QUALITY in SEASONAL ADJUSTMENT: CONFIDENCE INTERVALS

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ABSTRACT

Quality evaluation of seasonal adjustment process depends on classical diagnostics such as M diagnostics for X-11 type methods or AIC, BIC, autocorrelation measures for SEATS type methods; and revision analysis of both type of methods. However, these types of criteria do not ensure the efficient end-point estimation of current value of seasonal adjusted data. From this point of view, if criteria which minimizes the confidence interval of the growth rates of seasonal adjusted figures does exist, it can be suggested that the policy makers can take right decisions, especially in short term monetary policy analysis for important economic variables. In this study we examine that how confidence intervals can be calculated for growth rates of current SA data and can be used for optimal seasonal adjustment model specification selection procedure of EU-28 monetary aggregates and GDP data.

JEL CODES: ***C52, E20, E40***

INTRODUCTION

Seasonal adjusted data has a widespread use of area, especially in economic monitoring and policy making. The main reason is simply the need to understand current situation of the economic indicators interested. X12 (or X11)-ARIMA (thereafter, X12A; see [II]) and TRAMO/SEATS (thereafter, TS; see [IV]) are the most widely used methods for seasonal adjustment at present. The most important part of these methods is the model selection which affects the situation of current growth rate of seasonal adjusted indicator.

X12A and TS use model selection procedures which are similar in general. The selection procedure is based on minimization of model errors (measured by AICC or modified

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BIC) and parsimony principle. Then, both methods have incorporated an important set of diagnostics and quality assessments checks based on whether (for X12A) prior beliefs on how "reasonable" components should behave or (for TS) tests derived from the joint distribution of the optimal estimators of the components. In general, results of X12A and TS can be judged some criteria such as M statistics or ARIMA model-based diagnostics which may be regarded as quality indicators[4].

Despite the fact that one assumes the model which is selected by the procedure and is assessed according to the set of diagnostics, satisfies the general statistical conditions; the model does not even guarantee usefulness of resulting seasonal adjusted data by policy makers. In order to set the proper policy reaction, it is crucial for the policy makers to know whether precision of the growth over the last period for a seasonal adjusted economic indicator was high (or narrower confidence interval). For instance, having been set the short-term policy steps consistent with the longer term objectives, European Central Bank Monetary Policy Committees (MPC) must give high attention to estimate seasonal adjusted M1's or GDP's growth over the last period which has lowest confidence interval. Because, if seasonal adjusted M1's growth were sufficiently far away from the target, the MPC would take action to bring it back within the tolerance range (or, alternatively, the longer run objectives could be modified). On the other hand, if seasonal adjusted GDP's growth rate were lower than expected, the policies could be implemented to increase total demand (or compromise inflation targeting policy). But, if confidence intervals of growth rates are relatively large, the inferences based on the M1 or GDP data may be concluded by false policy reactions.

If we turn back to the model selection procedure in seasonal adjustment, it is known that "parsimony" principle is taken into consideration to avoid the tendency of AICC and BIC to overparametrization. But, implementation of the parsimony has several drawbacks. First, this principle directly affects the selection of the model to be used in seasonal adjustment, and the resulting model possibly may differ from the model which would have been selected by AICC or BIC criteria. On the other hand, one cannot assume that parsimony can increase the precision of the current data value of seasonal adjusted indicator. On the contrast, some loss of precision may arise in case of omitting additional parameters.

The aim of this paper is to develop a model selection procedure to enhance ability of producing precise estimate of period-to-period growth rate of seasonal adjusted series' current

[4] See [VI] and [VII] for detailed discussion on quality assessment of seasonal adjustment.

data. For this purpose, a new procedure is suggested incorporating both minimization of "model error" and "standard error of growth rates of seasonal adjusted series" rather than parsimony.

In the next part, suggested procedure is explained, and then the paper contains an application part which shows effects of this on seasonal adjustment models of GDP and a monetary aggregate (M1) of EU countries. Lastly, a conclusion part is given to summarize the paper.

METHODOLOGY

In this part, the discussion will continue only over TRAMO which includes the model selection part of TS, to keep the suggested methodology understandable. But, one can easily show that the new procedure can apply for Reg-ARIMA of X12A.

In TRAMO, model selection starts with a test for log-level specification [VIII] which uses Airline model. This is the airline model of [I]. Then, it uses two-stage method proposed by [III] to estimate unit roots. After that, HR [V] method is used to identify ARMA model orders for stationary (regular and seasonal differenced) series. HR method is based on modified BIC criteria. In HR method, smallest five BIC are first ordered in ascending order. Then, the model which has less parameter in seasonal part is selected considering with change in BIC value[5].

To explain suggested procedure clearly, we took the presentation simple without loss of generalization and we assumed that all series are logarithmic. Of course, the test used in TRAMO can be implemented in this procedure.

Instead of using proposed methods [III] and [V], we then propose "Policy Makers Information Criteria (PMIC) as follows. First, BIC values which belong all possible models are ordered in ascending order. Then, $PMIC_i$ as given (1) is calculated for smallest ten models according to BIC criteria. As seen easily in (1), $PMIC_i$ formula considers both BIC value and standard error (SE) of growth rate estimates of seasonal adjusted series vice parsimonious. Then, the model has the smallest P_i value is selected.

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[5] Detailed explanations can be found in [VIII].

$$PMIC_i = \left\{ \left(\frac{BIC_i - \overline{BIC_i}}{\sigma_{BIC_i}} \right) \left(\frac{SE_{G_t,SA_i} - \overline{SE_{G_t,SA_i}}}{\sigma_{G_t,SA_i}} \right) \right\} \quad (1)$$

where $i = 1,2,\dots,10$ and t represent current data point.

$PMIC_i$ is applied to all ARIMA model combinations for p,q=[0,1,2,3]; d=[0,1,2]; BP=BD=BQ=[0,1]. But, random walk and pure-MA model is excluded from model set since SEATS cannot decompose this type of models. It should be noted that if the series has no seasonality, standard error of growth rate estimates of seasonal adjusted series will be zero and BIC will be only identifier for the model to be selected.

APPLICATION

As we discussed above, precision of growth rates is really important for policy makers. Especially, growth rates of Gross Domestic Product (GDP) which shows where the general economic situation goes on, and growth rates of M1 represents a measure of currency in circulation carry more valuable and interpretable information than their levels.

To see the effect of PMIC on real data, we selected two critical economic variable namely, GDP and M1 series for EU-28 countries. Time span of the data set varies across the countries for each variable. Lastly, all data is downloaded from EUROSTAT web site. Results of PMIC are obtained and compared with TS' results in terms of diagnostics and graphical.

Comparison on Diagnostics

Model selection results of PMIC and comparison with automatic model procedure of TS by several quality diagnostics are given in Appendix 1 and 2. Due to the publication constraints, we used some abbreviations in the tables. Here, we explained them. S: Existence of Seasonality; Q: Residual autocorrelation test; QS: Residual seasonal autocorrelation test; Skew: Skewness test for residual; RUNS: Residual random distribution test. Also, we re-coded the tables using by critical value for each test with % 99 confidence levels to make it more interpretable.

M1 Monetary Aggregates

For M1 indicator, Latvia and Croatia are omitted from the analysis since there is not enough observation for modelling. According to results of remaining (26) series, 6 series have no significant seasonality. For these non-seasonal series, PMIC and TS identified same models for 5 of them. For Bulgaria, PMIC identified different model which has lower BIC than TS's.

Of course, we have to give more attention to the series which have seasonality (totally 20 series). Then, it can be easily said that PMIC has identified completely different models for the series from the TS's models. And, as we expected all models selected by PMIC for seasonal series have lower standard error for period to period growth rate of current data point and over-parameterized. By the way, it is welcome that PMIC is identified the models have lower BIC for 8 of 20 series. Lastly, diagnostic performance of models identified by PMIC completely agrees with the models identified by TS.

Gross Domestic Product

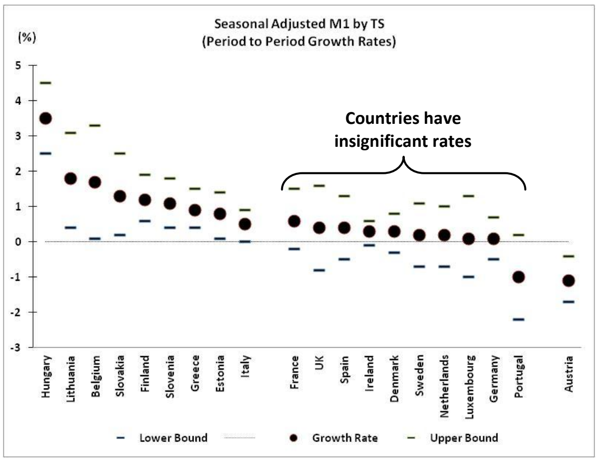
For GDP, all series of 28 countries have enough observation for modelling and have seasonality. It can be easily said that PMIC has identified different models (except for Ireland and Spain) for the series from the TS's models. And similar to M1 results, all models selected by PMIC for seasonal series have lower (equal only for Belgium) standard error for period to period growth rate of current data point and over-parameterized. By the way, it is welcome that PMIC is identified the models have lower BIC for 7 of 20 series. Lastly, it can be said that the diagnostic performance of models identified by PMIC show better that the models identified by TS.

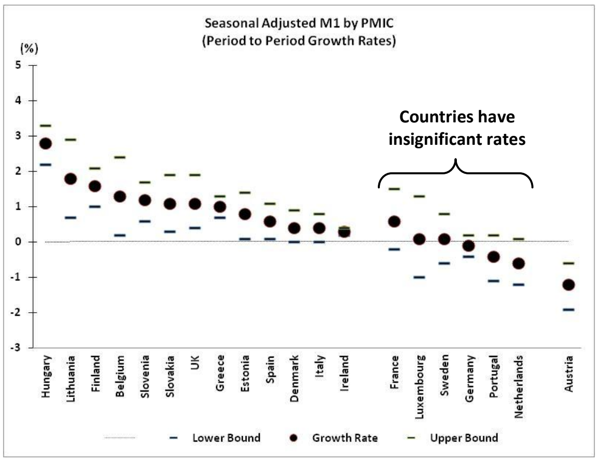
Graphical Comparison

In this part, we want to clarify the effect of PMIC on precision of period to period growth rate of current value of seasonal adjusted series.

M1 Monetary Aggregates

Panel 1 has two graphics which represent the March 2014 growth rates (over the February 2014) and confidence intervals of 20 countries' seasonal adjusted M1 series produced by TS and PMIC, accordingly. If TS's algorithm is used to select model to seasonally adjust the M1 figures, one would see that 10^{th} of 20 countries have insignificant growth rates in March for M1. But, if PMIC is used, one would see 6 countries of 20 countries have insignificant growth rates in March for M1. So, the countries Denmark, Ireland, Spain and UK would have been included to the basket of the countries had positively M1 grown in March 2014.

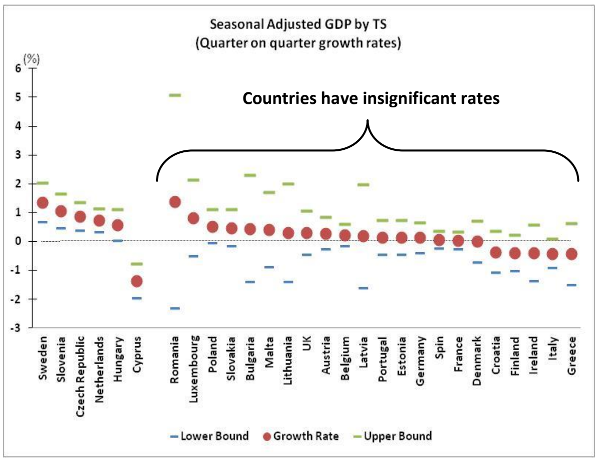


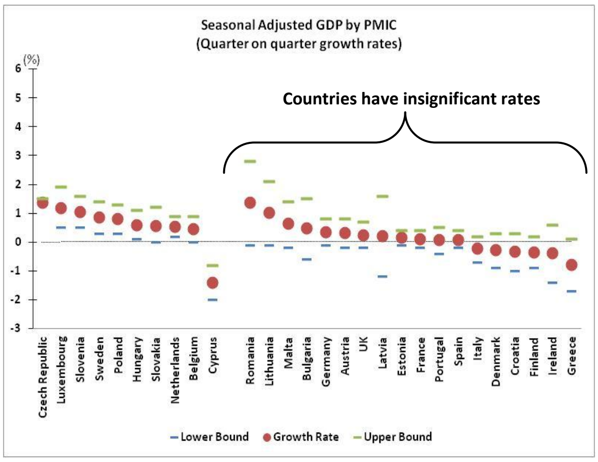


Panel 1. Graphical comparison for M1

Gross Domestic Product

Panel 2 has two graphics which represent the Q4-2013 growth rates (over the Q3-2013) and confidence intervals of 28 countries' seasonal adjusted GDP series produced by TS and PMIC, accordingly. If TS's algorithm is used to select model to seasonally adjust the GDP figures, one would see that 22nd of 28 countries have insignificant growth rates in Q4-2013 for GDP. But, if PMIC is used, one would see 18th of 28 countries have insignificant growth rates in Q4-2013 for GDP. So, the countries Belgium, Luxembourg, Poland and Slovakia would have been included to the basket of the countries had positively GDP grown in Q4-2013.





Panel 2. Graphical comparison for GDP

CONCLUSION

In general, seasonal adjustment is seen as data smoothing process to extract clearer information from the data. But, the precision of the seasonal adjusted data is more important for the policy makers. Especially, confidence interval of growth rates of seasonal adjusted macroeconomic series is crucial to take the right action in short term policies.

In this paper, a new criteria (PMIC) is suggested to use in model selection part of seasonal adjustment which use AIC or modified BIC in general. PMIC gives more importance to the precision of growth rate estimates rather than parsimony. Results indicate that PMIC shows good performance to model selection in terms of not only minimization of confidence interval but also fine tuning of classical model based diagnostic. As a practical conclusion, a number of countries' M1 and GDP growth rates are more interpretable and become more significant for the policy makers.

The results are motivated us to implement PMIC into the trend-cycle estimation. Also, PMIC criteria can be modified with incorporation of precision of year on year estimates.

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APPENDIX 1. Comparison between PMIC and TS model selection results for EU-28 M1 series

Country	S	Model PMIC	Model TS	BIC PMIC	BIC TS	SE PMIC	SE TS	Q PMIC	Q TS	QS PMIC	QS TS	SKEW PMIC	SKEW TS	RUNS PMIC	RUNS TS
Austria	Y	(0,1,1) (1,0,0)	(0,1,0) (1,0,0)	-8.041550	-8.046560	0.334831	0.342281	31.32	33.90	0.00	0.00	-0.90	-0.82	-0.72	1.01
Belgium	Y	(2,0,0) (1,1,1)	(0,1,1) (0,1,1)	-7.190630	-7.218330	0.555321	0.804597	14.40	16.96	0.00	1.30	0.27	0.37	-0.74	0.15
Bulgaria	N	(1,2,1) (0,0,0)	(1,1,2) (1,0,0)	-7.088240	-7.048480	0.000000	0.373896	24.97	17.16	5.95	0.00	-1.10	-1.40	-0.18	0.55
Cyprus	N	(0,1,1) (0,0,0)	(0,1,1) (0,0,0)	-7.084840	-7.084840	0.000000	0.000000	23.15	23.15	0.00	0.00	1.16	1.16	-0.81	-0.81
Czech Republic	N	(2,1,2) (0,0,0)	(2,1,2) (0,0,0)	-7.613250	-7.613250	0.000000	0.000000	14.72	14.72	3.70	3.70	0.81	0.81	0.00	0.00
Germany	Y	(2,1,0) (1,0,1)	(0,1,0) (0,1,1)	-8.985220	-9.044360	0.160778	0.312517	23.02	26.08	0.00	0.00	0.55	-0.44	-0.58	0.74
Denmark	Y	(3,0,3) (1,1,1)	(3,1,0) (1,0,0)	-8.550960	-8.570160	0.230860	0.274245	32.90	26.68	2.11	0.00	-0.55	0.15	-0.49	1.25
Estonia	Y	(0,1,0) (1,0,0)	(0,1,0) (1,0,0)	-7.663600	-7.663600	0.342039	0.342039	38.03	38.03	0.00	0.00	-1.27	-1.27	0.00	0.00
Spain	Y	(2,1,1) (1,1,1)	(3,1,0) (1,0,1)	-8.389810	-8.343960	0.244049	0.442996	32.66	18.24	0.65	0.21	0.07	0.44	0.00	-1.01
Finland	Y	(2,1,1) (1,1,1)	(3,1,0) (1,0,0)	-8.191610	-8.099420	0.294994	0.314417	28.80	26.05	0.00	0.00	0.57	0.49	-1.19	-0.87
France	Y	(0,1,2) (0,1,1)	(2,1,0) (0,1,1)	-8.397370	-8.424030	0.425278	0.437420	18.45	16.99	1.80	1.41	-1.45	-1.41	-1.04	0.00
UK	Y	(0,1,1) (1,0,0)	(0,1,1) (0,1,1)	-7.329830	-7.323340	0.379604	0.619065	22.49	18.04	0.00	0.59	-0.11	-1.53	-0.30	-0.77
Greece	Y	(2,2,2) (0,1,1)	(3,1,0) (0,1,1)	-8.359290	-8.358790	0.147744	0.286289	20.65	18.73	1.11	2.30	1.42	-0.24	-1.35	-0.30
Hungary	Y	(1,0,0) (1,1,1)	(0,1,0) (0,1,1)	-7.262850	-7.290900	0.276353	0.518307	21.48	20.94	0.00	0.00	-1.38	-1.18	0.00	0.55
Ireland	Y	(0,1,3) (0,1,1)	(2,1,0) (1,0,0)	-9.317480	-9.239510	0.050473	0.180821	32.79	30.32	0.00	0.01	-0.98	1.95	0.15	0.43
Italy	Y	(1,1,3) (1,1,1)	(3,1,0) (1,0,0)	-9.012930	-9.023390	0.204453	0.237774	19.71	25.38	0.26	0.00	-0.88	0.23	1.04	0.29
Lithuania	Y	(0,2,1) (1,0,1)	(0,1,1) (0,1,1)	-7.529940	-7.528350	0.548873	0.683589	13.41	32.60	0.00	0.41	1.88	0.85	0.93	0.58
Luxembourg	Y	(1,0,1) (0,1,1)	(0,1,1) (0,1,1)	-6.956840	-6.978050	0.568687	0.587555	26.02	20.48	4.59	3.22	-0.72	-3.16	-1.04	-1.19
Malta	N	(0,1,1) (0,0,0)	(0,1,1) (0,0,0)	-8.247870	-8.247870	0.000000	0.000000	16.56	16.56	2.23	2.23	1.03	1.03	1.73	1.73
Netherlands	Y	(1,1,0) (1,1,1)	(0,1,1) (1,0,0)	-7.677010	-7.562420	0.326640	0.439433	25.19	22.54	0.49	0.00	0.68	1.67	-0.15	-2.02
Poland	N	(0,1,0) (0,0,0)	(0,1,0) (0,0,0)	-6.548710	-6.548710	0.000000	0.000000	12.49	12.49	2.73	2.73	-1.16	-1.16	0.73	0.73
Portugal	Y	(0,1,3) (1,1,1)	(0,1,1) (0,1,1)	-7.710140	-7.686430	0.317868	0.618849	25.50	38.68	0.00	1.02	-0.76	-1.31	0.00	-1.64
Romania	N	(0,2,1) (0,0,0)	(0,2,1) (0,0,0)	-6.946560	-6.946560	0.000000	0.000000	24.44	24.44	1.52	1.52	-0.40	-0.40	1.73	1.73
Sweden	Y	(0,1,0) (1,0,1)	(0,1,0) (0,1,1)	-8.074350	-8.109180	0.372053	0.451833	20.47	23.72	0.00	0.00	2.05	2.16	1.16	1.21
Slovenia	Y	(3,1,0) (1,1,1)	(0,1,1) (1,0,0)	-8.025480	-8.044290	0.295219	0.363262	15.86	25.10	0.02	0.15	-0.99	-0.08	0.96	-0.37
Slovakia	Y	(0,1,0) (1,0,0)	(0,1,1) (0,1,1)	-7.878620	-7.943140	0.402985	0.599481	33.85	18.32	0.00	0.13	1.67	0.83	1.43	-0.87

S: Existence of Seasonality (**Y**es/**N**o);

Q: Residual autocorrelation test (if test value below 40, “Good”; otherwise “Bad”),

QS: Residual seasonal autocorrelation test (if test value below 9, “Good”; otherwise “Bad”),

Skew: Skewness test for residual (if test value below 2, “Good”; otherwise “Bad”),

RUNS: Residual random distribution test (if test value below 2, “Good”; otherwise “Bad”)

APPENDIX 2. Comparison between PMIC and TS model selection results for EU-28 GDP series

Country	S	Model PMIC	Model TS	BIC PMIC	BIC TS	SE PMIC	SE TS	Q PMIC	Q TS	QS PMIC	QS TS	SKEW PMIC	SKEW TS	RUNS PMIC	RUNS TS
Austria	Y	(1,1,0) (1,1,1)	(0,1,0) (0,1,1)	-8.8876	-9.0284	0.25	0.29	8.59	12.30	0.00	0.29	-1.04	-1.79	0.00	0.72
Belgium	Y	(2,0,3) (0,1,0)	(0,1,0) (0,1,1)	-10.044	-10.029	0.19	0.19	6.65	17.91	0.00	0.00	0.77	-0.42	-1.43	-2.15
Bulgaria	Y	(3,0,2) (1,1,0)	(2,0,0) (0,1,1)	-6.3005	-6.3143	0.53	0.94	24.58	13.84	3.99	0.00	2.16	2.07	-0.48	-1.66
Croatia	Y	(2,1,0) (0,1,0)	(1,0,1) (0,1,0)	-8.2163	-8.2992	0.34	0.36	14.18	13.35	0.14	0.20	-0.27	-0.57	-2.05	-1.51
Cyprus	Y	(0,1,1) (1,1,1)	(0,1,0) (0,1,0)	-8.9376	-9.0522	0.28	0.30	21.12	13.74	1.67	0.00	0.71	0.41	-0.48	-0.96
Czech Republic	Y	(3,1,2) (0,1,1)	(2,1,0) (1,1,1)	-8.9004	-8.8095	0.05	0.25	9.95	15.68	2.24	0.00	-1.33	-2.39	0.96	2.15
Denmark	Y	(0,1,0) (1,1,1)	(1,0,3) (0,1,0)	-8.7554	-8.719	0.31	0.36	13.20	13.10	1.14	0.11	-0.91	0.42	0.96	1.43
Estonia	Y	(1,1,0) (0,1,1)	(0,1,0) (0,1,1)	-8.0576	-8.0911	0.11	0.31	17.11	17.24	0.56	0.41	-0.85	-0.93	0.48	0.00
Finland	Y	(0,1,0) (1,1,1)	(0,1,0) (0,1,1)	-9.0174	-9.1106	0.29	0.32	9.46	9.36	0.01	0.03	0.62	0.54	-0.72	-0.72
France	Y	(3,1,1) (1,1,0)	(0,1,1) (0,1,1)	-10.459	-10.466	0.15	0.15	14.20	12.93	0.00	0.95	0.84	0.84	-0.96	-1.20
Germany	Y	(3,0,0) (0,1,1)	(0,1,0) (0,1,1)	-9.4296	-9.395	0.23	0.27	15.07	30.59	0.28	0.52	-0.05	-2.02	0.48	0.00
Greece	Y	(0,1,0) (1,1,1)	(0,1,1) (0,1,1)	-7.9612	-8.0515	0.46	0.54	16.54	15.71	0.21	0.00	-1.96	-1.90	0.48	0.24
Hungary	Y	(0,0,3) (1,1,0)	(1,0,0) (1,1,0)	-9.2314	-9.2607	0.24	0.27	15.90	20.77	0.00	0.05	0.05	-0.32	-0.48	-0.48
Ireland	Y	(1,1,0) (1,0,0)	(1,1,0) (1,0,0)	-7.4436	-7.4436	0.50	0.50	13.84	13.84	0.00	0.00	-0.51	-0.51	-0.50	-0.50
Italy	Y	(1,0,3) (0,1,0)	(0,1,2) (0,1,1)	-9.4746	-9.5143	0.22	0.25	6.98	10.47	0.00	0.00	-1.15	-0.92	1.67	1.67
Latvia	Y	(2,0,0) (1,1,1)	(0,1,0) (0,1,1)	-6.9112	-6.9764	0.70	0.92	10.61	18.48	0.43	1.03	0.66	0.06	0.24	3.11
Lithuania	Y	(3,1,2) (1,1,1)	(2,1,0) (0,1,1)	-7.5266	-6.931	0.56	0.86	6.53	11.41	0.05	1.05	1.03	0.13	-0.72	1.20
Luxembourg	Y	(0,1,1) (1,1,1)	(1,1,0) (0,1,1)	-7.7948	-7.7704	0.37	0.67	16.22	22.50	0.61	2.44	0.37	-0.23	1.44	0.24
Malta	Y	(0,0,2) (1,1,1)	(1,0,0) (0,1,1)	-7.8058	-7.8509	0.41	0.66	11.88	8.71	0.25	0.13	-0.55	-0.66	1.13	-0.85
Netherland	Y	(0,1,1) (1,1,1)	(0,1,1) (0,1,1)	-9.7042	-9.7874	0.19	0.21	9.84	7.80	0.40	0.22	-1.29	-1.10	0.48	0.24
Poland	Y	(0,0,3) (1,1,1)	(0,1,1) (0,1,0)	-8.8502	-8.8942	0.24	0.29	8.48	22.42	0.22	0.35	-0.39	-0.10	0.24	-0.24
Portugal	Y	(1,1,0) (1,1,1)	(1,1,0) (0,1,1)	-9.1356	-9.2129	0.23	0.30	14.15	15.05	0.00	0.02	-2.56	-2.96	-0.24	-0.72
Romania	Y	(2,0,0) (1,1,0)	(1,0,0) (0,1,1)	-6.406	-6.2634	0.74	1.89	7.48	21.98	0.00	0.00	-0.70	1.11	-0.53	-1.05
Slovakia	Y	(1,0,0) (0,1,1)	(0,1,0) (0,1,0)	-8.7875	-8.8958	0.30	0.33	3.56	4.58	0.13	0.76	1.12	1.19	-0.24	-0.24
Slovenia	Y	(1,0,2) (0,1,0)	(0,1,2) (0,1,0)	-8.6337	-8.6809	0.29	0.30	13.18	12.83	0.00	0.00	-0.43	-0.32	-0.72	0.24
Spain	Y	(0,1,0) (0,1,0)	(0,1,0) (0,1,0)	-10.328	-10.328	0.16	0.16	13.44	13.44	0.00	0.00	-1.26	-1.26	0.24	0.24
Sweden	Y	(1,0,0) (1,1,1)	(1,0,0) (0,1,1)	-8.9523	-8.9776	0.27	0.34	9.85	11.49	0.03	0.44	-1.52	-0.94	0.48	0.96
UK	Y	(0,1,1) (1,1,1)	(0,1,1) (0,1,1)	-8.6734	-8.7203	0.24	0.39	10.95	7.98	0.00	0.00	-1.14	-1.19	-0.48	0.24

S: Existence of Seasonality (**Y**es/**N**o);

Q: Residual autocorrelation test (if test value below 40, “Good”; otherwise “Bad”),

QS: Residual seasonal autocorrelation test (if test value below 9, “Good”; otherwise “Bad”),

Skew: Skewness test for residual (if test value below 2, “Good”; otherwise “Bad”),

RUNS: Residual random distribution test (if test value below 2, “Good”; otherwise “Bad”)