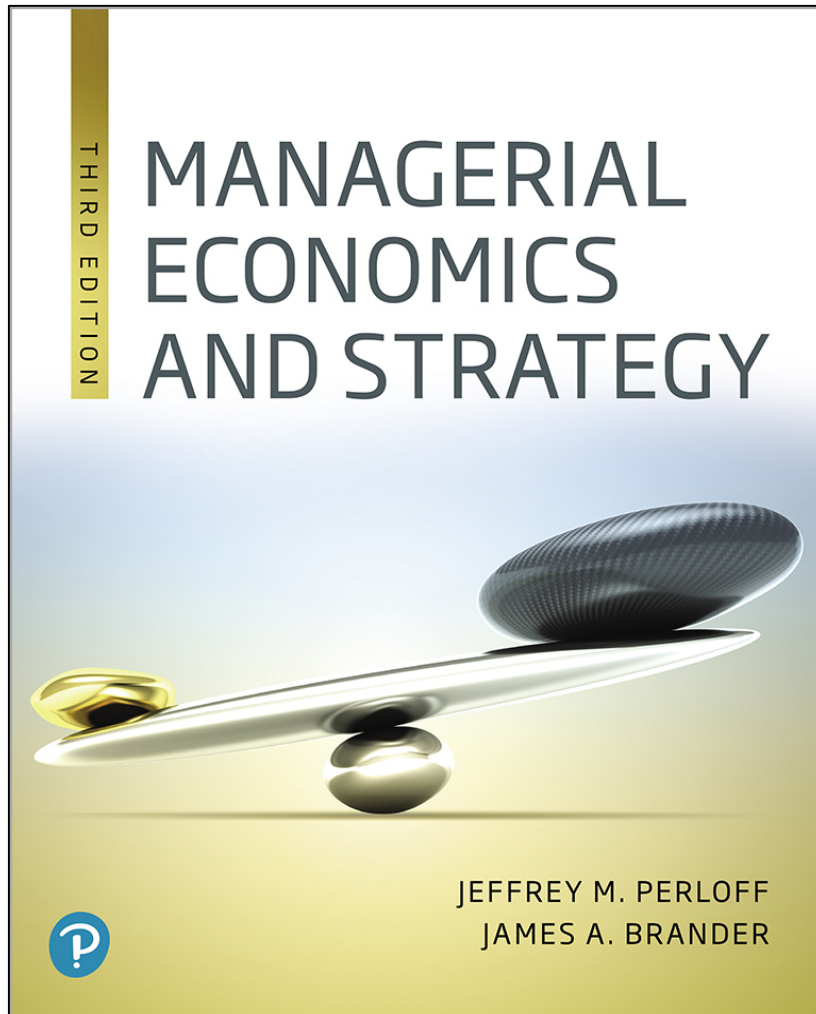


Managerial Economics and Strategy

Third Edition



Chapter 3

Empirical Methods for
Demand Analysis

Managerial Problem

Estimating the Effect of an iTunes Price Change

- How can managers use the data to estimate the demand curve facing iTunes? How can managers determine if a price increase is likely to raise revenue, even though the quantity demanded will fall?

Solution Approach

- Managers can use **empirical methods** to analyze economic relationships that affect a firm's demand.

Empirical Methods

- **Elasticity** measures the responsiveness of one variable, such as quantity demanded, to a change in another variable, such as price.
- **Regression analysis** is a method to estimate a relationship between a dependent variable (quantity demanded) and explanatory variables (price and income). It requires identifying the properties and statistical significance of estimated coefficients, as well as model identification.
- **Forecasting** is the use of regression analysis to predict future values of important variables as sales or revenue.

Learning Objectives (1 of 2)

3.1 Elasticity

Calculate elasticities and apply them to managerial problems

Regression Analysis

3.2 Use regression analysis to estimate business relationships

3.3 Properties and Statistical Significance of Estimated Coefficients

Determine the confidence we can place in a regression analysis

Learning Objectives (2 of 2)

3.4 Regression Specification

Explain how to choose an appropriate regression specification

3.5 Forecasting

Forecast important business variables using regression analysis

3.1 Elasticity (1 of 9)

The Price Elasticity of Demand

- The **price elasticity of demand** (or elasticity of demand or demand elasticity) is the percentage change in quantity demanded, Q , divided by the percentage change in price, p .

$$\varepsilon = \frac{\text{percentage change in quantity demanded}}{\text{percentage change in price}} = \frac{\Delta Q / Q}{\Delta p / p}. \quad (3.1)$$

Arc Elasticity: $\varepsilon = \frac{\Delta Q / \bar{Q}}{\Delta p / \bar{p}}.$

- It is an elasticity that uses the average quantity, $\bar{Q}$, and average price, $\bar{p}$ as the denominators for percentage calculations.
- In the formula $(\Delta Q / \bar{Q})$ is the percentage change in quantity demanded and $(\Delta p / \bar{p})$ is the percentage change in price.
- Arc elasticity is based on a discrete change between two distinct price-quantity combinations on a demand curve.

3.1 Elasticity (2 of 9)

Managerial Implication:

Changing Prices to Calculate an Arc Elasticity

- One of the easiest and most straightforward ways for a manager to determine the elasticity of demand for a firm's product is to conduct an experiment.
 - If the firm is a price setter and can vary the price of its product, the manager can change the price and observe how the quantity sold varies.
 - Armed with two observations—the quantity sold at the original price and the quantity sold at the new price—the manager can calculate an arc elasticity.
 - Depending on the size of the calculated elasticity, the manager may continue to sell at the new price or revert to the original price.
 - It is often possible to obtain useful information from an experiment in a few markets or even just one small submarket—in one country, in one city, or even in one supermarket.

3.1 Elasticity (3 of 9)

Point Elasticity: $\varepsilon = (\Delta Q / \Delta p) (p / Q)$

- Point elasticity measures the effect of a small change in price on the quantity demanded.
- In the formula, we are evaluating the elasticity at the point (Q, p) and $\Delta Q / \Delta p$ is the ratio of the change in quantity to the change in price.
- Point elasticity is useful when the entire demand information is available.

Point Elasticity with Calculus: $\varepsilon = (\partial Q / \partial p) (p / Q)$

- To use calculus, the change in price becomes very small.
- $\Delta p \rightarrow 0$, the ratio $\Delta Q / \Delta p$ converges to the derivative $\partial Q / \partial p$.

3.1 Elasticity (4 of 9)

Elasticity Along the Demand Curve

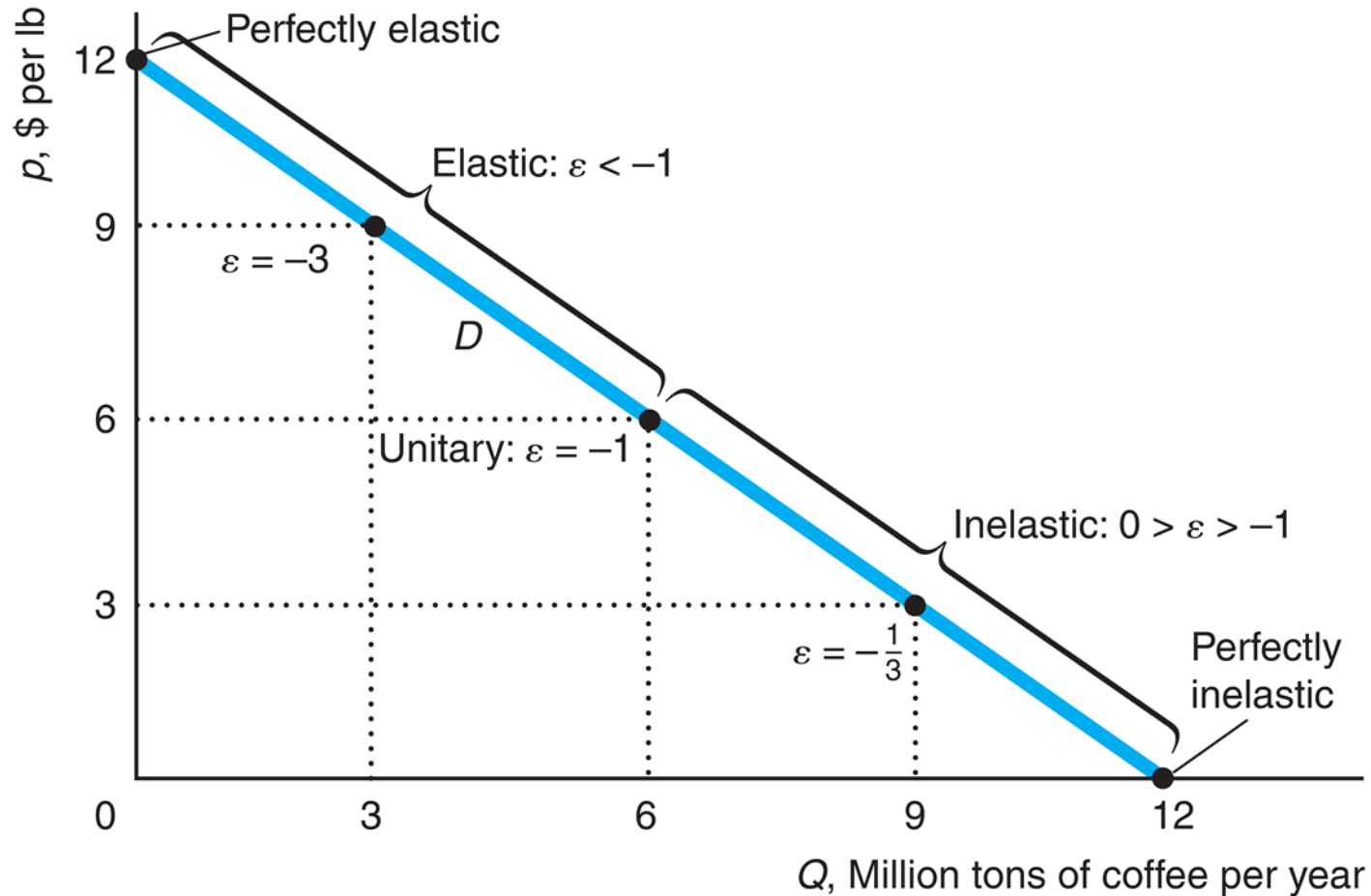
- The elasticity of demand is different at every point along a downward-sloping linear demand curve.
- However, horizontal and vertical demand curves, which are extreme cases of a linear demand curve, have the same elasticity at every point.

3.1 Elasticity (5 of 9)

Downward-Sloping Linear Demand Curves

- If the shape of the linear demand curve is downward sloping, elasticity varies along the demand curve.
 - The elasticity of demand is a more negative number the higher the price and hence the smaller the quantity.
- In Figure 3.1, the higher the price, the more elastic the demand curve. A 1% increase in price causes a larger percentage fall in quantity near the top of the demand curve than near the bottom.
 - The coffee demand curve is perfectly elastic ($\epsilon < -\infty$) where the demand curve hits the vertical axis at \$12 per lb.
 - It is elastic ($\epsilon < -1$) for high prices below \$12 and above \$6 per lb.
 - It has unitary elasticity ($\epsilon = -1$) at the midpoint.
 - It is inelastic ($\epsilon = 0$) for low prices below \$6 and above \$0 per lb.
 - It is perfectly inelastic ($\epsilon = 0$) where the demand curve hits the horizontal axis at \$0 per lb.

Figure 3.1 The Elasticity of Demand Varies Along the Linear Coffee Demand Curve



3.1 Elasticity (6 of 9)

Horizontal Demand Curves: $\varepsilon = -\infty$ at every point

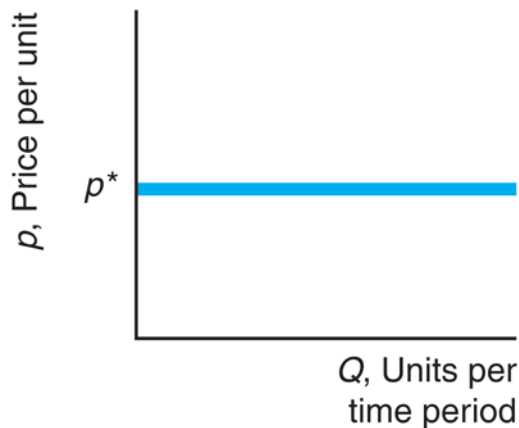
- If the price increases even slightly, demand falls to zero. In Figure 3.2, panel a, the demand is horizontal at p^* .
- The demand curve is perfectly elastic: a small increase in price causes an infinite drop in quantity.
- Why would a good's demand curve be horizontal? One reason is that consumers view this good as identical to another good and do not care which one they buy.

Vertical Demand Curves: $\varepsilon = 0$ at every point

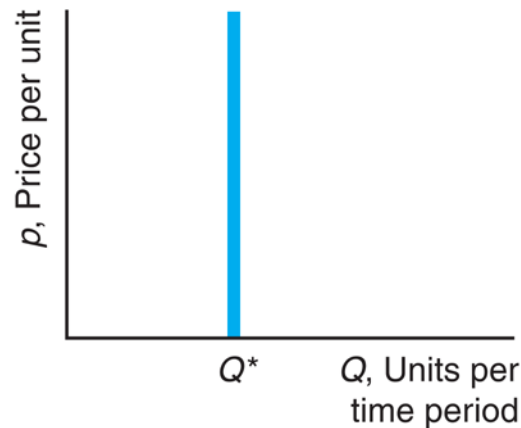
- If the price goes up, the quantity demanded is unchanged, so $\Delta Q=0$. In Figure 3.2, panel b, the demand is vertical at Q^* .
- The demand curve is perfectly inelastic.
- A demand curve is vertical for **essential goods**—goods that people feel they must have and will pay anything to get it.

Figure 3.2 Vertical and Horizontal Demand Curves

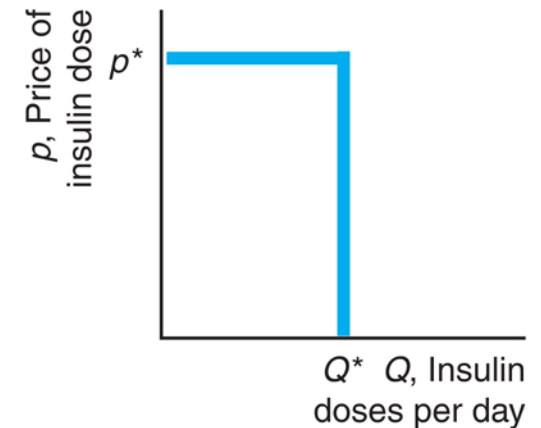
(a) Perfectly Elastic Demand



(b) Perfectly Inelastic Demand



(c) Individual's Demand for Insulin



3.1 Elasticity (7 of 9)

Other Types of Demand Elasticities

- Income Elasticity of Demand, $(\Delta Q / \Delta Y) (Y / Q)$
 - **Income elasticity** is the percentage change in the quantity demanded divided by the percentage change in income Y .
 - **Normal goods** have positive income elasticity, such as coffee.
 - **Inferior goods** have negative income elasticity, such as instant soup.
- Cross-Price Elasticity of Demand, $(\Delta Q / \Delta p_o) (p_o / Q)$
 - **Cross-price elasticity** is the percentage change in the quantity demanded divided by the percentage change in the price of another good, p_o
 - **Complement goods** have negative cross-price elasticity, such as cream and coffee.
 - **Substitute goods** have positive cross-price elasticity, such as cotton and wool.

3.1 Elasticity (8 of 9)

Demand Elasticities over Time

- The shape of a demand curve depends on the time period under consideration.
 - It is easy to substitute between products in the long run but not in the short run.
 - Liddle (2012) estimated gasoline demand elasticities across many countries and found that the short-run elasticity was -0.16 , and the long-run elasticity was -0.43 .

Other Elasticities

- The relationship between any two related variables can be summarized by an elasticity. A manager might be interested in:
 - The price elasticity of supply—percentage increase in quantity supplied arising from a 1% increase in price.
 - Or, the elasticity of cost with respect to output—percentage increase in cost arising from a 1% increase in output.
 - Or, during labor negotiations, the elasticity of output with respect to labor—the percentage increase in output arising from a 1% increase in labor input, holding other inputs constant.

3.1 Elasticity (9 of 9)

Estimating Demand Elasticities

- Managers use price, income, and cross-price elasticities to set prices.
- To calculate an **arc elasticity**, managers use data from before and after the price change.
 - By comparing quantities just before and just after a price change, managers can be reasonably sure that other variables, such as income, have not changed appreciably.
- A manager might want an estimate of the demand elasticity **before** actually making a price change to avoid a potentially expensive mistake.
 - A manager may fear a reaction by a rival firm in response to a pricing experiment, so they would like to have demand elasticity in advance.
 - A manager would like to know the effect on demand of many possible price changes rather than focusing on just one price change.
- However, managers might need an estimate of the entire demand curve to have demand elasticities before making any real price change. The tool needed is **regression analysis**.

3.2 Regression Analysis (1 of 6)

- A **regression analysis** is a statistical technique used to estimate the relationship between a **dependent variable** and **explanatory variables**.

A Demand Function Example

- **Demand Function:** $Q = a + bp + e$
 - Quantity is a function of price; Q to the left is the **dependent variable**; p to the right is the **explanatory variable**; e is the **random error** (unpredictable and unobservable effects on dependent variable).
 - It is a linear demand and the estimated sign of b **must** be negative
 - If a manager surveys customers about how many units they will buy at various prices, he is using data to estimate the demand function.
- **Inverse Demand Function:** $p = g + hQ + e$
 - Price is a function of quantity; p to the left is the **dependent variable**; Q to the right is the **explanatory variable**; e is the **random error**.
 - Based on the previous demand function, so $g = -a / b > 0$ and $h = 1 / b < 0$ and has a specific linear form. The sign of h **must** be negative
 - If a manager surveys how much customers were willing to pay for various units of a product or service, he would estimate the inverse demand equation.

3.2 Regression Analysis (2 of 6)

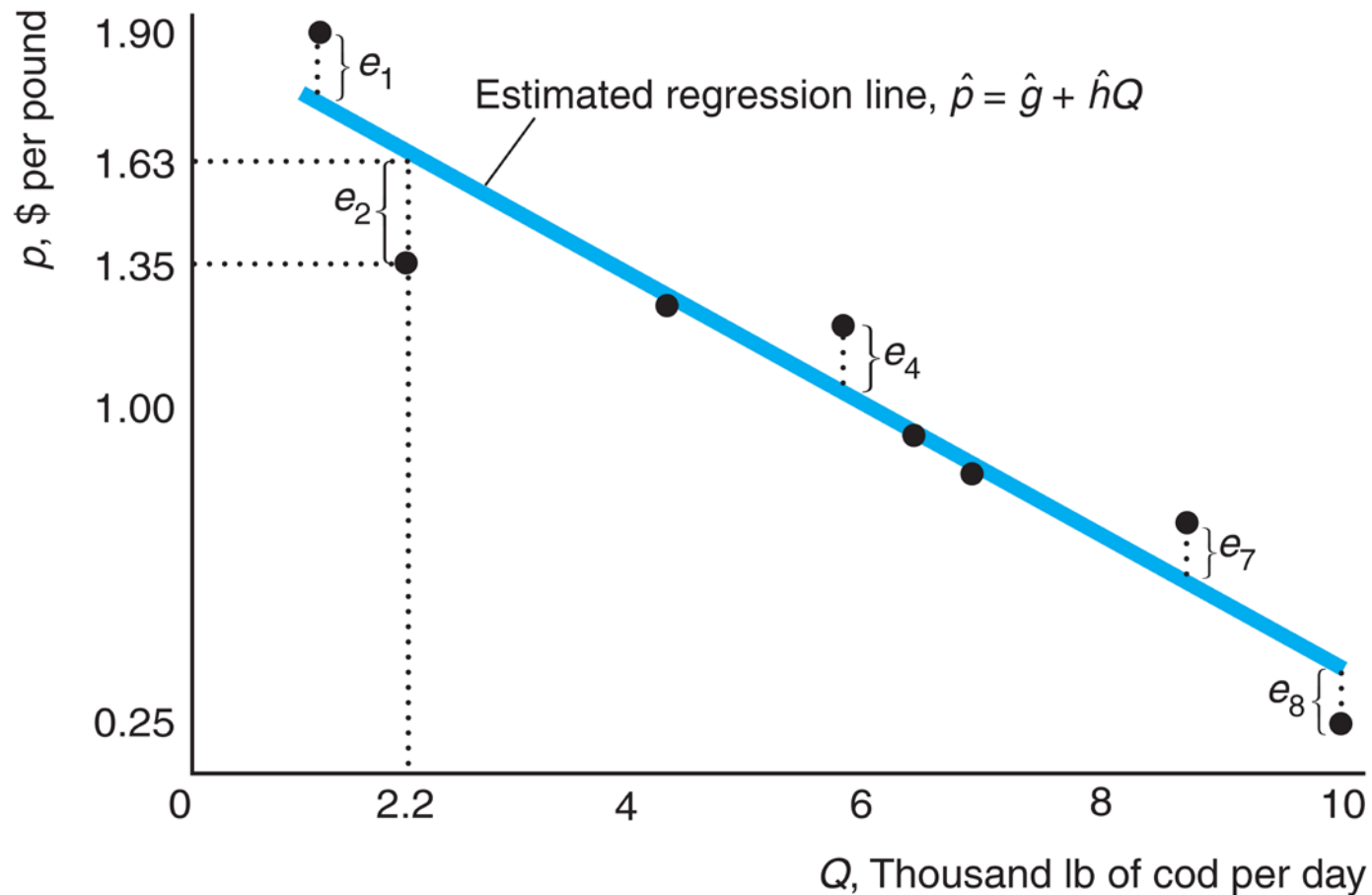
Regression Analysis Using Microsoft Excel

- Portland Fish Inverse Demand Function: $p = g + hQ + e$
 - g and h are true coefficients.
- Inverse Demand Function Estimation: $\hat{p} = \hat{g} + \hat{h}Q$
 - The OLS regression provides estimates of these coefficients, $\hat{g}$ and $\hat{h}$, which we can use to predict the expected price, $\hat{p}$, for a given quantity. It is assumed $e=0$.
 - Use **Microsoft Excel Trendline** option for scatterplots to estimate $\hat{g}$ and $\hat{h}$, using OLS and get the respective graph and function (steps next).
 - The estimated inverse demand curve is $\hat{p} = 1.96 - 0.15Q$
 - The estimated change in price needed to induce buyers to purchase one more unit (1,000 lbs) is $\hat{h} = -\$0.15 = -15\text{¢}$.

Ordinary Least Squares (OLS) Regression

- OLS is the most common regression method. It fits the line to minimize the sum of the squared residuals, as shown in Figure 3.4

Figure 3.4 An Estimated Demand Curve for Cod at the Portland Fish Exchange



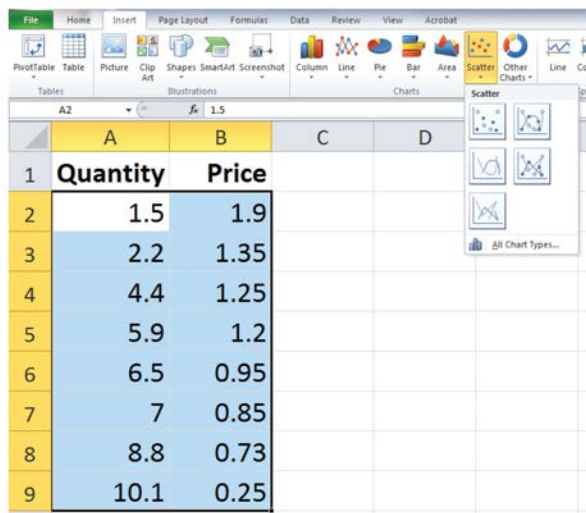
3.2 Regression Analysis (3 of 6)

Microsoft Excel Trendline Option for Scatterplots

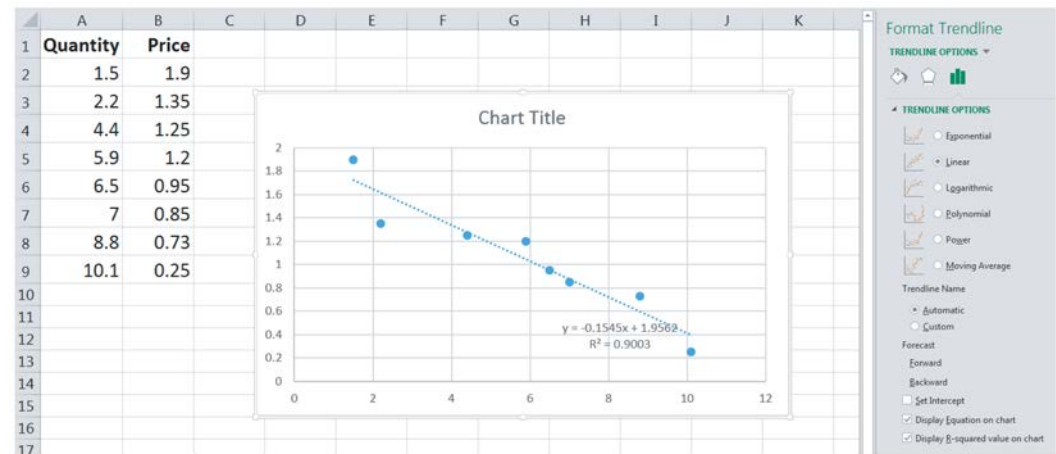
- Steps Inverse Demand Function Estimation: $\hat{p} = \hat{g} + \hat{h}Q$
 1. Enter the quantity data in column A and the price data in column B
 2. Select the data, click on the Insert tab, and select the “Insert Scatter (X, Y) or Bubble Chart” option in the Chart area of the toolbar. A menu of scatterplot types will appear (Excel Screenshots, panel a)
 3. Click “Scatter.” A chart appears in the spreadsheet.
 4. Click on the plus sign to obtain the Chart Elements menu.
 5. Place the cursor over the Trendline option and click on the arrow beside it to show an additional menu. Click on More Options. A Format Trendline dialog box opens to the right.
 6. Select the options “Linear,” “Display Equation on chart,” and “Display R-squared value on chart” (Excel Screenshots, panel b).
 7. The estimated regression line appears in the diagram. By default, Excel refers to the variable on the vertical axis as y (which is our p) and the variable on the horizontal axis as x (which is our Q).

Microsoft Excel Screenshots (Windows Version 2016) (1 of 2)

a) Scatter Options



b) Trendline Estimation



3.2 Regression Analysis (4 of 6)

Multivariate Regression: $p = g + hQ + iY + e$

- **Multivariate Regression** is a regression with two or more explanatory variables.
- The inverse demand function above incorporates both quantity Q and income Y as explanatory variables.
- g , h , and i are coefficients to be estimated, and e is a random error.

Corresponding Estimated Regression: $\hat{p} = \hat{g} + \hat{h}Q + \hat{i}Y$

- $\hat{g}$, $\hat{h}$, and $\hat{i}$ are the estimated coefficients and $\hat{p}$ is the **predicted value** of p for any given levels of Q and Y .
- The objective of an OLS multivariate regression is to fit the data so that the sum of squared residuals is as small as possible.
- A multivariate regression is able to isolate the effects of each explanatory variable holding the other explanatory variables constant.

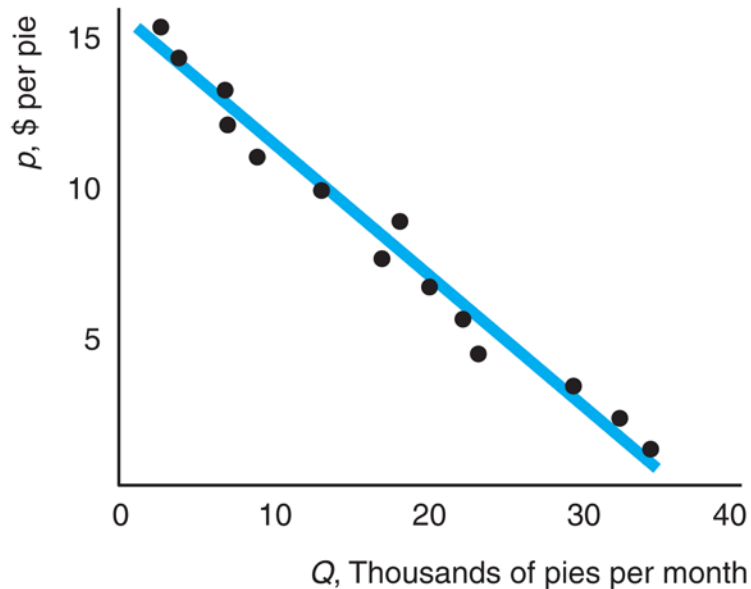
3.2 Regression Analysis (5 of 6)

Goodness of Fit and the R^2 Statistic

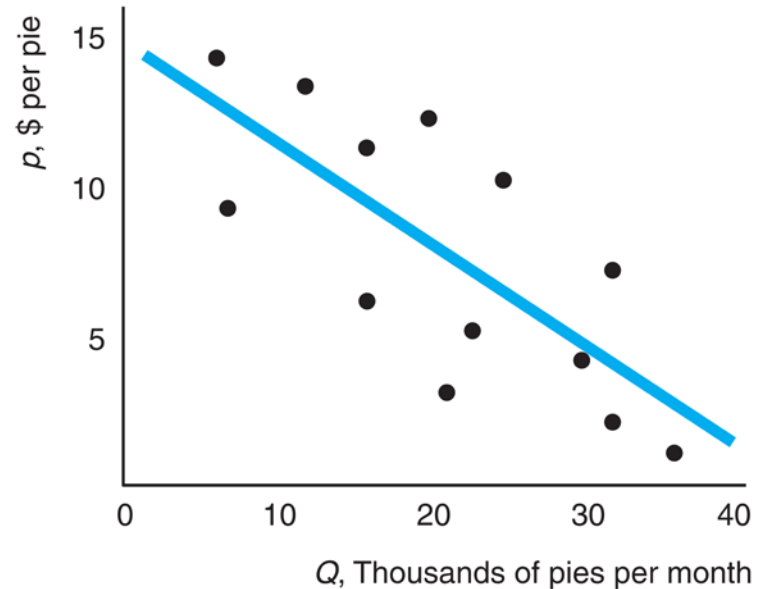
- The R^2 (R -squared) statistic is a measure of the **goodness of fit** of the regression line to the data.
 - The R^2 statistic is the share of the dependent variable's variation that is **explained by the regression**.
 - The R^2 statistic must lie between 0 and 1.
 - 1 indicates that 100% of the variation in the dependent variable is explained by the regression.
- Figure 3.5 shows two apple pie demand regressions for two different cities.
 - Data points in panel a are close to the linear estimated demand, while they are more widely scattered in panel b.
 - $R^2 = 0.98$ in panel a and $R^2 = 0.54$ in panel b.
 - Mai, the bakery owner, is more confident that she can predict the effect of a price change in the first town (panel a) than in the second (panel b).

Figure 3.5 Two Estimated Apple Pie Demand Curves with Different R^2 Statistics

(a) $R^2 = 0.98$



(b) $R^2 = 0.54$



3.2 Regression Analysis (6 of 6)

Managerial Implication: Focus Groups

- Managers interested in estimating market demand curves often can obtain data from published sources, as in our Portland Fish Exchange example.
- However, if managers want to estimate the demand function for their own individual firm, they must collect information about how many units customers would demand at various prices.
 - They can hire a specialized marketing firm to recruit and question a focus group (a number of actual or potential consumers).
 - Alternatively, the marketing firm might conduct an online or written survey of potential customers designed to elicit similar information.
 - Managers should use a focus group if it's the least costly method of learning about the demand curve they face.

3.3 Properties and Statistical Significance of Estimated Coefficients

- There are key questions when estimating coefficients:
 - How close are the estimated coefficients of the demand equation to the true values, for instance $\hat{a}$ respect to the true value a ?
 - How are the estimates based on a sample reflecting the true values of the entire population?
 - Are the sample estimates on target?

Repeated Samples

- The intuition underlying statistical measures of confidence and significance is based on repeated samples.
 - We trust the regression results if the estimated coefficients were the same or very close for regressions performed with repeated samples.
 - However, it is costly, difficult, or impossible to gather repeated samples to assess the reliability of regression estimates.
 - So, we focus on the properties of both **estimating methods** and **estimated coefficients**.

3.3 Properties and Significance of Coefficients (1 of 5)

Desirable Properties for Estimated Coefficients

- Ordinary Least Squares estimation method (OLS) is an **unbiased** estimation method under mild conditions.
 - It produces an estimated coefficient, $\hat{a}$, that equals the true coefficient, a , on average.
- OLS is a **consistent** estimation method.
 - OLS produces **consistent** estimates that vary less than other relevant unbiased estimation methods under a wide range of conditions.
- The smaller the standard error of an estimated coefficient, the smaller the expected variation in the estimates obtained from different samples.
 - Each estimated coefficient has a standard error.
 - We use the standard error to evaluate the significance of estimated coefficients.
 - We prefer a small standard error.

3.3 Properties and Significance of Coefficients (2 of 5)

A Focus Group Example

- Estimate a linear D curve for Toyota Camry cars, $Q = a + bp + e$
 - A focus group of 50 potential buyers are asked about their willingness to buy Camry's at prices from \$5,000 to \$40,000.
 - We use OLS using Microsoft Excel's Regression tool in the Data tab (steps in next slide).
- The estimated D curve is $= 53.857 - 1.438p$
 - The estimate of b is -1.438 , and its estimated standard error is 0.090 .
 - The estimate for a is 53.857 , and its estimated standard error is 2.260 .
 - R^2 is 0.977 . This high R^2 indicates that the regression line explains almost all the variation in the observed quantity.
- Use the estimated D to estimate the q for any p
 - If the price is 27 (\$27,000), we expect the focus group consumers to buy 15 cars [$53.857 - (1.438 * 27) = 15.031$].
 - If this focus group represented a large group, perhaps a thousand times larger, the quantity demanded estimate would be 15,031 cars.

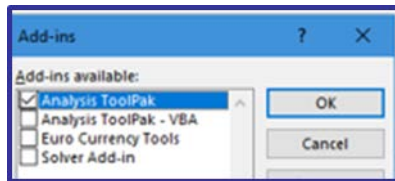
3.3 Properties and Significance of Coefficients (3 of 5)

Using Microsoft Excel's Regression Tool

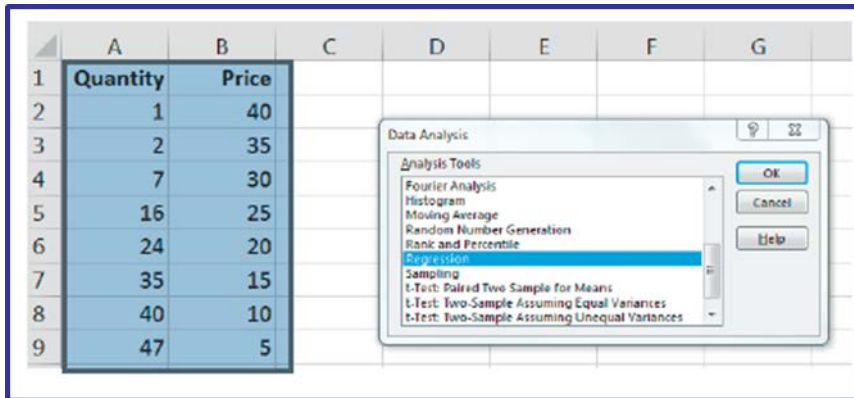
- Steps Linear Demand Function Estimation: $Q = a + bp + e$
 1. Verify you have Data Analysis under Data. If not, install Analysis ToolPak: go to Files => Options => Add-ins (Screenshots, panel a)
 2. Enter your data, click on the Data tab, then on the Data Analysis icon. The Data Analysis dialog box displays. Select "Regression" and click OK (Screenshots, panel b)
 3. In the Regression dialog, fill in the Input Y Range field (dependent variable), the Input X Range field (explanatory variable) and enter A22 in the box for the Output Range button (Screenshots, panel c). Then, click OK.
 4. Excel displays results starting in cell A22 with a Summary Output. The regression is $Q = 53.857 - 1.438p$. If the price is 27, we expect consumers to buy $Q = 53.857 - 1.438p = 15.03$ Camrys.
 5. The $R^2 = 0.977$, very high. Excel also displays standard errors and confidence intervals.

Microsoft Excel Screenshots (Windows Version 2016) (2 of 2)

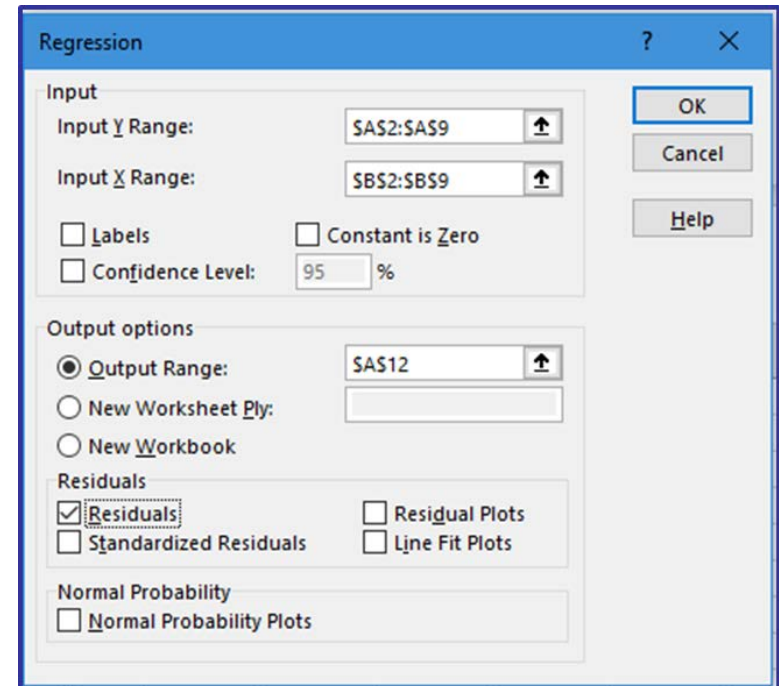
a) Analysis ToolPak



b) Data Analysis Box



c) Regression Box



3.3 Properties and Significance of Coefficients (4 of 5)

Confidence Intervals

- A confidence interval provides a range of likely values for the true value of a coefficient, centered on the estimated coefficient.
 - A 95% confidence interval is a range of coefficient values such that there is a 95% probability that the true value of the coefficient lies in the specified interval.
- Simple Rule for Confidence Intervals
 - In regressions with large sample sizes, the 95% confidence interval is approximately the estimated coefficient minus/plus twice its estimated standard error.
 - With smaller sample sizes, the confidence interval is larger and its calculation needs a **t-statistic** distribution table.
- If the confidence interval is small, then we are reasonably sure that the true parameter lies close to the estimated coefficient. Having a larger data set tends to increase our confidence in our results.

3.3 Properties and Significance of Coefficients (5 of 5)

Hypothesis Testing and Statistical Significance

- Null Hypothesis Problem
 - Suppose a firm's manager runs a regression where the demand for the firm's product is a function of the product's price and the prices charged by several possible rivals.
 - If the true coefficient on a rival's price is 0, the manager can ignore that firm when making decisions.
 - Thus, the manager wants to formally test the **null hypothesis** that the rival's coefficient is 0.
- Testing Approach Using the t-statistic
 - The **t-statistic** equals the estimated coefficient divided by its estimated standard error. That is, the *t*-statistic measures whether the estimated coefficient is large relative to the standard error.
 - In a large sample, if the **t-statistic** > 2 , we **reject** the null hypothesis that the proposed explanatory variable has no effect at the 5% significance level or 95% confidence level.
 - Most analysts would just say the explanatory variable is **statistically significant**.

3.4 Regression Specification (1 of 6)

- **Regression specification** is the first step in a regression analysis.
 - It includes the choice of the dependent variable, the explanatory variables, and the functional relationship between them (linear, quadratic, or exponential).

Selecting Explanatory Variables

- A regression analysis is valid only if the regression equation is correctly specified.
 - It should include all the observable variables that are likely to have a meaningful effect on the dependent variable.
 - It must closely approximate the true functional form.
 - The underlying assumptions about the error term should be correct.
 - We use our understanding of causal relationships, including those that derive from economic theory, to select explanatory variables.
- See an application in the next slide.

3.4 Regression Specification (2 of 6)

Selecting Variables, Mini Case: Determinants of CEO Compensation

- $Y = a + bA + cL + dS + fX + e$
 - The dependent variable, Y , is CEO compensation in 000 of dollars.
 - Explanatory variables are assets A , number of workers L , average return on stocks S , and CEO's experience X .
- OLS regression is $\hat{Y} = 6,787 + 11.4A + 14.0L + 35.1S + 79.9X$
 - t -statistics for the coefficients of A , L , S , and X are 10.1, 8.77, 5.25, and 3.40, respectively.
 - Based on these t -statistics, all four variables are “statistically significant.”
- Although these variables are **statistically significantly different than zero**, not all of them are **economically significant**.
 - For instance, S is statistically significant but its effect on CEO's compensation is very small: one percentage point increase of shareholder return would add \$35,000 per year to the CEO's wage.
 - So, S is statistically significant but economically not very important.

3.4 Regression Specification (3 of 6)

Correlation and Causation is a Common Confusion



3.4 Regression Specification (4 of 6)

Correlation and Causation—Common Confusion

- Two variables are **correlated** if they move together. However, **correlation does not necessarily imply causation**.
 - The q demanded and p are negatively correlated: p goes up, q goes down. This correlation is **causal**, changes in p directly affect q .
 - Sales of gasoline and the incidence of sunburn are positively correlated, but one doesn't cause the other.
 - Thus, it is critical that we do not include explanatory variables that have only a **spurious relationship** to the dependent variable in a regression equation. In estimating gasoline demand, we would include price, income, sunshine hours, but never sunburn incidence.

Omitted Variables

- These are variables not included in the regression specification because of lack of information. So, there is not too much a manager can do.
- However, if one or more key explanatory variables are missing, then the resulting coefficient estimates and hypothesis tests may be unreliable.
- A low R^2 may signal the presence of omitted variables, but theory and logic must determine what key variables are missing.

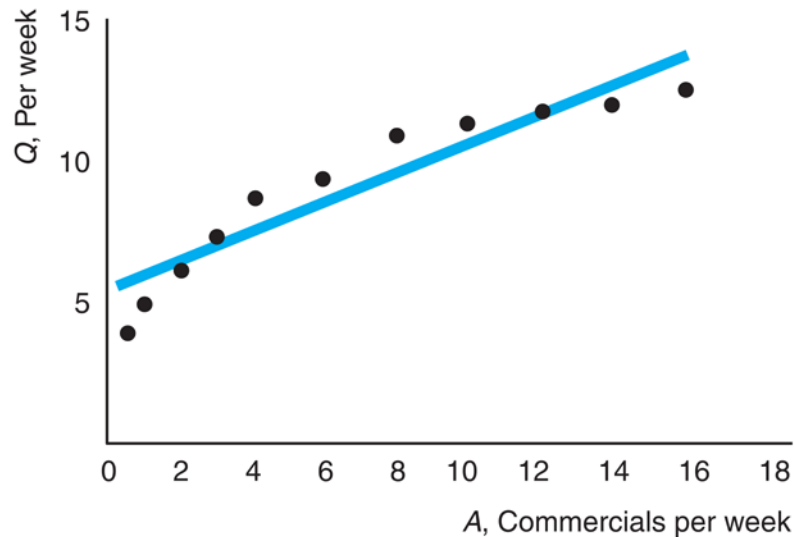
3.4 Regression Specification (5 of 6)

Functional Form

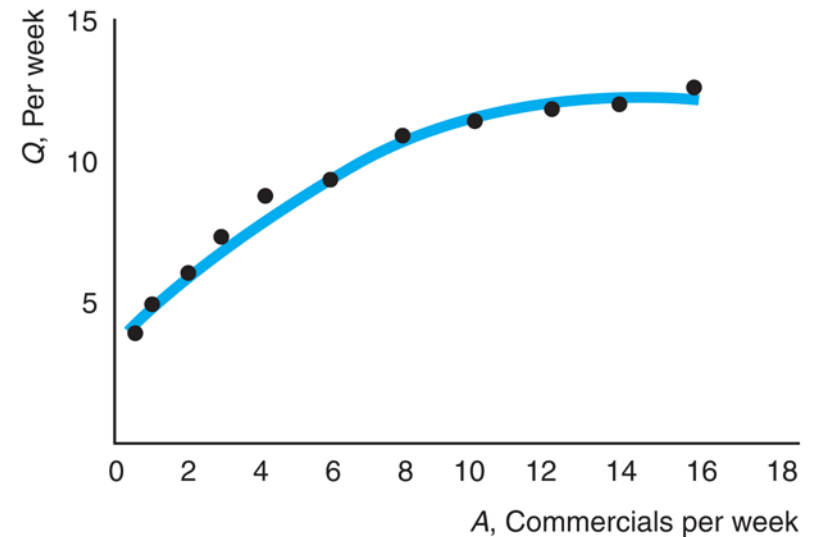
- We cannot assume that demand curves or other economic relationships are always linear.
 - Choosing the correct functional form may be difficult.
 - One useful step, especially if there is only one explanatory variable, is to plot the data and the estimated regression line for each functional form under consideration.
- Graphical Presentation in Figure 3.6
 - Panel a shows a linear regression line of the form $Q = a + bA + e$
 - Panel b shows a quadratic regression curve of the form $Q = a + bA + cA^2 + e$
 - **Linear form:** $R^2 = 0.85$. Quadratic form: $R^2 = 0.99$
 - **The** quadratic regression in panel b fits better than the linear regression in panel a.

Figure 3.6 The Effect of Advertising on Demand

(a) Linear regression line



(b) Quadratic regression



3.4 Regression Specification (6 of 6)

Managerial Implication: Experiments

- Many firms use controlled experiments.
 - For example, a firm can vary its price and observe how consumers react. Unfortunately, the firm cannot control other variables that affect consumer reactions.
- So, firms often use regressions to hold constant some variables that they could not control explicitly and to analyze their results.
 - Harrah's Entertainment relies its marketing on randomized tests of various hypotheses (compares answers from test and control groups).
 - Google shows on its website how a firm can run randomized experiments on the effectiveness of advertising while controlling for geographic or other differences.
- Managers can benefit from running experiments, particularly if they can make use of low-cost internet experiments, as Amazon, Facebook, Netflix, Google, and others do.

3.5 Forecasting (1 of 4)

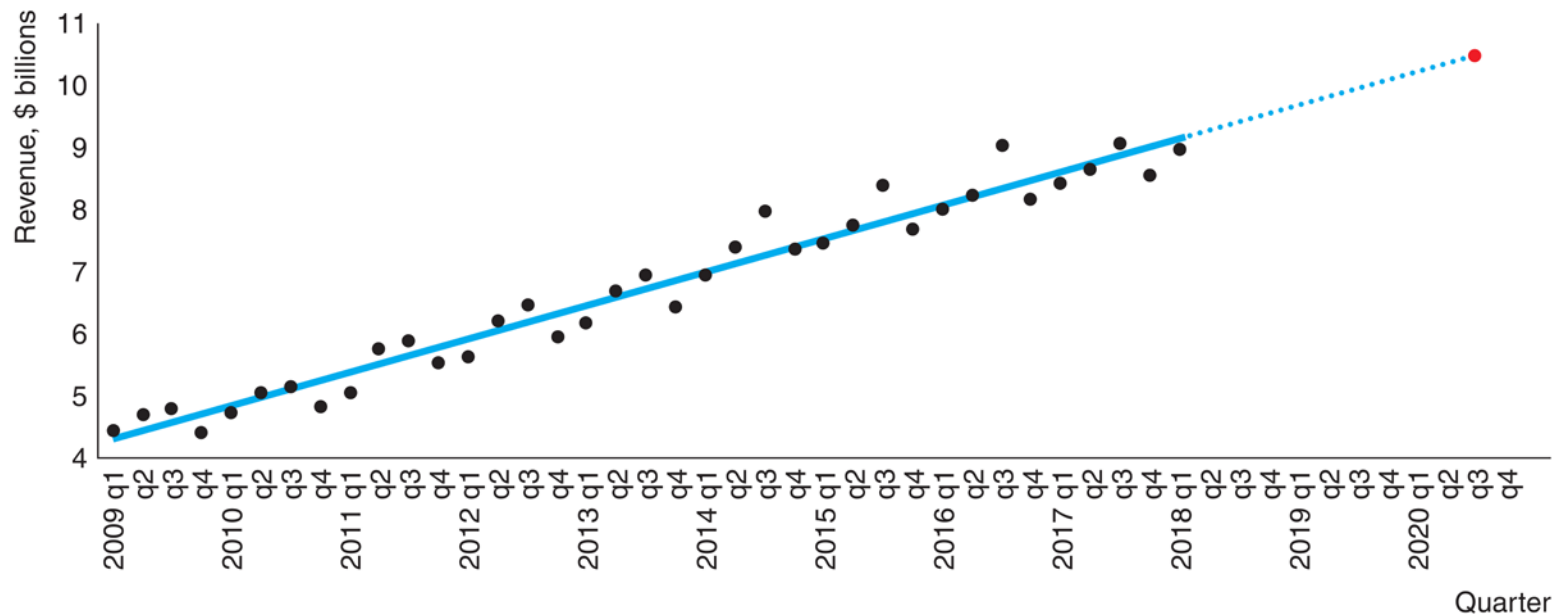
Extrapolation

- Extrapolation seeks to forecast a variable as a function of time.
- Extrapolation starts with a series of observations called time series.
- The time series is **smoothed** in some way to reveal the underlying pattern, and this pattern is then extrapolated into the future.
- Two linear smoothing techniques are **trend line** and **seasonal variation**.
- Not all time trends are linear.

Trends

- Trend line: $R = a + bt + e$, where t is time
 - If this is the trend for Nike's Revenue, a and b are the coefficients to be estimated.
- The estimated trend line is $R = 4.189 + 0.134t$, with statistically significant coefficients.
 - Nike could forecast its sales in the summer quarter of 2020, which is quarter 47, as $4.189 + (0.134 \times 47) = \10.502 billion (Figure 3.7).

Figure 3.7 Nike's Quarterly Revenue: 2009–2018



3.5 Forecasting (2 of 4)

Seasonal Variation

- It appears the demand for Nike products varies **seasonally**.
 - In Figure 3.7, there is a pattern around the trend line: revenue in every summer quarter and most spring quarters is above the trend line while revenue in every fall quarter and most winter quarters is below the trend.
- Seasonal variation model: $R = a + bt + c_1W + c_2S + c_3M + e$
 - Nike's revenue data shows a quarterly trend that is captured with **seasonal dummy variables**, W, S, and M.
- The new estimated trend is $R = 3.847 + 0.135t + 0.179W + 0.452S + 0.675M$, with all coefficients statistically significant.
 - The forecast value for the summer quarter of 2020 is
$$3.847 + (0.135 \times 47) + (0.179 \times 0) + (0.452 \times 0) + (0.675 \times 1) = \$10.84 \text{ billion.}$$
- This adjusted forecast is \$340 million more than our previous forecast that ignored seasonal effects.

3.5 Forecasting (3 of 4)

Nonlinear Trends

- Not all time trends are linear. In particular, the revenue growth of new products is often nonlinear.
 - After a new product first reaches the market, its market share often grows slowly, as consumers need some time to become familiar with the product.
 - At some point, a successful product takes off and sales grow very rapidly.
 - Then, when the product eventually approaches market saturation, sales grow slowly in line with underlying population or real income growth.
 - Ultimately, if other products displace this product, its sales will fall sharply.

3.5 Forecasting (4 of 4)

Theory-Based Econometric Forecasting

- We estimated Nike's revenue with time trend and dummy seasonal variables. However, revenue is determined in large part by the consumers' demand curve, and the demand is affected by variables such as income, population, and advertising. Extrapolation (pure time series analysis) ignored these structural (causal) variables.
- **Theory-based econometric forecasting** methods incorporate both extrapolation and estimation of causal or explanatory economic relationships.
- We use these estimates to make **conditional forecasts**, where our forecast is based on specified values for the explanatory variables.

Managerial Solution

Estimating the Effect of an iTunes Price Change

- How could Apple use a focus group to estimate the demand curve for iTunes to determine if raising its price would raise or lower its revenue?

Solution

- To generate data, authors asked a focus group of 20 Canadian college students how many songs they would download from iTunes at various prices, assuming income and other prices constant.
 - The estimated linear demand curve is $Q = 1024 - 413p$.
 - The t -statistic = -12.6 , so this coefficient for price is significantly different from zero. The $R^2 = 0.96$, so the regression line fits the data closely.
 - Apple's manager could use such an estimated demand curve to determine how revenue, $(R = p \times Q)$, varies with price. At $p = 99\text{¢}$, 615 songs were downloaded, so $R_1 = \$609$. When $p = \$1.24$, the number of songs drop to 512, $R_2 = \$635$. Revenue increased by \$26.
 - If the general population has similar tastes to the focus group, then Apple's revenue would increase if it raised its price to \$1.24 per song.

Table 3.1 Data Used to Estimate the Cod Demand Curve at the Portland Fish Exchange

Price, dollars per pound	Quantity, thousand pounds per day
1.90	1.5
1.35	2.2
1.25	4.4
1.20	5.9
0.95	6.5
0.85	7.0
0.73	8.8
0.25	10.1

Figure 3.3 Observed Price-Quantity Data Points for the Portland Fish Exchange

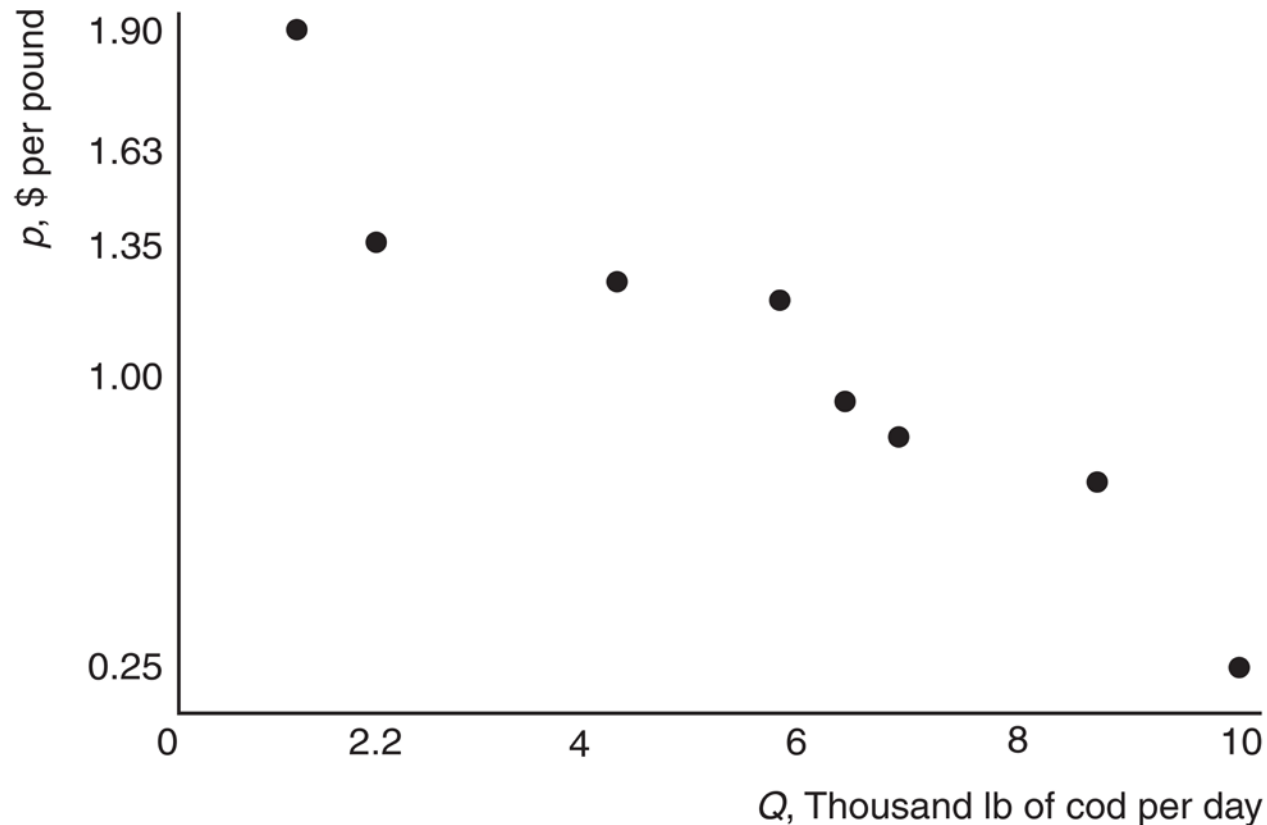


Table 3.2 Regressions of Quantity on Advertising

Linear Specification

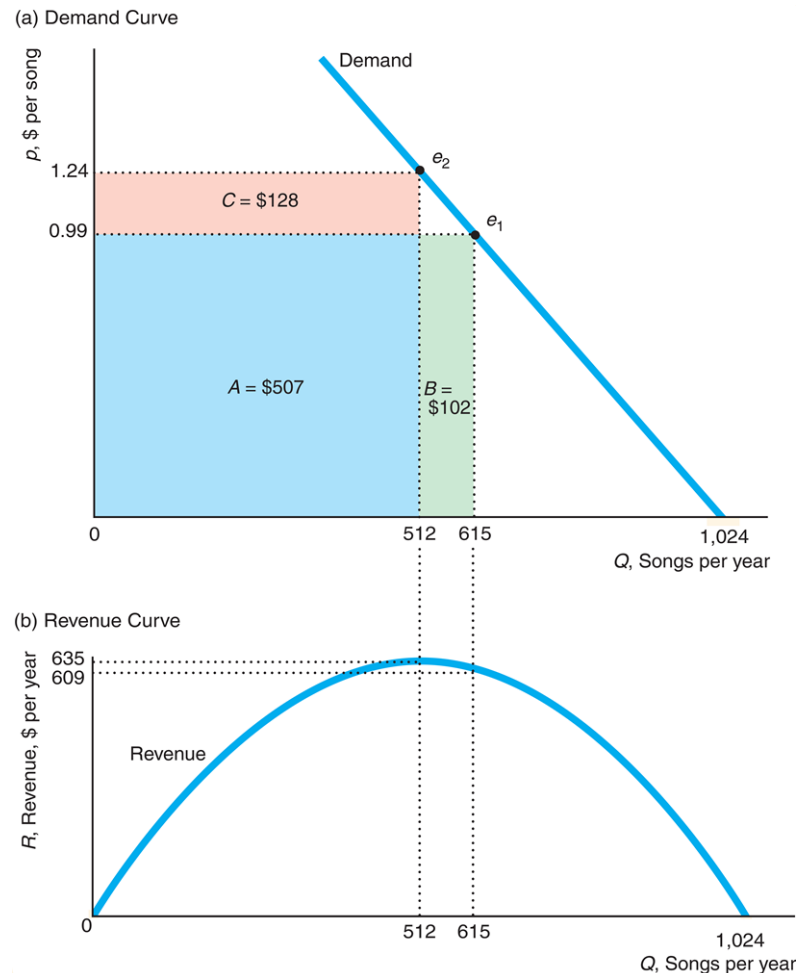
	Coefficient	Standard Error	<i>t</i> -Statistic
Constant	5.43	0.54	10.05*
Adverting, <i>A</i>	0.53	0.06	8.47*
Advertising, A^2			

Quadratic Specification

	Coefficient	Standard Error	<i>t</i> -Statistic
	3.95	0.30	13.18*
	1.20	0.10	12.18*
	-0.04	0.01	-7.05*

*indicates that we can reject the null hypothesis that the coefficient is zero at the 5% significance level.

Figure 3.8 iTunes Focus Group Demand and Revenue Curves



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