Dealing with outliers generated by the COVID-19 pandemic in the process of seasonal adjustment of macroeconomic time series

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1. Introduction

Economic activities have been severely affected by the COVID-19 outbreak. This causes the presence of outliers at the end point of time series, which may affect the revision of the seasonally adjusted series each time new data becomes available (Eurostat, 2020a). Given the special circumstances, as it is impossible to predict the development of the crisis, Eurostat considers that modelling outliers based solely on statistic criteria using the automatic is an acceptable solution; however, using statistical criteria and economic information is recommended (Eurostat, 2020a). It should also be noted that revisions of the increase rates calculated based on seasonally adjusted data should be kept reasonable (Mirica et al. 2016).). The economy is prone to various shocks, especially on long term, such as war crises, pandemics, and a "good" statistical approach can be compromised by fitting to data ignoring some assumptions or a time-series characteristic (Hendry et al. 2011). Using outliers when modelling implies high risk of inflated errors (Osborne at al. 2004). This, along with the fact that only 8% of the researchers report checks for outliers in their work as outlined by an empirical study (Osborne et al 2001), leads to concerns. The main problem with outliers is that they appear to be generated from a distribution that is different from the one that is modelled and based on which the assumptions are made. An illustration of this situation is presented by Hawkins D.M. who emphasizes that “an outlier is an observation which deviates so much from other observations as to arouse suspicions that it was generated by a different mechanism” (Hawkins, 1980, p.1). Modelling with outliers increase error variance, reduce the power of statistical test, and can decrease the normality (Osborne 2004). Besides the variance, outliers can add bias to the predictions or estimators (Zimmerman 1994). These uncontrolled or unexpected interventions leads to a “moderate to significant impact on the effectiveness of the standard methodology for time series analysis with respect to model identification, estimation and forecasting” (Chung and Lon-Mu 1993).

The outlier’s detection, although it seems easy, in temporal data becomes very challenging and it has been addressed from different perspectives (Battaglia et al. 2005; Caroni and Karioti 2004. In some cases, the outlier may have an economic interpretation such as fraud detection (Takeuchi and Yamanishi, 2006). An example of relatively new approach with good results for detecting additive outliers is based on genetic algorithms (Cucina et al. 2014).

One solution for modelling with outliers is presented by Kourentzes et al. 2014 and is based on ensemble of neural networks operators. The idea is to use a mode ensemble operator based on kernel density estimation, since this technique is insensitive to outliers and deviations from normality. Martinez et al (2018) suggest the use of a multidimensional nearest neighbours algorithms for modelling seasonal time series affected by outliers.

2. Data and methods

The purpose of this paper is to present a procedure for dealing with outliers observed at the end of a raw series. In this respect, the quarterly data for the Romanian GDP will be used. The data was retrieved from the Tempo Online Database of the National Institute of Statistics Romania on October 9th, 2020 and comprises of raw figures from the first quarter of 2015 up to the second quarter of 2020 (22 observations). Subsequently, new data points presenting different possible scenarios for the third quarter of 2020 have been added, resulting in 10 series:

1. GDP_0.9 – in this scenario GDP in the third quarter of 2020 is 90% of the GDP in the third quarter of 2019.
2. GDP_0.91 – in this scenario GDP in the third quarter of 2020 is 91% of the GDP in the third quarter of 2019.
3. GDP_0.92 – in this scenario GDP in the third quarter of 2020 is 92% of the GDP in the third quarter of 2019.
4. GDP_0.93 – in this scenario GDP in the third quarter of 2020 is 93% of the GDP in the third quarter of 2019.
5. GDP_0.94 – in this scenario GDP in the third quarter of 2020 is 94% of the GDP in the third quarter of 2019.
6. GDP_0.95 – in this scenario GDP in the third quarter of 2020 is 95% of the GDP in the third quarter of 2019.
7. GDP_0.96 – in this scenario GDP in the third quarter of 2020 is 96% of the GDP in the third quarter of 2019.
8. GDP_0.97 – in this scenario GDP in the third quarter of 2020 is 97% of the GDP in the third quarter of 2019.
9. GDP_0.98 – in this scenario GDP in the third quarter of 2020 is 98% of the GDP in the third quarter of 2019;

10. GDP_0.99 – in this scenario GDP in the third quarter of 2020 is 99% of the GDP in the third quarter of 2019.

Next, the facilities of the open-source software JDemetra+ 2.2.3 will be used for series treatment. JDemetra+ is the software officially recommended by Eurostat for seasonal adjustment (Eurostat, 2020b). This software has multiple features that will be briefly presented below.

Firstly, according to Grudkowska (2021a), JDemetra+ 2.2.3 incorporates adapted versions of TRAMO-SEATS and X13ARIMA-SEATS that permit the use of plugins and extensions within a graphical user interface. One should note that "*both methods are officially recommended by Eurostat, ECB, OECD, IMF and others and produce similar but not identical results*". (UNECE, 2020, p. 38). According to the same source, both methods share common features, however, X-13 offers highly adaptable tools for the pre-adjustment part as well as several filters to choose from for the decomposition part. Also, JDemetra+ incorporates an automatic procedure for seasonal adjustment both within TRAMO-SEATS and X13, that proved to be effective and easy to use (Toma et al, 2018). Better results were obtained with X13 for series affected by calendar effects or outliers (Mirica, 2019).

Secondly, JDemetra+ 2.2.3 includes two useful tools for the automatic detection of outliers: Anomaly Detection and Check last (Grudkowska 2021b). According to the same source, both these tools are built upon the TRAMO app, TERROR. TERROR stands for "TRAMO for errors" (Caporello et al. 2000, p.20). According to the same source, TRROR computes an ARIMA model for the time series, that is further used to compare the actual values with the adjusted values and if any of the given difference is higher than a value specified by the user, the point in the time series is identified as error (outlier).

Thirdly, JDemetra+ 2.2.3 offers an easy-to-use instrument for defining calendar effects (Grudkowska 2021c). This is an important component in the seasonal adjustment process, as most series are influenced by the daily intensity of the economic activity (Ladiray, 2006). In this respect, JDemetra+ 2.2.3 offers the possibility to set a specific weight for each holiday, predefined by the user, to account for the impact of that specific day on the entire series (Grudkowska 2021d).

3. Results

Firstly, the 10 series were tested for the presence of outliers using the outliers detection tool in JDemetra+2.2.3. As can be observed from table 1, there are significant outliers within the series.

Table 1

Series	Outlier type	**Period**	**Value**	**StdErr**	**TStat**
GDP_0.9	Level Shift	II-2020	-6095.6923	570.2203	-10.6901
GDP_0.91	Level Shift	II-2020	-5804.4633	566.5768	-10.2448
GDP_0.92	Transitory Change	II-2020	-5846.1316	764.0029	-7.6520
GDP_0.93	Transitory Change	II-2020	-5674.6938	726.7415	-7.8084
GDP_0.94	Transitory Change	II-2020	-5571.0726	700.1872	-7.9565
GDP_0.95	Transitory Change	II-2020	-5483.7524	688.7626	-7.9617
GDP_0.96	Transitory Change	II-2020	-5391.5962	629.5402	-8.5643
GDP_0.97	Transitory Change	II-2020	-5216.2521	643.3317	-8.1082
GDP_0.98	Transitory Change	II-2020	-5094.2040	671.2414	-7.5892
GDP_0.99	Additive Outlier	II-2020	-4331.5818	537.4194	-8.0600

Secondly, in order to perform the seasonal adjustment of these time series, a calendar is defined comprising of all the legal holidays in Romania including the Julian Easter and related holidays. The calendar is then incorporated within the X13 RSA5c specification available in JDemetra+ 2.2.3. With regard to the calendar definition, one can observe that we chose not to define special days for the periods corresponding to the emergency state and alert state related to COVID-19 outbreak within the second quarter of 2020 in Romania. That is because "*the selection of relevant calendar effects used for calendar adjustment should be kept constant over appropriately long time periods*" and "*changes in the selection of calendar effects should be based on both empirical evidence and economic explanation*" (Eurostat, 2008 p.2). As nobody can anticipate how long an emergency state or alert state along with underlying restrictions due to pandemics can occurs, we chose to preserve the consistency of the calendar, rather than introduce additional special days that might not affect the series on the long run. Also, as nobody can state the exact effects of the mitigation efforts on the economic activity, it would be impossible to choose an appropriate weight for such special days.

Thirdly, the automatic procedure for choosing the ARIMA Model and the Henderson filter available in JDemetra+ 2.2.3 for seasonal adjustment is used. This procedure has a built-in outlier detection and correction tool. This initial specification has a default TC rate (rate of decay of the transitory change outlier) of 0.7 and it can be changed with a number between 0 and 1. It also uses Msr as a default seasonal filter that can be changed with several other options: S3x1, S3x3, S3x5, S3x9, S3x15, Stable, X11 Default. The default critical value for detecting outliers is 4 and it can be changed with a value chosen by the user.

One should note that according to the press release 264/October 9th, 2020 of the National Institute of Statistics, GDP – Seasonally adjusted decreased by 11.9% in the second quarter of 2020 compared to the first quarter of 2020 and remained the same in the first quarter of 2020 compared to the last quarter of 2019. In order to obtain acceptable revisions (more specifically, in order to preserve the increase rates that the National Institute of Statistics Romania announced), some modifications had to be performed to the initial specification. Table 2 presents these modifications as well as the results of the seasonal adjustment procedure. As one can observe, performing these modifications resulted in satisfactory results from the perspective of the quality of the seasonal adjustment process. Moreover, the revised increase rates for the first and second quarters of 2020 are reasonable.

Table 2

	Modifications of the initial specification				Seasonal adjustment quality outcome	Increase rates (%)	
Series	Series span	TC rate	Seasonal filter	Critical values for outliers		revised for the first quarter	Revised for the second quarter
GDP_0.9 (log transform)	From 2016, first quarter	-	S3x9	6	good	0.01	-12.27
GDP_0.91 (log transform)	From 2016, first quarter	0.9	S3x1	6	good	0.04	-12.26

GDP_0.92 (auto transformation)	-	0.9	S3x1	-	good	0.13	-12.48
GDP_0.93 (auto transformation)	-	-	-	-	good	0.23	-11.38
GDP_0.94 (auto transformation)	-	0.6	S3x5	-	good	0.38	-11.36
GDP_0.95 (auto transformation)	-	0.942	S3x5	-	good	0.19	-11.47
GDP_0.96 (auto transformation)	-	0.91	S3x3	-	good	0.02	-11.64
GDP_0.97 (auto transformation)	-	0.92	-	-	good	0.53	-11.62
GDP_0.98 (auto transformation)	-	0.85	S3x3	-	good	0.05	-11.77
GDP_0.99 (auto transformation)	From 2016, first quarter	0.85	S3x9	6	Good	0.09	-11.74

Next, further justifications for the modifications performed to the initial specification are provided. More specifically, we will explain our choices with regard to the critical value for the detection of outliers, seasonal filter, transitory change rate and series span. In this process, one should also bear in mind the principle stated in the beginning of this paper, namely keeping revisions reasonable.

Regarding the critical value for the detection of outliers, one should note that the relative frequency of detection of an outlier when none is present decreases as the critical value increases (Kaiser and Maravall, 1999). Table 3 illustrates the outliers detected with the default critical value (4) as well as a critical value equal to 6. All other elements of the specification are kept the same as in table 2For the first 2 series, if the default critical value is used, the automatic procedure must correct for 4 and 2 outliers, respectively. However, the initial evaluation detected only one Level Shift within the series, that is the value for the second quarter of 2020. This means that if the critical value is set to default, the automatic procedure commits a type 1 error detecting outliers. Moreover, it was noted that the quality of the seasonal adjustment process is severe. For the last series, the automatic procedure finds an additive outlier if the critical value is set to default and a transitory change for critical value equal to 6. There are two possible approaches for this case: set the critical value to 4 as the output matches the initial evaluation of the outlier detection tool or set the critical value to 6 if there is uncertainty about the trend-cycle component being left untouched by the crisis (see Eurostat 2020a, with regard to the Additive outlier). The second approach may be used at least until more data become available. Therefore, it is safer to increase the critical value for outlier detection if there are too many detected outliers or if there is not enough data to support the existence of a certain type of outlier.

Table 3

Series	Outliers obtained and corrected with a critical value = 6	Outliers obtained and corrected with a critical value = 4
GDP_0.9; From 2016, first quarter	Level Shift (II, 2020); Probability = 0.0000	Level Shift (II, 2020); Probability = 0.0000 Level Shift (I, 2017); Probability = 0.0003 Transitory change (III, 2016); Probability = 0.0009 Additive outlier (I 2019); Probability = 0.0032
GDP_0.91; From 2016, first quarter	Level Shift (II, 2020); Probability = 0.0000	Level Shift (II, 2020); Probability = 0.0000 Level Shift (I, 2017); Probability = 0.0005
GDP_0.99; From 2016, first quarter	Transitory change (II, 2020); Probability = 0.0000	Additive Outliers (II, 2020); Probability = 0.0000

The Transitory change rate (TC rate) represents the rate of decay of a Transitory Change outlier, namely, parameter δ in the following equation, describing a time series y_t affected by such an outlier at time t = k (Galeano and Pena, 2013, p.248):

$$y_t = x_t + \frac{1}{1 - \delta B} \omega I_t^{(k)}$$

$$\delta \ tends \ to \ 1, Transitory \ change = Level \ Shift$$

$$\delta \ tends \ to \ 0, Transitory \ change = Additive \ Outlier$$

The choice of the TC rate towards 1 or 0 should be based on economic insights as the entire modelling process of outliers (Eurostat 2020a) as well as ensuring low revision rates for the previous rates of increase announced (Mirica et al. 2016).

With regard to the series span, Mirica et al. (2016) concluded that a series span of 20 to 24 quarters is the best choice for obtaining high quality seasonally adjusted data as well as reasonable revisions while the minimum length of a series that is to be seasonally adjusted is 16 to 20 quarters. According to the same source, one can choose to log-transform the series if the variance fluctuates along with the trend, as in the case of the Romanian quarterly GDP. For the purpose of this paper, we used mainly the auto function embedded within JDemetra+ for the transformation process. However, in the case of the first two series, if the auto function had been used, the increase rate on the seasonally adjusted series for the first quarter of 2020 would have been revised to -3% and -3.4% respectively. As these rates were far from the estimates published by the National Institute of Statistics for the first quarter of 2020, it is clear that the model needed some adjustments. In this respect, a log transformation has been applied to these series. Table 4 presents the results for different time spans and transformation choices for GDP_09, GDP_091 and GDP_099. The TC rate, Seasonal filter and Critical values for outliers were the ones from table 2 in each case. As one can observe, the lowest AIC for GDP_09 and GDP_091 is obtained for the log transformation and series span from 2016q1. Moreover, the lowest AIC for GDP_099 is obtained for the series span from 2016q1. This proves that shortening the time span as well as transforming the series is the best statistical choice also.

Table 4

Series	AIC value
GDP_09 log transformation, series span from 2016q1	239.4
GDP_09 log transformation, series span from 2015q1	278.6
GDP_09 no transformation, series span from 2016q1	263.0
GDP_09 no transformation, series span from 2015q1	327.4
GDP_091 log transformation, series span from 2016q1	240.0
GDP_091 log transformation, series span from 2015q1	279.5
GDP_091 no transformation, series span from 2016q1	263.5
GDP_091 no transformation, series span from 2015q1	327.9
GDP_099 series span from 2016q1	243.3
GDP_099 series span from 2015q1	317.7

In choosing the most suitable seasonal filter, the principle of minimum revision of the increase rate prevailed. In this respect, three rules emerged for each of our series: firstly, the increase rate for the first quarter must be positive; secondly, the increase rate for the second quarter must be as close to -11.9% as possible: thirdly, the increase rate for the first quarter must be as close to 0 as possible. Table 5 shows the increase rates for the different filters for each series.

Table 5

Series	Seasonal Filter	Increase rate q1 2020	Increase rate q2 2020
GDP_09	S3x1	0.52	-12.79
	S3x3	0.41	-12.67
	S3x5	0.16	-12.41
	S3x9	0.01	-12.27
	S3x15	0.02	-12.27
	Stable	0.02	-12.27
	X11 Default	0.16	-12.41
	Msr	0.16	-12.41
GDP_091	S3x1	0.04	-12.26
	S3x3	0.12	-12.30
	S3x5	-0.02	-12.15
	S3x9	-0.04	-12.11
	S3x15	-0.03	-12.11
	Stable	-0.02	-12.15
	X11 Default	-0.02	-12.15
	Msr	-0.02	-12.15
GDP_092	S3x1	0.13	-12.48
	S3x3	0.19	-12.47
	S3x5	-0.01	-12.3

	S3x9	-0.35	-12.02
	S3x15	-0.48	-11.82
	Stable	-0.48	-11.82
	X11 Default	-0.02	-12.26
	Msr	-0.02	-12.26
GDP_093	S3x1	0.68	-11.22
	S3x3	0.43	-11.31
	S3x5	0.18	-11.4
	S3x9	-0.13	-11.27
	S3x15	-0.21	-11.25
	Stable	-0.21	-11.25
	X11 Default	0.23	-11.38
	Msr	0.23	-11.38
GDP_094	S3x1	1.02	-10.97
	S3x3	0.66	-11.16
	S3x5	0.38	-11.36
	S3x9	0.02	-11.19
	S3x15	-0.05	-11.22
	Stable	-0.05	-11.22
	X11 Default	0.44	-11.36
	Msr	0.44	-11.36
GDP_095	S3x1	0.69	-11.33
	S3x3	0.45	-11.4
	S3x5	0.19	-11.47
	S3x9	-0.12	-11.33
	S3x15	-0.21	-11.32
	Stable	-0.21	-11.32
	X11 Default	0.23	-11.44
	Msr	0.23	-11.44
GDP_096	S3x1	-0.07	-11.65
	S3x3	0.02	-11.64
	S3x5	-0.25	-11.64
	S3x9	-0.44	-11.52
	S3x15	-0.58	-11.46
	Stable	-0.58	-11.46
	X11 Default	-0.19	-11.64
	Msr	-0.19	-11.64
GDP_097	S3x1	1.1	-11.33
	S3x3	0.75	-11.38
	S3x5	0.41	-11.46
	S3x9	0.06	-11.33
	S3x15	-0.02	-11.34
	Stable	-0.02	-11.34
	X11 Default	0.53	-11.62
	Msr	0.53	-11.62
GDP_098	S3x1	-0.02	-11.79
	S3x3	0.05	-11.77
	S3x5	-0.25	-11.73

	S3x9	-0.45	-11.6
	S3x15	-0.58	-11.53
	Stable	-0.58	-11.53
	X11 Default	-0.18	-11.74
	Msr	-0.18	-11.74
GDP_099	S3x1	0.05	-11.49
	S3x3	0.25	-11.99
	S3x5	0.1	-11.57
	S3x9	0.09	-11.74
	S3x15	0.08	-11.7
	Stable	0.08	-11.7
	X11 Default	0.1	-11.57
	Msr	0.1	-11.57

4. Conclusions

In this paper, a methodology for dealing with outliers when computing seasonally adjusted series was presented. This methodology is bases on two principles: (1) keeping the revisions in the increase rates of the seasonally adjusted series as low as possible and (2) using the automatic procedure in JDemetra+ as much as possible, with minimum modifications. Of course, a good quality of the seasonally adjusted data is crucial.

The automatic procedure in the X-13 package, RSA5c specification, in JDemetra+ 2.2.3 is very useful in dealing with outliers. However, some minor modifications should be performed to keep revisions reasonable. These modifications depend on the outlier type of the last data point and may consist of: transforming the series using the logarithm function; choosing a custom time span, TC rate or seasonal filter; setting a different critical value for the detection of the outliers. There is no specific order in performing these modifications, the process being iterative until the best possible combination is obtained.

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