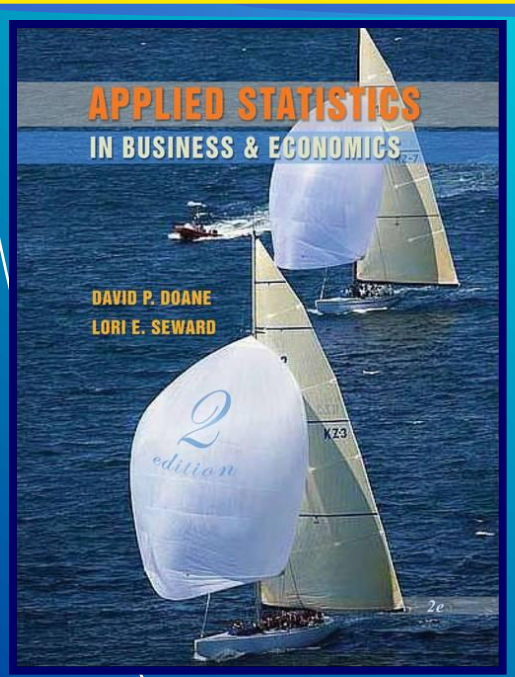
# Time-Series




Time Series Components

Trend Fitting

Assessing Fit

Moving Averages

Exponential Smoothing

Seasonality

Index Numbers

Forecasting: Final Thoughts

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# Time Series Components

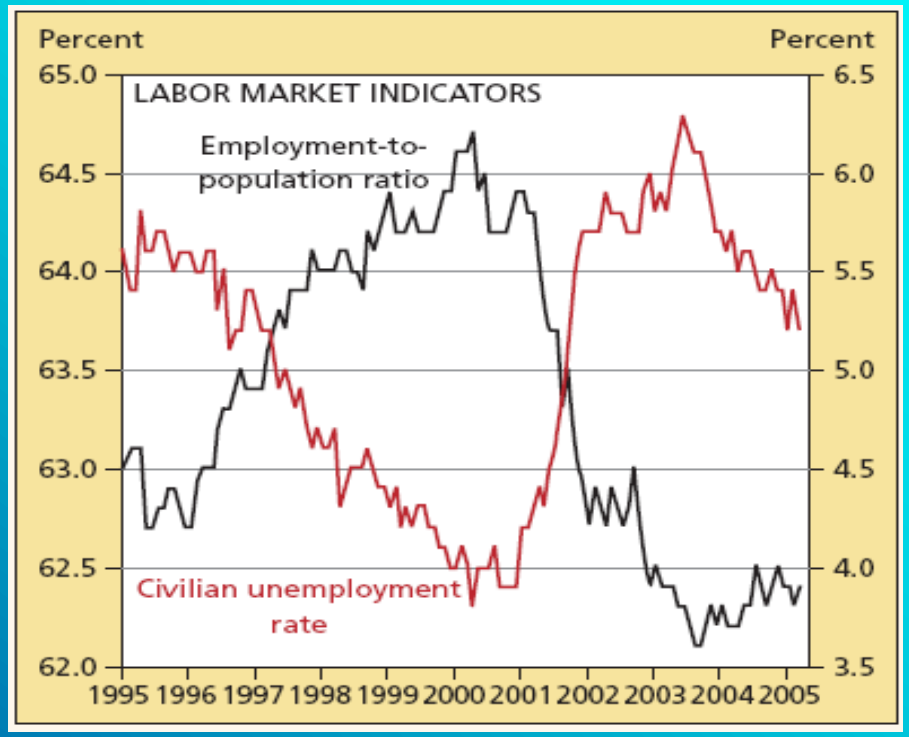
## *Time Series Data*

- A *time series variable* (*Y*) consists of data observed over *n* periods of time.
- Businesses use time series data
  - to monitor a process to determine if it is stable
  - to predict the future (forecasting)
- Time series data can also be used to understand economic, population, health, crime, sports, and social problems.

# Time Series Components

## *Time Series Data*

- Time series data are usually plotted as a line or bar graph.
- Time is on the horizontal (*X*) axis.
- This reveals how a variable changes over time.
- Fluctuations are easier to see on a line graph.






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# Time Series Components

## *Time Series Data*

- The following notation is used:

  $y_t$ is the value of the time series in period $t$

  $t$ is an index denoting the time period ($t = 1, 2, \ldots, n$)

  $n$ is the number of time periods

  $y_1, y_2, \ldots, y_n$ is the data set for analysis

- To distinguish time series data from cross-sectional data, use $y_t$ instead of $x_i$ for an individual observation.

# Time Series Components

## *Measuring Time Series*

- Time series data may be measured *at a point in time*.
- For example, *prime rate of interest* is measured at a particular point in time.
- Time series data may also be measured *over an interval of time*.
- For example, *Gross Domestic Product* (*GDP*) is a flow of goods and services measured over an interval of time.



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# Time Series Components

## *Periodicity*

- The *Periodicity* is the time interval over which data are collected.
- Data can be collected once every
  - decade
  - year (e.g., 1 observation per year)
  - quarter (e.g., 4 observations per year)
  - month (e.g., 12 observations per year)
  - week
  - day
  - hour

# Time Series Components

## *Additive versus Multiplicative Models*

- Time series *decomposition* seeks to separate a time series *Y* into four components:
  - Trend (*T*)
  - Cycle (*C*)
  - Seasonal (*S*)
  - Irregular (*I*)
- These components are assumed to follow either an additive or a multiplicative model.



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# Time Series Components

## *Additive versus Multiplicative Models*

| *Model* | *Components* | *Used For* |
|---|---|---|
| Additive | $Y = T + C + S + I$ | Data of similar magnitude (short run or trend-free data) with constant *absolute* growth or decline. |
| Multiplicative | $Y = T \times C \times S \times I$ | Data of increasing or decreasing magnitude (long run or trended data) with constant *percent* growth or decline. |

- **The multiplicative model becomes additive is logarithms are taken (for nonnegative data):**

$$\log(Y) = \log(T \times C \times S \times I) = \log(T) + \log(C) + \log(S) + \log(I)$$

# Time Series Components

## *A Graphical View*

- **Here is a graphical view of the 4 components of a hypothetical time series.**

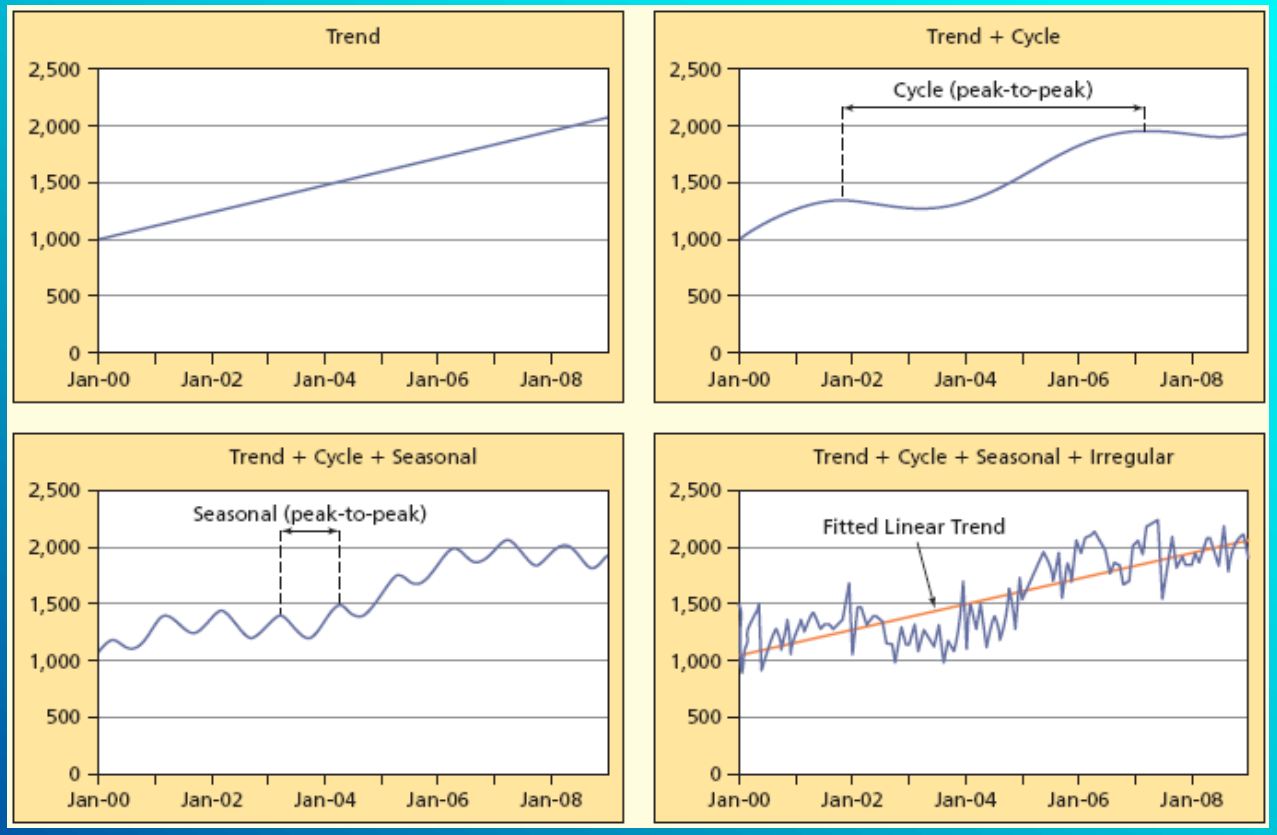


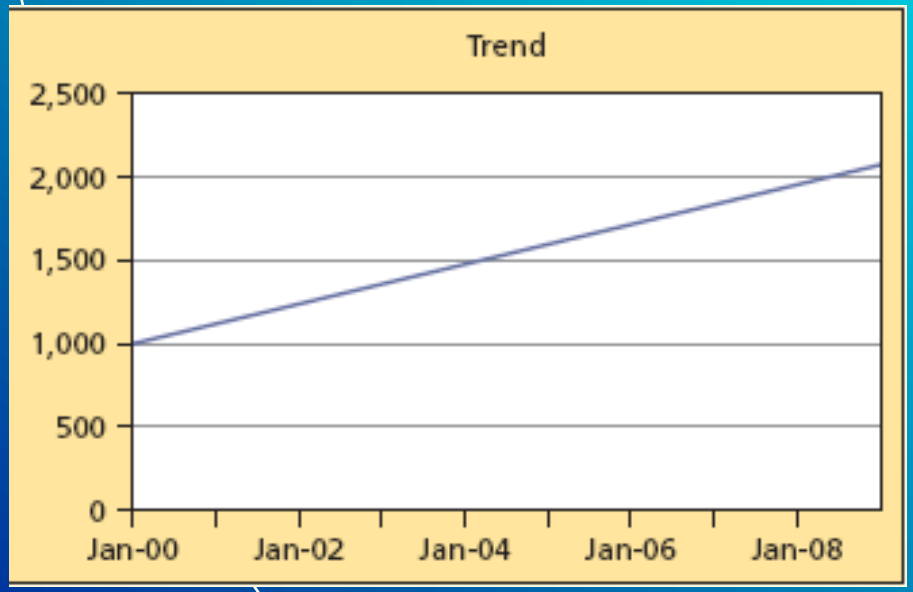

Figure 14.3



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# Time Series Components

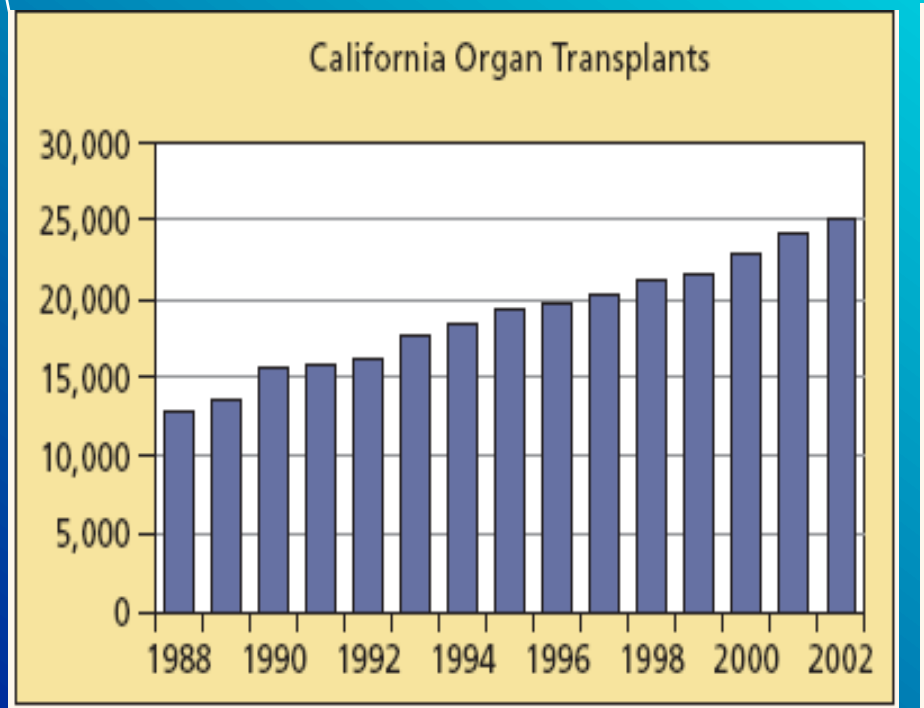
## *Trend*



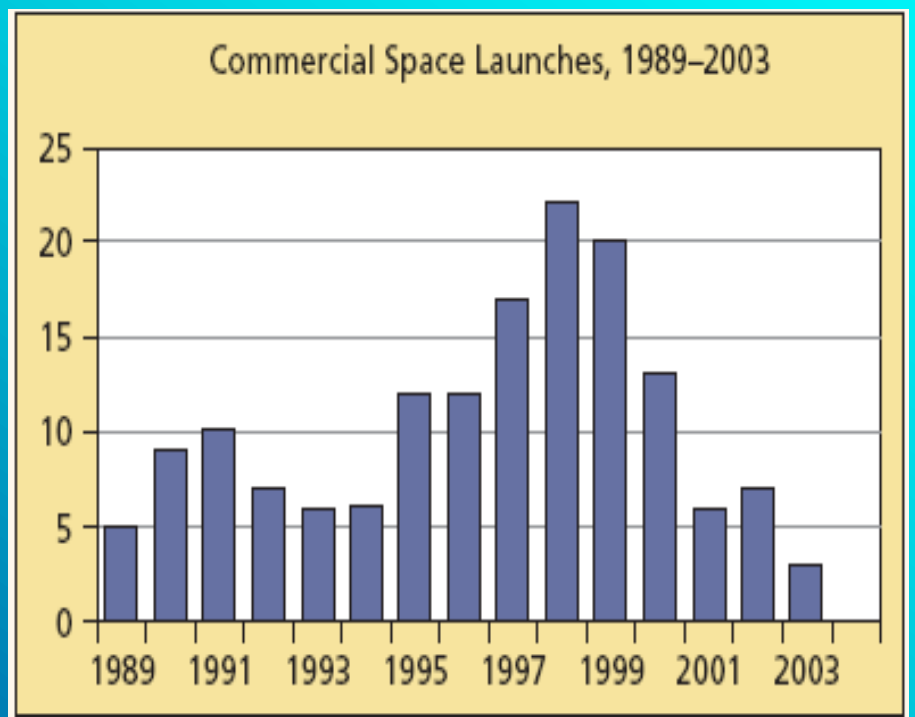

- *Trend* (*T*) is the general movement over all years (*t* = 1, 2, ..., *n*).
- Trends may be steady and predictable, increasing, decreasing, or staying the same.
- A mathematical trend can be fitted to any data but may or may not be useful for predictions.

# Time Series Components

## *Trend*




**Steady Trend**



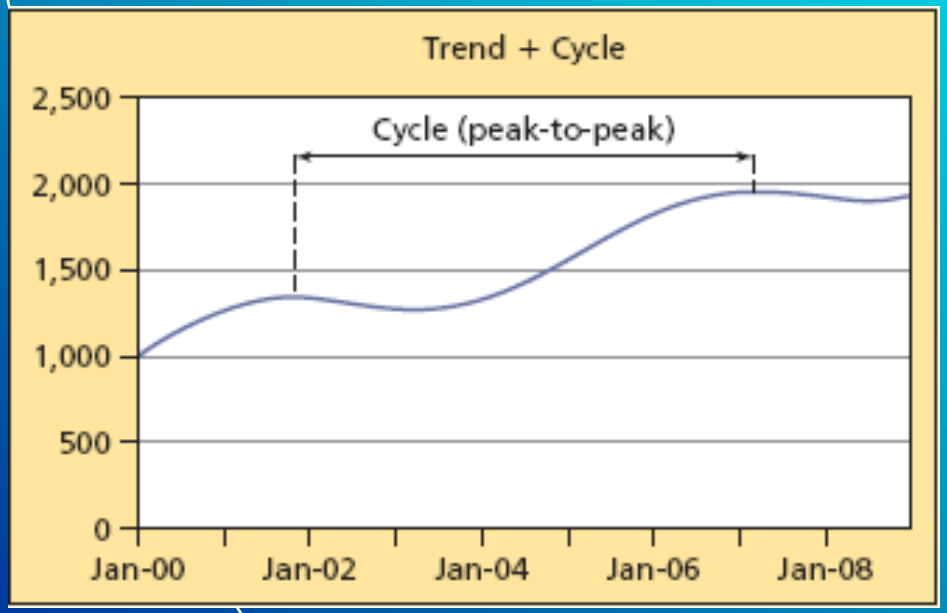

**Erratic Pattern**



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# Time Series Components

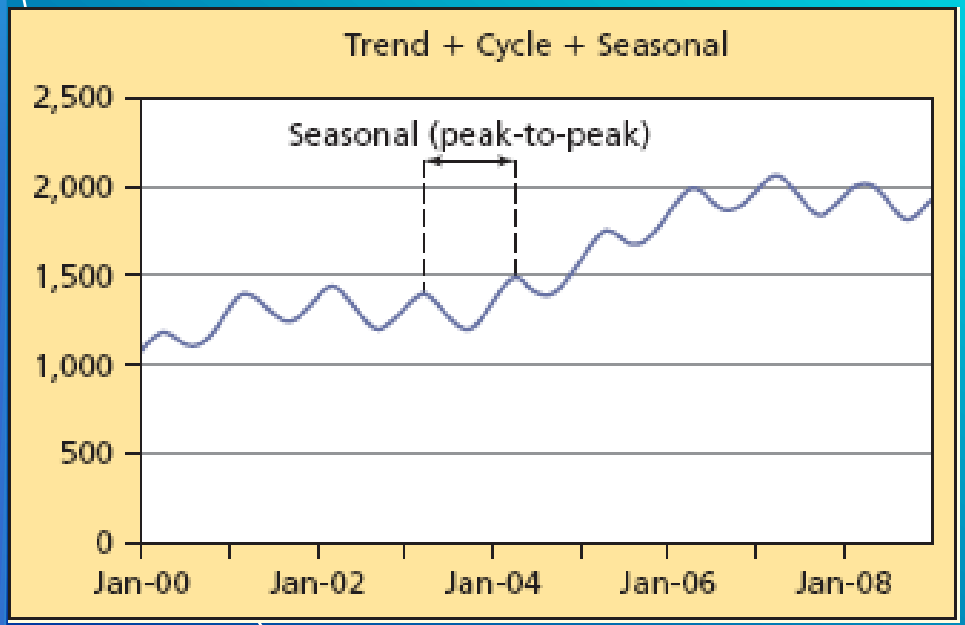
## *Cycle*




- ***Cycle* (*C*) is a repetitive up-and-down movement *about a trend* that covers several years.**
- **Over a small number of time periods, cycles are undetectable or may resemble a trend.**

# Time Series Components

## *Seasonal*



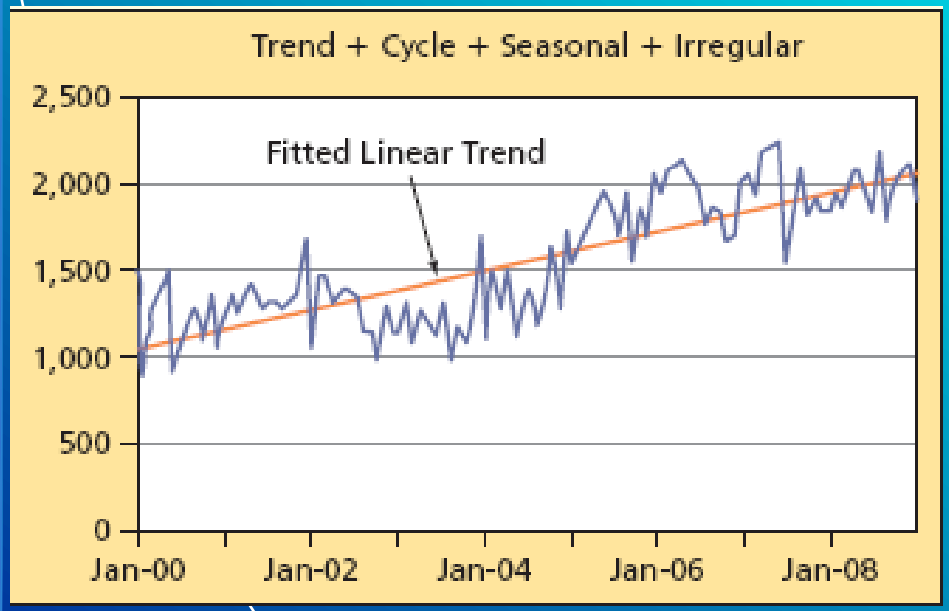

- ***Seasonal*** **(*S*) is a repetitive cyclical pattern *within a year* (or within a week, day, or other time period).**
- **Over a small number of time periods, cycles are undetectable or may resemble a trend.**
- **By definition, annual data have no seasonality.**



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# Time Series Components

## *Irregular*




- ***Irregular*** **(*I*) is a random disturbance that follows no pattern.**
- **It is also called the *error* component or *random noise* reflecting all factors other than trend, cycle and seasonality.**
- **Short run forecasts are best if data are irregular.**

# Trend Forecasting

- **The main categories of forecasting models are:**

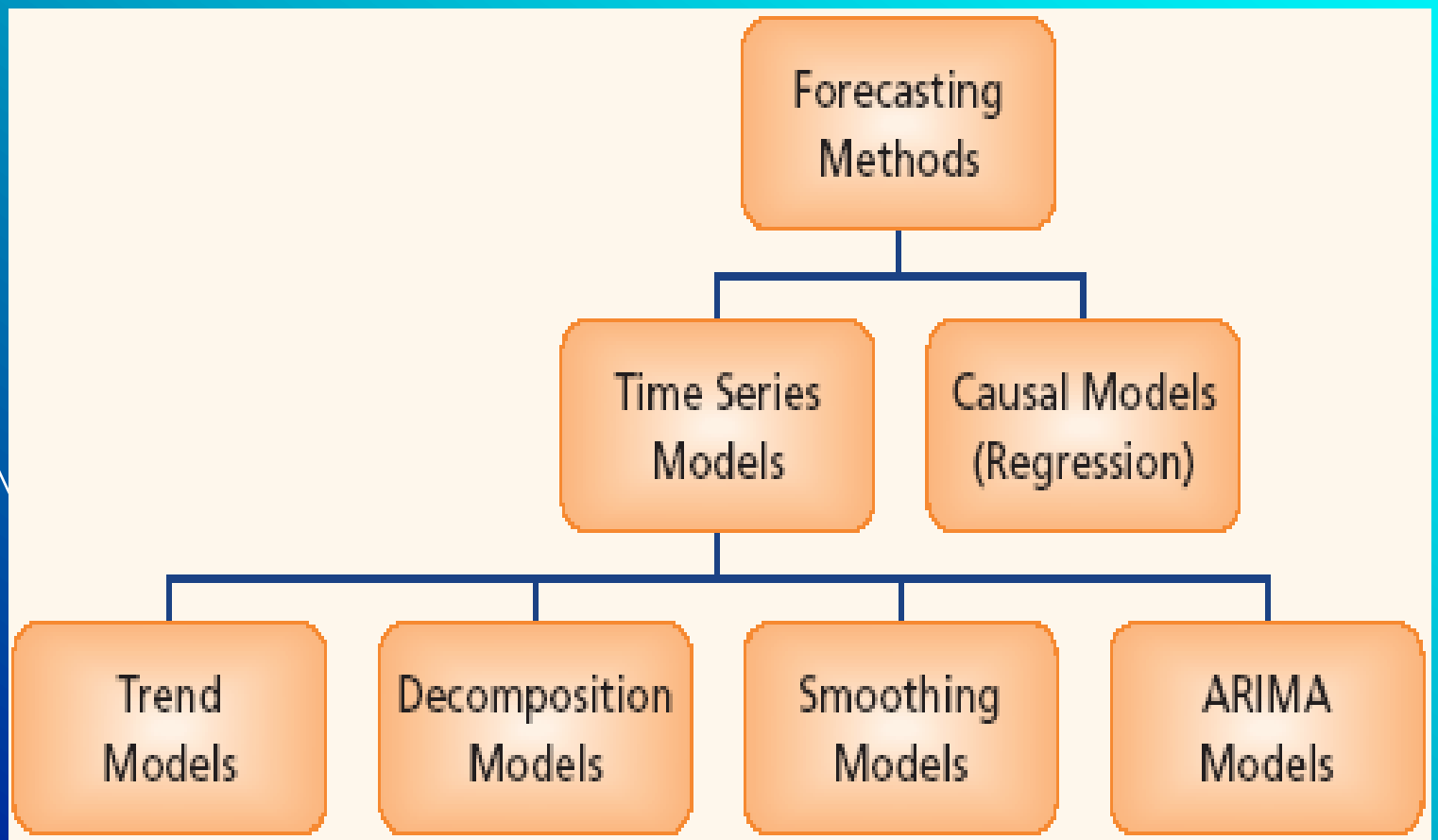



Figure 14.6



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# Trend Forecasting

## *Three Trend Models*

- **The following three trend models are especially useful in business applications:**

| | |
|---|---|
| $y_t = a + bt$ | for $t = 1, 2, \ldots, n$ (linear trend) |
| $y_t = ae^{bt}$ | for $t = 1, 2, \ldots, n$ (exponential trend) |
| $y_t = a + bt + ct^2$ | for $t = 1, 2, \ldots, n$ (quadratic trend) |

- **All three models can be fitted by Excel, MegaStat, or MINITAB.**

# Trend Forecasting

## *Linear Trend Model*

- The *linear* trend model has the form
  $y_t = a + bt$
- It is the simplest model and may suffice for short-run forecasting or as a baseline model.

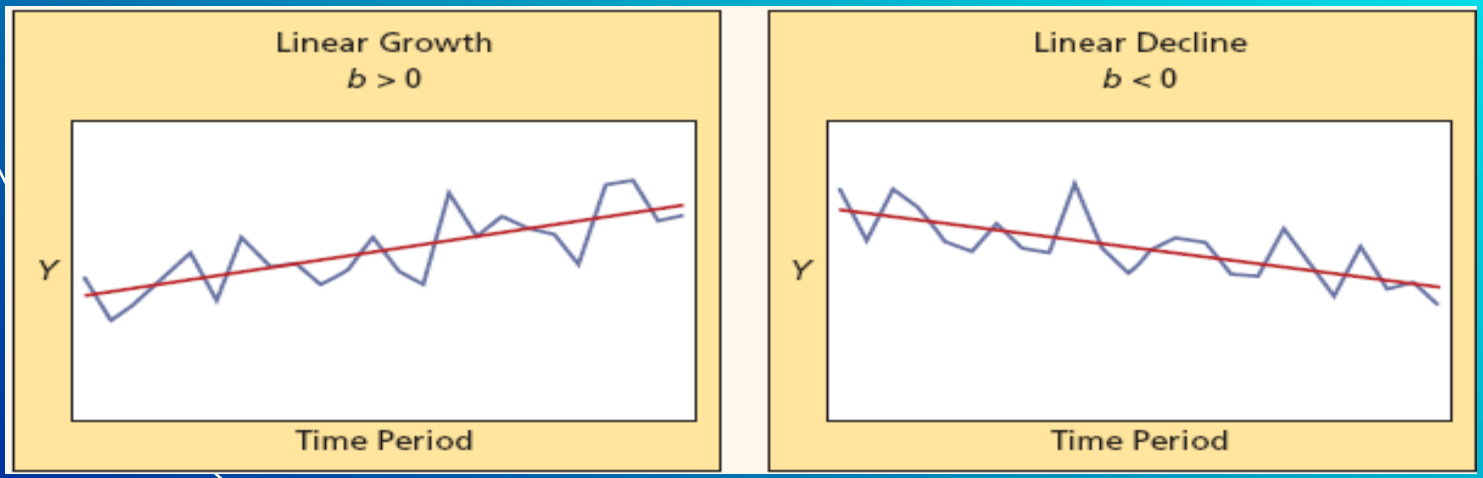



Figure 14.7



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# Trend Forecasting

## *Linear Trend Calculations*

- Linear trend is fitted by using ordinary least squares formulas.
- Note: instead of using the actual time values (e.g., years), use an index $x_t = 1, 2, 3, \ldots$.

$$\text{Slope:} \quad b = \frac{\sum_{t=1}^{n}(x_t - \bar{x})(y_t - \bar{y})}{\sum_{t=1}^{n}(x_t - \bar{x})^2}$$

$$\text{Intercept:} \quad a = \bar{y} - b\bar{x}$$

# Trend Forecasting

## *Forecasting a Linear Trend*

- Once the slope and intercept have been calculated, a forecast can be made for any future time period (e.g., year) by using the fitted model.
- For example,

$$\text{For 2003 } (t = 6)\text{: } y_6 = 22{,}860 - 235(6) = 21{,}450$$
$$\text{For 2004 } (t = 7)\text{: } y_7 = 22{,}860 - 235(7) = 21{,}215$$
$$\text{For 2005 } (t = 8)\text{: } y_8 = 22{,}860 - 235(8) = 20{,}980$$



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# Trend Forecasting

## *Linear Trend: Calculating $R^2$*

- $R^2$ can be calculated as

$$\text{Coefficient of determination:} \quad R^2 = 1 - \frac{\sum_{t=1}^{n} (y_t - \hat{y}_t)^2}{\sum_{t=1}^{n} (y_t - \bar{y})^2}$$

- An $R^2$ close to 1.0 would indicate a good fit to the *past* data.
- However, more information is needed since the forecast is simply a projection of current trend assuming that nothing changes.

# Trend Forecasting

## *Exponential Trend Model*

- The *exponential trend* model has the form $y_t = ae^{bt}$
- Useful for a time series that grows or declines at the same *rate* (*b*) in each time period.

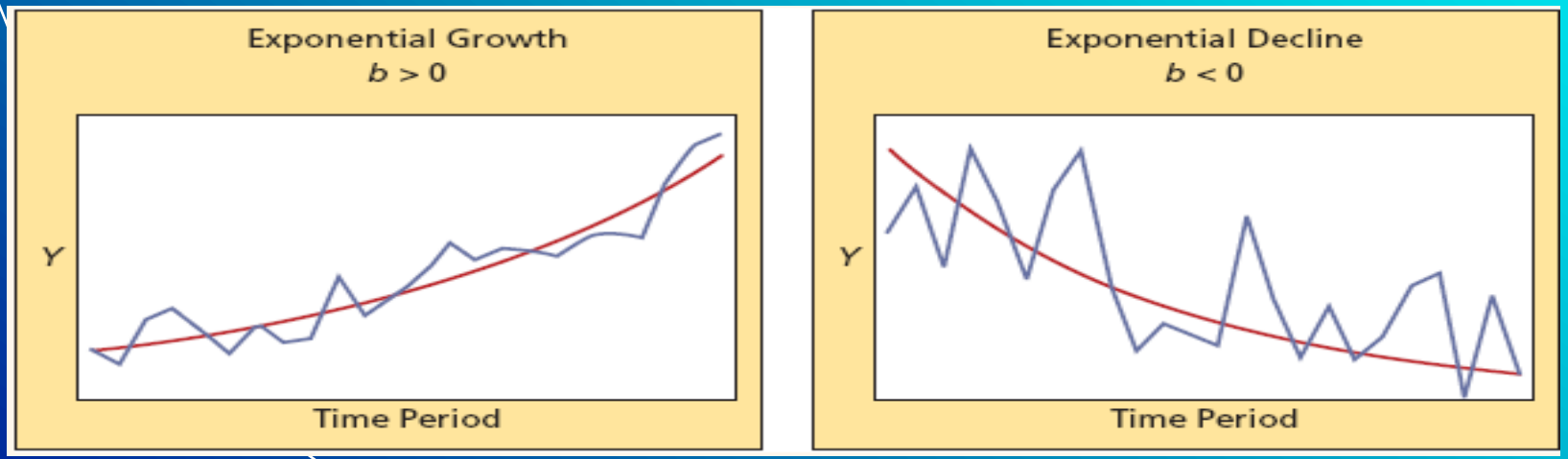



Figure 14.9



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# Trend Forecasting

## *When to Use the Exponential Model*

- This model is often preferred for financial data or data that covers a longer period of time.
- You can compare two growth rates in two time series variables with dissimilar data units (i.e., a percent growth rate is *unit-free*)
- There may not be much difference between a linear and exponential model when the growth rate is small and the data set covers only a few time periods.

# Trend Forecasting

## *When to Use the Exponential Model*

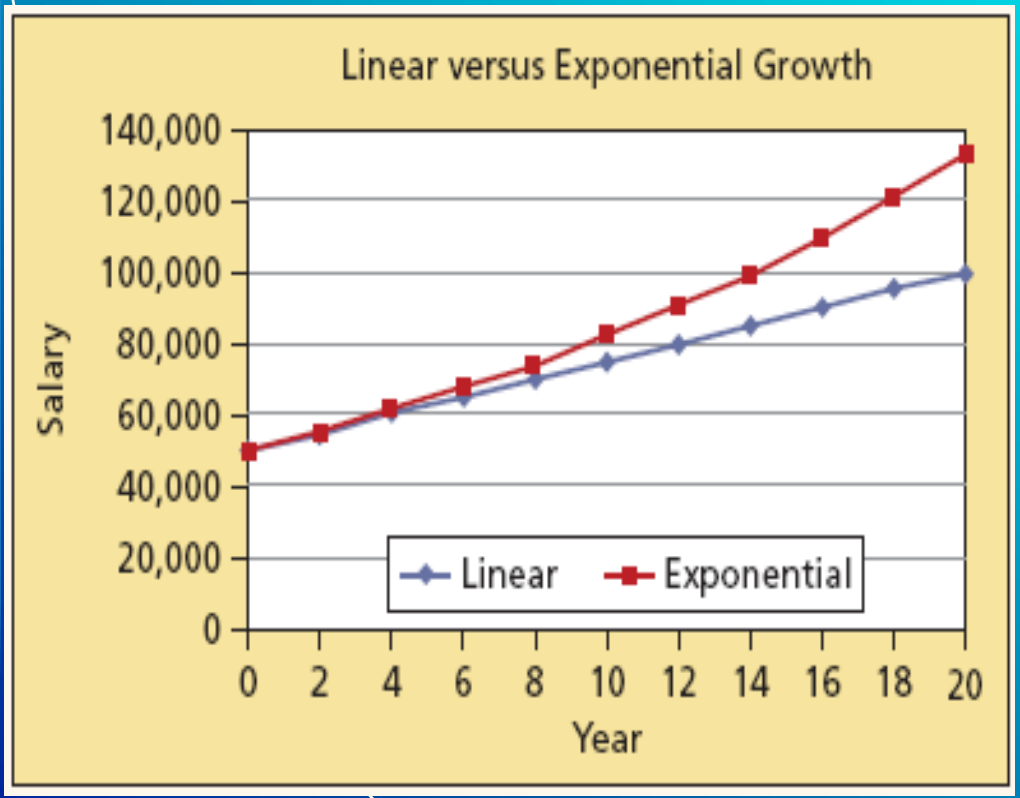



Figure 14.10

- The linear model ($y_t = a + bt$) and the exponential model ($y_t = ae^{bt}$) are equally simple because they are two-parameter models and a log-transformed exponential model is actually linear.



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# Trend Forecasting

## *Exponential Trend Calculations*

- **Calculations of the exponential trend are done by using a transformed variable $z_t = \ln(y_t)$ to produce a linear equation so that the least squares formulas can be used.**

$$\text{Slope:} \quad b = \frac{\sum_{t=1}^{n}(t-\bar{t})(z_t-\bar{z})}{\sum_{t=1}^{n}(t-\bar{t})^2} = \frac{32.12329}{82.5} = .3893732$$

$$\text{Intercept:} \quad a = \bar{z} - b\bar{t} = 3.481731 - (.3893732)(5.5) = 1.340178$$

# Trend Forecasting

## *Exponential Trend Calculations*

- Once the least squares calculations are completed, transform the intercept back to the original units by exponentiation to get the correct intercept.
- For example, if $b = 1.340178$ and $a = .3893732$,

  $a = e^{1.340178} = 3.8197$
- In the final form, the fitted trend line would be

  $y_t = ae^{bt} = 3.8197e^{1.340178t}$



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# Trend Forecasting

## *Forecasting an Exponential Trend*

- A forecast can be made for any future time period (e.g., year) by using the fitted model.
- For example,

$$\text{For 2008 } (t = 11)\text{: } y_{11} = 3.8197e^{.38937(11)} = 276.8$$
$$\text{For 2009 } (t = 12)\text{: } y_{12} = 3.8197e^{.38937(12)} = 408.5$$
$$\text{For 2010 } (t = 13)\text{: } y_{13} = 3.8197e^{.38937(13)} = 603.0$$

# Trend Forecasting

## *Exponential Trend: Calculating $R^2$*

- **All calculations of $R^2$ are done in terms of $z_t = \ln(y_t)$.**

$$R^2 = 1 - \frac{\sum_{t=1}^{n}(z_t - \hat{z}_t)^2}{\sum_{t=1}^{n}(z_t - \bar{z})^2}$$

- **An $R^2$ close to 1.0 would indicate a good fit to the *past* data.**



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# Trend Forecasting

## *Quadratic Trend*

- A *quadratic trend* model has the form $y_t = a + b_t + c_t^2$
- If $c = 0$, then the quadratic model becomes a linear model (i.e., the linear model is a special case of the quadratic model).
- Fitting a quadratic model is a way of checking for nonlinearity.
- If $c$ does not differ significantly from zero, then the linear model would suffice.

# Trend Forecasting

## *Quadratic Trend*

- Depending on the values of *b* and *c*, the quadratic model can assume any of four shapes:

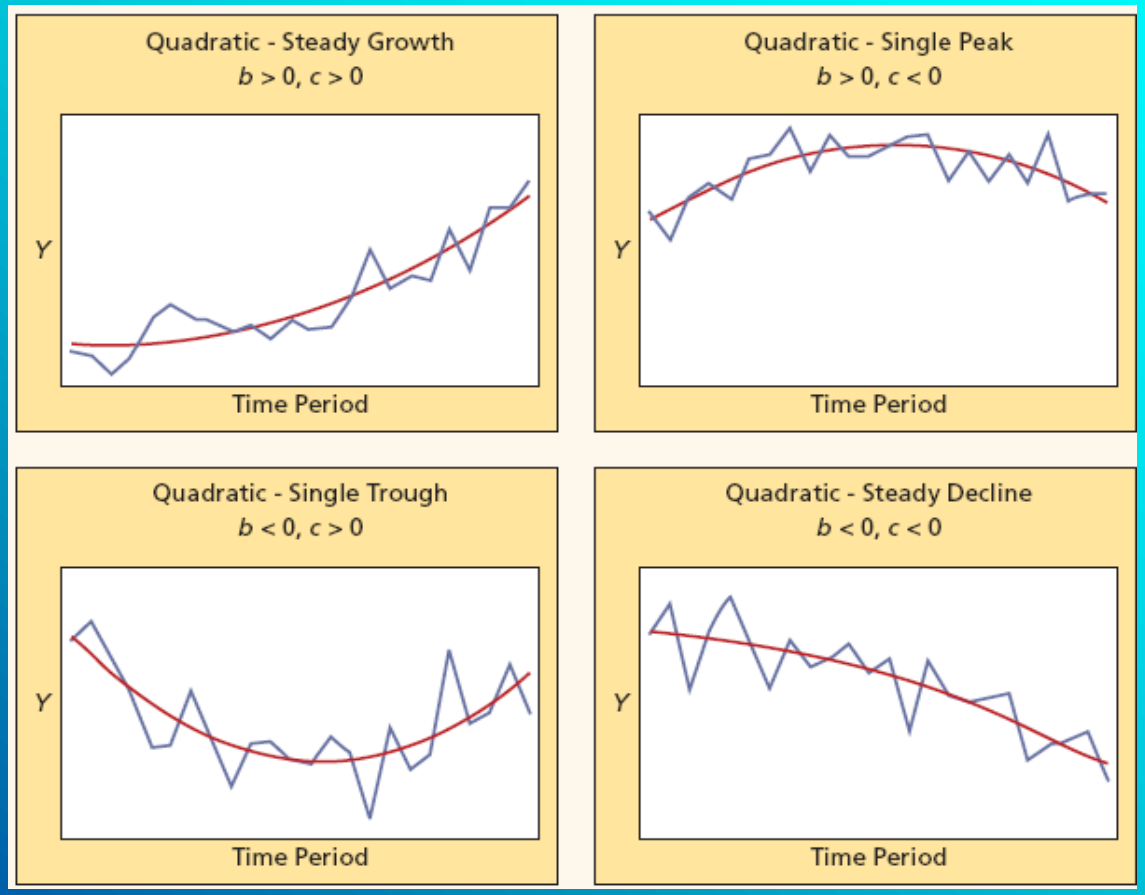



**FIGURE 14.12**
Four Quadratic Trend Models



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# Trend Forecasting

## *Quadratic Trend*

- **Because the quadratic trend model $y_t = a + b_t + c_t^2$ is a multiple regression with two predictors ($t$ and $t^2$), the least squares calculations can be obtained from MINITAB. For example,**

The regression equation is
Beds = 1119 − 36.2 Time + 2.39 Time2

| Predictor | Coef | SE Coef | T | P |
|---|---|---|---|---|
| Constant | 1119.43 | 8.10 | 138.15 | 0.000 |
| Time | −36.250 | 4.644 | −7.81 | 0.001 |
| Time2 | 2.3929 | 0.5673 | 4.22 | 0.014 |

S = 5.19959 R−Sq = 98.8% R−Sq(adj) = 98.2%

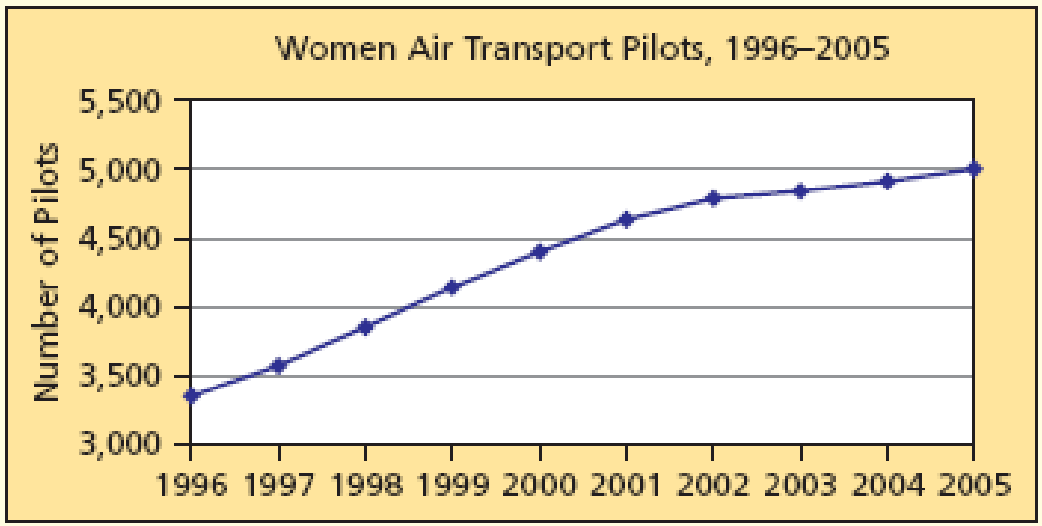
Figure 14.14

# Trend Forecasting

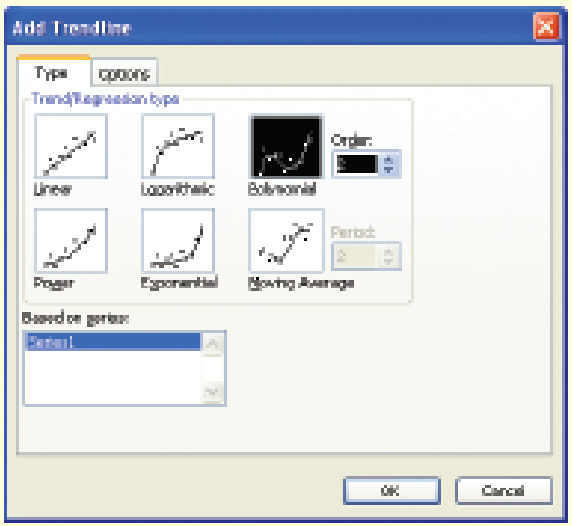
## *Using Excel for Trend Fitting*

- **Plot the data, right-click on the data and choose a trend. Click the *Options* tab if you want to display $R^2$ and the fitted equation on the graph.**

*Step 1: Click on the Data*




*Step 2: Select Trend to Fit*



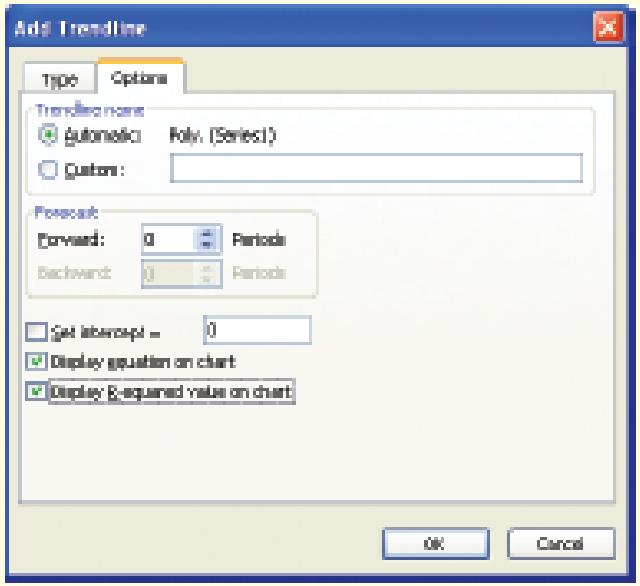



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# Trend Forecasting

## *Using Excel for Trend Fitting*

*Step 3: Select Options*




*Step 4: Trend Line and Equation*

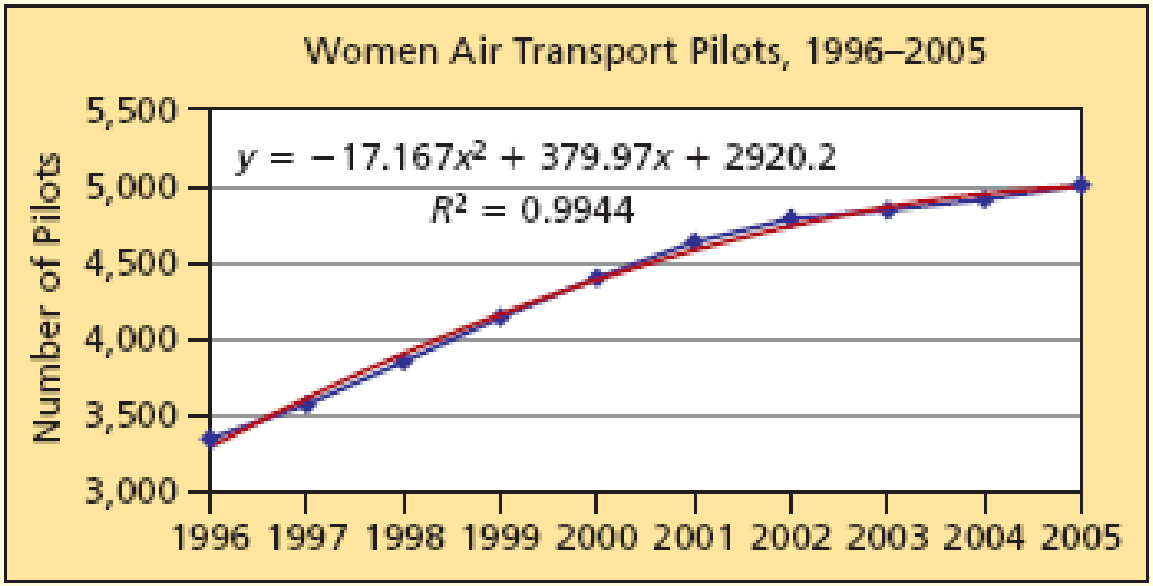



**FIGURE 14.15**
Excel's Trend-Fitting Menus WomenPilots

# Trend Forecasting

## *Trend-Fitting Criteria*

- **Criteria for selecting a trend forecasting model:**

| *Criterion* | *Ask Yourself* |
|---|---|
| • Occam's Razor | Would a simpler model suffice? |
| • Overall fit | How does the trend fit the past data? |
| • Believability | Does the extrapolated trend "look right"? |
| • Fit to recent data | Does the fitted trend match the last few data points? |



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# Trend Forecasting

## *Example: Comparing Trends*

- $R^2$ can usually be increased by choosing a more complex model.
- But $R^2$ measures fit to the *past* data.
- Look at forecasts (i.e., extrapolated trends) to see which of four fitted trends using the same data give the best fit.

# Trend Forecasting

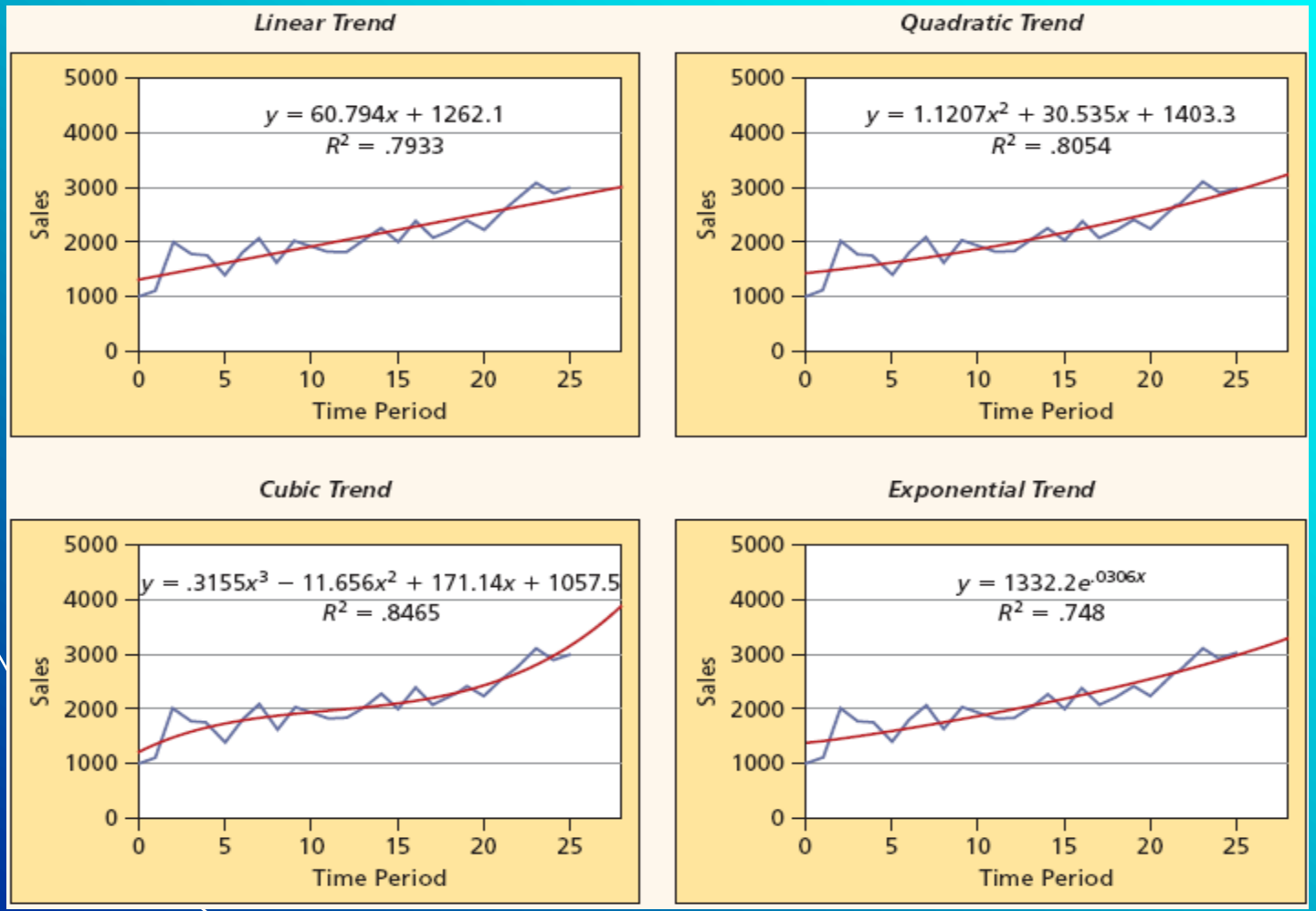



Figure 14.16



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# Trend Forecasting

## *Example: Comparing Trends*

- **Any trend model's forecasts become less reliable as they are extrapolated farther into the future.**
- **Consider the following three trend models**

| *Model* | *Pro* | *Con* |
|---|---|---|
| Linear | 1. Simple, familiar to everyone.<br>2. May suffice for short-run data. | 1. Assumes constant slope.<br>2. Can't capture nonlinear change. |
| Exponential | 1. Familiar to financial analysts.<br>2. Shows compound percent growth rate. | 1. Some managers are unfamiliar with $e^x$.<br>2. Data values must be positive. |
| Quadratic | 1. Useful for data with a turning point.<br>2. Useful test for nonlinearity. | 1. Complex and no intuitive interpretation.<br>2. Gives weird forecasts if extrapolated too far. |

# Assessing Fit

## *Five Measures of Fit*

- **"Fit" refers to how well the estimated trend model matches the observed historical past data.**

| *Statistic* | *Description* | *Pro* | *Con* |
|---|---|---|---|
| $R^2 = 1 - \frac{\sum_{t=1}^{n}(y_t - \hat{y}_t)^2}{\sum_{t=1}^{n}(y_t - \bar{y}_t)^2}$ | Coefficient of determination | 1. Unit-free measure.<br>2. Very common. | 1. Often interpreted incorrectly (e.g., "percent of correct predictions"). |
| $MAPE = \frac{100}{n}\sum_{t=1}^{n}\frac{\lvert y_t - \hat{y}_t\rvert}{y_t}$ | Mean Absolute Percent Error (MAPE) | 1. Unit-free measure (%).<br>2. Intuitive meaning. | 1. Requires $y_t > 0$.<br>2. Lacks nice math properties. |
| $MAD = \frac{1}{n}\sum_{t=1}^{n}\lvert y_t - \hat{y}_t\rvert$ | Mean Absolute Deviation (MAD) | 1. Intuitive meaning.<br>2. Same units as $y_t$. | 1. Not unit-free.<br>2. Lacks nice math properties. |
| $MSD = \frac{1}{n}\sum_{t=1}^{n}(y_t - \hat{y}_t)^2$ | Mean Squared Deviation (MSD) | 1. Nice math properties.<br>2. Penalizes big errors more. | 1. Nonintuitive meaning.<br>2. Rarely reported. |
| $SE = \sqrt{\sum_{t=1}^{n}\frac{(y_t - \hat{y}_t)^2}{n-2}}$ | Standard error | 1. Same units as $y_t$.<br>2. For confidence intervals. | 1. Nonintuitive meaning. |

Table 14.10



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# Assessing Fit

## *Interpretation*

- These fit statistics are most useful in comparing different trend models for the same data.
- All the statistics (especially the *MSD*) are affected by unusual residuals.
- The standard error (*SE*) is useful if we want to make a prediction interval for a forecast.

$$\hat{y}_t \pm t_{n-2}\text{SE}\sqrt{1+\frac{1}{n}+\frac{(x_t-\bar{x})^2}{\sum_{t=1}^{n}(x_t-\bar{x})^2}}$$

# Moving Averages

## *Trendless or Erratic Data*

- In cases where the time series $y_1, y_2, \ldots, y_n$ is erratic or has no consistent trend, there may be little point in fitting a trend line.
- A conservative approach is to calculate either a *trailing* or *centered moving average*.



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# Moving Averages

## *Trailing Moving Average (TMA)*

- The *TMA* simply averages over the last *m* periods.

$$\hat{y}_t = \frac{y_t + y_{t-1} + \cdots + y_{t-m+1}}{m}$$

- The *TMA* smooths the past fluctuations in the time series in order to see the pattern more clearly.
- Choosing a larger *m* yields a "smoother" *TMA* but requires more data.

# Moving Averages

## *Trailing Moving Average (TMA)*

- The value of $\hat{y}_t$ may also be used as a forecast for period $t + 1$.
- There is no way to update the moving average beyond the observed data range.
- This is a *one-period-ahead forecast.*
- For example, consider the following graph

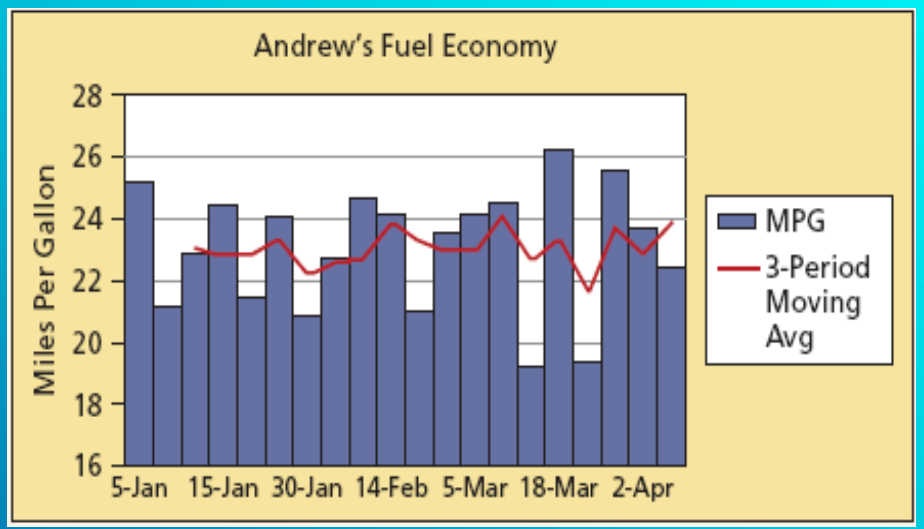



Figure 14.19



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# Moving Averages

## *Centered Moving Average (TMA)*

- **The *CMA* smoothing method looks forward *and* backward in time to express the current "forecast" as a mean of the current observation *and* observations on either side of the current data. For example, using *m* = 3 periods, the CMA is:**

$$\hat{y}_t = \frac{y_{t-1} + y_t + y_{t+1}}{3}$$

# Moving Averages

## *Centered Moving Average (TMA)*

- When *n* is odd (*m* = 3, 5, etc.), the *CMA* is easy to calculate.
- When *n* is even, the mean of an even number of data points would lie between two data points and would not be correctly centered.
- In this case, we would take a double moving average to get the resulting *CMA* centered properly.



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# Exponential Smoothing

## *Forecast Updating*

- The ***exponential smoothing*** model is a special kind of moving average.
- Its one-period-ahead forecasting technique is utilized for data that has up-and-down movements but no *consistent* trend.
- The updating formula is $F_{t+1} = \alpha y_t + (1 - \alpha) F_t$

where

$F_{t+1}$ = the forecast for the next period
$\alpha$ = the "smoothing constant" $(0 \leq \alpha \leq 1)$
$y_t$ = the actual data value in period $t$
$F_t$ = the previous forecast for period $t$

# Exponential Smoothing

## *Smoothing Constant ($\alpha$)*

- The next forecast $F_{t+1}$ is a weighted average of $y_t$ (the current data) and $F_t$ (the previous forecast).
- The value of $\alpha$ (the *smoothing constant*) is the weight given to the latest data.
- A small value of $\alpha$ would give low weight to the most recent observation.
- A large value of $\alpha$ would give heavy weight to the previous forecast.
- The larger the value of $\alpha$, the more quickly the forecasts adapt to recent data.



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# Exponential Smoothing

## *Choosing the Value of α*

- If α = 1, there is no smoothing at all and the forecast for the next period is the same as the latest data point.
- The effect of our choice of α on the forecast diminishes as time increases.
- To see this, replace $F_t$ with $F_{t-1}$ and repeat this type of substitution indefinitely to obtain

$$F_{t+1} = \alpha y_t + \alpha(1-\alpha)y_{t-1} + \alpha(1-\alpha)^2 y_{t-2} + \alpha(1-\alpha)^3 y_{t-3} + \cdots$$

- The next forecast depends on all the prior data.

# Exponential Smoothing

## *Initializing the Process*

- Note that $F_{t-1}$ depends on $F_t$, which in turn depends on $F_{t-1}$, and so on all the way back to $F_1$.
- Where do we get the initial forecast $F_1$ (i.e., how do we initialize the process)?
- ***Method A***
  Use the first data value. Set
  $$F_1 = y_1$$
- Although simple, if $y_1$ is unusual, it could take a few iterations for the forecasts to stabilize.



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# Exponential Smoothing

## *Initializing the Process*

- ***Method B***

  Average the first 6 data values. Set

  $$F_1 = 1/n(y_1 + y_2 + y_3 + y_4 + y_5 + y_6)$$

- This method consumes more data and is still vulnerable to unusual *y*-values.
- ***Method C***

  Backward extrapolation. Set

  $F_1$ = prediction from *backcasting*

- ***Backcasting*** fits a trend to the data *in reverse order* and extrapolates the trend to predict the initial value.

# Exponential Smoothing

## *Smoothing with Trend and Seasonality*

- **Single exponential smoothing is for *trendless* data.**
- **For data with a trend, use *Holt's method* with *two* smoothing constants (one for *trend* and one for *level*).**
- **For data with both trend and seasonality, use *Winters's method* with *three* smoothing constants (for *trend*, *level*, and *seasonality*.**



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# Seasonality

## *When and How to Deseasonalize*

- When the data periodicity is monthly or quarterly, calculate a seasonal index and use it to *deseasonalize* it.
- For the multiplicative model, a seasonal index is a *ratio*.
- The seasonal indexes must sum to 12 for monthly data or to 4 for quarterly data.

# Seasonality

## *When and How to Deseasonalize*

**Step 1:** Calculate a centered moving average (*CMA*) for each month (quarter).

**Step 2:** Divide each observed $y_t$ value by the *MA* to obtain seasonal ratios.

**Step 3:** Average the seasonal ratios by the month (quarter) to get raw seasonal indexes.

**Step 4:** Adjust the raw seasonal indexes so they sum to 12 (monthly) or 4 (quarterly).

**Step 5:** Divide each $y_t$ by its seasonal index to get deseasonalized data.



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# Seasonality

## *Seasonal Forecasts Using Binary Predictors*

- Estimate a regression model using *seasonal binaries* as predictors in order to address seasonality.
- For example, for quarterly data, the fourth quarter binary *Qtr4* (arbitrarily chosen), would be excluded in order to prevent multicollinearity.

| Obs | Year | Quarter | Sales | CMA | Sales/CMA | Seasonal Index | Deseasonalized |
|---|---|---|---|---|---|---|---|
| 1 | 2002 | 1 | 259 | | | 1.252 | 206.9 |
| 2 | | 2 | 236 | | | 1.021 | 231.1 |
| 3 | | 3 | 164 | *226.125* | 0.725 | 0.740 | 221.7 |
| 4 | | 4 | 222 | 240.000 | 0.925 | 0.987 | 224.9 |
| 5 | 2003 | 1 | 306 | 251.125 | 1.219 | 1.252 | 244.4 |
| 6 | | 2 | 300 | 260.875 | 1.150 | 1.021 | 293.8 |
| 7 | | 3 | 189 | 276.625 | 0.683 | 0.740 | 255.5 |
| 8 | | 4 | 275 | 281.000 | 0.979 | 0.987 | 278.6 |
| 9 | 2004 | 1 | 379 | 282.875 | 1.340 | 1.252 | 302.7 |
| 10 | | 2 | 262 | 292.125 | 0.897 | 1.021 | 256.6 |
| 11 | | 3 | 242 | 293.500 | 0.825 | 0.740 | 327.2 |
| 12 | | 4 | 296 | 306.125 | 0.967 | 0.987 | 299.8 |
| 13 | 2005 | 1 | 369 | 321.625 | 1.147 | 1.252 | 294.7 |
| 14 | | 2 | 373 | 333.000 | 1.120 | 1.021 | 365.3 |
| 15 | | 3 | 255 | 361.000 | 0.706 | 0.740 | 344.7 |
| 16 | | 4 | 374 | 379.250 | 0.986 | 0.987 | 378.8 |
| 17 | 2006 | 1 | 515 | 389.750 | 1.321 | 1.252 | 411.3 |
| 18 | | 2 | 373 | 418.375 | 0.892 | 1.021 | 365.3 |
| 19 | | 3 | 339 | 450.375 | 0.753 | 0.740 | 458.3 |
| 20 | | 4 | 519 | 484.500 | 1.071 | 0.987 | 525.7 |
| 21 | 2007 | 1 | 626 | 512.000 | 1.223 | 1.252 | 500.0 |
| 22 | | 2 | 535 | 515.375 | 1.038 | 1.021 | 524.0 |
| 23 | | 3 | 397 | | | 0.740 | 536.7 |
| 24 | | 4 | 488 | | | 0.987 | 494.3 |

**TABLE 14.16**

Calculation of Deseasonalized Sales ($n = 24$ quarters)

FloorSales

# Index Numbers

- A simple way to measure changes over time is to convert time-series data into ***index numbers***.
- The idea is to create an index that starts at 100 in a *base period*.
- Indexes are most often used for financial data.



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# Index Numbers

## *Relative Indexes*

- To convert a time series $y_1, y_2, \ldots y_n$ into a ***relative index***, divide each data value $y_t$ by the data value $y_I$ in a base period and multiply by 100.
- The relative index $I_t$ for period t is

$$I_t = 100 \times \frac{y_t}{y_1}$$

- The index in the base period is always $I_t = 100$.

# Index Numbers

## *Weighted Indexes*

- **A different calculation is required for a *weighted index* such as the *Consumer Price Index*.**
- **The basic formula for a simple weighted price index is**

$$I_t = 100 \times \frac{\sum_{i=1}^{m} p_{it} q_i}{\sum_{i=1}^{m} p_{i1} q_i} = 100 \times \frac{p_{1t}q_1 + p_{2t}q_2 + \cdots + p_{mt}q_m}{p_{11}q_1 + p_{21}q_2 + \cdots + p_{m1}q_m}$$

**Where $I_t$ = weighted index for period t**

**$p_{it}$ = price of good I in period t**

**$q_t$ = weight assigned to good i**



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# Index Numbers

## *Importance of Index Numbers*

- The CPI affects nearly all Americans because it is used to adjust things like retirement benefits, food stamps, school lunch benefits, alimony, and tax brackets.
- Other familiar price indexes, such as the *Dow Jones Industrial Average* (DJIA) have their own unique methodologies.

# Forecasting: Final Thoughts

## *Role of Forecasting*

- Forecasting resembles planning.
- *Forecasting* is an analytical way to describe a "what-if" situation in the future.
- *Planning* is the organization's attempt to determine a set of actions it will take under each foreseeable contingency.
- Forecasts tend to be self-defeating because they trigger homeostatic organizational responses.



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# Forecasting: Final Thoughts

## *Behavioral Aspects of Forecasting*

- Forecasts can facilitate organization communication.
- A quantitative forecast helps *make assumptions explicit*.
- Forecasts *focus the dialogue* and can make it more productive.

# Forecasting: Final Thoughts

## *Forecasts are Always Wrong*

- A forecast is never precise. There is always some error.
- Use the error measure to track forecast error.
- The *Box-Jenkins method* uses several different types of time series modeling techniques that fall into a class called *ARIMA* (Autoregressive Integrated Moving Average) models.
- *AR* (autoregressive) models take advantage of the dependency that might exist between values in the time series.



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# Forecasting: Final Thoughts

***To Ensure Good Forecast Outcomes***

- Maintain up-to-date databases of *relevant* data.
- Allow sufficient lead tome to analyze the data.
- State several alternative forecasts or scenarios.
- Track forecast errors over time.
- State your assumptions and qualifications.
- Bear in mind the purpose of the forecasts.
- Consider the time horizon for the decision.
- Don’t underestimate the power of a good graph.

# Forecasting: Final Thoughts

## *Principle of Occam's Razor*

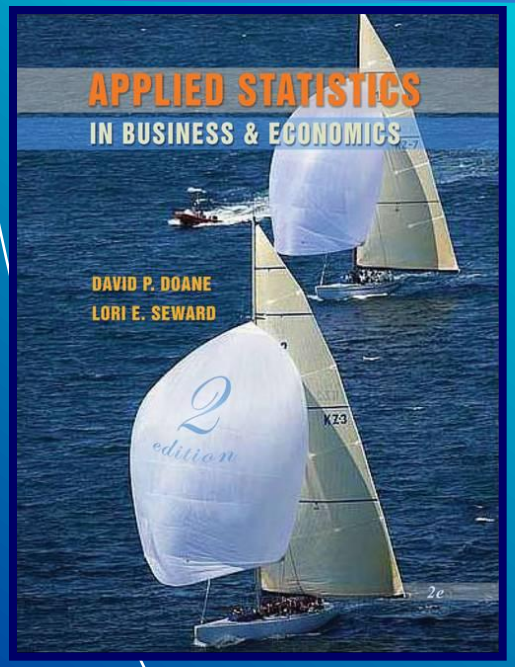
**Given two *sufficient* explanations, we prefer the simpler one.**

**-- William of Occam (1285-1347)**



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# Applied Statistics in Business & Economics




## End of Chapter 14


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