ISSN: 2281-1346

UNIVERSITÀ DI PAVIA
Department of Economics and Management

DEM Working Paper Series

A data-driven test approach to identify COVID-19 surge phases: an alert-warning tool

Arianna Agosto
(University of Pavia)

Paola Cerchiello
(University of Pavia)

 # 214 (10-23)

Via San Felice, 5
I-27100 Pavia

https://economiaemanagement.dip.unipv.it/it

A data-driven test approach to identify COVID-19 surge phases: an alert-warning tool

Arianna Agosto[1] and Paola Cerchiello[2]

[1] Department of Economics and Management, University of Pavia, 27100 Pavia, Italy; arianna.agosto@unipv.it (corresponding author)

[2] Department of Economics and Management, University of Pavia, 27100 Pavia, Italy; paola.cerchiello@unipv.it

Abstract

The effective monitoring of the pandemic emergency and, specifically, the early detection of surge phases are crucial to define proper health policies. We propose a statistical testing approach to identify the acceleration in contagion growth that potentially marks the start of new waves, based on the study of the reproduction rate dynamics. The proposed method can be considered as a supplementary early warning system that can assist policymakers in the attempt to anticipate and tailor countermeasures. It can also be used as an ex-post tool to date-stamp surge phases and evaluate the impact of the implemented strategies on their timing. The effectiveness of our approach is exemplified on ten countries' contagion data, reaching robust and insightful results in assessing the timing and severity of COVID-19 surge phases.

Keywords: COVID-19 pandemics, Reproduction rate, Explosivity tests, Epidemic surge detection.

1 Introduction

The spread of the COVID-19 virus at the beginning of 2020 caught many governments by surprise. Before the start of vaccination, at the end of 2020, governments have focused on so-called non-pharmaceutical interventions (NPIs), such as generalized lockdowns or targeted lockdowns and quarantines for infected individuals, in the attempt to reduce the reproduction rate of the virus and thereby limit the number of new cases by preventing human-to-human transmission (so-called "suppression" strategy). Some countries resorted to generalized lockdowns, while others have, at least initially, considered milder measures, such as mask-wearing and targeted quarantine, after contact tracing, in the attempt to mitigate the overall social and economic cost for the whole community. The start of vaccination campaigns - together with the outbreak of new virus variants - added complexity to the evaluation of health policy measures, raising the issue of assessing whether vaccination rates in combination with a certain amount of NPIs are able to delay the occurrence of waves and/or influence their duration.

From its onset, the COVID-19 pandemic has infected more than 760 million people and caused almost 7 million deaths in more than 200 countries around the world. The associated real and social costs are paramount. Some estimates raise the global real cost of the COVID-19 pandemic to several USD trillion (IMF, 2020). A great concern has been the virus spread into countries with weaker epidemic management systems. Nevertheless, it is likely that the world will continue to face epidemic risks, which many countries are still ill-positioned to manage (Bitetto et al., 2021). In addition to climate change and urbanization, global population displacement and migration — now happening in nearly every corner of the world — create favorable conditions for the emergence and spread of new pathogens.

Most efforts in the containment of the spread and effects of epidemics use the results of prediction models (Rivers et al., 2019; Polonsky et al., 2019). The prediction of the COVID-19 behavior has deployed sophisticated methods that include big data, social media information, stochastic models and data science/machine learning techniques along with medical (symptomatic and asymptomatic) parameters (Shinde et al., 2020; Nikolopoulos et al., 2021). However, prediction accuracy can be harmed by the relatively short period of data availability, the data quality, the specific flaws in the data collection process, the mutation of the virus, the jeopardized vaccination hesitancy in specific subgroups of the populations but also by inaccurate algorithms and models.

The literature on epidemics forecast is vast and diversified according to the employed methodologies, the data and the specific aims. That said, we can imagine classifying field papers into two large categories:

- Compartmental models. Such literature assumes that the population can be compartmentalized into groups based on their status of infection and recovery, where the typical ones are Susceptible (S), Infectious (I), or Recovered (R). Consequently, an analysis of the transmission process among the groups is performed using either deterministic or stochastic methods. The most famous and simple example of such class is the SIR (or SEIR) model, and many models are built upon this basic form (Arik et al., 2020; Harko et al., 2014; Kröger & Schlickeiser, 2020). The main limitation of such models lies in the determination of the parameters that are influenced by many uncontrollable and dynamically changing factors (Zelenkov & Reshettsov, 2023).

- Statistical or Machine learning models. This type of approach implements a more flexible and unstructured framework, fitting directly the data in accordance with a specific data model. Some works combine the predictive aim with the interpretation of parameters driving the infection count dynamics, to analyse the differences between countries and pandemic phases (Agosto et al., 2021; Giudici et al., 2023). Several papers also employ quite advanced and sophisticated non-linear approaches like deep learning ones (Utku, 2023; Rodriguez et al., 2021; Gao et al., 2021; Jin et al., 2021; Chauhan & Bedi, 2023). Those models typically show high levels of flexibility that represents either an advantage or a disadvantage since it can impose too simplistic assumptions that barely match with the complexity of the phenomenon.

It is also important to refer to the extensive work put in place by both the Centers for Disease Control and Prevention (CDC) and the European Center for Disease Control and Prevention (ECDC), which fostered a collaborative effort of worldwide scholars to produce ensemble forecast models (Cramer et al., 2022). Such initiatives allowed to greatly improve predictive accuracy thanks to the averaging of results of several models fitted according to different contexts, data, time horizons, approaches.

Given such general view of the main approaches to pandemic data analysis, we should stress that one of the most relevant issues, in sketching proper health policy strategies, is the identification of new waves of the disease and their extent, in terms of severity (impact) and duration. This is true, independently of the presence and types of countermeasures put in place by countries. This is particularly valid during the first phases of any pandemic, when neither vaccinations nor systematized restrictions policies are put in place. Nevertheless, even during more advanced pandemic phases, a complete and exhaustive set of all the needed information that would be beneficial to the proper assessment of any virus spread, tends to be challenging and in most cases unrealistic. Data are typically collected with delays, flaws, inconsistencies and differences among countries, thus making even more difficult any quantitative exercise.

Some works, such as Ayala et al. (2021) and Zhang et al. (2021), tried to identify COVID-19 waves by fixing thresholds on the reproduction rate. Others focused on comparing the impact of different COVID-19 waves (Salyer et al., 2021; Soriano et al., 2021). However, there is still no standard definition of "waves", nor a consensus method to identify them. Indeed, to the best of our knowledge, the study and prediction of waves is still an underrated research area, yet the compartmental models class typically focuses on the prediction of the number of cases per se. Thus, there exists an utmost request for an objective and data-driven mechanism able to support and convey the detection of the imminent surge of the virus spread by epidemiologists and policymakers. In addition, the cited identification methods can be considered more heuristic strategies, based on the observation of the reproduction rate and its permanence above a given level for a chosen number of days, without considering either the reproduction rate dynamics or the underneath stochastic process.

1.1 Our Contribution

In the present paper, our goal is to offer an objective and data-driven approach to help the identification of phases of particularly rapid acceleration of the COVID-19 pandemic (and, more generally, of any virus spread) that could mark the beginning of a new wave, using the time series of the reproduction rate. We take advantage of and properly contextualize an econometric unit root test to study the evolution of the reproduction rate and to detect the potential occurrence of new waves, using an approach previously employed to identify speculative bubbles within the financial markets. The unit root testing approach was applied to COVID-19 data by Shi et al. (2021), but with a focus on the dynamics of case-fatality ratios.
Insofar, we contribute to the existing literature with a method to control and manage

the evolution of pandemics that offers:

1. a monitoring tool of the pandemic patterns based on a robust econometric model that takes into account the time series of the reproduction rate with a system of backward-expanding rolling windows;
2. a set of signals/warnings country by country regarding the surge of the wave that policymakers can use to anticipate and tailor countermeasures;
3. an ex-post tool to date-stamp contagion waves and evaluate the impact of the implemented strategies on their timing and severity.

It is important to stress that the proposed approach is valid whatever virus epidemics we consider, provided the reproduction rate time series. Moreover, in order to avoid confounding effects and endogeneity problems, we analyze separately the time series of different countries, also avoiding the systematic underestimation of any influencing factor connected to the country-specific differences (like age distributions of the population, population density, health system, approaches to containment measures, etc.).

2 Methods

Our method to monitor the COVID-19 contagion process is based on the application of statistical tests to detect *explosive* phases in the reproduction rate time series. According to the econometric definition, explosive processes are a class of non-stationary time series. In non-stationary processes, the effect of a shock that occurred at a given time persists indefinitely in the future, thus the unconditional joint probability distribution changes with time.

The main idea driving our proposal is that changes in the time series properties of the reproduction rate can be used as signals of transition between different pandemic phases. Indeed, while stationarity in the reproduction rate time series, with daily fluctuations around the mean, corresponds to periods of stability in the number of new infections, a switch to a random walk (unit root) process - that belongs to the class of non-stationary processes - indicates a trend in the number of new cases, typical of phases with moderate contagion growth. Finally, when the reproduction rate time series move from a unit root to an explosive process (characterized by exponential growth), the extremely rapid increase in infections characterizing the spread of new waves has possibly started.

The occurrence of an explosive phase in a time series can be detected through explosivity (or right-sided unit root) tests. Specifically, to identify and date-stamp the start of explosive phases in the evolution of reproduction rate, we rely on the Backward Superior Augmented Dickey Fuller (BSADF) testPhillips et al. (2015). This method was already used in the econometric and financial literature to identify explosivity in financial time series (so-called speculative bubbles).

Before defining the BSADF test, it is useful to recall the Augmented Dickey Fuller (ADF) statistics Dickey & Fuller (1979) to evaluate the stationarity of a time series y_t, based on the following regression model:

$$y_t = \mu + \phi y_{t-1} + \sum_{i=1}^{p} \psi_i \Delta y_{t-i} + \varepsilon_t, \qquad \varepsilon_t \sim \mathcal{N}(0, \sigma^2) \tag{1}$$

where μ is the constant term, Δy_{t-i} is the lagged differenced dependent variables, p is the considered number of lags of Δy_t (that can be chosen based on model selection criteria, such as Akaike or Bayesian Information Criterion) and ε_t is a normally distributed error component with constant variance σ^2.

In the standard ADF test, Equation (1) is used to test the null hypothesis that the ϕ coefficient associated with the lagged dependent variable is equal to 1, corresponding to the random walk process, against the alternative of stationarity ($\phi < 1$).

In the right-tailed unit root test for explosivity proposed by Phillips et al. (2015), the null hypothesis is still the random walk one, but the alternative is $\phi > 1$, corresponding to explosive behaviour. The ADF test applied to the full sample can be denoted as $ADF_0^1(p)$ (where 0 and 1 denote the beginning and the end of the considered subsample expressed as a fraction of the total number of observations; this means that all the time series is considered, differently from what is done in the BSADF test, as explained in the following).

In particular, Phillips et al. (2015) proposed a backward ADF test, named BSADF, based on repeated estimation of the ADF test statistic using a backward-expanding rolling-windows technique, to allow for date-stamping of explosive phases:

$$BSADF_{r_2} := \sup_{r_1 \in [0, r_2 - r_0]} \left\{ ADF(p)_{r_1}^{r_2} \right\} \tag{2}$$

According to Equation 1, at every r_2 time (usually day), the BSADF value is defined as the maximum ADF value calculated over intervals expanding from [0, r_2] to [$r_2 - r_0$, r_2], where r_0 is the minimum window width chosen by the analyst. In other terms, to evaluate explosivity in r_2, one fixes r_2 and considers all ADF values in expanding windows starting from the initial date of the sample. Based on this method and as shown in Phillips et al. (2015), the origination date of an explosive period is defined as the first time in which the BSADF statistic exceeds the critical value, while the first observation, following the origination date, whose BSADF statistic goes back below the critical value is considered as the termination date of the explosive period. Critical values for the BSADF test can be obtained through simulation experiments based on the limiting distribution derived by Phillips et al. (2015) or through the bootstrap approach proposed by Astill et al. (2023). In the present analysis, we apply the BSADF test to the COVID-19 reproduction rate time series and rely on critical values provided by the MultipleBubbles R library, which implements the methodology of Phillips et al. (2015) (details on the specific code employed are available upon request).

The backward-expanding rolling windows technique allows a daily update of the monitoring tool (i.e. the test statistic is re-calculated and compared with the critical value every day), while, at the same time, taking into account the past history of the national pandemic evolution.

The beginning of an explosive period indicates an acceleration of contagion growth, which could mark the beginning of a critical phase, or even of a new wave. Indeed, the exponential growth detected by the test typically occurs at the beginning of a new wave and ends when the plateau is nearly reached. The test output can thus be used as an early warning signal for policy-making purposes and it can possibly be coupled with other indicators chosen by the regulators. For decision-making purposes, it is important to stress how test results should be interpreted; it is not enough to have a signal on a given day to declare the start of an explosive phase. Rather, we identify the warning signal on a given day if and only if two conditions are met for at least 5 days out of a 7-day window. The choice of such numbers of days is consistent with the protocol followed by many policymakers, that during the pandemic used to update, modify or initialize countermeasures on a 7 days monitoring basis.

The two conditions, that we set, are:

1. Increased reproduction rate with respect to the previous day;

2. Rejection of the null hypothesis of random walk, in favor of explosivity.

The signal variable assumes a value of 1 if the two conditions are satisfied, and 0 otherwise. Based on this strategy, if, on a given day, these two criteria are satisfied, then the dummy variable activates and consequently the warning signal, lasting until the above-defined conditions occur. Formally, an *explosive* phase starts when the dummy variable representing the signal moves to 1 from 0 and, conversely, ends when the dummy variable comes back to 0. Note that this definition of explosive phase is more delimited than the one used in the BSADF test procedure, as, in our strategy, the rejection of the null hypothesis on a single day is not a sufficient condition to activate the warning signal. Table 1 provides some examples of how the signal relative to a given day (Day 1 in Table 1) can be detected in different scenarios and according to the definition provided above. Based on our approach, the two defined conditions are checked for every day, but, before deciding whether a signal is activated on Day 1, it is necessary to wait until Day 7. At that point, we evaluate whether the two conditions occurred for at least 5 - even non-consecutive - days. This is coherent with the need not to have many false positive signals, that could provide hurried indications to the policymakers. Based on the information provided in Table 1, the signal on Day 1 is activated in both Scenario 1 and 3, representing an explosive phase prodromal to a potential new wave. It is interesting to note that Scenario 1 and 3 lead to the same conclusion, despite different in the order of days on which the conditions are satisfied. Scenario 2, instead, clearly does not satisfy the conditions for enough time: in other words, the signals can be considered as due to random fluctuations. We remark that, in the three scenarios, we evaluate the possible presence of a signal just on Day 1. The following days could be potentially signal days if the conditions are met in the relative 7 days window, on which we suppose not to have the complete set of information (for example in Day 2 we only see the following 5 days).
We underlie that the currently limited literature on wave detection typically focuses solely on the analysis of the first condition, disregarding any robust evaluation of the stochastic dynamic process underneath the reproduction rate random variable. Moreover, our approach is flexible enough to allow policymakers the fine-tuning of the day window to be considered (5 out of 7 in the current paper) and the significance level

	Condition 1 & Condition 2							Signal on Day 1
	Day 1	**Day 2**	**Day 3**	**Day 4**	**Day 5**	**Day 6**	**Day 7**	
Scenario 1	YES	YES	NO	YES	YES	NO	YES	*Signal*
Scenario 2	YES	YES	NO	YES	YES	NO	NO	*No Signal*
Scenario 3	YES	NO	NO	YES	YES	YES	YES	*Signal*

Table 1: Examples of how the signal can be detected on Day 1 in different scenarios and according to the provided definition.

used in the econometric test - here set at 5% - that can be modified to increase the sensitivity or the specificity of the signal.

3 Empirical Evidence

3.1 Data

We download, from the OurWorldInData data repository[1], the time series of reproduction rate for ten countries: Austria, Czechia, Denmark, France, Germany, Italy, Portugal, Spain, Sweden and United Kingdom. The choice of those countries is justified by the need to consider a comprehensive and diversified set of countries representative of the different European regions and of the approaches to the pandemic. Indeed, countries like France, Germany and Italy were particularly severe and stringent, while Czechia, Sweden and United Kingdom - and for some time Portugal too - were more indulgent and reluctant towards too strict countermeasures.

Our data cover the period ranging from 1 June 2020 to 31 August 2022[2]. We do not consider data beyond the end of August 2022 because of the presence of inconsistencies, flaws and missing values in the time series, that may compromise results reliability.

3.2 Results

The left panels in Figures from 1 to 10 show the BSADF statistics applied to the reproduction rate of the considered countries, together with the test critical values at the 5% significance level calculated using the *'MultipleBubbles'* R package. Based on

[1] https://github.com/owid/covid-19-data/tree/master/public/data

[2] Due to the technical characteristics of the test, the first results can be calculated starting from 29 July 2020, as the previous days are used to populate the first expanding window in order to have statistically significant results. Nevertheless, starting from 1 June 2020 avoids the inclusion of the very first wave of the pandemic, which does not offer a previous time series useful for fitting the model as no pandemic was of course in place before January 2020.)

our testing approach, when the value of the BSADF statistic (blue line) overcomes the critical value (red line), according to the econometric test the contagion growth is considered as *explosive* until the BSADF statistic goes back below the critical value. A value of the test statistic higher than the critical value on a given day is used to verify the occurrence of Condition 2 in our early warning signal methodology, explained in the Methods section. In addition, the value of the test statistic provides a statistically robust measure of the magnitude of contagion growth.

First, it can be seen that the periods characterized by the most explosive contagion dynamics are summer 2021 - when the Delta variant, after its initial spread in United Kingdom in May, became dominant - and the period between the end of 2021 and the beginning of 2022 when Europe experienced the spread of the Omicron variant. Among the considered countries, Austria, Spain, Italy and France are the ones characterized by the lowest number of peaks of the explosivity test statistic, while Portugal and Sweden show the most erratic behavior. Differently from most countries, the highest peak in the explosivity test statistic of United Kingdom occurs in summer 2022, when the BA.4 and BA.5 Omicron variants, not severe but characterized by a strong capacity of reinfecting people, caused a new acceleration in the number of new cases. Also France, Czechia, Denmark and Portugal saw a strong acceleration of the pandemic in summer 2022, while a peak occurs a few months before, in spring 2022, in Sweden.

As explained in the Methods section, the output of the explosivity test, together with the observation of the reproduction rate evolution, can be used to identify a warning signal and, thus, detect, the beginning and the end of *explosive phases*, that in our definition are characterized by the occurrence of both a rejection of the random walk hypothesis and an increasing reproduction rate for at least 5 out of 7 subsequent days. The right panels in Figures from 1 to 10 show the output of such warning signal identification strategy. Specifically, the red-shaded areas mark the explosive phases according to our definition and are represented together with the reproduction rate time series (black line). It can be seen that the identified explosive phases always correspond to periods of rapid increase in the reproduction rate. Indeed, the vice versa does not hold, as not all the periods of increase in the reproduction rate are characterized by the exponential contagion growth that potentially marks the beginning of a particularly critical phase or even of a new wave, that should be promptly detected to set appropriate policies.

Table 2 provides a summary of the test results, by reporting, for each of the analyzed countries, the number of detected explosive phases, the maximum value of the test statistic and the date when it occurred. It can be noticed that Portugal and Sweden are the countries showing the highest number of explosive phases, but not the ones with the highest maximum test statistics, as Austria, followed by Spain and United Kingdom, show the highest values. Interestingly, for most countries the highest explosivity peak was detected in summer 2021, when the Delta variant spread over Europe. United Kingdom is the only country for which the maximum explosivity value is reported in 2022.

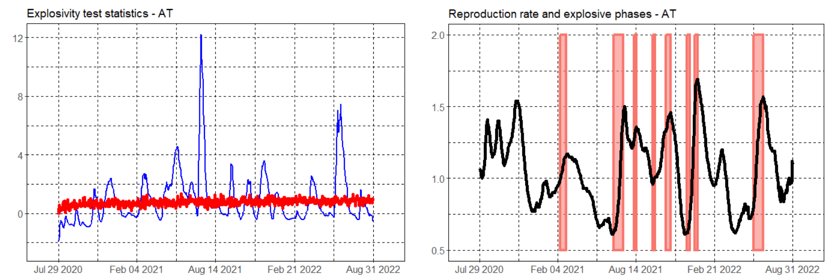

Figure 1: Results of explosivity test for Austria. Left panel: time series of BSADF statistics (blue line) and related critical values at the 5% significance level (red line). Right panel: reproduction rate (black line) and critical phases identified through the explosivity test (red shaded areas).

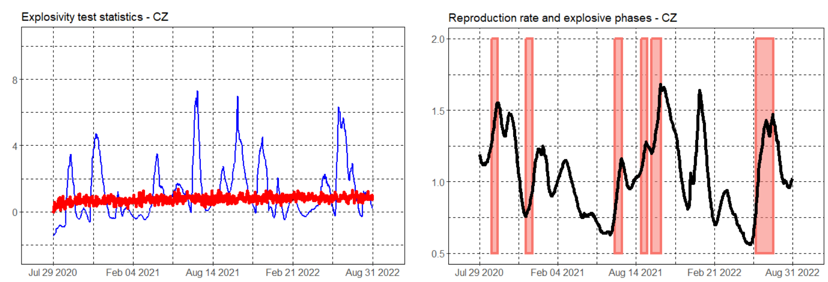

Figure 2: Results of explosivity test for Czechia. Left panel: time series of BSADF statistics (blue line) and related critical values at the 5% significance level (red line). Right panel: reproduction rate (black line) and critical phases identified through the explosivity test (red shaded areas).

Figure 3: Results of explosivity test for Germany. Left panel: time series of BSADF statistics (blue line) and related critical values at the 5% significance level (red line). Right panel: reproduction rate (black line) and critical phases identified through the explosivity test (red shaded areas).

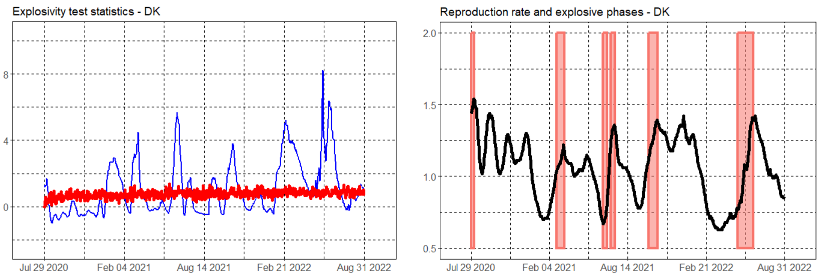

Figure 4: Results of explosivity test for Denmark. Left panel: time series of BSADF statistics (blue line) and related critical values at the 5% significance level (red line). Right panel: reproduction rate (black line) and critical phases identified through the explosivity test (red shaded areas).

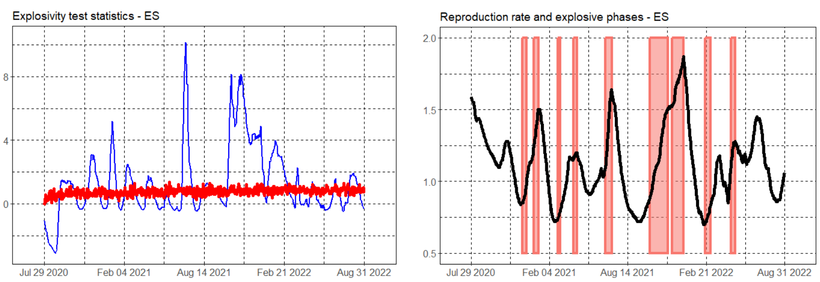

Figure 5: Results of explosivity test for Spain. Left panel: time series of BSADF statistics (blue line) and related critical values at the 5% significance level (red line). Right panel: reproduction rate (black line) and critical phases identified through the explosivity test (red shaded areas).

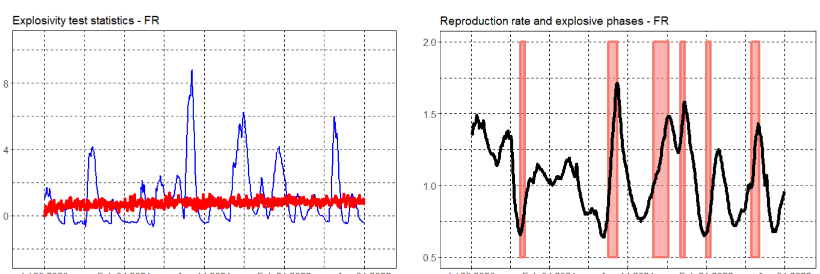

Figure 6: Results of explosivity test for France. Left panel: time series of BSADF statistics (blue line) and related critical values at the 5% significance level (red line). Right panel: reproduction rate (black line) and critical phases identified through the explosivity test (red shaded areas).

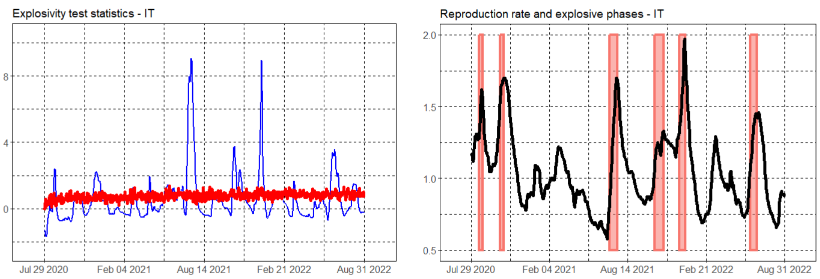

Figure 7: Results of explosivity test for Italy. Left panel: time series of BSADF statistics (blue line) and related critical values at the 5% significance level (red line). Right panel: reproduction rate (black line) and critical phases identified through the explosivity test (red shaded areas).

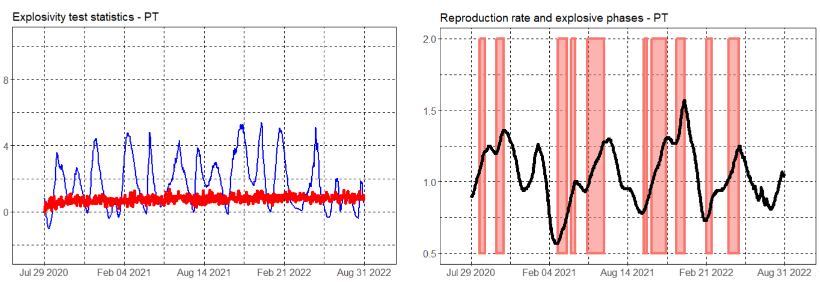

Figure 8: Results of explosivity test for Portugal. Left panel: time series of BSADF statistics (blue line) and related critical values at the 5% significance level (red line). Right panel: reproduction rate (black line) and critical phases identified through the explosivity test (red shaded areas).

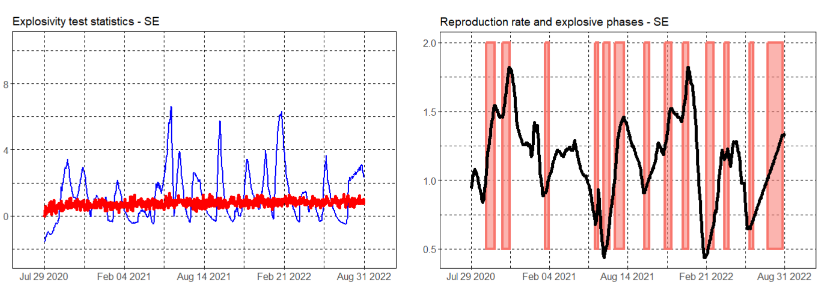

Figure 9: Results of explosivity test for Sweden. Left panel: time series of BSADF statistics (blue line) and related critical values at the 5% significance level (red line). Right panel: reproduction rate (black line) and critical phases identified through the explosivity test (red shaded areas).

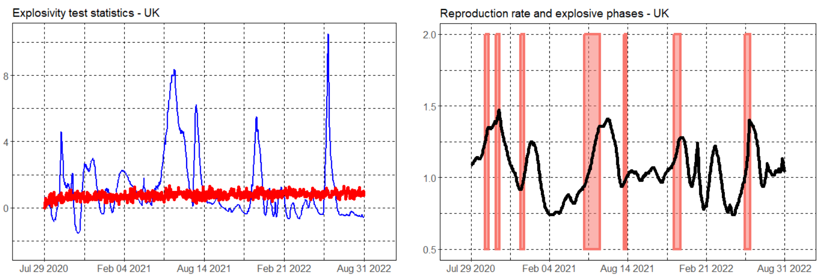

Figure 10: Results of explosivity test for United Kingdom. Left panel: time series of BSADF statistics (blue line) and related critical values at the 5% significance level (red line). Right panel: reproduction rate (black line) and critical phases identified through the explosivity test (red shaded areas).

Country	# of explosive phases	Max test statistics	Date
Austria	8	12.22	July 10th 2021
Czechia	6	7.33	July 08th 2021
Denmark	6	8.22	May 24th 2021
France	6	8.78	July 16th 2021
Germany	7	7.11	July 13th 2021
Italy	6	9.05	July 14th 2021
Portugal	10	5.41	Dec 29th 2021
Spain	9	10.15	July 01st 2021
Sweden	13	6.61	May 27th 2021
UK	7	10.51	June 06th 2022

Table 2: Description of the patterns of the considered countries in terms of number of critical phases, maximum value reached by the considered test statistics and date of occurrence of the latter.

4 Conclusions

The recent COVID-19 pandemic, started in January 2020 in China and declared concluded as a public health emergency (but still a potential risk) by the World Health Organization (WHO) on the 5th of May 2023, has showed the level of unpreparedness and the lack of proper management plans. Countries have faced any kind of difficulty: lack of proper countermeasures, disorganized hospitals, severe drop of economic production, procurement scarcity, population fear and hesitancy, social disintegration. New strategies, recovery plans, burst in the development and production of vaccines, have become crucial and unavoidable. However, most of the actions was undertaken ex-post when waves were already largely hitting the populations, when severe NPIs countermeasures were the only available option to contain the pervasive virus diffusion phase. In this context, we contribute to the existing literature by developing a monitoring tool for the pandemic patterns based on a robust econometric model applied to the time series of the reproduction rate. We show how this tool can be used to provide signals and/or warnings country by country regarding the surge of virus spread, that policy-makers can use to anticipate and tailor countermeasures.
The proposed approach requires the analysis of the sole reproduction rate time series, thus avoiding problems in the acquisition of different data sources and the consequent issues with relative reconstruction and harmonization. Moreover, one can analyze each country separately, preserving the inherent characteristics and peculiarities. Nevertheless, the proposed approach could be applied to an aggregate time series, that puts together all the needed countries, as for example 27 EU ones or 51 US states. This could be of interest to supranational agencies or regulators like ECDC/CDC or HaDea in the attempt to monitor and prepare countermeasures at a larger scale.
As a possible limitation of the proposed approach, we should mention the fact that a purely data-driven and epidemiologically-agnostic approach to evaluate disease spread could be misleading in some situations. The weekly modulation of testing and case reporting can potentially lead to 5-day abnormal trends that could lead to false signals and thus would require to be corrected through nowcasting, still bearing in mind the difficulties in data collection. We will consider these issues in a future extension of our work.

By applying the proposed approach to a representative set of countries, we obtain insightful results in assessing the timing and severity of COVID-19 surge phases and shed light on the differences in the country-specific contagion dynamics.

In future development of the present study, we will also consider an augmented version of the test that takes into account relevant covariates. In particular, we will evaluate whether the introduction of explicative variables can, on one hand, improve the power of the test and, on the other hand, add more insights regarding the patterns of explosive phases.

References

Agosto, A., Campmas, A., Giudici, P., & Renda, A. (2021). Monitoring covid-19 contagion growth. *Statistics in Medicine*, *40*(18), 4150–4160.

Arik, S., Li, C.-L., Yoon, J., Sinha, R., Epshteyn, A., Le, L., ... others (2020). Interpretable sequence learning for covid-19 forecasting. *Advances in Neural Information Processing Systems*, *33*, 18807–18818.

Astill, S., Taylor, A. R., Kellard, N., & Korkos, I. (2023). Using covariates to improve the efficacy of univariate bubble detection methods. *Journal of Empirical Finance*, *70*, 342–366.

Ayala, A., Villalobos Dintrans, P., Elorrieta, F., Castillo, C., Vargas, C., & Maddaleno, M. (2021). Identification of covid-19 waves: Considerations for research and policy. *International Journal of Environmental Research and Public Health*, *18*(21), 11058.

Bitetto, A., Cerchiello, P., & Mertzanis, C. (2021). A data-driven approach to measuring epidemiological susceptibility risk around the world. *Scientif Reports*, *11*.

Chauhan, J., & Bedi, J. (2023). Effvit-covid: A dual-path network for covid-19 percentage estimation. *Expert Systems with Applications*, *213*, 118939.

Cramer, E. Y., Huang, Y., Wang, Y., Ray, E. L., Cornell, M., Bracher, J., ... others (2022). The united states covid-19 forecast hub dataset. *Scientific data*, *9*(1), 462.

Dickey, D. A., & Fuller, W. A. (1979). Distribution of the estimators for autoregressive time series with a unit root. *Journal of the American statistical association*, *74*(366a), 427–431.

Gao, J., Sharma, R., Qian, C., Glass, L. M., Spaeder, J., Romberg, J., ... Xiao, C. (2021). Stan: spatio-temporal attention network for pandemic prediction using real-world evidence. *Journal of the American Medical Informatics Association*, *28*(4), 733–743.

Giudici, P., Tarantino, B., & Roy, A. (2023). Bayesian time-varying autoregressive models of covid-19 epidemics. *Biometrical Journal*, *65*(1), 2200054.

Harko, T., Lobo, F. S., & Mak, M. (2014). Exact analytical solutions of the susceptible-infected-recovered (sir) epidemic model and of the sir model with equal death and birth rates. *Applied Mathematics and Computation*, *236*, 184-194. Retrieved from `https://www.sciencedirect.com/science/article/pii/S009630031400383X` doi: https://doi.org/10.1016/j.amc.2014.03.030

IMF. (2020). Exceptional times, exceptional action. In *Opening remarks for spring meetings press conference.*

Jin, X., Wang, Y.-X., & Yan, X. (2021). Inter-series attention model for covid-19 forecasting. In *Proceedings of the 2021 siam international conference on data mining (sdm)* (pp. 495–503).

Kröger, M., & Schlickeiser, R. (2020, nov). Analytical solution of the sir-model for the temporal evolution of epidemics. part a: time-independent reproduction factor. *Journal of Physics A: Mathematical and Theoretical*, *53*(50), 505601. Retrieved from `https://dx.doi.org/10.1088/1751-8121/abc65d` doi: 10.1088/1751-8121/abc65d

Nikolopoulos, K., Punia, S., Schäfers, A., Tsinopoulos, C., & Vasilakis, C. (2021). Forecasting and planning during a pandemic: Covid-19 growth rates, supply chain disruptions, and governmental decisions. *European journal of operational research*, *290*(1), 99–115.

Phillips, P. C., Shi, S., & Yu, J. (2015). Testing for multiple bubbles: Historical episodes of exuberance and collapse in the s&p 500. *International economic review*, *56*(4), 1043–1078.

Polonsky, J. A., Baidjoe, A., Kamvar, Z. N., Cori, A., Durski, K., Edmunds, W. J., ... others (2019). Outbreak analytics: a developing data science for informing the response to emerging pathogens. *Philosophical Transactions of the Royal Society B*, *374*(1776), 20180276.

Rivers, C., Chretien, J.-P., Riley, S., Pavlin, J. A., Woodward, A., Brett-Major, D., ... others (2019). Using "outbreak science" to strengthen the use of models during epidemics. *Nature communications*, *10*(1), 3102.

Rodriguez, A., Tabassum, A., Cui, J., Xie, J., Ho, J., Agarwal, P., ... Prakash, B. A. (2021). Deepcovid: An operational deep learning-driven framework for explainable real-time covid-19 forecasting. In *Proceedings of the aaai conference on artificial intelligence* (Vol. 35, pp. 15393–15400).

Salyer, S. J., Maeda, J., Sembuche, S., Kebede, Y., Tshangela, A., Moussif, M., ... others (2021). The first and second waves of the covid-19 pandemic in africa: a cross-sectional study. *The Lancet*, *397*(10281), 1265–1275.

Shi, Z., Zhang, H., Zhang, R., & Zhu, L. (2021). Stochastic dynamics of the covid-19 case-fatality ratios in indonesia, malaysia, and the philippines: economic implications for the post-covid-19 era. *Frontiers in Public Health*, *9*, 755047.

Shinde, G. R., Kalamkar, A. B., Mahalle, P. N., Dey, N., Chaki, J., & Hassanien, A. E. (2020). Forecasting models for coronavirus disease (covid-19): a survey of the state-of-the-art. *SN computer science*, *1*, 1–15.

Soriano, V., Ganado-Pinilla, P., Sanchez-Santos, M., Gómez-Gallego, F., Barreiro, P., de Mendoza, C., & Corral, O. (2021). Main differences between the first and second waves of covid-19 in madrid, spain. *International Journal of Infectious Diseases*, *105*, 374–376.

Utku, A. (2023). Deep learning based hybrid prediction model for predicting the spread of covid-19 in the world's most populous countries. *Expert Systems with Applications*, *231*, 120769. doi: https://doi.org/10.1016/j.eswa.2023.120769

Zelenkov, Y., & Reshettsov, I. (2023). Analysis of the covid-19 pandemic using a compartmental model with time-varying parameters fitted by a genetic algorithm. *Expert Systems with Applications*, *224*, 120034. doi: https://doi.org/10.1016/j.eswa.2023.120034

Zhang, S. X., Arroyo Marioli, F., Gao, R., & Wang, S. (2021). A second wave? what do people mean by covid waves?–a working definition of epidemic waves. *Risk Management and Healthcare Policy*, 3775–3782.

Acknowledgements

The authors acknowledge the European HORIZON 2020 PERISCOPE Project (Contract Number 101016233).

Author contributions statement

A.A. and P.C. developed the methodology, A.A. conducted the empirical analysis, A.A. and P.C. analyzed the results. All authors reviewed the manuscript.

Competing interests

The authors declare no competing interests.