Equilibrium. Quarterly Journal of Economics and Economic Policy
Volume 15 Issue 2 June 2020
p-ISSN 1689-765X, e-ISSN 2353-3293
www.economic-policy.pl

ORIGINAL ARTICLE

Citation: Kufel, T. (2020). ARIMA-based forecasting of the dynamics of confirmed Covid-19 cases for selected European countries. *Equilibrium. Quarterly Journal of Economics and Economic Policy*, *15*(2), 181–204. doi: 10.24136/eq.2020.009

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Received: 30.05.2020; Revised: 12.06.2020; Accepted: 16.06.2020; Published online: 25.06.2020

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ARIMA-based forecasting of the dynamics of confirmed Covid-19 cases for selected European countries

JEL Classification: *C22; C53; C82; I12; I18*

Keywords: *Covid-19 epidemic; ARIMA model; forecasting; infection control; non-pharmaceutical intervention*

Abstract

Research background: On 11 March 2020, the Covid-19 epidemic was identified by the World Health Organization (WHO) as a global pandemic. The rapid increase in the scale of the epidemic has led to the introduction of non-pharmaceutical countermeasures. Forecast of the Covid-19 prevalence is an essential element in the actions undertaken by authorities.
Purpose of the article: The article aims to assess the usefulness of the Auto-regressive Integrated Moving Average (ARIMA) model for predicting the dynamics of Covid-19 incidence at different stages of the epidemic, from the first phase of growth, to the maximum daily incidence, until the phase of the epidemic's extinction.
Methods: ARIMA(p,d,q) models are used to predict the dynamics of virus distribution in many diseases. Model estimates, forecasts, and the accuracy of forecasts are presented in this paper.
Findings & Value added: Using the ARIMA(1,2,0) model for forecasting the dynamics of Covid-19 cases in each stage of the epidemic is a way of evaluating the implemented non-pharmaceutical countermeasures on the dynamics of the epidemic.

Introduction

Covid-19 has infected over 7 million people since its appearance, covering 114 countries (status for 8 June 2020). The epidemic began in December 2019 in China. The first lockdown was introduced on 23 January 2020 in

Hubei province in China. Efficient models for short-term forecasting are needed to forecast the number of future cases. In this context, it is essential to develop strategic planning methods in the public health system to avoid deaths, as well as to introduce non-pharmaceutical countermeasures, such as ordered school closure, case-base measures, the banning of public events, the encouragement of social distancing, and lockdown, to reduce infection. In Europe, the first non-pharmaceutical countermeasures, including an ordered lockdown, were introduced by many countries between 11 and 24 March 2020. These countermeasures were aimed at reducing the number of people infected with Covid-19 while also reducing the dynamics of the infection and allowing health care services to operate effectively. Disease rate projections allow recommendations on an effective date and the date of withdrawal from government interventions. This issue has been widely presented in previous papers (Flaxman *et al*., 2020, 2020a; Guzzetta *et al*., 2020; Rogers, 2020; Patwardham, 2020; Mena, 2020; Marsland III & Mehta, 2020; Pai, 2020; Azad & Poonia, 2020; Iacus *et al*., 2020; Kumar, P. *et al*., 2020; de Wolff *et al*., 2020; Radiom & Berret, 2020; Ainslie *et al*., 2020). In European countries, the first restrictions began to be introduced very early in some countries, like Switzerland (5 March), and much later in other countries, such as Russia. In some countries, there were no restrictions, such as in Belarus. In previous studies (Grassly *et al.*, 2020; de Wolff *et al*., 2020), the authors pointed out the critical role of testing strategies, as different countries have adopted different testing models. This fact should also be taken into account when considering disease dynamics.

Typical mathematical epidemiological models are built as a system of differential equations for Susceptible-Infected-Removed (SIR) sequences. SIR models, i.e., models for immunocompromising diseases, such as Covid-19, have been presented in many publications (Kucharski *et al*., 2020; Flaxman *et al*., 2020, 2020a; Lesniewski, 2020; Sonnino, 2020; Bertschinger, 2020; Casella, 2020; Pugliese & Sottile, 2020; Mora *et al*., 2020; Vattay, 2020; Kumar *et al*., 2020; Hotz *et al.*, 2020). Kobayashi *et al.* (2020) joined SIR models with State Space Modeling, while Kuniya (2020) used the Susceptible-Exposed-Infected-Removed (SEIR) compartmental model to estimate the peak of the epidemic, and Xu (2020) used the generalized fractional-order SEIR model. To assess the dynamics of epidemic diseases, time series analysis tools, including ARIMA models, have been widely used.

The aim of this article is to evaluate the usefulness of the ARIMA (1,2,0) model for predicting the dynamics of Covid-19 cases at each stage of the epidemic, i.e., at the first stage of development, at the stage of reaching the maximum number of daily cases, and at the stage of the epidemic's extinction. The choice of such models resulted from the cumulative confirmed cases of Covid-19 and was also confirmed by diagnostic measures of the model.

The remainder of this paper is as follows. In the first section, the review of the literature shows examples of the use of ARIMA models and their modifications for forecasting epidemics. The research methodology section contains a description of the procedure for selecting parameters of the ARIMA(p,d,q) model using the ADF test and AIC information criterion, as well as a discussion of forecasting errors. We also carry out data characterization. The Results section includes an evaluation of the usefulness of the ARIMA (1,2,0) model for forecasting the disease dynamics using the example of 32 European countries for 6 time moments for 7 days. The last section concludes the study.

Literature review

The issues of forecasting the dynamics of confirmed cases of Covid-19 have been widely discussed in many publications over the last three months (as to June 2020). Publications related to the application of time series analysis methods are dominated by the following models: ARIMA, SutteARIMA, Wavelet, ARIMA-WBF (wavelet-based forecasting), long short term memory (LSTM) (Ahmar & del Val, 2020; Ceylan, 2020; Chinatalapudi, 2020; Kumar, 2020; Azad & Poonina, 2020; Patwardhan, 2020; Perone, 2020; Tandon *et al.*, 2020; Yonar *et al*., 2020; Ding *et al*., 2020; Li *et al.*, 2020; Benvenuto *et al*., 2020; Dehesh *et al.*, 2020; Ribeiro *et al*., 2020).

A comparative analysis of forecast accuracy indicated the advantage of ARIMA models over the wavelet neural network or the support vector machine (see Zhang *et al*., 2019). In Singh *et al.* (2020), the advantages of a hybrid model of discrete wavelet decomposition and ARIMA were indicated. Similarly, in Chakraborty and Ghosh (2020), the modified ARIMA-WBF model was used. In the work of Fong *et al.* (2020), 11 methods of machine learning (deep learning) were compared to ARIMA in the forecasting of epidemics, and no clear advantage of any of the machine learning methods was found. Similar studies for machine learning modeling can be found in previous paper (Tuli *et al*., 2020; Magri & Doan, 2020). In contrast, Chimmula and Zhang's work (2020) points the greater usefulness of the LSTM approach compared to ARIMA models, but it points out that ARIMA has been used for many years, while only the first attempts have been made to use the LSTM approach. LSTMs were also used in previous work by Yan *et al*. (2020) and Yudistira (2020). Wu *et al.* (2020) presented a dynamic model of the spread of the epidemic from Wuhan (China) to other Chinese cities and beyond China. Spatial dynamics forecasting was presented by Wang *et al.* (2020) for the USA, Azad and Poonia (2020) for India, and Kevrekidis *et al*. (2020) for Greece and Andalusia (Spain). Bandt (2020) presented simple statistical indicators to assess the turning point of an epidemic. The work by Radio and Berret (2020) identified three types of model for each phase of the epidemic. The Bayes approach is presented in work by Calvetti *et al.* (2020) for selected US counties.

On many websites, real-time systems that re-estimate models and forecasts with daily frequency for all countries of the world can be found, for example, in the paper by Tarassow (2020). The mentioned publications show the importance of two elements: the accuracy of forecasts and the simplicity of the used models.

Research methodology

The ARIMA(p,d,q) model is a classic time series model and is determined by three parameters. The parameters p and q are the lag order in the AR(p) component and the MA(q) component, respectively, while d is the differentiation level (Box *et al*., 2015). The ARIMA(p,d,q) model has the form:

$$\begin{gathered}(1-u)^d Y_t = \alpha + \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \cdots + \phi_p Y_{t-p} + \varepsilon_t + \\ \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \cdots + \theta_q \varepsilon_{t-q} + + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \\ \cdots + \theta_q \varepsilon_{t-q}\end{gathered} \tag{1}$$

where u is the time-shift operator $u^d Y_t = Y_{t-d}$.

The differentiation parameter of process Y_t was set at d = 2, which derives from two arguments. The cumulative number of confirmed cases of Covid-19 was analyzed, where the first differences $\Delta Y_t = Y_t - Y_{t-1}$ indicated the daily number of infections. The second difference is due to the non-stationary variance for ΔY_t, which was indicated by the ADF test results (Dickey & Fuller, 1981). Moreover, for the $\Delta^2 Y_t$ process, a correlogram (ACF and PACF) was estimated in order to initially assess the order of magnitude of the delay for AR(p) and MA(q) polynomials. The final choice of parameters for d = 2 and p,q = {0,1,2,3} was made using the Akaike Information Criterion (AIC). All calculations were done in the open-source software gretl (Cottrell & Lucchetti, 2020; Baiocchi & Distaso, 2003).

Data source

A broad overview of Covid-19 databases is presented in the paper by Alamo *et al*., 2020. Recommended databases are maintained by the Johns Hopkins University Center for Systems Science and Engineering (JHU CCSE). This database contains information on confirmed cases, deaths, and recovered cases for more than 250 countries/provinces since 22 January 2020 with a daily update. The JHU CCSE database is made available to DBnomics (db.nomisc.world), which enables automatic data downloading by gretl software. Figure 1 presents the cumulative number of confirmed cases (Y_t) and Figure 2 presents the daily cases (ΔY_t) of Covid-19 for a selected European country for the period 1 February 2020 to 24 May 2020.

Results

The 32 European countries with the highest infection levels were selected for analysis (a full list of countries is presented in Table 1). The first confirmed cases of Covid-19 were reported in France (24 Jan), Finland (29 Jan), and Italy, the UK, Sweden, and Russia (31 Jan), and the last were reported in Turkey (11 Mar) and Bulgaria (8 Mar). For each country, 6 ARIMA models were estimated, which differed in terms of their sample periods. The starting date was the first date of a confirmed case, and the end date was 15 Mar, 29 Mar, 12 Apr, 26 Apr, 10 May, or 24 May, i.e., each sample period was extended by 14 days. The number of observations (T) for the first period from the beginning of the epidemic in a given country until 15 Mar was between T = 52 days (France) and T = 5 days (Turkey). Figure 1 presents the cumulative number of confirmed cases of Covid-19 for a selected European country in the period from 1 Feb 2020 to 24 May 2020, while Figure 2 shows the first differences.

For a vast majority (over 80%) of the estimated ARIMA(p,2,q) models for p, q={0,1,2,3}, the minimum value of the AIC criterion pointed to the ARIMA(1,2,0) model. Other model parameters (p≠1, q≠0) occurred in models with small samples, or outliers, or situations when the forecast cumulative number of cases decreased, which is in contrast to the epidemic theory (usually obtained when the epidemic was extinguishing). This also refers to the model for France (for the period 24 Jan–12 Apr), where, on 5 Apr, confirmed cases were corrected (decreased) by over 25,000 cases. The above automatic selection of parameters is consistent with the results obtained in previous studies (Beneventuto *et al*., 2020; Ceynan, 2020; Chintalapudiet *et al*., 2020; Tarrasow, 2020) and is the basis for further analyses and forecasts. For each model, a forecast of 7 days was calculated. The forecasts and their errors are presented in Figure 3. Table 1 presents estimated models with the sample (Start, End), number of observations (T), coefficient estimates (*const* (α), phi_1 (φ1)), standard error (sigma), R-squared (R2), and the following forecast errors: the mean absolute percentage forecast error for horizon one day and 7 days (MAPE(1) and MAPE(7)) and the mean forecast error for 7 days (ME(7)).

An essential feature of the ARIMA(1,2,0) is modeling the $\Delta^2 Y_t$ process by the autoregression model of order 1. In the parameters of the estimated equations, for all models, φ_1 satisfies the condition of the AR process stationarity ($|\varphi_1|<1$). For most models, it has a negative value, which means that the estimated predictions will oscillate (sinusoidally) to the expected value of the process. The constant term (const) has a meaningful interpretation. The value of the constant parameter indicates a daily increase in new cases. A comparison of this parameter for subsequent samples reveals the direction of dynamics in the number of new cases. For example, the constant terms for the following countries are as follows:

- For Austria (AUT), Switzerland (CHE), Czechia (CZE), Germany (DEU), Denmark (DNK), Estonia (EST), Finland (FIN), Greece (GRC), Ireland (IRL), Iceland (ISL), Lithuania (LTU), Norway (NOR), Slovakia (SVK), and Slovenia (SVN), the *const* parameter is estimated to be below 1, which means that the recent number of cases (Y_T) will not increase significantly;
- For Belgium (BEL), Spain (ESP), France (FRA), Italy (ITA), the Netherlands (NLD), Portugal (PRT), Romania (ROU), and Sweden (SWE), the value of the *const* parameter has noticeably decreased, so the extinction of the epidemic is significant, slow and visible;
- For Bulgaria (BRG) and Hungary (HUN), the *const* parameter has not reached a high level and is slowly decreasing;
- For Poland (POL), Ukraine (UKR), and Belarus (BLR), the value of the *const* parameter indicates that there has not yet been a decrease in the number of cases, i.e., the epidemic will be spread over time;
- For the United Kingdom (GBR) and Turkey (TUR), the value of the *const* parameter is high but lower than in previous sub-periods;
- For Russia (RUS), the value of the *const* parameter is the highest among European countries, and the increase in the number of cases is significant.

The evaluation of the accuracy of the forecasts indicates two aspects: the usefulness for governments to determine the effectiveness of non-pharmaceutical countermeasures and the location of the disease curve. During the initial period of the epidemic, when a rapidly growing number of cases is observed, one can notice the underestimation of forecasts (ME < 0); the forecasting errors are high (over 5%–10%). For the extinction stage of the epidemic, the forecast errors are lower (less than 2%), while ME > 0 (overestimated forecast). For Bulgaria (BGR), Belarus (BLR), the United Kingdom (GBR), Poland (POL), Romania (ROU), Russia (RUS), Sweden (SWE), Turkey (TUR), and Ukraine (UKR), we can observe a continuous and significant increase in the number of cases (status for 24 May 2020), that is, the extinction of the epidemic is still not coming and will last for a longer time.

Discussion

ARIMA(1,2,0) was used to assess the dynamics of the epidemic, although in some countries for different sub-periods, the AIC criterion indicated different parameters. An alternative set of parameters usually resulted from single outlier observations, which negatively affected the accuracy of forecasts (explosive prognoses). For the period of the epidemic's extinction, ARIMA models with the parameters $p=\{2, 3\}$ caused a decrease in the cumulative number of forecast cases, which is contrary to the theory. Similar issue has appeared in work of Perone (2020).

For some sub-periods, in several countries, the effect of weekly periodicity could be observed, but this is only the result of the ARIMA model's approximative adjustment to the time series. Therefore, at the stage of assumptions, the inclusion of the periodical component was rejected.

Some publications indicate that ARIMA models are useful only for short-term forecasts. However, the ARIMA(1,2,0) model for the assessment of cumulative case dynamics and parameter analysis is highly useful.

Conclusions

The article presented the usefulness of the ARIMA(1,2,0) model for predicting the dynamics of COVID-19 cases at different stages of the development of the epidemic, i.e., at the first stage of development, at the time when the maximum number of daily cases is reached, and at the stage of the epidemic's extinction. ARIMA(1,2,0) models were estimated for 32 European countries for six samples, and forecasts for 7 days were made for each sample. The obtained results (parameter estimates) can be interpreted and compared between countries and, more importantly, between different stages of the epidemic.

The results of Covid-19 forecasts using the ARIMA(1,2,0) model should be addressed in further studies in terms of the roles of two elements limiting the number of cases: non-pharmaceutical interventions and population testing policies. Moreover, the evaluation should also concern the impact of non-pharmaceutical interventions on economic aspects. The first adverse effects of the pandemic on the economy are presented in a number of previous papers (Iacus *et al*., 2020; Karina *et al*., 2020; Centeno & Marquez, 2020; Narajewski & Ziel, 2020).

By employing Covid-19 databases that are updated daily (by DBnomics), models and forecasts can be re-estimated daily, which is also indicated by (Benvenuto *et. al*., 2020). That is why ARIMA models can be viewed as an immediate and straightforward system for monitoring the epidemic at national and regional levels.

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Acknowledgements

The research was funded by a grant awarded in the CRUSH programme within Nicolaus Copernicus University’s "Excellence Initiative - Research University” project (ID-UB).

Annex

Table 1. Estimates of ARIMA(1,2,0) models for six subperiods and 32 selected countries

Start	End	T	Const	phi_1	Sigma	R2	MAPE(1)	MAPE(7)	ME(7)
AUT—Austria									
25-Feb	15-Mar	20	**9.6304**	-0.5089	30.8	0.9861	3.3450	15.0030	382.9
25-Feb	29-Mar	34	**16.4626**	-0.5033	198.9	0.9946	2.4894	3.4458	-219.7
25-Feb	12-Apr	48	**3.6892**	-0.4915	179.9	0.9989	0.7375	1.8461	-268.9
25-Feb	26-Apr	62	**1.2420**	-0.4900	159.4	0.9994	0.1954	0.6231	-96.7
25-Feb	10-May	76	**0.5878**	-0.4926	144.3	0.9995	0.2407	0.1253	3.3
25-Feb	24-May	90	**0.3034**	-0.4947	133.0	0.9996	0.0134	0.0373	4.0
BEL—Belgium									
4-Feb	15-Mar	41	**4.2540**	-0.6121	35.3	0.9698	0.8651	14.2170	387.7
4-Feb	29-Mar	55	**31.9932**	-0.3755	142.8	0.9976	6.2070	16.5110	-2684.4
4-Feb	12-Apr	69	**23.0458**	-0.1969	189.3	0.9995	2.1571	4.8351	-1706.6
4-Feb	26-Apr	83	**10.5997**	-0.4126	307.6	0.9996	0.7775	2.8238	-1383.2
4-Feb	10-May	97	**5.3165**	-0.3990	291.0	0.9998	0.3075	1.5907	-869.6
4-Feb	24-May	111	**2.5955**	-0.3949	273.4	0.9999	0.0738	0.7530	-437.0
BGR—Bulgaria									
8-Mar	15-Mar	8	**1.4193**	-0.2470	6.5	0.8828	24.5110	12.0380	-4.2
8-Mar	29-Mar	22	**0.9228**	-0.3411	11.4	0.9901	3.0869	2.4448	7.8
8-Mar	12-Apr	36	**0.4659**	-0.4498	10.8	0.9977	1.4705	5.2310	41.4
8-Mar	26-Apr	50	**0.7838**	-0.4825	21.0	0.9968	2.0645	2.0920	31.4
8-Mar	10-May	64	**0.6984**	-0.4119	20.2	0.9988	1.1078	2.6142	-55.7
8-Mar	24-May	78	**0.2934**	-0.4004	18.9	0.9994	0.8310	2.2106	-54.9
BLR—Belarus									
28-Feb	15-Mar	17	**-0.0173**	-0.3977	4.7	0.7981	25.0670	48.0590	29.7
28-Feb	29-Mar	31	**-0.0133**	-0.6723	5.5	0.9767	38.1730	60.4610	209.6
28-Feb	12-Apr	45	**7.4129**	-0.2464	58.4	0.9907	0.2097	3.7571	74.8
28-Feb	26-Apr	59	**14.6478**	-0.4392	227.4	0.9933	0.3852	0.4648	-54.1
28-Feb	10-May	73	**12.8404**	-0.4382	206.1	0.9991	0.0820	0.3215	-90.7
28-Feb	24-May	87	**10.9877**	-0.4386	189.0	0.9997	0.0487	0.6980	-286.8
CHE—Switzerland									
25-Feb	15-Mar	20	**28.5520**	-0.9154	116.1	0.9791	14.8740	14.3030	-146.5
25-Feb	29-Mar	34	**27.2192**	-0.6246	226.5	0.9977	0.3082	1.4056	-263.9
25-Feb	12-Apr	48	**8.4123**	-0.5781	233.2	0.9994	0.7460	1.6991	-457.9
25-Feb	26-Apr	62	**3.0060**	-0.5598	210.0	0.9997	0.3315	1.0066	-298.6
25-Feb	10-May	76	**0.6630**	-0.5579	190.6	0.9998	0.0345	0.1533	-46.8
25-Feb	24-May	90	**0.1498**	-0.5586	175.3	0.9998	0.0167	0.0394	9.0

Table 1. Continued

Start	End	T	Const	phi_1	Sigma	R2	MAPE(1)	MAPE(7)	ME(7)
				CZE—Czechia					
1-Mar	15-Mar	15	**3.9821**	-0.6307	15.2	0.9616	5.1687	17.5650	149.4
1-Mar	29-Mar	29	**8.1348**	-0.3859	53.3	0.9960	2.5770	1.4410	-34.5
1-Mar	12-Apr	43	**3.2412**	-0.5587	67.9	0.9990	1.0393	2.9532	-190.7
1-Mar	26-Apr	57	**1.0643**	-0.4956	67.1	0.9994	0.3489	0.4219	-24.8
1-Mar	10-May	71	**0.3382**	-0.4792	61.5	0.9996	0.3583	1.3191	110.7
1-Mar	24-May	85	**0.8054**	-0.4839	57.4	0.9997	0.2777	1.1215	-103.9
				DEU—Germany					
27-Jan	15-Mar	49	**22.7022**	-0.6102	187.1	0.9767	5.6864	28.9970	5427.8
27-Jan	29-Mar	63	**76.4129**	-0.1944	618.6	0.9983	0.2579	2.0990	1797.1
27-Jan	12-Apr	77	**38.2867**	0.0097	692.0	0.9997	0.5904	1.7374	-2417.7
27-Jan	26-Apr	91	**14.0175**	-0.0772	731.3	0.9998	0.1914	0.2958	-484.4
27-Jan	10-May	105	**5.3948**	-0.0669	688.9	0.9999	0.0719	0.1796	314.0
27-Jan	24-May	119	**2.8254**	-0.0951	661.1	0.9999	0.0370	0.2519	441.2
				DNK—Denmark					
27-Feb	15-Mar	18	**2.0766**	0.0464	48.2	0.9813	1.1498	9.2126	114.9
27-Feb	29-Mar	32	**6.0513**	-0.0129	40.7	0.9971	0.6840	5.4931	205.6
27-Feb	12-Apr	46	**3.8696**	0.0011	46.6	0.9994	0.5993	0.8935	-62.7
27-Feb	26-Apr	60	**2.3523**	-0.1141	47.1	0.9997	0.2483	0.3405	-31.8
27-Feb	10-May	74	**1.4775**	-0.1046	43.8	0.9999	0.2539	1.4900	-161.0
27-Feb	24-May	88	**0.7933**	-0.1161	40.9	0.9999	0.3820	1.0363	-119.9
				ESP—Spain					
1-Feb	15-Mar	44	**30.3395**	-0.5875	425.6	0.9366	8.3940	22.7310	4865.7
1-Feb	29-Mar	58	**124.2310**	-0.6389	808.9	0.9983	0.4069	1.1034	593.7
1-Feb	12-Apr	72	**58.1815**	-0.5640	833.0	0.9998	0.6836	0.9065	-555.9
1-Feb	26-Apr	86	**25.0692**	-0.5561	2130.4	0.9992	0.2848	1.4174	-3051.2
1-Feb	10-May	100	**7.5364**	-0.5571	1986.4	0.9995	1.0248	0.8140	1864.8
1-Feb	24-May	114	**4.1776**	-0.5565	1888.7	0.9996	0.3618	0.2156	-146.6
				EST—Estonia					
27-Feb	15-Mar	18	**2.8154**	-0.5299	14.1	0.9073	7.6633	47.0510	-135.7
27-Feb	29-Mar	32	**1.4888**	-0.5606	24.7	0.9862	2.8680	3.9661	-7.0
27-Feb	12-Apr	46	**0.3691**	-0.4165	26.3	0.9967	0.0302	3.2733	48.2
27-Feb	26-Apr	60	**0.2419**	-0.4350	24.2	0.9984	0.8450	1.6434	-27.7
27-Feb	10-May	74	**0.0859**	-0.4343	22.0	0.9989	0.2867	0.4972	-8.8
27-Feb	24-May	88	**0.0611**	-0.4357	20.3	0.9992	0.3463	0.2147	1.3
				FIN—Finland					
29-Jan	15-Mar	47	**0.6573**	-0.3018	16.0	0.9134	0.8107	8.3266	40.3
29-Jan	29-Mar	61	**1.4721**	-0.4404	18.1	0.9969	1.0013	3.4526	-27.6
29-Jan	12-Apr	75	**1.3001**	-0.7111	34.3	0.9983	0.9422	1.1637	6.0
29-Jan	26-Apr	89	**1.0449**	-0.6718	35.3	0.9994	0.6467	0.4901	16.8
29-Jan	10-May	103	**1.0312**	-0.6570	37.9	0.9996	1.6900	4.1957	-259.8
29-Jan	24-May	117	**0.1564**	-0.6077	38.0	0.9998	0.0516	1.0958	73.5

Table 1. Continued

Start	End	T	Const	phi_1	Sigma	R2	MAPE(1)	MAPE(7)	ME(7)
				FRA—France					
24-Jan	15-Mar	52	**4.7387**	-0.3747	239.8	0.9537	27.2270	46.0040	5426.2
24-Jan	29-Mar	66	**51.1608**	-0.5838	483.7	0.9975	1.1703	8.0500	4934.8
24-Jan	12-Apr	80	**222.1480**	-0.6381	2708.4	0.9920	6.7576	35.1960	-50753
24-Jan	26-Apr	94	**10.0816**	-0.5297	3322.8	0.9963	1.5726	0.8828	1285.0
24-Jan	10-May	108	**3.0564**	-0.5265	3183.0	0.9978	0.0503	0.1518	190.6
24-Jan	24-May	122	**2.9745**	-0.5266	2999.3	0.9984	0.1044	1.4146	2588.2
				GBR—United Kingdom					
31-Jan	15-Mar	45	**1.3377**	-0.2131	72.4	0.9363	21.2900	50.9500	1947.8
31-Jan	29-Mar	59	**41.9625**	-0.2673	248.5	0.9968	0.4635	10.5060	4156.0
31-Jan	12-Apr	73	**73.0447**	-0.5710	679.9	0.9990	1.1615	2.3200	-2473.6
31-Jan	26-Apr	87	**53.4937**	-0.5402	677.0	0.9998	0.3051	0.4732	-522.4
31-Jan	10-May	101	**38.9837**	-0.4183	743.3	0.9999	0.0403	0.8757	-2080.0
31-Jan	24-May	115	**22.2725**	-0.3896	806.8	0.9999	0.3931	0.5398	-1341.3
				GRC—Greece					
26-Feb	15-Mar	19	**4.1131**	-0.7548	21.0	0.9475	18.4760	45.1960	-218.0
26-Feb	29-Mar	33	**2.9401**	-0.7089	25.7	0.9947	3.6324	4.8392	-75.8
26-Feb	12-Apr	47	**1.0279**	-0.6732	26.8	0.9986	1.3347	5.6306	-124.9
26-Feb	26-Apr	61	**0.2084**	-0.6314	32.5	0.9988	0.0988	0.6510	16.9
26-Feb	10-May	75	**0.1433**	-0.6307	29.6	0.9992	0.1626	0.6254	16.3
26-Feb	24-May	89	**0.0183**	-0.6313	27.6	0.9993	0.0684	0.5906	17.2
				HUN—Hungary					
4-Mar	15-Mar	12	**0.3993**	-0.5577	3.5	0.8819	1.6441	18.6470	17.5
4-Mar	29-Mar	26	**2.2579**	-0.4772	6.8	0.9973	4.2139	13.5860	-84.1
4-Mar	12-Apr	40	**2.6682**	-0.4050	26.5	0.9955	4.3792	11.4120	-196.7
4-Mar	26-Apr	54	**0.7293**	-0.4414	33.9	0.9983	1.9398	4.5237	128.7
4-Mar	10-May	68	**0.6690**	-0.4037	31.7	0.9992	0.7273	1.9105	-65.2
4-Mar	24-May	82	**0.3615**	-0.4030	29.3	0.9995	0.4347	1.2854	-49.3
				IRL—Ireland					
29-Feb	15-Mar	16	**0.4600**	-0.2332	16.1	0.8821	17.9520	56.9470	350.6
29-Feb	29-Mar	30	**7.4846**	-0.2942	51.3	0.9958	1.9812	7.0278	299.2
29-Feb	12-Apr	44	**17.3248**	-0.3210	183.9	0.9953	1.9364	2.2318	228.8
29-Feb	26-Apr	58	**10.8513**	-0.3089	195.9	0.9990	1.1661	6.3422	-1324.7
29-Feb	10-May	72	**3.2374**	-0.3088	183.2	0.9995	0.4149	1.2210	-290.6
29-Feb	24-May	86	**0.7154**	-0.3089	173.2	0.9997	0.0195	0.2269	-56.5
				ISL—Iceland					
28-Feb	15-Mar	17	**0.9506**	-0.1721	5.9	0.9884	4.6214	23.6520	99.9
28-Feb	29-Mar	31	**2.0372**	-0.4762	19.2	0.9964	0.1498	1.1481	-8.1
28-Feb	12-Apr	45	**0.2762**	-0.3803	20.9	0.9989	0.1836	0.8410	-14.7
28-Feb	26-Apr	59	**0.0248**	-0.3827	18.3	0.9994	0.0922	0.1429	-2.6
28-Feb	10-May	73	**-0.0038**	-0.3842	16.5	0.9995	0.0003	0.0424	0.8
28-Feb	24-May	87	**0.0000**	-0.3850	15.1	0.9996	0.0213	0.0160	-0.2

Table 1. Continued

Start	End	T	Const	phi_1	Sigma	R2	MAPE(1)	MAPE(7)	ME(7)
				ITA—Italy					
31-Jan	15-Mar	45	**80.0970**	-0.2789	279.0	0.9984	1.5493	5.1787	2225.3
31-Jan	29-Mar	59	**88.3659**	0.0036	407.0	0.9998	1.2309	3.6608	-4354.7
31-Jan	12-Apr	73	**55.5008**	0.0589	449.3	0.9999	0.5992	2.4265	-4173.5
31-Jan	26-Apr	87	**26.7028**	0.0248	477.7	1.0000	0.3060	0.9335	-1936.0
31-Jan	10-May	101	**7.8720**	0.0238	456.2	1.0000	0.0268	0.2568	557.0
31-Jan	24-May	115	**4.6200**	-0.0022	438.0	1.0000	0.1025	0.1711	-396.8
				LTU—Lithuania					
28-Feb	15-Mar	17	**0.1657**	-0.7973	0.7	0.9555	13.5110	36.4170	27.9
28-Feb	29-Mar	31	**1.7732**	-0.6718	11.4	0.9927	3.6272	7.0654	-47.1
28-Feb	12-Apr	45	**0.6018**	-0.6324	12.6	0.9989	1.7874	3.0469	-21.1
28-Feb	26-Apr	59	**0.2229**	-0.4999	16.0	0.9991	0.2301	7.1662	-99.4
28-Feb	10-May	73	**0.3486**	-0.5381	22.8	0.9985	1.0106	4.5717	-69.6
28-Feb	24-May	87	**0.0973**	-0.5376	21.1	0.9989	0.1323	0.3435	-5.1
				LUX—Luxembourg					
29-Feb	15-Mar	16	**0.4814**	0.0321	3.5	0.9689	12.7570	61.9810	291.2
29-Feb	29-Mar	30	**4.7446**	-0.2534	45.9	0.9946	5.7375	5.2971	-132.7
29-Feb	12-Apr	44	**0.4230**	-0.2699	50.8	0.9984	0.3114	2.0177	63.4
29-Feb	26-Apr	58	**0.2193**	-0.2670	46.2	0.9990	0.1970	0.1938	2.8
29-Feb	10-May	72	**0.1139**	-0.2688	41.6	0.9993	0.1630	0.1699	-6.6
29-Feb	24-May	86	**0.0383**	-0.2708	38.1	0.9994	0.0737	0.0511	-0.6
				NLD—Netherlands					
27-Feb	15-Mar	18	**9.7207**	-0.6695	60.7	0.9690	7.0651	22.7390	701.2
27-Feb	29-Mar	32	**35.3328**	-0.2723	88.3	0.9993	2.3824	7.0786	-1093.7
27-Feb	12-Apr	46	**25.9117**	-0.1035	124.4	0.9998	0.9540	4.0555	-1225.6
27-Feb	26-Apr	60	**10.9160**	0.0391	137.0	0.9999	0.6942	3.1602	-1254.7
27-Feb	10-May	74	**3.2971**	0.0221	139.4	0.9999	0.2016	0.4868	-212.3
27-Feb	24-May	88	**1.9536**	0.0208	129.5	0.9999	0.774	0.0492	-8.9
				NOR—Norway					
26-Feb	15-Mar	19	**6.4304**	-0.5395	63.9	0.9757	0.6704	2.1690	11.6
26-Feb	29-Mar	33	**8.2163**	-0.5002	60.6	0.9979	2.6057	6.7592	-357.0
26-Feb	12-Apr	47	**2.3507**	-0.4680	65.4	0.9992	0.4789	2.1225	-146.7
26-Feb	26-Apr	61	**0.5021**	-0.4816	63.1	0.9995	0.5185	1.0081	78.1
26-Feb	10-May	75	**0.1766**	-0.4799	57.5	0.9996	0.1193	0.3808	31.3
26-Feb	24-May	89	**0.0936**	-0.4799	52.9	0.9997	0.0242	0.2349	19.8
				POL—Poland					
4-Mar	15-Mar	12	**2.1833**	-0.8384	5.7	0.9789	12.4620	28.1830	121.1
4-Mar	29-Mar	26	**9.2498**	-0.6342	23.1	0.9986	3.0156	3.8801	69.2
4-Mar	12-Apr	40	**8.9785**	-0.6995	50.2	0.9994	1.8938	2.7054	-215.5
4-Mar	26-Apr	54	**6.7101**	-0.5910	63.5	0.9997	0.7691	2.3908	-314.8
4-Mar	10-May	68	**4.8088**	-0.5394	66.3	0.9999	0.0610	1.1509	203.3
4-Mar	24-May	82	**4.4878**	-0.5625	75.9	0.9999	0.2327	0.2565	-48.2

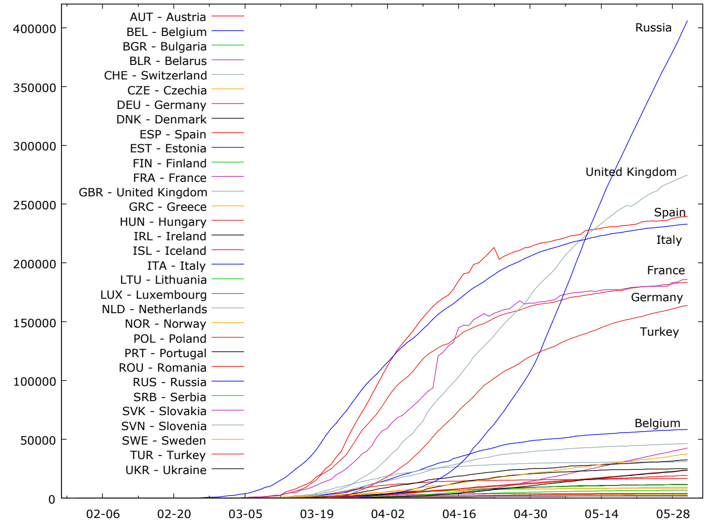
Table 1. Continued

Start	End	T	Const	phi_1	Sigma	R2	MAPE(1)	MAPE(7)	ME(7)
				PRT—Portugal					
2-Mar	15-Mar	14	**5.2361**	-0.3441	14.6	0.9641	2.8701	23.2720	247.8
2-Mar	29-Mar	28	**30.4859**	-0.5741	92.5	0.9975	7.1340	7.8984	-745.6
2-Mar	12-Apr	42	**13.8209**	-0.4990	215.2	0.9985	1.3482	2.3122	-438.9
2-Mar	26-Apr	56	**9.2807**	-0.5303	209.8	0.9994	1.6166	4.9787	-1246.0
2-Mar	10-May	70	**2.3456**	-0.4540	221.5	0.9995	0.2298	0.3810	90.8
2-Mar	24-May	84	**2.2564**	-0.4553	203.5	0.9997	0.1444	0.6636	196.6
				ROU—Romania					
26-Feb	15-Mar	19	**0.8396**	-0.4247	10.7	0.9356	4.2797	23.4910	76.3
26-Feb	29-Mar	33	**8.7697**	-0.6521	46.3	0.9917	2.3178	5.7592	-146.1
26-Feb	12-Apr	47	**8.1700**	-0.4795	80.5	0.9982	1.3752	3.5953	-282.5
26-Feb	26-Apr	61	**5.8121**	-0.3689	89.0	0.9994	0.3391	2.1623	-271.8
26-Feb	10-May	75	**3.4661**	-0.4383	88.4	0.9997	0.3143	1.3186	-216.8
26-Feb	24-May	89	**2.1732**	-0.4337	83.2	0.9998	0.1443	-.4654	-80.9
				RUS – Russia					
31-Jan	15-Mar	45	**0.1260**	-0.2536	3.1	0.9552	22.5620	50.6240	121.7
31-Jan	29-Mar	59	**4.6343**	0.0898	16.0	0.9981	1.3078	20.4660	854.2
31-Jan	12-Apr	73	**29.4419**	-0.0859	100.4	0.9995	2.0985	12.7780	4363.9
31-Jan	26-Apr	87	**72.2945**	-0.3945	314.8	0.9998	0.1239	1.6044	1670.7
31-Jan	10-May	101	**108.9590**	-0.1089	411.1	0.9999	0.2460	1.1655	-2903.0
31-Jan	24-May	115	**75.8326**	-0.1694	451.8	1.0000	0.0331	0.2683	-971.4
				SRB—Serbia					
6-Mar	15-Mar	10	**0.1445**	0.0628	4.6	0.9571	9.8715	44.1060	63.8
6-Mar	29-Mar	24	**5.1537**	-0.4758	39.7	0.9638	13.0830	8.1041	-31.0
6-Mar	12-Apr	38	**6.9104**	-0.4992	52.6	0.9977	3.7287	8.9109	485.4
6-Mar	26-Apr	52	**5.2798**	-0.3720	59.8	0.9995	0.5984	3.2380	-296.1
6-Mar	10-May	66	**0.4855**	-0.5628	72.1	0.9996	0.9154	1.8902	197.1
6-Mar	24-May	80	**0.8450**	-0.5670	67.7	0.9998	0.3117	1.1819	-134.1
				SVK—Slovakia					
6-Mar	15-Mar	10	**1.0602**	-0.2392	3.7	0.9622	4.4319	12.1100	14.1
6-Mar	29-Mar	24	**0.9399**	-0.4226	12.6	0.9847	0.5237	1.6898	3.0
6-Mar	12-Apr	38	**0.3588**	-0.3978	18.7	0.9940	1.6770	15.5750	161.8
6-Mar	26-Apr	52	**0.1511**	-0.4179	24.6	0.9970	0.5170	1.2986	-18.2
6-Mar	10-May	66	**0.0171**	-0.4156	21.9	0.9984	0.0819	0.9476	13.7
6-Mar	24-May	80	**0.0444**	-0.4192	20.0	0.9988	0.0918	0.4748	-7.2
				SVN—Slovenia					
5-Mar	15-Mar	11	**3.5911**	-0.2644	9.1	0.9854	3.5848	29.8990	-100.9
5-Mar	29-Mar	25	**1.8891**	-0.1877	15.3	0.9955	3.0913	6.0387	-55.6
5-Mar	12-Apr	39	**0.4885**	-0.2586	14.4	0.9988	1.1105	1.3823	-17.5
5-Mar	26-Apr	53	**0.1732**	-0.2835	13.3	0.9993	0.3000	0.8830	-12.6
5-Mar	10-May	67	**0.0418**	-0.2794	12.0	0.9995	0.0228	0.4802	-7.0
5-Mar	24-May	81	**-0.0054**	-0.2804	10.9	0.9996	0.0685	0.2473	3.6

Table 1. Continued

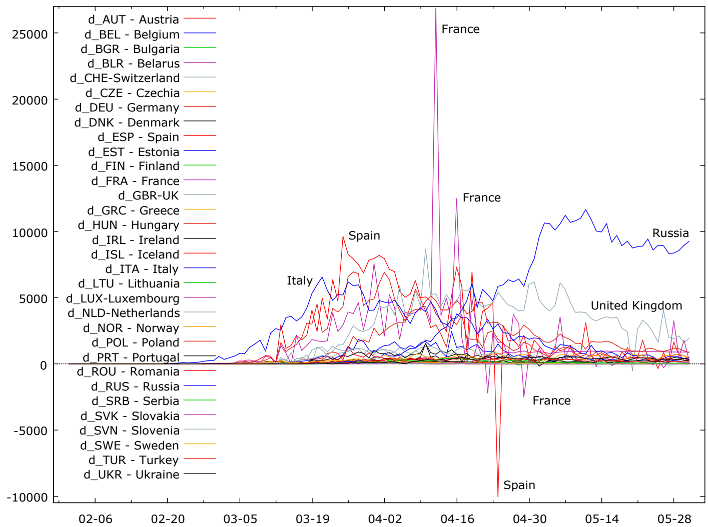
Start	End	T	Const	phi_1	Sigma	R2	MAPE(1)	MAPE(7)	ME(7)
				SWE—Sweden					
31-Jan	15-Mar	45	**1.8877**	-0.3694	28.3	0.9881	1.3013	5.8482	88.0
31-Jan	29-Mar	59	**5.1481**	-0.6072	37.7	0.9986	0.2278	8.1940	493.1
31-Jan	12-Apr	73	**4.6212**	-0.0389	69.9	0.9994	1.1233	5.4588	724.4
31-Jan	26-Apr	87	**5.2901**	0.0181	79.1	0.9998	0.9486	1.6189	292.9
31-Jan	10-May	101	**4.3691**	-0.1812	105.5	0.9998	0.3913	1.3047	350.5
31-Jan	24-May	115	**2.4459**	-0.1041	114.4	0.9999	0.2927	3.1014	1132.0
				TUR—Turkey					
11-Mar	15-Mar	5	**0.0512**	-0.6450	1.8	0.6331	64.2270	90.0830	365.3
11-Mar	29-Mar	19	**95.0683**	0.0997	265.7	0.9903	2.7861	4.9767	960.5
11-Mar	12-Apr	33	**149.1350**	-0.2642	336.4	0.9996	1.6000	5.7595	-4493.9
11-Mar	26-Apr	47	**49.9571**	0.0169	440.1	0.9999	0.2375	0.4557	-473.9
11-Mar	10-May	61	**25.2745**	0.0590	412.9	0.9999	0.3231	0.2737	-397.1
11-Mar	24-May	75	**15.1882**	0.0396	385.9	1.0000	0.1057	0.3905	-275.4
				UKR—Ukraine					
3-Mar	15-Mar	13	**-0.0277**	-0.5168	0.7	0.5577	57.7420	83.3660	25.9
3-Mar	29-Mar	27	**3.2843**	-0.8172	16.5	0.9835	1.4023	7.4405	77.2
3-Mar	12-Apr	41	**6.7111**	-0.2023	40.1	0.9973	1.3679	5.7731	275.1
3-Mar	26-Apr	55	**8.9530**	-0.1724	54.3	0.9995	1.1997	2.6222	-278.5
3-Mar	10-May	69	**7.5807**	-0.1763	57.0	0.9999	0.7265	2.8594	-493.9
3-Mar	24-May	83	**4.9145**	-0.0580	60.4	0.9999	0.7235	1.2244	-275.4

Figure 1. Cumulative number of confirmed cases of Covid-19 for selected European countries (1 Feb 2020–31 May 2020)—Y_t



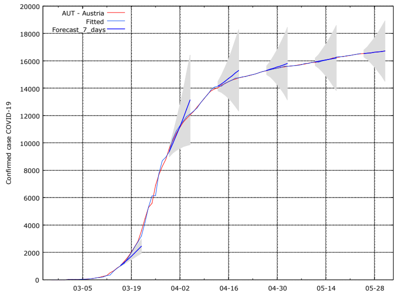
Source: own calculation based on db.nomics.world data.

Figure 2. Number of daily confirmed cases of Covid-19 for selected European countries (1 Feb 2020–31 May 2020)—ΔY_t

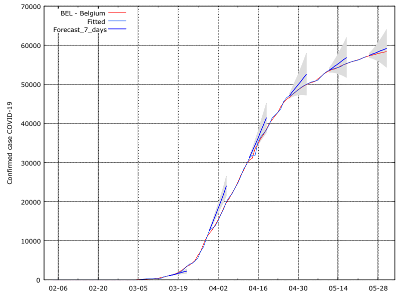


Source: own calculation based on db.nomics.world data.

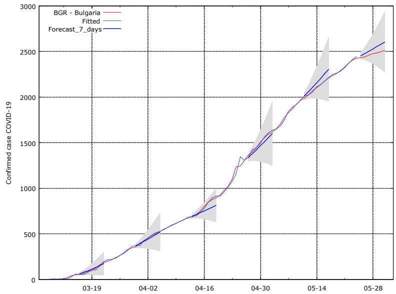
Figure 3. Forecast (7 days) of confirmed cases of COVID-19 ARIMA(1,2,0) based for 6 periods for 32 selected countries



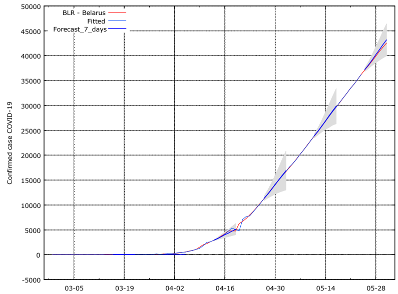
AUT—Austria



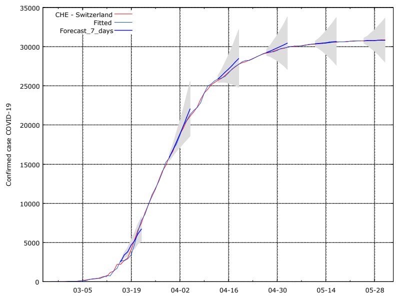
BEL—Belgium



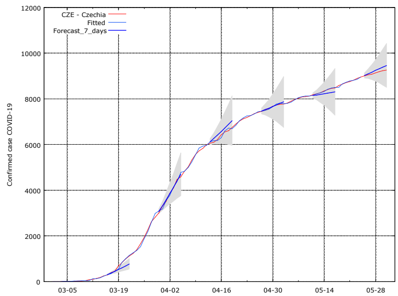
BGR—Bulgaria



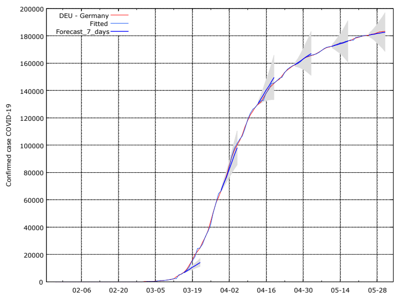
BLR—Belarus



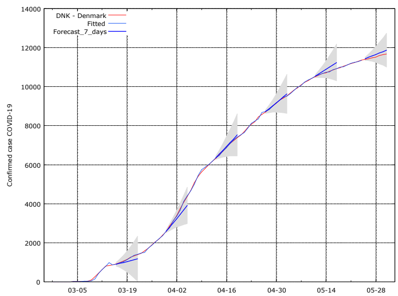
CHE—Switzerland



CZE—Czechia

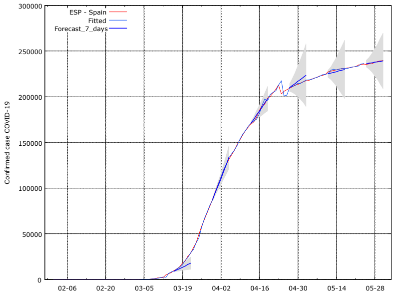


DEU—Germany

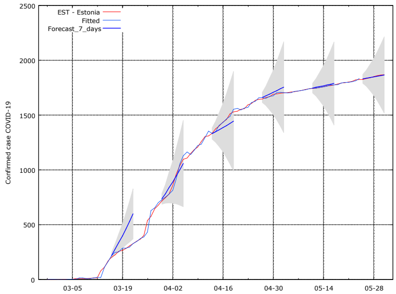


DNK—Denmark

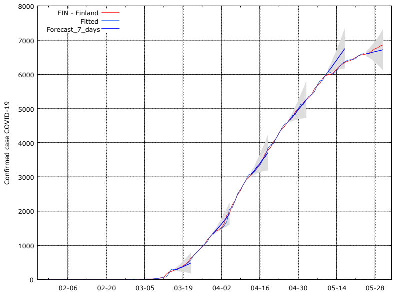
Figure 3. Continued



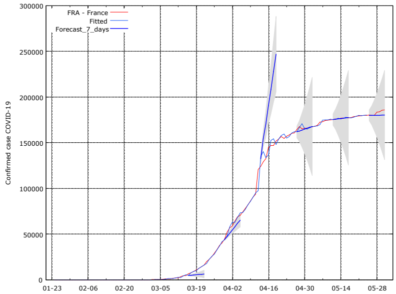
ESP—Spain



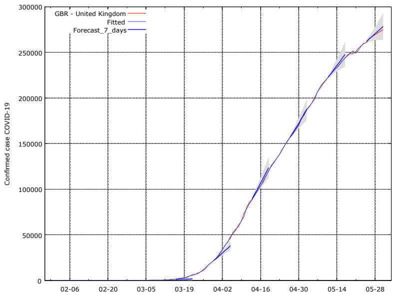
EST—Estonia



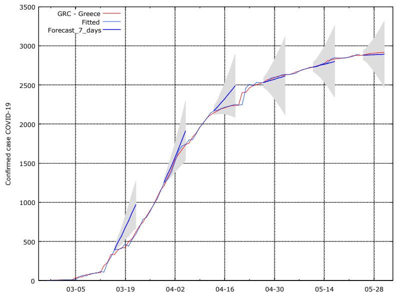
FIN—Finland



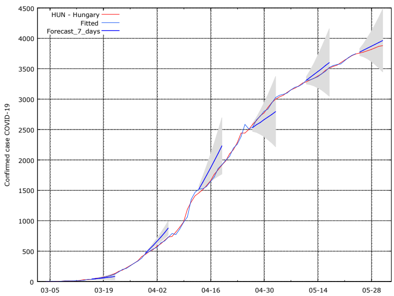
FRA—France



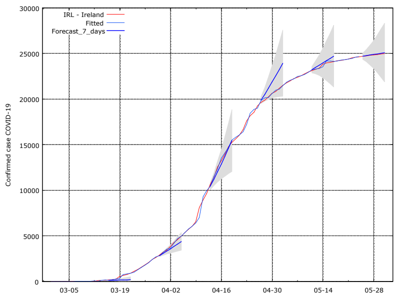
GBR—United Kingdom



GRC—Greece

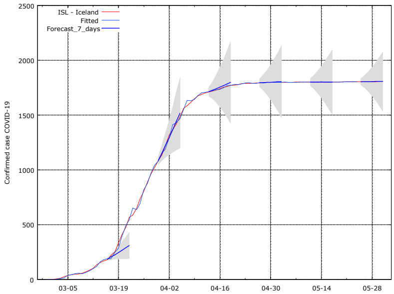


HUN – Hungary

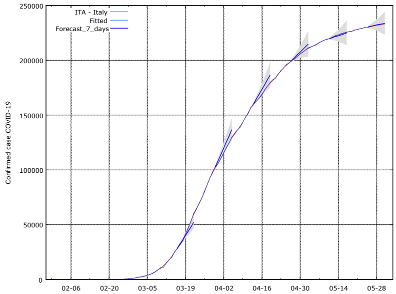


IRL - Ireland

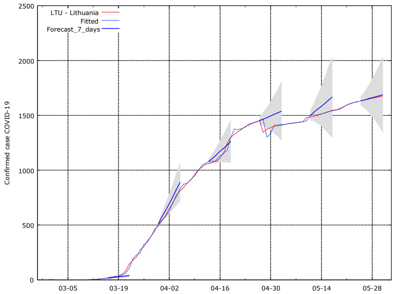
Figure 3. Continued



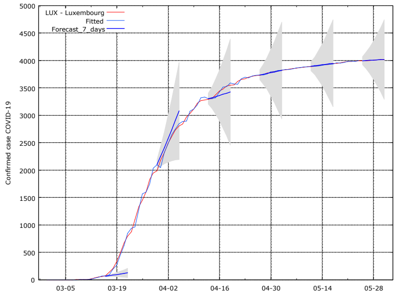
ISL—Iceland



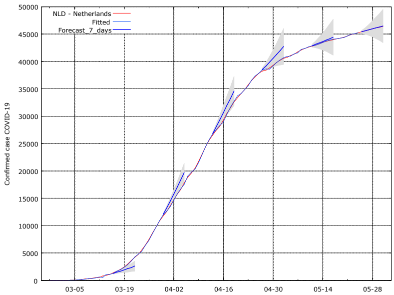
ITA—Italy



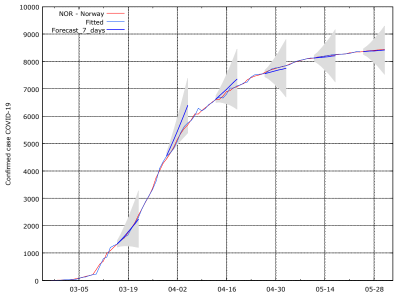
LTU—Lithuania



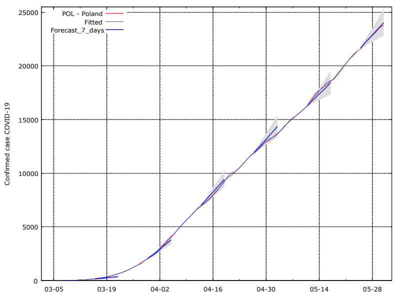
LUX—Luxembourg



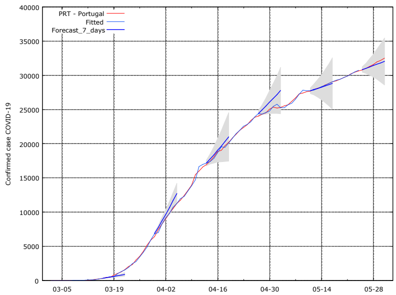
NLD—Netherlands



NOR—Norway

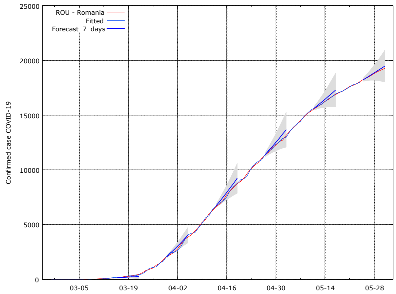


POL—Poland

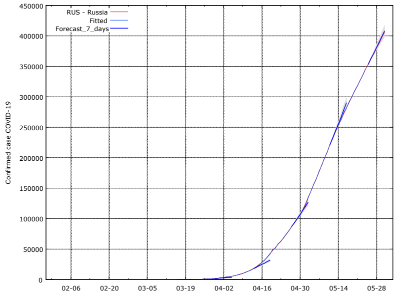


PRT—Portugal

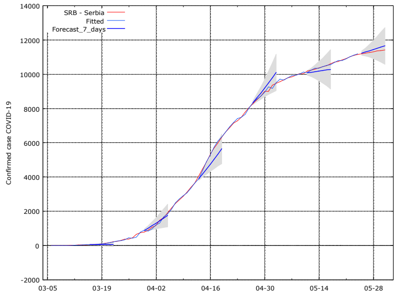
Figure 3. Continued



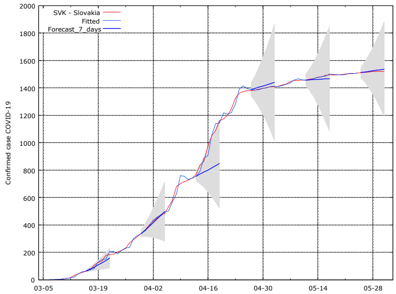
ROU—Romania



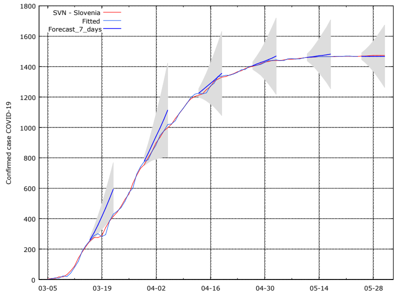
RUS—Russia



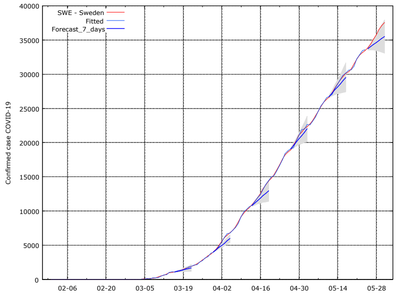
SRB – Serbia



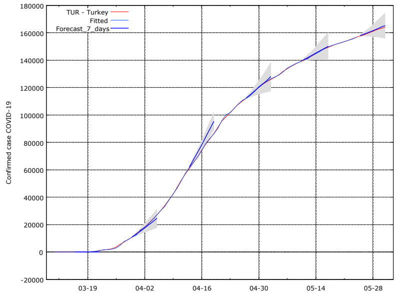
SVK – Slovakia



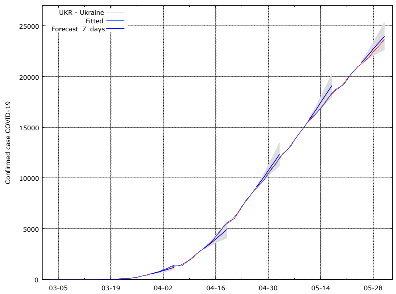
SVN—Slovenia



SWE—Sweden



TUR—Turkey



UKR—Ukraine