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How Effective are Policy Interventions Against the COVID-19 Infection Rates?

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Abstract

Studies on the COVID-19 pandemic are more likely to concentrate on the effects of the virus while ignoring its time-series characteristics, particularly its stationarity characteristics. Thus, this study attempts to investigate the effectiveness of policy interventions against COVID-19 by determining the permanent or transitory effects in 5 major regions and the ten most infected countries. Using the endogenous multiple breaks unit root tests introduced by Kapetanios (2005), the findings indicate that only the impacts of shocks to COVID-19 infection rates in France are likely to be permanent. However, the transitory effect is found in Brazil, Germany, Iran, Italy, Russia, Spain, Turkey, the United Kingdom, and the United States. The country where the shock has a permanent impact is suitable for policy interventions, including lockdowns, social isolation, and local isolation. While herd immunity, which protects the entire population against COVID-19, is better ideal for application in countries that experience shocks with a transitory effect.

Keywords:
COVID-19; infection rates; permanent shock; transitory shock; unit root

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INTRODUCTION

A novel coronavirus was eventually identified in Wuhan, Hubei Province in China in late December 2019. The International Committee of Taxonomy of Viruses (ICTV) termed the virus as the Severe Acute Respiratory Syndrome Coronavirus 2 (SARS-CoV-2) while the World Health Organization (WHO) named the disease as the coronavirus disease 2019 (COVID-19) (Cui, 2019; Lai et. al., 2020a; WHO, 2020). COVID-19 is a highly contagious disease caused by a strain of coronavirus known to cause respiratory infections in humans, which can transfer through communities more swiftly than the methodical pace of science can produce vital answers (Harrington et al., 2021). COVID-19 is thought to spread mainly through person-to-person close contact when a person touches their eyes, nose, or mouth after touching a surface or object that the coronavirus has contaminated. Then, the WHO issued a global alert about this deadly new infectious disease in early January 2020. At least 215 countries have reported cases of this new coronavirus, infecting more than 5 million people with a death toll of over 300 thousand worldwide by mid-May 2020. Thus, this pandemic has been declared as a global health emergency and has caused an unprecedented human and health crisis.

To date, scientists are working at breakneck speed to find an effective vaccine for COVID-19. In mid-March 2020, Europe was at the epicentre of the COVID-19 pandemic, followed by the United States in April 2020. Because of the alarming levels of spread, severity, and inaction of the political parties, billions of people were sent into lockdowns as health services struggled to cope (Liao et al., 2020). Several countries brought in travel restrictions on flights and visitors from the at-risk area were quarantined on arrival. Furthermore, travel within major cities across the globe has ground to a halt as restrictions on movement and social contact have come into force (Honey-Rosés et al., 2020). In doing so, the spread of the coronavirus has taken a toll on global economic players and is poised to increase global unemployment as it has potentially pummelled global economies.

Given that the COVID-19 epidemic has re-written almost every aspect of people's lives, a variety of studies have considered the possible impacts of COVID-19 on financial markets, political uncertainty, poverty, society, tourism, as well as the global environment (e.g., Al-Malkey & Al-Sammak, 2020; Goodell, 2020; Mamun & Ullah, 2020; Lai et al., 2020b; Nicola et al., 2020; Sharif et al., 2020; Yezli & Khan, 2020). On the contrary, studies of the microbiological underpinnings of the COVID-19 pandemic on human-to-human differences have taken place. For instance, Stehlík et al. (2020) have identified the exponential curve from a microbiological point of view as a reasonable model for the outbreak of COVID-19 epidemics. Furthermore, Buonsenso et al. (2020) explored the microbiological and immunological aspects of SARS-CoV-2 infection in children, which emphasises the key distinctions from adult SARS-CoV-2 infection.

To this end, studies on the COVID-19 pandemic are more likely to focus on the impacts of COVID-19 while neglecting the time-series characteristics, particularly the stationarity properties of the COVID-19 infection series. It is imperative to know whether the time-series data is either stationary or non-stationary as this knowledge has significant implications for policymaking and econometric modelling, as highlighted

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in Rath &Akram (2021) and Narayan & Popp (2010). More specifically, if the series of COVID-19 infection rates is found to be non-stationary (or a unit root), then any shock that influences the series tends to have a permanent effect because it would not return to its long-run growth path, meaning that the infection rates of COVID-19 would permanently shift from one level to another.

On the contrary, if the series of COVID-19 infection rates is found to be stationary, then the impact of shock (or policy shock)[1] on the series tends to be transitory as the effect would diminish gradually and the series would return to its long-run growth path. As a result, a policy shock on COVID-19 tends to have a short-span effect. In terms of forecasting, if the series is found to be stationary, then the future movement of COVID-19 infection rates is predictable with respect to its past values since it is mean-reverting. Nonetheless, the infection rates are unpredictable if the series is non-stationary because the series tends to deviate from its mean either in a positive or negative direction whenever it is exposed to shock. Obviously, knowledge of the degree of stationarity of COVID-19 data contributes not merely to the literature, but more importantly, also helps in public policymaking and benefits society in general. In light of these implications and uniqueness, we contribute to the literature and policymaking by investigating empirically the degree of stationarity of the COVID-19 infection rates in the 5 major geographical regions of the world (e.g., the Americas, Europe, Asia, Africa, and Oceania) and the 10 most infected countries. In an effort to affirm the stationarity of COVID-19 infection rates, we employ the multiple breaks (*m*-break) unit root tests introduced by Kapetanios (2005). Unlike the earlier procedures (e.g., Zivot & Andrews, 1992; Lumsdaine & Papell, 1997), the *m*-break unit root test utilises the sequential strategy of Bai & Perron (1998) to improve the efficiency and consistency in detecting the unknown breakpoints. As a result, it is more advanced and precise than previous unit root tests with structural breaks.

The balance of this paper is as follows. The methodology and data used in this study will be discussed in Section 2. The findings and discussion of this study will be reported in Section 3 and Section 4 respectively. Finally, Section 5 provides the concluding remarks.

METHODS

The purpose of this study is to examine the stationarity of COVID-19 infection rates. In an effort to validate whether COVID-19 infection rates belong to a stationary or non-stationary process, we conduct the endogenous single- and double-break unit root tests introduced by Kapetanios (2005), which are extended from the Zivot and Andrews (1992). To perform the Kapetanios' *m*-break unit root test, we estimate the following Model A (break in the intercept), Model B (break in the slope), and Model C (break in both the intercept and the slope):

[1] Any government policy or unpredictable events that have significant economic impacts are referred to as policy shocks. In this study, the term "policy shock" refers to any measure taken by the government to combat the COVID-19 epidemic, such as lockdown, quarantine, and so forth.

$$\text{Model A: } y_t = \alpha_0 + \alpha_1 t + \delta y_{t-1} + \sum_{i=1}^{k} \omega_i \Delta y_{t-i} + \sum_{j=1}^{m} \theta_j \, \mathrm{DU}_{j,t} + \varepsilon_t \quad (1)$$

$$\text{Model B: } y_t = \alpha_0 + \alpha_1 t + \delta y_{t-1} + \sum_{i=1}^{k} \omega_i \Delta y_{t-i} + \sum_{j=1}^{m} \gamma_j \mathrm{DT}_{j,t} + \varepsilon_t \quad (2)$$

$$\text{Model C: } y_t = \alpha_0 + \alpha_1 t + \delta y_{t-1} + \sum_{i=1}^{k} \omega_i \Delta y_{t-i} + \sum_{j=1}^{m} \theta_j \, \mathrm{DU}_{i,t} + \sum_{j=1}^{m} \gamma_j \mathrm{DT}_{j,t} + \varepsilon_t \quad (3)$$

Where $\Delta = (1 - L)y_t$, L is the lag operator, t is the deterministic time trend variable, and ε_t is the disturbance term assumed to be normally distributed and white noise. Δy_{t-i} is the lagged dependent variable accommodated into the model to account for the existence of a serial correlation problem. Besides, we set the maximum lag length at fourteen days before choosing an optimum lag (k) using the Bayesian Information Criterion (BIC), which is equivalent to the incubation period of coronavirus. In this study, we set m = 2 which is the maximum number of unknown breakpoints.[2] $\mathrm{DU}_{i,t}$ is the level shift dummy variable while $\mathrm{DT}_{i,t}$ is the trend break dummy variable. $\mathrm{DU}_{i,t} = 1$ if $(t > \mathrm{TB}_i)$, $\mathrm{DT}_{i,t} = 1$ if $(t > \mathrm{TB}_i)(t - \mathrm{TB}_i)$, zero otherwise where $\mathrm{TB}_i + 1$ represents the dates of the ith breakpoints. This implies that if ($t > \mathrm{TB}_{i,t}$), then the time trending break variable ($\mathrm{DT}_{i,t}$) started from the period of $\mathrm{TB}_i + 1$ will be accommodated into the model to capture the slope trend break. The breakpoint, (TB_i) is ascertained endogenously by the maximum value of $t(\hat{\lambda}_{\text{inf}})$ for δ in absolute terms. It is important to note that despite the unit root test with structural break usually superior to the standard one, especially when the series is confronted with structural change, the results remain sensitive to the choice of model. In the aspect of modelling, Sen (2003) documented that Model C is preferable to other models because it tends to have a smaller error. Nonetheless, Narayan (2005) argued that there is no consensus evidence that Model C is superior to other models. Motivated by these conflicting arguments, we extend the general-to-specific principle of Chang & Nieh (2004) to select the best model for the m-break unit root test based on the t-significance of the level shift and slope dummy variables. The model selection procedure begins by estimating the double-breaks model (also known as Model CC) which consists of both level shift and slope dummy variables ($\mathrm{DU}_{1,t}$, $\mathrm{DU}_{2,t}$, $\mathrm{DT}_{1,t}$, and $\mathrm{DT}_{2,t}$). The double-breaks Model CC will be selected if all the specified dummy variables are statistically significant. However, the double-breaks Model AA will be selected if only both of the levels shift dummy variables ($\mathrm{DU}_{1,t}$, and $\mathrm{DU}_{2,t}$) are significant. Likewise, if only both of the slope dummy variables ($\mathrm{DT}_{1,t}$, and $\mathrm{DT}_{2,t}$) are found to be significant, the double-breaks Model BB will be chosen for testing the presence of a unit root. Subsequently, if only part of the specified dummy variables is significant, then the single-break model will be used (i.e., Model A, B and C) for testing the presence of a unit root.

[2] Despite the fact that the m-break unit root test allows one to examine the presence of a unit root up to five unknown breaks, the Monte Carlo simulation of Kapetanios (2005) reveals that the power of the test is generally low for models with a higher number of unknown breakpoints. Hence, the present study considers only cases with one and two unknown structural breaks in order to avoid an unnecessary reduction in sample power.

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The analysis of this study used the daily data of the COVID-19 infection rates from 1st February 2020 to 14th May 2020. The data used in this study are collected from the *Our World in Data*.[3] The series are converted into natural logarithms in an effort to induce stationarity. The choice of sample is mainly based on data availability and the severity of the infected countries. As such, the sample period varies across the countries and regions under review. The sample and descriptive statistics are reported in Table 1. This study covers the 5 major regions in the world (e.g., Africa, the Americas, Asia, Europe, and Oceania) and also the 10 most infected countries, namely the United States, Spain, Russia, the United Kingdom, Italy, Brazil, Germany, Turkey, France, and Iran.

Table 1. Sample and Descriptive Statistics

Countries	Sample	Obs.	Min	Mean	Max	Std. Dev.
World	01-Feb – 14-May	104	527	41336.38	101445	36457.61
Regions:						
Americas	25-Feb – 14-May	80	1	23622.59	62037	18258.47
Europe	22-Feb – 14-May	83	14	19560.72	37256	12116.30
Asia	01-Feb – 14-May	104	413	6768.72	18254	5410.29
Africa	12-Mar – 14-May	64	13	1131.78	3730	921.19
Oceania	27-Feb – 14-May	78	1	107.37	662	158.61
Top 10 countries:						
United States	27-Feb – 14-May	78	1	17829.40	48529	13067.22
Spain	24-Feb – 14-May	81	1	2839.75	9222	2684.13
Russia	12-Mar – 14-May	64	4	3785.33	11656	4020.77
United Kingdom	28-Feb – 14-May	77	2	2983.01	8719	2230.75
Italy	22-Feb – 14-May	83	14	2675.92	6557	1799.39
Brazil	11-Mar – 14-May	65	9	2906.91	11385	3166.08
Germany	26-Feb – 14-May	79	2	2193.57	6294	1934.99
Turkey	16-Mar – 14-May	60	16	2385.20	5138	1459.17
France	26-Feb – 14-May	79	2	1781.29	7578	1658.78
Iran	20-Feb – 14-May	85	2	1356.29	5275	898.56

RESULT AND DISCUSSION

This study attempts to explore the time series property of COVID-19 infection rates. The empirical results of the present study are reported and discussed in this section. Before examining the time series property, it is best to review the pattern and the growth rates of the COVID-19 infection cases over the analysis period as shown in Table 2. In general, the infected cases of COVID-19 in the world and the selected countries show

[3] One may concern about the reliability of the data source. In fact, *Our World in Data* has been cited in many scientific works and widely used in research articles, reports, books, lectures, videos, radio programmes, podcasts, and presentations cite. Chagla and Pai (2021), Mathieu et al. (2021) and Murthi and Reed (2021) are among the excellence examples. In addition, *Our World in Data* is a trusted database in research and media including *Science*, *Nature*, PNAS, and *the Wall Street Journals*. More importantly, it has been used in teaching at various reputable academic institutions including Harvard, Stanford, Cambridge, MIT, Oxford and California Berkeley. Therefore, the data extracted from *Our World in Data* has achieved the scientific integrity that the data is complete, verified, and undistorted.

an accelerating trend. Among the 5 major regions, results show that approximately 86.3 per cent of the infected cases are discovered in Asia, while the other regions covered less than 15 per cent of the cases, especially in February 2020. However, the diseases spread rapidly to countries in other regions in the following month. For example, we find that at the end of February 2020, the selected 10 most infected countries covered just a small fraction of the world's infected cases, which is approximately 1.8 per cent.

Table 2. The Patterns and the Average Growth Rates of COVID-19 Cases

Countries	29-Feb	31-Mar	30-Apr	14-May	Average Growth (%) (Mar-May)
World	85203	777187	3131487	4298983	170.10
Regions:					
Americas	41 (0.05)	188701 (24.28)	1293563 (41.31)	1889807 (43.96)	315.80
Europe	1097 (1.29)	427186 (54.97)	1291060 (41.23)	1623540 (37.77)	113.99
Asia	73468 (86.23)	159341 (20.50)	493162 (15.75)	703947 (16.37)	126.12
Africa	–	5032 (0.65)	36630 (1.17)	72434 (1.68)	362.84
Oceania	4 (0.00)	5302 (0.68)	8114 (0.26)	8375 (0.19)	28.13
Top 10 countries:					
United States	66 (0.08)	164620 (21.18)	1039909 (33.21)	1390746 (32.35)	282.72
Spain	34 (0.04)	85195 (10.96)	213435 (6.82)	272646 (6.34)	89.13
Russia	2 (0.00)	1836 (0.24)	99399 (3.17)	242271 (5.64)	2728.81
United Kingdom	18 (0.02)	22141 (2.85)	165221 (5.28)	229705 (5.34)	342.63
Italy	888 (1.04)	101739 (13.09)	203591 (6.50)	222104 (5.17)	54.60
Brazil	1 (0.00)	4579 (0.59)	78162 (2.50)	188974 (4.40)	874.37
Germany	57 (0.07)	61913 (7.97)	159119 (5.08)	172239 (4.01)	82.62
Turkey	–	10827 (1.39)	117589 (3.76)	143114 (3.33)	503.89
France	57 (0.07)	44550 (5.73)	128442 (4.10)	140734 (3.27)	98.94
Iran	388 (0.46)	41495 (5.34)	93657 (2.99)	112725 (2.62)	73.03

Note: The data are collected from *Our World in Data*. Figures in the parenthesis (.) indicate the proportion of coronavirus-infected cases.

Surprisingly, the proportion of infected cases in these countries increases drastically to around 70 per cent of the world's infected cases in the subsequent months. Despite the United States' lead in coronavirus cases, our preliminary assessment infers that the spread of the disease in the United States is far behind Russia, Brazil, Turkey, and the United Kingdom. For example, from March to early May 2020, the cases of the outbreak

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in the United States grew on average at a rate of nearly 283 per cent every month, but the virus spread extraordinarily at the rates of approximately 2729 per cent, 874 per cent, 504 per cent and 343 per cent in Russia, Brazil, Turkey, and the United Kingdom, respectively. Indeed, the monthly growth rates of infected cases in other countries, such as Spain, Italy, France, Germany, and Iran, are also greater than 50 per cent. The quick spread of the disease in these countries is probably attributed to the lack of national pandemic prevention action (e.g., implementing lockdowns, social distancing, or isolation measures) because the political leaders have under-estimated the severity of the diseases (Plümper & Neumayer, 2020). Besides, this outcome may also be associated with the aspect of tourism. Tourism is another possible channel that accelerates the transmission of the diseases since the highly infected countries, particularly the United States, Spain, France, Germany, the United Kingdom, Turkey, and Italy, under our investigation, are the world's most visited destinations (World Tourism Organisation, 2019). Given that these countries are the epicentre of the outbreak, it is crucial to further extend our study to analyse whether the shock to COVID-19 infection rates has a permanent or transitory effect via the Kapetanios (2005) *m*-break unit root test.

Table 3 portrays the unit root results from the broader perspective, i.e., the world and the regional levels. Based on the results reported in Table 3, most of the regions under investigation, except for Europe, are subjected to two structural breaks, despite the break dates varying marginally across the regions, ranging from 24 February to 20 April. Moreover, we find that only Models CC, BB, and B are selected. This implies that rates of COVID-19 infection are more likely under a break in the slope of the trend function (Models B and BB) and a simultaneous break in the level and the slope of the trend function (Model CC). As such, the rates of COVID-19 infections across the regions are likely to grow over time.

Focusing on the estimated coefficients for the dummy variables for the breakpoint (DU_1, DT_2, DU_2, and DT_2), we discover that most of the dummy variables are statistically significant at the 5 per cent level. Specifically, the results show that the world's COVID-19 infection rates are subjected to two breaks in the slope of the trend function (DT_1, DT_2) with the estimated coefficients of 0.106 and –0.066. This suggests that the world's COVID-19 infection increases more rapidly after 25 February, then declines gradually after 28 March. The same pattern was also found in the Asia region after 24 March and 8 April. However, the estimated coefficients show that the trend of COVID-19 infection rates in Africa, the Americas, and Europe tends to decline by approximately 0.151, 0.130 and 0.051 respectively. Likewise, our results show that the level shift in Africa is approximately –0.527 on 28 March and –0.205 on 6 April. Furthermore, the COVID-19 infection rates in the Oceania region are subjected to both level shifts and trend breaks but their effects are inconsistent. We find that there is an upward level shift in the COVID-19 infection by 0.527 on 24 March but it shifts downward by 0.279 on 20 April. In contrast to the level shift, our results show that the trend break of the COVID-19 infection in Oceania decreased by 0.279, then increase by approximately 0.095.

Table 3. Results of the Kapetanios Unit Root Test with Structural Breaks by Regions

	World	Africa	Americas	Asia	Europe	Oceania
Model	BB	CC	BB	BB	B	CC
Lag length (k)	1	0	2	7	8	1
$t(\hat{\lambda}_{\inf})$	–13.375***	–10.696***	–6.891***	–5.725***	–3.797	–5.643
TB_1	25-Feb	28-Mar	22-Mar	24-Mar	20-Mar	24-Mar
TB_2	28-Mar	06-Apr	01-Apr	08-Apr	–	20-Apr
DU_1	–	–0.527*** (0.000)	–	–	–	0.527** (0.042)
DT_1	0.106*** (0.000)	–0.151*** (0.000)	–0.130*** (0.000)	0.036** (0.012)	–0.051*** (0.001)	–0.279*** (0.000)
DU_2	–	–0.205* (0.076)	–	–	–	–0.581** (0.019)
DT_2	–0.066*** (0.000)	–0.039* (0.068)	–0.159*** (0.000)	–0.017*** (0.000)	–	0.095*** (0.000)
Diagnostic tests						
χ^2_{NORMAL}	0.013 (0.993)	0.424 (0.809)	0.461 (0.794)	3.467 (0.177)	2.090 (0.352)	0.385 (0.825)
χ^2_{SERIAL}	1.611 (0.447)	4.103 (0.128)	3.146 (0.207)	2.744 (0.253)	1.060 (0.588)	2.532 (0.282)
χ^2_{ARCH}	2.268 (0.132)	0.333 (0.564)	2.553 (0.110)	1.158 (0.282)	0.187 (0.665)	0.059 (0.808)
Critical values		Model B		Model BB		Model CC
1 per cent		–5.014		–5.616		–6.587
5 per cent		–4.495		–5.096		–6.113
10 per cent		–4.144		–4.784		–5.847

Note: ***, ** and * denote statistical significance at the 1, 5 and 10 per cent levels, respectively. The optimal lag length (k) is determined by the Bayesian Information Criterion (BIC) and (.) denotes the p-values. The critical values are collected from Kapetanios (2005). TB_1 and TB_2 refer to the dates of the first and second breakpoints, respectively. DU_1 and DU_2 are the level shift dummy variables whereas DT_1 and DT_2 are the trend break dummy variables. Finally, $t(\hat{\lambda}_{\inf})$ is the t-statistic for δ which is the coefficient of y_{t-1}.

Turning to the computed statistics of the m-breaks unit root test in Table 3, we find that the null hypothesis of a unit root can be rejected at the 5 per cent or better significance levels in the aggregated world data. It is also worth noting that the null hypothesis of a unit root is also rejected at the 5 per cent level in three regions, namely Africa, the Americas, and Asia. In light of these findings, we can deduce that the infection rates of COVID-19, in general, do not possess a unit root (or follow a trend-stationary process), except for Europe and Oceania. Given that the series is stationary in Africa, the Americas, and Asia, the infection rates of COVID-19 in these regions are less vulnerable to any shock. Thus, a shock, either positive or negative[4], causes the deviation of COVID-19 infection rates in these regions tend to be transitory rather than a permanent change. This is in accordance with the time-series literature, which states that the data following the stationary process will gradually revert to

[4] The positive shock is that the government strategies, such as movement control orders, travel restrictions, isolation of suspected cases, and the establishment of quarantine centres, are designed to battle COVID-19 or prevent its spread. A negative shock, on the other hand, denotes a lack of cohesion in the government's approach to controlling the COVID-19 epidemic and a relaxation of intervention measures.

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its mean value, even if it deviates transitorily due to a shock or policy intervention. However, our results infer that the shock to COVID-19 infection rates has a permanent effect in Europe and Oceania.

Apart from that, we further validate our unit root findings by implementing a number of diagnostic tests to ensure that the residuals are spherically distributed, serially uncorrelated, and homogenous. To adhere to this purpose, we apply the widely acknowledged Jarque-Bera's test for normality, Breusch-Godfrey's test for serial correlation, and Engle's test for autoregressive conditional heteroskedasticity (ARCH). The results of diagnostic tests are reported in Table 3 and Table 4. We find that the computed statistics of the Jarque-Bera test in all the estimated models do not reject the null hypothesis at the 5 per cent level, demonstrating that the residuals are normally distributed. Likewise, at the same level of significance, the statistics of Breusch-Godfrey's test and Engle's test both consistently do not reject the null hypothesis. These suggest that the estimated models for unit root tests are free from serial correlation and heteroskedasticity problems. Therefore, we can deduce that our unit root findings reported in Table 3 and Table 4 are both reliable.

After establishing the diagnostic tests, we augment our analysis to the 10 most infected countries, and the results are presented in Table 4. We find that most of the estimated coefficients for dummy variables are negative and statistically significant at the 5 per cent level or better, indicating that the model's anticipated structural break dates are strongly accepted and the COVID-19 infection rates decline gradually. Our findings demonstrate that only Turkey and the United States among the top ten infected countries exhibit an upward shift in the COVID-19 infection rates of around 0.730 and 0.688, respectively. However, the infection rates in the majority of the selected countries show at least one negative trend break ranging from approximately –0.033 to –0.289. This finding implies that the infection rates of COVID-19 in the selected countries are steadily dropping.

In tandem with the findings at the regional level, the majority of the COVID-19 infection data at the individual country level was also confronted with two breaks in the slope of the trend function (Models BB, B, and C), except for Iran and Turkey. Consistently, we find that the break dates of the individual countries are mostly distributed around March to April 2020.

Among the 10 selected countries, we were able to reject the null hypothesis of a unit root at the 5 per cent significance level in 9 out of 10 countries, namely Brazil, Germany, Iran, Italy, Russia, Spain, Turkey, the United Kingdom, and the United States. In contrast to Bayyurt and Bayyurt (2020), our results show that the COVID-19 infection rates in these countries are likely to be trend-stationary. This implies that if there is a shock, for example, a large-scale meeting, the infection rates of COVID-19 will increase, but after some time the infection rates will gradually revert to their long-run growth path equilibrium, probably due to the improvement of people's immune systems as suggested by the herd immunity hypothesis.

Table 4: Results of the Kapetanios Unit Root Test with Structural Breaks of 10 Most Infected Countries

	Brazil	**France**	**Germany**	**Iran**	**Italy**	**Russia**	**Spain**	**Turkey**	**United Kingdom**	**United States**
Model	BB	BB	B	A	BB	BB	BB	AA	BB	C
Lag length (*k*)	1	6	10	0	8	1	5	0	5	3
$t(\hat{\lambda}_{\text{inf}})$	–6.042***	–4.550	–6.989***	–6.241***	–5.327**	–13.391***	–5.487**	–11.888***	–8.332***	–7.668***
TB_1	21-Mar	15-Mar	21-Mar	05-Apr	19-Mar	01-Apr	15-Mar	25-Mar	28-Mar	17-Mar
TB_2	04-Apr	01-Apr	–	–	23-Apr	19-Apr	27-Mar	22-Apr	11-Apr	–
DU_1	–	–	–	–0.232** (0.012)	–	–	–	0.730*** (0.000)	–	0.688*** (0.000)
DT_1	–0.137*** (0.001)	–0.152*** (0.002)	–0.289*** (0.000)	–	–0.148*** (0.000)	–0.068*** (0.000)	–0.152*** (0.000)	–	–0.203*** (0.000)	–0.041*** (0.003)
DU_2	–	–	–	–	–	–	–	–0.199*** (0.001)	–	–
DT_2	–0.033** (0.035)	–0.197*** (0.000)	–	–	–0.028*** (0.001)	–0.104*** (0.000)	–0.180*** (0.000)	–	–0.102*** (0.000)	–
Diagnostic tests										
χ^2_{NORMAL}	1.043 (0.593)	1.352 (0.509)	1.198 (0.549)	2.602 (0.272)	4.417 (0.109)	1.622 (0.444)	1.264 (0.531)	1.909 (0.385)	0.619 (0.733)	2.914 (0.233)
χ^2_{SERIAL}	3.263 (0.195)	1.828 (0.401)	3.356 (0.187)	2.491 (0.288)	2.598 (0.273)	0.587 (0.746)	2.514 (0.284)	0.230 (0.891)	4.237 (0.120)	3.144 (0.208)
χ^2_{ARCH}	2.368 (0.124)	0.009 (0.922)	0.473 (0.491)	0.102 (0.750)	0.005 (0.946)	1.030 (0.310)	0.012 (0.910)	0.135 (0.713)	0.002 (0.963)	0.006 (0.939)
Critical values		Model A		Model B		Model C		Model AA		Model BB
1 per cent		–5.338		–5.014		–5.704		–6.162		–5.616
5 per cent		–4.930		–4.495		–5.081		–5.685		–5.096
10 per cent		–4.661		–4.144		–4.820		–5.467		–4.784

Note: ***, ** and * denote statistical significance at the 1, 5 and 10 per cent levels, respectively. The optimal lag length (*k*) is determined by the Bayesian Information Criterion (BIC) and (.) denotes the *p*-values. The critical values are collected from Kapetanios (2005).

Likewise, despite social distancing would effectively alleviate the infection rates of COVID-19, the effect is likely to be transitory due to its mean-reverting behaviour. Nevertheless, we find evidence of the permanent effect of a shock only in France. This result suggests that any policies designed to control the spread of COVID-19, such as the movement control ordering or lockdown policy, would permanently (or effectively) lower the infection rates of COVID-19 in France.

The breaks date as in Table 3 and Table 4 concur with numerous chains of COVID-19 transmission clusters in the infection's countries. In the majority of the cases, the structural break dates were identified in early 2020, especially in February and March. These structural breaks might coincide with some events or policy interventions. The outbreaks in these countries were identified by importing infections that arrived from China and European countries (Giovanetti et al., 2020). At the same time, the virus spread very quickly due to the failure of leadership in countries such as Brazil, Turkey, Russia, and the United States. Populist leaders across the political spectrum are handling the COVID-19 outbreaks with their optimistic bias and ignorance of science, which puts their countries at risk (Plümper & Neumayer, 2020). Moreover, the restrictions on travel implemented differ from country to country after April 20, 2020, causing a spike in coronavirus infections originating from overseas travellers such as Iran, European

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nations, and the United States (Russel et al., 2021). Thus, strict policy measures and effective steps should be put in place based on the findings to contain the epidemic.

On the other hand, the findings indicate that the shocks are found to permanently influence the COVID-19 infection rates in France alone since there is a unit root. The spread of the pandemic in France was traced back to a cluster found in February that was linked to a prayer meeting at an evangelical church in Mulhouse. These clusters triggered the country's pandemic and spread across the nations, causing authorities to struggle with a lack of professional and medical equipment to contain a rapidly spreading virus (Desson, 2020). Additionally, France had the mistaken belief in the pre-crisis period that their health system was sufficient to protect against the epidemic and that they were mainly safe from pandemics (Rowe et al., 2020). When the number of infections accelerates, the government to reduce the spread of COVID-19 in France has included which leads to an overloaded health system, containment measures —lockdown policies—. Furthermore, many people have lingering fears about resurgence cases, fear of dying alone, and anxiety about asymptomatic cases. Thus, the stringent social distancing or lockdown in France could be made obliged to avoid a disastrous rebound in coronavirus cases and break the chain of transmission through the population.

Furthermore, the results also suggest that the effect of a shock like social distancing on the COVID-19 infection rates in Brazil, Germany, Iran, Italy, Russia, Turkey, the United Kingdom, and the United States is only transitory. This advocates that the social distancing measures might only temporarily decrease the rates of infection. Therefore, a herd immunity strategy should be recommended for these countries where it depends on the majority of the population gaining antibodies or immunity that the patient has acquired and offers him protection (Randolph & Barreiro, 2020). If the government wants to let the herd immunity approach go live, then the governments and policymakers must strengthen their public health system by expanding its testing, tracing, and treatment capacity (OECD, 2020), as this approach relies on allowing a large number of the population to become infected (Randolph & Barreiro, 2020). For instance, the nation's citizens must scarify their digital privacy to allow contact tracers to retrace the movements of infected people and everyone they have been in close contact with. Public authorities need to keep monitoring the situation closely, and most importantly, the hospital must have enough capacity to resist the overwhelming numbers of infected patients while waiting for a cure and a vaccine.

CONCLUSION

This study attempts to examine the time-series property of COVID-19 infection rates in the 5 major geographical regions and the 10 most infected countries. Regarding the empirical findings, we discover that the infection rates of COVID-19 are stationary in Africa, the Americas, and Asia, except for the European and Oceania regions. Furthermore, only 8 out of the 10 most infected countries are observed to be stationary. On the other hand, the COVID-19 infection rates data are found to be non-stationary only in France. As such, we may conclude that a shock or any COVID-19 related policy intervention in France tends to have a permanent impact on COVID-19 infection rates.

Therefore, lockdown, social distancing, and community-level isolation would be able to flatten the epidemic curve since these will have permanent effects on the infection rates in France. On the other hand, the shock would have a transitory effect in 8 of the 10 most infected countries. Thus, the decision to introduce herd immunity is essential to protect the whole population against COVID-19. The success of disease control will be highly dependent on the support of the international community which could have collective action in disease surveillance and continuous self-monitoring.

Although this study adds to the policymaking on COVID-19 and the applied time-series literature, particularly in the model selection procedure for unit root tests with breaks, it has a handful of limitations. Likewise, this study merely looked at the unit root property of COVID-19 infection rates in a few selected countries, while downplaying the importance of COVID-19 fatality and recovery rates in a larger sample of countries. Therefore, the current findings might not perfectly reflect the global scenario of COVID-19. Another weakness of the present study resides in the use of the Kapetanios (2005) *m*-break test to determine the presence of a unit root. Even though the *m*-break unit root test is an advanced version of the unit root test with structural breaks as it can cover up to 5 structural breaks endogenously, the power of the test decreases drastically whenever the number of breaks increases. In light of these imperfections, future studies may revisit the subject by expanding the sample, diversifying the indicators of COVID-19, and applying different types of unit root tests to provide more comprehensive and insightful evidence. To further enhance robustness, future studies might also consider utilising panel unit root tests both with and without structural breaks. Finally, future research may also segregate the countries based on their levels of economic development and health-related indices and examine the factors that determine whether the impacts are temporary or permanent.

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