6

Dealing with Seasonal Fluctuations

"Nature has established patterns originating in the return of events, but only for the most part. New illnesses flood the human race, so that no matter how many experiments you have done on corpses, you have not thereby immposd a limit on the nature of events so that in the future they could not vary."

Von Leibniz, 1703

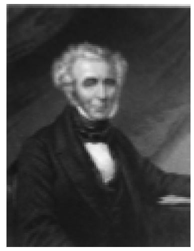
i) Many business time series show seasonal fluctuations. Time series data have been adjusted for seasonal fluctuations in business and financial applications for about a century. Businesses may need to know when a change in a time series is due to more than the typical seasonal variation. Government agencies adjust statistical indicators for seasonality before publication and distribution to the public.

There are generally three distinct uses of seasonal adjustment: the historical adjustment of available past data, the current adjustment of each new value, and the predicted seasonal factors for future adjustment. This chapter describes how seasonal effects can be removed and adjusted for in historical data. We examine how the centered moving average and related smoothers play a central role in a number of widely used seasonal-adjustment procedures.

The X-13ARIMA-SEATS seasonal adjustment programs from the U.S. Census Bureau are accepted standards for the large-scale analysis of publicly reported seasonal adjustments of monthly and quarterly data. These data-driven seasonal adjustment procedures involve smoothing data to eliminate unwanted irregular variation from the patterns that are meaningful to the analyst.

Seasonal Influences

One of the first people to study periodicity in economic time series was the British astronomer William Herschel (1738–1822), *left*, who tried to find a relationship between sunspots and wheat prices. Another was the banker James W. Gilbart (1794–1863), *right*, who discovered that the Bank of England notes were in high demand in January, April, July, and October due to the payment of dividends in these months. He used this information to argue against attempts by smaller country banks to issue their notes during these periods.

Today we see many examples of seasonality in economic time series and tourism demand series. Anyone who shops at the end of the calendar year realizes that retail, toy, and card stores have a surge in demand at year end. Some businesses have 25% or most of all their yearly sales in December. In other countries, it can peak at a different religious holiday. Even Peruvian anchovy production shows seven-year repeating patterns caused by recurring changes in ocean currents.

In Chapter 5, we defined **seasonality** as periodic fluctuations that recur every year with about the same timing and intensity. For example, farm income from all farms in the United States may rise steadily each year from early spring until fall and then drop sharply. For agricultural economists, it is important to determine whether a recession has reached bottom or whether there is a predictable pattern in the duration, amplitude, or slope of the business cycle expansions and contractions. In this case, the main use of methods for seasonally adjusting farm income data is to remove any seasonal fluctuations in order to expose an underlying trend-cycle pattern.

Seasonality is described by periodic fluctuations that recur every year with about the same timing and intensity.

Many business time series are recorded over calendar months, which create a seasonal movement because the number of working days varies from month to month. The timing of major public holidays (e.g., Christmas, Ramadan and Easter, etc.), school openings and closings, dividend payments by corporations, and fiscal tax years all contribute seasonal effects, because these events tend to occur at similar times each year.

Often companies have to deal with seasonal fluctuations when making decisions about price and inventory policy or the commitment of capital expenditures. In these situations, the demand forecaster wants to know whether changes in business activity over a given period were larger or smaller than normal.

Business forecasters are not in general agreement on how best to deal with seasonality in forecasting. Some advocate using data-driven methodologies for seasonally adjusting data before forecasting them; others advocate using model-driven approaches for making seasonality explicit in a model for the data. Because, advanced model-driven approaches to seasonal adjustments are beyond the scope of this book, we follow a hybrid model-based, data-driven approach in this chapter.

There may be times when seasonally adjusted data are the only data readily available. For instance, computerized data banks containing a wide variety of seasonally adjusted economic data, both global and regional are available on the Internet. It often makes sense to use commercially available sources rather than adjusting many of these series ourselves, even if the unadjusted data are available. For adjusting internal data, the Census Bureau programs are available at no charge with a user-friendly interface programs.

Removing Seasonality by Differencing

In Chapter 7, we introduce differencing as a means of removing trends from data. For example, a first difference (also called a regular difference of period 1) of the time series Y_t results in a new time series Z_t of successive changes defined by $Z_t = Y_t - Y_{t-1}$. Successive values are separated by one period. This can be seen by visualizing a set of points lying on a straight line. The first difference is a horizontal line (= the slope, no trend).

In addition to removing trends, differencing can also be used to remove seasonal influences from data.

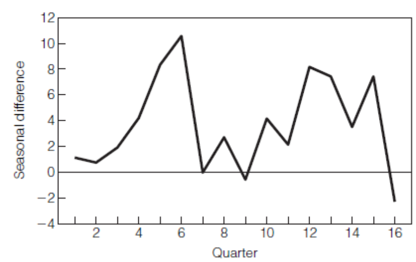
In the retail industry, for example, it is common to see a high fourth quarter, because it is the most important selling season. In order to detect patterns in the data underneath the quarterly seasonal movements, we can compare successive changes between values separated by four time periods. In this fashion, $Z_t = Y_t - Y_{t-4}$ is called a seasonal difference of period 4. Here, Z_t is the difference between a value of the time series and the value of the series four periods earlier. For quarterly data, this represents a year-over-year change and so should be free of any quarterly pattern.

In Figure 5.20, we noted that the seasonal contribution in a quarterly series of automobile sales in Quebec City was 68.2%. With the differenced data, the seasonal contribution to the total variability is reduced to 4.3%, for trend = 11.5% and irregular = 84.2 %. A time plot and the calculation for the seasonal difference of period 4 for these data are in Figure 6.1.

The differencing operation needed to remove seasonal fluctuations in monthly data is the seasonal difference of period 12:

ii)

$$Z_t = Y_t - Y_{t-12}$$



Sales	Seasonal difference of period 4
27.304	*
42.773	*
24.798	*
27.365	*
28.441	1.137
43.531	0.758
26.728	1.93
31.59	4.225
36.824	8.383
54.115	10.584
26.708	−0.02
34.313	2.723
36.232	−0.592
58.323	4.208
28.872	2.164
42.496	8.183
43.681	7.449
61.855	3.532
36.273	7.401
40.244	−2.252

iii)

Figure 6.1 Quarterly automobile sales: time plot (*top*) of seasonal differences of period 4 (*bottom*). (*Source*: Figure 4.20)

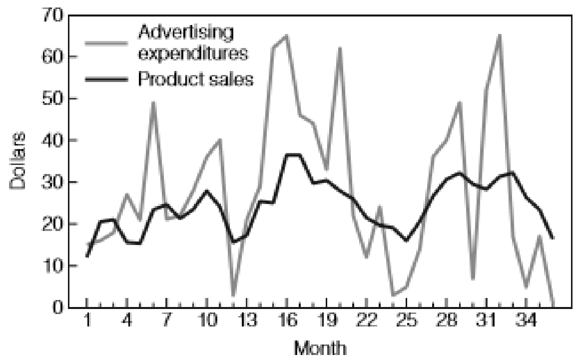


Figure 6.2 Time plots of monthly sales and advertising expenditures over 36 months. (*Source*: Cryer and Miller, *Statistics for Business*, 1994; SALESADS.DAT)

For the following data on the sales of a weight-control product and expenditures on monthly advertising, an exploratory ANOVA two-way table analysis (described in Chapter 5) resulted in the following interpretation for the trend and seasonal contributions:

iv)	Sales: trend = 20%, seasonality = 47%, irregular = 33%
v)	Advertising: trend = 7%, seasonality = 51%, irregular = 42%

When developing formal regression models with these variables, a relatively high noise component suggests that much of the variation is not explainable by trend and seasonal influences alone. The time plots in Figure 6.2 clearly show the seasonal patterns in the two series, as well as the greater volatility in the advertising expenditures. In addition, peaks and troughs appear to correlate reasonably well. These are important considerations when modeling the data.

With the seasonal differenced data, the seasonal contribution to the total variability in the differenced sales is only approximately 17% (irregular = 64%, trend = 19%). The results for the differenced advertising variable now shows: trend = 23%, seasonal = 36%, and irregular = 41%. Although the seasonal contribution to sales and advertising has been reduced by differencing, this analysis has its weaknesses. The relative scarcity of data (only 24 values of differenced data) does not support drawing strong conclusions about the actual strength of these components in the data; it only helps us to quantify their relative influences.

Figure 6.3 depicts time plots and a scatter diagram for the seasonal differences of period 12 for the sales and advertising data. With the seasonal influences removed, an apparent association still exists between the two variables. We are interested in exploring other patterns, such as a lag relationship, in the data. This is dealt with again in Chapter 10 where we develop a linear regression model.

In a forecasting model, the objective is to predict product sales from advertising expenditures. To do this, we can correlate

- unadjusted sales and unadjusted advertising expenditures
- seasonally adjusted sales and seasonally adjusted advertising expenditures
- seasonal differenced sales and seasonal differenced advertising expenditures

In addition, we can use the previous approaches with log-transformed sales and log transformed advertising expenditures as well as with lagged advertising expenditures. Each of these approaches will lead to different models and hence different forecasts. Only experimentation and experience can uncover the most appropriate models.

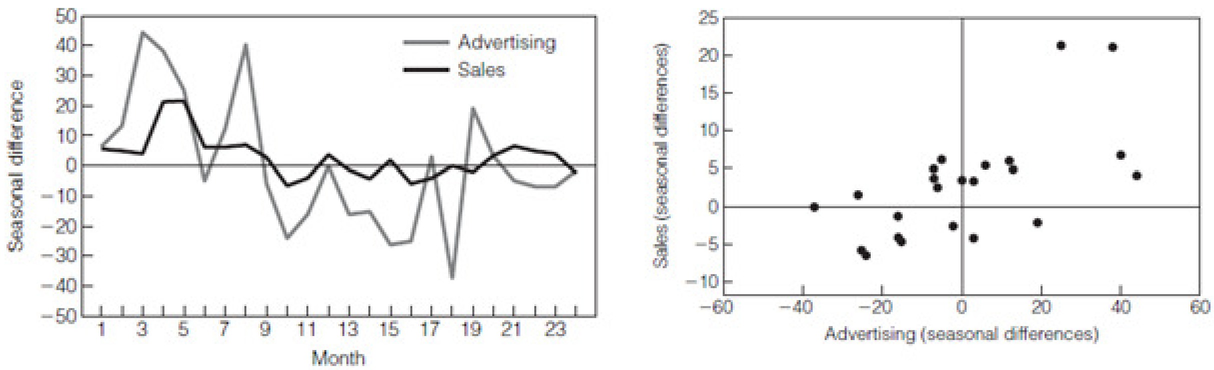
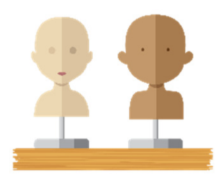


Figure 6.3 Time plots (*left*) and scatter diagram (*right*) of seasonal differences for sales and advertising.

Seasonal Decomposition



There are a wide variety of factors that influence economic data, so it is often difficult to determine precisely the way seasonal influences affect changes in a time series. The more commonly used methods of seasonal decomposition for large-scale adjustments are data-driven; they are less frequently based on formal statistical models. These methods use smoothing procedures extensively. However, most methods are based on assumption that seasonal fluctuations can be measured in terms of a constant set of factors that can be identified apart from underlying trend-cycle and other fluctuations.

The objective of a seasonal decomposition procedure for demand forecasting is to measure typical or average seasonal movements in monthly or quarterly data.

If the magnitude of the seasonal increase or decrease is assumed to be essentially constant and independent of the level of the time series, an additive decomposition is appropriate:

Data = Trend-cycle + Seasonal + Irregular

Recall that irregular is the catch-all word for all unexplained 'noisy' variations including random error.

More often, the magnitude of the seasonal change tends to increase or decrease with level, so that seasonality might be assumed to be proportional to the level of the time series. This leads to the multiplicative decomposition:

Data = Trend-cycle • Seasonal • Irregular

Even in this circumstance, an additive decomposition could be used if we transform the original time series with logarithms (provided there are no zeros or negatives in the data).

A logarithmic transformation of the data tends to stabilize the magnitude of the seasonal pattern and allows us to use additive decomposition on the transformed series. One major limitation of using the log-transformed model, however, is that the constraint that annual sums of the seasonal factors must be 0 in an additive model does not give the same result as the constraint that the product of seasonal indices must be 1 for the log additive model.

Because all methods have their limitations, the demand forecaster needs to be aware of the pros and cons of seasonal-adjustment procedures in the context of the particular application. One desired feature of a good seasonal-adjustment procedure is that the seasonal component not change too much over time. The choice between an additive or multiplicative method may be important here. There are also methods that make simultaneous additive and multiplicative adjustments.

Uses of Seasonal Adjustment

Consider the following simplified example showing how a forecaster uses seasonal factors. Seasonal factors can be used to identify turning points that are not apparent in the raw data, and adjust seasonality out of the data so that forecasting techniques that cannot handle seasonally unadjusted data (e.g., exponential smoothing models found in Chapter 8) can be applied to the seasonally adjusted data.

Figure 6.4 shows three rows of numbers. The first row shows the actual demand for a product during a given year. The second row shows seasonal factors that were developed, based on historical data and projected for the same year. The third row shows the seasonally adjusted data under an assumed additive decomposition:

$$\text{Data - Seasonal factor = Trend-cycle + Irregular}$$

In this example, the actual values decline from January through May. The seasonal factors indicate that the first three months are generally strong, April has no significant seasonality, and May is generally weak. After adjusting for the seasonal effect, we can see that the adjusted demand grows after February. This might be a result of an economic recovery that is not apparent in the actual values.

Figure 6.4 also highlights the importance of assuring ourselves that the seasonal factors are appropriate. Otherwise, inappropriate conclusions can be drawn from a faulty seasonal adjustment.

Description	Jan.	Feb.	Mar.	Apr.	May
Actual data	2000	1900	1700	1300	1100
Seasonal factors	1000	900	600	0	- 400
Seasonally adjusted data	1000	1000	1100	1300	1500

Figure 6.4 Using seasonal factors to adjust a data set.

In Figure 6.5, the same actuals are used, but a different seasonal pattern is assumed. After we adjust for the seasonal effect, the data show a flat demand pattern. In Figure 6.6, the same actuals are used, but the seasonal factors have been distorted as a result of severe outliers in the prior year's actuals - that is, the seasonal factors in Figure 6.5 are correct, but the method used to derive the seasonal factors in Figure 6.6 has incorrectly handled the outliers in the prior year. These distorted factors have then been projected into the current year, altering the April and May seasonal factors. In the seasonally adjusted data, it appears that demand is falling off when it really is not.

	Jan.	Feb.	Mar.	Apr.	May

Actual data	2000	1900	1700	1300	1100
Seasonal factors	500	400	200	- 200	- 400
Seasonally adjusted data	1500	1500	1500	1500	1500

Figure 6.5 Using different seasonal factors to adjust the data.

	Jan.	Feb.	Mar.	Apr.	May
Actual data	2000	1900	1700	1300	1100
Seasonal factors	500	400	100	0	- 100
Seasonally adjusted data	1500	1500	1500	1300	1200

Figure 6.6 Using seasonal factors that have been impacted by outliers in the prior year's data to adjust the data set.

Multiplicative and Additive Seasonal Decompositions

We can gain some insight from a seasonal decomposition into the model building considerations with forecasting models. A strong seasonal pattern suggests that particular attention should be paid to accurately representing the seasonal influences in the data.

The complete chapter can be found in

Change & Chance Embraced

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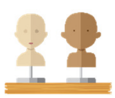

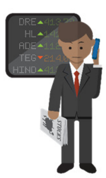

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