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Evolution and early government responses to COVID-19 in South America

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This article analyses the evolution of COVID-19 and early government responses to the pandemic in eight South American countries. To this aim, this study explores indicators which trace the progression of the pandemic and analyses factors related of state capacity which impacted on the early response of governments of implementing restrictive policies of social distancing associated with a suppression strategy. The pressure on the health systems is evaluated with early projections of the growth-phase of the epidemic, which is incorporated as an indicator in the analysis of early interventions based on Cox proportional hazards models. The results indicate that fiscal expenditure on health, regional and local government capacity, and pressure on the health system accelerate government response with stringent interventions. A counter-intuitive finding is that the economic strength of a country delays these types of reactions. The effect of these interventions is something that should be studied in greater depth, considering, for example, sociocultural factors. Lastly, only cases such as Uruguay and Paraguay show some signs of having the pandemic relatively under control by mid-May, while Brazil and Peru face very adverse scenarios. In this context, considering the characteristics of the states in the region and the level of informal employment, it will be a public policy challenge to keep the equilibrium between restrictive measures and the economic and social problems which these responses imply in the medium term.

1. Introduction

The new coronavirus SARS-CoV-2, which causes the disease COVID-19, has generated unprecedented socioeconomic disruption on a global scale. On March 11, 2020, the World Health Organisation (WHO) declared it a pandemic. By that point, the outbreak had already reached more than a hundred countries with over a hundred thousand cases worldwide. Most European countries and the United States, as seen in the second half of March, had to deal with the accelerated growth of infections and enormous pressure on their health systems. A growing number of patients needed beds in intensive care units (ICU), and the propagation rate of the disease could reach its peak with demand over the ICU bed capacity in many countries (Adolph, Amano, Bang-Jensen, Fullman, & Wilkerson, 2020; Sun, Chen, & Viboud, 2020).

Whereas in Europe and the United States, cases started to grow exponentially, in South America, there was a small margin to take drastic measures against the pandemic and attempt to contain the infection. The countries of South America started to register their first cases between the end of February and the beginning of March. Paradoxically, even though Brazil registered the first cases in the region, President Jair Bolsonaro has persistently rejected social distancing recommendations made by international and Brazilian organisms, going as far as to declare on several occasions that the pandemic is just a light flu. By contrast, the Argentinian president, Alberto Fernández, considered this pandemic a severe threat to his country. On March 19, he addressed the nation, after meeting with all the governors, to announce a presidential decree imposing obligatory social isolation, accepting the adverse effects this would have on the country’s economy.

These two examples can be associated with the strategies of mitigation and suppression, respectively. Both are fundamental strategies of non-pharmaceutical intervention in the context of government responses considering the absence of a vaccine for the virus (Ferguson et al., 2020). As long as mitigation seeks to slow down the propagation of the virus, reducing pressure on the health system, suppression attempts to reduce epidemic growth to a
minimum, in line with the strategy followed by New Zealand. Whichever the approach, social distancing appears to be the only way of stopping infection and reducing pressure on health systems given that since neither a vaccine for the virus nor a proven treatment exist yet, the rate of reproduction of the virus is quite high, and the existence of asymptomatic or light cases, which are infection vectors, makes it tremendously challenging to trace the chain of infection (Adolph et al., 2020; Bai et al., 2020; Niu & Xu, 2020).

This study pursues to answer the question: What factors impacted on early government responses to COVID-19 in South America? To this end, we explore non-pharmaceutical interventions related with measures of social distancing, closure of schools, workplaces, public transport and restrictions on meetings and national and international travel in eight South American countries: Argentina, Bolivia, Brazil, Chile, Colombia, Paraguay, Peru, and Uruguay. This article identifies the factors that have impacted on the early government response to the pandemic in these cases, specifically measures associated with the suppression strategy. This is relevant since these are cases which, although historically have shown a weaker state capacity, over the past few decades their state has become strengthened in different ways. The latter is evidence of the heterogeneity among countries and within their civil services. Moreover, these cases had a window of opportunity of approximately two weeks since the first cases until the WHO declared the outbreak a pandemic and the European countries showed signs of collapse and implemented significant suppression measures. In this context, the governments of the region had to decide whether to follow the European model of emergency closures in a scenario of high uncertainty, weaker social protection networks, and a higher level of informal employment.

2. State capacity and crisis management

The development of the state capacity in Latin America during the twentieth century is usually associated with historical processes (Luna, 2020; Mahoney, 2010), as well as with socioeconomic inequalities and lack of trust in institutions (Centeno, 2009; Grassi & Memoli, 2016). State capacity is related with the idea of infrastructural power, which in turn is associated with the control exercised by a state, the ability to implement public policies and to enforce the established norms (Soifer & von Hau, 2008; see also Mann, 1993; Soifer, 2015).

Although Latin America has lagged historically in terms of the development and consolidation of its states, the unusual recent economic growth in the region has implied an expansion of infrastructural and public services. The case of Peru is an excellent example of poverty reduction and the increase of state capacity in recent years (Dargent, Feldmann, & Luna, 2017; Luna, 2020). However, this economic boom not only powered the formal economy but is also associated with a significant expansion of informal markets, often linked to illegal activities like, for example, in the cases of Bolivia, Peru, and Paraguay (Dewey, 2012; Luna, 2020). In this context, although the Latin American states today possess comparatively greater infrastructural capacity, there are warning signs of their being overwhelmed at a local level. This due to their incapacity to retain the monopoly of the use of force and adequately provide public goods and services to the population (Luna, 2020).

State capacity has three dimensions, making its measurement complex. Some capacities are related with the size of budgets and government bureaucracies, while on the other hand, the impact of state action in areas such as tax collection or indicators of specific policies are also relevant (Bull, 2020). For example, Hanson and Sigman (2013) analyse half a century of state capacity in Latin America and position Chile and Uruguay as leaders in the region, followed by Brazil and Bolivia. However, it is important to bear in mind that not only there are discrepancies among countries, and there are also profound differences between the public services within one country and in its regions (Bull, 2020; Gingerich, 2012).

Crisis, for their part, can be understood as a threat to the core values or functions of a social system, which generates high levels of uncertainty and requires immediate corrections (Christensen, Laegreid, & Rykkja, 2016; Rosenthal, Charles, & Hart, 1989). These corrections are related to the management of and response to specific crises like natural disasters, terrorist attacks or, in this case, a pandemic. Christensen et al. (2016) understand crisis management as a combination of legitimacy and capacity conditioned by the scale of the crisis and its level of uncertainty. Legitimacy, for its part, is interwoven with citizen expectations about the management of the crisis. These expectations condition the perception of government actions; therefore, the coincidence or discord between expectations and responses is an intricate link between capacity and legitimacy (Schneider, 2011). On the other hand, capacity can be understood as state or administrative capacity, although strictly speaking both are involved. Administrative capacity may be a somewhat vague concept, but it can be divided into at least four components which allow for a more direct measurement: (i) delivery capacity, related with the provision of public goods; (ii) regulatory capacity associated with state control and supervision of different sectors; (iii) coordination capacity for joint state action; and (iv) analytical capacity to evaluate risks and vulnerabilities (Lodge & Wegrich, 2014).

This study focuses on the three dimensions of administrative capacity, which should be most strongly linked to the crisis: delivery, coordination, and analysis. First, delivery capacity is related to the provision of public goods; in this case, the capacity of health systems to deal with the epidemic. Consequently, certain variables are used which reflect investment in state capacity in health, understanding investment as the assignment of scarce resources, whether they be monetary, technical or political to improve a specific area (Brieva, 2018). Coordination capacity, on the other hand, is evaluated with respect to the coordination between the central administration, and regional and local governments. In general, the literature tends to indicate that a key element in crisis management is the existence of a certain level of decentralisation for better response, maintaining a balance which implies not diluting responsibilities at the central level (Boin, 2008; Boin, Ekengren, & Rhinard, 2014; Christensen et al., 2016). Lastly, analytical capacity is related to the evaluation of risk and vulnerability in crises, which eventually permits better decisions to be taken.

The effect of variables related to the above dimensions in the early response by governments in South America is evaluated. As mentioned previously, non-pharmaceutical interventions can be grouped into two main types: mitigation and suppression (Ferguson et al., 2020). Both strategies can be evaluated according to the basic reproduction number \( R_0 \), which indicates the number of infections produced by one single case. When the value is below one, the outbreak is under control; hence, it is a useful measure for evaluating the response of health systems (Cori, Ferguson, Fraser, & Cauchemez, 2013; Thompson et al., 2019). The mitigation strategy seeks to reduce propagation speed without completely interrupting transmission. Consequently, its objective is to reduce \( R_0 \) to the minimum without it falling below one and build herd immunity in the population. On the other hand, the suppression strategy seeks to reduce \( R_0 \) to less than one to eliminate transmission.

The government responses are assessed in relation with the suppression approach and the implementation of social distancing measures, the closure of schools, workplaces and public transport, the cancellation of public events, restrictions on meetings and movement within countries, as well as international travel controls. These interventions are in line with those mentioned in stud-
ies such as Ferguson et al. (2020), Adolph et al. (2020), Toshkov, Yesilkagit, and Carroll (2020), as well as those compiled by Hale et al. (2020) with the Oxford COVID-19 Government Response Tracker (OxCGRTR).

3. Methods

3.1. Data

The Center for Systems Science and Engineering at the Johns Hopkins University COVID-19 Dataset is used to measure confirmed cases, recovered, and deaths (CSSE, 2020). This information enables us to calculate the incidence, epidemic curves, and serial interval distribution (SI). The latter is the time between infection and the onset of symptoms in a new case. In addition, government responses are measured with the OxCGRTR, developed by the Blavatnik School of Government at the University of Oxford, which permits to track the stringency of measures such as the closure of schools, non-essential businesses, stay at home requirements, among others (Hale et al., 2020).

This data is integrated with a code programmed available in the Supplementary material for Argentina, Bolivia, Brazil, Chile, Colombia, Paraguay, Peru, and Uruguay. This data set incorporates information from other sources like Our World in Data, a project coordinated by the Martin Programme on Global Development at the University of Oxford (Roser et al., 2020), from the Health Information Platform for the Americas of the Pan American Health Organization (PAHO, 2019), from the V-Dem project (Coppedge et al., 2020), World Bank, 2018 indicators (World Bank, 2018; see also Piburn, 2018). In this way, it is possible to codify different variables for the analyses.

3.2. Proportional hazards models and early projections

The econometric strategy is based on stratified, pooled Cox proportional hazards models to evaluate the early response of governments in the region, specifically concerning the implementation of suppression strategies between February 26 ($t_0$) and April 30 ($t_1$). On the one hand, critical strategies related to the closure of schools, non-essential workplaces, stay at home requirements, and the implementation of strict policies on testing and contact tracing are evaluated. These measures are also used in descriptive analysis. Furthermore, the econometric models incorporate other interventions such as the cancellation of public events, restrictions on gatherings, public transport closure, restrictions on movement and international travel controls, in particular, bans on high-risk regions and border closure. Since the early response is evaluated with respect to the implementation of suppression strategies, the more stringent decisions are considered, specifically explicit prohibitions and their implementation at a national level. Measures not implemented before $t_1$ are treated with administrative censure.

This study evaluates the effect of variables associated with three dimensions of administrative capacity: delivery, coordination, and analysis. These variables are controlled by GDP per capita of each country, constant in dollars (World Bank, 2018). First, delivery is evaluated according to Current Health Expenditure (CHE) per capita controlled by purchasing power parity (PPP) with information from PAHO, 2019. The second dimension is evaluated with the V-Dem division of power index, which is based on a scale between zero and one, where the highest values are related to cases where local and regional governments are elected and operate without relevant restrictions.

Finally, analytical capacity is measured with three variables. First, the number of confirmed cases at the end of the third week of March is used. This date is critical since the week before the WHO had declared COVID-19 a pandemic and governments found themselves pressured to take decisions. Second, the number of hospital beds per 1,000 people is taken from PAHO, 2019. Although this can also be related to the delivery, it is used as a foresight indicator and analysis capacity. Third, a projected burden index is used to measure pressure on health systems (see González, Munoz, Moya, & Kiwi, 2020).

The projected burden index is calculated using confirmed cases * 0.15 divided by the number of ICU beds * 0.25. Hereby, when the index equals one, the limits of the health system have been reached. The weightings correspond to 15% of cases that could require intensive care (Hopman, Allegrenzi, & Mehtar, 2020; Liew, Siow, MacLaren, & See, 2020) and a 75% of ICU beds occupancy according to OECD indicators (González et al., 2020). The number of cumulative cases is estimated with early projections simulated until April 30 based on information from the third week of March. The effective reproduction number ($R_t$) and a maximum likelihood estimation with a SI parametrised with a Gamma distribution $\mu = 7.5$ and $\sigma = 3.4$, following the Wuhan cases study of Li et al. (2020), are used. Based on that information, 1,000 Bayesian simulations of $R_t$ are carried out, and the epidemic curves are projected until the end of April, which implies carrying out a total of 48,000 simulations per country and 384,000 in total.

Consequently, the time of response $t_0$ is observed for the $i$th interventions of the $j$th strata according to its type, where $\sum_{j=1}^J$ and $J = 11$ within $n = 8$ countries. The country-level is used as clusters to adjust standard errors. The proportional hazards model is extended to include variables. If $X_k$ denotes a $k$th variable for $i$, the intervention rate is given by:

$$\lambda(t_i; X_1, \ldots, X_k) = \lambda_0(t_i) \exp \left[ \sum_{k=1}^m \beta_k X_k + e_k \right]$$ (1)

In the equation, $\lambda_0(t)$ is the baseline hazard, which is calculated from an estimate of the cumulative hazard $\Lambda_0(t)$ and a baseline survivor function. The baseline hazard is stratified across the pooled interventions in $J_m$ strata, similar to the analysis of responses by Adolph et al. (2020). Furthermore, the tied interventions are controlled by the Efron method, and the maximum of events per predictor variable rule is used (Vittinghoff & McCulloch, 2006). Therefore, three different models are fitted according to the above equation alternating the value of $k$ with different variables to test the analytical capacity.

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1. In the case of Uruguay, there is a problem with the data of confirmed cases on April 12, but this only involves 2.87% of the total analysed. On the other hand, initially, Venezuela and Ecuador were considered interesting cases since they are the countries with the least state capacity in the region (Hanson & Sigman, 2013). However, Venezuela was excluded because it does not have updated information for measuring administrative capacity. Ecuador was also omitted since it presented a data mismatch of 9.89% in confirmed cases.

2. $R_0$, on the one hand, is the number of expected cases on average in a homogeneous population and is affected by susceptible people, the density of the population, infectiousness, among other factors. On the other hand, $R_t$ is the number of people that can be infected by a case at any specific time, and it is affected by the contact between confirmed cases and susceptible ones, behaviour, and interventions (Aronson, Brassey, & and Mahtani, 2020).

3. Available in the appendices are the figures per country (Fig. 2) which contrast confirmed cases and early projections with additional information about the most relevant suppression strategies implemented and their expected effects according to three-weeks term since the intervention pointed by Ferguson et al. (2020). This projection method is used because, in March, the epidemic was still in an early growth-phase in the region. For intermediate and advanced stages, it is recommendable, for instance, to use each component of a log-incidence model to measure correctly the growth and the decay-phase of the epidemic, respectively.
It is relevant to note that a key indicator associated with the analytical capacity variables is confirmed cases, which in the context of this ongoing crisis could be inaccurate and generate biased models since a number of reasons. For instance, cross-national differences in testing and tracing policies, inappropriate laboratory conditions or lack of personnel or reagents. This could be associated with an endogeneity effect since testing and contact tracing are measures evaluated in the analysis. In order to address this, a fourth model is fitted in which these policies are extracted from the pool and used to create new clusters. Accordingly, $\sum_{j=1}^{J}$ and $J = 9$ within two groups $(n = 2)$. Analogously to the previous models, the group-level is used to adjust standard errors.

Finally, a number of statistical tests are applied to check the models. First, the proportional hazards assumption (PHA) is tested (Box-Steffensmeier & Jones, 2004), and the C-Index is calculated. This index, in this case, indicates the proportion of all pairs of countries for which the prediction trends adequately which government will adopt a specific intervention first (Harrell, Lee, & Mar, 1996; see also Adolph et al., 2020). Subsequently, AIC and VIF are calculated and reported in the models. After that, additional tests are carried out to measure the influential cases with Schoenfeld residuals and non-linearity with Martingale ones (Therneau, Grambsch, & Fleming, 1990). The former is available in the Supplementary material.

4. Results

4.1. An early outlook of the pandemic in South America

The third week of March was key in the regional context since governments started to take decisions to stop the pandemic. In Brazil, for instance, three weeks had already passed since the first case, and more than 700 cases had been registered. Additionally, an $R_c$ of 3.203 had been verified, surpassed at that time only by Chile and Uruguay with 3.273 and 3.243, respectively. At the other extreme, the first infections in Uruguay and Bolivia were registered just over a week before, and the realities they reflected were highly dissimilar. Uruguay with more than 100 cases and Bolivia with fewer than 20. At this point, Bolivia boasted the lowest $R_c$ of the countries analysed, at 1.542.

For that reason, although in South America the differences in timing are not substantial, each case is at a different point in time along the epidemic curve, which is also conditioned by demographic and socioeconomic disparities, and state and detection capacities. Fig. 1 shows an early outlook of the evolution of the pandemic in the region with the focus on confirmed cases, deaths, recovered, and the current burden index adjusted for recovered cases. It is important to note that COVID-19 confirmed cases data is undoubtedly inaccurate in the context of this ongoing crisis; therefore, this indicator should be considered as underestimated. Furthermore, some countries have bought mechanical ventilators and expanded their ICU capacity over the last weeks, which although may be relatively marginal in an early stage, it is relevant to bear in mind that it is not reflected in this measurement.4

Four categories of cases can be identified based on three key characteristics associated with the management of the pandemic: (i) central measures of the suppression strategy such as the closure of schools, non-essential businesses, and stay at home requirements; (ii) testing policy; and (iii) contact tracing. In the first category, the only country that features is Paraguay, which has promoted a strict suppression strategy, implementing in the third week of March the closure of schools, workplaces, and stay at home instructions. Moreover, it has stringent testing and case tracing policy. This is reflected in the low incidence of cases registered in mid-May and in how well its health system is holding out. Although at the beginning of May it registered an $R_c$ of approximately five, Paraguay managed to reduce it rapidly and at the moment shows signs of having controlled the pandemic with just over 105 cases and 1.5 deaths per million population.

The second category pertains to cases that combine suppression strategies with a consistent testing policy. This is the case of Chile and Colombia. In Chile, schools and universities were closed in mid-March, and teleworking was promoted. Colombia, for its part, implemented similar measures with just a few days of delay in the restrictions of workplaces. Furthermore, both countries have implemented a consistent testing policy, which allows us to assume that, like in Paraguay, there is not a significant underestimation of infections.5 Although both countries also promote a policy of contact tracing, this is not as effective as an early response since they implemented stricter measures between the end of March and beginning of April, when tracing the chain of infection transmission was already complex. Despite these efforts, both countries register a significant number of cases, and their health systems are practically overwhelmed, although $R_c$ remains stable at below two. For instance, Chile is the second country in cases per million inhabitants above 1,900 in mid-May.

In the third category are Argentina and Peru. Both countries implemented stringent suppression strategies and stay at home requirements in the third week of March. Strictly speaking, far more extreme measures than the abovementioned countries. However, in both countries, testing is laxer, and contact tracing presents the same problem of late response as in Chile and Colombia. For example, Argentina was performing 2.1 tests per 1,000 population on May 15 and Peru around 2.8. This leads one to assume that infections are moderately underestimated.

On the one hand, Argentina has not shown signs of being a complex case due to its reduced number of infections and moderate pressure on its health system, although its $R_c$ increased slightly in May, reaching 1.682 by the end of the second week. Peru, on the other hand, despite having managed to reduce its $R_c$ to close to one during May, is one of the most worrying cases due to the cumulative incidence and the immense pressure on the health system. In mid-May Peru had shown the worst indicators adjusted per population in the region: more than 2,400 cases and around 68 deaths per million people.

Finally, in the fourth category are the countries that did not implement stringent suppression strategies or promote strict testing and tracing policies. Therefore, it is possible to assume a more considerable underestimation of confirmed cases. In this group, we find Bolivia, Uruguay, and Brazil. However, there are substantial differences among the three countries. Although Bolivia and Uruguay have not promoted exhaustive testing and case traceability policies, both implemented school closures in mid-March and the closure of non-essential workplaces was promoted at the end of March in Bolivia. Despite the low number of cases and that the $R_c$ containment in Bolivia has been relatively effective, the weakness of the health system is a problem. Moreover, Bolivia had carried out only 0.8 tests per 1,000 inhabitants on May 15. Uruguay, for its part, is one of the most successful cases in the region accord-

4 In the appendices, there are figures for each country, showing the $R_c$ between February 26 and May 15 (Fig. 3). Moreover, there is tabular data updated to mid-May with information about cases and deaths per million people, as well as tests performed per 1,000 inhabitants based on Roser et al., 2020 data (Table 2).

5 This indicator should be contrasted with the number of tests per people. While Chile is the most remarkable case of testing policy in the region and worldwide with 17.9 per 1,000 people in mid-May, Colombia and Paraguay just performed about 3.6 and 2.6, respectively. Moreover, the differences across countries in the number of tests could be associated with their detection capacities in terms of laboratory conditions, qualified personnel, and reagents stocks.
ing to these indicators with almost nine tests per 1,000 population in mid-May, as well as just over 200 cases and approximately five deaths per million people.

On the other hand, Brazil is the only country in the region that has not systematically implemented at the national level any key suppression policy or clear strategies of detection and tracing of infections. This is evident in evaluating almost any indicator, the possible overwhelm of its health system, as well as the confirmed cases and deaths per million inhabitants: over 950 and about 65, respectively.

With regards to the strict implementation of other measures at a national level, all countries, except for Brazil, have combined different measures. The cancellation of public events was implemented transversally during March, but the strict limiting of gatherings has not been applied in Chile and Uruguay. Closure of public transport has only been implemented in Argentina, Bolivia and, at the beginning of May, in Peru. The restriction of internal movement, for its part, has been more transversal, except for Chile, whose implementation has been late and ineffective. The only measures adopted by all of the countries during March, including Brazil, concern the international travel controls with bans on high-risk regions and border closure.

4.2. Determinants of suppression strategies

Table 1 presents the four Cox proportional hazards models fitted. Models I and II use confirmed cases and hospital capacity as variables related to analytical capacity. In both cases, only the number of confirmed cases is a significant variable that delays the implementation of suppression interventions, which suggests that this information is not good enough for decision-making.6

On the other hand, by using the projected burden index as an indicator of the analytical capacity in models III and IV, this has a significant statistical effect which accelerates the government response in stringent interventions. It is relevant to remember that model IV extracts from the pooled interventions, both testing and contact tracing policies and uses them to generate clusters and adjust standards errors in order to control endogeneity.

The well-known hazard ratio, which is obtained from the exponentiated coefficients, in this case, operates as a response ratio if the other covariates are held constant. For instance, the projected burden index increases the response by a factor of $e^{b} = 1.031$ ($p = 0.000$ and CI 95%: 1.016 to 1.047), this is 3.1% and 3.5% by a unit of the index in model III and IV, respectively. Moreover, in model III, public expenditure on health ($e^{b} = 5.045 + 01$, $p = 0.001$, and CI 95% = 5.016e + 00 to 5.075e + 02) and more autonomous regional and local governments ($e^{b} = 2.639 + 04$, $p = 0.000$, and CI 95% = 3.358e + 02 to 2.074e + 06) are also related significantly to more rapid interventions, but with higher degrees of uncertainty. Similarly, model IV confirms the findings with slight differences in $b$ coefficients: an increase of 8.1% in expenditure on health and 16.5% in the division of power.

The GDP per capita, on the other hand, turns out to be a factor which delays the implementation of suppression measures by 98.6% by logged unit of GDP in model III ($e^{b} = 1.446e−02$, $p = 0.000$, and CI 95%: 1.558e−03 to 1.341e−01). This finding is

6 In an alternative analysis of model II, ICU beds were used instead of hospital capacity and very similar coefficients were obtained, but the PHA test was not meet.
confirmed in model IV with 99% by logged unit of GDP ($e^b = 9.876 \times 0.000, \ p = 0.000, \ \text{and CI } 95\%: 5.484 \times 0.000$ to $1.778 \times 0.000$). These results are counter-intuitive since the more prosperous countries should be more prepared to shoulder economic costs by adopting strict measures in the management of the crisis. However, in the cases analysed this tends to function inversely, which should possibly be analysed in contrast with sociocultural and ideological variables.

5. Conclusion

As from the third week of March, most of the South American countries implemented a number of measures in an effort to halt the pandemic. Although some indicators are undoubtedly underestimated, especially confirmed cases, it is possible to note some trends such as heterogeneity in the growth-phase of the crisis in the region. Some countries, like Uruguay and Paraguay, have managed to contain the pandemic relatively successfully, while others appear to be overwhelmed by COVID-19 like Brazil and Peru. Apart from this heterogeneity in the evolution of the epidemic, state capacity and, in particular, analytical capacity associated with the adequate evaluation of pressure on the health system, are identified as significant factors for the rapid implementation of suppression strategies. Nevertheless, for as long as there is not a vaccine, this may be a risk. Keeping the equilibrium between the adverse economic effects associated with paralysing a country and stringent interventions may be a complex challenge for governments in the region over the coming months.

Declaration of Competing Interest

The author declares that he has no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A

See Figs. 2 and 3 and Table 2.

### Table 1

|                     | Model I          | Model II         | Model III        | Model IV         |
|---------------------|------------------|------------------|------------------|------------------|
| Log CHE per capita  | $-1.044 \ (0.980)$ | $-1.044 \ (1.374)$ | $3.921 ^{***} \ (1.620)$ | $4.238 ^{***} \ (1.707)$ |
| Division of power index | $-0.429 \ (1.475)$ | $-0.889 \ (1.625)$ | $10.181 ^{***} \ (3.651)$ | $11.863 ^{***} \ (3.889)$ |
| Confirmed cases (third week) | $-0.003 \ (0.001)$ | $-0.003 \ (0.001)$ | $-0.003 ^{***} \ (0.204)$ | $-0.003 ^{***} \ (0.012)$ |
| Hospital beds (per 1,000 people) | $0.155 \ (1.475)$ | $0.155 \ (1.137)$ | $0.155 \ (1.204)$ | $0.155 \ (1.137)$ |
| Burden index        | $0.031 ^{***} \ (0.001)$ | $0.031 ^{***} \ (0.001)$ | $0.031 ^{***} \ (0.001)$ | $0.031 ^{***} \ (0.001)$ |
| Log GDP per capita  | $0.710 \ (0.937)$ | $1.224 \ (1.137)$ | $-4.237 ^{***} \ (1.504)$ | $-4.618 ^{***} \ (3.889)$ |
| Log-Rank            | $15.925 ^{***}$ | $16.107 ^{***}$ | $15.974 ^{***}$ | $19.459 ^{***}$ |
| AIC                 | $164.503$ | $165.931$ | $167.703$ | $149.699$ |
| C-Index             | $0.703$ | $0.716$ | $0.716$ | $0.752$ |
| PHA Test            | $0.125$ | $0.089$ | $0.199$ | $0.172$ |
| VIF                 | $1.164$ | $1.180$ | $1.120$ | $1.120$ |
| Events              | $53$ | $53$ | $53$ | $49$ |
| N                   | $88$ | $88$ | $88$ | $72$ |
| Log Likelihood      | $-78.252$ | $-77.965$ | $-79.852$ | $-70.850$ |

*shape p < 0.1; **shape p < 0.05; ***shape p < 0.01.
Source: Author’s calculations from February 26 to April 30, 2020, based on Coppedge et al., 2020; CSSE, 2020; Hale et al., 2020; PAHO, 2019; 2018 data.
Appendix B. Supplementary data

Supplementary data associated with this article can be found, in the online version, at https://doi.org/10.1016/j.worlddev.2020.105180.

References

Adolph, C., Amano, K., Bang-Jensen, B., Fullman, N., and Wilkerson, J. (2020). Pandemic politics: Timing state-level social distancing responses to COVID-19. https://doi.org/10.33774/apsa-2020-af6ps.

Christensen, T., Laegreid, P., & Rykkja, L. H. (2016). Organizing for crisis management: Building governance capacity and legitimacy. Public Administration Review, 76(6), 887–897. https://doi.org/10.1111/puar.12558.

Coppedge, M., Gerring, J., Knutsen, S. I., Carl Henrik, L., Teorell, J., Altman, D., et al. (2020). V-Dem Country-Year Dataset v10. Dataset Varieties of Democracy (V-Dem) Project at the University of Gothenburg. Available at https://doi.org/10.23696/vdemds20.

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Fig. 2. Confirmed cases, early projections, and key interventions by country, between February 26 and May 15, 2020. Early projections until April 30. Source: Author’s calculations based on CSSE (2020) and Hale et al. (2020) data.

Fig. 3. Effective reproduction number by country, between February 26 and May 15, 2020. Source: Author’s calculations based on CSSE (2020) data.

Table 2

| Country | Cases   | Deaths | Tests  |
|---------|---------|--------|--------|
| Argentina | 157,559 | 7,810  | 2,144  |
| Bolivia  | 288,871 | 13,021 | 0,828  |
| Brazil   | 954,641 | 65,831 |        |
| Chile    | 1,937,623 | 18,728 | 17,865 |
| Colombia | 267,477 | 10,318 | 3,599  |
| Paraguay | 105,713 | 1,542  | 2,644  |
| Peru     | 2,444,631 | 68,756 | 2,812  |
| Uruguay  | 208,422 | 5,470  | 8,084  |

Source: Cases and deaths per million and tests per 1,000 people based on Roser et al., 2020 data.

Aronson, J.K., Brassey, J., and Mahtani, K.R. (2020). When will it be over?: An introduction to viral reproduction numbers, R0 and Re. Working Paper COVID-19 Evidence Service Team, Centre for Evidence-Based Medicine, Nuffield Department of Primary Care Health Sciences at the University of Oxford. Available at https://www.cebm.net/covid-19/when-will-it-be-over-an-introduction-to-viral-reproduction-numbers-r0-and-re/.

Bai, Y., Yao, L., Wei, T., Tian, F., Jin, D.-Y., Chen, L., & Wang, M. (2020). Presumed asymptomatic carrier transmission of COVID-19. JAMA, 323(14), 1406–1407. https://doi.org/10.1001/jama.2020.2565.

Boin, A. (2008). Introduction to crisis management (Vol. 1) London: Sage Publications.

Boin, A., Ekengren, M., & Rhinard, M. (2014). Transboundary crisis governance. In J. Sperling (Ed.), Handbook of governance and security. https://doi.org/10.4337/9781781953174.00027.

Box-Steffensmeier, J. M., & Jones, B. S. (2004). Event history modeling. A guide for social scientists. New York: Cambridge University Press.

Brieba, D. (2018). State capacity and health outcomes: Comparing Argentina’s and Chile’s reduction of infant and maternal mortality, 1960–2013. World Development, 101, 37–53. https://doi.org/10.1016/j.worlddev.2017.08.011.

Bull, B. (2020). Elites y capacidad estatal en América Latina: una perspectiva basada en recursos sobre los cambios recientes en El Salvador. In P. Andrade (Ed.), Estado en América Latina: problemática y agenda de investigación. Corporación Editora Nacional: Quito.

Coppedge, M., Gerrig, J., Knutsen, S. I., Carl Henrik, L., Teorell, J., Altman, D., et al. (2020). V-Dem Country-Year Dataset v10. Dataset Varieties of Democracy (V-Dem) Project at the University of Gothenburg. Available at https://doi.org/10.23696/vdemds20.

Box-Steffensmeier, J. M., & Jones, B. S. (2004). Event history modeling. A guide for social scientists. New York: Cambridge University Press.
Cori, A., Ferguson, N. M., Fraser, C., & Cauchemez, S. (2013). A new framework and software to estimate time-varying reproduction numbers during epidemics. *American Journal of Epidemiology*, 178(9), 1505–1512. https://doi.org/10.1093/aje/kwt133.

CSSE (2020). COVID-19 Data Repository by the Center for Systems Science and Engineering (CSSE) at Johns Hopkins University. Dataset CSSE at the Johns Hopkins University. Available at https://github.com/CSSEGISandData/COVID-19.

Dargent, E., Feldmann, A. E., & Luna, J. P. (2017). Greater state capacity, lesser stateness: Lessons from the Peruvian commodity boom. *Politics & Society*, 45(1), 3–34. https://doi.org/10.1177/0022216x16683364.

Dewey, M. (2012). Illegal police protection and the market for stolen vehicles in buenos aires. *Journal of Latin American Studies*, 44(4), 679–702. https://doi.org/10.1017/s0022216x12000831.

Ferguson, N., Laydon, D., Nedjati Gilani, G., Imai, N., Ainslie, K., Baguelin, M., et al. (2020). Impact of non-pharmaceutical interventions (NPIs) to reduce COVID19 mortality and healthcare demand. Working Paper Imperial College COVID-19 Response Team. http://dx.doi.org/10.25561/77482.

Gingerich, D. W. (2012). Governance indicators and the level of analysis problem: Empirical findings from South America. *British Journal of Political Science*, 43(3), 505–540. https://doi.org/10.1017/s0007123412000403.

González, R., Munoz, F., Moya, P. S., and Kiwi, M. (2020). Is a COVID19 Quarantine justified in Chile or USA Right Now? https://doi.org/10.1101/2020.03.23.20042002.

Grassi, D., & Memoli, V. (2016). Political determinants of state capacity in Latin America. *World Development*, 88, 94–106. https://doi.org/10.1016/j.worlddev.2016.07.010.

Hale, T., Angrist, N., Kira, B., Petherick, A., Phillips, T., and Webster, S. (2020). Variation in Government Responses to COVID-19. Working Paper 5.0 Blavatnik School of Government at the University of Oxford. Available at http://www.bsg.ox.ac.uk/covidtracker.

Hanson, J. K., & Sigman, R. (2013). Leviathan’s Latent Dimensions: Measuring state capacity for comparative political research. In *APSA 2011 Annual Meeting Paper*. Available at SSRN: https://ssrn.com/abstract=1899933.

Harrell, F. E., Lee, K. L., & Mar, D. B. (1996). Multivariable prognostic models: issues in developing models, evaluating assumptions and adequacy, and measuring and reducing errors. *Statistics in Medicine*, 15(4), 361–387.

Hopman, J., Allegranzi, B., & Mehtar, S. (2020). Managing COVID-19 in Low- and Middle-Income Countries. *JAMA*, 323(16). https://doi.org/10.1001/jama.2020.4169.

Li, Q., Guan, X., Wu, P., Wang, X., Zhou, L., Tong, Y., et al. (2020). Early transmission dynamics in Wuhan, China, of novel coronavirus-infected pneumonia. *New England Journal of Medicine*, 382(13), 1199–1207. https://doi.org/10.1056/nejmoa2001316.

Liew, M. F., Sow, W. T., Maclaren, C., & See, K. C. (2020). Preparing for COVID-19: Early experience from an intensive care unit in Singapore. *Critical Care*, 24(83). https://doi.org/10.1186/s13054-020-2814-x.

Lodge, M., & Węgrzyn, K. (2014). The problem-solving capacity of the modern state. *Oxford: Oxford University Press*. https://doi.org/10.1093/acprof:oso/9780198716365.001.0001.

Luna, J. P. (2020). Estado en América Latina: problemática y agenda de investigación. In P. Andrade (Ed.). *Nuevos enfoques para el estudio de los Estados latinoamericanos*. Quito. Corporación Editora Nacional.

Mahoney, J. (2010). *Colonialism and postcolonial development: Spanish America in comparative*. Cambridge: Cambridge University Press.

Mann, M. (1993). The sources of social power. Vol. 2, *Nation-states, 1760–1914*. Cambridge: Cambridge University Press.

Niu, Y., & Xu, F. (2020). Deciphering the power of isolation in controlling COVID-19 outbreaks. *The Lancet Global Health*, 8(4), e452–e453. https://doi.org/10.1016/s2214-109x(20)30085-1.

PAHO (2019). Health information platform for the Americas: Core indicators. Dataset Pan American Health Organization. Available at https://www.paho.org/data/index.php/en/..

Piburn, J. (2018). Programmatic access to data and statistics from the World Bank API. *Package Oak Ridge National Laboratory. Package ‘statsrs’ version 0.2.*

Rosenthal, U., Charles, M. T., & Hart, P. T. (1989). Coping with crises: The management of disasters, riots and terrorism. *Springfield: Charles C. Thomas.*

Roser, M., Ritchie, H., Ortiz-Ospina, E., and Hasell, J. (2020). Coronavirus pandemic (COVID-19). Dataset Martin Programme on Global Development at the University of Oxford. Available at https://ourworldindata.org/coronavirus..

Schneider, S. K. (2011). Dealing with disaster: Public management in crisis situations. *New York: Routledge*. 10.4324/9781315705279.

Soifer, H. D. (2015). *State building in Latin America*. New York: Cambridge University Press.

Soifer, H. D., & vom Hau, M. (2008). Unpacking the strength of the state: The Utility of State infrastructural power. *Studies in Comparative International Development*, 43(3–4), 219–230. https://doi.org/10.1177/0106549608323102.

Sun, K., Chen, J., & Viboud, C. (2020). Early epidemiological analysis of the coronavirus disease 2019 outbreak based on crowdsourced data: A population-level observational study. *The Lancet Digital Health*, 2(4), e201–e208. https://doi.org/10.1016/j.lindig.2020.03.002.

Therneau, T. M., Grambsch, P. M., & Fleming, T. R. (1990). Martingale-based residuals for survival models. *Biometrika*, 77(1), 147–160. https://doi.org/10.1093/biomet/77.1.147.

Thompson, R. N., Stockwin, J. E., van Gaalen, R. D., Polonsky, J. A., Kamvar, Z. N., Demarsh, P. A., et al. (2019). Improved inference of time-varying reproduction numbers during infectious disease outbreaks. *Epidemics*, 29. https://doi.org/10.1016/j.epidem.2019.100356 100356.

Toshkov, D., Yesilkagit, K., and Carroll, B. (2020). Government Capacity, Societal Trust or Party Preferences? What accounts for the variety of national policy responses to the COVID-19 pandemic in Europe? https://doi.org/10.31219/osf.io/7chpu..

Vittinghoff, E., & McCulloch, C. E. (2006). Relaxing the rule of ten events per variable in logistic and cox regression. *American Journal of Epidemiology*, 165(6), 710–718.

World Bank (2018). *World Bank Open Data*. Dataset World Bank. Available at https://data.worldbank.org/..