# **Seasonal Decomposition**

#### **Objectives**

Understand the logic behind seasonal decomposition. Learn how to create a seasonally adjusted series for reporting purposes or further analysis.

#### **Data**

We illustrate seasonal decomposition (the multiplicative model) on Australian beer production data series that was used in Lab02.

#### Introduction

If you have data in which seasonality is present, then applying a smoother, such as a moving average, whose span is equal to the number of periods in a season, should largely smooth out seasonal variation. Moving averages at seasonal spans form the basis of decomposition methods. A number of government and some business statistics are reported after seasonal adjustment. This chapter will review the principles behind such adjustment, and we will create a seasonally adjusted series of monthly beer production.

## What is Seasonal Decomposition?

Seasonal decomposition is a seasonal-adjustment time series technique that separates the total variation in a series into the following components:

- The variation in the series which is attributed to seasonal factors
- The variation in the series which is attributed to trend and cyclical factors
- Unexplained variation (error).

In addition, seasonal decomposition programs also produce what is called the Seasonally Adjusted Series (also known as the "smoothed series"). It is the original series with the seasonal components removed; in other words, it is the combination of the trend/cycle and error components.

There are two methods that can be used to seasonally decompose a time series: the additive and multiplicative methods of seasonal decomposition.

## The Main Uses of Seasonal Decomposition

Seasonal decomposition can be used for reporting purposes. For example, the national unemployment statistics in Ireland are reported in terms of seasonally adjusted values. Thus the unemployment figure for the third quarter of a specific year is adjusted based on the fact that unemployment figures typically increase during the third quarter. Similarly, since retail sales are usually highest in the fourth quarter, a seasonally adjusted figure allows us to evaluate a specific fourth quarter after removing the estimated effect of it being a fourth quarter.

In SPSS, when the seasonal decomposition procedure is used, four new variables are created from the original series:

- a seasonal factor variable called SAF
- a trend and cyclical variable called STC
- a smoothed variable called SAS
- an error variable called ERR.

We now demonstrate seasonal decomposition using a multiplicative model on a data series of monthly beer production from January 1991 to August 1995. Open the beerprod.sav data file and define the dates as in Lab 02.

\*beerprod.sav [DataSet2] - SPSS Data Editor File Edit View Data Transform Analyze Graphs Utilities Add-ons Window Help 164 beerprod 164.00 YEAR MONTH DATE 199 148.00 1991 2 FEB 1991 152.00 1991 3 MAR 1991 144 00 1991 4 APR 1991 155.00 5 MAY 1991 1991 125.00 1991 6 JUN 1991 153.00 1991 7 JUL 1991 146.00 8 AUG 1991 138.00 1991 9 SEP 1991 190.00 1991 10 OCT 1991 192.00 1991 11 NOV 1991 192.00 1991 12 DEC 1991 1 JAN 1992 147.00 1992 133.00 2 FEB 1992 1992 14 163.00 1992 3 MAR 1992 150.00 4 APR 1992 5 MAY 1992 129.00 1992 131.00 1992 6 JUN 1992 145.00 1992 7 JUL 1992 137.00 1992 8 AUG 1992 9 SEP 1992 138.00 1992 168.00 10 OCT 1992 1992 11 NOV 1992 176.00 1992 188.00 1992 12 DEC 1992 1 JAN 1993 139.00 1993 143.00 1993 2 FEB 1993 150.00 1993 3 MAR 1993 154.00 1993 4 APR 1993 Data View / Variable View / SPSS Processor is ready

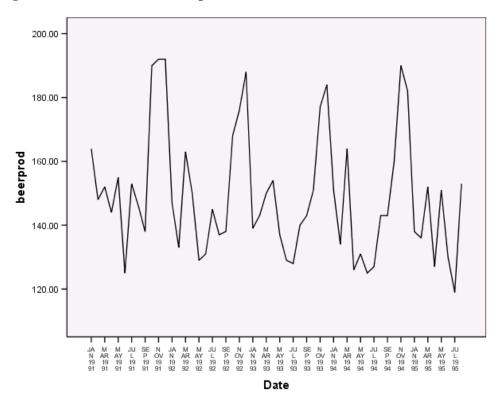
Figure 22.1 Beer Production data with dates defined

We'll ask for the usual sequence chart to review the time series.

Click on **Analyze...Forecasting...Sequence Charts**Move **beerprod** into the Variables list box (not shown)

Click OK

Figure 22.2 Beer Production Sequence Plot



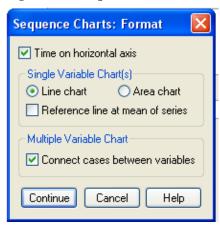
The first step in identifying the seasonal pattern can be the creation of a smoothing variable and then to display it along with the original series. Since the data are monthly, we will create a moving average of span 12 in order to remove the seasonal effects.

Click **Transform...Create Time Series**Move **beerprod** into the New Variables list box
Change beerprod\_1 to **ma12** in the Name text box
Select **Centered Moving Average** from the Function drop-down list
Replace 1 with **12** in the Span text box
Click **Change**Click **OK** 

Next we create a sequence plot comparing the actual series with the new variable, i.e., the moving average.

Click the Recall Tool , and then click **Sequence Charts**Move **ma12** into the Variables list box (beerprod is already there)
Click the **Format** pushbutton
Click the **Connect cases between variables** check box

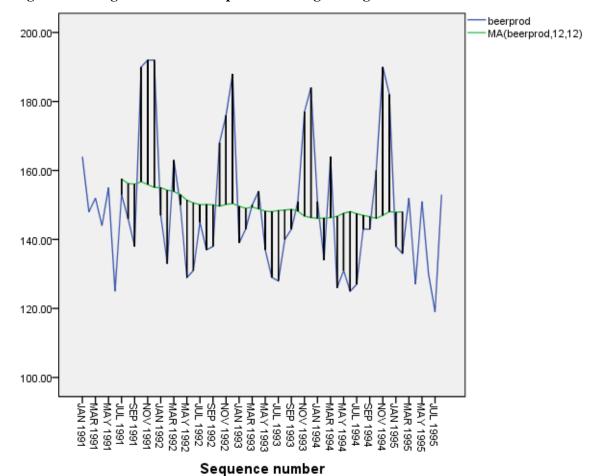
Figure 22.3 Sequence Charts Format Dialog Box



Connecting cases between variables will better show the difference between original variable and the smoother.

Click Continue Click OK

Figure 22.4 Original Series with Span-12 Moving Average Smoother



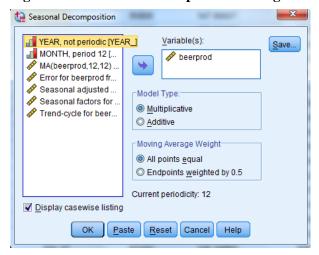
The seasonality is largely absent from the smoothed series. By the nature of the moving average, there are missing values at each end.

## Seasonal Decomposition (Multiplicative)

The Seasonal Decomposition procedure employs seasonal moving averages when applying the multiplicative method.

Click Analyze...Forecasting...Seasonal Decomposition Move beerprod into the Variables list box. Make sure the Multiplicative model option button is selected Click the Display casewise listing check box

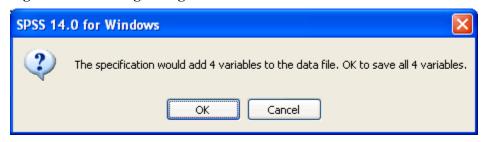
Figure 22.5 Seasonal Decomposition Dialog Box



Click OK

When you click OK, SPSS warns you that four new variables will be saved (the ones we listed above). We want to create them.

Figure 22.6 Warning Dialog About Variables to be Saved



Click OK

Figure 22.7 Casewise List of Results (part of output)

#### **Seasonal Decomposition**

Series Name: hearnrod

Series Name: beerprod							
Case	Original	Moving	Ratio of	Seasonal	Seasonally	Smoothed	Irregular (Error) Component
	Series	Average	Original	Factor (%)	Adjusted Series	Trend-Cycle	
		Series	Series to			Series	
			Moving				
			Average				
			Series (%)				
1	164.000			93.9	174.616	162.712	
2	148.000			92.0	160.872	160.443	
3	152.000			104.2	145.839	155.903	
4	144.000			97.5	147.666	154.127	
5	155.000			89.1	173.919	157.512	
6	125.000			87.0	143.754	157.452	
7	153.000	158.2500	96.7	91.5	167.167	157.939	
8	146.000	156.8333	93.1	93.6	155.963	156.700	
9	138.000	155.5833	88.7	94.1	146.593	157.696	
10	190.000	156.5000	121.4	111.0	171.139	159.219	
11	192.000	157.0000	122.3	121.4	158.119	158.675	
12	192.000	154.8333	124.0	124.5	154.168	156.386	
13	147.000	155.3333	94.6	93.9	156.516	153.503	
14	133.000	154.6667	86.0	92.0	144.568	151.945	
15	163.000	153.9167	105.9	104.2	156.394	151.913	
16	150.000	153.9167	97.5	97.5	153.819	150.995	
17	129.000	152.0833	84.8	89.1	144.746	150.889	
18	131.000	150.7500	86.9	87.0	150.654	150.942	
19	145.000	150.4167	96.4	91.5	158.426	151.180	
20	137.000	149.7500	91.5	93.6	146.349	150.118	
21	138.000	150.5833	91.6	94.1	146.593	148.721	
22	168.000	149.5000	112.4	111.0	151.323	148.260	
23	176.000	149.8333	117.5	121.4	144.942	148.219	
24	188.000	150.5000	124.9	124.5	150.956	149.501	
25	139.000	150.3333	92.5	93.9	147.998	149.516	
26	143.000	148.9167	96.0	92.0	155.438	151.003	
27	150.000	149.1667	100.6	104.2	143.921	151.133	
28	154.000	149.5833	103.0	97.5	157.921	152.538	
29	137.000	148.1667	92.5	89.1	153.722	150.832	

The second column contains the observed series. The decomposition "model" assumes that the observed series can be decomposed into the components of the multiplicative form that we reviewed earlier.

The *Moving Averages Series* column shows the span-12 moving averages. These numbers average out the seasonal variation. Thus, they contain little or no seasonal variation, and can be considered a very smooth Trend-Cycle term.

If you divide the moving averages into the observed series (and multiply by 100), you get the *Ratio of* ... column, which can be thought of as the Seasonal-Irregular piece, that is, a first-round estimate of the seasonal factors.

The ratios are "massaged" via averaging and other techniques to produce the *Seasonal Factor* piece. The seasonal factor for a given month is the same across years. The convention in reporting seasonal factors is to shift the decimal point two places to the right. The procedure saves the seasonal factors in a variable called *SAF 1*.

If you divide the seasonal factors into the observed series, you obtain the *Seasonally Adjusted Series*. This is the series that interests us. You might plot the seasonally adjusted series against the observed series. The seasonally adjusted series is saved in a variable named *SAS\_1*.

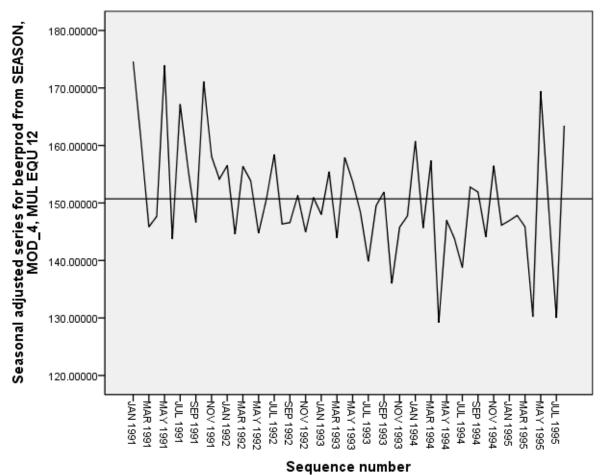
The *Smoothed Trend-Cycle* shown in the output is a 3-by-3 double moving average with endpoint adjustments applied to the seasonally adjusted series. This definition has an arbitrary element to it. Earlier we indicated that the 12-term "centered moving average" could be thought of as a smoothed trend-cycle, but the moving averages are too smooth for our purposes. So, instead, a shorter (3 by 3) smoother is applied to the seasonally adjusted series to produce a smoothed trend-cycle. You should try other smoothers on the variable *SAS\_1* to produce your own smoothed trend-cycle. Seasonal Decomposition's smoothed trend-cycle is saved in a variable named *STC\_1*.

Finally, the irregular component is found in the column of that name. The irregular component is the factor which when combined with smoothed trend-cycle gives rise to the seasonally adjusted series. As implemented in this procedure, the irregular component is not necessarily a white noise series. The irregular component is saved in the variable *ERR\_1*.

Let's view the seasonally adjusted series.

Click the Recall Too , and then click **Sequence Charts** Click on the **Reset** button Move **SAS\_1** into the Variables list box (not shown) Click on **OK** 



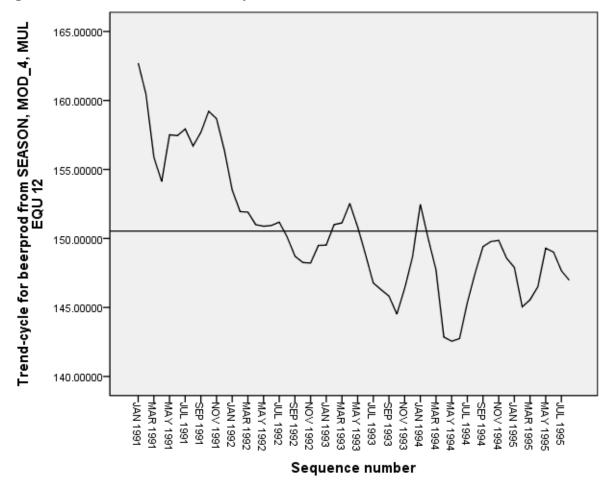


The seasonally adjusted series better shows the true variation in beer production, month by month, over the observed time span. This is the series that would be used for reporting and analysis of the variation in beer production. You can see how the seasonality has been largely removed, although there is still lots of short-term variation from month to month.

Now we examine the smoothed trend-cycle.

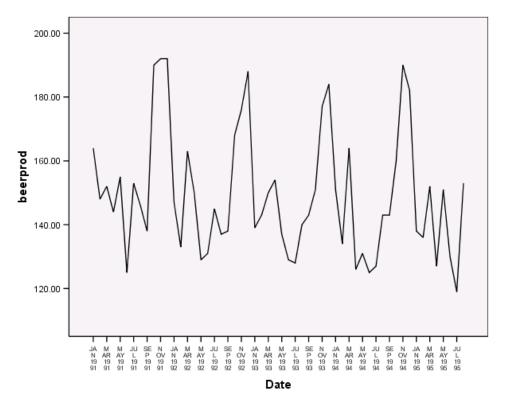
Click the Dialog Recall button , and then click **Sequence Charts** Replace **SAS\_1** with **STC\_1** in the Variables list box Click **OK** 

Figure 22.9 Plot of Smoothed Trend-Cycle



Does the smoothed trend-cycle show the trend in the series better than the seasonally adjusted series? Is the trend in beer production characterised by linearity? As comparison, Figure 22.10 reproduces the original series.

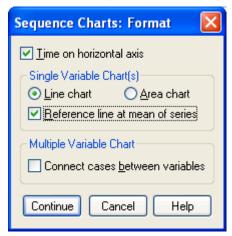
Figure 22.10 Original Beer Production Series



Finally, we view the seasonal adjustment factors.

Click the Dialog Recall button , and click **Sequence Charts** Click on the **Reset** pushbutton Move **SAF\_1** into the Variables list box Click the **Format** pushbutton Click the **Reference line at mean of series** check box

**Figure 22.11 Sequence Charts: Format Dialog Box** 



Click **Continue** Click **OK** 

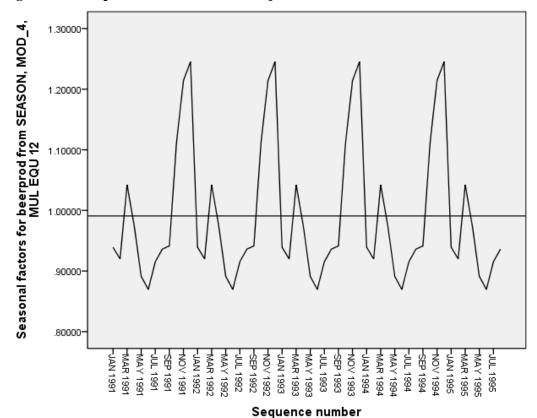


Figure 22.12 Sequence Plot of Seasonal Adjustment Factors

Seasonal Decomposition assumes that the seasonal factors are fixed, not changing, across the observed span of the series.

### Brief Appraisal of Seasonal Decomposition

You should be aware that criticisms of the Seasonal Decomposition have arisen, and that other methods exist.

Criticisms include the following:

- The 12-period moving average cannot be applied to the initial and last part of the series since there are no observations available. This is particularly unfortunate at the finish of the series, since that is where recent information is and where you are likely to want to forecast.
- Averages have the usual defects. They are not robust.

Averages blunt peaks and troughs, distort slopes, and shift turning points. All of these defects
make it more difficult to use seasonally adjusted series for forecasting, especially medium range
forecasting.

- This method ignores trading day variation. Trading day variation occurs because the calendar is irregular, and therefore months (or quarters) differ across years in the number and composition of days comprising them. For example, some business is transacted exclusively Mondays through Fridays. Months of June from different years are in some sense not equivalent if the number of business days varies across years. Other business realizes large activity on weekends. Sundays at shopping malls might be big volume sales days. An extra Sunday in December might mean a longer, more profitable Christmas shopping season.
- It ignores holiday variation. As an example, Easter might occur in March one year and in April another. There is a lot of sales activity (clothing, eggs, etc.) which is contingent on when Easter occurs.
- It ignores irregular, unpredictable, or extreme events such as strikes and tornadoes and their effect on economic activity (although methods can have this same weakness).
- Seasonal Decomposition assumes that seasonality is fixed, whereas seasonality might be stochastic over a span of time.

Despite the criticisms, seasonal adjustment will undoubtedly persist because of its intuitive appeal. Governments report economic statistics in adjusted form, and consumers of economic information want it that way.