorded the number of COVID-19 cases and deaths per day (i.e. count values) from 21 January to 18 May 2020. There were many days, particularly at the beginning of the pandemic, in which those numbers (cases and deaths) were zero for many countries, resulting in the study data set showing overdispersion (i.e. greater variability than expected) and, of course, an excess of zeros. Given that framework, the Zero-Inflated Negative Binomial (ZINB) distribution [30] is an appropriate approach, as it assumes that overdispersion and the excess zeros are generated by a separate process from the count values (i.e. number of COVID-19 cases and deaths per day) and that the excess zeros can be modelled independently. Therefore, we applied a Bayesian spatiotemporal approach, assuming ZINB distributions, to evaluate the relation between COVID-19 spread (outcome) and government control policies as well as their time-lag effect (independent variables of interest) adjusted by the following confounders: INFORM Index, WHO transmission classification, the number of days since the last COVID-19 new case, country-income level and population density. The models assessing COVID-19 mortality evolution were adjusted for all the previous factors plus ICU beds per 100,000 population, the proportion of population aged $\geqslant$70 years, DALYs for CVDs, neoplasms, diabetes and kidney diseases, respiratory infections and tuberculosis. DALYs and the proportion of the population aged $\geqslant$70 years were included/taken into account mostly due to their related nature with COVID-19 mortality and their potential effect as modifiers or mediators [31–33]. Before fitting all models, we tested the intercorrelation among variables. If the correlation between two variables was >0.70, then the variable was removed from the model to avoid multicollinearity issues [34]. We selected the best-fitting model based on the deviance information criterion [35]. All model details are presented in the accompanying Supplemental Material. Bayesian spatiotemporal models were used as a first step to capture spatial and concurrent in-time effects between the outcomes and predictors covariates. These models were applied to detect not only temporal but also spatial interrelationships between countries (for more details, please see the Supplemental Material). The analyses for these models were carried out using the R package *R-INLA* in R v3.6.3 (The R Foundation for Statistical Computing, Vienna, Austria).

Mixed models based on stepped wedged methodology. We also fit a negative binomial mixed model for each government intervention category (intermediate, high and very high), using the average (global, country-income groups) effect of time between 21 January and 18 May 2020, clustering pre- or post-intervention periods of COVID-19 new cases and deaths and adjusting for countries preparedness in epidemics, COVID-19 type of transmission for each country through time, the number of days since the last COVID-19 new case occurred for each country in each date, ICU beds, the proportion of older adult population aged ⩾70 years and burden of communicable and non-communicable disease. As in the Bayesian regression, the proportion of the population aged ⩾70 years and disease burden were applied in the mortality mixed models for their potential effect as modifiers or mediators [32]. Again, all models were tested for intercorrelations among the inserted variables [34]. In this analysis, COVID-19 cases and deaths were the outcomes, and government control policies were the independent variables of interest. Post- and pre-intervention clustering followed certain categorisation. Specifically, post-intervention clusters included intermediate, high and very high levels of government interventions and were compared each time with their direct pre-intervention levels (e.g. post intervention (high policy level estimates) vs. pre-intervention (intermediate and low policy level estimates); for more details, see the Supplemental Material). The confounders were assumed as fixed effects of the model, as the government intervention variable, while the intercept was assumed to be random, varying among country-income groups and intervention levels within dates (nested random factors) and among dates and among countries (crossed random factors). The natural logarithm of the total population was added as an offset to the linear predictor function of the Negative Binomial component (NB) to account for the variable number of new cases and new deaths per country (for more details of the applied model formula, see the Supplemental Material). In addition, similar stratified regression models by country-income level were applied. The maximum likelihood estimation procedure was used to fit those multilevel analysis models. Goodness of fit for the mixed models was measured with conditional R^2 which explains the models' variance based on fixed and random effects. The higher the R^2, the higher the explanation of our model. Mixed-model analysis based on stepped wedged methodology was carried out using the R package *glmmTMB* in R v4.0.2.

Results

COVID-19 spread and mortality evolution in relation to government interventions, control policies and other determinants

Of the 218 countries with full data, interventions implemented varied by extent of virus spread. In March, among countries with at least one case, 5% of countries implemented low-intervention policies, 20% intermediate, 26% high and 26% very high. By mid-May, 6% of countries implemented low-intervention policies, 37% intermediate and 57% high or very high (data shown only in text). Before COVID-19 cases were detected, 10 countries implemented interventions.

Table I presents the spatiotemporal regression analysis assessing the COVID-19 spread along with government interventions and other factors among 179 countries. The Bayesian spatiotemporal analysis shows that the strictness of government policies had an effect on COVID-19 spread, with a clear gradient showing that very high intervention policies suppressed COVID-19 spread much more than intermediate and high policies (95% Bayesian credible interval (CI); intermediate intervention level applied: 0.78, 95% CI 0.70–0.85; high intervention level applied: 0.35, 95% CI 0.28–0.42; very high intervention level applied: 0.19, 95% CI 0.11–0.26). Among other factors influencing virus spread, community transmission and transmission under investigation when compared to sporadic clusters was inversely related to COVID-19 spread (see table I in for more information on terminology please visit the WHO COVID-19 situation reports [3] for description of the WHO terminology); greater interval period

Table I. Bayesian spatiotemporal regression analysis to evaluate COVID-19 spread with government interventions and other factors globally.

Items	β-coefficient	95% CI
Low interventions	Reference category	
Intermediate interventions	0.78	0.70, 0.85
High interventions	0.35	0.28, 0.42
Very high interventions	0.19	0.11, 0.26
Sporadic-cluster transmission	Reference category	
Community transmission	−0.87	−0.98, −0.76
Transmission under investigation	−0.25	−0.33, −0.17
Days since last case	−10.04	−11.55, −9.13
HICs	Reference category	
LICs	−6.23	−8.20, −4.26
LMICs	−4.80	−6.25, −3.35
UMICs	−2.35	−3.43, −1.29
Population density (km^2)	0.00	−0.001, 0.00
ICU beds per 100,000 population	0.003	0.000, 0.005
INFORM (0–10)	0.27	−0.14, 0.69

Transmission description can be found in the WHO COVID-19 situation reports see ref [3].

HICs: high-income countries; LMICs: lower middle-income countries; UMICs: upper middle-income countries; LICs: low-income countries; days since last case: days since last case appeared in a country/region; INFORM: Index for Risk Management Epidemic Risk Index; ICU: intensive care units; 95% CI, 95% Bayesian credible interval.

among new COVID-19 cases was inversely related to virus spread; countries' epidemic preparedness as reflected by the INFORM Index was not related to COVID-19 spread; and COVID-19 spread was lower in LICs, LMICs and UMICs compared to HICs. Supplemental Figure 1 shows on a global map the neighbouring countries effect in virus spread as reflected by the Bayesian regression analysis from January to May 2020.

Table II presents the evolution of COVID-19 mortality among government interventions and control policies, as well as with other factors. Implementing very high levels of intervention policies was shown to reduce COVID-19 mortality compared to implementing intermediate and high levels of policies (intermediate intervention level applied: 1.79, 95% CI 0.80–1.92; high intervention level applied: 0.78, 95% CI 0.68–1.64; very high intervention level applied: 0.40, 95% CI 0.29–0.50). Analysis of the determinants of mortality showed that the type of transmission, the discontinuity in the appearance of daily deaths and the country's preparedness shared similar patterns with COVID-19 deaths as the models of spread.

Trajectories in COVID-19 spread and mortality evolution clustered by pre- and post-government interventions and control policies globally and by country-income level

COVID-19 spread and mortality evolution globally and by country-income level are reported in Table

Table II. Bayesian spatiotemporal regression analysis to evaluate COVID-19 mortality evolution with government interventions and other factors globally.

Items	β-coefficient	95% CI
Low interventions	Reference category	
Intermediate interventions	1.79	0.80, 1.92
High interventions	0.78	0.68, 1.64
Very high interventions	0.40	0.29, 0.50
Sporadic-cluster transmission	Reference category	
Community transmission	−0.86	−1.30, −0.73
Transmission under investigation	−0.03	−0.26, 0.08
Days since last case	−1.29	−1.43, −1.05
HICs	Reference category	
LICs	0.63	−4.45, 571.54
LMICs	−0.29	−2.38, 3.52
UMICs	1.02	−1.33, 128.09
Population density (km^2)	0.000	−0.001, 0.003
Proportion of populated aged ⩾70 years	11.43	−12.63, 65.15
ICU beds per 100,000 population	0.001	−0.002, 0.006

Spatiotemporal regression models were also adjusted for INFORM, age-adjusted cardiovascular diseases, cancer, respiratory infections and tuberculosis, diabetes and kidney disease disability-adjusted life years, as obtained from the GBD 2017 repository. Transmission description can be found in https://www.who.int/docs/default-source/coronaviruse/situation-reports/20200409-sitrep-80-covid-19.pdf.

HICs: high-income countries; LMICs: lower middle-income countries; UMICs: upper middle-income countries; LICs: low-income countries; days since last case: days since last case appeared in a country/region; INFORM: Index for Risk Management Epidemic Risk Index.

III. Our mixed-model results show that the higher the post-intervention level, the lower the COVID-19 spread at the global level when compared to pre-government intervention clustering (intermediate intervention level β-coefficient 0.94, 95% CI 0.83–1.05; high intervention level 0.57, 95% CI 0.49–0.66; very high intervention level 0.31, 95% CI 0.22–0.39). Similar trends in COVID-19 spread and intervention types existed across different country incomes (Table III).

Mortality evolution globally and by country-income level is reported in Table IV. Results may be sensitive to variability in surveillance infrastructure and/or the degree of policy enforcement across countries, which can lead to inaccurate reporting or inconsistent relationships. Therefore, we conducted a stratified analysis by country-income level to reflect more homogenous health-care infrastructure and enforcement [22]. When we stratified by country-income level, we observed similar trends in COVID-19 mortality evolution among government policies on different country-income levels as globally (intermediate intervention level β-coefficient 2.55, 95% CI 2.30–2.79; high intervention level 1.24, 95% CI 1.09–1.39; very high intervention level 0.65, 95% CI 0.49–0.82).

Discussion

The present study analysed COVID-19 spread and mortality evolution and their relation with specific

Table III. Mixed-model regression analysis to evaluate the COVID-19 spread with government interventions and other factors globally and by income categorization.

Items	Global analysis	
	β-coefficient	95% CI
Post intermediate (vs. pre intermediate) interventions (Model I)	0.94	0.83, 1.05
Post high (vs. pre high) interventions (Model II)	0.57	0.49, 0.66
Post very high (vs. pre very high) interventions (Model III)	0.31	0.22, 0.39
	High income	
Post intermediate (vs. pre intermediate) interventions (Model I)	1.23	1.09, 1.37
Post high (vs. pre high) interventions (Model II)	1.00	0.89, 1.12
Post very high (vs. pre very high) interventions (Model III)	0.50	0.36, 0.63
	Upper middle income	
Post intermediate (vs. pre intermediate) interventions (Model I)	0.75	0.57, 0.93
Post high (vs. pre high) interventions (Model II)	0.66	0.52, 0.80
Post very high (vs. pre very high) interventions (Model III)	0.31	0.13, 0.48
	Lower middle income	
Post intermediate (vs. pre intermediate) interventions (Model I)	1.20	1.01, 1.40
Post high (vs. pre high) interventions (Model II)	0.28	0.10, 0.46
Post very high (vs. pre very high) interventions (Model III)	0.69	0.53, 0.85
	Low income	
Post intermediate (vs. pre intermediate) interventions (Model I)	1.21	0.85, 1.56
Post high (vs. pre high) interventions (Model II)	0.39	0.13, 0.66
Post very high (vs. pre very high) interventions (Model III)	0.19	–0.11, 0.49

All Stringency Index levels were compared to the low level in separate models. All three models where possible were adjusted for Index for Risk Management (INFORM) Epidemic Risk Index, World Health Organization transmission classification, and days since last case appeared in a country/region. The Stringency Index was categorized in four quartiles, reflecting low to very high government intervention.

determinants between 21 January and 18 May 2020. Results provide a global and regional assessment of COVID-19 spread and its mortality between different settings and country-income levels with major observations. First, more strict government control policies reduced COVID-19 spread and mortality at the global level. Second, as governments modified strategies in response to the pandemic, the higher the level of control policies, the more effective was constraining COVID-19 spread and mortality. This may be explained by factors such as implementation timing and observed intervention adherence from the population. Third, analyses by country-income classifications showed that COVID-19 spread and mortality evolution among all government control policies followed similar patterns as observed globally. Fourth, the availability of ICU beds was marginally related to COVID-19 spread evolution but was not consistently related to COVID-19 mortality.

The global trend of COVID-19 spread showed that very high interventions and policies suppressed COVID-19 spread by almost half the magnitude of high-level policies when compared to the low intervention period (Bayesian model results in Table I). Findings are in line with the literature in the field [36,37] and support more strict and targeted control policies against the epidemic [16,19,38,39]. Results from trend analysis by country-income levels also showed similar patterns as observed globally. LICs, LMICs and UMICs regions when compared to HICs had negative COVID-19 spread based on the spatiotemporal regression. In addition, government policies at a very high level in the aforementioned areas apart from LMICs, when compared to those of HICs, showed lower COVID-19 spread coefficients (Table III). This lower virus spread observed in LICs, LMICs and UMICs may be explained by fewer imported cases due to relatively less travel from Asia, Europe and the USA to Africa [40] and other low and middle-income countries, in that period of time. In addition, these regions have low screening test capacity and other limited health and public resources [41] that could mask the current dynamics of the spread. Other studies in later waves of the COVID-19 pandemic resulted in more intensive spatial spread among developing countries such as in Latin American countries [42]. This would require more investment in surveillance and monitoring [43] (especially among low- and middle-income countries) and a rapid and targeted shift from the initial containment policies as soon as possible to more strict interventions with minimal delay [38,44], suggesting that non-pharmaceutical interventions can contain transmission [45].

In terms of global trends of COVID-19 mortality, very high levels of government interventions and policies suppressed the magnitude of mortality evolution to lower levels when compared to low government policies (Bayesian model results). Stratified model results by country-income level showed

Table IV. Mixed-model regression analysis to evaluate COVID-19 mortality with government interventions and other factors globally and by income categorization.

Items	Global analysis	
	β-coefficient	95% CI
Post intermediate (vs. pre intermediate) interventions (Model I)	2.55	2.30, 2.79
Post high (vs. pre high) interventions (Model II)	1.24	1.09, 1.39
Post very high (vs. pre very high) interventions (Model III)	0.65	0.49, 0.82
	High income	
Post intermediate (vs. pre intermediate) interventions (Model I)	3.10	2.78, 3.43
Post high (vs. pre high) interventions (Model II)	0.88	0.65, 1.11
Post very high (vs. pre very high) interventions (Model III)	0.32	0.11, 0.53
	Upper middle income	
Post intermediate (vs. pre intermediate) interventions (Model I)	1.83	1.51, 2.15
Post high (vs. pre high) interventions (Model II)	2.07	1.79, 2.35
Post very high (vs. pre very high) interventions (Model III)	1.16	0.74, 1.58
	Lower middle income	
Post intermediate (vs. pre intermediate) interventions (Model I)	3.44	3.00, 3.88
Post high (vs. pre high) interventions (Model II)	1.37	0.99, 1.75
Post very high (vs. pre very high) interventions (Model III)	1.49	1.20, 1.78
	Low income	
Post intermediate (vs. pre intermediate) interventions (Model I)	1.54	0.95, 2.13
Post high (vs. pre high) interventions (Model II)	0.87	0.35, 1.39
Post very high (vs. pre very high) interventions (Model III)	1.43	0.66, 2.20

All Stringency Index levels were compared to the low level in separate models. The Stringency Index was categorized in four quartiles, reflecting low to very high government intervention. All three models were adjusted for Index for Risk Management (INFORM) Epidemic Risk Index, proportion of population aged ⩾70 years, neoplasms disability-adjusted life years (DALYs), respiratory infections and tuberculosis DALYs and diabetes and kidney diseases DALYs.

similar trends, consistent with global analysis, where mortality coefficients were lower for very high levels of government policies (Table IV). This finding could be attributed to similar explanations as described previously for virus spread. Those latter ideas should draw the attention of stakeholders, funders and researchers in the area for targeted COVID-19 data collection now and in the future. Our study attempts to provide information with data that could help regional stakeholders better organise COVID-19 health-care system planning, especially among low- and middle-income regions as the epidemic evolves [40].

There is increasing debate regarding the role of determinants which influence COVID-19 spread and mortality [31]. Spatiotemporal analysis showed that ‘community transmission’ was inversely associated with COVID-19 spread and mortality evolution when compared to sporadic clusters. As already mentioned, sporadic transmission in this analysis reflects not only sporadic transmission but also clusters and local transmission – a fact that in conjunction with the correlation among neighbouring countries assumed by the model, the undetermined pathway of virus transmission, its high contagiousness among asymptomatic individuals [46] and data quality limitations (see limitations section) among countries on screening testing, diagnosis and reporting of COVID-19 could explain the present findings. Thus, this result could also be influenced by a confounder or a set of confounding variables which have been not measured and might miss the association or result in spurious correlations. Therefore, more research is needed on this in the future. On the contrary, discontinuous daily reports of new cases was the determinant that had an inverse relation to both spread and mortality. These results can be used by stakeholders, including policymakers, as crucial indicators as to when interventions could be lifted. As others recently reported, premature relaxation of government policies without specific strategies will lead to further waves of the virus [47], as has already been seen in Europe and the USA since September 2020. Additionally, a country’s preparedness for epidemics and emergencies seems to mask each region’s real status, as our assessment showed. Based on the INFORM Index, several countries are classified as well prepared, but this index was not related to virus spread in these respective countries. We also observed that ICU bed availability was not related to mortality and was marginally related to positive COVID-19 spread at a global level, marking the necessity for alternative ICU hospital planning and emergency enhancement strategies. These findings could be used for planning future control policies among infectious diseases of a similar nature.

Limitations

This study shares common limitations with previous studies of this kind [27]. Specifically, there were challenges in capturing uncertainty (completeness of the

WHO COVID-19 data set, government interventions being announced one day but not actually be applied for several days, differences in cases and death reports) and lags in data availability (tourist travel flows, ICU bed availability) which may not fully capture temporal COVID-19 trends in spread and mortality. Additionally, we acknowledge that our data set includes a variety of regions with quite different cultures, age structures, health-care infrastructures, income and economies, which could have played a role in the quality of the COVID-19-related data. As an example, some countries have good surveillance systems, whereas others do not, or surveillance may exist but methods for the monitoring, surveillance and reporting of COVID-19 cases and deaths may vary. More specifically, in the early months of COVID-19, low- and low-middle-income regions were susceptible to poor capacity for screening, testing, diagnosis and reporting [48]. Another example is that during the early period of the pandemic reflected in this paper, electronic health records did not have a systematic method for identifying COVID-19 patients, and it was not until April 2020 that COVID-19 was included in the International Classification for Diseases (ICD)-10 [49]. These factors may have affected the validity of the data, even though they were all obtained from the WHO situation reports. However, we recognise that all countries report cases and deaths at the national level to the WHO using certain criteria. Thus, we applied stratified mixed-model analysis among HICs, MICs and LICs to partition diversity more effectively among surveillance and health-care systems [50], and the results remained consistent with the global analysis. We should report here that previous studies that analysed areas with comparable health-care infrastructures and economies, during the same period as our study, were in line with our results [14]. A further limitation is that the WHO mortality data only consider patients who died of or with COVID-19, while excess mortality is not taken into account. This could affect our modelling estimates related to government interventions and policies for COVID-19. Another limitation is that the data analysis could not adjust for other factors such as daily screening COVID-19 tests [51] per country (when this paper was written, data were publicly available for a limited number of countries), which could alter the estimates. This research did not intend to explain causality, only statistical associations. Our inferences are drawn using observational data. To the extent of the data available, our inferences adjust for the differential covariates across observational units. Ideally, we should have fitted the models in a randomised design, but such design is impossible to pursue in the current settings. However, an extension of this work could use post-randomisation techniques based on matching or weighting-based random sampling methods that specifically target potentially varying background characteristics. Our analysis focused on completed data, but handling missingness, for instance using a multiple imputation strategy, is a possible strategy to follow in future studies. Finally, the applied modelling methodologies in this study may not fully capture the trends and patterns of the evolving COVID-19 pandemic, as they are time-limited and restricted to the first-wave virus variants. Additionally, our investigation focused on data variations in the COVID-19 spread from January to May 2020. Therefore, our results should be interpreted with caution, as they only relate to the underlying data collection conditions and period. As COVID-19 is an infection with dynamic transmission and the analysed variables may vary among future periods, we do not think it would be appropriate to make conclusions beyond May, as further data and analysis would be required.

Conclusions

We found that globally, a very high level of government interventions and control policies appeared to be successful in suppressing COVID-19 spread and mortality evolution during the first four months of the pandemic (the first COVID-19 wave period). In addition, stricter government policy measures reduced virus spread and mortality at the global level. Similar patterns in virus spread and mortality for each implemented government intervention were observed for different country-income levels and regions. Although COVID-19 has developed many variants which differ significantly from the initial one (on which our analysis was based), in terms of transmissibility and disease severity, the current findings could be used to facilitate future government decision making for outbreaks of a similar nature and magnitude.

Declaration of conflicting interests

The authors declared no potential conflicts of interest with respect to the research, authorship and/or publication of this article.

Funding

The authors disclosed receipt of the following financial support for the research, authorship and/or publication of this article: Daniel Fernández is a Serra Húnter Fellow who was supported by the Ministerio de Ciencia e Innovación (Spain) [PID2019-104830RB-I00/ DOI (AEI):

10.13039/501100011033], and by grant 2021 SGR 01421 (GRBIO) administrated by the Departament de Recerca i Universitats de la Generalitat de Catalunya (Spain). Stefanos Tyrovolas was supported by the Foundation for Education and European Culture (IPEP), the Sara Borrell postdoctoral program (reference no. CD15/00019 from the Instituto de Salud Carlos III (ISCIII – Spain) and the Fondos Europeo de Desarrollo Regional (FEDER, UE). William Pan is supported by NASA-ROSES grant NNX15AP74G.

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Supplemental material

Supplemental material for this article is available online.

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