

COVID-19 in 38 countries: a structural breaks approach

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ABSTRACT

In this paper we estimate econometric models of daily data on the number of new cases from COVID-19. Our primary purpose is to test for the presence of structural breaks in each time series and then to incorporate these breaks in the estimation process. Government Response Stringency Index is also included as explanatory variable and interacting with the factor variables resulting from the breaks. We found different number and different dates for the structural breaks across the countries. We also observe that the last structural break is more or less contemporaneous for most of countries (24 in 38). By considering the curvature of the quadratic function we can guess if the peak already occurred. Latin America, Australia, Asia and Africa countries seem to reach already the peak. The same conclusion does not apply to European countries, USA and Canada. Including the GRSI increases the fit significantly.

Keywords: Quadratic function, likelihood ratio test, break dates, stringency.

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Journal of Economic Literature (JEL) Classification: C22, I10

1 Introduction

The academic effort of analysing the pandemic dynamics of COVID-19 is huge and econometrics and statistics were often called upon to answer several questions. Next we mention a few studies that are closely related to ours. (Manski and Molinari, 2021) analyze how reliable and informative the data is. They argue that, due to the absence of bounds on infection rates that are credible and informative, the infection rate might be substantially higher than reported.

Several studies try to guess what is going to happen next in terms of deaths and infections. (Li and Linton, 2021) carry out some analysis of the daily data on the number of new cases and the number of new deaths by (191) countries. They use a quadratic time trend model applied to the log of new cases for each country to predict when the peak of the epidemic will arise in terms of new cases and new deaths per country. (Deb and Majumdar, 2020) showed

that a time-dependent quadratic trend successfully captures the log incidence pattern of the disease among Chinese provinces. (Li, Feng and Quan, 2020) use time series modelling to fit the infections and fatalities in China, an apparent quadratic trend and turning points are found. According to (Alvarez and Kreinovich, 2000) the existing models do not work well: indeed, these models usually predict smooth changes, while for the current pandemic the changes are heavily oscillating, even after they try to smooth this data by taking five-day averages instead of daily data. They propose a simple quantitative model that explains better such oscillations.

Other studies focuses on the consequences of the intervention policies during the COVID-19 outbreak. For example, (Yasmin, Ali, Rahman and Salma, 2021) focus on university students' feasibility regarding online classes in Bangladesh during COVID-19 pandemic. A significant relationship was found between student's preference of online classes with the lack of logistic support they had and poor internet connectivity. (Cho, 2020) estimates the effect of nonpharmaceutical intervention policies on public health by considering the case of Sweden. (Huang, Makridis, Baker, Medeiros and Guo, 2020) using new high-frequency data that covers a representative sample of small businesses in the United States, investigate the effects of the COVID-19 pandemic and the resulting state policies on the hospitality industry.

Structural breaks induced by national lockdowns constitutes also an important investigation topic. (Bonacini, Gallo and Patriarca, 2020) propose a machine learning procedure to identify structural breaks in the time series of COVID-19 cases. (Zhao and Liang, 2020) explore and examine the structural breaks in the number of daily new COVID-19 by using generalized regression models with a Poisson likelihood framework. In (Güney, Yetkin, Özdemir, Gökalp and Arslan, 2020) the breakpoint linear regression analysis is performed to analyze the trends of daily active cases, recovered, and deaths in Turkey.

In this paper we analyze the number of infected people by COVID-19 in thirty eight countries from Asia, Africa, North America, South America, Europe and Australia, including those with the largest number of cases. We use daily data from March 1, 2020 to January 8, 2021. The main purpose is to analyze how the Health and Governments Authorities responses have impacted on the evolution of the COVID-19 pandemic.

The paper's contribution is threefold. First, in line with (Bonacini et al., 2020), but using the algorithm proposed by (Bai and Perron, 1998) and (Bai and Perron, 2003), we identify the structural breaks date (Bolukbasi and Yildirtan, 2010) and confidence intervals for the day of the break in the time series of daily new cases per country. The number of detected breaks goes from 1 (Germany, Sweden and Turkey) to 5 (Iran, Saudi Arabia and India). Second, following (Li and Linton, 2021), (Cho, 2020) and (Bonacini et al., 2020) we estimate a quadratic time trend model applied to the natural log of new cases per country, taking into account the structural breaks identified before. Third, as novelty, the lockdown strictness of each country is assessed according to the Government Response Stringency Index (GRSI), which is a composite measure based on nine response indicators including school closures, workplace closures, and travel bans, rescaled to a value from 0 to 100 (100 = strictest response). We include also GRSI interacting with dummy variables resulting from the breaks.

The remainder of this paper is organized as follows. In Section 2 we discuss the econometrical methods used in the paper. In Section 3 we give a brief description of the data we use: the daily number of new infected people by COVID-19 in thirty eight countries. Section 4 shows the dates for the structural breaks in each country and the estimation results of the three regression models under analysis. Section 5 concludes the analysis and sheds some light on the differences between countries in terms of daily new cases, specially in the most recent past.

2 Econometric methodology

The econometric methodology (Rasheed, Adnan, Saffari and Pati, 2015) is composed of two sequential parts. Firstly, to test the presence of structural breaks on the time series of daily new cases per country, we used the algorithm described in (Bai and Perron, 1998) and (Bai and Perron, 2003) for simultaneous estimation of multiple breakpoints. The algorithm starts by evaluating the optimal one-break partition with sub-samples that have a sufficient number of observations. The authors suggest that a trimming as small as 5% of the total sample can lead to tests with substantial size distortions. For this purpose, computations were performed using the R package `strucchange` (Zeileis, Leisch, Hornik and Kleiber, 2002). To that effect, it was used the function `breakpoints` with a single constant regressor, and setting the minimum break size at 15% of the time series length:

$$y_t = \beta_1 + \varepsilon_t. \quad (2.1)$$

Thus, we test the mean changes on the time series of daily new cases per country. As in (Zeileis et al., 2002) we consider the Bayesian Information Criteria (BIC) as the rule to choose the proper number of structural breaks. (Bai and Perron, 2003) alerts for some drawbacks of using information criteria as AIC, BIC and LWZ.

In the second stage, we exploit the effect of structural breaks in the number of new daily cases and the impact of Government Response Stringency Index (GRSI) by studying its interaction with the structural break dynamics. Thus, to analyze different regimes in the mean of new daily cases and how the Health and Governments Authorities responses have impacted on the evolution of the COVID-19 pandemic, we estimate and compare three models. Firstly, the benchmark and baseline model is a quadratic time trend model applied to the natural log of daily new cases per country (Li and Linton, 2021):

$$y_t = \beta_1 + \beta_2 t + \beta_3 t^2 + \varepsilon_t, \quad (2.2)$$

where $y_t = \ln(Y_t + 1)$ and Y_t represents the number of daily new cases per country. We add one to the count as this is necessary for some countries with sparse data records or at early stages of the epidemic when zero counts were common. The log transformation can help in reducing heteroskedasticity and other issues that arise from the non-negative count nature of Y_t .

A quadratic is the simplest function that reflects the possibility of a turning point. A well defined maximum of y_t occurs if and only if $\beta_3 < 0$ and occurs at the time $t = -\beta_2/2\beta_3$, which results in the maximal value of cases per day of $y_{tmax} = \beta_1 - \beta_2^2/4\beta_3$.

Secondly, we expand the benchmark model by introducing time dummy variables corresponding to the structural breaks identified before, to control for possible time-variant dynamics in the daily number of new cases:

$$y_t = \beta_1 + \beta_2 t + \beta_3 t^2 + \sum_{j=2}^m \gamma_j D_{jt} + \varepsilon_t, \quad (2.3)$$

where m represents the number of sub-samples resulting from the structural breaks, $D_{jt} = 1$ if t belongs to the sub-sample j and $D_{jt} = 0$ otherwise. The first sub-sample, resulting from the first structural break, is the reference in terms of the coefficients interpretation. Thus, 2.2 is the model without breaks and 2.3 is the model with $m - 1$ segments.

Thirdly, we include the Government Response Stringency Index (GRSI) and the interactions with the dummies resulting from the structural breaks:

$$y_t = \beta_1 + \beta_2 t + \beta_3 t^2 + \sum_{j=2}^m \gamma_j D_{jt} + \delta_1 GRSI_t + \sum_{j=2}^m \delta_j D_{jt} * GRSI_t + \varepsilon_t. \quad (2.4)$$

The models are estimated by OLS of the log of counts (daily new cases). HAC-based standard errors are also considered, but the statistical significance of the estimates does not change substantially. The best specification is assessed by computing the BIC. We also provide the likelihood ratio (LR) statistic that can be used to test the difference between the three estimated models. By using the maximum log-likelihood values from the model without restrictions: (2.3) or (2.4), from the models when restrictions are imposed: $\gamma_j = 0$ (2.2) and $\delta_j = 0$ (2.3), a nested Likelihood Ratio test can be constructed to compare the in-sample goodness-of-fit of model (2.2) against (2.3) and model (2.3) against (2.4). Let l_0 be the maximum log-likelihood value under the null hypothesis that the true model is (2.2) or (2.3), and l_1 be the maximum log-likelihood value under the alternative that the true model is (2.3) or (2.4), then

$$LR = 2(l_1 - l_0) \quad (2.5)$$

should have a χ^2 distribution with $m - 1$ and $2m - 1$ degrees of freedom, respectively, when the null hypothesis is true.

3 Data

We use daily data, from March 1, 2020 to January 8, 2021, on new cases downloaded from the website of the European Centre for Disease Protection and Control (ECDC), which is an agency of the European Union. We consider thirty eight countries from Asia, Africa, North America, South America, Europe and Australia, including those with the largest number of

cases. Specifically, cases are the reported daily count of detected and laboratory (and sometimes, depending on the country reporting them and the criteria adopted at the time, also clinically) confirmed positive and sometimes – depending on the country reporting standards – also presumptive, suspect, or probable cases of detected infection.

Table 1: New daily cases per country – descriptive statistics

Country	Mean	Median	St Dev	Kurt	Skew	Range	Min	Max	Sum
USA	69,627	44,705	67,099	1.062	1.462	301851	7	301858	21862748
India	33,296	26,848	28,985	-0.902	0.531	97893	1	97894	10454793
Brazil	25,521	24,265	18,798	-0.672	0.362	87842	1	87843	8013716
Russia	10,577	7,504	8,556	-0.477	0.868	29498	1	29499	3321167
Spain	9,794	7,078	10,381	2.524	1.487	54983	36	55019	3075189
UK	9,446	3,319	13,155	4.530	2.077	68186	6	68192	2966183
France	8,932	3,167	14,745	11.053	2.588	106090	1	106091	2804646
Italy	7,123	1,792	10,139	1.552	1.619	40901	1	40902	2236762
Germany	6,069	1,586	9,114	3.513	1.980	49028	16	49044	1905559
Colombia	5,591	6,597	4,388	-0.845	0.217	18220	1	18221	1755577
Argentina	5,455	4,960	4,900	-0.944	0.492	18325	1	18326	1713000
Mexico	4,802	4,809	3,642	6.369	1.545	28114	1	28115	1507935
Turkey	4,727	1,600	8,279	6.053	2.642	44505	1	44506	1484369
Poland	4,349	551	7,080	2.393	1.820	32732	1	32733	1365650
Iran	4,057	2,560	3,440	1.532	1.595	13666	385	14051	1273921
South Africa	3,798	1,944	4,461	2.289	1.634	21979	1	21980	1192578
Ukraine	3,630	1,208	4,372	0.338	1.252	16584	1	16585	1139815
Netherlands	2,774	756	3,496	0.001	1.156	13071	1	13072	871058
Belgium	2,105	708	3,708	11.279	3.214	23920	1	23921	660854
Canada	2,067	1,101	2,421	3.965	1.824	16139	2	16141	648910
Chile	2,017	1,703	1,737	13.323	2.777	13989	1	13990	633386
Iraq	1,915	1,960	1,553	-1.289	0.207	5054	1	5055	601415
Sweden	1,559	358	4,047	27.032	4.776	32484	1	32485	489519
Israel	1,520	841	1,860	3.237	1.885	9077	1	9078	477352
Portugal	1,486	445	2,049	3.017	1.850	10175	1	10176	466714
Austria	1,200	293	1,886	4.101	2.111	9584	2	9586	376784
SaudiArabia	1,158	552	1,194	0.469	1.194	4918	1	4919	363589
Hungary	1,076	66	1,725	1.802	1.699	6818	1	6819	337751
Japan	875	512	1,133	9.540	2.614	7849	14	7863	274702
Denmark	571	168	854	4.210	2.127	4507	1	4508	179181
Equador	569	476	421	1.078	1.053	2146	1	2147	178554
Egypt	471	227	477	0.040	1.174	1773	1	1774	147814
Greece	457	128	720	3.635	2.064	3315	1	3316	143498
Ireland	433	219	945	38.547	5.825	8226	1	8227	135889
Norway	173	85	216	7.676	2.147	1679	1	1680	54466
Finland	121	70	138	2.904	1.605	839	1	840	38073
Australia	91	22	138	3.944	2.062	715	1	716	28559
China	55	33	58	22.038	3.382	575	1	576	17214

Table 1 summarizes the basic statistical properties of the data. The top five countries accord-

ing to the daily mean of new cases and total infected people are USA, India, Brazil, Russia and Spain. The maximum number of new cases in one single day is more than three hundred thousand in USA and more than one hundred thousand in France. The empirical distributions are all asymmetric positive, with a long right tail, to accommodate the days with a high number of new cases. The mean is substantially higher than the median reflecting the extreme observations. The excess of kurtosis is very high for some countries (France, Belgium, Chile, Sweden and Ireland) reflecting also the days with abnormal number of new cases.

4 Empirical results

The empirical study is conducted in two sequential steps. Firstly, we test the presence of structural breaks on the time series of daily new cases per country. Next we exploit the effect of structural breaks in the number of new daily cases and the impact of Government Response Stringency Index (GRSI) by studying its interaction with the structural break dynamics. Models in (2.2), (2.3) and 2.4 are estimated by OLS.

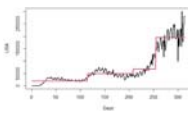
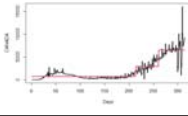
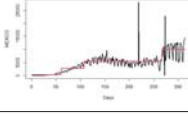
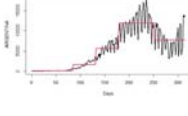
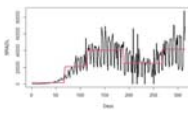
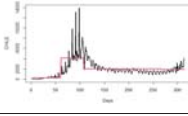
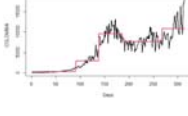
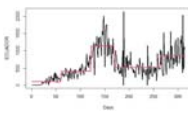
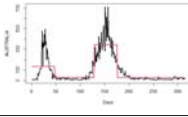
4.1 Structural breaks

The methodology presented in Section 2 allows for the identification of the number and dates of structural breaks in the path of COVID-19 cases. The algorithm proposed by (Bai and Perron, 1998) and (Bai and Perron, 2003), implemented in the `strucchange` R package (Zeileis et al., 2002), automatically selects the number and dates of structural breaks by using the Bayesian information criterion (BIC). For example, in case of USA, the algorithm found 3 structural breaks, on dates 2020-06-22, 2020-09-23 and 2020-09-11. Next, four dummy variables have been created. The first one is equal to 1 from 2020-03-01 to 2020-06-22 and 0 otherwise, the dummy two is equal to 1 from 2020-06-23 to 2020-09-23 and 0 otherwise, and so on. Thus, we create so many dummy variables as the number of sub-samples resulting from the structural breaks. Later we include these dummy variables directly in the regression model or interacting with the GRSI lockdown stringency variable. The structural breaks per country and continents are shown in Tables 2, 3, 4 and 5. 95% confidence intervals for the break day are also shown under the columns “2.5%” and “97.5%”. “Average” represents the daily average number of new cases in each sub-sample resulting from the structural breaks. For most of countries the largest average occurs in the last sub-sample.

To analysis the relation between the starting/ending date of lockdowns and structural breaks we consider the Wikipedia information per country¹. As the number of structural breaks is almost always greater than the number of lockdowns (there is only a small number of countries with more than one total lockdown) it is not easy to find a relationship between them. For example, by choosing to stay open rather than instituting a policy of lockdown, Sweden’s policies have drawn both international praise and criticism. As one can see, countries act differently in

¹https://en.wikipedia.org/wiki/COVID-19_lockdowns

Table 2: Structural breaks – America and Australia

Country	2.50%	Break day	97.50%	Break date	Average	Plot
USA	112	114	116	22/06/2020	20,246	
	183	207	210	23/09/2020	49,711	
	252	254	255	09/11/2020	69,020	
					194,795	
Canada	209	213	214	29/09/2020	746	
	255	260	261	15/11/2020	2,988	
					6,472	
Mexico	57	60	61	29/04/2020	297	
	99	107	109	15/06/2020	2,818	
	258	266	269	21/11/2020	5,550	
					9,901	
Argentina	80	84	85	23/05/2020	135	
	129	131	132	09/07/2020	1,688	
	176	178	179	25/08/2020	5,722	
	245	251	255	06/11/2020	11,907	
					7,685	
Brazil	63	67	68	06/05/2020	1,890	
	109	114	117	22/06/2020	20,848	
	180	188	196	04/09/2020	40,342	
	253	267	274	22/11/2020	25,058	
					41,326	
Chile	71	75	76	14/05/2020	560	
	121	122	129	30/06/2020	5,050	
					1,844	
Colombia	86	90	91	29/05/2020	297	
	136	137	138	15/07/2020	2,946	
	181	186	195	02/09/2020	9,554	
	256	267	269	22/11/2020	7,594	
					10,790	
Ecuador	56	60	62	29/04/2020	111	
	118	121	122	29/06/2020	413	
	166	168	172	15/08/2020	1,143	
	249	263	270	18/11/2020	522	
					851	
Australia	46	47	68	16/04/2020	137	
	125	128	129	06/07/2020	28	
	174	175	178	22/08/2020	342	
					27	

terms of lockdown decisions and it is not clear that structural breaks occur near to a lockdown starting/ending date. For example, in Germany the second lockdown started on 2020-11-02 and the unique structural break occurred at 2020-10-22, a few days before. In Belgium, the second lockdown started on 2020-11-02 and the second structural break occurred on 2020-11-21 a few days after. In Austria, the second lockdown started on 2020-11-03 and the second structural break occurred few days before, at 2020-10-21. In England, 2020-11-05 is the starting date of the second lockdown and 2020-10-25 is the second structural break date, less than 10 days before. In France the second lockdown started on 2020-10-30 and the last structural break occurred on 2020-11-22, less than one month later. The impact of this second lockdown seems to have a stronger impact, because the average daily number of new COVID-19 cases decreases from 32,244 to 13,021 (column "Average"). Thus, based on this sample, it seems that we cannot conclude what causes what, whether it is the lockdowns that determine the structural breaks or vice versa.

Since the total lockdown is the most restrictive measure, and there are just a few countries with more than one lockdown, next we analyze the impact of other stringent measures by introducing the Government Response Stringency Index (GRSI) in the regression models, interacting with the dummies resulting from the structural breaks. For now it is important to analyze the differences resulting from the structural breaks in terms of daily average of new cases.

As one can see, we found different number and different dates for the structural breaks across countries under scrutiny. In spite of the disparity among countries, specially in the occurring dates, we can observe that the last structural break is more or less contemporaneous for several countries. By taking the confidence interval for the break day, we conclude that the difference is not statistically significant. It occurs during November's 2020, between the 2nd and 22th days. The exceptions are Chile, Australia, Austria, Germany, Greece, Hungary, Italy, Netherlands, Norway, Portugal, Sweden and UK (12 in 38 countries). Despite this similarity, the consequences of COVID-19 are quite different among countries in the sub-sample resulting from the last structural break. Taken the average of daily new cases, Chile and Australia are the only countries showing a decrease in the group "America and Australia". The increase is substantial for the other countries, specially in USA, where the daily average number of new infected people more than tripled after 2020-11-09, the date of the last structural break. In the group of "Asia and Africa" the reduction occurs only in Saudi Arabia, Iraq and India. The worse scenario occurs in Israel, Japan and South Africa, where the daily average number of new cases more than tripled, when compared to the sub-sample before. In Europe, there is also an increase in the average number of cases per day in the recent past. Exceptions are Belgium, France, Poland and Spain. The worse cases are Germany, Netherlands, Italy, Sweden, Turkey, Portugal and UK, where the daily average number of new cases more than quadrupled.

In conclusion, the structural breaks allows us to identify turning points, for better or worse, in the evolution of the COVID-19 pandemic.

Table 3: Structural breaks – Asia and Africa

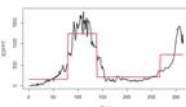
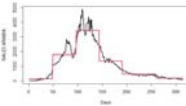
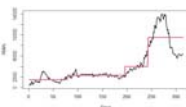
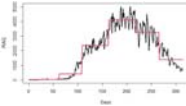
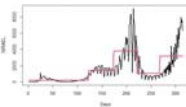
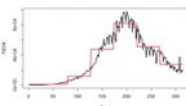
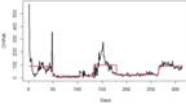
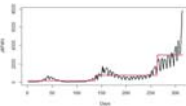
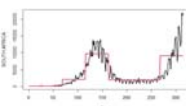
Country	2.50%	Break day	97.50%	Break date	Average	Plot
Egypt	78	79	80	18/05/2020	162	
	137	138	140	16/07/2020	1,237	
	260	267	268	22/11/2020	211	
					740	
Saudi Arabia	46	48	49	17/04/2020	149	
	94	96	97	04/06/2020	1,792	
	142	143	145	21/07/2020	3,461	
	189	190	193	06/09/2020	1,380	
	258	259	261	14/11/2020	468	
Iran	77	78	86	17/05/2020	1,533	
	189	195	196	11/09/2020	2,373	
	238	242	243	28/10/2020	4,061	
					9,526	
Iraq	58	61	63	30/04/2020	34	
	107	108	109	16/06/2020	439	
	161	162	163	09/08/2020	2,360	
	210	216	220	02/10/2020	4,114	
	264	265	267	20/11/2020	3,255	
					1,422	
Israel	120	122	123	30/06/2020	208	
	162	173	174	20/08/2020	1,459	
	219	220	228	06/10/2020	3,794	
	253	267	269	22/11/2020	1,088	
					3,150	
India	76	79	80	18/05/2020	1,270	
	124	126	127	04/07/2020	12,188	
	172	173	176	20/08/2020	47,503	
	218	220	222	06/10/2020	81,943	
	265	267	270	22/11/2020	50,696	
					27,977	
China	47	48	49	17/04/2020	92	
	125	132	133	10/07/2020	15	
	177	179	182	26/08/2020	102	
	264	265	266	20/11/2020	26	
					94	
Japan	131	136	137	14/07/2020	163	
	257	262	263	17/11/2020	784	
					2,956	
South Africa		68		07/05/2020	121	
	113	115	116	23/06/2020	2082	
	161	162	164	09/08/2020	9654	
		267		22/11/2020	1979	
					9040	

Table 4: Structural breaks – Europe

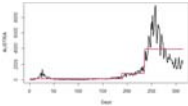
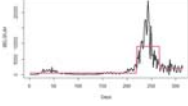
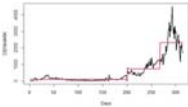
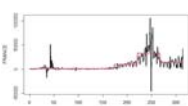
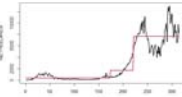
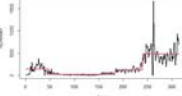
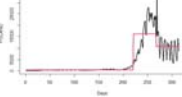
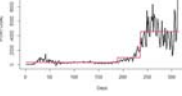
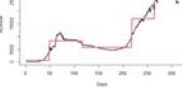
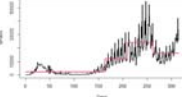
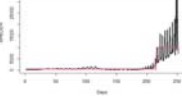
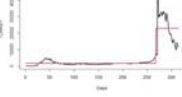
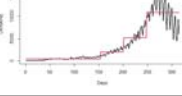
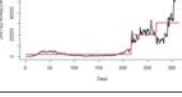
Country	2.50%	Break day	97.50%	Break date	Average	Plot
Austria	184	188	189	04/09/2020	153	
	229	235	236	21/10/2020	866	
					3,891	
Belgium	215	219	223	05/10/2020	604	
	265	266	274	21/11/2020	9,036	
					2,162	
Denmark	196	200	201	16/09/2020	105	
	263	267	268	22/11/2020	746	
					2,301	
Finland	76	78	90	17/05/2020	81	
	209	212	213	28/09/2020	25	
	253	262	264	17/11/2020	198	
France					354	
	169	173	178	20/08/2020	1,556	
	208	220	221	06/10/2020	8,681	
Germany	266	267	285	22/11/2020	32,244	
					13,021	
					1,711	
Greece	232	236	237	22/10/2020	19,253	
Hungary	158	163	164	10/08/2020	35	
	234	240	241	26/10/2020	334	
					1,513	
Ireland						
	191	194	195	10/09/2020	53	
	238	243	244	29/10/2020	1,182	
Italy					3,797	
	208	213	216	29/09/2020	168	
		267		22/11/2020	643	
					1,392	
	56	57	61	26/04/2020	3,448	
	173	187	188	03/09/2020	579	
	231	234	235	20/10/2020	3,437	
					22,543	

Table 5: Structural breaks – Europe

Country	2.50%	Break day	97.50%	Break date	Average	Plot
Netherlands	163	173	174	20/08/2020	386	
	218	220	221	06/10/2020	1,778	
					7,666	
Norway	46	47	55	16/04/2020	146	
	180	183	184	30/08/2020	28	
	234	239	240	25/10/2020	130	
					488	
Poland		220		06/10/2020	474	
	259	267	292	22/11/2020	16,107	
					10,730	
Portugal	178	188	189	04/09/2020	316	
	231	235	236	21/10/2020	996	
					4,563	
Russia	47	48	49	17/04/2020	667	
	114	116	121	24/06/2020	8,442	
	215	217	218	03/10/2020	5,868	
	263	264	266	19/11/2020	17,028	
					26,444	
Spain	157	162	163	09/08/2020	2,303	
	198	209	212	25/09/2020	12,355	
	254	261	286	16/11/2020	24,070	
					16,410	
Sweden		215		01/10/2020	549	
					10,042	
Turkey		267		22/11/2020	1,674	
					22,754	
Ukraine	151	153	154	31/07/2020	467	
	196	200	201	16/09/2020	2,027	
	243	247	248	02/11/2020	5,274	
					10,824	
UK	46	47	55	16/04/2020	2,399	
	180	183	184	30/08/2020	1,646	
	234	239	240	25/10/2020	9,646	
					27,859	

4.2 Testing the effect of structural breaks

To analyze the impact of structural breaks in the estimation process, we fit the models (2.2), (2.3) and (2.4) on each country's case data separately with the data available from March 1, 2020 until January 8, 2021 and report the most important estimates in Tables 6, 7 and 8.

First we analyze the estimates for the coefficients of the quadratic function fitted to the log of data. The coefficient β_3 of the quadratic term t^2 tells both the direction and steepness of the curvature (a positive value indicates the curvature is upwards – convex – while a negative value indicates the curvature is downwards – concave). We can take the sign of the estimate for β_3 as an indication of whether the daily maximum number of cases has been already reached. With just a few exceptions, the estimate is always negative and statistically significant for Latin America, Australia, Asia and Africa countries. As the curvature of the estimated function is downwards, we can conclude that the daily maximum number of cases has already been reached and their peak has passed, unless a trend reversal takes place. As far as USA, Canada and European countries are concerned, the conclusion does not seem so encouraging: a number of countries still have yet to reach their peak. Excluding Poland, Ukraine and Russia, the β_3 estimate is positive and statistically significant for all the other countries pointing for an upwards curvature. It seems that the number of daily cases is increasing again and the daily number of cases may return to the peak previously reached (Italy and Spain, for example) or that peak is yet to arrive (Ireland, Portugal and United Kingdom, for example).

Next we compare the fit of the three proposed regressions (2.2), (2.3) and (2.4) based on the Likelihood Ratio test. In the past there was not much to choose between the models, for all the countries. As one can see in Tables 6, 7 and 8, the model with more predictors (the one with the quadratic trend, plus the dummies to control for possible time-variant in the daily number of cases, plus the Government Response Stringency Index (GRSI) and the interactions with the dummies resulting from the structural breaks) fits significantly better when compared to the other simplest models, and it seems the best one to explain the dynamics in COVID-19 new cases. The exception is China where the difference for model (2.3) is not statistically significant. Thus, including GRSI and its interaction with structural break dummies increases the fit significantly. The regressions generally have high adjusted R^2 and the third model is also favored by the adjusted R^2 , with the highest value for all countries (except China). BIC values are always smaller than those reported by the other models favoring also model (2.4).

Regarding the coefficients of temporal dummies γ_j resulting from the structural breaks, there is quite a bit of heterogeneity across the estimates consistent with different countries being at different stages of the cycle and having taken different approaches to managing the epidemic and having different demographics. We will focus mainly on the sub-sample resulting from the last structural break in each country trying to envision the evolution of the pandemic. We can split the countries according to the signal and the significance for the estimate of the coefficient corresponding to the last dummy (and the most recent sub-sample). The results are interpreted for model (2.4). If the estimate is positive, it means that lately it is happening an increase in the daily rate of new cases when compared to the initial phase of the pandemic,

before the first structural break was observed. We can also infer that the pandemic is not yet controlled. The countries in this group are: USA, Canada, Mexico, Brazil (positive but not statistically significant), Chile, Iran, Iraq, Israel, Japan, Austria, Denmark, Finland, Germany, Greece, Hungary, Italy, Netherlands, Norway, Poland, Portugal, Russia and UK. Thus, most of European countries are included in this group. In case of USA, for example, the value of the estimate is always increasing from the first to the last sub-sample, meaning that the pandemic is getting worse. If the estimate is negative, there is a decrease in the daily rate of new cases when compared to the initial phase of the pandemic. The countries in this group are: Argentina, Colombia, Ecuador, Australia, Egypt, South Arabia, India, China, Japan, South Africa, Belgium, Ireland (not statistically significant), Spain and Ukraine, pointing to a possible control of the pandemic (unless the trend is reversed).

Now, regarding GRSI – Government Response Stringency Index, the estimate for the coefficient δ_1 is positive in the sub-sample before the first structural break. At the beginning the lockdown strictness of each country had a counterintuitive impact on the daily number of new cases. In the next sub-samples, and more recently, the estimate for the GRSI coefficient becomes negative in a large number of countries. Thus, by summing the estimates for δ_1 and δ_j (the ones associated to the interaction effects with structural breaks), $j > 1$, we can assess the impact of stringent measures in the daily number of new cases for each sub-sample resulting from the structural breaks. Considering the last sub-sample, the estimate for $\delta_1 + \delta_j$ (assessing the total effect of GRSI) becomes negative in USA, Canada, Mexico, Brazil, Iraq, Israel, Austria, Denmark, Finland, Germany, Greece, Hungary, Italy, Netherlands, Norway, Poland, Portugal, Russia and Spain. Thus, stringent measures have an alleviation effect on the daily spread of the novel coronavirus. For the other countries, the signal is negative in the intermediate sub-samples; the stringent measures have also a significant impact on the reduction in the number of cases. However, it becomes positive (or the result in “NA”) in the last sub-sample; the estimate is quite stable and similar to the one estimated for the sub-sample before the first break, revealing the little effectiveness of stringent measures in reducing the number of cases. The other explanation can be the elapsed time between the application of more stringent measures and the reduction in the number of cases. The estimation results did not adjust yet to the last lockdown strictness measures. Thus, it is expected that a higher index will contribute later for a reduction in the daily number of cases, following the significant effects observed in the intermediate sub-samples.

Table 6: Estimation results – America and Australia

Country	β_1	β_2	β_3	γ_2	γ_3	γ_4	γ_5	δ_1	δ_2	δ_3	δ_4	δ_5	R^2	BIC	LR
USA	(1) 7.667*	0.0287*	-0.00005***	-0.863*	-0.736***	1.110***							0.5911	925.3	
	(2) 6.952*	0.0495*	-0.00012*	1.813	7.387*	8.669*		0.104*	-0.013	-0.097*	-		0.6613	880.4	62.2*
	(3) 2.341*	0.0022	0.00001*								0.105*		0.9581	243.0	660.4*
Canada	(1) 5.401*	0.0047	0.00002*	1.825*	3.375*								0.4467	1002.6	
	(2) 4.962*	0.0204*	-0.00007*	1.149*	13.630*			0.081*	NA	-0.2023***			0.5138	971.5	42.61*
	(3) 1.466*	-0.0142*	0.00007*										0.8534	604.5	378.5*
Mexico	(1) 2.782*	0.0621*	-0.00015*	0.127*	-1.536*	0.706*							0.7280	967.4	
	(2) 1.685*	0.0929*	-0.00024*	6.125*	6.689*			0.046*	-0.063**	-0.074**	NA		0.8092	870.2	114.4*
	(3) 1.061*	0.0317*	-0.00008*										0.8751	751.4	136.4*
Argentina	(1) 1.107*	0.074*	-0.00016*	-0.143	-0.511***	-0.886**							0.9294	643.9	
	(2) 0.976*	0.077*	-0.00015*	2.985	-2.028	-0.6788	-1.363*	0.020*	-0.028	0.026*	0.039	NA	0.9309	656.4	10.5**
	(3) 0.092*	0.057*	-0.00010*				-0.6788						0.9421	619.7	59.7*
Brazil	(1) 4.033*	0.0679*	-0.00017*	-0.812***	-3.118*	-5.152*	-2.763*						0.5461	1235.4	
	(2) 2.308*	0.1169*	-0.00027*	1.792	1.236	5.200	5.815	0.074*	-0.019	-0.020	-	-0.08152	0.6816	1143.0	115.4*
	(3) -0.370	0.0573*	-0.00013*								0.097**		0.7484	1092.7	79.1*
Chile	(1) 3.601*	0.0489*	-0.00013*	0.237	-2.667*								0.5453	972.9	
	(2) 2.587*	0.0739*	-0.00017*	1.319*	4.192*			0.077*	NA	-0.055*			0.7211	828.9	155.5*
	(3) 0.112	0.0125*	-0.00003*										0.8900	546.27	294.1*
Colombia	(1) 1.793*	0.0692*	-0.00015*	-0.771*	-1.279*	-2.526*	-1.827*						0.9170	648.8	
	(2) 1.091*	0.0873*	-0.00018*	0.1189*	0.4956*	-1.025*	-0.097*	0.045*	NA	-0.004	0.009	NA	0.9506	504.7	167.1*
	(3) -1.055*	0.0541*	-0.00009*										0.9818	206.1	315.9*
Ecuador	(1) 2.337*	0.0451*	-0.00011*	-1.110*	-2.130*	-3.904*	-2.345*						0.5394	988.7	
	(2) 1.119*	0.0836*	-0.00019*	-5.352*	-9.958*	0.00002	-0.668*	0.035*	0.059	0.120	-	0.005	0.6861	887.2	124.5*
	(3) -0.757*	0.0577*	-0.00013*								0.025**		0.7894	785.4	130.5*
Australia	(1) 2.985*	0.0161*	-0.00006*	-2.387*	0.020	-2.469*							0.1408	1103.1	
	(2) 3.500*	0.0259*	-0.00007*	-1.555	4.459**	-4.412*		0.038*	-0.016	-0.066*	0.022***		0.5661	902.8	217.5*
	(3) 1.783*	0.0162**	-0.00003**										0.6763	829.7	96.1*

NA: the Government Response Stringency Index (GRSI) did not change in this sub-sample period. *, **, *** denote statistically significant at the 1%, 5% and 10% significance levels, respectively. (1), (2) and (3) refers to the models in equations (2.2), (2.3) and (2.4).

Table 7: Estimation results – Asia And Africa

Country	β_1	β_2	β_3	γ_2	γ_3	γ_4	γ_5	γ_6	δ_1	δ_2	δ_3	δ_4	δ_5	δ_6	$\bar{R}^2$	BIC	LR
Egypt	(1) 3.434*	0.0275*	-0.00007*	-0.030	-3.278*	-1.114*	-	-	0.033*	-	-0.071*	0.209*	-	-	0.25	1058	
	(2) 1.879*	0.0657*	-0.00016*	1.639***	3.236*	-12.410*	-	-	-	-	-	-	-	-	0.73	750	326*
	(3) 0.748*	0.0370*	-0.00009*	-	-	-	-	-	-	-	-	-	-	-	0.85	575	197*
S. Arabia	(1) 3.153*	0.0562*	-0.00018*	0.661*	-0.7192***	-2.740*	-	-3.125*	-	-	-	-	-	-	0.64	921	
	(2) 1.809*	0.0849*	-0.00021*	-	-	-	3.770*	-	-	-	-	-	-	-	0.85	670	280*
	(3) -0.592*	0.0426*	-0.00014*	3.791*	20.561*	2.467**	7.848*	-4.678	0.048*	-	-0.260*	-	-0.116*	0.139**0.94	0.85	390	315*
Iran	(1) 7.116*	0.0033*	0.00001*	0.281*	0.946*	2.155*	-	-	0.034*	-	-0.009	-	-	-	0.74	297	
	(2) 7.006*	0.0074*	-0.00002*	2.244*	1.435*	6.113*	-	-	-	-	-	-	-	-	0.86	125	189*
	(3) 5.437*	0.0028***	-0.00001*	-	-	-	-	-	-	-	-	-	-	-	0.89	49	99*
Iraq	(1) 1.037*	0.0710*	-0.00017*	-0.171	0.574**	0.358	0.200	0.169	0.032*	0.129*	NA	-	-0.046*	-	0.94	500	
	(2) 1.263*	0.0649*	-0.00016*	-10.490*	2.151*	5.702*	6.177*	6.273*	-	-	-	-	-	-	0.94	484	45*
	(3) -0.656*	0.0384*	-0.00010*	-	-	-	-	-	-	-	-	-	-	-	0.96	369	144*
Israel	(1) 3.183*	0.0318*	-0.00006*	1.675*	1.850*	-0.127	0.171	-	0.069*	-	-0.065*	-	-0.059	-	0.55	1023	
	(2) 3.967*	0.0089**	0.00001	6.553*	7.040*	2.045**	3.456*	-	0.055*	-	-	-	-	-	0.68	942	104*
	(3) -0.3434*	-0.0106*	0.00008*	-	-	-	-	-	-	-	-	-	-	-	0.81	796	175*
India	(1) 2.325*	0.0896*	-0.00022*	-1.387*	-2.340*	-2.877*	-	-2.589*	-	-	-	-	-	-	0.94	592	
	(2) 1.372*	0.1195*	-0.00028*	-	-	-	-	-	-	-	-	-	-	-	0.97	459	162*
	(3) 0.141	0.0991*	-0.00022*	-11.250*	6.110*	-4.456*	3.281*	-2.239*	0.025*	0.139*-0.095*	0.032**	0.003	NA	NA	0.98	282	205*
China	(1) 3.792*	-0.0128*	0.00005*	-2.863*	-1.289*	-2.833*	-	-	-	-	-	-	-	-	0.15	975	
	(2) 3.888*	0.0151*	-0.00003*	-	-	-	-	-	-	-	-	-	-	-	0.60	761	237*
	(3) 2.445**	0.0235*	-0.00004*	-0.744	-2.036*	-2.670*	-	-	0.017	-	NA	-	0.022	-	0.60	780	4.14
Japan	(1) 4.197*	0.0072*	0.00002*	-	-	-	-	-	-	-	-	-	-	-	0.65	824	
	(2) 4.549*	0.0006	0.00000	1.852*	3.118*	-	-	-	-	-	-	-	-	-	0.74	741	95*
	(3) 1.409*	0.0138*	-0.00003*	4.185*	2.891*	-	-	-	0.064*	-	-0.022	-	-	-	0.77	719	39*
S. Africa	(1) 2.354*	0.0590*	-0.00014*	0.250*	0.103	-2.718*	-	-	-	-	-	-	-	-	0.68	1027	
	(2) 1.274*	0.0810*	-0.00018*	-	-	-	-	-	-	-	-	-	-	-	0.89	708	342*
	(3) 0.310*	0.0373*	-0.00005	10.010*	13.800*	-0.706	0.705	-	0.035*	-	-0.152	0.004	0.042***	-	0.94	541	196*

NA: the Government Response Stringency Index (GRSI) did not change in this sub-sample period. *, **, *** denote statistically significant at the 1%, 5% and 10% significance levels, respectively. (1), (2) and (3) refers to the models in equations (2.2), (2.3) and (2.4).

Table 8: Estimation results – Europe

Country	Model	β_1	β_2	β_3	γ_2	γ_3	γ_4	γ_5	δ_1	δ_2	δ_3	δ_4	δ_5	$\bar{R}^2$	BIC	LR
Austria	(1)	4.339*	-0.0059*	0.00007*	1.964*	3.235*			0.029*	0.008	-0.02763***			0.6751	950.2	
	(2)	4.301*	0.0009	0.00000	1.964*	3.235*								0.7432	885.8	75.9*
	(3)	2.300*	0.0063**	0.00000	1.409*	3.817*								0.7874	840.7	62.4*
Belgium	(1)	5.254*	0.0013	0.00003*	1.802*	-0.705*								0.3134	1164.4	
	(2)	5.639*	-0.0069	0.00005*	1.802*	-0.705*								0.4641	1096.2	79.8*
	(3)	2.227*	-0.0241*	0.00015*	8.891*	-23.240*			0.062*	-0.154*	0.311*			0.6797	948.7	164.7*
Denmark	(1)	4.561*	-0.0174*	0.00001*										0.5589	1069.1	
	(2)	4.561*	-0.01459*	0.00007*	1.881*	1.690*								0.5948	1051.9	28.6*
	(3)	0.268*	-0.0213*	0.00012*	4.445*	7.680*			0.075*	-0.068*	-0.156*			0.7022	969.5	99.7*
Finland	(1)	3.932*	-0.0179*	0.00009*										0.4263	1016.1	
	(2)	2.763*	0.0325*	-0.00007*	-3.179*	-1.487*	-0.664*							0.6381	886.5	146.8*
	(3)	0.053	0.0140**	0.00004**	-5.098*	4.651*	6.174*		0.058*	0.071*	-0.200*	-0.227*		0.7769	754.5	155.0*
France	(1)	6.272*	0.0033	0.00003**										0.3587	1183.7	
	(2)	6.886*	-0.0063	0.00002	2.476*	3.705*	2.285**							0.5310	1102.4	98.5*
	(3)	2.608*	-0.0133**	0.00012*	11.660*	5.317*	-7.164		0.058*	-0.211	-0.083*	0.046		0.6135	1062.2	63.1*
Germany	(1)	7.319*	-0.0179*	0.00009*										0.6183	901.6	
	(2)	7.142*	-0.0119*	0.00006*	1.103*									0.6355	891.8	15.5*
	(3)	3.827*	-0.0344*	0.00017*	11.870*				0.067*	-0.203*				0.8241	672.6	230.8*
Greece	(1)	2.155*	0.0091*	0.00003*										0.7063	978.9	
	(2)	2.412*	0.0087*	-0.00002	2.330*	3.826*								0.7772	901.7	88.7*
	(3)	1.143*	0.0057***	0.00001	2.293	8.413*			0.020*	-0.008	-0.081*			0.7956	888.7	30.2*
Hungary	(1)	2.401*	-0.0004	0.00007*	3.424*	4.459*								0.7137	1107.1	
	(2)	2.375*	0.0085**	-0.00001*	3.606*	8.676*			0.058*	NA	-0.094*			0.8035	998.3	120.3*
	(3)	-1.272*	0.0065**	0.00002										0.8509	921.1	88.7*
Ireland	(1)	4.428*	-0.0121*	0.00007*										0.3419	1152.8	
	(2)	4.678*	-0.0178*	0.00009*	0.789***	-0.571			0.058*	-0.133*	-0.019			0.3796	1143.7	20.5*
	(3)	1.525*	-0.0377*	0.00019*	8.247*	-3.060								0.7249	902.6	258.4*
Italy	(1)	8.377*	-0.0339*	0.00014*										0.6724	888.4	
	(2)	8.024*	-0.0017	0.00000	-1.756*	0.168	2.360*							0.8435	671.3	234.3*
	(3)	0.170	-0.0086**	0.00004*	3.946*	5.676*	12.650*		0.091*	-0.051*	-0.052**	-0.137*		0.8926	572.4	121.9*
Netherlands	(1)	5.416*	-0.005***	0.00006*	1.708*	3.058*								0.6575	944.7	
	(2)	5.578*	-0.0036	0.00002***	1.708*	3.058*			0.039*	0.023	-0.049*			0.7328	876.3	79.9*
	(3)	3.202*	-0.0036	0.00003*	0.213	4.970*								0.8337	741.6	151.9*
Norway	(1)	4.599*	-0.0249*	0.00011*										0.5304	956.5	
	(2)	4.695*	-0.0075***	0.00003**	-1.398	0.151	0.735		0.019*	0.044*	0.028	-0.081**		0.6270	898.4	75.3*
	(3)	3.167*	0.0097	0.00002	-4.792*	-3.057	1.709							0.6871	862.1	59.3*
Poland	(1)	3.666*	0.0204*	0.00000										0.7523	924.1	
	(2)	3.361*	0.0332*	-0.00008*	2.934*	3.079*								0.8363	803.6	132.1*
	(3)	0.286***	0.0312*	-0.00003*	2.119*	13.720*			0.047*	-0.025*	-0.205*			0.9401	502.2	318.6*
Portugal	(1)	4.528*	0.0067**	0.00002***										0.5691	960.9	
	(2)	4.287*	0.0178*	-0.00005*	0.991*	3.053*			0.065*	-0.234**	-0.080*			0.6358	917.7	54.7*
	(3)	0.569*	0.0034***	0.00001	14.980*	7.519*								0.8781	589.3	345.6*
Spain	(1)	6.678*	0.0058**	0.00002**										0.5061	998.3	
	(2)	7.387*	-0.0099*	0.00005*	1.851*	1.875*	0.534							0.6504	904.0	111.6*
	(3)	4.177*	-0.0165*	0.00001*	-0.961	6.542*	-1.630*		0.051*	0.042	-0.086*	NA		0.8166	715.6	205.7*
Ukraine	(1)	1.989*	0.0504*	-0.00009*										0.8460	842.6	
	(2)	1.585*	0.0631*	-0.00015*	-0.494**	0.301	1.748*							0.8683	807.6	52.2*
	(3)	-1.150*	0.0672*	-0.00014*	0.716	6.315*	-6.745		0.035*	-0.025	-0.109*	0.123		0.9333	613.1	217.5*
Russia	(1)	4.131*	0.0504*	-0.00011*										0.6149	1086.1	
	(2)	2.685*	0.0750*	-0.00020*	1.552*	-0.928***	0.353	2.213*						0.8196	866.8	242.2*
	(3)	-1.294*	0.0278*	-0.00005*	3.214**	5.635*	10.639*	3.809*	0.083*	-0.017	-0.063*	-0.156*	NA	0.9712	310.0	579.8*
UK	(1)	7.284*	-0.0094*	0.00007*										0.5996	927.9	
	(2)	7.284*	-0.0062***	0.00004*	1.721*	1.233*			0.060*	-0.083*	-0.041			0.6604	885.6	53.8*
	(3)	4.637*	-0.0323*	0.00014*	6.488*	1.757								0.8673	604.8	298.1*

NA: the Government Response Stringency Index (GRSI) did not change in this sub-sample period. *, **, *** denote statistically significant at the 1%, 5% and 10% significance levels, respectively. (1), (2) and (3) refers to the models in equations (2.2), (2.3) and (2.4).

5 Conclusions

In this paper we estimate econometric models of daily data on the number of new cases from COVID-19 in 38 countries worldwide. Our benchmark model is a regression of log outcomes on a deterministic quadratic time trend for each country. Our primary purpose is to test for the presence of structural breaks in each time series and then to incorporate these breaks in the estimation process. For that we expand the benchmark model by introducing time dummy variables corresponding to the structural breaks identified before, to control for possible time-variant dynamics in the daily number of new cases. We include also the Government Response Stringency Index (GRSI) and the interactions with the dummies resulting from the structural breaks to assess the impact of Health and Governments Authorities responses on the COVID-19 pandemic.

We found different number and different dates for the structural breaks across the countries. In spite of this disparity, specially in the dates, we can observe that the last structural break is more or less contemporaneous for most of countries (24 in 38); it occurs during November's 2020, between the 2nd and 22th days, the last wave for most of countries.

By considering the curvature of the quadratic function we can guess if the peak already occurred. With just a few exceptions, Latin America, Australia, Asia and Africa countries seem to reach already the peak. As far as European countries, USA and Canada are concerned, the conclusion does not seem so encouraging, with several countries still increasing the average number of daily infections.

Regarding the coefficients of temporal dummies resulting from the last structural break, we can split the countries in two groups: USA, Canada, Mexico, Brazil, Chile, Iran, Iraq, Israel, Japan, Austria, Denmark, Finland, Germany, Greece, Hungary, Italy, Netherlands, Norway, Poland, Portugal, Russia and UK, where we observe an increase in the daily rate of new cases when compared to the initial phase of the pandemic. Thus, we can infer that the pandemic is not yet controlled. The countries where the estimate is negative, representing a decrease in the daily rate of new cases when compared to the initial phase of the pandemic, are: Argentina, Colombia, Ecuador, Australia, Egypt, South Arabia, India, China, Japan, South Africa, Belgium, Ireland, Spain and Ukraine, pointing to a possible control of the pandemic (unless the trend is reversed).

In terms of GRSI – Government Response Stringency Index, the estimate for the coefficient δ_1 is positive in the sub-sample before the first structural break. At the beginning the lockdown strictness of each country had a counterintuitive impact on the daily number of new cases. However, for the next sub-samples the estimate for the GRSI coefficient becomes negative in a large number of countries: USA, Canada, Mexico, Brazil, Iraq, Israel, Austria, Denmark, Finland, Germany, Greece, Hungary, Italy, Netherlands, Norway, Poland, Portugal, Russia and Spain. Thus, stringent measures have an alleviation effect on the daily spread of the novel coronavirus. For the other countries, the signal is negative in the intermediate sub-samples; the stringent measures have also a significant impact on the reduction in the number of cases.

However, it becomes positive in the last sub-sample; the estimate is quite stable and similar to the one estimated for the sub-sample before the first break, revealing the little effectiveness of stringent measures in reducing the number of cases.

In conclusion, this paper has provided one piece of empirical evidence on heterogeneity across countries about the COVID-19 evolution and the current state of the pandemic.

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