HUNGARIAN CENTRAL STATISTICAL OFFICE

October 2017

About seasonal adjustment

Contents

Why do we need seasonal adjustment?

When examining an economic or social phenomenon a key question is how the particular phenomenon changes (increases or decreases) over time. This question is often interesting in the short term, i. e. within one year, however, these types of studies require special considerations. Just think about ice cream. It is quite probable that if we had statistics on the number of eaten scoops of ice cream, we would find that the number decreases significantly from August to September. However, this obviously does not mean that there would be huge problems with the ice cream sector, it only shows that in the autumn we eat less ice cream than in the summer, and this phenomenon occurs similarly year by year, even if not completely to the same extent. So the **direct comparison of data generated at two different moments or intervals in time** (for example in August and in September) **can lead to false conclusions.** And when ice cream consumption is peaking in the hot summer days in Hungary, at the same time it is winter on the southern hemisphere, so ice cream consumption there probably reaches its minimum then. In other words, **data measured at different locations are not necessarily comparable either.**

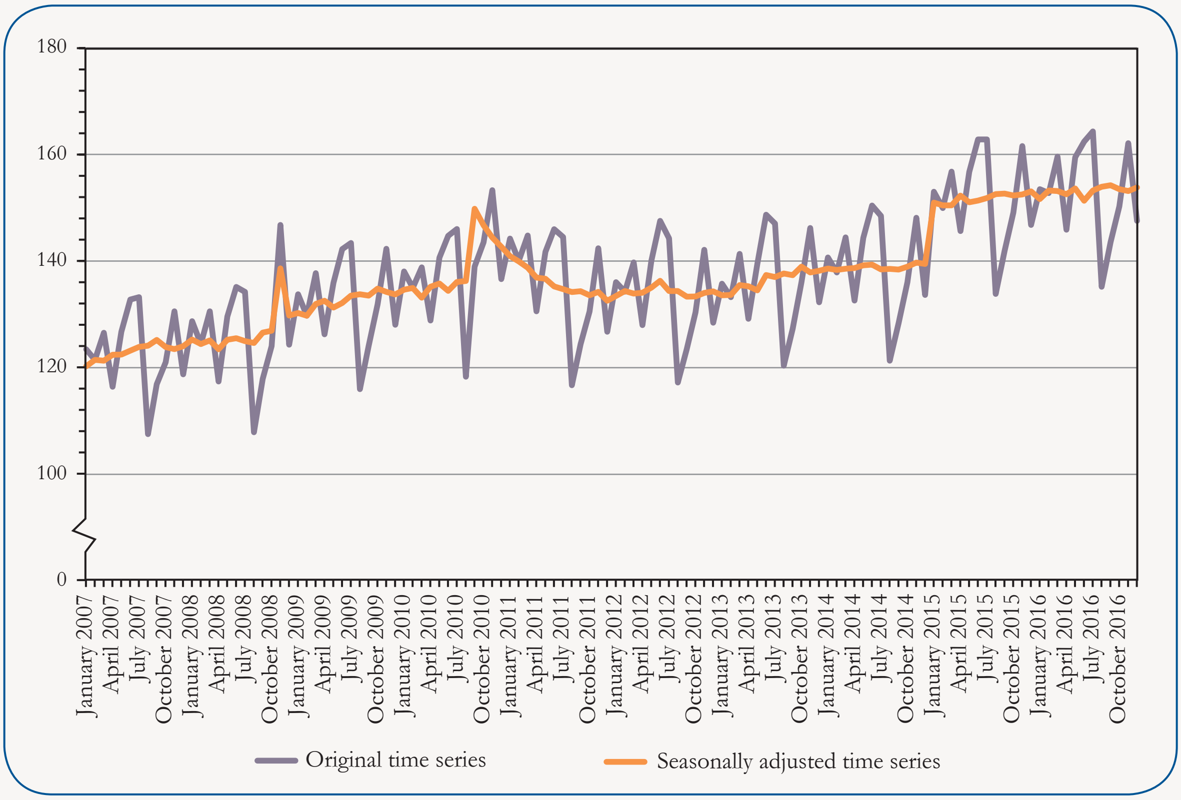
One of the **goals** of seasonal adjustment is that **data can be compared across space and over time.** For this purpose we remove from the time series[1)] the fluctuations which repeat themselves regularly/periodically each year and could hide the long-term characteristics of processes and make it difficult to examine the relationship between the different time series.

During seasonal adjustment we eliminate the effects of fluctuations within a year, so there is no reason for applying the process on annual or less frequently produced data. In official statistical practice this means that seasonal adjustment is mostly applied on monthly or quarterly data.

Figure 1 shows a simulated time series and its seasonally adjusted[2)] data between January 2007 and December 2016.

Figure 1

Simulated time series data



1) An observed **time series** is a sequence of measurements of a given phenomenon taken at regular time intervals (however, missing values may occur).

2) We produced simulated data to simultaneously demonstrate the factors influencing the process of seasonal adjustment.

What is removed from raw data during seasonal adjustment?

In line with international practice, when referring to seasonally adjusted data we actually mean **seasonally and calendar adjusted data,** only expressed with a shorter term. **Seasonality** means that the time series changes in the same direction and to almost the same extent in the same periods of different years, i.e. periodical repetitions are observed in the time series. By **calendar effects** we mean non-annual still regularly repeated effects which can be well described and estimated with the help of the calendar. By calendar effects we mean the whole of the following effects:

– The **working day effect**[3)] means that the number of working days in a given period (month or quarter) influences the time series. It can differ between months and quarters or between the same periods of different years. When allowing for the effect, holidays in the examined country are taken into consideration as well. The number of working days influences data not in all the time series. For example, in an industry where the factories produce products continuously, irrespective of whether on working days or on off days, the number of working days has no effect on the time series observed.
– The **leap year effect** means that in leap years the one day longer periods of February and of the first quarter have an influence on the behaviour of the time series.
– The **Easter effect (moving holiday effect**[4)]**)** means that Easter and the preceding period[5)], which can be in March or April (in the first or the second quarter), influence the particular time series. It is important to note that the non-working days in connection with moving holidays also affect the number of working days and off days, however, this effect is already included in the working day effect. In Hungary there are other moving holidays as well related to Easter (e.g. Whit Monday), but as they do not have such an implicit effect on time series as Easter has (for example the production of chocolate products in food industry), they are not specifically considered from this point of view.

What else is taken into consideration when performing seasonal adjustment?

Outliers often come in the centre of attention in seasonal adjustment as well as during other types of statistical analyses. Outliers are real data which do not fit in the tendency of the time series observed. In the case of outliers a single (or very rarely repeated) event[6)] affects the process to such an extent that it makes it more difficult to identify the repetitions already mentioned above.

It is important to note that while seasonal and calendar effects can hide key interconnections, outliers are important events for users. Therefore, **during seasonal adjustment we manage the effects of outliers but do not eliminate them from the processes.**

During seasonal adjustment we examine the following types of outliers:

– **Additive outlier (AO):** the effect influences the value of only one observation. For example, extreme weather conditions may cause production to stop for one or two days in a period.
– **Temporary change (TC):** it starts with one extremely high or low value, later on the deviation gradually decreases and at last the process returns to the initial level. Examples include the market emergence of some technological invention, for which there is an outstandingly high interest first, slowly weakening later on.

3) In Hungarian it is not referred to otherwise, however, in English trading day and working day effects are distinguished. From the former approach every day (Monday, Tuesday, etc.) has a different effect, while from the second one a difference is only made between working days and non-working days.

4) The moving holiday effect is a bit more general, but as in Hungary it means only Easter, the term Easter effect is much more widespread here. Other moving holidays occur, too, in countries with other religions.

5) Other, non-moving holidays have indirect effects, too (for example Christmas), but as they are in the same period every year, this effect is the part of seasonality.

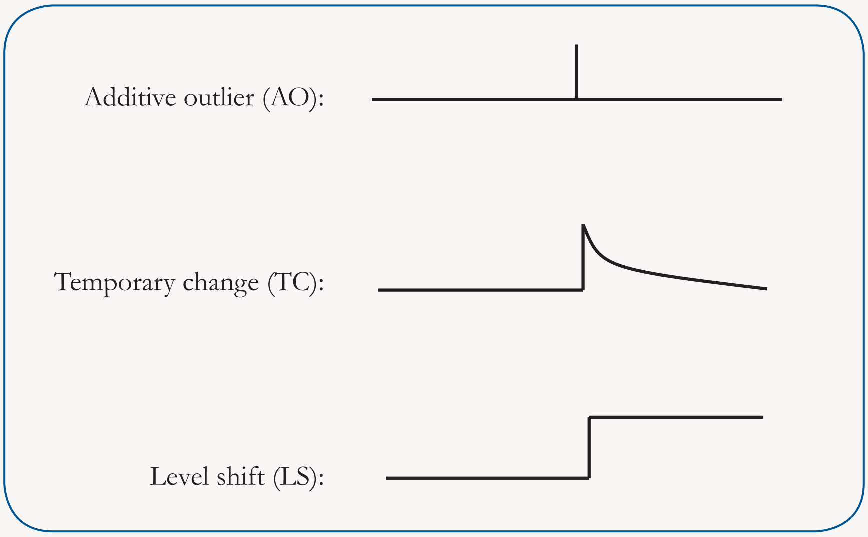
6) The event can be economic, social and even environmental.

– **Level shift (LS):** from a given point in time, further values of the time series shift by the same value (to positive or negative direction), permanently changing the level of the time series. For example, a dominant or large player in an industry may leave the market.

The types of outliers are illustrated in Figure 2.

Figure 2

Illustration of types of outliers



Out of the above-mentioned three outliers, level shift is the only one affecting the long-term tendency of the time series, the other two have only short-term, temporary effects on the series.

How is seasonal adjustment conducted?

One of the key objectives of the Hungarian Central Statistical Office (HCSO) as a member of the European Statistical System (ESS) is to produce statistical information of the best possible quality, comparable with statistical data produced by other member states and published at ESS level. Its implementation is to be supported by the European Statistical System's guidelines on seasonal adjustment. Accordingly, HCSO applies the TRAMO/SEATS procedure, one of the most prevalent methods at international level. As the method is developed and improved continuously, HCSO uses – instead of the JDemetra software – the JDemetra+ software for the seasonal adjustment of data, starting from the first reference periods in 2017. It is a free, open-source, platform-independent and flexibly expandable software, recommended for seasonal adjustment within the European Statistical System.

The procedure of seasonal adjustment consists of several steps, during which we decompose the original time series (Y) to directly non-observed, independent components, of which then we compile the final components. Figure 3 illustrates the whole process of seasonal adjustment. In Figure 4 you can see how we re-structure data from the original time series' components into the final components. At last, Figures 5, 6 and 7 show the same relations on the example of Figure 1.[7)]

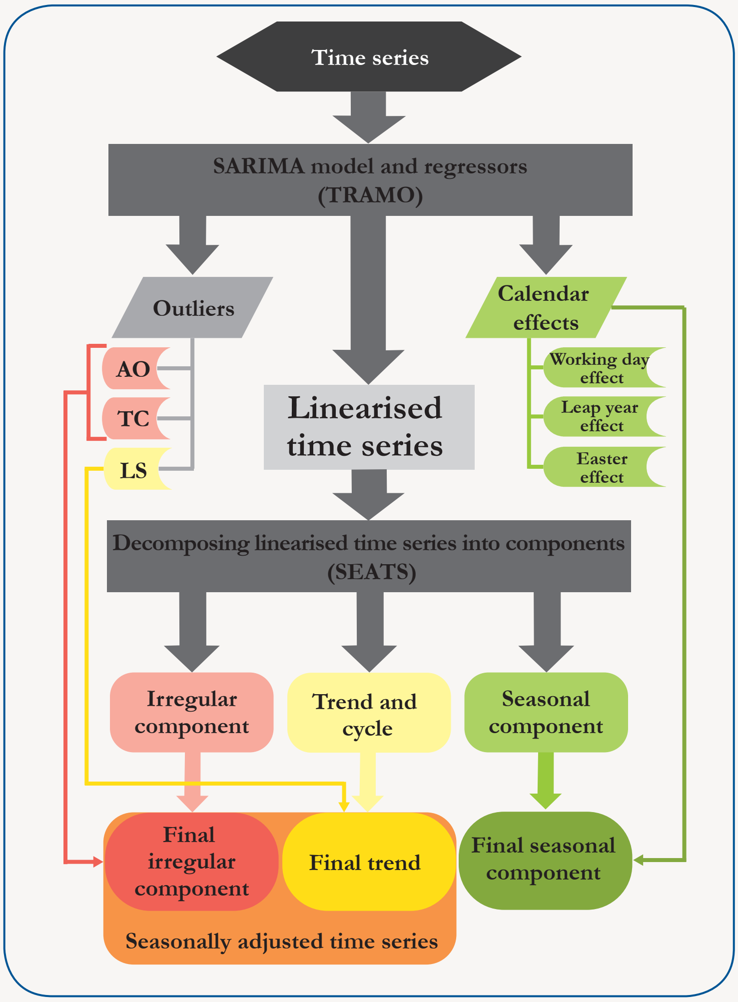
In the first step of seasonal adjustment we fit a relatively complex time series model on the original time series, indicated in dark grey in Figure 3. We identify the formerly presented calendar effects (light green) and the outliers (grey) with the aid of this model. For the modelling of these effects, on the one hand we consider the solid professional knowledge on the series (if Easter has an effect on the given

7) The figures were prepared so that particular colours in the different figures indicate the same components.

time series or not, etc.), and, on the other hand, mathematical and statistical tests also support us in the decisions. Based on these results of the modelling we remove from the time series the effects of the outliers and of the calendar. The resulting cleaned time series is referred to as the **linearised time series** (light grey).

Figure 3

Process of seasonal adjustment



In the next part of the process we break down the linearised time series into three directly non-observed components:

1. **Trend and cycle:** the trend part shows the long-term tendency, while the cycle part the long-term fluctuations (over a year) of a given time series, and these together make up the trend and cycle component (light yellow).
2. **Seasonal component:** shows short-term (within a year), more or less regular and periodic fluctuations from the trend (light green).
3. **Irregular component:** the component including unpredictable, random effects (pink).

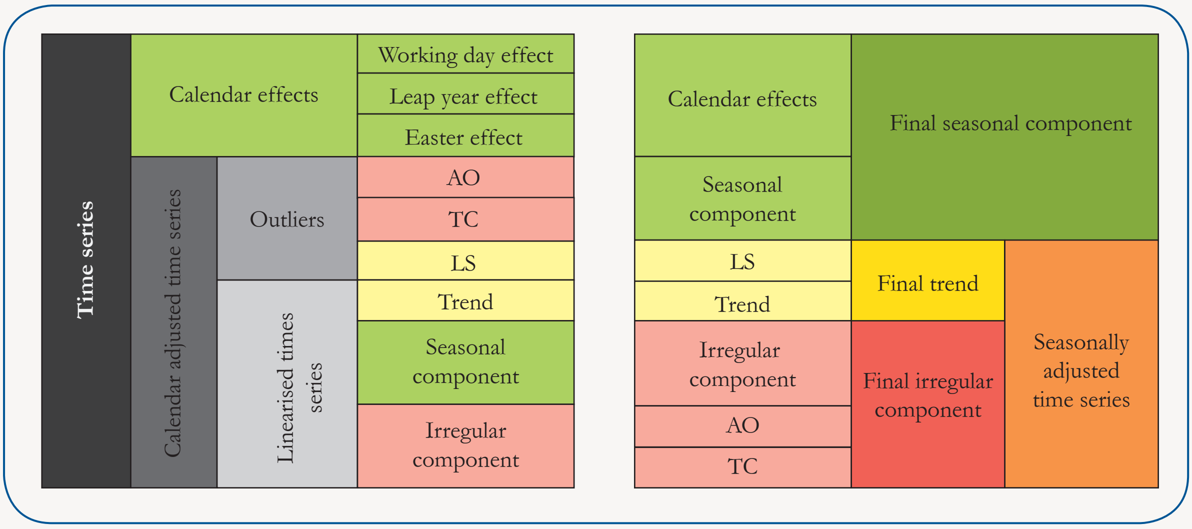
From the components thus obtained we produce the following final components:

1. The trend and cycle component of the linearised time series and the effect of the level shift (light yellow) out of the outliers make up the **final trend** (T) (yellow), describing the long-term tendency of the original time series.

2. The irregular component of the linearised time series and the effect of the additive outlier and of the temporary change (both pink) out of the outliers make up the non-repeating part of the deviation from the trend, referred to as the **final irregular component** (I) (red).
3. The final irregular component and the final trend together make up the **seasonally adjusted data** (SA) (orange).
4. The seasonal component of the linearised time series and calendar effects make up the **final seasonal component** (S) (dark green).

Figure 4

Illustration of composition of time series components



So in Figures 3 and 4 you can follow up how we divide the time series into components to compile of these the final components. Now let us take a look at it on a specific example!

The final components of the time series presented in Figure 1 – simulated time series data between January 2007 and December 2016 – can be seen in Figures 5, 6 and 7. The original time series (Figure 1) is the product of the components in Figures 5, 6 and 7 (final seasonal component, final trend and final irregular component).[8)] There are two ways to obtain the seasonally adjusted time series shown in Figure 1: as the product of the series in Figures 6 and 7 on the one hand, and by dividing the original data by data of the final seasonal component in Figure 5 on the other hand, namely

$$Y=T \cdot S \cdot I$$
$$SA=T \cdot I=Y/S.$$

It is clear from this (as also seen in Figures 3 and 4) that the seasonally adjusted time series is produced by removing the final seasonal component from the original time series.

The simulated time series in this example was produced so that it should include all the three types of outliers examined. The first outlier is in November 2008 and affects only that month, therefore it is an additive outlier in the model. The second change, shown for September 2010, is an outlier as well, which decreases slowly, so it is a temporary change in the model. As described before, both the additive outlier and the temporary change are part of the irregular component, so their effect can be seen in November 2008 data and September 2010 data in Figure 7. It is also easy to observe in the Figure how the deviation in the case of the temporary change decreases gradually over time.

The third outlier is in January 2015. At this time there is a positive change, too, which has an effect in the long run as well, so it is a level shift in the model. This outlier affects the trend component, which you can see in Figure 6.

8) So in the example the original time series is the product of the components. In other cases the original time series may be the sum of the components. Which of these two cases to be applied for the particular time series depends on the data.

Figure 5

Final seasonal component
Simulated time series data

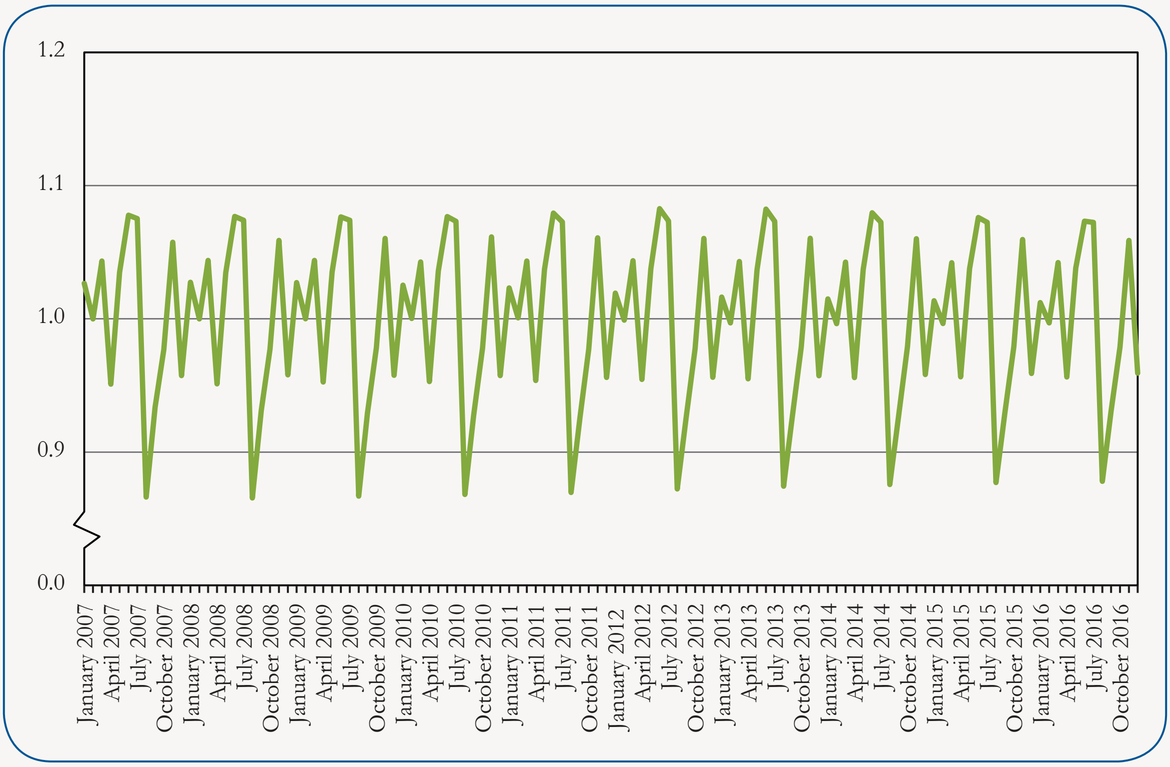


Figure 6

Final trend component
Simulated time series data

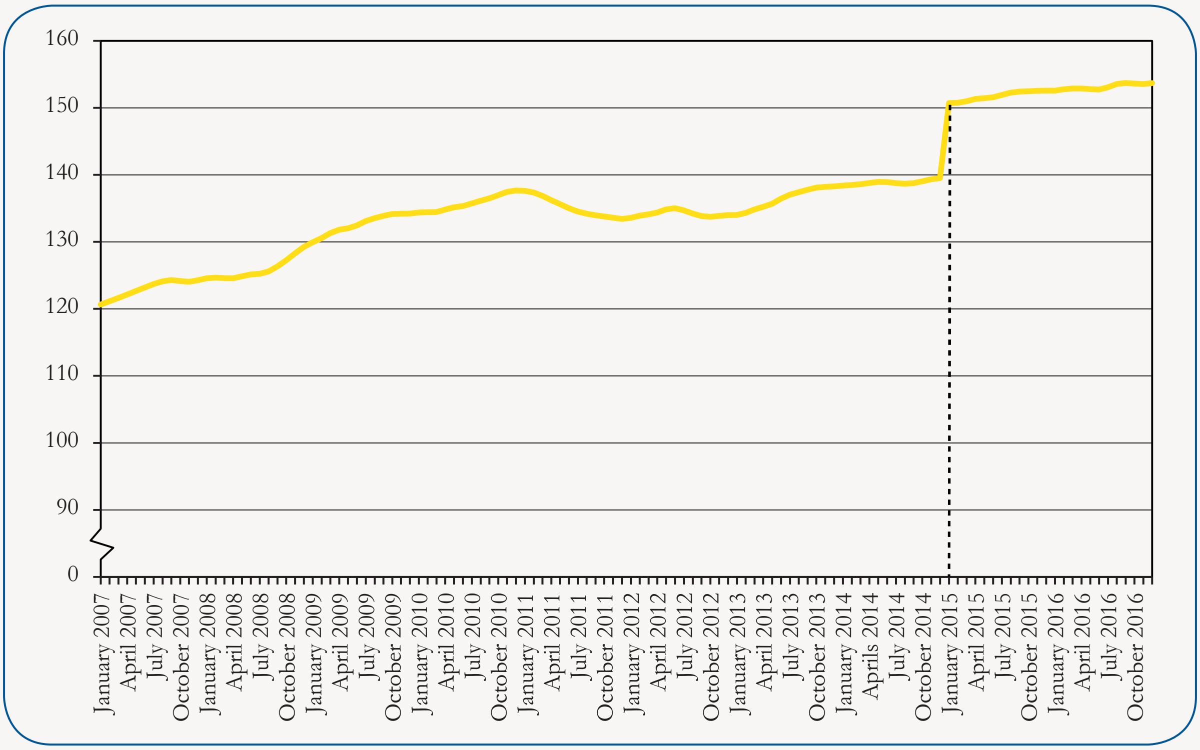
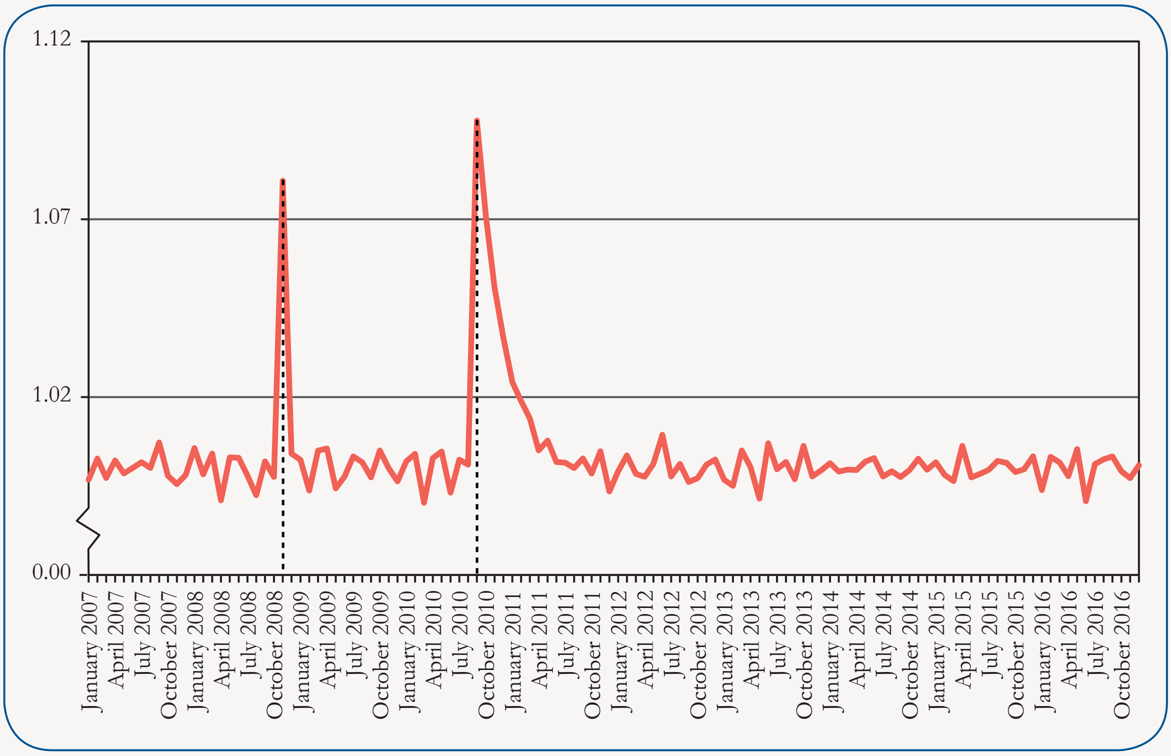


Figure 7

Final irregular component
Simulated time series data



What are the results of seasonal adjustment and how can you interpret them?

One of the most important results of seasonal adjustment is seasonally (and calendar) adjusted data. These data are significant in case you want to analyse the short-term changes of a time series (within a year), as seen in the ice cream example in the introductory part. **Changes within a year (e.g. month / previous month or e.g. quarter / previous quarter) should be analysed on seasonally adjusted data.** Certainly not all data have seasonality, in such cases the original data are considered as seasonally adjusted data, and in these cases we analyse changes on the original data.

Besides the final results we often publish the different partial results of seasonal adjustment. One of the most common such results is calendar adjusted data. It is to be noted here as well that if the series does not contain any calendar effects, then the original data will be considered as calendar adjusted data. It is worth to analyse this series, too, because seasonal effects more or less offset one another within a year, which is not true for calendar effects. As a result, if you want to compare the change to the same period of the previous year, you have three options: on the original time series, on the calendar adjusted series or on the seasonally and calendar adjusted series. The calendar adjusted series can be more realistic compared to the original one. If you suppose that there are any effects in seasonality which are longer than a year,[9)] then in this case it may be reasonable to analyse seasonally adjusted data as well.

According to its current practice, HCSO makes comparisons to data of the same period of the previous year on the original data or on the calendar adjusted time series, unless some international regulation (for example EU legislation) requires different publication.

[9)] Moving seasonality, i.e. there is a slow change in the seasonal factor.

What issues may arise with seasonal adjustment?

We tried to emphasise above that seasonal adjustment was absolutely necessary in some cases, since without it you might get misleading answers to important questions. However, as in any procedure, some factors and issues that make understanding more difficult arise here too.

1.) The issue of data revision

Any kind of process we use, in seasonal adjustment we apply methods and models that might change whenever there is a new datum in the original time series. This is necessary because all available factors observed in the time series can affect seasonal adjustment. However, this has the consequence that seasonally adjusted data change retroactively as well. This phenomenon can also be observed if the original (seasonally unadjusted) data are unchanged but the time series is completed with data of a new period of observation.

In order to make this attribute of seasonal adjustment – necessary, but often difficult to understand for users – more acceptable let us see an example requiring an essentially simpler "modelling" than seasonal adjustment. Let us suppose that we observe the scholastic result of students (e.g. in case of PISA measures, as time goes by, the competence result of more and more 15-year-old students becomes known), let it be the original data. However, it could be an interesting question, too, how each student performs compared to the average result. Therefore, we calculate the average performance of students (where we know results) and each result compared to this average. If the result of a further student becomes known, that will typically change the average performance of students and the result of students compared to the average will also change, even if the original data are otherwise unchanged. Due to similar reasons, data change retroactively in seasonal adjustment too.

To make the size of revisions of seasonally adjusted data as low as possible within each year, in its current practice HCSO determines the model used for seasonal adjustment only once a year, before the first period of the particular year. It deviates from this in case when a revision of such a size is made on the original data that as an effect of this the applied model does not fit any more. Thus during the year the model is not updated but its parameters are refreshed. So we take into consideration the latest available information, though to a limited extent. Besides, we continuously test the outliers arising in the meantime and, if reasonable, build them into the model.

2.) The problem of outliers at the end of time series

If a new outlier appears at the end of the time series, then the size of revisions due to seasonal adjustment might be especially high. The reason for this is that from a mathematical and statistical point of view the type of these outliers is uncertain, since it turns out only with knowledge of later data if the impact is on one (AO), some (TC) or all other (LS) data. So the type of outliers may change depending on newly obtained data. If well-founded experts' information, usable at the appropriate time, is available on economic, social or environmental impacts on the time series, then accordingly the type of outliers can be set, reducing this way uncertainties at the end of the time series and thus the size of revisions.

3.) The question of direct or indirect seasonal adjustment

Let us suppose that you know the number of unemployed women and men in the country. At the level of raw data you know the number of all unemployed people as well since the sum of the two data should be equal to the total number of unemployed people in the country. So you have three time series and you have the possibility to directly adjust seasonally the three time series independently of one another. This way you can be sure that you eliminate seasonality from all the three time series to the highest possible extent. However, the sum of the seasonally adjusted numbers of unemployed women and men will typically not be equal to the total seasonally adjusted number of unemployed people. There is no perfect solution to this problem. You have the possibility though to apply "indirect seasonal adjustment", i.e. only the numbers of unemployed women and unemployed men are adjusted seasonally, and their total is considered as the total seasonally adjusted number of unemployed people. The problem with this, however, is that in this case seasonality may remain in the theoretically seasonally adjusted data for the total number of unemployed people. So the total figure will not necessarily be suitable for comparisons over time or across space.

HCSO's present practice prefers direct seasonal adjustment. Note that with knowledge of data adjusted with the direct procedure it is easy to produce the result of indirect adjustment (the relevant series need to be aggregated), however, this is not true conversely.

4.) The question of temporal aggregation

There is a problem in the case of temporal aggregation, too: the annual sum of seasonally adjusted data is not necessarily equal to the annual sum of original, unadjusted data. If these two sums need to be equal, then the difference can be distributed among the seasonally adjusted data of a particular year, but this way you introduce bias to the seasonally adjusted data. This bias can be significant if, for example, calendar effects, moving seasonality or other non-linear effects can be detected in the time series. In the practice of HCSO, similar corrections are made on GDP data, more details of which can be found in national accounts' methodological information.

As a summary it can be said that while seasonally unadjusted data are the raw values of a time series, seasonally adjusted data provide more accurate information on changes to the base process. The Hungarian Central Statistical Office conducts seasonal adjustment based on an integrated methodology, which is in accordance with domestic and international expectations. It is ensured this way among others that our data are accepted internationally, too, and are comparable across space and over time, by means of which our users can have a more complete picture of the development of phenomena over time.

References

ESS Guidelines on Seasonal Adjustment (2015 edition)
EUROSTAT Manuals and Guidelines
http://ec.europa.eu/eurostat/documents/3859598/6830795/KS-GQ-15-001-EN-N.pdf
Bauer Péter, Földesi Erika – Szezonális kiigazítás [Seasonal adjustment] (2005)
Statisztikai Módszertani Füzetek, 43
http://www.ksh.hu/docs/hun/xftp/idoszaki/pdf/szezonkiig.pdf
E. Földesi, P. Bauer, B. Horváth, B. Urr – Seasonal Adjustment Methods and Practices (2007)
HCSO – https://www.ksh.hu/docs/files/527167.PDF
Bauer Péter, Földesi Erika – Észrevételek az idősorelemzési módszerek alkalmazásával kapcsolatos kérdésekhez [Notes on issues in connection with application of time series analysis methods] (2003)
Statisztikai Szemle
http://www.ksh.hu/statszemle_archive/2003/2003_09/2003_09_826.pdf
James D. Ashley – Why Seasonal Adjustment – Draft (2001)
http://www.catherinechhood.net/WhySeasAdj.pdf
Sylwia Grudkowska – JDemetra+ User Guide (2015)
Narodowy Bank Polski - https://ec.europa.eu/eurostat/cros/system/files/jdemetra_user_guide.pdf
Sylwia Grudkowska – JDemetra+ Reference Manual Version 1.1 (2015)
Narodowy Bank Polski
https://ec.europa.eu/eurostat/cros/system/files/jdemetrareference_manual._version_1.1_0.pdf

Contact details:
kommunikacio@ksh.hu
Contact us!
Telephone: +36 (1) 345 6789

If you have any questions of or comments on the methodology of seasonal adjustment, please contact our experts at szezon@ksh.hu