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Original Article

# Early detection of regional COVID-19 pandemic status changes

**Thomas M. Treptow***

Department of Business and Economics, Former Professor at IBA, University of Cooperative Education, Nuremberg, Germany

**ABSTRACT**

This study shows that with a certain expression of a standard econometric test we can detect regional pandemic status changes early from information already embedded in the actual data of the daily number of new infections. The COVID-19 pandemic and taken countermeasures cause substantial social and economic costs. The lack of knowledge and experience concerning the development of the regional virus spread impedes cost-saving timely policy decisions when fighting the pandemic. The ability to detect regional pandemic status changes and especially the beginning of a phase of increasing growth in the number of new infections early is extremely important. Here, we show that with a certain expression of a standard econometric test we can detect regional pandemic status changes early from information already embedded in the actual data of the daily number of new infections. For the emerged second COVID-19 cycles in Australia, Austria, Germany, Italy, the Republic of Korea, and the United Kingdom the study shows, that we can identify pandemic status changes earlier and in a statistically reliable way when compared with a purely visual inspection of the data. In addition, we identify in our study different patterns of emerging COVID-19 pandemic cycles. These range from an immediately growing number of new infections to continuously following short phases of stability that altogether constitute a complete pandemic cycle. A combination of the results of the proposed test and test strategy with analysis from other scientific disciplines (especially epidemiological analysis) can provide further insights into the broader nature of pandemic status changes and patterns in emerging COVID-19 pandemic cycles.

**Keywords:** Pandemic status change test, regional pandemic analysis, pandemic cycle, testing for unit roots

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## INTRODUCTION

Epidemiological theory models the spread of a virus over time often in the form of a cycle. The growth rate of daily new infections first increases and then from a certain point in time on decreases until it reaches a value of nil.[1-4] In practice and as in the case of the COVID-19 pandemic, the regional development of the virus spread in time can consist of several of these cycles. In countries that have taken early and successful non-pharmaceutical countermeasures in their first cycle such as Austria, China, Germany,[5-9] we see that the development of the number of daily new infections seems to be in line with theory [Figure 1]. Although the number of daily new infections between the cycles does not fall to zero, the mean of the empirical distribution of daily new infections between two cycles remains stable on a low level. From an ex-post perspective, these cycles can be easily identified. When fighting the pandemic policy management tries to minimize overall costs,[10] including the costs of non-pharmaceutical countermeasures.[11-15] It is therefore important to understand the current situation of the pandemic development as early as possible. Obviously, it makes a difference, if we are in a temporarily stable situation, or in a situation with a 1-time shift of the level of new infections, or in a phase of a continuously increasing growth rate of new infections. Especially at the beginning of a pandemic cycle, when the number of new infections grows at a very high rate, it clearly makes a difference, if we can identify the start of this development 1 week or even a few days earlier than otherwise. In general, the earlier a status change can be identified the faster countermeasures can be taken to limit social and economic costs. For such early assessments, we must distinguish between

**Address for correspondence:** Dr. Thomas M. Treptow, Former Professor at IBA, University of Cooperative Education, Nuremberg, Germany. E-mail: ttreptowemail@gmail.com

pandemic situations where we are in a stable situation with maybe only a few daily outliers of the number of new infections or face a sustainable change in the level of new infections or find ourselves at the beginning of a continuously growing number of daily new infections.

In this study we propose a certain expression of a standard econometric test. With a specific interpretation of the test results and with continuous testing we can identify status changes of a regional pandemic development for a determined level of significance. For the analyzed time series of new COVID-19 infections in Australia, Austria, Germany, Italy, the Republic of Korea, and the United Kingdom we see that the test can detect pandemic status changes comparatively early from actual daily observations especially when compared with a purely visual inspection of the development of the number of new infections. In addition, we can learn about the patterns of a regional COVID-19 pandemic development. A test strategy that continuously looks for pandemic status changes in over-lapping time intervals can support health and economic policy management when fighting the pandemic.

## METHODS

Using general theoretical and empirical findings of virus spread behavior and especially of COVID-19 behavior [16,17] we can exhaustively assume, that the time series of the number of daily new COVID-19 infections shows at the beginning of an emerging pandemic cycle or generally at a status change either an infinite variance or a random behavior around a deterministic trend or a random behavior around a stochastic trend [Figures 1 and 2]. Following our aim to identify changes in the status of the pandemic as early as possible we are not primarily interested in distinguishing between these cases.

To detect a systematic increase in the daily number of new infections we use Augmented Dickey-Fuller (ADF) tests. [18,19] In general, ADF tests investigate the null hypothesis that an analyzed time series - here the number of daily new COVID-19 infections - exhibits an infinite variance (a unit root).

We define the test equation of a standard ADF test without a deterministic time trend and only with a deterministic intercept $\mu$ and with as much lag variables $p$ to account for a possible corresponding autoregressive structure in the data generating process. (Otherwise, the test results would be unintendedly influenced).

$$\Delta x_t = \mu + \alpha^* x_{t-1} + \sum_{i=1}^{p-1} \alpha_i^* \Delta x_{t-i} + \varepsilon_t \quad \varepsilon_t \sim i.i.d.\left(0, \sigma^2\right) \tag{1}$$

with $\Delta x_t$ = difference of number of daily new infections at time $t$ and $t$-$1$, $\alpha^*$ = difference between coefficient of the pure autoregressive process $p$ and 1, $x_{t-1}$ = number of daily new infections at time t-1, $\alpha_i^*$ = coefficient of the $i^{th}$ lag term, $p$ = number of lags of the assumed autoregressive process according to Schwarz information criterion, $t$ = time, $\varepsilon_t$ = disturbance term, *i.i.d.*= identical and independently distributed, $(0, \sigma^2)$ = distributed with an expected value of nil and a variance of $\sigma^2$.

This way we obtain a test equation that leads for a defined level of significance to the non-rejection of the null hypothesis when the analyzed time series shows either an infinite variance (a unit root) or a deterministic trend behavior (and not a unit root). The latter is the case because for an existing deterministic time trend in the data and in the absence of a deterministic trend component in the test equation the here applied ordinary least squares estimation technique can only maximize the total variance explained by setting $\alpha^* = 0$, thereby forcing the test to accept the null hypothesis. But this is the same situation as if the test identifies an infinite variance in the time series. An acceptance of the null hypothesis for our so defined pandemic status change test therefore means the detection of a stochastic or a deterministic trend in the data.

In general, the specification of a test influences the achieved results. We have defined the test equation in such a way that best suits our needs to reliably identify pandemic status changes.

- The frequently given problem of ADF testing, especially when the number of observations is small, that trend stationary time series processes can be approximated very well by processes with a unit root (and vice versa)[20-22] here provides no problem. In our context, we are not interested in distinguishing between these cases as they both correspond to a pandemic status change. We have defined our test equation in such a way that it accepts the null hypothesis not only for a stochastic trend (a unit root) but also in case of a deterministic time trend in the data generating process. Normally undetected structural breaks in time series data can lead to an under-rejection of the null hypothesis. When we define a structural break in a broader sense also as pandemic status change the acceptance of the null hypothesis in such cases is an adequate result within our test logic
- With respect to deterministic seasonality, the general recommendation for unit root testing is to use seasonal unadjusted data as otherwise, adjustments distort the properties of the data[21] and there would be a tendency to reject the null less often than it should be rejected.[21]
- In case of undetected non-stationary seasonality in the data the results of our ADF tests, that do not explicitly account

for unit roots at seasonal frequencies, remain valid as long as there are enough lag terms in the test equation.[23] We identify this number by the conservative Schwarz criterion. (When compared with the alternative Akaike criterion the Schwarz criterion is more conservative. Conservatively accounting for a possible autoregressive structure in the data with enough lag variables in the test equation also avoids the tendency of over rejecting the null when it is true).

We apply our test continuously to overlapping time intervals, each time analyzing 35 daily observations of the number of new COVID-19 infections. For each next test, we roll the underlying time interval 7 days further. We have chosen 35 daily observations (5 weeks) for each test as the ADF test usually requires some observations to model an underlying lag structure of the data generating process. We are so losing degrees of freedom but can keep a minimum number of approximately 30 observations as a minimum prerequisite for statistical inference. (Choosing the number of observations must consider the trade-off between appreciated statistical properties and the requirement to analyze most actual data. In addition, we acknowledge, that with the here underlying small number of observations of each test we do not fulfill the assumptions for asymptotical inferences.) For each next test, we roll the underlying time interval 7 days further, as this is half of the estimated maximum incubation time.[24]

## RESULTS AND DISCUSSION

### Early Detection of Regional COVID-19 Cycles

Figure 1 shows the development of the daily number of new COVID-19 infections and test results for the time interval from June the 1st to September the 30th around the second cycle in the six countries of our study. (We acknowledge that there also exists a number of hidden infection cases and our database may comprise false positive detected cases.[25,26] Our analysis therefore only considers reported new infection cases. In addition, we acknowledge, that there are also different regional spreading dynamics within each country, for example for the second cycle in Germany.[27]

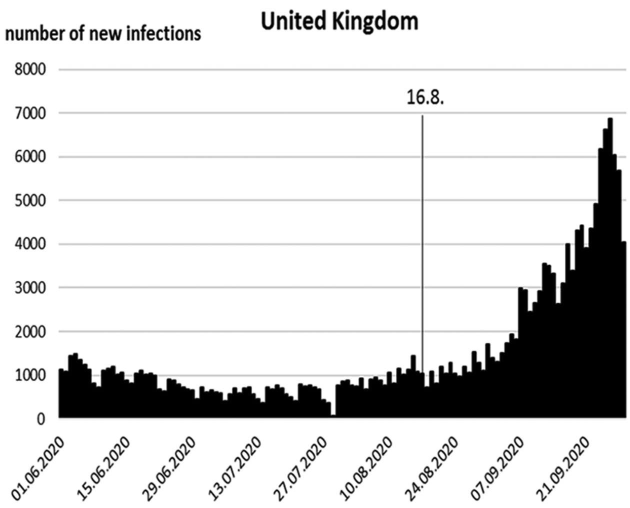
For Australia and the Republic of Korea we directly see that the proposed test strategy has early identified the pandemic status changes and the beginning of the second pandemic cycles. For the U.K., Austria, Germany, and Italy the emergence of the second cycles has meanwhile deeply confirmed.[28-31] The country-specific test results here strongly support the hypothesis that the proposed test and test strategy have the capability of identifying pandemic status changes very early.

For the U.K. we see that in a period until mid-July the number of daily new infections decreased before moving into a phase of stable development. (Our test also identifies a decreasing number of daily new infections by the acceptance of the null hypothesis. This can be helpful, for example for monitoring the effects of taken countermeasures). The tested time interval ending mid-August and the acceptances of the null for the following time intervals indicate the continuous increase in the number of daily new infections. The test result from August the 16th thus indicated a status change comparatively early and, when combined with the later results, also marked the new emerging pandemic cycle in the U.K.

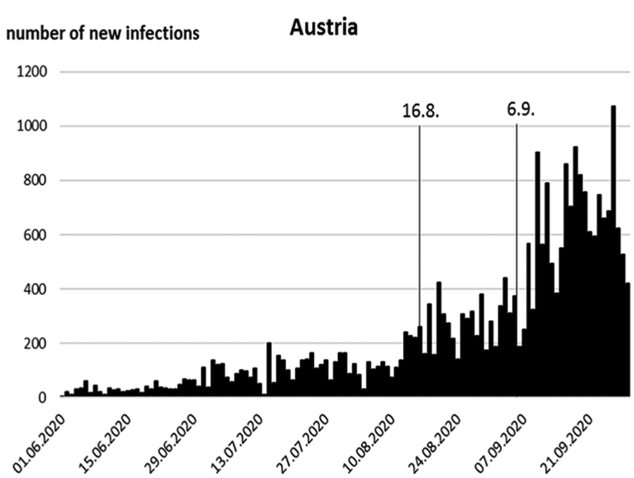
The development in Austria shows that a pandemic cycle can also emerge step by step following phases of relative stability when each new phase exhibits a higher mean of the empirical distribution of daily new infections. From a phase of a low mean of daily new infections until the beginning of July the increase of the number of new infections led to a phase of relative stability between July and mid-August. A further but shorter stable time interval with an even higher mean of daily new infections in the second half of August finally led to a continuous growth situation until the end of September.

In the beginning of the COVID-19 pandemic, Germany had a very similar development as Austria. From mid-July on this seems to have changed. After a period with a rather constant and low mean of the number of daily new infections from June to July, the analyzed data indicates a continuous growth of daily new infections, only interrupted by a 1-month stable phase between mid-August and mid-September before the number of daily new infections starts to rise again. The indication of the emerging second cycle in Germany starting with test results from July the 26th on is a salient result, since until mid-October 2020 there were intensive discussions in Germany, whether a second pandemic cycle had started or not.[32]

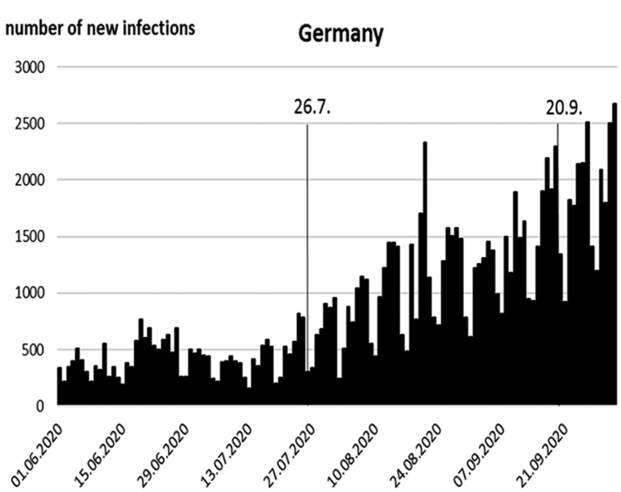
Austria and Germany are both examples for a pandemic cycle pattern that can consist of multiple phases of stability, which together form an overall emerging cycle. Phases of stability in an emerging cycle seem to exhibit a higher finite variance around a higher finite mean of the number of daily new infections. This is a relevant observation when fighting the pandemic as in our cases these phases of stability indicate a special pattern of a growing development rather than a sustainable overall stable situation.




| test interval from | to | test result null hypothesis "status change" at 5% level of significance | probability |
|---|---|---|---|
| 01.06. | 05.07. | acceptance | 85,03% |
| 08.06. | 12.07. | acceptance | 30,72% |
| 15.06. | 19.07. | acceptance | 13,56% |
| 22.06. | 26.07. | rejection | 0,79% |
| 29.06. | 02.08. | rejection | 0,02% |
| 06.07. | 09.08. | rejection | 1,41% |
| 13.07. | 16.08. | acceptance | 8,63% |
| 20.07. | 23.08. | acceptance | 33,75% |
| 27.07. | 30.08. | acceptance | 13,82% |
| 03.08. | 06.09. | acceptance | 88,72% |
| 10.08. | 13.09. | acceptance | 99,19% |
| 17.08. | 20.09. | acceptance | 91,22% |
| 24.08. | 27.09. | acceptance | 91,57% |



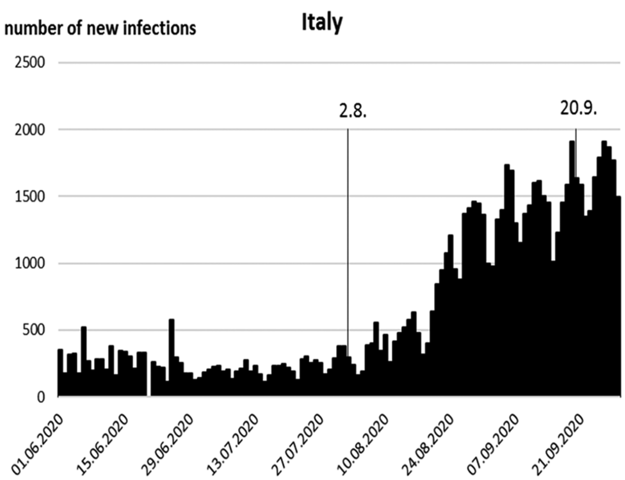

| test interval from | to | test result null hypothesis "status change" at 5% level of significance | probability |
|---|---|---|---|
| 01.06. | 05.07. | acceptance | 99,41% |
| 08.06. | 12.07. | acceptance | 62,52% |
| 15.06. | 19.07. | rejection | 0,08% |
| 22.06. | 26.07. | rejection | 0,05% |
| 29.06. | 02.08. | rejection | 0,00% |
| 06.07. | 09.08. | rejection | 0,00% |
| 13.07. | 16.08. | rejection | 1,36% |
| 20.07. | 23.08. | acceptance | 56,67% |
| 27.07. | 30.08. | acceptance | 49,15% |
| 03.08. | 06.09. | rejection | 0,85% |
| 10.08. | 13.09. | acceptance | 73,10% |
| 17.08. | 20.09. | acceptance | 78,55% |
| 24.08. | 27.09. | acceptance | 58,71% |



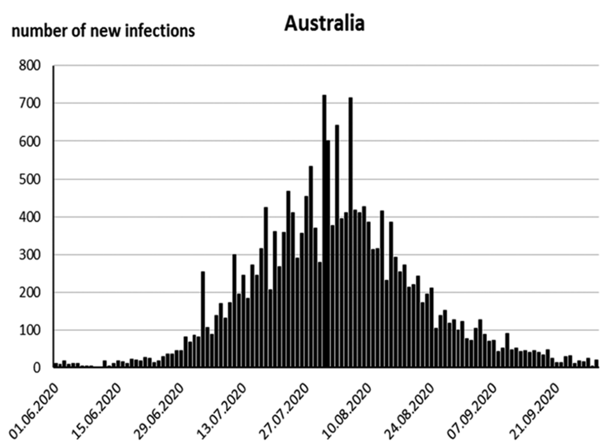

| test interval from | to | test result null hypothesis "status change" at 5% level of significance | probability |
|---|---|---|---|
| 01.06. | 05.07. | rejection | 2,47% |
| 08.06. | 12.07. | rejection | 1,68% |
| 15.06. | 19.07. | rejection | 1,46% |
| 22.06. | 26.07. | acceptance | 88,42% |
| 29.06. | 02.08. | acceptance | 99,94% |
| 06.07. | 09.08. | acceptance | 99,98% |
| 13.07. | 16.08. | acceptance | 99,86% |
| 20.07. | 23.08. | acceptance | 95,47% |
| 27.07. | 30.08. | acceptance | 62,91% |
| 03.08. | 06.09. | acceptance | 25,94% |
| 10.08. | 13.09. | rejection | 0,06% |
| 17.08. | 20.09. | rejection | 0,21% |
| 24.08. | 27.09. | acceptance | 99,01% |

**Figure 1:** Development of daily new COVID-19 infections in the United Kingdom, Austria, Germany, Italy, Australia, Republic of Korea

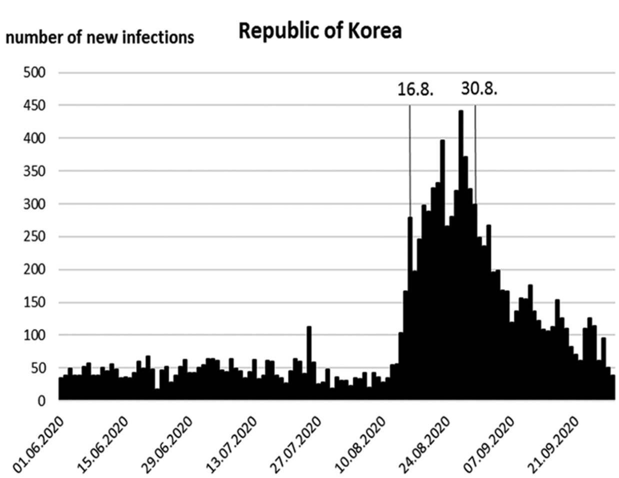
*(Contd...)*




| test interval from | to | test result null hypothesis "status change" at 5% level of significance | probability |
|---|---|---|---|
| 01.06. | 05.07. | rejection | 0,00% |
| 08.06. | 12.07. | rejection | 0,00% |
| 15.06. | 19.07. | rejection | 0,00% |
| 22.06. | 26.07. | rejection | 0,00% |
| 29.06. | 02.08. | acceptance | 98,96% |
| 06.07. | 09.08. | acceptance | 99,58% |
| 13.07. | 16.08. | acceptance | 99,99% |
| 20.07. | 23.08. | acceptance | 100,00% |
| 27.07. | 30.08. | acceptance | 93,55% |
| 03.08. | 06.09. | acceptance | 85,16% |
| 10.08. | 13.09. | acceptance | 64,40% |
| 17.08. | 20.09. | rejection | 0,09% |
| 24.08. | 27.09. | acceptance | 74,66% |




| test interval from | to | test result null hypothesis "status change" at 5% level of significance | probability |
|---|---|---|---|
| 01.06. | 05.07. | acceptance | 100,00% |
| 08.06. | 12.07. | acceptance | 99,90% |
| 15.06. | 19.07. | acceptance | 99,99% |
| 22.06. | 26.07. | acceptance | 98,91% |
| 29.06. | 02.08. | acceptance | 94,98% |
| 06.07. | 09.08. | acceptance | 36,06% |
| 13.07. | 16.08. | rejection | 0,12% |
| 20.07. | 23.08. | acceptance | 84,72% |
| 27.07. | 30.08. | acceptance | 93,87% |
| 03.08. | 06.09. | acceptance | 72,28% |
| 10.08. | 13.09. | acceptance | 58,54% |
| 17.08. | 20.09. | acceptance | 14,99% |
| 24.08. | 27.09. | acceptance | 14,21% |




| test interval from | to | test result null hypothesis "status change" at 5% level of significance | probability |
|---|---|---|---|
| 01.06. | 05.07. | rejection | 0,24% |
| 08.06. | 12.07. | rejection | 0,15% |
| 15.06. | 19.07. | rejection | 0,01% |
| 22.06. | 26.07. | rejection | 0,01% |
| 29.06. | 02.08. | rejection | 0,13% |
| 06.07. | 09.08. | rejection | 0,10% |
| 13.07. | 16.08. | acceptance | 99,96% |
| 20.07. | 23.08. | acceptance | 99,28% |
| 27.07. | 30.08. | acceptance | 75,32% |
| 03.08. | 06.09. | acceptance | 48,41% |
| 10.08. | 13.09. | acceptance | 30,05% |
| 17.08. | 20.09. | acceptance | 74,57% |
| 24.08. | 27.09. | acceptance | 65,69% |

**Figure 1:** *(Continued)*

One-sided probability values at 5% level of significance, critical values according to MacKinnon.[33] Number of daily new infections between June the 1st and September the 30, 2020. All data were taken from the World Health Organization[34] except German data taken from Robert Koch Institute.[35]

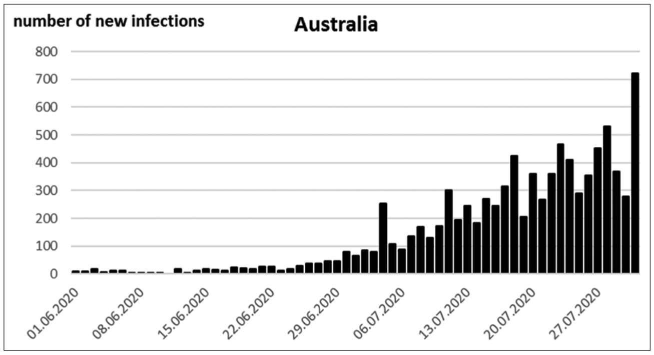



**Figure 2:** Daily new COVID-19 infections in Australia from June 1st to July the 31, 2020

The development in Italy shows a very fast increase of the number of new infections in the second half of August, whereas the beginning of the new cycle has already been indicated by the July test result. Between mid-August and mid-September Italy has had a phase of stability with a high mean and variance before the last test result in September indicates another growth situation. Developments in Australia and in the Republic of Korea are two examples that show how different the speed of regional pandemic developments can be. While the second Australian cycle shows a stable phase when it reached its top (between mid-July and mid-August), albeit with a high variance, the dynamic in the Republic of Korea is so fast, that after reaching the top of the second pandemic cycle a phase of a decreasing number of new infections follows immediately. The fast development in the Republic of Korea shows a limitation of our test and test strategy. Since the positive (and negative) growth rates are extremely high and we technically need a certain number of observations for our test and statistical analysis, feasible time intervals, after the peak of the second cycle has been reached, comprise a complete cycle, for example from August the 10th (or August the 17th) to September the 13th (to September the 20th). With tested time intervals that comprise a complete pandemic cycle (or a substantial part of it), we must admit that the information content derived from these tests is rather limited.

Under a very cautious interpretation and acknowledging that when back-testing we have information that we would not have had in the past, we dare to conclude, that our proposed test and testing strategy may have the property to identify pandemic status changes comparatively early and with a certain reliability based on reported daily new infections. This is especially underscored when we compare the test results, where we at first identified the start of emerging pandemic cycles with a purely visual inspection of the development of the number of daily new infections, see for example U.K. (Germany, Italy) for the test interval ending August the 16th (July the 26th, August the 2nd). From the test results of the six countries of our study, we can furthermore directly deduce that there are different patterns of emerging regional pandemic cycles. Careful analysis of identified phases of stability is therefore necessary as these can be the contributing blocks of an emerging pandemic cycle (see e.g. Austria for the period ending September 6th and Germany for the period ending September 20th in [Figure 1]). In the cases of the U.K., Austria, Germany, and Italy the identified situation of an emerging second pandemic cycle has meanwhile been confirmed. (Probability values of 81,04%, 71,22%, 99,47%, and 99,82% of four tested time intervals ending July 18th, July 25th, August 1st, and August 8, 2021 indicated early a status change and the beginning of the fourth pandemic cycle in Germany.[36]

## Pandemic Status Change Test and Test Strategy

It is generally accepted that to achieve reliable results from unit root testing in a statistical sense requires an approach that exploits available ex ante information about the real data generating process[37] and an explicit testing strategy.[38,39] The proposed pandemic status change test, that is based on ADF unit root testing, is defined in that sense. For a defined level of significance, the null hypothesis of the test equation, a pandemic status change, cannot be rejected in case of a stochastic or a deterministic trend in the underlying data of the daily number of new infections. The test so offers a high sensitivity with respect to the early detection of a pandemic status change. With the strategy of continuously testing overlapping time intervals, we obtain a series of test results that allows a reliable analysis of the regional pandemic development with respect to the number of new infections.

The assessment, if identified status changes at the time of their first emergences either indicate a level change of the mean of the following emerging empirical distribution of daily new infections or the immediate beginning of a new pandemic cycle, depends on the test results of the subsequent pandemic development. The defined test strategy under these conditions will for later time windows lead to a rejection of the null for level changes (e.g. Austria after July the 12th) or to the continuous rejection of the null for the beginning of a new emerging cycle (e.g. the U.K. from August on). A first non-rejection of the null of a continuous testing strategy may lead to the ambiguity, whether we are about to identify a level change or an immediate newly beginning pandemic cycle. Careful analysis and the results from subsequent tests can then help to distinguish between these situations. The basic idea of the proposed test is to identify pandemic status changes as early as possible from information that is already embedded in the actual available data. However, the reliability of the results directly depends on the quality of the provided data. Obvious lacks in the daily reporting of the number of new infections, (e.g. obvious weekend effects in the French data reported to the World Health Organization) may introduce some kind of (technical) seasonality in the data and ask for special attention in econometric modeling. On the other hand, they do not level off the overall local development. In addition, deterministic and non-stationary seasonality do not pose a serious problem in our application of unit root testing since we implicitly account for them in our test specification and parameterization.

## CONCLUSION

In our top-down approach to test for pandemic status changes, we do not ask or try to explain the underlying reasons. Our analysis is descriptive in nature. We expect that a combination of our test results with epidemiological and virological analysis may provide further insights into the nature of status changes and patterns in emerging pandemic cycles. The proposed pandemic status test should therefore only be understood as a contributing element in a broader pandemic analysis.

As usual, the results of our econometric analysis for six countries and an analysis of past observations cannot naively be taken as generally reliable predictors for future developments. The derived test results therefore require a careful and prudent analysis and interpretation. In addition, it needs further theoretical and empirical study to assure that the proposed pandemic status test exhibits all assumed characteristics so that it can even more eligibly be applied in the described way. This also concerns the power and the size of the test. Nevertheless, the results of our study seem to be promising, indicating that the achievable information has the potential to support practical health and economic policy management considerations when fighting the COVID-19 pandemic. This is of importance given the lack of knowledge and experience concerning the development of the COVID-19 pandemic.

## REFERENCES

1. Halloran ME. Concepts of transmission and dynamics. In: Thomas JC, Weber DJ, editors. Epidemiologic Methods for the Study of Infectious Disease. Oxford, United Kingdom: Oxford University Press; 2001. p. 56-85.
2. Bacaër N. A Short History of Mathematical Population Dynamics. London: Springer; 2011.
3. Weber DJ, Weber L, Menajovsky B, Wenzel R. Investigation of Outbreaks. In: Thomas JC, Weber DJ, editors. Epidemiologic Methods for the Study of Infectious Disease. Oxford, United Kingdom: Oxford University Press; 2001. p. 291-310.
4. Robert Koch-Institut. COVID-19: Acting now, planning proactively. Complementing strategy to recommended infection protection measures and related targets. Epidemiol Bull 2020;12:3-6.
5. Gibney E. Whose Coronavirus strategy worked best? Scientists hunt most effective policies. Nature 2020;581:15-6.
6. Farr C. Germany’s Coronavirus Response is a Master Class in Science Communication; 2020. Available from: https://www.cnbc.com/2020/07/21/germanys-coronavirus-response-masterful-science-communication.html [Last accessed on 2020 Jul 28].
7. Ruktanonchai NW, Floyd JR, Lai S, Ruktanonchai CW, Sadilek A, Rente-Lourenco P, *et al*. Assessing the impact of coordinated COVID-19 exit strategies across Europe. Science 2020;369:1465-70.
8. Maier BF, Brockmann D. Effective containment explains subexponential growth in recent confirmed COVID-19 cases in China. Science 2020;368:742-6.
9. Zhang J, Litvinova M, Wang W, Wang Y, Deng X, Chen X, *et al*. Evolving epidemiology and transmission dynamics of Coronavirus disease 2019 outside Hubei province, China: A descriptive and modelling study. Lancet Infect Dis 2020;20:793-802.
10. Cheng C, Barceló J, Hartnett AS, Kubinec R, Messerschmidt L. COVID-19 government response event dataset (CoronaNet v.1.0). Nature Hum Behav 2020;4:756-68.
11. Haushofer J, Metcalf CJ. Which interventions work best in a pandemic? Science 2020;368:1063-5.
12. Haldane A. Model lives and livelihoods in lockstep. Nature 2020;581:357.
13. Coyle D. Economists must collaborate courageously. Nature 2020;582:9.
14. Bedford J, Enria D, Giesecke J, Heymann DL, Ihekweazu C, Kobinger G, *et al*. COVID-19: Towards controlling of a pandemic. Lancet 2020;395:1015-18.
15. Cornwall W. Can You Put a Price on COVID-19 Options? Experts Weigh Lives Versus Economics; 2020. Available from: https://www.sciencemag.org/news/2020/03/modelers-weigh-value-lives-and-lockdown-costs-putprice-COVID-19 [Last accessed on 2020 Oct 31].
16. Flaxman S, Mishra S, Gandy A, Unwin HJ, Mellan TA, Coupland H, *et al*. Estimating the effects of non-pharmaceutical interventions on COVID-19 in Europe. Nature 2020;584:257-61.
17. Hsiang S, Allen D, Annan-Phan S, Bell K, Bolliger I, Chong T, *et al*. The effect of large-scale anti-contagion policies on the COVID-19 pandemic. Nature 2020;584:262-7.
18. Dickey DA, Fuller WA. Distribution of the estimators for autoregressive time series with a unit root. J Am Stat Assoc 1979;74:427-31.
19. Dickey DA, Fuller WA. Likelihood ratio statistics for autoregressive time series with a unit root. Econometrica 1981;49:1057-72.
20. Campbell JY, Perron P. Pitfalls and opportunities: What macroeconomists should know about unit roots. In: Blanchard OJ, Fischer S, editors. NBER Macroeconomics Annual. Vol. 6. Cambridge, Massachusetts, United States: MIT Press; 1991. p. 141-220.
21. Harris R, Sollis R. Applied Time Series-Modelling and Forecasting. New York, United States: John Wiley & Sons; 2003.
22. Davidson R, MacKinnon JG. Estimation and Inference in Econometrics. Oxford, United Kingdom: Oxford University Press; 1993.
23. Ghysels E Lee HS, Noh J. Testing for unit roots in seasonal time series. J Econometr 1994;62:415-42.
24. Linton NM, Kobayashi T, Yang Y, Hayashi K, Akhmetzhanov AR, Jung SM, *et al*. Incubation period and other epidemiological characteristics of 2019 novel Coronavirus infections with right truncation: A statistical analysis of publicly available case data J Clin Med 2020;9:538-46.
25. Böhning D, Rocchetti I, Maruotti A, Holling H. Estimating the undetected infections in the COVID-19 outbreak by harnessing capture-recapture methods. Int J Infect Dis 2020;97:197-201.
26. Surkova E, Nikolayevskyy V, Drobniewski F. False-positive COVID-19 results: Hidden problems and costs. Lancet Respir Med 2020;8:1167-8.
27. Schuppert A, Polotzek K, Schmitt J, Busse R, Karschau J,

Karagiannidis C. Different spreading dynamics throughout Germany during the second wave of the COVID-19 pandemic: A time series study based on national surveillance data. Lancet Reg Health Eur 2021;6:100151.

28. Office for National Statistics. Coronavirus (COVID-19) Infection Survey Technical Article: Waves and Lags of COVID-19 in England. United Kingdom: Office for National Statistics; 2021. Available from: https://www.ons.gov.uk/peoplepopulationandcommunity/healthandsocialcare/conditionsanddiseases/articles/coronaviruscovid19infectionsurveytechnicalarticle/wavesandlagsofcovid19inenglandjune [Last accessed on 2021 Nov 14].
29. Leichsenring K, Schmidt A, Staflinger H. The Second Wave has Hit Austria Harder-Also in Care Homes; 2020. Available from: https://www.ltccovid.org/2020/11/27/the-second-wave-has-hit-austria-harder-also-in-care-homes [Last accessed on 2021 Nov 14].
30. Ellyatt H. One Chart Shows how Bad Germany's Second Wave of the Coronavirus is, CNBC; 2020. Available from: https://www.cnbc.com/2020/12/01/germanys-second-wave-of-covid-19-has-been-worse-than-the-first.html [Last accessed on 2021 Nov 14].
31. Balmer C, Amante A. Why us Again? Italy Suffers Disproportionate toll in Second COVID Wave; 2020. Available from: https://www.reuters.com/article/health-coronavirus-italy-dead-idukkbn28o20i [Last accessed on 2021 Nov 14].
32. Stössel S. Why the Second Wave is So Flat in Germany; 2020. Available from: https://www.welt.de/vermischtes/plus216664642/corona-pandemie-warum-die-zweite-welle-in-deutschland-so-flachverlaeuft.html [Last accessed on 2021 Nov 20].
33. MacKinnon JG. Numerical distribution functions for unit root and co-integration tests. J Appl Econometr 1996;11:601-18.
34. World Health Organization. WHO Coronavirus Disease (COVID-19) Dashboard. Geneva: World Health Organization; 2020. Available from: https://www.covid19.who.int [Last accessed on 2020 Oct 07].
35. Robert Koch-Institut. COVID-19: Fallzahlen in Deutschland und Weltweit, Fallzahlen in Deutschland; 2020. Available from: https://www.rki.de/de/content/infaz/n/neuartiges_coronavirus/fallzahlen.html [Last accessed on 2020 Oct 07].
36. RND. Mediciners Push for a Corona Strategy Change: 4th Wave can Change the Game Completly; 2021. Available from: https://www.rnd.de/politik/corona-top-mediziner-draengen-auf-kurswechsel-vierte-welle-kann-alles-bisherige-in-den-schatten-4xjsbsdr25hi7npqxmmwvh6mrq.html [Last accessed on 2021 Nov14].
37. Elder J, Kennedy PE. Testing for unit roots: What should students be taught? J Econ Educ 2001;32:137-46.
38. Perron P. Trends and random walks in macroeconomic time series: Further evidence from a new approach. J Econ Dyn Control 1988;12:297-332.
39. Dolado JJ, Jenkinson T, Sosvilla-Rivero S. Co-integration and unit roots. J Econ Surv 1990;4:249-73.