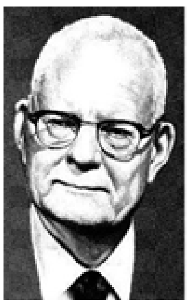
5

Characterizing Demand Variability: Seasonality, Trend, and the Uncertainty Factor



Without data you're just another person with an opinion

W. Edwards Deming
1900–1993

In chapter 2, we saw why exploratory data analysis is so basic to the demand forecasting process. We now focus on data that are ordered sequentially in time, better known as time series. When sales volumes, inventory counts, and such are reported as a time series, the data may contain important components that we can effectively visualize, quantify, and create models for. Time series analysis is a useful tool for

- identifying essential components in historical data so that we can select a good starting model
- comparing a number of traditional and innovative analytical tools to increase our understanding of data that are typical or representative of the problem being studied (such data are accurate in terms of reporting accuracy and also have been adjusted, if necessary, to eliminate nonrepresentative or extreme values)

This chapter will present techniques that help you prepare historical data in a variety of graphical ways, allowing you to see that

- not only do data summaries help explain historical patterns, but the requirements of an appropriate modeling strategy can also be visualized
- analysis of deseasonalized, detrended, smoothed, transformed data (e.g., logarithms and square roots), fitted values, and residuals can all be most effectively presented graphically,

Visualizing Components in a Time Series

As to the propriety and justness of representing sums of money, and time, by parts of space, tho' very readily agreed to by most men, yet a few seem to apprehend that there may possibly be some deception in it, of which they are not aware.

WILLIAM PLAYFAIR

The first known time series using economic data was William Playfair's *Commercial and Political Atlas*, published in London in 1786 and beautifully reprinted in Ed Tufte's masterful *The Visualization of Quantitative Information* (1983). Playfair (1759–1823), an English political economist, preferred graphics (Figure 5.1) to tabular displays because he could better show the shape of the data in a comparative perspective. In one example, he plotted three parallel time series—prices, wages, and the reigns of British kings and queens, noting:

You have before you, my Lords and Gentlemen, a chart of the prices of wheat for 250 years, made from official returns; on the same plate I have traced a line representing, as nearly as I can, the wages of good mechanics, such as smiths, masons, and carpenters, in order to compare the proportion between them and the price of wheat at every different period. (Quoted in Tufte, 1983, p. 34)

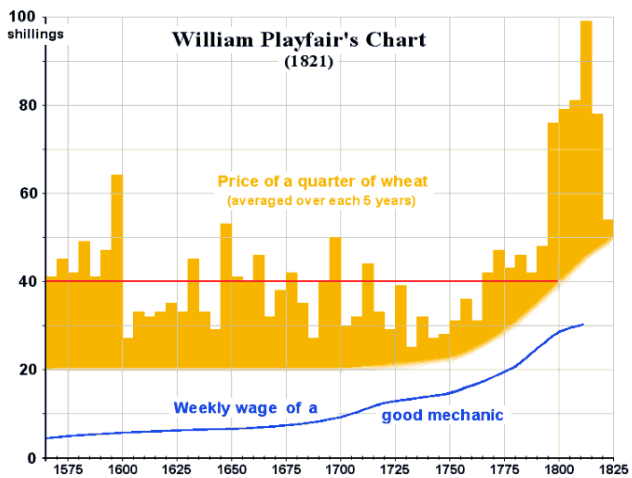
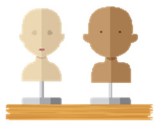


Figure 5.1 Playfair's 1821 chart comparing the "weekly wages of a good mechanic" and the "price of a quarter of wheat" over time.

The purpose of analyzing time series data is to expose and summarize its components as a prelude to a model-building process.



Business forecasters commonly assume that variation in a time series can be expressed in terms of several basic components: a long-term trend plus an economic cycle, seasonal factors, and an irregular or random term. For a given time series, it may not be possible to observe a particular component directly due to the existence of other components that are more dominant. If appropriate, it is also desirable to correct, adjust, and transform data before creating forecasting models (see Chapters 5, 8, and 9).

Trends and Cycles

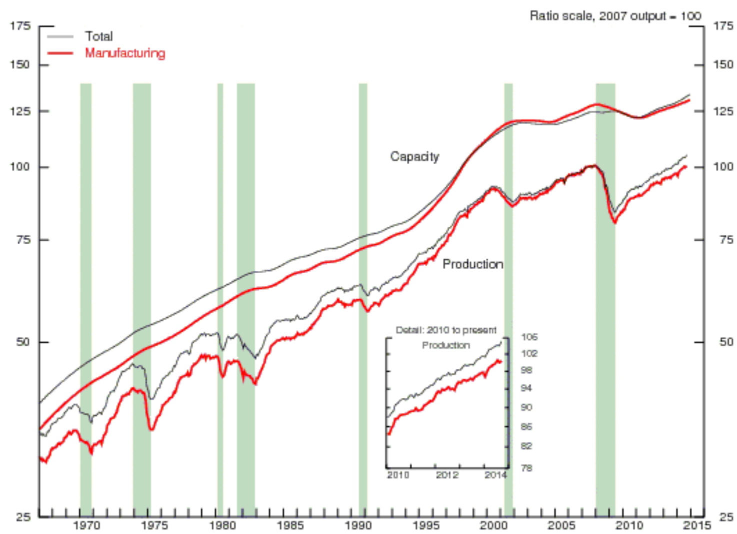


Figure 5.2 Time plot of FRB index of industrial production. (*Source*: Board of Governors of the Federal Reserve System, *http://www.federalreserve.gov/feeds/g17.html*)

It is not unusual for practicing forecasters to use the term trend when referring to a straight-line projection. But a trend does not need to be a straight-line pattern; a trend may fall or rise and can have a more complicated pattern than a straight line. The U.S. Federal Reserve Board (FRB) index of industrial production (Figure 5.2), highlighting the shaded areas for business recession periods, is a good example of a time series that is predominantly upward trending. The industrial production index measures output in the manufacturing, mining, and electric and gas utilities industries; the reference period for the index is 2007.

How do we know a time series is trending? The inspection of a time series plot often indicates strong trend patterns. Fitting trend lines is a simple and convenient way of exposing detail in data. A useful way of presenting the FRB index is to compare it to some trend line, such as an exponential or straight line trend. This type of analysis brings out sharply the cyclical movements of the FRB index, and it also shows how the current level of output compares with the level that would have been achieved had the industrial sector followed its historical growth rate.

In a time series, a trend is seen as the tendency for the same pattern to be predominantly upward or downward over time.

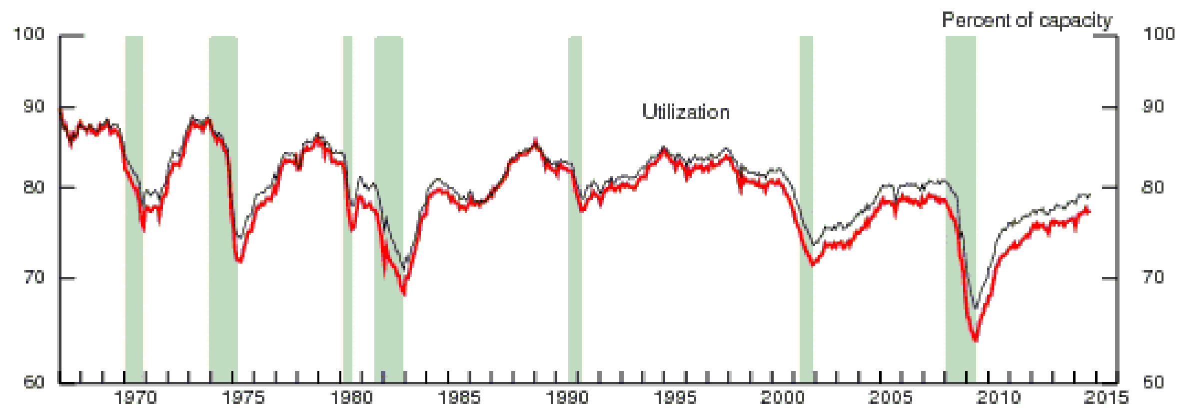


Figure 5.3 Time plot of the FRB index as a percentage of capacity. Shaded areas show periods of business recession as defined by the U.S. National Bureau of Economic Research (NBER). (*Source*: Figure 5.2)

Although this may not be the best or final trend line for the data, the straight-line trend is a simple summary tool. In order to assess the value of this simple procedure, the deviations of the data (like peeling a layer from the onion) from this trend line of the FRB data are known as residuals.

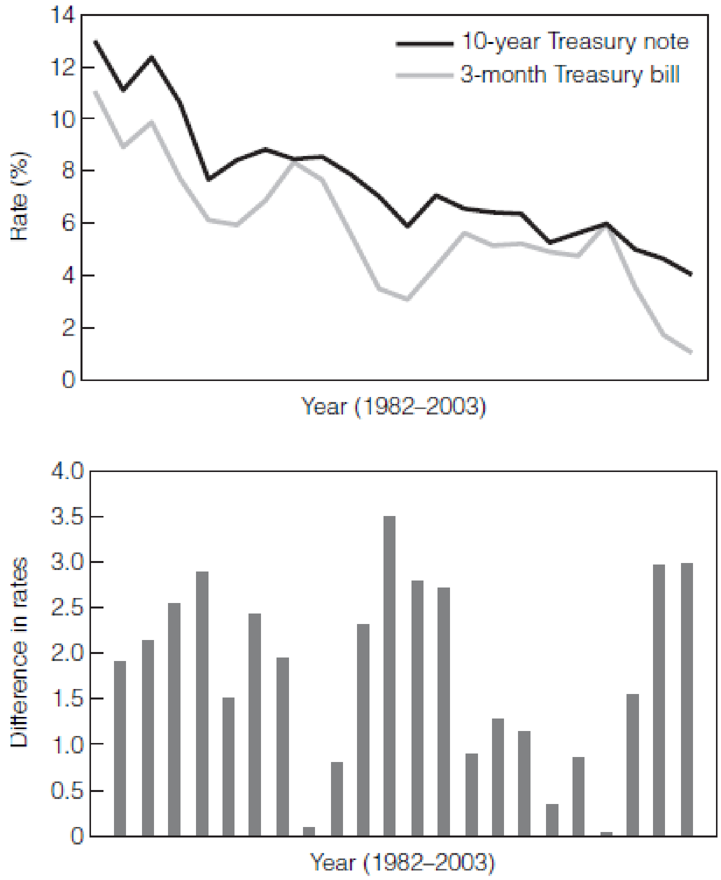
In Figure 5.3, the FRB index is shown as a percent of another trending series. It is evident that elimination of trend in the data now reveals a cyclical component that appears to correspond to economic expansions and contractions. Modeling can often be thought of as a process of stripping away the essential variation to expose some hidden detail.

Some financial data can also be useful for analyzing and predicting economic cycles. Figure 5.4a shows time plots of U.S. Treasury rates (a plot of the interest rates paid on U.S. securities ranging from three-month bills to 30-year bonds), which have been used by investors and market analysts to decide which Treasury bond or note offers the best interest rate. Typically, 10-year notes yield between one and two percentage points more than 3-month bills and the yield curve bends up. However, if long-term rates fall below the short-term rates, the curve inverts and arcs downward.

Economist Frederic Mishkin (b. 1951) of the Federal Reserve Bank of New York has discovered that every time the yield curve has inverted, a recession followed a year or so later. A way of looking at this is to plot the difference between the 3-month and 10-year Treasury rates. As shown in Figure 5.4b, every time the difference has sunk below zero, a recession followed roughly 12 months later. Business cycle analysis, leading indicators and a method of cycle forecasting are taken up in Chapter 7.

The definition of a cycle in demand forecasting is somewhat specialized in that the duration and amplitude of the cycle are not constant. This characteristic is what makes cycle forecasting so difficult. Although a business cycle is evident in so many economic series, modeling is one of the most challenging problems in time series analysis.

In practice, trend and cycle are often considered as a single component, known as the trend-cycle.



(*Source*: http://www.federalreserve.gov/releases/H15/data/a/tcm10y.txt)

Figure 5.4 Time plots (*top*) of the three-month and 10-Year U.S. Treasury rates; bar plot (*bottom*) of the differences between three-month and 10-Year U.S. Treasury rates

Other time series data that are not strongly dominated by seasonal and trend effects, such as the University of Michigan Survey Research Center's (SRC) index of consumer sentiment (Figure 5.5). In this case, the dominant pattern is a cycle corresponding to contractions and expansions in the economy. Of course, a large irregular component is present in this series because there are many unknown factors that significantly affect the behavior of consumers and their outlook for the future.

Based on an exploratory ANOVA decomposition method, we determine that the total variability in the consumer sentiment index (Figure 5.5) is made up of 80% trend-cycle effect, 3% seasonal and 17% other (unknown). When using this index as a factor in a useful forecasting model, the driver would not have to be seasonally adjusted, while the demand variable to be forecasted may need to be seasonally adjusted first.

Similar consumer sentiment indices are available on the Internet for many countries. In this situation, the dominant pattern is a cycle corresponding to contractions and expansions in the economy. (Contrast Figure 5.5 with the index of industrial production (Figure 5.3). Of course, a large irregular component present in this series because there are other unknown factors that can significantly affect the behavior of consumers and their outlook on future spending.

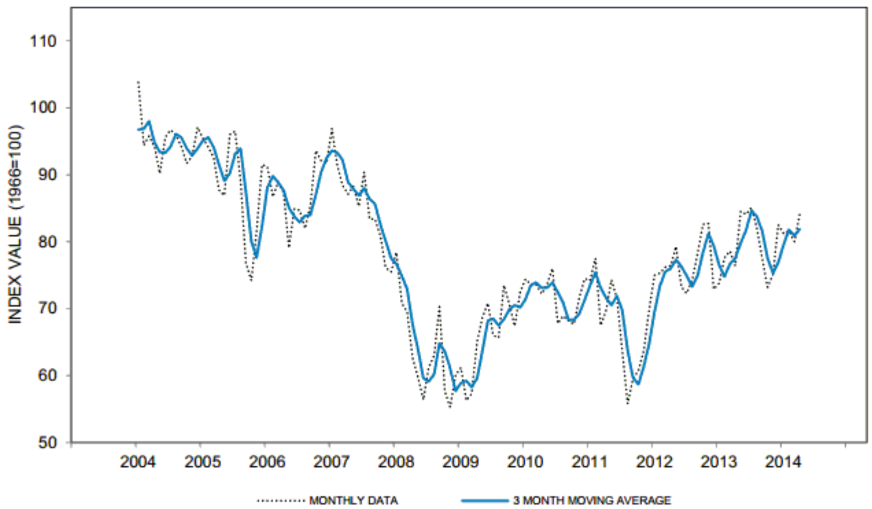


Figure 5.5 Time plot of the SRC index of consumer sentiment (monthly) from 2004-1 to 2014-4. (*Source*: University of Michigan Survey Research Center, *http://www.sca.isr.umich.edu/*)

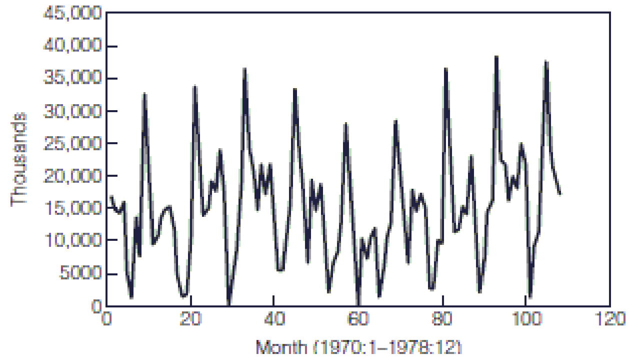
Seasonality

Certain sales data show strong peaks and troughs within the years, corresponding to a seasonal pattern. Consumer habits, like family holidays and festivals, give rise to seasonal patterns. When seasonality is removed from these data, secondary patterns reveal themselves that may still be useful and informative.

Figure 5.6 depicts a time series strongly dominated by seasonal effects, namely, monthly changes in telephone access lines connections and disconnections some years ago; today, this would be more like TV/Internet cable connections and disconnections to the home. The seasonality results from the installation of access lines coincident with school openings and removal of access lines with school closings each year as families relocate. Thus, the seasonal peaks and troughs appear with regularity each year.

The positive trend in telephone access lines used to be related to the growth in households and the increasing use of telephone services by former nonusers. Today, such relationships may not be the same in the telecommunications industry. Thus, both trend and seasonal components are superimposed on one another, as well as some residual effects, which are not readily discernible from the raw data.

Although seasonality is the dominant pattern, there is also some changing variability in the highs and lows with trend. The seasonality also appears to be additive in the sense that the seasonal deviations from a trend for the same period each year appear relatively constant.



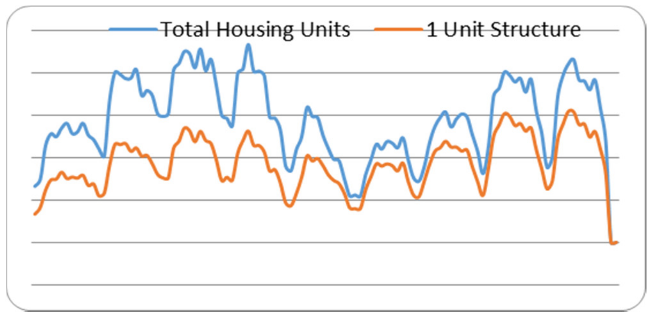


Figure 5.6 *(top)* Time plot of monthly fluctuations in telephone access lines over a 9-year period.

Figure 5.7 (*bottom*) Time plot of monthly new privately owned housing units started over the same period as that shown in Figure 5.6 (1970-1 to 1978-12). (*Source*: *http://www.census.gov/const/C20/startsua.xls*)

Contrast this seasonal pattern with that of the monthly housing starts shown in Figure 5.7. This economic time series is the result of survey data reported by contractors and builders for use by government and private industry. Based on an exploratory ANOVA decomposition, we see that the total variability in the data is made up of 38% seasonal effect, 50% trend-cycle effect and 12% other (unknown or uncertain).

In the consumer goods industry, housing starts can be used as a driver of the demand for hard goods (e.g. refrigerators, dishwashers and washing machines). The housing starts over time are also subject to the business cycle fluctuations as do consumer hard goods. Even visually, there appears to be a close association between Figures 5.6 and 5.7. There are other industries where demand forecasters can establish such linkages with economic or demographic factors.

Using a visual assessment, the seasonality appears to be *additive* when the repeating seasonal effect in the data is represented by *constant amounts* around a trend-cycle.

Most commonly, seasonality refers to regular periodic fluctuations that recur every year with about the same timing and intensity. Seasonality can also occur as fluctuations that recur during months, weeks or days.

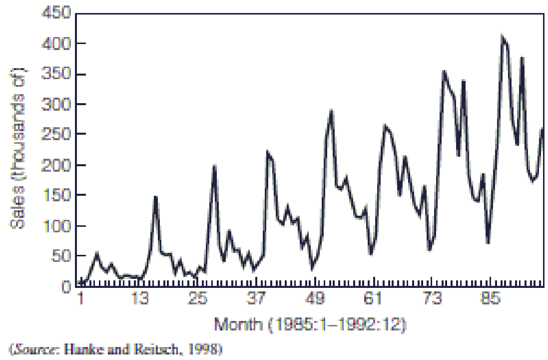


Figure 5.8 Time plot of monthly sales of formal-wear rentals over an 8-year period. (Source: J. E. Hanke and A. G. Reitsch, Business Forecasting, 1998)

When we see the seasonal variation around a trend appear more like constant percentages, we say this represents a *multiplicative* seasonality. Sales data for fast moving consumer goods may fall in this category.

In contrast to the patterns in Figures 5.6 and 5.7, the sale of formal-wear rentals (Figure 5.8) has a pronounced multiplicative seasonal component because seasonality tends to increase with the increase of the level of the data.

Based on the preliminary ANOVA decomposition, we determine that the total variability in the formal wear rental data is made up of 57% trend effect, 31% seasonal effect and 12% other (unknown or uncertain). This should not be misinterpreted because the ANOVA procedure assumes additivity in trend and seasonal impact. Later, we will have a test for non-additivity between the trend and seasonal effect.

When looking for useful forecasting models, the most dominant driver should be considered first. Any characterization of the uncertainty factor should be based on the residuals after removing the effect of the dominant factors. We will also contrast additive and multiplicative seasonal patterns using a diagnostic test for non-additivity to highlight the difference between additive and multiplicative (non-additive) seasonality.

Many economic series show seasonal variation. For example, income from a farm in the United States may rise steadily each year from early spring until fall and then drop sharply. In this case, the main use of a seasonal adjustment procedure is to remove such fluctuations to expose an underlying trend-cycle. Many industries also have to deal with similar seasonal fluctuations.

To make decisions about price and inventory policy and about the commitment of capital expenditures, the business community wants to know whether changes in business activity over a given period of time were larger or smaller than normal seasonal changes. It is important to know whether a recession has reached bottom, for example, or whether there is any pattern in the duration, amplitude, or slope of business cycle expansions or contractions.

The semiconductor industry, for instance, plays a crucial role in the size, growth, and importance of information technology. The industry is subject to a number of forces that influence growth and cyclical behavior. Competitive forces, economic climate, pricing, and political events have a way of making demand forecasting a complex process.

In addition, seasonal patterns are frequently present in the monthly sales demand and unit-shipment figures because of the need for chips in the consumer electronics products and the fast-growing markets for hand-held devices.

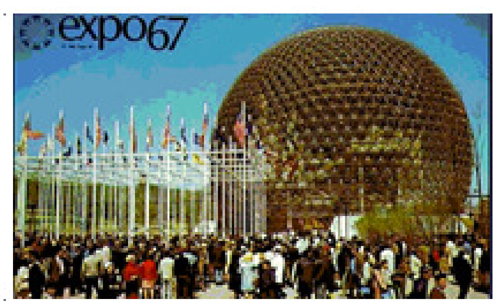
A closely watched indicator of the strength and weakness of this market is the book-to-bill ratio, which compares orders with shipments of semiconductors - a number above 1 indicates positive growth and a ratio of 1.22 indicates that, for every $100 of chips shipped during the month, $122 of chips were ordered. Clearly, to make sense of this indicator we require a seasonal adjustment of the ratio or a seasonal adjustment of the components of the ratio. Seasonal adjustment procedures are treated in Chapter 6.

Irregular or Random Fluctuations

Irregular fluctuation is the catchall category for all patterns that cannot be associated with trend-cycle, or seasonality. Except for some cyclical fluctuations, the plot of the consumer sentiment index (Figure 5.5) does not suggest any systematic variation that can be readily identified. Irregular fluctuations most often create the greatest difficulty for the demand forecaster because they are generally unexplainable. A thorough understanding of the source and accuracy of the data is required to get full benefit of their use in modeling.

An example of an irregular fluctuation, an unusual or rare event arising in a time series, is depicted in Figure 5.9, which shows a monthly record of landline telephone installations in Montreal over a 10-year period. Although a predominantly trend and seasonal pattern, the unusually low September 1967 figure is greatly reduced because of the influence of the 1967 world's fair held in that city. At the time, residential telephone installations normally accompanied a turnover (by law) of apartment leases during September; however, a large number of apartments were held for visitors (like myself) to the world's fair that year. The dotted line depicts what might have happened under normal conditions (in the absence of this unusual event).

The irregular component consists of atypical values, which may be caused by unusual or rare events, errors of transcription, administrative decisions, and random variation.



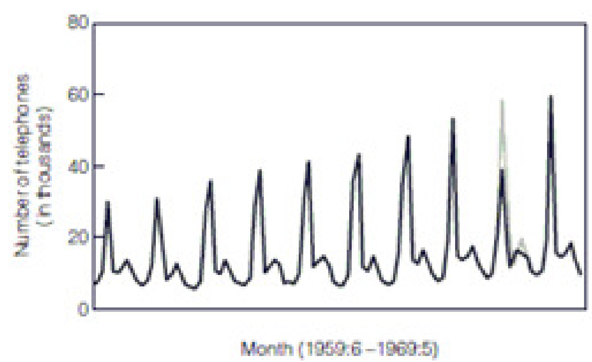


Figure 5.9 Impact of Expo '67 on monthly installations of landline telephones in Montreal, Quebec.

We may also see these kinds of unusual events in consumer demand data affected by holidays, festivals, fairs and popular events. In a more current example, an inventory shortfall in residential refrigerators created a backlog of sales during a peak selling season (Figure 5.10 *left*). We will want to know how to adjust (Figure 5.10 *right*) or normalize the data so that trend-seasonal models will function properly.

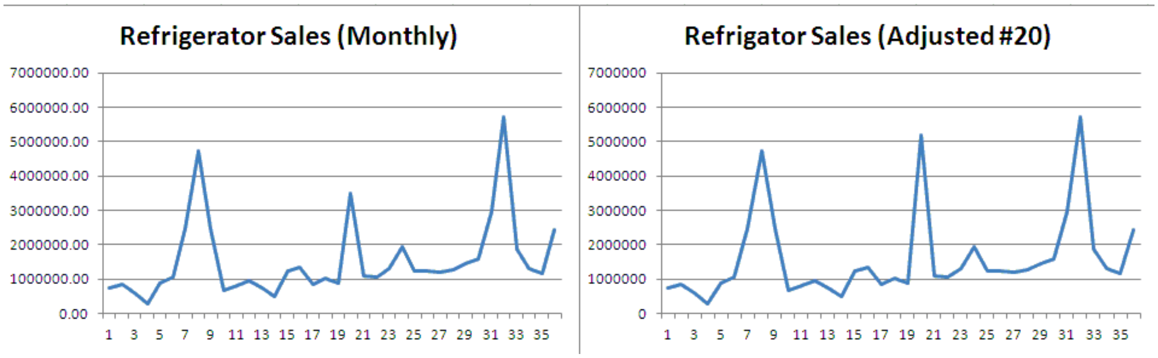


Figure 5.10 Refrigerator sales during a Ramadan holiday selling season, original (*left*) and adjusted (*right*) for period #20

Figure 5.11 shows how an administrative decision can influence a time series. The series represents the number of access lines (telephones for which separate numbers are issued) in service in a specific region. The saturation (or filling-up) of a neighboring exchange for a period necessitated a transfer of new service requests from that exchange to the one depicted in Figure 5.11, distorting the natural growth pattern. Any useful modeling effort based on these data must be preceded by an adjustment to the historical data to account for this unusual event. There are many other examples like this where openings and closings of retail stores or hospitals, shifts of production among manufacturing or distribution centers as a result of natural disasters can create distortions in historical data.

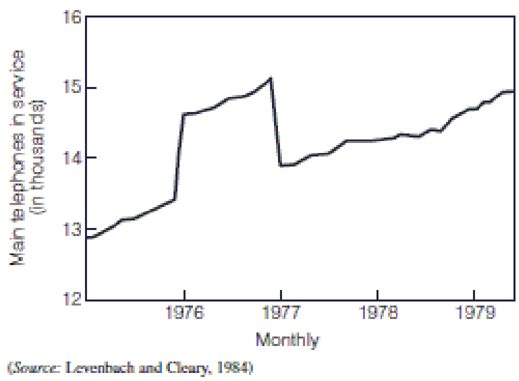


Figure 5.11 Time plot of access lines in service in a telephone exchange.

May time series do not illustrate any seasonality, whereas others, such as weather data, are not affected by the business cycle. In practice, we may a need to be able to identify and describe additional patterns in data, such as sales cycles, promotions, and other calendar variation that will impact how we use models for forecasting purposes.

The complete chapter can be found in

Change & Chance Embraced

ACHIEVING AGILITY WITH DEMAND FORECASTING IN THE SUPPLY CHAIN

HANS LEVENBACH, PhD

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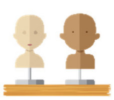

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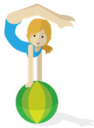

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