SEASONALITY TESTING FOR MACROECONOMIC TIME SERIES – COMPARISON OF X-12-ARIMA AND TRAMO/SEATS PROCEDURES

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Summary: Economic time series can be impacted by seasonal factors. If present but not identified, seasonality may lead to incorrect conclusions derived from the analysis. Seasonality is not always easily identifiable as time series are shaped by other factors as well, such as one-off events or natural disasters. There is a variety of methods to deal with seasonality in data. An attempt was made to compare the outcome of two popular methods: X-12-ARIMA and TRAMO/SEATS. They were applied to analyse seasonality for the business climate index in the construction industry in Poland. Both procedures were used to produce a seasonally adjusted series for the business climate index. Comparison of model's diagnostics proved that TRAMO/SEATS performed slightly better for the analysed series within a chosen time range, which is consistent with some more general results found in the literature.

Keywords: seasonality, X-12-ARIMA, TRAMO/SEATS

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1. Introduction

Macroeconomic time series offer some useful information on general economic soundness providing that they can be correctly interpreted. This interpretation may be misled if we do not take into account significant factors like seasonality. As a result, incorrect conclusions are derived. Macroeconomic time series represent real data that sometimes can be difficult to model as they are often impacted by seasonal influences or one-off events. A similar problem may arise if we wish to use such series as inputs to the models that predict future market conditions or in any other type of research. Some statistical tests or forecasting procedures assume that the series are free from seasonality. Hence, an adjustment is required.

There is a variety of methods based on statistical techniques that can help identify seasonality. X-12-ARIMA and TRAMO/SEATS, applied by national banks and census offices of many countries, belong to the most popular.

The recent research on the topic was done by Grudkowska and Paśnicka [2007] who compare the performance of the methods depending on the sample length. They conclude that TRAMO/SEATS performs better even if the sample is significantly reduced. Cabra et al. [2003] and Feldpausch et al. [2004] discuss which criteria should be considered when comparing the quality of seasonality check models. Kaiser and Maravall [2000] apply both methods to the German retail sales turnover and encounter problems with X-12-ARIMA. The procedure is unable to address the presence of different moving patterns for some months.

The purpose of this paper is to carry out a seasonality check using both procedures and compare results to assess which model performs better when inspecting seasonality in macroeconomic series. This exercise is taken using the business climate index for the construction industry in Poland published by Central Statistical Office (Główny Urząd Statystyczny). The series is published as unadjusted data. Calculations are carried out using Demetra. The software offers several statistical tests against stable and moving seasonality for both procedures as well as techniques like spectral analysis to conclude on seasonality presence or absence.

In section 2 the seasonality in data and its implications are discussed. In section 3 the X-12-ARIMA and TRAMO/SEATS procedures are compared. A variety of statistical tests carried out as a part of these procedures is presented. In section 4 an empirical analysis is conducted using sample data, namely the business climate index for the construction industry. The final results of both procedures are similar, but in general the model built with TRAMO/SEATS turns out to be better. Section 5 presents the main findings and recommendations.

The outcome of the paper is a comparison of models developed with these two procedures. The produced seasonally adjusted series is of a good quality and can be applied in any further research like business climate index forecast for next periods.

It is essential to find a method that performs well irrespective of the length of the series when analyzing business indices for Poland as they are relatively short. This is related to the transition in the Polish economy. Severe structural changes make it difficult for seasonality detection procedures to build a reliable model. Therefore information concerning periods before the transition would be of no use as the economic context was entirely different.

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2. Seasonality in time series

2.1. General considerations

Macroeconomic time series provide useful information on general economic soundness. The data are usually gathered in quarterly or monthly intervals. Many business decisions are taken based on their value. To correctly interpret the series an identification of seasonal factors may be required. Undetected presence of seasonality may result in incorrect conclusions. Seasonality removal facilitates the understanding of non-seasonal changes that influence the series.

Taking into account the type of activity measured by macroeconomic series we may assume that the data will be a subject to seasonal influences. Therefore a seasonality check needs to be carried out prior to using the series as an input to any further analysis. We expect summer, spring and autumn to be a busy period in the construction industry.

2.2. Impact of seasonal factors

Seasonality can be defined as a regular variation from the trend that is observed in a cycle [Cieślak 2011, p. 64]. It is repeated in a stable or evolving manner in subsequent periods. Undetected presence of seasonal factors may provide with a misleading interpretation of cross-month values in the analysed series. Moreover, the magnitude of unseasonal impacts cannot be easily compared as they are hidden behind seasonal factors. Therefore the series may require adjustments. Eliminating seasonal fluctuations helps identify the actual trend in data.

Seasonality can be identified in the process of series decomposition. There are several components that build the original series: trend-cycle component, trading days effect, moving holidays effect and random component [Grudkowska, Paśnicka 2007]. As the number of non-business days impacts economic activity, the series needs to be adjusted to eliminate such effects and irregular components. Irregular components, such as random components or outliers, may either cause a single distortion or a permanent change in the trend.

2.3. Seasonality detection

Many economic time series like business indices or the GDP and its components undergo the process of seasonal adjustments before they are further analysed. Adjusted data show impacts of factors that might otherwise be hidden behind seasonal influences. Potential errors in data sets are also more visible. Unadjusted data may be of an equal importance however, as they show the actual events that occurred. To perform the full analysis both types of series may be required.

Seasonal adjustment means that particular components of a series are identified and seasonal impacts removed. Seasonality detection may not be straightforward due to the following:
– impact of irregular events that make seasonality less identifiable;
– interpretation of rates of change for particular months – comparison of year-to-year rates may be useless due to the different number of working days or a holiday period falling in a different month;
– series length.

Some special techniques are required to address that. There is no agreement on the optimal approach to seasonally adjust data, neither which criterion should be conclusive while comparing the methods[1]. Therefore the comparison is carried out at various levels. TRAMO/SEATS and X-12-ARIMA are one of the most popular methods of seasonality check. As there are some differences in how they are constructed, they are often applied in parallel [Grudkowska, Paśnicka 2007]. Both procedures identify the following components:
– trend-cycle component – which shows general data pattern and business cycles;
– seasonal component – takes into account calendar effects like a working-day effect or a moving holidays effect. It includes relatively stable seasonal effects such as Christmas as well as those effects the impact of which differs from one year to another, e.g. number of working days in a month. These types of effects are predictable and systematic;
– irregular component – includes outliers, unpredictable and other irregular effects. The presence of a strong irregular component may result in difficulties in adjusting data properly.

The product of a seasonal adjustment is the trend-cycle component plus the irregular component.

3. Comparison of seasonality detection procedures

3.1. X-12-ARIMA

The method is an extension to X-11, which was one of the first techniques of seasonal adjustment, developed by the U.S. Bureau of the Census. X-11 decomposes the series based on moving average filters. The

[1] This is discussed e.g. by Cabra et al. [2003] and Feldpausch et al. [2004].

method was enriched by the ARIMA model [Box et al. 1994]. This serves the purpose of extrapolating the series backward and forward to apply symmetric filters at the series ends [Findley et al. 1998]. An initial estimation is carried out before proceeding with the actual seasonal adjustment. The initial model, REGARIMA, takes into account all components: trend-cycle, seasonal fluctuations, calendar and Easter effect and random component. ARIMA is combined with traditional regression techniques, which is to control for autocorrelation and nonstationarity in the original series [Grudkowska, Paśnicka 2007]. Outliers and effects are removed from the series. Nevertheless to ensure that the filtering procedure is run correctly and it identifies seasonal effects, some preadjustments may be needed before applying X-12-ARIMA such as a temporal removal of outliers, shifts in the variable level, unseasonal changes or identified irregular impacts. This may be needed if we assume that such effects will not be symmetrically distributed around their expected value thus the seasonal moving average filters may not remove them fully.

The next step is to identify ARIMA parameters: p, d, q and seasonal P, D, Q. In X-12-ARIMA the set of filters is extended and a seasonal filter is added. The procedure estimates the spectral density function and periodogram that is an estimator of spectral density [Cieślak 2011, pp. 107].

The model's quality is assessed based on the value of test statistics for all components. In the process of spectral analysis it is verified if values of seasonal and trading days effect frequencies are significantly different from adjacent values. If the series is noticeably impacted by seasonal fluctuations, values of the spectrum for seasonal frequencies reach a local maximum at these points [Bloem et al. 2001].

3.2. TRAMO/SEATS[2]

The procedure was developed by Maravall and Gomez [1996]. It uses optimal filtering and is based on ARIMA. In the initial step of TRAMO, the ARIMA model is automatically selected. Outliers are identified using the maximum likelihood method and corrected. The series is checked for trading days and Easter effects by estimating independent variables responsible for these effects. Initially adjusted and linearized series is tested by the SEATS procedure and undergoes the process of

[2] TRAMO – Time series Regression with ARIMA noise, Missing values and Outliers; SEATS – Signal Extraction in ARIMA Time Series.

decomposition. Stochastic process interpretation can be carried out through the harmonic analysis. One of the characteristics of the process is spectral density function that identifies the series harmonic structure [Cieślak 2011, p. 107]. This serves to identify the impact of particular components on the process variance. Spectral density function is decomposed into single functions for the trend-cycle, seasonal and irregular components. An assumption is made that they are independent. For each component estimators, standard deviation of estimators and their forecasts are determined. This is possible through applying the Wiener-Kołmogorow filter on components extended backward and forward [Grudkowska, Paśnicka 2007]. Estimators are then analysed on an extended sample. In the final phase outliers and previously removed effects are added back to the series.

3.3. Comparison of X-12-ARIMA and TRAMO/SEATS

There are some differences in how TRAMO/SEATS and X-12-ARIMA are built. Table 1 presents the comparison.

Table 1. Comparison of seasonal adjustment procedures: TRAMO/SEATS and X-12-ARIMA

Criterion	TRAMO/SEATS	X-12-ARIMA
Filter Selection	Adjusted to the structure of the series; selection based on statistical tests results	The same set of filters irrespective of the series structure
Spectral Analysis	Decomposition based on spectral analysis	Spectral analysis to assess model's quality
ARIMA	Estimated for each component	Estimated only for the original series
ARMA Model Selection	Based on information criteria: BIC, AIC and statistical tests	Based on information criteria: BIC, AIC, HQC
Outliers Detection	Detects level shifts, transitory changes and additive outliers	Detects additive outliers and level shifts
Series Smoothing	Seasonal filters selection based on statistical tests results	*Ad hoc* seasonal filters
Series Length	TRAMO/SEATS usually better irrespective of a series length*	
Sample Size Reduction vs Model´s Quality	Decrease in model's quality faster for TRAMO/SEATS than for X-12-ARIMA**	

* Research carried out by [Fischer 1995] for national accounts and trade balance of various European countries.

**Finding from [Mazzi, Savio 2005].

Source: author's study.

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Main differences arise from the different construction of the procedures. Analysing various criteria (filter selection, ARMA model selection, spectral analysis) we may conclude that the approach for TRAMO/SEATS is more comprehensive and it recognizes another type of outlier: a transitory change.

There is a variety of methods to check model's accuracy. As the goal is to produce a seasonally adjusted series it is important to verify if calendar and seasonal residual effect are present while we expect not to observe them in the series. Determining if the direction of the adjusted series reflects the general direction observed in data can serve as a consistency measure. The test against the normality of distribution is conducted. Another measure of quality is an average sum of squared differences between current seasonal values and seasonal values for the preceding period. Seasonally adjusted data are subject to revisions. The difference between initially adjusted data and final estimates once future observations are known should not be significant which is verified with the revisions' average value and their standard deviation.

Sliding spans help measure the goodness of a fit. The approach is designed to check the stability of seasonal adjustment. As an initial step overlapping subsets are constructed to be compared in terms of stability. The first set contains observations from 1 to k, where k indicates the length of a set. The initial and final observations of remaining subsets are shifted by one year. In general we examine if adding observations to the adjusted series affects it significantly. We aim to assess if there are many outliers or if the seasonality pattern changes rapidly.

The comparison of the two procedures can be based on a measure which verifies the degree of conformity for annual growth rates of seasonally adjusted and unadjusted series. A large proportion of observations for which there is a difference in the sign of growth rates of the two series proves that there is inconsistency. This is less detectable if the trend is a dominant component [Grudkowska, Paśnicka 2007].

4. Empirical analysis

To test the performance of both methods a business climate index for the construction industry in Poland is chosen. As it is published as seasonally unadjusted data, there may be a need to remove seasonal influences so as to analyse fluctuations caused by other factors.

We assume that the index is considerably impacted by seasonal factors. Construction works are carried out from spring to autumn and a decrease is expected in winter. The goal is to produce a seasonally adjusted time series using a reliable model.

The index measures CEO's subjective views on general economic soundness in the sector [Główny Urząd Statystyczny 2013]. It constitutes a monthly time series. The information is gathered in surveys and is based upon criteria such as current and expected financial soundness, current and expected level of incoming orders or delays in settling liabilities by contractors. It enriches the knowledge about prospects for the construction industry. The index is available starting from 2000. Figure 1 presents the full series.

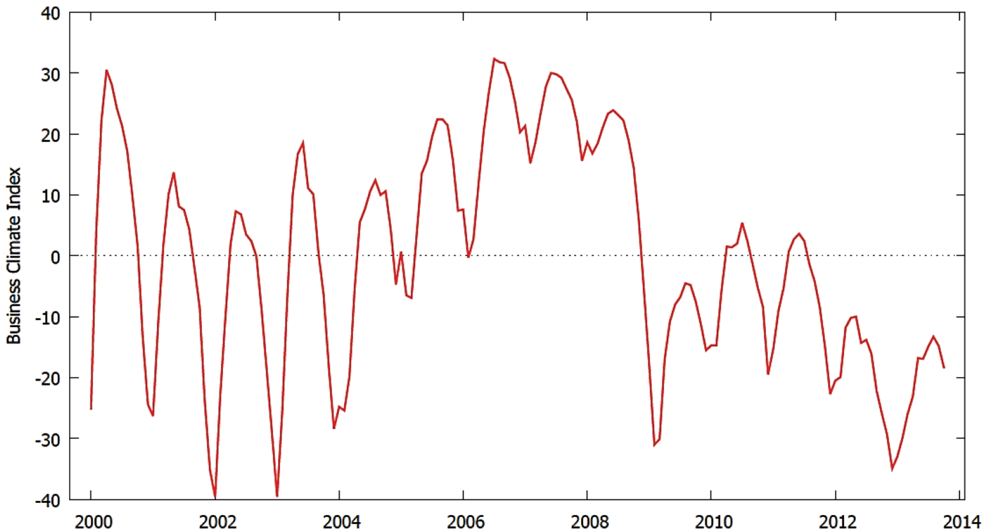

Figure 1. Monthly business climate index for the construction industry for Jan 2000 – Oct 2013

Source: author's calculations.

The data show significant fluctuations that may arise from seasonal impacts. Generally peaks are observed for the period from May to September and the index is in decrease in winter months, which was expected. There is also a change in a data pattern. Starting from 2004, the amplitude of fluctuations is smaller. The change might have been caused by joining the European Union by Poland in May 2004, which posed some positive prospects for many sectors. Knowing that we will consider analysing a shorter period as such a change may be difficult to be recognised by the procedures.

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Calculations are carried out with Demetra. The models built for the full time series turned out to be of a poor quality due to unreliable results of test statistics. In such cases it is advised to treat the series case by case [Grudkowska 2011]. It was identified that the most relevant period is the time just before joining and post-joining the EU. Therefore the sample was narrowed to Nov 2002 – Oct 2013 to keep the same number of observations for each month. A good model quality is achieved for the reduced series. There are 132 observations now, which is enough to achieve a reliable result.

4.1. TRAMO/SEATS

General assessment of the model's quality is considered *good*, which is the best result that can be achieved[3]. The procedure detects one outlier – a transitory change from 1/2003 to 10/2004, which covers the pre- and post-accession period, with a *t*-value of -6.84. As this is a business climate index we assume that it reflects entrepreneurs' expectations on changing market conditions related to the EU membership.

No trading or Easter effect is detected. The procedure decomposes the series into the trend, seasonally adjusted, seasonal and irregular components. Table 2 presents the innovation variance of the components.

Table 2. Series decomposition

Innovation Variance	
Seasonally adjusted	0.6490
Trend	0.2320
Seasonal	0.0521
Irregular	0.0685

Source: author's calculations.

We wish to minimize the innovation variance of the seasonal component, therefore when comparing two models we expect the better model to have a lower value.

Figure 2 presents the original time series (Y) against the seasonally adjusted series (SA) and the trend (T). The plot shows that the irregular component does not have a significant effect as there are no considerable

[3] Demetra package offers a general assessment of the procedure that is based on a selection of produced test statistics. There are several categories: *good* – allows for accepting the model; *bad*, *uncertain*, *severe*, *error* or *missing* – indicate a poor quality due to errors, missing values or unreliable test statistics.

differences between the seasonally adjusted series and the trend line, except for the initial period: 2003 and the beginning of 2004. Therefore the noise has a second-order role.

The variation from index average values for particular months is plotted in Figure 3. Dots indicate the ratio between the original series

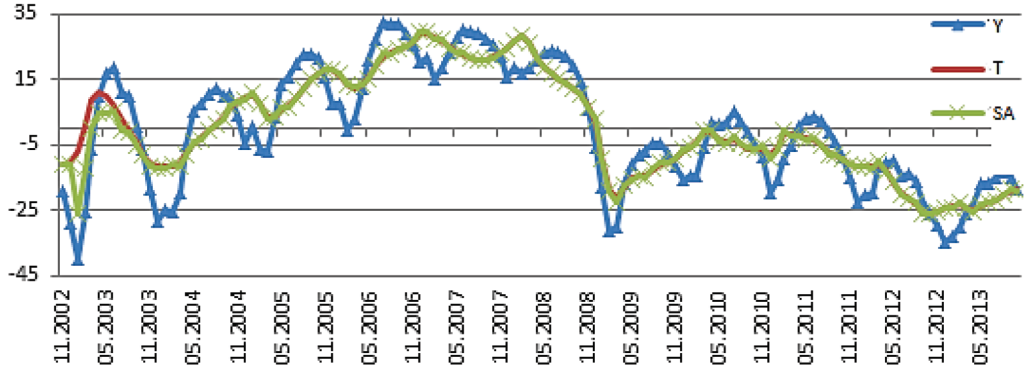

Figure 2. Original series plotted against seasonally adjusted data and trend

Source: author's calculations.

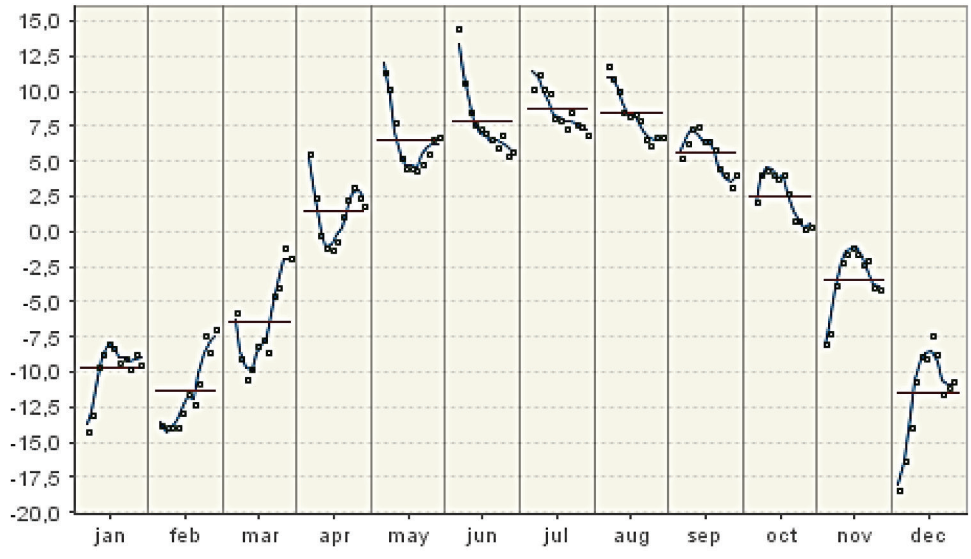

Figure 3. Variation from index average values for particular months

Source: Demetra output.

and the trend. The irregular lines reflect the influence of seasonal factors. Their shape may be an evidence of unstable or moving seasonality. The horizontal lines reflect the average impact of all factors.

TRAMO/SEATS procedure is based on seasonal ARIMA (1,1,0)(1,0,1), giving the model shown in Table 3.

Table 3. ARIMA parameters - TRAMO/SEATS procedure Source: author's calculations

	Coefficients	*T*-Stat
Regular AR	–0.5154	–6.64
Seasonal AR	–0.9195	–24.44
Seasonal MA	–0.5250	–4.87

Information Criteria	
AIC	720.3486
BIC (corrected for length)	2.6513

Source: author's calculations.

All coefficients are significant. Information criteria will be compared with X-12-ARIMA. Fitting criteria are however not enough to choose the model. Apart from inspecting series decomposition, some model's quality measures are next verified.

The model is re-estimated for the linearized series of 113 observations[4]. For the last 18 periods a forecast is built. There are no significant differences for the test and learning sets in the mean square error with the *p*-value of 0.98. Mean of forecast errors can be assumed 0 for both samples with $p = 0.91$ for the learning set and $p = 0.79$ for the last 18 observations. This indicates that the procedure is stable over the out-of-sample period that is considered.

The Portmanteau tests of Ljung-Box and Box-Pierce are used to check the normality, independence, randomness and linearity of residuals. For the test against the normality of residuals the null hypothesis cannot be rejected at the 10% significance level. The null hypothesis of independence cannot be rejected with the *p*-values for different tests presented in Table 4.

The null hypothesis of the randomness of residuals cannot be rejected with the *p*-value equal to 0.13. The null hypothesis of the linearity of the residuals cannot be rejected with the *p*-value equal to 0.64 for the Ljung-Box test and 0.74 for the Box-Pierce test.

[4] The outlier is excluded.

Table 4. Independence of the residuals

Test	*p*-value
Ljung-Box	0.71
Box-Pierce	0.81
Ljung-Box on seasonal residuals	0.35
Box-Pierce on seasonal residuals	0.45

Source: author's calculations.

The ACF and PACF functions show no autocorrelation for the seasonally adjusted series. Autocorrelation is also verified for the trend, seasonal and irregular components for the lag order 12 as this is a monthly series. No autocorrelation is observed for any lag. There is also no evidence of cross correlation between the following pairs of components: trend – seasonal, trend – irregular, seasonal – irregular with the *p*-value equal to 0.94, 0.92 and 0.74 respectively.

The Kruskal-Walis test against seasonality assuming stable seasonality cannot be rejected at the 1% significance level. The null hypothesis of the F test for the presence of seasonality assuming moving seasonality cannot be rejected at the 5% level. The conclusion derived from these results is that seasonality is identifiable in the series, the seasonality type is however not certain. Results plotted in Figure 3 may indicate moving seasonality. It must be stated that if the series range is reduced and starts from 2004 or later, the same tests give the evidence of stable seasonality while the null hypothesis of moving seasonality is rejected, though the model is of a lower quality. As for the purpose of this paper it is not necessary to conclude on the seasonality type, we take advantage of the longer series available.

Spectral plots are generated for residuals, the irregular component and the seasonally adjusted series. The regular vertical lines in Figure 4 indicate seasonal frequencies and the dotted lines – trading day frequencies. No significant peaks are observed for seasonal frequencies for the seasonally adjusted data, which would indicate incorrect decomposition of the series. For a trading day frequency the autoregressive spectrum has a peak close to the red line. This may arise from the fact that the calendar in Demetra was not updated with Polish holidays[5]. Spectral seasonal peaks are observed for the residuals at the 10% significance level.

[5] This option is not yet available in the Demetra version that was used.

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For the sliding spans method the three subsets are generated: 1/2003 – 10/2011, 1/2004 – 10/2012 and 1/2005 – 3/2013. Seasonal tests indicate the presence of seasonality assuming stable seasonality (the Kruskal-Wallis test). The test against moving seasonality fails for the first span, i.e. the null hypothesis of the presence of moving seasonality is rejected, while for the other spans it cannot be rejected. Nevertheless, seasonality is identified in all spans. No abnormal values are reported in the sliding spans panel. A high number of such unstable estimates would indicate model's poor quality.

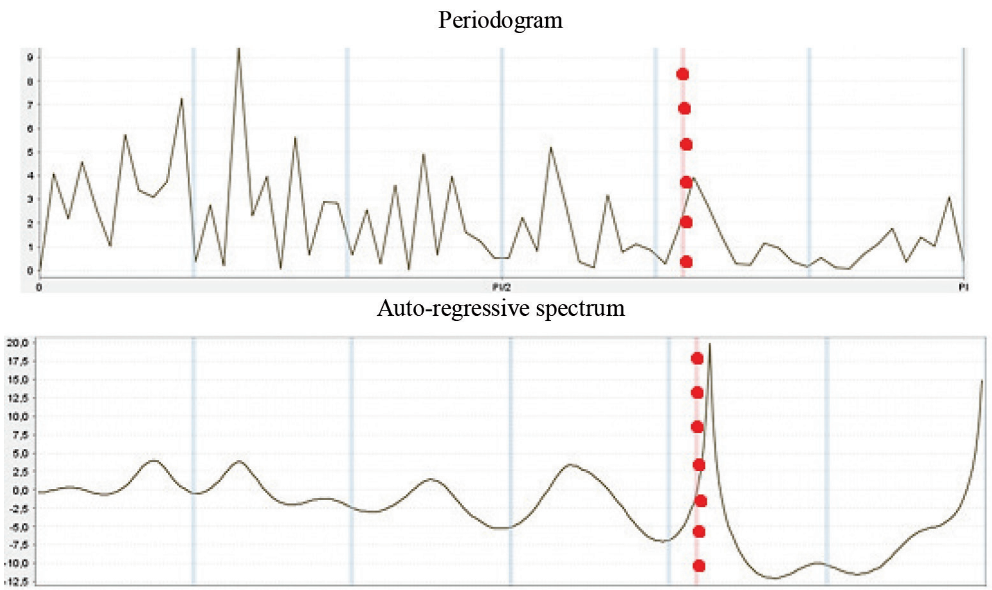

Figure 4. Spectral plots for the seasonally adjusted series

Source: Demetra output.

Based on the results of the above tests, Demetra classifies the model as good. We conclude on identifiable seasonality. The model generated with TRAMO/SEATS is a good fit, therefore the produced seasonally adjusted series can be considered reliable.

4.2. X-12-ARIMA

The same series range is applied. Neither Easter nor trading day effect is detected. One outlier is identified. It shows the same type of a transitory change as TRAMO/SEATS for the period 1/2003 – 10/2004,

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with the *t*-value of –7.08. General model diagnostics is considered good. Figure 5 shows the original series (Y) against the trend (T) and the seasonally adjusted series.

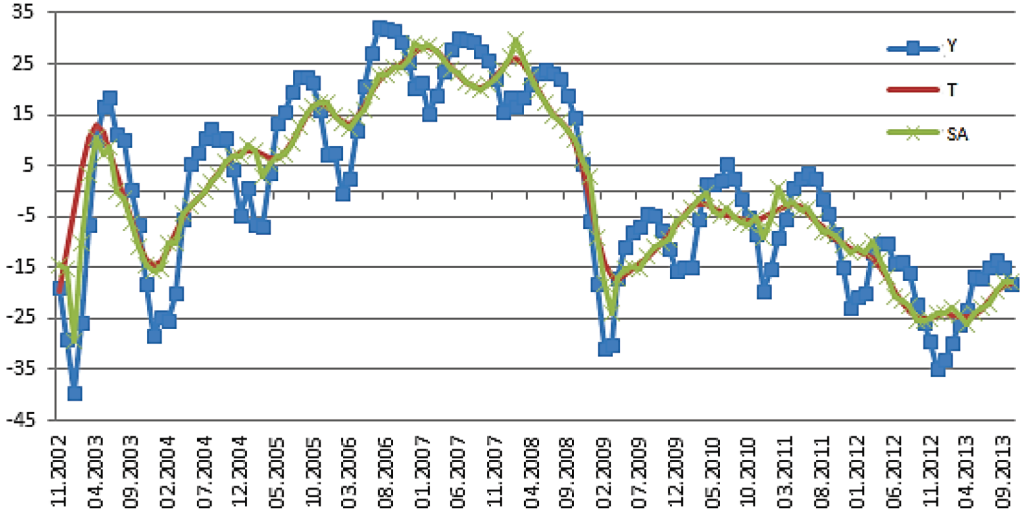

Figure 5. Original series plotted against seasonally adjusted series and the trend

Source: author's calculations.

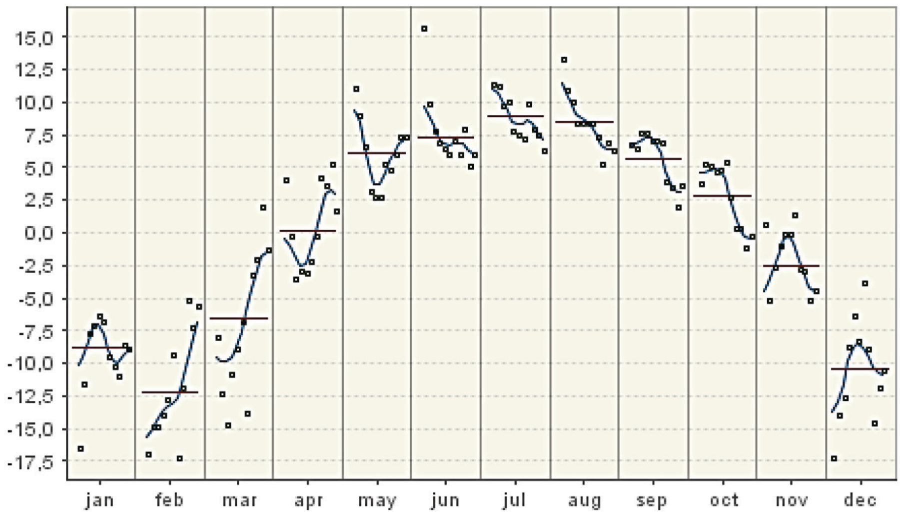

Figure 6. Variation from index average values for particular months

Source: Demetra output.

Fluctuations of seasonally adjusted series from the trend are more significant than in TRAMO/SEATS, which may indicate that X-12-ARIMA recognised more irregular impacts. Figure 6 shows that dots are much more dispersed around average seasonal values. The irregular pattern of the blue lines reflecting seasonal influences may be an evidence of moving seasonality.

The ARIMA (1,1,0)(0,1,1) model is selected with parameters shown in Table 5.

Table 5. ARIMA parameters – X-12-ARIMA procedure

	Coefficients	*T*-Stat
Regular AR	–0.5077	–6.44
Seasonal MA	–0.5828	–6.38

Information Criteria	
AIC	652.6568
BIC (corrected for length)	2.6556

Source: author's calculations.

In terms of information criteria, the Akaike information criterion is slightly lower for X-12-ARIMA, while Bayesian information criterion for TRAMO/SEATS.

The model was re-estimated for the linearized series of 101 observations and for the other 18 periods a forecast was built[6]. There are no significant differences for the test and learning sets in the mean square error with the p-value of 0.97. Mean of forecast errors can be assumed 0 for both samples with $p = 0.73$ for the learning set and $p = 0.71$ for the last 18 observations. The procedure is stable for the out-of-period sample.

The analysis of residuals shows no autocorrelation. The ACF and PACF functions are examined for this purpose. The null hypothesis of the independence is not rejected either for the Ljung-Box or Box-Pierce tests, with the p-values shown in Table 6.

The null hypothesis of the randomness of residuals cannot be rejected with $p = 0.64$. The null hypothesis of the linearity of residuals cannot be rejected with $p = 0.78$ for the Ljung-Box test on squared residuals and $p = 0.89$ for the Box-Pierce test on squared residuals. For the test against the normality of residuals the null hypothesis cannot be rejected at the 10% level.

[6] 119 effective observations are chosen for the model.

Table 6. Independence of the residuals

Test	*p*-value
Ljung-Box	0.63
Box-Pierce	0.75
Ljung-Box on seasonal residuals	0.36
Box-Pierce on seasonal residuals	0.40

Source: author's calculations.

For the sliding spans method three subsets are generated: 1/2003 – 10/2011, 1/2004 – 10/2012 and 1/2005 – 10/2013. Seasonal tests indicate the presence of seasonality assuming stable seasonality. The same tests against moving seasonality fail for the first span, i.e., the null hypothesis of the presence of moving seasonality is rejected, while for the other spans it cannot be rejected. No abnormal values are reported in the sliding spans panel. The Kruskal-Wallis test against seasonality assuming stable seasonality cannot be rejected at the 1% significance level. The null hypothesis of the F test for the presence of seasonality assuming moving seasonality cannot be rejected at 5% level. The conclusion for these results is that seasonality is identifiable in the series, however, the seasonality type is not certain.

The value of M-statistics are lower than 1 except for M-10[7] and M-11[8], which indicates a good quality of the model. Q and Q without $M2$ are combined results of M-statistics, that should also be lower than 1. In this case they equal 0.3633 and 0.4099 respectively, which ensures that the model is good.

Spectral plot for the seasonal adjusted series shows no peaks for seasonal frequencies. Spectral plot shows peaks for seasonal frequencies for the residuals, therefore the model may require some adjustments. Restricting the series range does not improve that result.

4.3. Comparison criteria

Further comparison of the methods can be done through verifying the degree of conformity for annual growth rates of seasonally adjusted and unadjusted series, which measures consistency between these two. A proportion of observations for which there is a difference in growth rates signs is 18% for TRAMO/SEATS against 20% for X-12-ARIMA.

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[7] M-10 – the size of fluctuations in seasonal component in recent years.
[8] M-11 – the average linear movement in the seasonal component in recent years.

Hence the first procedure is slightly better. It is assumed that this proportion should be lower than 25% [Grudkowska, Paśnicka 2007], which is fulfilled for both approaches.

4.4. Seasonally adjusted series

Plotting together the two seasonally adjusted series shows that there are no significant differences between them (Figure 7). The results obtained with the two procedures are similar.

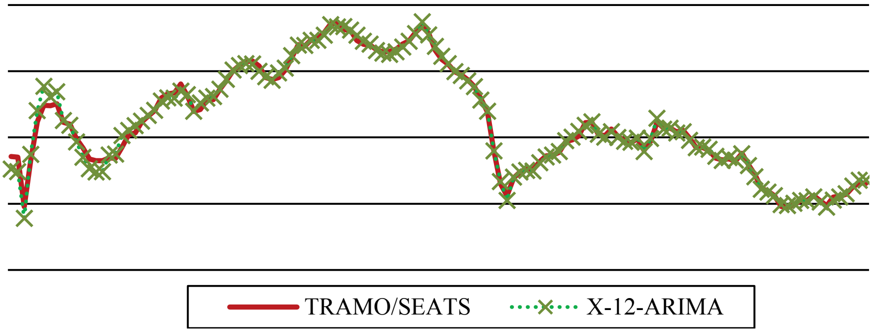

Figure 7. Series adjusted seasonally with TRAMO/SEATS and X-12-ARIMA – comparison

Source: author's calculations.

5. Concluding remarks

In this paper the two popular methods of seasonal adjustment are described. They were applied to the business climate index to produce a seasonally adjusted series. Their performance is compared based on various criteria. Both methods produced a good quality model. There is no agreement on which criteria should be conclusive while deciding on the optimal procedure. The goodness of a fit is satisfying for both procedures and comparison criteria indicate that TRAMO/SEATS performs slightly better. Nevertheless both can be used to produce a reliable seasonally adjusted series.

We also conclude that the quality of the model depends heavily on the series length. An interpretation of the graphical presentation of the series should first be considered to decide if the entire period is relevant.

Findings from this paper are consistent with more generic results tested across various industries and for a different series length. Kaiser and Marvall [2000] encounter issues while applying X-12-ARIMA to the German retail sales turnover. One of such issues is its inability to deal with heteroscedasticity. This arises from the fact that different moving patterns for some months are observed. On the other hand TRAMO/SEATS provides a stable result when applied to the same series. Ongan [2002] compares the results for the Turkish price index and recommends TRAMO/SEATS but his research is limited to long time series.

Similar conclusions are drawn by Astolfi et al. [2003] who test more general data sets. The authors state that the quality of both methods decreases while reducing a sample size but the drop is more significant for TRAMO/SEATS. The same result is achieved by Hood and Findley [2003] on simulated data. Grudkowska and Paśnicka [2007] have built a model for industrial production index achieving better results with TRAMO/SEATS for all criteria except sliding spans. For a reduced sample TRAMO/SEATS still performs better in general but the difference between the methods is not significant. X-12-ARIMA outperforms the first method when it comes to the analysis of an irregular component. The authors recommend TRAMO/SEATS for most of the series that they analysed.

In several cases the goodness of the fit depends on series characteristics. Findings by [Hood 2002] show that TRAMO/SEATS can be a good fit providing that the series is actually seasonal. Scott et al. [2007] recommend TRAMO/SEATS only under some conditions, like a series subject to outliers, when seasonality may be difficult to adjust. This conclusion is based on the research carried out for a group of series representing employment, consumer prices and producer prices. According to these findings, none of the methods is dominating.

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WERYFIKACJA SEZONOWOŚCI DLA MAKROEKONOMICZNYCH SZEREGÓW CZASOWYCH – PORÓWNANIE METOD X-12-ARIMA I TRAMO/SEATS

Streszczenie: Ekonomiczne szeregi czasowe mogą być kształtowane przez czynniki sezonowe. Niezidentyfikowanie sezonowości może prowadzić do niewłaściwych wniosków. Wpływy sezonowe nie zawsze są łatwe do wykrycia, ponieważ szeregi czasowe kształtowane są również przez inne czynniki, takie jak jednorazowe zdarzenia czy klęski żywiołowe. Istnieje wiele metod identyfikacji sezonowości. Podjęta została próba porównania dwóch najpopularniejszych: X-12-ARIMA i TRAMO/SEATS. Metody wykorzystano do analizy sezonowości wskaźnika klimatu koniunktury w budownictwie dla Polski oraz do skonstruowania odsezonowanego szeregu. Porównanie kryteriów jakości szeregów dało nieco lepsze wyniki dla TRAMO/SEATS dla analizowanego szeregu w badanym okresie czasu, co jest zgodne z ogólniejszymi wynikami omówionymi w literaturze przedmiotu.

Słowa kluczowe: sezonowość, X-12-ARIMA, TRAMO/SEATS.