

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 imposed 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. Gilbert (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.

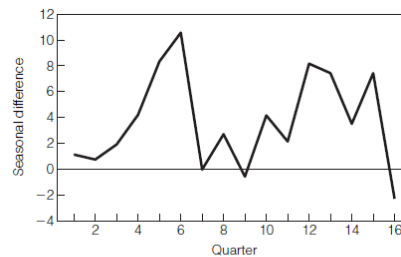
In the retail industry, for example, it is common to see a high fourth quarter, because it is the most important selling season. In order to detect patterns in the data underneath the quarterly seasonal movements, we can compare successive changes between values separated by four time periods. In this 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)

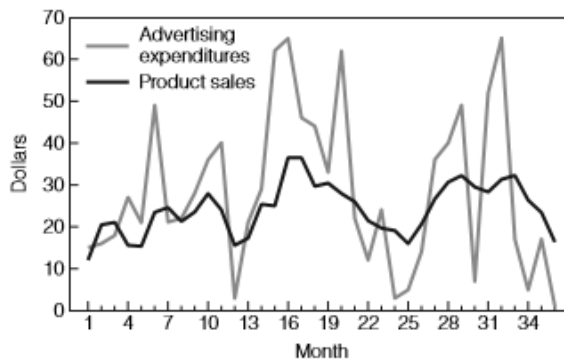


Figure 6.2 Time plots of monthly sales and advertising expenditures over 36 months. (Source: Cryer and Miller, *Statistics for Business*, 1994; SALESADS.DAT)

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.

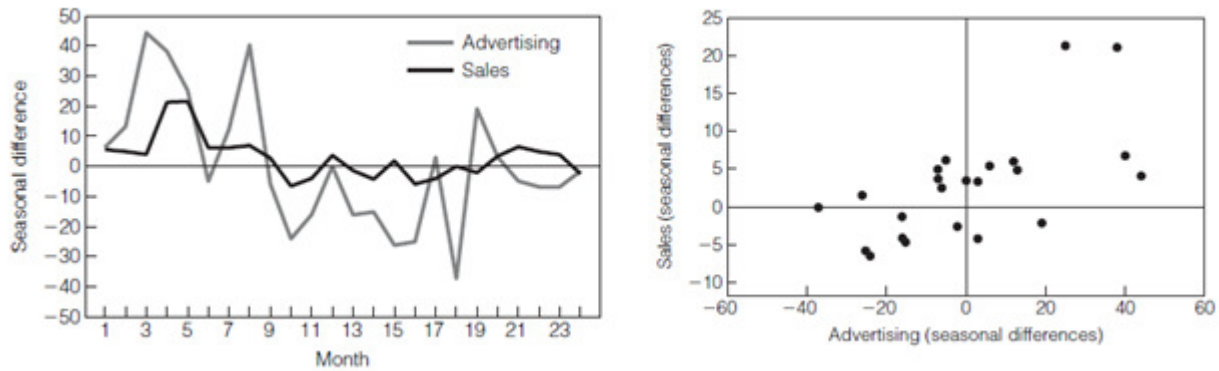
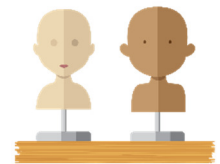


Figure 6.3 Time plots (*left*) and scatter diagram (*right*) of seasonal differences for sales and advertising.

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:

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

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:

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

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:

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

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

ACHIEVING AGILITY WITH DEMAND

FORECASTING IN THE SUPPLY CHAIN

HANS LEVENBACH, PhD

Copyright © 2017 Hans Levenbach

ISBN-10:0692945989

ISBN-13:978-069294588

Cover art: Rose Tannenbaum, Berkshire TypeGraphic, www.tgo.com

Cartoon art: Don Engel, Isographic LLC

Copy editor: David Coen, Freelance copyeditor

Printed by Createspace, www.createspace.com

ALL RIGHTS RESERVED. No part of this work may be used or reproduced, transmitted, stored or used in any form or by any means graphic, electronic, or mechanical, including but not limited to photocopying, recording, scanning, taping, Web distribution, information networks or information storage and retrieval systems, or in any manner whatsoever without prior written permission.

Professional development: Certified Professional Demand Forecaster (CPDF®), www.cpdftraining.org

Agile Forecasting®, CPDF® are registered trademarks of Delphus, Inc.

Contents



Chapter 1 - Embracing Change & Chance

Inside the Crystal Ball **Error! Bookmark not defined.**

Determinants of Demand	
Demand Forecasting Defined	
Why Demand Forecasting?	
The Role of Demand Forecasting in a Consumer-Driven Supply Chain	4
Is Demand Forecasting Worthwhile?	7
Who Are the End Users of Demand Forecasts in the Supply Chain?	8
Learning from Industry Examples	9
Examples of Product Demand	10
Is a Demand Forecast Just a Number?	11
<i>Creating a Structured Forecasting Process</i>	14
The PEER Methodology: A Structured Demand Forecasting Process	14
<i>Case Example: A Consumer Electronics Company</i>	15
PEER Step 1: Identifying Factors Likely to Affect Changes in Demand	16
The GLOBL Product Lines	17
The Marketplace for GLOBL Products	18
Step 2: Selecting a Forecasting Technique	19
Step 3: Executing and Evaluating Forecasting Models	22
Step 4: Reconciling Final Forecasts	22
<i>Creating Predictive Visualizations</i>	22
<i>Takeaways</i>	26



Chapter 2 - Demand Forecasting Is Mostly about Data:

Improving Data Quality through Data Exploration and Visualization

<i>Demand Forecasting Is Mostly about Data</i>	29
Exploring Data Patterns	29
Learning by Looking at Data Patterns	30
<i>Judging the Quality of Data</i>	30
<i>Data Visualization</i>	35
Time Plots	35
Scatter Diagrams	36
<i>Displaying Data Distributions</i>	37
Overall Behavior of the Data	38

Stem-and-Leaf Displays	39
Box Plots	41
Quantile-Quantile Plots	43
<i>Creating Data Summaries</i>	44
Typical Values	44
The Trimmed Mean	45
Variability	45
Median Absolute Deviation from the Median	45
The Interquartile Difference	46
Detecting Outliers with Resistant Measures	47
<i>The Need for Nonconventional Methods</i>	48
M-Estimators	49
A Numerical Example	49
<i>Why Is Normality So Important?</i>	51
<i>Case Example: GLOBL Product Line B Sales in Region A</i>	52
<i>Takeaways</i>	54



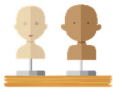
Chapter 3 - Predictive Analytics: Selecting Useful Forecasting Techniques..... 55

<i>All Models Are Wrong. Some Are Useful</i>	56
Qualitative Methods	56
Quantitative Approaches	59
Self-Driven Forecasting Techniques	60
Combining Forecasts is a Useful Method	61
Informed Judgment and Modeling Expertise	62
A Multimethod Approach to Forecasting	64
<i>Some Supplementary Approaches</i>	64
Market Research	64
New Product Introductions	65
Promotions and Special Events	65
Sales Force Composites and Customer Collaboration	65
Neural Nets for Forecasting	66
<i>A Product Life-Cycle Perspective</i>	66
<i>A Prototypical Forecasting Technique: Smoothing Historical Patterns</i>	68
Forecasting with Moving Averages	69
Fit versus Forecast Errors	71
Weighting Based on the Most Current History	73
<i>A Spreadsheet Example: How to Forecast with Weighted Averages</i>	75
Choosing the Smoothing Weight	78
Forecasting with Limited Data	78
Evaluating Forecasting Performance	79
<i>Takeaways</i>	79



Chapter 4 - Taming Uncertainty: What You Need to Know about Measuring Forecast Accuracy80

<i>The Need to Measure Forecast Accuracy</i>	82
Analyzing Forecast Errors	82
Lack of Bias	82
What Is an Acceptable Precision?	83
<i>Ways to Evaluate Accuracy</i>	86
The Fit Period versus the Holdout Period	86
Goodness of Fit versus Forecast Accuracy	87
Item Level versus Aggregate Performance	88
Absolute Errors versus Squared Errors	88
Measures of bias	89
Measures of Precision	90
Comparing with Naive Techniques	93
Relative Error Measures	94
<i>The Myth of the MAPE . . . and How to Avoid It</i>	95
Are There More Reliable Measures Than the MAPE?	96
<i>Predictive Visualization Techniques</i>	96
Ladder Charts	96
Prediction-Realization Diagram	97
<i>Empirical Prediction Intervals for Time Series Models</i>	100
Prediction Interval as a Percentage Miss	101
Prediction Intervals as Early Warning Signals	101
Trigg Tracking Signal	103
<i>Spreadsheet Example: How to Monitor Forecasts</i>	104
<i>Mini Case: Accuracy Measurements of Transportation Forecasts</i>	107
<i>Takeaways</i>	112



Chapter 5 - Characterizing Demand Variability: Seasonality, Trend, and the Uncertainty Factor 114

<i>Visualizing Components in a Time Series</i>	115
Trends and Cycles	116
Seasonality	119
Irregular or Random Fluctuations	122
Weekly Patterns	124
Trading-Day Patterns	124
<i>Exploring Components of Variation</i>	126
Contribution of Trend and Seasonal Effects	127
A Diagnostic Plot and Test for Additivity	130
<i>Unusual Values Need Not Look Big or Be Far Out</i>	132
<i>The Ratio-to-Moving-Average Method</i>	134

- Step 1: Trading-Day Adjustment 135
- Step 2: Calculating a Centered Moving Average 135
- Step 3: Trend-cycle and Seasonal Irregular Ratios 136
- Step 4: Seasonally Adjusted Data 137

GLOBL Case Example: Is the Decomposition Additive or Not? 137

APPENDIX: A Two-Way ANOVA Table Analysis 139

Percent Contribution of Trend and Seasonal Effects 140

Takeaways 140



Chapter 6 - Dealing with Seasonal Fluctuations 141

Seasonal Influences 141

Removing Seasonality by Differencing 143

Seasonal Decomposition 145

Uses of Seasonal Adjustment 146

Multiplicative and Additive Seasonal Decompositions 146

Decomposition of Monthly Data 146

Decomposition of Quarterly Data 151

Seasonal Decomposition of Weekly Point-of-Sale Data 153

Census Seasonal Adjustment Method 156

The Evolution of the X-13ARIMA-SEATS Program 157

Why Use the X-13ARIMA-SEATS Seasonal Adjustment Program? 157

A Forecast Using X-13ARIMA-SEATS 158

Resistant Smoothing 158

Mini Case: A PEER Demand Forecasting Process for Turkey Dinner Cost 162

Takeaways 168



Chapter 7 - Trend-Cycle Forecasting with Turning Points 171

Demand Forecasting with Economic Indicators 171

Origin of Leading Indicators 174

Use of Leading Indicators 174

Composite Indicators 176

Reverse Trend Adjustment of the Leading Indicators 176

Sources of Indicators 178

Selecting Indicators 178

Characterizing Trending Data Patterns 180

Autocorrelation Analysis 180

First Order autocorrelation 182

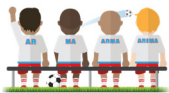
The Correlogram 183

Trend-Variance Analysis	187
<i>Using Pressures to Analyze Business Cycles</i>	189
<i>Mini Case: Business Cycle Impact on New Orders for Metalworking Machinery</i>	191
1/12 Pressures	192
3/12 Pressures	193
12/12 Pressures	193
<i>Turning Point Forecasting</i>	194
Ten-Step Procedure for a Turning-Point Forecast	195
Alternative Approaches to Turning-Point Forecasting	195
<i>Takeaways</i>	196



Chapter 8 - Big Data: Baseline Forecasting With Exponential Smoothing Models 197

<i>What is Exponential Smoothing?</i>	198
Smoothing Weights	199
The Simple Exponential Smoothing Method	201
<i>Forecast Profiles for Exponential Smoothing Methods</i>	202
Smoothing Levels and Constant Change	204
Damped and Exponential Trends	208
Some Spreadsheet Examples	210
Trend-Seasonal Models with Prediction Limits	216
The Pegels Classification for Trend-Seasonal Models	219
Outlier Adjustment with Prediction Limits	221
Predictive Visualization of Change and Chance – Hotel/Motel Demand	221
<i>Takeaways</i>	225



Chapter 9 - Short-Term Forecasting with ARIMA Models ..226

<i>Why Use ARIMA Models for Forecasting?</i>	226
The Linear Filter Model as a Black Box	227
<i>A Model-Building Strategy</i>	229
Identification: Interpreting Autocorrelation and Partial Autocorrelation Functions	230
Autocorrelation and Partial Autocorrelation Functions	231
An Important Duality Property	233
Seasonal ARMA Process	234
<i>Identifying Nonseasonal ARIMA Models</i>	236
Identification Steps	236
Models for Forecasting Stationary Time Series	236
White Noise and the Autoregressive Moving Average Model	237
One-Period Ahead Forecasts	239
L-Step-Ahead Forecasts	239
Three Kinds of Short-Term Trend Models	241
A Comparison of an ARIMA (0, 1, 0) Model and a Straight-Line Model	241
<i>Seasonal ARIMA Models</i>	244

A Multiplicative Seasonal ARIMA Model	244
Identifying Seasonal ARIMA Models	246
<i>Diagnostic Checking: Validating Model Adequacy</i>	247
<i>Implementing a Trend/Seasonal ARIMA Model for Tourism Demand</i>	249
Preliminary Data Analysis	249
Step 1: Identification	250
Step 2: Estimation	250
Step 3: Diagnostic Checking	251
<i>ARIMA Modeling Checklist</i>	254
<i>Takeaways</i>	255
<i>Postscript</i>	256



Chapter 10 - Demand Forecasting with Regression Models 258

<i>What Are Regression Models?</i>	259
The Regression Curve	260
A Simple Linear Model	260
The Least-Squares Assumption	260
<i>CASE: Sales and Advertising of a Weight Control Product</i>	262
<i>Creating Multiple Linear Regression Models</i>	263
Some Examples	264
<i>CASE: Linear Regression with Two Explanatory Variables</i>	266
<i>Assessing Model Adequacy</i>	268
Transformations and Data Visualization	268
Achieving Linearity	269
Some Perils in Regression Modeling	270
<i>Indicators for Qualitative Variables</i>	273
Use of Indicator Variables	273
Qualitative Factors	274
Dummy Variables for Different Slopes and Intercepts	275
Measuring Discontinuities	275
Adjusting for Seasonal Effects	276
Eliminating the Effects of Outliers	276
<i>How to Forecast with Qualitative Variables</i>	277
Modeling with a Single Qualitative Variable	278
Modeling with Two Qualitative Variables	279
Modeling with Three Qualitative Variables	279
<i>A Multiple Linear Regression Checklist</i>	281
<i>Takeaways</i>	282



Chapter 11 - Gaining Credibility Through Root-Cause

Analysis and Exception Handling 283

***The Diagnostic Checking Process in Forecasting*..... 284**

***The Role of Correlation Analysis in Regression Modeling* 284**

Linear Association and Correlation 285
The Scatter Plot Matrix 286
The Need for Outlier Resistance in Correlation Analysis 287

***Using Elasticities* 288**

Price Elasticity and Revenue Demand Forecasting 290
Cross-Elasticity 291
Other Demand Elasticities 292
Estimating Elasticities 292

***Validating Modeling Assumptions: A Root-Cause Analysis* 293**

A Run Test for Randomness 296
Nonrandom Patterns 297
Graphical Aids 299
Identifying Unusual Patterns 299

***Exception Handling: The Need for Robustness in Regression Modeling* 301**

Why Robust Regression? 301
M-Estimators 301
Calculating M-Estimates 302

***Using Rolling Forecast Simulations* 304**

Choosing the Holdout Period 304
Rolling Origins 305
Measuring Forecast Errors over Lead Time 306

***Mini Case: Estimating Elasticities and Promotion Effects* 306**

Procedure 308
Taming Uncertainty 310

***Multiple Regression Checklist* 311**

***Takeaways* 313**



Chapter 12 - The Final Forecast Numbers: Reconciling Change & Chance

.....316

***Establishing Credibility* 317**

Setting Down Basic Facts: Forecast Data Analysis and Review 317
Establishing Factors Affecting Future Demand 318
Determining Causes of Change and Chance 318
Preparing Forecast Scenarios 318

<i>Analyzing Forecast Errors</i>	319
Taming Uncertainty: A Critical Role for Informed Judgment	320
Forecast Adjustments: Reconciling Sales Force and Management Overrides	321
Combining Forecasts and Methods	322
Verifying Reasonableness	323
Selecting 'Final Forecast' Numbers	324
<i>Gaining Acceptance from Management</i>	325
The Forecast Package	325
Forecast Presentations	326
<i>Case: Creating a Final Forecast for the GLOBL Company</i>	328
Step 1: Developing Factors	329
Impact Change Matrix for the Factors Influencing Product Demand	330
The Impact Association Matrix for the Chosen Factors	331
Exploratory Data Analysis of the Product Line and Factors Influencing Demand	332
Step 2: Creating Univariate and Multivariable Models for Product Lines	334
Handling Exceptions and Forecast Error Analysis	335
Combining Forecasts from Most Useful Models	337
An Unconstrained Baseline Forecast for GLOBL Product Line B, Region A	338
Step 3: Evaluating Model Performance Summaries	341
Step 4: Reconciling Model Projections with Informed Judgment	342
<i>Takeaways</i>	343



Chapter 13 - Creating a Data Framework for Agile Forecasting and Demand Management..... 344

<i>Demand Management in the Supply Chain</i>	345
Data-Driven Demand Management Initiatives	346
Demand Information Flows	347
<i>Creating Planning Hierarchies for Demand Forecasting</i>	349
What Are Planning Hierarchies?	349
Operating Lead Times	350
Distribution Resource Planning (DRP)—A Time-Phased Planned Order Forecast	350
Spreadsheet Example: How to Create a Time-Phased Replenishment Plan	352
<i>A Framework for Agility in Forecast Decision Support Functions</i>	353
The Need for Agile Demand Forecasting	354
Dimensions of Demand	354
A Data-Driven Forecast Decision Support Architecture	355
Dealing with Cross-Functional Forecasting Data Requirements	358
Specifying Customer/Location Segments and Product Hierarchies	358
<i>Automated Statistical Models for Baseline Demand Forecasting</i>	360
Selecting Useful Models Visually	363
Searching for Optimal Smoothing Procedures	367
Error-Minimization Criteria	368
Searching for Optimal Smoothing Weights	368
Starting Values	368
Computational Support for Management Overrides	369
<i>Takeaways</i>	372



Chapter 14 - Blending Agile Forecasting with an Integrated Business Planning Process 373

PEERing into the Future: A Framework for Agile Forecasting in Demand Management 374

The Elephant and the Rider Metaphor	374
Prepare	374
Execute	376
Evaluate	376
Reconcile	381

Creating an Agile Forecasting Implementation Checklist 385

Selecting Overall Goals	385
Obtaining Adequate Resources	386
Defining Data	386
Forecast Data Management	387
Selecting Forecasting Software	387
Forecaster Training	388
Coordinating Modeling Efforts	388
Documenting for Future Reference	388
Presenting Models to Management	389

Engaging Agile Forecasting Decision Support 389

Economic/Demographic Data and Forecasting Services	389
Data and Database Management	390
Modeling Assistance	390
Training Workshops	390

The Forecast Manager's Checklists 391

Forecast Implementation Checklist	391
Software Selection Checklist	392
Large-Volume Demand Forecasting Checklist	393

Takeaways 394