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Coronavirus in Latin America. The effects of government measures along different phases of the pandemic

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Coronavirus in Latin America

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Covid-19 pandemic has left more than 30 million confirmed cases and one million deaths. The challenge has been enormous, different governments have adopted diverse measures in order to reduce the number of new infections and deaths, and the consequences in economic terms. The scenarios have been changing and successful strategies have to change because they loose effectiveness or became obsolete. The aim of this paper is to analyze the effects that different kinds of measures taken by Latin American governments had on the daily new cases. The main hypothesis of this work is that the effect of the government responses to Covid-19 has varied throughout the different phases of the pandemic. The countries analyzed were Argentina, Bolivia, Chile, Colombia, Costa Rica, El Salvador, Guatemala, Honduras, México, Panamá, Peru, Paraguay, Dominican Republic and Uruguay. A Time Series Cross Section analysis was performed, to allows studying the evolution of the number of daily cases over time and by country. The period of time studied is from the day the first case of corona virus was registered in a country, until September 14, 2020. We used data from COVID-19 Dashboard database of Johns Hopkins University, and the Oxford COVID-19 Government Response Tracker dataset.

Key words: Comparative Politics, Public policies, Latin America, Coronavirus, Government Responses, Phases of pandemic

Note to the editor: This paper is part of the special edition of SSQ titled "Public Policy, Opinions, Behavior, and Health Outcomes during the COVID Pandemic."

1. Introduction

Up to September 2020, the new Coronavirus pandemic has left more than 30 million confirmed cases and one million deaths. Moreover, a large part of the globe has been under quarantine (or under some type of movement restriction policies), several national health systems collapsed and governments struggled to contain or mitigate the crisis. The challenge has been enormous, different governments adopted diverse measures aimed at reducing the number of new infections and deaths while coping with dire economic consequences. The strategies varied greatly from country to country. While some countries delayed the application of measures, others reacted as soon as the first few cases were registered. Many countries maintained extended quarantines (or stay at home orders), whereas in others it was less extended in time and some never imposed any human mobility restrictions. Among the measures adopted, the menu of options was likewise extensive. Contact tracing, widespread and massive testing, information campaigns, huge investments on health care equipment such as respiratory assist devices and research for vaccines and treatments have been among the sanitary containment measures. Other usual measures included human mobility restrictions, social distancing, schools closure, the obligation to wear facemasks, and a ban on public events, social gatherings, meetings, etc. Economic measures were also adopted to support people during the crisis, to sustain the restrictions and to allow facing the economic paralysis that the lockdown implied.

Different measures were adopted over time, being usually stricter at the beginning of the pandemic and progressing into different degrees of relaxation after five months. Both, the measures and their consequences have varied over time. The scenarios were changing and initially successful strategies had to change because they lost effectiveness or even became obsolete. Moreover, measures that were not successful in reducing infections at the beginning, improved over time. In this article we intend to classify and evaluate the different types of government responses of Latin American countries to the Covid-19 pandemic, over time. In addition to a review of the policies implemented by fifteen Latin American countries to manage daily new cases, we intend to study the way in which policies have changed throughout the different phases of the pandemic. Because the responses of the countries under study are non-linear over time, we divided the analysis into three different phases, an initial, an intermediate and a final phase of the pandemic. This topic will be extensively discussed and justified in the next sections.

The countries analyzed in this study are Argentina, Bolivia, Chile, Colombia, Costa Rica, El Salvador, Guatemala, Honduras, Mexico, Panama, Peru, Paraguay, Dominican Republic and Uruguay. We performed a Time Series Cross Section analysis, to study the evolution of the number of daily new cases over time on a country-by-country basis. The studied period of time comprises from the day when the first case of the new coronavirus (SARS-Cov-2) was diagnosed in a country until September 14th, 2020. Furthermore, a multiple linear regression model (MLR) was implemented to understand the effects that different kinds of measures taken by the governments had on the dynamics of the pandemic in each country. The MLR is segmented to study the effects of government actions throughout the different phases of the pandemic. For this, we use the data from the COVID-19 Dashboard database of the Center for Systems Science and Engineering (CSSE) of Johns Hopkins University, which has variables that measure new daily infections, deaths and various dimensions of the pandemic for each country, and the Oxford COVID-19 Government Response Tracker (OxCGRT) dataset that has different indicators to evaluate the restrictive, economic and sanitary containment measures that governments carried out in the face of the pandemic.

The main hypothesis of this work is that the effectiveness of the measures adopted by the governments has varied over time during the pandemic.

An approach from comparative politics and public policies

Our research mainly used two theoretical approaches, namely: the tools of comparative politics and the study of public policies. Within the former, we will return to the historical approach to neo-institutionalism related to comparative politics as a method (Sartori, 1984; Collier, 1993). The comparison of the responses adopted by different Latin American governments to face the crisis imposed by Covid-19 constituted the focus of the analysis. When describing specific responses to the same phenomenon, comparisons under the modality of the method of similarities (Mill, 1843; Lijphart, 1971) become extremely useful. For that matter, a series of countries must be selected by virtue of their common characteristics except for the phenomenon under study. This technique makes it possible to focus on the different independent variables that could be the cause of divergent results that in this work are the daily new cases over time.

Within the latter approach, the study of public policies, it should be mentioned that after several years of globalization the States became more diffuse having a reduced regulatory capacity (Peters 2003, 2). In a highly interconnected world, their centrality is often under question. Today, in the frame of the Covid-19 pandemic, the States have shown once again a leading role dealing with this unprecedented crisis. This situation invites to think again whether the State is a problem or a solution (Evans 1996). In this sense, the pandemic is testing the capacity of governments to lead the society and the economy towards a common goal, i.e. their governance capacity (Pierre and Peters 2001). The Covid-19 pandemic has clearly forced States to regain their central role as the organizer of the social order in a given territory, backed by a centralized coercive guarantee (Acuña and Chudnosvky 2013, 14; Paz-Noguera 2020). In this scenario, the organization of collective priorities for the achievement of common goals is a competence of the State (Peters 1998, 3). The focus here is the competence of the different national States to respond to the pandemic-induced social an economic crisis by facilitating the provision of public goods and, therefore, by improving public welfare (Saylor 2014: 2). This is so because the States manage the public resources. From this point of view, three State dimensions have relevance: it is a place of confluence of common interests; it is under public and open scrutiny by its citizens, and it is the depositary and administrator of public resources (Aguilar Villanueva 1992, 36). In this sense, the global characteristics of the pandemic demand broad national goals to satisfy the *public benefit* and the *common goods*, although on the contrary, regional institutions had a marginal role in the coordination of public policy (Riggirozzi, 2020).

Public policies are the decisions made by the States with the objective of guaranteeing the common good, with public resources. Therefore, "public policies" are referred to as the procedures, decisions and results related to the political decision-making actions of a State (Lindblom 1991). Without entering into a debate regarding the autonomy of the public administration (Aguilar Villanueva 1993), we consider the definition of the problem as the first instance in shaping the public policies. That is what happened with the definitions adopted in this case; the pandemic quickly filled the public and governmental agenda of the countries, forcing governments to put aside other prepandemic developments (Subirats 2001, 262; Rodrigo y Ciappina 2020). In many cases, a battery of complex policies was put into action in order to obtain the essential resources needed for managing the problem. Such policies required coordination-coherence of multiple government levels. It is worth making an analytical distinction here, we consider two interlocking types of coordination: horizontal and vertical (Acuña 2019). The first one refers to coordination between public policy areas (2019, 2) while the second one relates to coordination between government levels: federalism, multilevel government and coordination of jurisdictions that have relative autonomy (2019, 7). Furthermore, Martínez Nogueira (2010, 19) indicated that for the coordination to converge into public policies, their coherence is required.

Two central dimensions of public policies emerge here, their coordination and their coherence, which are stressed by the need to manage the pandemic. Both dimensions were put to test in the Latin American States. In addition, the timing in the adoption of policies was a fundamental issue under the new scenario. Public policies not only had to be coherent but also needed to be coordinated at a specific time. Governments had to modify their strategies to contain the new coronavirus spread along different times of pandemic. They experimented a dynamic scenario where the strategies had to respond to the different challenges presented by the pandemic. Azerrat *et al.* (2020) discussed the need to generate public policy aiming to respond to the requirements of each stage without losing efficiency. **¡Error!Marcador no definido.**This is because the measures taken by governments in the context of the new coronavirus pandemic had impacts in the social behaviors of the citizens (Van Bavel, *et al*, 2020: 461; Hoh Teck Ling and Mee Chyong Ho, 2020:313). The levels of compliance and adherence to measures adopted by the governments were changing during the different moments of the pandemic[i]. The level of adherence to restrictive measures was not the same at the beginning, when the world population was in shock and with fear, than after several months when restrictions on mobility, for example, were increasingly difficult to maintain. Thus, the (dis)coordination and the (in)coherence had so far marked the degree of success of the different strategies of the region governments along the different phases of pandemic. The results are remarkably diverse and led us to analyze the effect of public policies implemented over time (Matus 1987; Heredia 2000; Young 2003; Przeworski 2007, 155) in the face of the new coronavirus emergency.

Due to the contemporary nature of the Covid-19 pandemic, little research was published regarding the effects of the pandemic and the government responses to the crisis. Some works considered the consequences of political leadership in the decision making process under an environment of radical uncertainty like that presented by the pandemic (Tourish, D. 2020: 262). Another study focused on what factors influenced citizen adherence to restrictive measures taken by the government (Devine, D., et al, 2020: 2). Thus, they provided interesting insights to understand the connection between social and political trust on governmental and citizen responses to the pandemic.

Recognizing the importance of the individual causes that allow greater or lesser adherence to government measures, in this paper we instead focused on studying the effects of the measures adopted by the different governments of Latin America to control the pandemic. There are few articles that evaluate the way in which Latin American States have been managing the crisis, albeit it is possible to point out important precedents[ii]. Barberia *et al.* (2020a) used the same variables from the OxCGRT database to measure the responses of the different states within Brazil[iii] and found a high heterogeneity on the social distancing measures implemented by them. Later, Barberia *et al.* (2020b) found that the effectiveness of social distancing in Brazilian states is greater when broader measures were taken and sustained over time including, for example, economic support. This promotes a higher level of observance by citizens (Barberia *et al.* 2020: 15). Moreover, Balayeth Hussain (2020) used the same dataset analyzed in this work and found that countries with stricter government responses and measures experienced greater compliance regarding the "social distancing" advice and, therefore, experienced slower Covid-19 spread rates than countries with fewer restrictions. Finally, Jayatilleke *et al*. (2020) concluded, based on OxCGRT as well, that the timing with which some measures were adopted and relaxed was as important as the kind of measures being implemented.

The objective of the present work is to study the effects that the different restrictive and economic measures had on the dynamics of daily new infections (DNI) throughout the different phases of the pandemic.

Data, Variables and Analysis

For this study, the Center for Systems Science and Engineering (CSSE) database of the Johns Hopkins University was used. It contains Covid-19 daily information for worldwide countries, useful for evaluating the impact of the different types of measures implemented by Latin American. For this study, 15 Latin American countries were selected: Argentina; Bolivia; Chile; Colombia; Costa Rica; El Salvador; Guatemala; Honduras; Mexico; Panama; Peru; Paraguay, the Dominican Republic, Uruguay and Venezuela. Brazil was excluded for two main reasons. First, the country did not implement any sort of unified response to the emergency. Instead, as it was mentioned before, different policies were implemented by each Brazilian state, in some cases even contradicting national guidelines. Second, because of the difference in the scale and the leverage effect introduced in the MLR by its much larger number of DNI (detected using a PCA analysis). Ecuador and Nicaragua were also excluded because its records suffer from many data loading errors and inconsistencies. Cuba was also excluded because its records had no data for GDP per capita and for extreme poverty.

In the CSSE database the number of DNI and deaths is reported daily, by country, as well as the accumulated amounts. The DNI will be the dependent variable as it allowed evaluating the daily progression of the pandemic and the changes in the trends over time and between countries. In addition, this database was complemented with data obtained from the OxCGRT database, which has quantitative indicators that estimate the strength or the extent of different measures taken by the governments. In this sense, two[iv] indexes were used that ponder restrictive, and economic and fiscal measures. Firstly, the restrictiveness index (Stringency Index) of government measures includes an assessment of the closure of educational institutions and workspaces, cancellation of public events and public transportation, public information campaigns, restrictions to the internal movement of people, restrictions on international travel and borders closure. All these variables, daily measured by country, are then integrated into an index that varies between 0 (maximum flexibility) and 100 (maximum restriction). We expect a significant and negative in sign regression coefficient, indicating that the more restrictive the government measures are, the lower the number of DNI registered in a given country. Secondly, the index of economic and fiscal measures (Economic Index) includes evaluations of the policies implemented to stimulate the economy and to contain the pandemic effects, such as fiscal policies, monetary intervention policies, emergency investments in the health system, and massive public vaccination campaigns. All of this is summarized in an index that varies from 0 (without economic stimulus and containment measures) to 100 (maximum economic and fiscal support of the state). A negative and significant regression coefficient of this variable would mean that in the face of a greater package of fiscal and economic support measures, fewer new infections would be registered.

Therefore, other variables were also incorporated as control into the model. These variables were: population density, GDP per capita, and extreme poverty. These variables had fixed values by country and therefore, they are expected to normalize the effects per country, thus correcting for socio-demographic differences between countries.

There is a great variation of contexts and pandemic dynamics among the 15 Latin American countries considered for this study. For this reason, we decided to incorporate the variable '*Deaths Regime'*. This variable indicates the level of severity with which the pandemic stroke each of the countries. Then, countries were grouped according to their accumulated number of deaths within the timeframe of this study. The use of this variable in the analysis allowed to identify different regimes of evolution of the pandemic and to distinguish among different impact levels. The measures adopted by governments also changed according to the number of deceased people. Three groups were identified from the analysis: the first one considered countries that reached up to 100 accumulated deaths throughout the entire period under study, and it only includes Uruguay. The second group considered countries that accumulated between 101 and 1000 deaths. This group is composed by Bolivia, Costa Rica, Dominican Republic, El Salvador, Guatemala, Honduras, Panama, Paraguay and Venezuela. Finally, the third group has countries with more than 1,000 accumulated deaths and comprises Argentina, Chile, Colombia, Mexico, and Peru.

There are certain limitations to the present analysis. The first one is related to the quality of the data informed by each country. Every country uses its own set of criteria to register Covid-19 confirmed cases, suspected cases, and deaths. In addition, many of the characteristics of the Covid-19 disease are still largely unknown. What is now known is based on the knowledge and information that are currently being gathered. It is important to emphasize that this knowledge constantly evolves due to new findings and research breakthroughs. In addition to the dynamism imposed by this fact, the quality of records can vary according to the stage of the epidemic that each country is experiencing. As an example, Mexico ran out of death certificates at a point and, for sure, that considerably delayed the official report of deaths. In sum, the conclusions that could be drawn from such a model should be solely considered as indicative of possible relationships.

Phases of the pandemic and the main hypothesis

The main hypothesis of this work is that the effect of the measures taken by the governments changes over time throughout the pandemic. Thus, erroneous conclusions could be reached if these effects were not analyzed separately for different periods of the pandemic. We stated before that a successful measure to control DNI at the beginning might cease to be so as the time passes. On the contrary, a policy that initially had no significant effect on controlling DNI may become relevant over the course of the pandemic. We have found useful to divide the analysis into three different phases: initial, intermediate, and later phases within the timeframe of this study that covers until mid-September 2020. Each phase was considered to characterize a particular period in the evolution of the pandemic and has its own features with regard to the measures adopted by the different governments of Latin America during the phase.

The initial phase (Phase 1), was considered from the onset of the pandemic (first registered case in each country) until day 50. During this initial period some restrictive measures began to be adopted, although they were uneven. Considering that the incubation period of Covid-19 is up to 14 days and that this phase comprises 50 days, it is only at the end of this stage that the effects of the first measures aiming to control DNI start to be noticeable in some of the countries. The intermediate phase (Phase 2), was considered between day 51 and 149. During this phase some time has passed since the first cases of Covid-19 were diagnosed in all countries and governments had time to react and take measures intended to contain the DNI. The later phase (Phase 3) was considered between days 150 and 200, the end of the period under analysis.

Table I summarizes the values found for the Stringency and Economic Indexes for each phase and each country. The pooled mean values are also presented in the table.

During Phase 1, the pooled mean of the Stringency Index is 74. The lower values correspond to countries like Mexico that took very few measures. In comparison, countries that rapidly adopted more restrictive measures such as Guatemala and El Salvador have higher mean values for this index. During Phase 1, economic measures were not so common which is reflected in a relatively low index for each country. The Economic Index pooled mean value was 32. In sum, the countries responded in a very heterogeneous way along Phase 1; some did it faster and with a greater number of measures and resources whereas others did it later and with fewer measures. There is no single pattern because the virus was just beginning to manifest in each of the countries and governments have had a short time to react.

At the beginning of Phase 2 the effects of restrictive measures became apparent. During this second phase the most restrictive measures were taken and there was a greater compliance from the citizenship to the government measures. All countries, except for Uruguay, show an increase in the Stringency Index. The pooled mean for Phase 2 is 84, increasing more than 10 units compared to the mean of the former phase. The lower Stringency Index value for this period corresponds to Uruguay, 46, while the highest value corresponds to Honduras, with 98, more than two times higher. All countries, except for Mexico, increased fiscal and economic measures. The Economic Index pooled mean for the period was 59, roughly doubling the mean of Phase 1. Mexico was the only country that did not take measures of this kind, while the value for Honduras, 88, reflects the highest level of economic support.

At the time of Phase 3, five months passed since the beginning of pandemic and the citizens started to show signs of weariness after experiencing long restrictions. Isolation was sustained for several months and highly restrictive measures lost acceptance and adherence. Consequently, several restrictive measures were relaxed. The Stringency Index pooled mean decreased to 67, almost 17 points lower compared to Phase 2. This is also the lowest value for this index since the beginning of the pandemic. The country with the lowest Stringency Index value is 28 (Uruguay), while the highest value is 85 (Bolivia and Chile). Although the Economic Index values also decreased, they did not do so as much as Stringency. Thus, the pooled mean of the Economic Index for Phase 3 is 50 (9 points below Phase 2). While Mexico continued without taking these types of measures and Bolivia reduced them to less than half, other countries such as Chile and Uruguay display an important increase in this indicator. In conclusion, during Phase 3 most countries began to relax most of the measures considered by the Stringency Index, although the choose to keep the economic support at similar levels to those of Phase 2.

(TABLE 1 ABOUT HERE)

About the regression model used

This work was based on a multivariate regression analysis (MLR) of the Time Series Cross Sectional (TSCS) type (Beck and Katz 1995; Podestá 2002; Stimson 1985). TSCS is used in datasets where there are repeated observations (in our case, day of the pandemic) in fixed units by groups (countries). Unlike panel data, the TSCS model is used when there are many observations over time and there are several small or medium-sized groups. The simple MLR model becomes problematic with these data as it breaks several assumptions of the regression. The TSCS models, on the other hand, allow temporally and spatially correlated errors and heteroscedasticity corrections using panel corrected standard errors (Beck and Katz 1995), calculating more accurately the parameters and applying transformations to deal with auto-correlation of the data (details and model assumptions and diagnostics can be seen in the Appendix)[v].

TCSC modeling has the advantage of being able to simultaneously evaluate the impact of the different types of government measures on the DNI, allowing to distinguish between countries and to study the temporal sequence of the data. The database was established by country and by day of the epidemic. Day one was set when the first case of Covid-19 was detected in each country, and it runs until September 14th due to the time frame of the study. The maximum number of days was 198 and the average between the countries under study was 95 days.

The general approach of the model is as follows:

$$DNI_{tj} = \beta_0 + \beta_1 X_{1\,(t-1)j} + \beta_2 X_{2\,tj} + \beta_3 X_{3\,tj} + \beta_4 X_{4\,tj} + \beta_5 X_{5\,(t-14)j} + \beta_6 X_{6\,(t-14)j} + \beta_7 X_{7\,tj} + e_{tj} \qquad (1)$$

The TCSC was estimated for the three different phases already described: Phase 1 (day 1 to 50), Phase 2 (day 51 to 149) and Phase 3 (day 150 to 200). Here, β_0 is a constant and β_1 to β_7 are the coefficients of the different variables. Variables X_i account for the different components of the model. X_1 corresponds to DNI. Three control variables of the socio-demographic block were then included: X_2, X_3 and X_4 that account for the population density, per capita GDP, and extreme poverty (in percent), respectively. These variables allowed to normalize the factor of response of the different countries. The next block of variables comprises the government response to the pandemic: X_5, and X_6 corresponding to the Stringency and Economic Indexes, respectively. The *Death Regime* variable, X_7

allowed to distinguish three groups of countries in accordance with their accumulated number of Covid-19-related deaths. Finally, *e* is the additive error term. Each variable has two additional sub-indexes, namely *t* and *j*. The sub-index *t* indicates the time expressed in days from the onset of the pandemic. The sub-index *j* corresponds to each country. The time sub-index of variables X_1, X_5 and X_6 appears between parenthesis to indicate a given time lag in days for the corresponding variable. As an example, variable X_1 is lagged 1 day following Beck and Katz (1995) recommendation to avoid first order autocorrelation error (AR-1). Then, the sub-index reads *(t-1)* in that case. Stringency and Economic Indexes are both lagged 14 days to account for the delayed effect of the imposed measures, as their impact became visible two weeks after their implementation (people already incubating Covid-19 when the measures were put in place, had already been infected).

The pandemic in Latin America

Before we delve deeper into the analysis of the 15 selected Latin American countries, we will briefly review what happened in the region. The first case of coronavirus was registered in Brazil on February 26th, 2020. By March 19th, it had reached all the countries of the region and by June, Latin America became the epicenter of the pandemic. The countries of the region implemented different political strategies to face the emerging situation. The results obtained during the crisis management were very dissimilar as well. There were countries where the responses were lax, poorly coordinated or delayed that ended up having an exponential growth of DNI. For example, Peru registered 722,832 accumulated cases and 30,526 deaths by mid-September, whereas Colombia had 716,319 accumulated cases and 22,924 deaths and Mexico registered 668,381 accumulated cases and 70,821 deaths by the same date. Other countries such as Uruguay responded faster in a more coordinated manner and managed to keep the number of infections contained, with 1,780 accumulated cases and 45 deaths as of September 14th. Ultimately, countries such as Argentina or Bolivia, took immediate measures when the first cases of Covid-19 were registered and were able to keep the contagions contained for up to four months, after which, and perhaps due to the difficulty of sustaining the mobility restrictive measures, they began to show an increased spread of the disease.

To better understand the trajectory of the different countries of the region throughout the Covid-19 pandemic, it is important to consider socio-demographic variables such as the population of each country.

(FIGURE 1 ABOUT HERE)

Fig. 1 shows the evolution of DNI per population for each country. It can be seen in the figure that up to the day 110th, the growth experienced by most of the studied countries was exponential with the sole exception of Uruguay. After that point, rates began to decline and DNI growth became arithmetic in countries such as El Salvador, Guatemala and Bolivia, while in others like Mexico and Panama a plateau was reached. In Argentina and Peru, the growth was still not under control.

Towards an explanation

As stated before, the TSCS model was used to evaluate the possible relationships and influences that the different types of measures implemented by the different governments had on the curve of DNI, by country and throughout the three different phases of the pandemic.

(TABLE 2 ABOUT HERE)

The parameters corresponding to the three TSCS multilinear regression models are shown in Table 2. The coefficients were calculated with PCSE for Phases 1, 2 and 3[vi]. Each column presents the coefficients corresponding to one of the phases of the pandemic, as described before. The three regressions were statistically significant and reached an acceptable goodness of fit.

Phases 1 and 3 are characterized by the same β_1 coefficient (DNI, lagged 1 day), which has a lower value than for Phase 2. This difference probably reflects that the growth in DNI was arithmetic in the former two phases and exponential in the latter one. The socio-demographic variables show some variability between phases. Population density was significant only at Phase 3 and inversely related to DNI. This counter-intuitive result may be related to a better management of the most populous countries in the region during this phase. The GDP per capita was significant for Phases 2 and 3. In Phase 2, the GDP effect is strongly inversely, indicating that countries with more available resources were able to use them to curb the contagion spread. In Phase 3, GDP (β_3) had almost no effect meaning that the pandemic has finally affected all countries in the region in a similar manner. Extreme poverty's coefficient (β_4) was only significant for Phase 1, which is concordant with the argument that richer countries were the most affected during this phase due the increased mobility associated with international commerce and tourism. Then, the coefficients sign changed for Phase 2 to become positively related to DNI. At this stage, most countries were experiencing an exponential growth of DNI and the poorest countries were the most affected. As people living under extreme poverty conditions were forced move in search of any sort of income they got exposed to contagions. In other words, poverty generated an increased general mobility, disregarding the isolation measures still in place.

Stringency and Economic Indexes (β_5 and β_6) that include relevant government measures, present significant differences across the considered phases. The Stringency Index did not have a significant influence at the beginning of the pandemic but turned out to be significant and inversely related to DNI during Phases 2 and 3. On the contrary, the Economic Index was not statistically significant for any of the phases.

The *Deaths Regime* variable (β_7), which classifies countries according to the number of accumulated deaths, was significant throughout the study. The coefficients values increased as the phases proceeded, indicating a stronger relation with DNI. The proposed country grouping in terms of the pandemic impact severity remained unchanged for the three phases. As the β_7 coefficient increased over time, the separation into these groups became more important to the analysis.

Effects along the phases of pandemic

So far, we have been able to verify that the effect of the stringency measures adopted by governments on the DNI varied across the different phases of the pandemic being more significant in keeping DNI low as time passed. The restrictive measures implemented during Phases 2 and 3 were effective in reducing DNI of Covid-19. Fiscal and economic measures aimed to compensate individuals and businesses for the recession of the local economies provoked by the restrictive measures might have had an impact on the overall well-being of the population. However, according to the present analysis, their effect over DNI is not significative. Therefore, the focus will be put on evaluating the restrictive measures (Stringency Index), which were the most specific and effective measures taken by countries up to now. The analysis considers that country economies are already under considerable pressure and probably unable to guarantee further support. In addition, it was taken into consideration that the main debate that governments were facing at the time of the analysis is how to sustain the isolation / mobility restriction measures, or even if these policies make sense after nine months of evolution of the pandemic.

To better understand the effect that the restrictive measures had on DNI we used three different degrees of the Stringency Index to perform an analysis based on each of the parameters estimated of TSCS models. Each consisted of 10,000 Monte Carlo simulations for each phase[vii].

(FIGURE 2 ABOUT HERE)

The results of the Monte Carlo simulations made for Phase 1 are presented in Fig. 2. The overlap of the confidence intervals imply that the effects of the Stringency Index were not significant for this time frame, as no change on the prediction of DNI was observed. During Phase 1, the number of overall DNI was low, the pandemic had just arrived Latin America and the government measures were gradually implemented. Likewise, considering the 14-day coronavirus incubation time between the contagion to when symptoms arise, we understand that in this first phase it is not possible to distinguish the effects of the different restrictive measures implemented by governments. Their effect probably overlap with the evolution of DNI during Phase 2, that comprises a wider time frame and an advanced development of the epidemic in each country.

(FIGURE 3 ABOUR HERE)

The different effects of the three levels of restrictive measures along with the effect of the lag of DNI can be clearly observed in Fig. 3. During the Phase 2, the more restrictive measures impacted drastically in DNI as medium and maximum Stringency Index values yielded approximately 10% to 20% of the infections in comparison to the application of minimum restrictions. The more restrictive measures can stabilize the number of DNI to about 1,000 per day compared to the 5,000 plus if minimum restrictions are imposed. If we consider a 14 day lag, the difference between implementing maximum and minimum restrictive measures implies going from 900 DNI to just over 5600 DNI.

(FIGURE 4 ABOUT HERE)

The simulation of the effects of the restrictive measures upon the DNI for Phase 3 (between days 149 and 198) is shown in Fig. 4. As it was the case during Phase 2, the strength of restrictive measures play a role on curbing the increase in the number of DNI in the Phase 3 as well. At this stage, when restrictive measures are minimal, the number of DNI is about 8,000. When moving to average or maximum values of restrictive measures, the DNI are reduced. This effect is greater was the time passes. If we take lag 14 as a reference, going from having minimum to maximum restrictive measures implies a reduction of 6,000 DNI. Imposing a maximum level of stringency results in about 1,800 DNI during Phase 3. If an intermediate level of stringency is imposed, the result is slightly under 3,000 DNI.

Most Latin American countries were still experiencing many daily cases by September 2020 and were finding the pandemic difficult to contain. Sustaining isolation measures, while effective in principle, was becoming more difficult. First, people were becoming familiar with the idea of being infected with the virus and, thus, they lowered their awareness and self-care. Second, there was an increasing sense of isolation wear as people longed for interpersonal contact and social activity. In addition, some local political parties were using the discourse of global anti-quarantine movements as a tool for undermining the government authority.

According to our findings, maintaining some restrictive measures would help to keep DNI stable or even lower them (Fig. 5). However, governments should build a base of support for those measures. Otherwise, their effectiveness would be affected.

Conclusions

The new Covid-19 disease emerged just some months ago. In a short period of time, the SARS-Cov-2 coronavirus traveled the world and drastically transformed our daily lives. Traditional forms of social organization have been transformed and the executive capacity of governments is been challenged in unprecedented ways. Each world region has been, at some point, the epicenter of the pandemic and different countries implemented diverse measures aimed at containing contagions and sustaining the local economies. As a result of these diverse measures, largely different numbers of infections and deaths were obtained. Some governments took time to respond or did it in a lax way, hoping that this kind of action would preserve the level of economic activity. In general, the consequence of this approach was the saturation (or straining) of the national health system and an inevitable strong economic recession. Other countries adopted early and effective measures, thereby managing to contain the health situation and preventing the depletion of health resources. As the pandemic goes on, the measures adopted by governments are being put into question and become increasingly difficult to sustain.

In this article we set out to evaluate the effect of the different types of measures adopted by governments. For the sake of the analysis, we divided them into restrictive and economic measures, and looked upon them in 15 Latin American countries. We found useful to divide the timeframe going from the first recorded case in each country up to September 14th, 2020 into three phases. We have evaluated the effect of the imposed measures throughout these different phases, showing that the pandemic scenarios were changing and that it was not the same at the beginning (0 to 50 days), in the middle phase (between 50 and 150 days), or in a later stage. Governments had to face those changing dynamics as well. During Phase 1, neither the restrictive measures nor the economic measures had visible effects on the number of DNI. We understand that during this initial phase, the pandemic barely registered the first cases in the 15 countries studied and governments were still adapting to this new reality. The effects were not yet clear, also considering the incubation window (10-14 days) of the disease.

During Phase 2, between days 50 to 149, the effects became clearer. The greater the restrictive measures, the lower the number of DNI. Regarding the specific effect of the restrictive measures, the higher the value of the restrictive measures, the less increase in the number of new cases there was. Monte Carlo simulations showed that the difference between applying minimal restrictive measures or an intermediate level of restriction implied reducing from more than 4,500 new cases to approximately 1,200 new cases. Going to a maximum value of stringency lowers the number of new cases to about 900. The Economic Index did not show a similar relevance.

During the third phase of the pandemic, the effect of restrictions became even clearer. Here again, more restrictive measures implied a reduction in the number of DNI. Again, Monte Carlo simulations allowed us to recognize that the impact of sustaining restrictive measures was significant and implied, considering a 14 day lag, having about 6,500 fewer new daily cases. Even in this later phase, continuing to support restrictive measures can mean a reduction between 4,000 and 6,000 new cases per day. This is a number that can make the difference between the availability of health resources, and their collapse.

The main challenge posed by the pandemic development in Latin America has to do with the exit strategy from the most restrictive policies implemented by some governments. So far, there is no clear answer on how to get out of quarantine (mandatory or partial) without translating it into an incontrollable increased rate of contagions. The present work leaves us some reflections in this sense. As the pandemic progresses, the adoption of extensive and strict lockdowns is resented by large parts of the population. The data that we provide here seems to support the interpretation that today it is possible to begin thinking in some kind of partial relaxation of restrictive measures. However, maintaining at least a medium level of such restrictions is what could allow controlling the increase in new daily cases.

In conclusion, we can say that the response of governments is crucial for containing the pandemic and its possible consequences on the population, but it also becomes essential to understand the different moments or phases of the pandemic.

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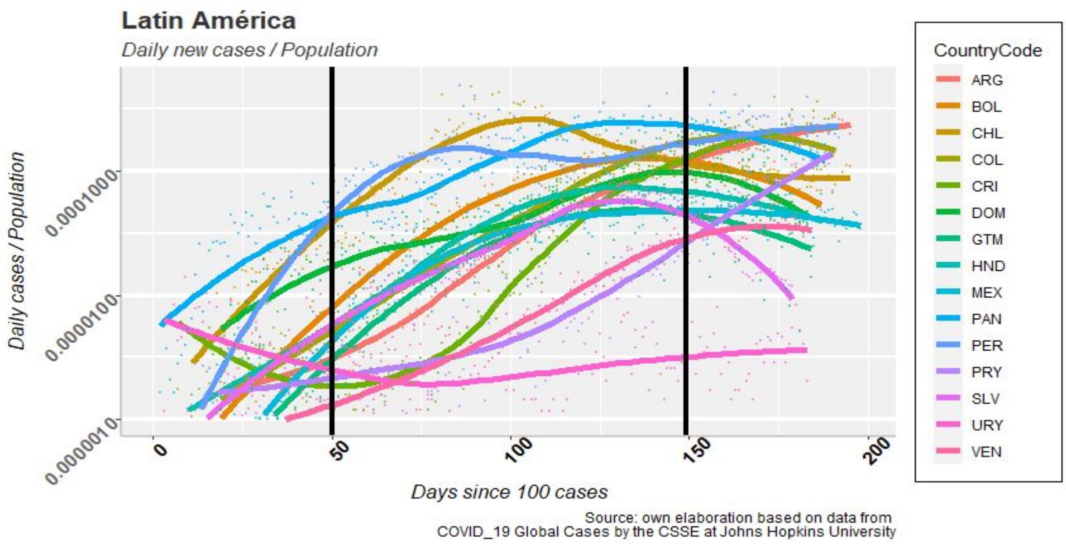


Fig. 1: Daily new cases over population for 13 countries of Latin America since the day where the 100th case was registered.

Table I: Stringency and Economic indexes for the countries under study for each pandemic phase.

	Phase 1		**Phase 2**		**Phase 3**	
Countries	*Stringency*	*Economic*	*Stringency*	*Economic*	*Stringency*	*Economic*
Argentina	73,07	42,34	90,81	75	80,51	65,62
Bolivia	86,45	29,59	91,6	40,75	85,15	24,3
Chile	65,18	24,01	79,85	54	85,18	93,12
Colombia	66,89	47,44	87,37	75	68,56	60,32
Costa Rica	62,73	25,51	73,1	50	51,53	37,14
Dom. Rep.	61,82	11,97	83,94	25	77,43	25
El Salvador	89,75	44,38	93,49	75	58,68	39,89
Guatemala	90,15	16,86	95	75	62,64	39,89
Honduras	91,7	46,42	97,78	87,5	71,36	69,18
Mexico	39,62	0	76,24	0	72,27	0
Panama	75,18	0	86,22	61,25	63,45	55,04
Paraguay	81,89	38,77	84,26	75	60,2	55,35
Peru	81,11	57,65	87,54	75	82,18	72,97
Uruguay	62,54	56,37	45,59	65	28,48	84,92
Venezuela	80,89	41,36	84,22	50	58,44	31,25
Pooled Mean	**73,93**	**32,18**	**83,80**	**58,90**	**67,07**	**50,27**

Table 2: Parameters of TSCS linear regression models with panels corrected standard errors (PCSEs) used to explain the new daily infections of Covid-19 in 15 Latin American countries, throughout the three different phases of the pandemic.

VA. Dependent: Number of Daily New Infections per day (DNI)	Phase 1	Phase 2	Phase 3
Daily infections 1 day before (β_1)	0.75*** (0.09)	0.83*** (0.02)	0.75*** (0.48)
Population density (β_2)	-0.15 (0.05)	-0.14 (0.14)	-1.22*** (0.41)
GDP per capita (β_3)	1.03 (1.17)	-9.63* (4.17)	-0.0003** (0.00001)
Extreme poverty (β_4)	-1.58* (0.70)	3.06 (2.99)	-4.30 (7.62)
Stringency Index (β_5)	0.40 (0.22)	-10.16*** (2.07)	-18.34*** (6.28)
Economic Index (β_6)	0.35 (0.19)	-0.64 (1.10)	-2.13 (2.12)
Regime (β_7)	49.83*** (14.70)	495.89*** (79.28)	1395.59*** (296.58)
Constant (β_0)	-73.12** (30.25)	651.70*** (172.39)	748.90 (368.56)
General R^2	64%	82%	85%
N observations	525	1500	592
Prob.> chi2	0.0000	0.0000	0.0000
Observations per group	35/35/35	100/100/100	30/39/49

Source: COVID-19 Dashboard from the Center for Systems Science and Engineering (CSSE) at Johns Hopkins University and Oxford COVID-19 Government Response Tracker (OxCGRT).

Note: The regression coefficients and standard errors (between parenthesis) are expressed for each variable. The asterisks indicate the level of significance (p) of the coefficients: α<0,01 (***); 0,05< α <0,1 (**); α>0,1 (*); no asterisk means that the regression coefficient was not significant. The dependent variable was DNI by country and by day of the pandemic. See the Appendix for a more detailed description of the independent variables. The models were estimated with Panel Corrected Standard Errors and DNIlag1 of independent variable. Model with PRAIS Watson transformation is reported in the Appendix.

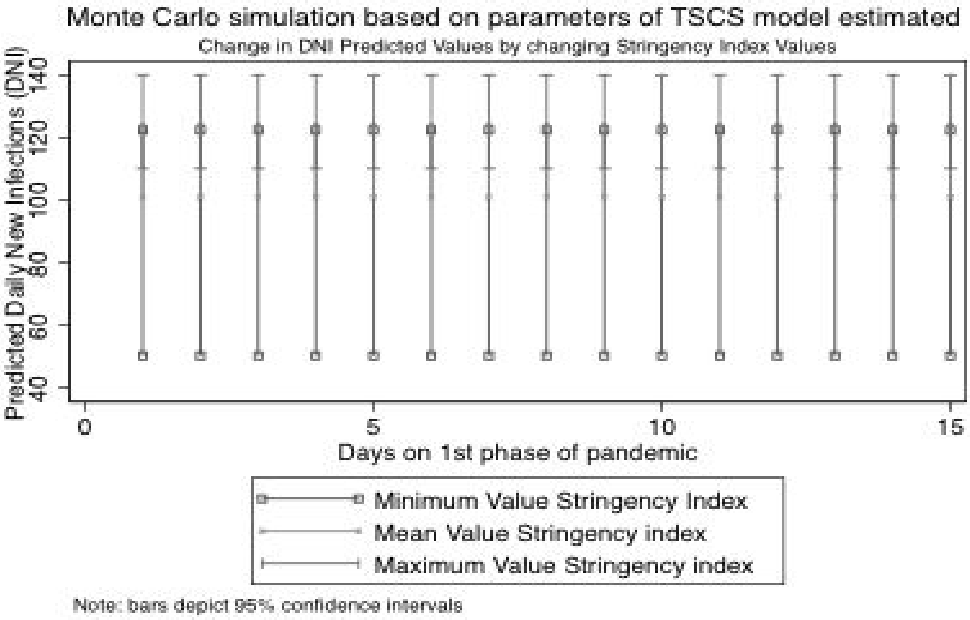


Fig. 2: Relationship between predicted DNI and Stringency Index for Phase 1 in Latin American countries.

The change in predicted DNI for any day shows the direct effect of Stringency Index in this day and the cumulative lagged effect of DNI on the previous day for a country that imposes a restrictive measure on day *t*. 10,000 Dynamic Monte Carlo simulations were performed for this early phase. Simulations started with a mean value of DNI $_{(t-1)}$ (79) and consider three values for SI: minimum (2.78); mean (68.0); and maximum (100). The values of the rest of variables were set in their means as resulted from the model calculation.

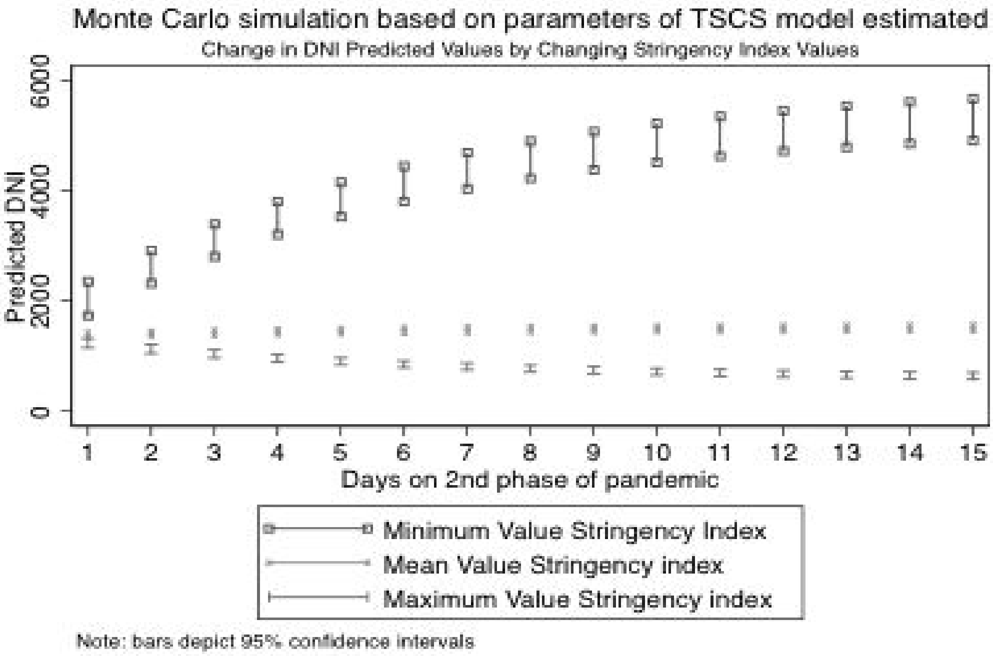


Fig. 3: Relationship between the predicted DNI and Stringency Index for Phase 2 in Latin American countries.

The change in predicted DNI for any day shows the direct effect of Stringency Index on this day and the cumulative lagged effect of DNI on the previous day for a country that take a restrictive measure on day *t*. 10,000 Dynamic Monte Carlo simulations were performed for Phase 2. Simulations started with a mean value of DNI $_{(t\text{-}1)}$ (1350) and considered three values for the Stringency Index: minimum (20); mean (85); and maximum (100). The values of the rest of variables were set in their means as resulted from the calculated model for Phase 2.

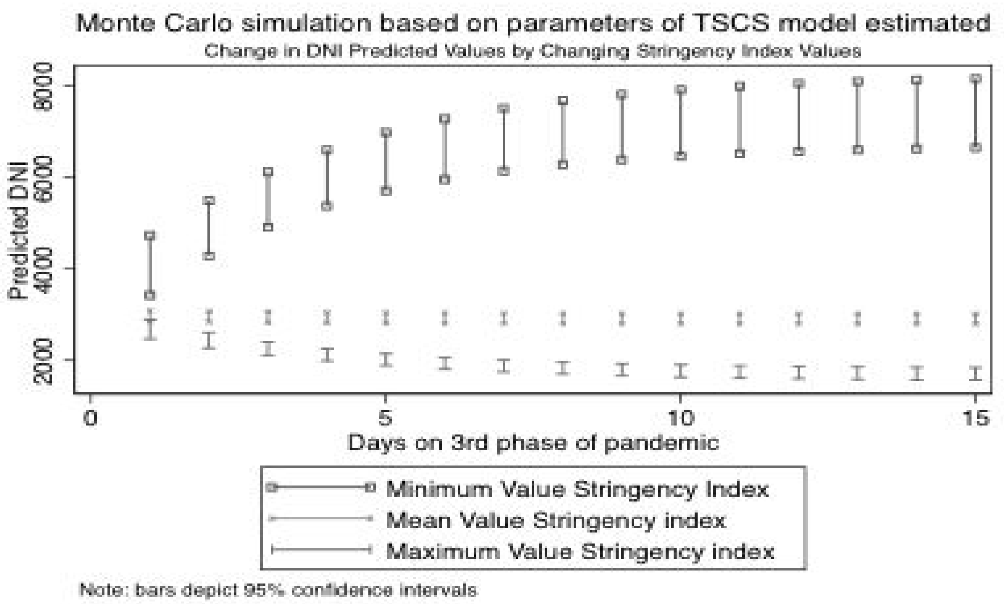


Fig. 4: Relationship between the predicted DNI and Stringency Index for the Phase 3 of the Covid-19 pandemic in Latin American countries.

The change in predicted DNI for any day shows the direct effect of Stringency Index on this day and the cumulative lagged effect of DNI on the previous day, for a country that take a restrictive measure in day *t*. Ten thousand Dynamic Monte Carlo simulations were performed for this late phase. Simulations started with a mean value of DNI $_{(t\text{-}1)}$ (2993) and considered three values for Stringency Index: minimum (20); mean (81); and maximum (96). The values of the rest of variables were set in their means as resulted from the model for Phase 3.

Notes

i Studies based on survey research have shown that in some age groups, adherence to government recommendations such as to avoid attending a large gathering (10+ people) was lower over time. While essential activities remained consistent over time, more individuals attended gatherings of 10 or more people as cases rose, particularly in the 18-29 age group (Sheehan, Pooh, Speaker, and Rothberg, 2020). Likewise, other factors also intervene in the adherence to the new guidelines of social behavior that Covid-19 has implied. Previous research has shown that the adherence decisions may be reliant on several factors. In the context of personal health compliance behavior, individuals follow health protection suggestions based on the perception of severity and vulnerability of a situation (Rogers, 1975 and Floyd, Prentice-Dunn, Rogers, 2000, cited on Al-Hasan A, Yim D, Khuntia J. 2020). Also, citizen's perceptions about government efforts in the COVID-19 situation influenced the adherence to the measures (Al-Hasan A, Yim D, Khuntia J. 2020).

[ii] See also Gutiérrez Cham; Herrera Lima y Kemner (2020).

[iii] To see another interesting background at the subnational level, refer to Behrend and Karamaneff 2021. They explore socioeconomic measures adopted by subnational governments in Argentina during the sanitary crisis unleashed by the COVID-19 pandemic.

[iv] Initially we tested also sanitary contained measures, but this variables reported high collinearity with stringency and economic measures into the model. For this reason we decided to excluded that from the analysis.

v For more details on the estimation and the ways to control the model, read Beck and Katz 1995.

[vi] Statistics under PRAIS Watson transformation are reported in the Appendix, to deal with auto-correlation of the data. Both results were similar in all aspects (sign and significance) with those reported in Table 1.

[vii] To see an another example of this kind of dynamic simulations refers to Poe and Tate (1994)

Coronavirus in Latin America

The effects of government measures along different phases of the pandemic

Appendix Material: 1 Codebook

Dependent Variable: New Daily infections	New Daily infections, by country and day Source: COVID-19 Dashboard base of the Center for Systems Science and Engineering (CSSE) of Johns Hopkins University
Independent Variables	
New Daily infections, 1 days before	New Daily infections, Lagged 1 days before Source: (CSSE) of Johns Hopkins University
Population density	People per square kilometer Source: OurWorld Data
GDP per capita	GDP per capita is adjusted for price differences between countries (it is expressed in international dollars). Source: OurWorld Data
Extreme poverty	Percentage of the total population of each country under extreme poverty Source: OurWorld Data
Stringency Index	It is a Government Restrictive Measures Index. This includes an assessment of the closure of educational institutions and workspaces, cancellation of public events and public transport, public information campaigns, restrictions on the internal movement of people and restrictions on international travel. All these variables measured daily by country, are then integrated into an index that varies between 0 (maximum flexibility) and 100 (maximum restriction). This variable was lagged 14 days before Source: Oxford COVID-19 Government Response Tracker (OxCGRT)
Economic Index	This includes evaluations of the fiscal policies to stimulate the economy, monetary intervention policies, emergency investments in the health system, and massive public vaccination campaigns. All of this is summarized in an index that varies from 0 (without economic stimulus and containment measures) to 100 (maximum economic and fiscal support of the government). This variable was lagged 14 days before Source: OxCGRT
Death Regimen	This variable classifies the countries in according to the numbers of deaths due to Covid 19 disease into 3 groups. Value 0: Uruguay, which registers only 45 deaths throughout the study range. Value 1: another group with a low average, varying between 101 and 10000 total deaths. In this group are the following countries: Bolivia (7344), Costa Rica (590), Panama (2166), Paraguay (525), Honduras (2079), El Salvador (785), Venezuela (485), Dominican Republic (1681), and Guatemala (2957). Value 2: the last group is with countries that have more than 10000 deaths. These are: Argentina (11352), Chile (11949), Colombia (22924), Mexico (70821), and Peru (30526). Source: OxCGRT

Sources:

- COVID-19 Dashboard base of the Center for Systems Science and Engineering (CSSE) of Johns Hopkins University. Retrieved from https://coronavirus.jhu.edu/map.html
- OurWorld Data. Retrieved from https://ourworldindata.org/coronavirus-source-data
- Oxford COVID-19 Government Response Tracker (OxCGRT). Retrieved from https://www.bsg.ox.ac.uk/research/research-projects/coronavirus-government-response-tracker

List of variables:

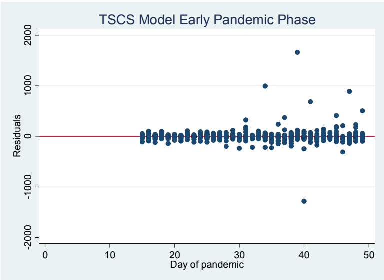
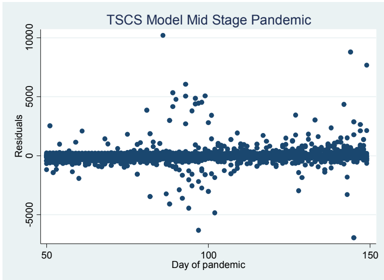
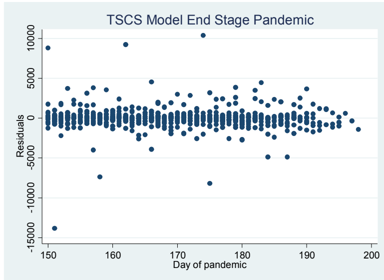
Variable	Obs	Mean	Std. Dev.	Min	Max
New Daily infections	2827	1375.9	2459.7	0	21358
New Daily infections, lagged 1 days before	2812	1370.8	2456.4	0	21358
Population density	2827	77.4	82.5	10.2	307.8
GDP per capita	2827	14006474	5722091	4541795	22767037
Extreme poverty	2827	4.3	4.4	0.1	16
Stringency Index	2617	80.5	19.1	2.78	100
Economic Index	2617	51.8	29.0	0	100
Deaths Regimen	2827	1.3	0.575	0	2

Model diagnostics and additional results

PRAIS Watson transformation for Auto-correlation

Dependent Variable; DNI per country	Phase 1	Phase 2	Phase 3
New Daily infections, Lagged 1 day before	0.97*** (0.02)	0.93*** (0.01)	0.84*** (0.02)
Population density	-0.004 (0.04)	-0.07* (0.21)	-0.77 (0.65)
GDP per capita	-6.4e-09 (7.1e-07)	-5.5e-06 (3.9e-06)	-1.6e-05 (1.1e-05)
Extreme poverty	-0.45 (0.85)	1.4 (4.35)	-4.4 (13.6)
Stringency Index	0.04 (0.13)	-5.13*** (1.8)	-9.32** (4.8)
Economic Measures Index	0.15 (0.12)	-0.22 (0.7)	0.84 (1.65)
Regimen	14.6*** (6.14)	238.9*** (42.17)	823.0*** (166.6)
Intercept	-13.4 (19.8)	336.8*** (162.6)	339.9 (355.5)
Adj R-squared	0.8982	0.9217	0.9187
rho	-0.63	-0.42	-0.31
N observations	510	1485	577
Prob> chi2	0.0000	0.0000	0.0000
Durbin-Watson statistic (original)	2.80	2.55	2.37
Durbin-Watson statistic (transformed)	2.32	2.16	1.71

Residuals

Phase 1	Phase 2	Phase 3
		

Collinearity

Independent variable	Phase 1		Phase 2		Phase 3	
	VIF	1/VIF	VIF	1/VIF	VIF	1/VIF
New Daily infections, Lagged 1 day before	1.65	0.607210	2.64	0.378288	4.50	0.222349
Population density	1.85	0.541158	2.79	0.358613	2.51	0.398509
GDP per capita	5.10	0.196214	7.08	0.141328	7.56	0.132269
Extreme poverty	2.51	0.398728	3.40	0.294328	3.77	0.265352
Stringency Index	7.67	0.130462	43.17	0.023166	44.83	0.022304
Economic Measures Index	2.39	0.418418	8.18	0.122274	6.50	0.153771
Regimen	5.80	0.172454	14.20	0.070436	28.10	0.035585
Mean VIF	**3.85**		**11.64**		**13.97**	