Nova School of Business and Economics

Assignment 1

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2272 Financial Econometrics

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Part I

The following analysis is based on the data provided in the spreadsheet "owid-covid-data". The data set contains relevant data on the Covid-19 pandemic of various countries. According to the task, only the contained sub-sample with data for "*new cases*" (y_t) in Portugal is considered. The time series contains 351 observations from 2$^{\text{nd}}$ February 2020 to 6$^{\text{th}}$ February 2021.

1 Modelling

1.1 Graph the new daily cases and its first difference. Comment on the stationarity of both series.

In the following, the group will first examine the time series for stationarity by using the plot as shown in Figure 1 below. In a next step, we will test with the **A**ugmented **D**icky **F**uller (ADF) and the KPSS test to validate our analysis. To comment on the time dependence, we will then look at the **A**uto**C**correlation **F**unction (ACF) and **P**artial **A**uto**C**correlation **F**unction ($PACF$). Using the same methodology, the group also tests the *first difference of new cases*, i.e., ($\Delta y_t = y_t - y_{t-1}$) for stationartiy.

In general, a time series process $\{Y_t \mid t \in T\}$ is weakly stationary (or second-order stationary) if

1. The mean function is constant and finite - $\mu_t = \mathbb{E}[Y_t] = \mu < \infty$
2. The variance function is constant and finite - $\sigma_t^2 = \mathrm{Var}[Y_t] = \sigma^2 < \infty$
3. The autocovariance and autocorrelation functions only depend on the lag

It is also important to note that a stationary time series will have no predictable patterns in the long-term. Time plots will show the series to be roughly horizontal (although some cyclic behaviour is possible), with constant variance [1].

The starting point for the examination of the time series for stationarity is the plot, shown in Figure 1 below. Observing the trending behaviour in the graph it can be assumed that the series is nonstationary. This also clearly observable, when looking at the rolling standard-deviation and mean in the plot. Both lines have a constant variation in the beginning, which indicates a stationary behavior, however, starting in September 2020, the original time-series, mean and standard deviation show an explosive upward movement. This already shows that forecasting unstable processes by explosive models, like one can see in the below plot, may have significant consequences in terms of forecast variability. This means, that in order to transform the data into a stationary time-series, a first-order differencing may not be enough.

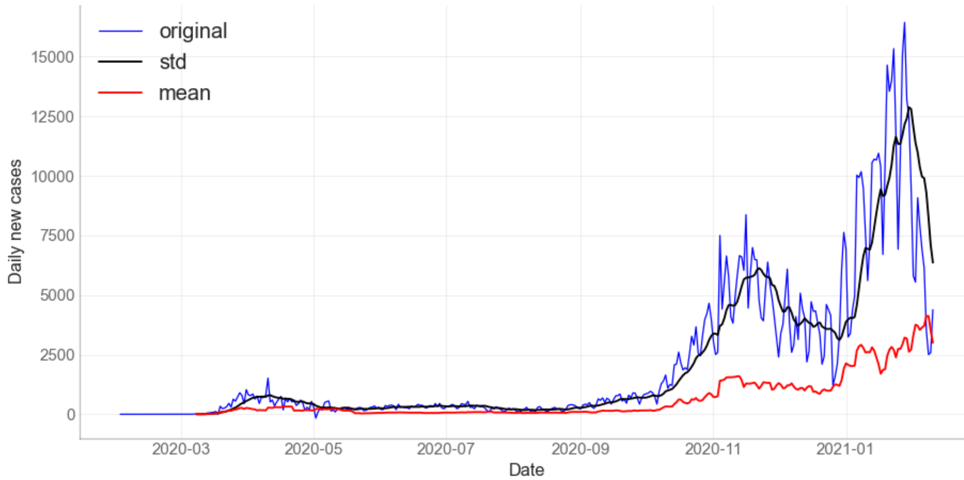

Figure 1: New daily cases in Portugal

After a first visual conclusion, the group investigated the stationarity of the data by conducting two well-known tests (Augmented-Dickey-Fuller and KPSS), most commonly used in the academic literature. The Augmented Dickey-Fuller test allows for higher-order autoregressive processes by including Δy_{t-p} in the model where Δy_t can be written as

$$\Delta y_t = \alpha + \beta t + \gamma y_{t-1} + \delta_1 \Delta y_{t-1} + \cdots + \delta_p \Delta y_{t-p} + \epsilon_t$$

The null hypothesis for the test is that the investigated data is non-stationary:

$$H_0 : \gamma = 0$$
$$H_1 : \gamma < 0$$

While the null-hypothesis of the ADF test investigates if the data is non-stationary, the null hypothesis for the KPSS test investigates if the data is stationary. As a result, one does not want to reject H_1.
We simulated the critical values of the ADF test with constant and trend with 14 lags and 351 obeservations with the help of Professor Paulo M. M. Rodrigues. The results of the simulation are as follows in table1:

Test	0.01	0.05	0.1
ADF with augmentation	-3.9852	-3.3776	-3.1011
ADF without augmentation	-3.9928	-3.4142	-3.1305

Table 1: Simulation results of ADF tests with constant & trend with 351 observations

In Table 2 below the group displayed the results for the Augmented Dickey-Fuller and KPSS test for the respective time-series (Note: a confidence level of 95% was applied while conducting the tests). By looking at the test results, one can see that they are yielding a different outcome: while the ADF tests with a p-value of 0.0125 indicates stationarity, the KPSS test however shows non-stationarity in the data.

Test	Test Statistic	p-value	Result
Augmented Dickey-Fuller	-3.35678	0.062524	non-stationary
KPSS	1.31843	0.016442	non-stationary

Table 2: Non-Statinoarity & Stationarity Test-Results for daily new cases

As requested as part of the subquestion in **1.1**, the group also looked into the first-difference of the time series. In simple terms, the first difference of a time series is the series of changes from one period to the next, which helps to stabilize the mean [2]. The result of the first-difference is depicted in Figure 2 below.

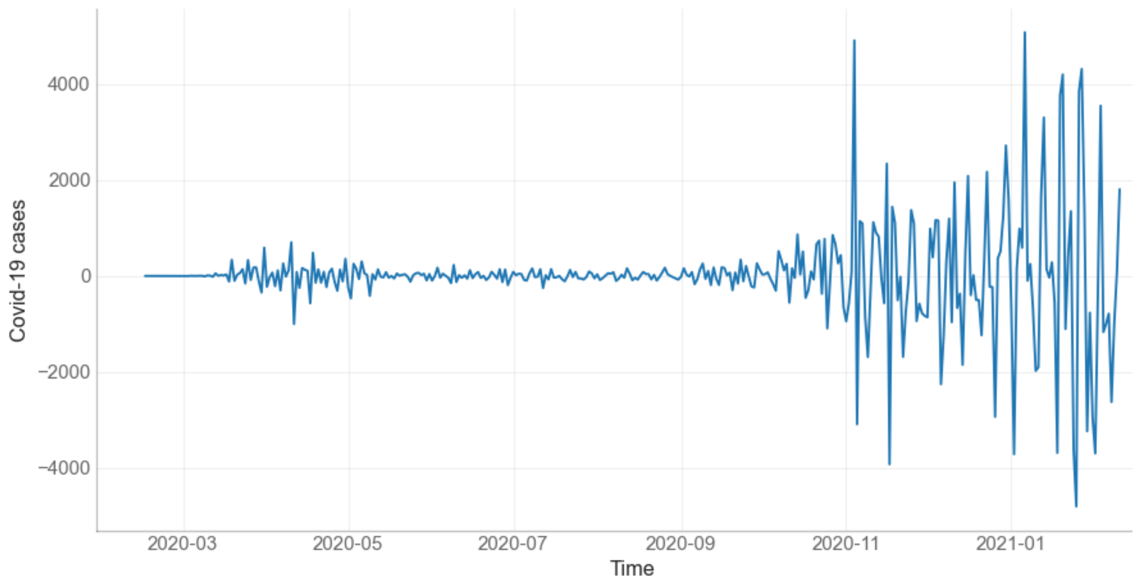

Figure 2: New daily cases in Portugal (First-Difference)

Unlike the time series of the new cases, the first differentiation based on the mean behaviour appears stationary in an optical examination. For a more informed analysis we again perform the Augmented Dickey-Fuller and KPSS test to assess if the differenced time-series is stationary or not.

Test	Test Statistic	p-value	Result
Augmented Dickey-Fuller	-4.36340	0.00034	stationary
KPSS	0.03833	0.14613	stationary

Table 3: Non-Statinoarity & Stationarity Test-Results for daily new cases

By conducting the test results for the first difference, one can see that both test yield to the same outcome: the ADF tests with a p-value of approx. 0.00 and KPSS test with a p-value of 0.15 indicate stationarty of the series.

It should be noted at this point that if we look at the two plots alone, a structural break in November 2020 cannot be ruled out in either time series. This can lead to a weaker significance of the two tests. It would be interesting to examine this more closely in a subsequent paper.

1.2 Graph the correlogram for both series and comment on its time dependence.

Just as correlation measures the extent of a linear relationship between two variables, autocorrelation measures the linear relationship between lagged values of a time series [1] and is calculated with the following formula:

$$\rho_k = \frac{Cov\left(y_t, y_{t-k}\right)}{Var\left(y_t\right)} = \frac{\gamma_k}{\gamma_0}$$

The two figures below show the ACF and PACF plot of the time series for the daily new cases and the first difference. The blue area behind the respective values of the autocorrelation represent the significance level, which is derived from the Q-statistic (Ljung-Box test), which is a test for the joint significance. The significance level is 5%.

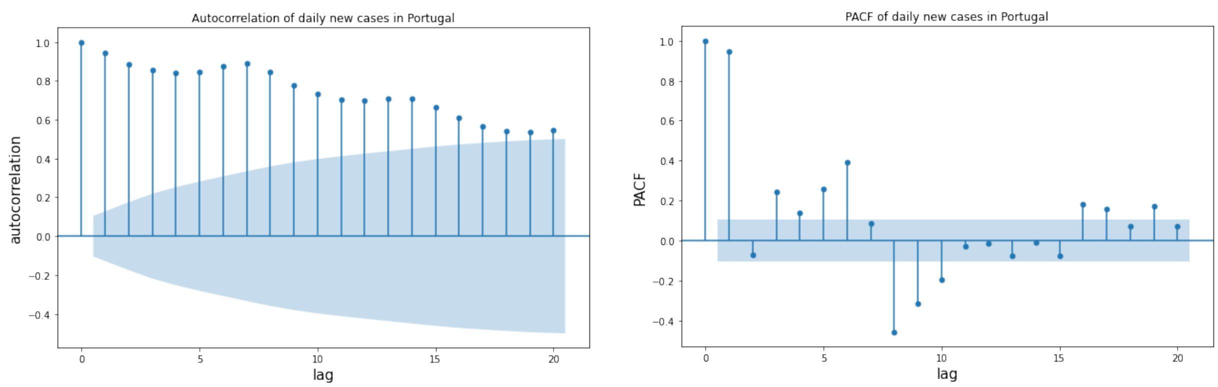

Figure 3: ACF and PACF for daily new cases

The ACF in Figure 3 for the daily new cases confirms by persistence that the time series is non-stationary. The PACF alternates between positive and negative values at irregular intervals. However, since the first lag shows a significantly stronger correlation than the still significant following ones, this suggests an auto-regressive behavior of the time series. In this case, *autoregressive* dynamics could describe the process well. The memory of an $AR(p)$, as can be seen from the ACF plot, however, goes beyond the period p.

The ACF in Figure 4 of the first differential is clearly less persistent than the level time series. It alternates between negative and positive values. What is striking, however, is that both the seventh and the fourteenth lag are clearly significant. Such a picture of the ACF suggests seasonality in the data. Since the present time series contains daily data, it may be a weekly seasonality. This is consistent with empirical results from other countries, for example Germany, and is due to the reporting structures of the respective agencies that report the official case numbers.

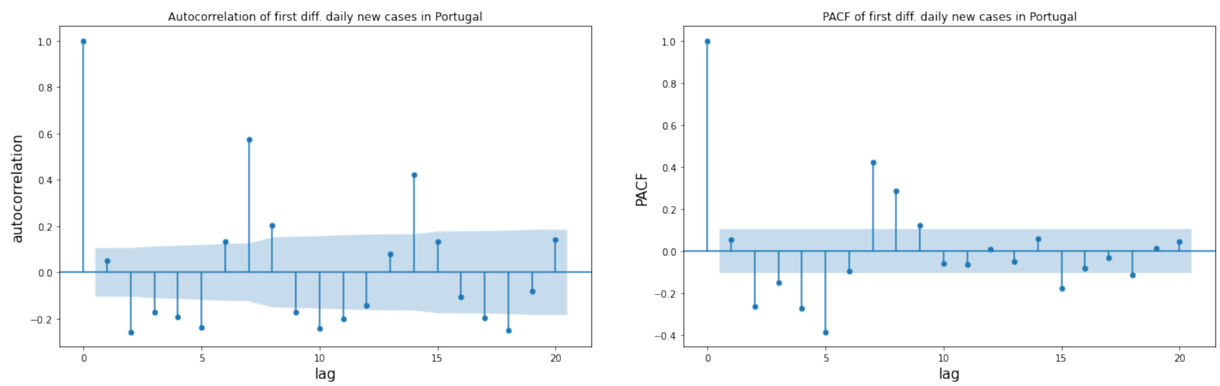

Figure 4: ACF and PACF for first diff. daily new cases

The PACF alternates less strongly between negative and positive values. Furthermore, the lags are clearly less significant. However, no precise statement or parameter estimate can be made for the model on the basis of the ACF and PACF plots. Nevertheless, it is reasonable to reflect the seasonality in the AR part of the ARMA model without estimating a mixed seasonal ARMA ($ARMA(p,q) \times (P,Q)$). The group estimates the parameters of the ARMA model in the following section.

The group also conducted a test to check for normality in the differenced time-series by using the Jarque-Bera test. Jarque-Bera tests for the following hypothesis:

$$H_0: \text{ The data is normally distributed}$$
$$H_A: \text{ The data is not normally distributed}$$

The test statistic is 977.61 and the corresponding p-value is 0.0. Since this p-value is not less than 0.05, the group fails to reject the null hypothesis, meaning that there is not sufficient evidence to say that the data has a skewness and kurtosis that is significantly different from a normal distribution [3].

1.3 Estimate an optimal ARMA model for the first difference

Using the results from the first two sections, the group estimated an ARMA model for the first difference of the daily new cases. To determine the included lags in the final model, the group used the information criterion according to Schwarz [4] (BIC). The model was preferred, which minimised this criterion. For this task, the group used the renown Python package pmdarima, which is equivalent to R's auto.arima function.

$$BIC = log\frac{1}{T}\sum_{n=1}^{T}\epsilon_t^2 + \frac{k}{T}\,logT$$

	y	No. Observations:	351
Model:	ARMA(7, 0, 2)	Log Likelihood	-2826.114
AIC	5674.229	BIC	5716.698

Table 4: Fitted ARMA(7, 2) model

As one can see in Table 4, the group's estimated model is an **A**uto-**R**egressive-**M**oving-**A**verage model with specification ARMA(7,2).

	coef	**std err**	**z**	**P> |z|**	**[0.025**	**0.975]**
const	6.9038	37.220	0.185	0.853	-66.047	79.854
ar.L1.y	0.4677	0.093	5.043	0.000	0.286	0.649
ar.L2.y	-0.4345	0.107	-4.075	0.000	-0.643	-0.226
ar.L3.y	0.0367	0.062	0.588	0.556	-0.086	0.159
ar.L4.y	-0.1337	0.066	-2.026	0.043	-0.263	-0.004
ar.L5.y	-0.1139	0.063	-1.821	0.069	-0.236	0.009
ar.L6.y	0.1215	0.063	1.931	0.053	-0.002	0.245
ar.L7.y	0.3595	0.075	4.809	0.000	0.213	0.506
ma.L1.y	-0.7469	0.094	-7.935	0.000	-0.931	-0.562
ma.L2.y	0.3917	0.124	3.155	0.002	0.148	0.635

Table 5: Estimated parameters for ARMA(7, 2) model

In Table 5, the group presents the estimated parameters. It can be seen that, as expected, the first difference in the original time series has no constant. In other words, the constant is not significant. Furthermore, lags 3, 5 and 6 in the AR part are not significant. On the other hand, all lags of the MA part are significant.

In Figure 5 the group plotted the residuals $\hat{\epsilon}_t$ of the fitted model. If the model has been fitted sufficiently well, the residuals must correspond to a white noise process i.e. no autocorrelation which seems not be the case here. As mentioned before, there seems to be a structural break in November 2020.

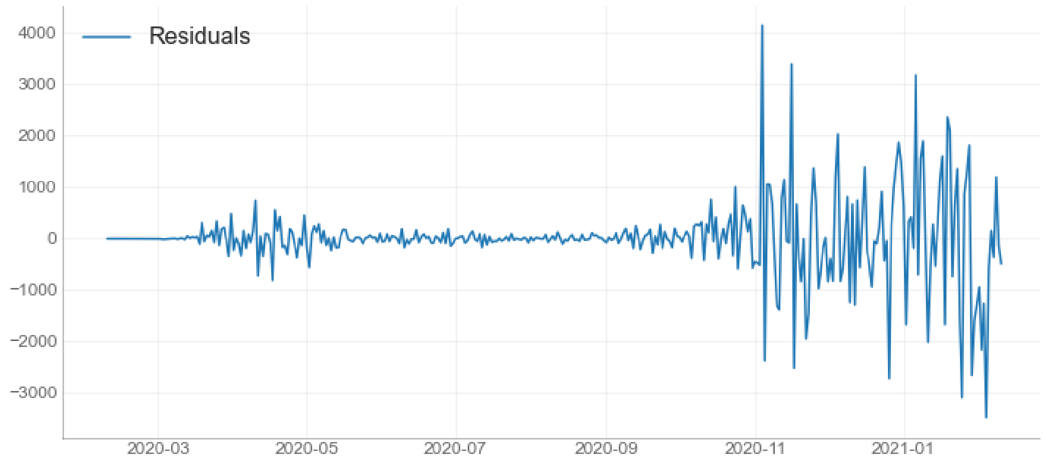

Figure 5: Residuals of fitted values from an ARMA(7,2)

To test the group's impression, a **Breusch-Godfrey** test, which investigates the presence of serial correlation of the residuals and a **Ljung-Box** test were performed. The Breusch-Godfrey test is especially good to use where lagged values of the dependent variables are used as independent variables in the model's representation, as it is the case in the ARMA model. One might use the Ljung-Box test on the residuals of the respective model to look for autocorrelation, ideally the residuals should be white noise.

Breusch-Godfrey tests the following hypothesis:

$$H_0: \text{ There is no serial correlation}$$
$$H_A: \text{ There is serial correlation present}$$

Ljung-Box tests the following hypothesis:

$$H_0: \text{ Data are independently distributed}$$
$$H_A: \text{ Data exhibit serial correlation}$$

Below, the group summarized the test results from the Breusch-Godfrey and Ljung-Box test. As one can see, both tests yield the same result: no serial correlation is present in the data.

Test	Test Statistic	p-value	Result
Breusch-Godfrey	68.59	0.0001	autocorrelation
Ljung-Box	46.60	0.0272	serial-correlation

Table 6: Autocorrelation Test-Results

Below, the group plotted the ACF and $PACF$ of the residuals from fitted ARMA (7,2) model. The results of the two tests in table 6 are confirmed. The two significant lags 13 and 15 indicate that there is autocorrelation in the residuals. It must be assumed that the model selection based on the BIC does not sufficiently capture the dynamics of the underlying time series.

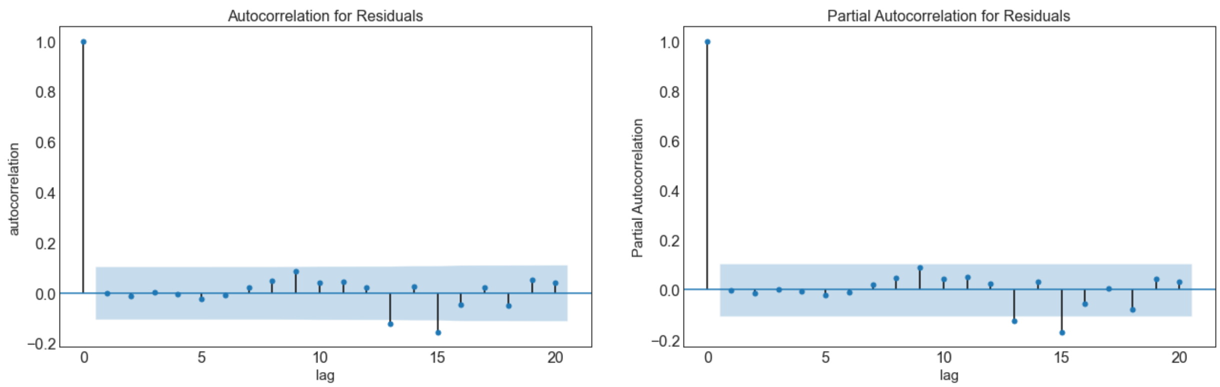

Figure 6: ACF and PACF for ARMA(7,2) model

In a second estimation, the Akaike information criterion (AIC) [5] was chosen for lag determination. Again, the decision is made in favour of the model that minimises this criterion.

$$AIC = log\frac{1}{T}\sum_{n=1}^{T}\epsilon_t^2 + \frac{k}{T}\,2$$

Table 7 and **??** document the results of the re-estimation. Our second model is an ARMA(7,7). Based on the properties of the underlying time series described above, we expect a better fit of this model, since both AR and MA now pick up the seven-day dynamics.

	y	No. Observations:	350
Model:	ARMA(7, 7)	Log Likelihood	-2815.807
AIC	5663.614	BIC	5725.341

Table 7: Fitted ARMA(7, 7) model

Table 8 shows the specification of the parameters of the $ARAM(7,7)$. What is noticeable is that the additional lags in the MA part of the model are all significant with the exception of $ma.L4$.

Figure 7 shows the residuals of the new estimated model. Again, a visual inspection does not allow us to conclude whether the model better captures the dynamics of the time series.

	coef	std err	z	P¿—z—	[0.025	0.975]
const	12.4932	72.150	0.173	0.863	-128.917	153.904
ar.L1	0.1082	0.094	1.151	0.250	-0.076	0.292
ar.L2	0.0941	0.069	1.364	0.173	-0.041	0.229
ar.L3	-0.3178	0.084	-3.803	0.000	-0.482	-0.154
ar.L4	-0.0621	0.093	-0.665	0.506	-0.245	0.121
ar.L5	0.1339	0.077	1.736	0.083	-0.017	0.285
ar.L6	-0.1182	0.082	-1.449	0.147	-0.278	0.042
ar.L7	0.6383	0.080	7.991	0.000	0.482	0.795
ma.L1	-0.3525	0.099	-3.543	0.000	-0.548	-0.158
ma.L2	-0.2896	0.081	-3.557	0.000	-0.449	-0.130
ma.L3	0.5033	0.090	5.615	0.000	0.328	0.679
ma.L4	-0.0521	0.103	-0.504	0.614	-0.255	0.151
ma.L5	-0.4078	0.085	-4.776	0.000	-0.575	-0.240
ma.L6	0.3488	0.096	3.622	0.000	0.160	0.538
ma.L7	-0.1938	0.096	-2.009	0.045	-0.383	-0.005
sigma2	622500.0000	25300.000	24.559	0.000	573000.000	672000.000

Table 8: Estimated parameters ARMA(7,7)

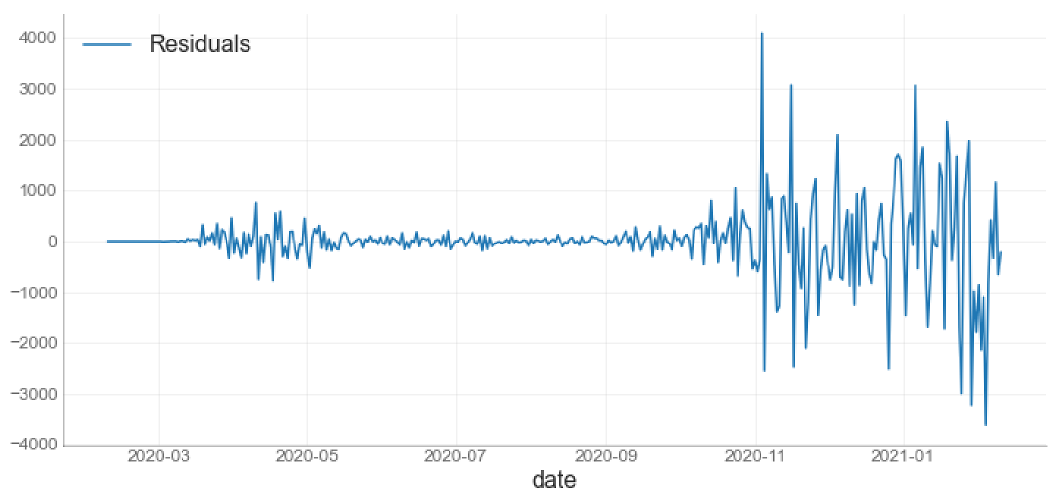

Figure 7: Residuals of ARMA(7,7) model

To examine the residuals for autocorrelation and to evaluate whether the $ARMA(7,7)$ has advantages over the $ARMA(7,2)$, the ACF is shown in figure 8. It can be seen clearly that there is no autocorrelation even at higher lags. This is an indication that with the new model we can indeed better describe the dynamics of the development of the first difference of daily new cases.

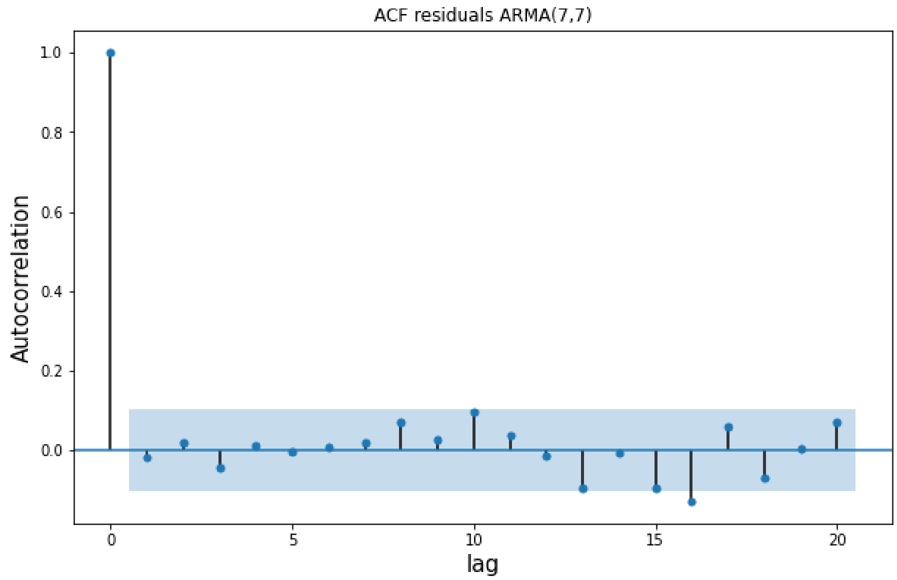

Figure 8: ACF of ARMA(7,7) residuals

Part II

Consider the paper "The impact of COVID-19 on emerging stock markets". You are requested to replicate the paper for 3 advanced economies. Ignoring the panel dimension of the paper, you should estimate 3 time series models (one for each economy). Covid related data may be extracted from owid-covid-data.xls. For the other variables, you may follow the authors' sources or extract the data from Bloomberg.

1 Methodology

1.1 Regression considered

Similarly to the paper, the regression considered for this replication is the following:

$$sm_{i,t} = \alpha_0 + \alpha_1 exc_{i,t} + \alpha_2 oil_{i,t} + \alpha_3 covid_{i,t} + \epsilon_{i,t} \tag{1}$$

where the subscripts $t = \{1, \ldots, T\}$ corresponds to the time period and $i = \{BEL, ITA, GER\}$, i.e. the three chosen advanced economies **(Belgium, Italy and Germany)**.

The variables are defined as follows

1. Dependent variable $sm_{i,t}$: daily relative stock market returns to the countries' national indexes prior to COVID-19. It is computed as such:

   $$sm_{i,t} = sm^*_{i,t} - \mu_i \tag{2}$$

   where $sm^*_{i,t}$ is the daily index return and μ_i a daily one-month return average, assumed as the benchmark return prior to the crisis. The one-month average is computed one month prior to the first case in the chosen countries.

   The national indexes are: BEL 20, DAX and FTSE MIB.

   The first covid case in Belgium was reported on February 4, 2020 [6], in Italy on February, 21 2020 [7] and in Germany on January 27, 2020 [8].

2. Independent variable $exc_{i,t}$: EUR per USD exchange rate.

3. Independent variable $oil_{i,t}$: Real Brent Crude Oil prices. Real prices were constructed by deflating the USD oil price in EUR using the Harmonised Index of Consumer Prices (HICP) for the first wave period [9]. Note that the HICP base month is 2015, different from the paper's 2010. The GARCH procedure of the paper was ignored.

4. Independent variable $covid_{i,t}$: Infection rates by country during the first wave period, constructed as total cases divided by population.

1.2 First wave period

The paper based the start of the first wave period on March 10, 2020, based on the first day when all countries reported at least one positive case. However, it is not explained why April 30, 2020 is the ending date used in the period analyzed.
We decided to look at the three selected countries individuals' first wave new cases curves.

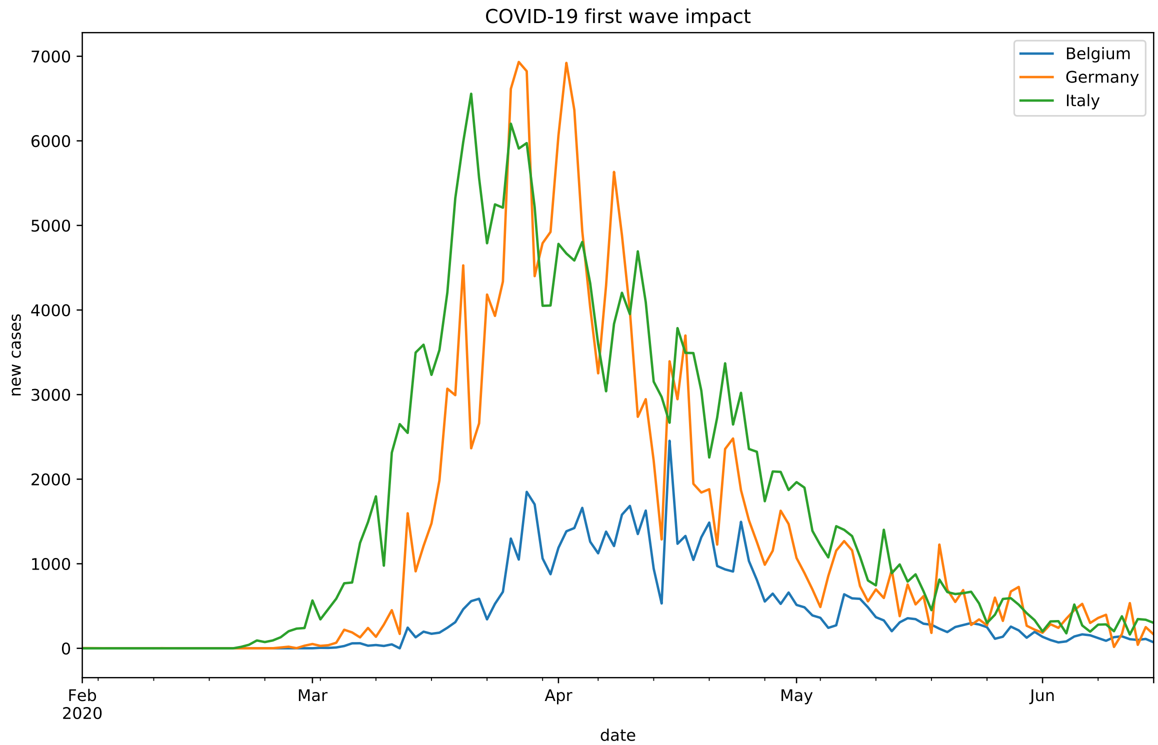

Figure 9: First wave per country period

From figure 9, we observe that the first wave periods vary slightly between the three countries, e.g. it started earlier in Italy and later in Belgium.

Therefore, given that our main goal is to analyze the effects during the first wave, we decided to adjust these starting and ending first wave dates to exactly match the selected countries.

To do so, the following methodology as applied: the start of the first wave is the **first detected case of local transmission** and the end when **the country eased its lockdown measures** [10].

1. For Belgium, the first case of local transmission was on March 6, 2020 [6]. The lockdown measures were eased on May 11, 2020, when all shops were once again allowed to be open for the public [6].

2. For Italy, the first Covid case produced by local transmission was reported on February, 21 2020 in the region of Lombardy [7]. May 16, 2020 was chosen as the ending date since from that day the lockdown restrictions were eased and people were allowed to move freely again inside the country [11].

3. For Germany, the first case of the novel Coronavirus was reported on January 27, 2020 [8], however, the first incidences of local transmission occurred around February 25, 2020, which is when the selected time series starts. As the end date, May 3, 2020 was selected, when the lockdown was eased [12].

Note that for each of the three regressions, the starting and ending dates may slightly vary to what is provided above due to business days.

1.3 Exploratory analysis

In order to provide some context on the dependent time series, which of course does not warrant causal inference, the mean relative returns were computed for each country in question. Together with information about the size of each country's economic relief package (only immediate fiscal stimulus was considered here), these computations are presented in the following table. The data was retrieved from Bruegel, a think-tank [13].

Country	Mean $sm_{i,t}$	Stimulus (as % of 2019 budget)
Belgium	0.00504	1.4%
Germany	-0.00217	8.3%
Italy	-0.00664	3.4%

Table 9: Fiscal Stimulus vs. Mean relative returns

While the Belgian stock market returns relative to the benchmark period prior to the global outbreak of COVID-19 seems to be slightly above that of Germany and Italy, subsequent analysis dispelled with that notion. In fact, using pairwise *Kolmogorov-Smirnov* tests, no evidence could be found as to a different distribution of relative returns. The table results

	Belgium	Germany	Italy
Belgium	X	0.6968 0.1344	0.83384 0.11904
Germany	0.6968 0.1344	X	0.696795 0.134370
Italy	0.83384 0.11904	0.696795 0.134370	X

Table 10: P-value of *Kolmogorov-Smirnov* test. Test statistic below

show that despite the apparent difference in mean relative returns, we fail to reject the null hypothesis that the underlying distribution structure of the mean returns between the three countries is significantly different for every pair considered. This means we lack a tantalizing clue as to the performance of national stock markets during the first wave of COVID-19.

1.4 Individual results

For Belgium, all time series were stationary apart from the infection rate. We had to take two times the first differential of the series to make it stationary.

Augmented Dickey-Fuller	p-value	Result
$covid_{BEL,t}$	0.29006	non-stationary
$covid_{BEL,t}$'	0.37732	non-stationary
$covid_{BEL,t}$"	2.0912e-08	stationary
$oil_{i,t}$	0.005891	stationary
$exc_{i,t}$	0.03794	stationary
$sm_{i,t}$	0.00346	stationary

Table 11: Belgium stationary tests

As for the regression results, refer to table 12.

	coef	std err	z	$P > \|z\|$	[0.025	0.975]
α_0	-1.5706	0.520	-3.019	0.003	-2.590	-0.551
$covid_{BEL,t}$"	-0.3003	1.218	-0.247	0.805	-2.688	2.087
$oil_{i,t}$	0.0001	0.001	0.106	0.915	-0.002	0.002
$exc_{i,t}$	1.7094	0.567	3.015	0.003	0.598	2.821

Table 12: Belgium regression results ($R^2 = 0.32$)

We observe that only the EUR per USD time series is significant. The two other variables are not significant at all.

For Italy, none of the variables was stationary and, therefore, the calculation of the corresponding differences of the variables was needed. The table below presents both the variables and the results from the Augmented-Dickey-Fuller test.

Similarly, the results from running the final regression are reported in table 14.

Augmented Dickey-Fuller	p-value	Result
$covid_{ITA,t}$	0.51358	non-stationary
$covid_{ITA,t}$'	0.06249	non-stationary
$covid_{ITA,t}$"	0.55345	non-stationary
$covid_{ITA,t}$"'	2.0796e-17	stationary
$oil_{i,t}$	0.05038	non-stationary
$oil_{i,t}$'	1.4459e-08	stationary
$exc_{i,t}$	0.15666	non-stationary
$exc_{i,t}$'	4.5714e-07	stationary
$sm_{i,t}$	0.05645	non-stationary
$sm_{i,t}$'	8.6838e-19	stationary

Table 13: Italy stationary tests

	coef	std err	z	$P > \|z\|$	[0.025	0.975]
α_0	0.0041	0.008	0.521	0.602	-0.011	0.019
$covid_{ITA,t}$"'	5.3099	6.223	0.853	0.394	-6.888	17.507
$oil_{i,t}$'	0.0086	0.002	3.522	0.000	0.004	0.013
$exc_{i,t}$'	0.1239	1.081	0.115	0.909	-1.995	2.242

Table 14: Italy regression results ($R^2 = 0.141$)

For Germany, none of the variables were stationary prior to any transformation. The necessary differencing steps and the corresponding test statistics for the stepwise Augmented-Dickey-Fuller test are reported in the table below.

As for the regression results, refer to table 16.

From the regression results below, we can infer that the only significant variable is the first-order difference of the oil price. No other variables are significant and, in addition to that, exhibit high standard errors. The regression fit is also poor with an R^2-value of only 0.136.

Augmented Dickey-Fuller	p-value	Result
$covid_{GER,t}$	0.66787	non-stationary
$covid_{GER,t}$'	0.06419	non-stationary
$covid_{GER,t}$"	0.55870	non-stationary
$covid_{GER,t}$"'	1.3835e-13	stationary
$oil_{i,t}$	0.2096	non-stationary
$oil_{i,t}$'	8.0112e-07	stationary
$exc_{i,t}$	0.67550	non-stationary
$exc_{i,t}$'	0.378513e-11	stationary
$sm_{i,t}$	0.108259	non-stationary
$sm_{i,t}$'	0.00489	stationary

Table 15: Germany stationary tests

	coef	std err	z	$P > \|z\|$	[0.025	0.975]
α_0	0.0047	0.009	0.536	0.592	-0.012	0.022
$oil_{i,t}$'	0.0075	0.002	3.243	0.001	0.003	0.012
$exc_{i,t}$'	0.0769	1.074	0.072	0.943	-2.028	2.182
$covid_{GER,t}$"'	0.2732	6.456	0.042	0.966	-12.381	12.927

Table 16: Germany regression results ($R^2 = 0.136$)

1.5 General conclusion

The results reported above show a very mixed picture regarding the performance of the model proposed in Topcu and Gulal (2020, 2) [14].

Firstly, given the nature of the data, some modifications were made to the individual series. One such example was the oil real price regime. Whereas the authors applied a GARCH-methodology, this was not done here, which could account for the differing significances of the real oil price variable across the countries investigated. Additionally, while the original article applied panel methods, the approach pursued is entirely located within the time-series domain.

The group also investigated the effects of increasing the time period of the benchmark return prior to COVID-19. Instead of having a one-month average daily return prior to the first country case, we tried respectively three and six months averages. Unfortunately, it did not improve the statistical significance of the regression coefficients. It can be seen that for Belgium the only statistically significant coefficients are the constant and the exchange rates, whereas both for Germany and Italy the coefficient of the brent crude oil seems to be the only one statistically significant in the their respective time series regressions.

Compared with the original study, we found similar results regarding the significance of the COVID-19 infection rate in that for the full sample, which was considered, there seems to be no significant coefficient. The authors also emphasized that the impact is the [sic!] modest in Europe (Topcu, Gulal 2020, 4). Our results confirm this conclusion.

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