CHAPTER 7

The Demand Planning Brief

The next generation demand management process is more than just creating an accurate demand forecast. It is a business analytics function embedded downstream in the sales and marketing organization, providing analytics support to drive demand generation. As such, demand analysts working closely with sales and marketing provide predictive analytics support to validate and justify sales tactics and marketing strategies that drive the final demand response. Demand-driven is more than just being responsive, it is about being interactive with the goal of optimizing market investment (spend) in support of the unconstrained demand forecast.

The challenge for supply chain executives is to gain commitment from sales and marketing through improved processes, metrics, and technologies, while addressing the question, "What's in it for sales and marketing?" It's a journey, with a series of steps required to encourage sales and marketing to take ownership, and more importantly, accountability. Although sales plays a significant role in providing inputs, it is marketing that influences demand, and that has a direct impact on the unconstrained demand forecast. The best way for an organization to build trust and accountability is by providing proven analytical support and becoming a trusted adviser to the commercial organization. Embracing downstream data, learning how to provide valued insights through predictive analytics, and most of all, collaborating in a meaningful way are the keys to getting sales and marketing to take ownership in the demand planning process.

Sponsorship and leadership play significant roles in the involvement of sales and marketing within the monthly demand planning, as well as the sales and operations planning (S&OP) processes. The demand planning team must become an integral member of the commercial team to gain alignment to drive the business strategy. A vision with an end state in mind, along with a roadmap that builds improvements over time, is a necessary ingredient to improve sales and marketing accountability for the unconstrained demand forecast.

The mistake that organizations make is that either they request a forecast of everything sales and marketing plans to sell, or they are not held accountable for providing any forecast. Neither approach is correct nor serves to hold sales and marketing accountable for forecast accuracy improvements.

Demand sensing and shaping capabilities not only provide the ability to predict demand more accurately, but also can uncover deep insights into customer/consumer behavior by identifying those key performance indicators that influence consumer demand and replenishment policies. These factors can be quantified (measured), and used to shape future demand based on sales and marketing tactics and strategies. As such, those tactics and strategies need to be tested and validated using predictive analytics and documented to maintain accountability and ownership. To that point, the demand planning process needs to support those activities using a combination of analytics and domain knowledge. The demand analyst has the analytics knowledge and the sales and marketing team has the domain expertise. It is all about accountability, ownership, and participation in the demand planning process. By hiring and embedding demand analysts (also, called *data scientists*) downstream in the commercial organization you begin to create a partnership and trust with sales and marketing becoming over time their analytic confidant.

The best way to build accountability and ownership of the unconstrained demand forecast is through sound testing using analytics, and documentation of the assumptions (tactics and strategies) that were used to justify the demand forecast. Then, get sign-off by the sales and marketing senior management team prior to the S&OP meeting. The best course of action is documenting the demand forecasting and planning process by implementing a monthly *demand planning brief* that outlines in detail what tactics and strategies were tested to validate the assumptions using data and analytics versus *gut feeling* judgment. Formalizing a process and documentation to capture this information not only provides a benchmark for justification of continuous improvement but also builds accountability and ownership.

DEMAND PLANNING BRIEF

The monthly demand planning brief is a living document that rolls across a weekly time horizon and allows the organization to continuously look ahead and plan based on sales tactics and marketing investment strategies. It contains the details and actions taken by the demand forecasting and planning team working closely with the sales and marketing organizations using feedback from actual execution to final demand response. This tight collaboration in maintaining this document between the demand forecasting and planning and sales and marketing organizations tends to create trust, accountability, and ownership. Here is a standard monthly demand planning brief template along with an embedded *analytic snapshot* report outlining the statistical methods evaluated, what-if scenarios executed, and recommendations.

To gain sales and marketing accountability for the unconstrained demand forecast means making the two organizations accountable for their role in the demand planning process. It starts with identifying and documenting the agreed-to inputs and responsibilities during the creation of the weekly demand plan so that sales and marketing clearly understands its role within the process. It also means actively revisiting input assumptions and testing their validity using proven analytic approaches based on sales tactics and marketing strategies that include sales promotions, in-store merchandizing, competitive activities, and market assumptions that influence revenue and profit goals. Most companies do not revisit these assumptions with regularity to identify forecast error and improve inputs from sales and marketing.

The purpose of the demand planning brief is not only to analyze and document assumptions, but also to conduct monthly *post-reconciliation* to determine what programs worked and what tactics did not meet expectations. It also puts the focus on whether sales executed against those assumptions, rather than blaming the forecast models for the poor results. It is about accountability against execution, with the intention to learn and take course-corrective actions.

To provide more perspective and understanding, here is an actual example of a demand planning brief for a winery.

The XYZ Winery

Demand Planning Brief

Monthly Demand Planning Brief

Template

Brands/Product Group/Products __________

Region ____ Channel _____

Forecast Cycle ____

Date: ___________

Part1

Executive Summary

Business Brief: Analytic Snapshot

Model Comparison Chart

Part 2

Forecasting Strategy Overview

What-If Scenarios (Demand Shaping)

Strengths & Weaknesses

Strategy Detail

Summary

Monthly Demand Planning Brief

The XYZ Winery Case Study

Executive Summary

OVERVIEW

The demand planning team has performed time series analysis in support of the sales and marketing teams to leverage historical wine demand data to achieve higher forecast accuracy and to increase revenue from pricing and sales promotion actions. More than three years of the winery's historical demand was analyzed to evaluate the effectiveness of sales promotions, create weekly forecasting models, and predict the effects of price increases across all products and markets.

BACKGROUND

XYZ Winery produces four wine varieties: Table Red, Table White, Value Red, and Vintage Red.

These wines are marketed in four regions of the United States: Northeast (Region 1), Central (Region 2), Southeast (Region 3), and West (Region 4). There are two sales promotions reflected in the historical demand data:

1. **May Promotion:** Buy one case of wine and get a 15 percent discount, starting the week of May 5, 2015, and lasting four weeks.
2. **December Promotion:** Buy one case of wine and get a 10 percent discount, run in 2013 and 2014. In 2013, the sales promotion started the week of December 25 and ran for one week. In 2014, the sales promotion started the week of December 31 and ran for one week.

RECOMMENDED FORECAST METHODOLOGY

We built a product hierarchical set of forecast models, including a top-level model that forecasts company-wide sales for the XYZ winery; sales demand on a per-region basis; and sales for each type of wine within each region. We used middle-out reconciliation, as this resulted in the lowest final MAPEs, and is consistent with our desire to make business decisions at the regional level.

The final top-level (total company level) model shown in Figure 7.1 has a final MAPE of 4.55 percent and shows forecasts continuing to increase through the end of 2015.

These models were built using the winery's sales promotion information, unit prices, and demand history. Of the original 21 system-generated models, 7 models were further revised to reduce

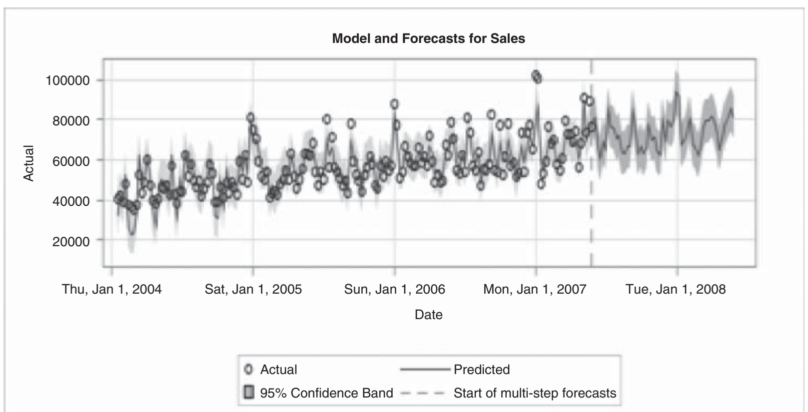


Figure 7.1 Demand forecast results at the top company level.

their out-of-sample (holdout) MAPE to meet the targeted goal of 14 percent. Overall recommendations regarding key findings about promotions, price increase strategies, and a quick view of the model summary (analytics snapshot) are captured in the following demand planning brief.

MODEL HIERARCHY

We were asked by the senior management team to determine the best models to deploy across regions and wine type, and in doing so it was felt that optimal business decisions could be made at the regional level. This is attributable to the evident variation among the regions; therefore, a middle-out forecast by region was selected as the reconciliation level in the hierarchy, as seen in Figure 7.2. Regions 1 (Northeast) and 2 (Central) make up for almost 88 percent of the total wine sales. Upper management would want to focus on these regions in particular to fine tune the models to inherently optimize sales demand.

MODEL SELECTION CRITERIA

Over the demand history (176 weeks), trends, seasonality, sales promotional events, holidays, and outliers were considered in optimizing the best possible model across the regions and types. To accurately

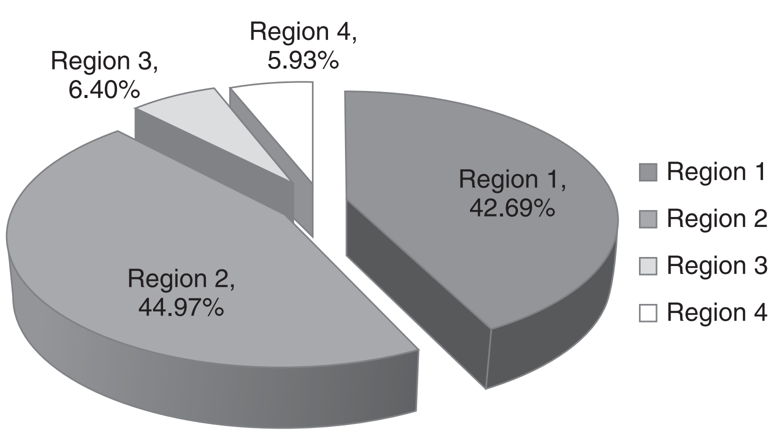


Figure 7.2 Wine sales by region.

capture the variability among the regions and wine types, we used ARIMA, exponential smoothing, and multiple regression models for each level of the product hierarchy.

For each level of the hierarchy, we used the holdout MAPE as our criterion for selecting a final best model from the set of candidate model types. We used a holdout sample of 13 weeks based on the following factors:

- We were asked to consider the impact of price increases through the remainder of 2015. This required us to use the models to generate forecasts for the next 31 weeks. We wanted to use an out-of-sample (holdout) for a minimum of one quarter, since this allows us to assess the models' forecasting accuracy on previously unseen data covering the company's agreed to frozen forecast horizon of three months.
- Wine sales demand follows an annual seasonal pattern, and we wanted to preserve at least three full seasons' worth of data when building and selecting our models. This requirement limited us to no more than 13 weeks of data to effectively test the models' accuracy. Three years of data is the minimum required to capture the full effect of seasonality.

Only one model, the overall model for the Northeast Region-2 was *not* selected based on the lowest holdout MAPE. The holdout MAPE for the final Northeast Region overall ARIMA model, accounting for seasonality and differencing (capture trend effects) with base price, was only 2 percent greater than the best system-generated exponential smoothing model. However, the ARIMA model yielded predictions that closely track the known seasonality of the data. Therefore, we determined it was worthwhile to select the model that yields more useful predictions over a model with mean-based predictions and only a slightly better holdout MAPE.

Once our initial models were built, we focused on improving the accuracy of system-generated models with a final MAPE of >14 percent. Most of these could be improved upon, even if by a few percent.

In addition to the promotional events that we were asked by senior management to assess, we also added holiday events into our models.

These events were only kept if they proved significant. Additionally, an outlier analysis was performed. One example of a model that uses outlier events is the Northeast region Vintage wine model. This ARIMA system-generated model determined August 14, 2004, to be a significant outlier. By adding this event into the model, 1,735 cases of wine were accounted for during this week. We are working closely with the sales and marketing teams to uncover any local events that may have taken place to better explain the outlier.

SUPPORTING INFORMATION

It is worth mentioning some general patterns/consistencies across all the models. Selection of the exponential smoothing models was predominant for the table red and white wines in all regions. Holt-Winters Additive Exponential Smoothing models chosen at the region/type level for table red and white present both a trend/cycle and a seasonal component, which makes the Holt-Winters Three-Parameter model the optimal model in this case. Vintage wine models could not be explained by only trend, seasonality, and cyclical elements. Vintage models were greatly improved upon by using ARIMA models with base price as an independent variable. As seen in Table 7.1, vintage wines' sales demand in all regions and price are highly correlated; therefore, integrating a causal (influence) factor such as price into the models explained more of the variation in demand.

Value wines make up only 11 percent of the total wine sales, and are typically less affected by seasonality and sales promotions keeping

Table 7.1 Correlation between Sales and Price for Each Region/Wine Type

	Table Red	Table White	Value	Vintage
Region 1	0.36	.036	–0.39	–0.91
Region 2	0.35	0.35	0.39	–0.80
Region 3	0.36	0.36	0.39	–0.90
Region 4	0.38	0.38	0.38	–0.97

them significantly stable compared to the other wines primarily due to the low volume of sales. Some caution should be used when reviewing the value wine models, particularly in the Northeast region. The trends of the value wine sales demand appear to be exponential, linear downward as time increases, which explains the selection of the Linear Holt ES models for Regions 1, 3, and 4. Forecasts produced by this model are smoothed and less sensitive to past swings in demand. The Northeast region was best modeled by an ARIMA seasonal model using base price as an influence factor. This situation lead to additional questions since the low volume of sales should have made the value wine models consistent across the regions. We further investigated the data for value wine and found the average price for value wine was higher than table red and white wines (see Figure 7.3). We further subset the data to only look at base price of value wines by region and found that the Northeast region was extremely different from the other regions.

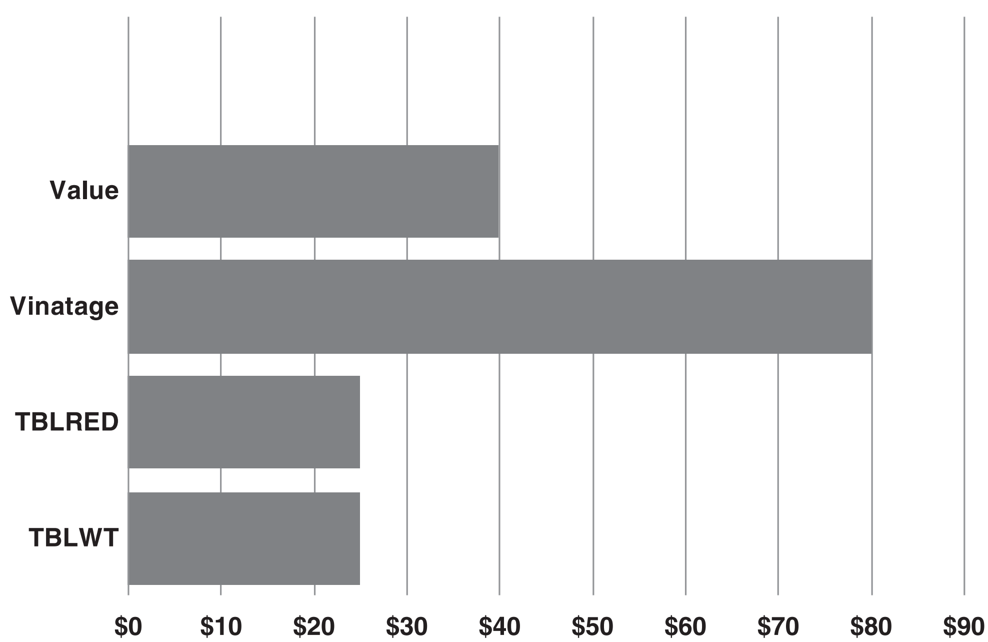


Figure 7.3 Base price for wine types: value priced higher than red/white.

ANALYTIC SNAPSHOT

Models Evaluated
ARIMA, Exponential Smoothing, and Dynamic Regression models were created using the middle-out method as the best method of hierarchical forecasting. Based on adjusted R-square values, model fit statistics, interpretability, and forecasting charts the optimal models for each region and type of wine were selected in order to forecast demand and plan promotions.

Model Summary
Overall, 21 models were system-generated. Using a holdout MAPE of under 14% as an acceptable cutoff point, there were 7 models requiring additional attention to improve accuracy and predictability.

"What If" Scenarios
A 5% price increase per case across the board will result in:

- 4.5% drop in unit sales
- 0.3% rise in revenue

Recommendation Methods
Due to the limited effects of an overall price increase, a more targeted price increase is recommended as below:

- Strongly recommend a 5% price increase in Western value wines & white wines, and in Central region for all types.
- Cautiously recommend a 5% price increase in Southeast for all types, and in Western vintage wines.
- Do *not* recommend a price increase either in Northeast for all types, or in Western red wines.

Strengths

- The December promotion (10% discount) was more effective for any given week than the May promotion (15% discount).
  - During the December promotion, the forecast showed an estimated 24.39% weekly increase in sales, with estimated forecasts in the Northeast and the Southeast regions with a higher increase of over 30%.
  - A one-week 10% discount promotion repeated four times throughout the year may be a better program for increasing sales than a single 15% discount with a four-week duration.

Weaknesses

- Both the May and December promotions had limited effect in generating incremental sales demand for the Central region.
- The May promotion was so recent that the forecast models could not be tested for accuracy once it was included in the model. However, based on the fitted model estimates the May promotion suggested a moderate increase in incremental sales demand.

Recommendations

- Run quarterly promotions where the customer buys one case and gets a 10% discount in West, Northeast, and Southeast regions. Sales from these promotions would help counteract the negative effects on sales volume from the price increases taken, and would raise overall revenue.
  - Institute an ongoing process of updating and revising forecast models with newer sales data in order to better understand and shape demand.

Key Differentiators

- Although the December sales promotion provided significant incremental sales demand due to the holiday (Christmas/New Year) there was a significant pantry load, which actually created a slight negative impact over sales for the two week period. However, running a 10% off sales promotion four times a year may have an overall positive impact generating significant incremental sales demand.
- A 5% price increase per case across the board will result in:
  - 4.5% drop in unit sales
  - 0.3% rise in revenue

Methodology

Historical wine sales demand history starting from January 2014 to May 2015 were used to conduct the analysis. In order to accurately forecast demand and plan promotions and sales for the remainder of 2015, the process flow outlined in Figure 7.4 was adopted.

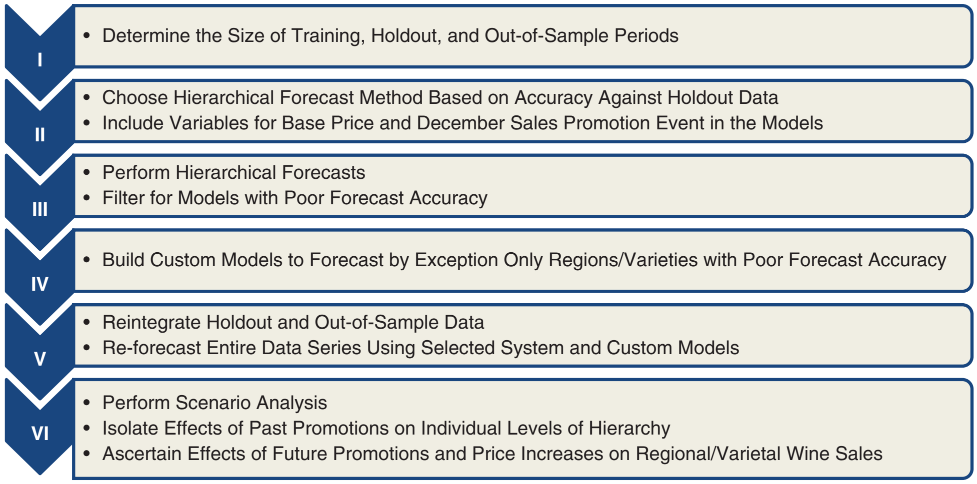


Figure 7.4 Demand forecasting and planning process flow.

As the winery's four-week-long promotion in May 2015 happened to occur at the tail end of the data series, determining the period of data to be set aside for model validation was the first and most crucial step in the aforementioned process flow. Including the unique sales behavior of those four weeks within the validation data would distort any accuracy statistics, as it would not be representative of the rest of the data series. Hence it was decided to split the series into three components as shown in Figure 7.5.

Demand historical data for a full three-year period was considered necessary to accurately model the forecasts. The remaining 13 weeks of data were further split into Holdout and Out-of-Sample components in such a way that the holdout data still captured a full quarter of a year, while data pertaining to the May 2015 promotion was left out of the original training data set and validation phases of the forecasting process flow.

Training Data	Holdout Data	Out-of-Sample Data
157 Weeks (or 3 Years) From 17-January-2004 To 13-January-2007	15 Weeks To 28-April-07	4 Weeks To 26-May-07

Figure 7.5 Breakdown of the data series.

With the above training and holdout samples in place, weekly demand for the remainder of 2015 was forecast using all three hierarchical methods, top-down, middle-out, and bottom-up, and with causal factors for base price and the December sales promotion event (with two occurrences in 2013 and 2014). Table 7.2 summarizes the comparative qualities of the middle-out method, and highlights the system-generated forecast models and the mean absolute percent errors (MAPEs) at each level of the hierarchy. It is sorted in ascending order of the MAPE for the holdout portion of the historical demand data series.

It may be noted that the reconciled MAPEs of the entire data series were used in selecting the best method and level of hierarchical forecasting. Clearly, the middle-out method generated more accurate forecasts than the top-down method across all levels of the hierarchy. Although the bottom-up method proved more accurate at the varietal wine level, middle-out remained the preferred method for two reasons:

1. To avoid introducing too much noise at the granular level into higher level forecasts; and
2. Because that noise might be further accentuated by the unique sales behavior of the May 2015 sales promotion.

Once the appropriate hierarchical forecasting method was chosen, the holdout MAPE was the measure of interest and the agreed to benchmark MAPE to beat (14 percent), as it measures model accuracy against a representative subset of the data. As is evident from Table 7.2, the majority of the forecasts had a holdout MAPE under 10 percent. For instance, the overall model had a holdout MAPE of 5.91 percent; that is to say, it estimated the holdout data with over 94 percent accuracy. For the varietal forecasts with high holdout MAPEs, a MAPE under 14 percent was deemed satisfactory, especially since they accounted for a fairly small proportion of overall sales. The hierarchical levels that warranted further modeling in order to bring down the MAPE are highlighted in the box in Table 7.2. The custom models built to improve these MAPEs are evaluated and compared in the following section (Model Selection and Interpretation).

Table 7.2 System-Generated Hierarchical Forecasts with Corresponding Error Percentages

		MAPE (%)		Reconciled MAPE (%)		
Region	Type	Holdout ↓	Training + Holdout	Middle-Out	Top-Down	System-Generated Model
Central	All	0.19	0.52	0.52	0.92	ARIMAX (012) (100)
Central	Vintage	0.55	1.12	1.13	1.53	ARIMAX (012) (100)
Central	Table White	1.62	1.73	1.48	1.87	ARIMAX (012) (100)
Central	Table Red	1.63	1.80	1.50	1.90	ARIMAX (012) (100)
Central	Value	2.06	2.80	2.88	2.76	Smoothing (Linear Exponential)
Overall	All	5.91	15.13	14.79	15.13	ARIMAX (Intercept)
West	All	6.18	16.38	16.38	16.71	ARIMAX (100) (000)
Southeast	All	6.22	15.73	15.73	16.07	ARIMAX (100) (000)
Northeast	All	6.61	14.41	14.41	14.75	ARIMAX (Intercept)
Southeast	Vintage	6.70	15.13	18.38	18.72	ARIMAX (Intercept)
Northeast	Vintage	7.72	12.74	14.52	14.88	UCM
West	Vintage	9.23	16.81	20.74	21.07	UCM
Northeast	Table Red	12.81	13.63	15.74	16.07	Smoothing (Winters' Additive)
Northeast	Table White	12.99	13.86	16.17	16.50	Smoothing (Winters' Additive)
West	Table Red	14.26	13.43	17.46	17.79	Smoothing (Winters' Additive)
Southeast	Table Red	14.26	13.43	17.00	17.33	Smoothing (Winters' Additive)
West	Table White	14.26	13.43	17.46	17.79	Smoothing (Winters' Additive)
Southeast	Table White	14.26	13.43	17.00	17.33	Smoothing (Winters' Additive)
Northeast	Value	14.94	27.54	27.41	27.15	Smoothing (Linear Exponential)
West	Value	14.95	27.60	27.86	27.58	Smoothing (Linear Exponential)
Southeast	Value	14.95	27.60	27.53	27.25	Smoothing (Linear Exponential)

The custom models for these seven levels and the system-generated models for the remaining levels were then run again, this time including the out-of-sample data, as well as including an event variable for the May 2015 sales promotion. The following section also includes an interpretation of the results from these demand forecasts. Finally, what-if scenarios were constructed and compared to examine the effects of the two promotional events (December and May) and of a hypothetical price increase on overall sales as well as on sales in specific regions and of specific wine varieties (see Scenario Analysis).

MODEL SELECTION AND INTERPRETATION

Model Comparison and Building

Separate models were built via automatic selection for each variety of wine (vintage, value, table white, and table red) within each region of sales, for the individual sales regions, and on the entire combined dataset. The demand forecasting and planning system built exponential smoothing models (ESM), auto-regressive integrated moving average (ARIMA), and multiple regression models for each, and automatically selected the best models based on the lowest holdout MAPE. A cutoff level was set at 14 percent MAPE accuracy prior to modeling, which was deemed to be an acceptable error rate given the supply chain's ability to protect against a 14 percent swing in demand using safety (buffer) stock. Using this cutoff, seven models received additional attention to improve forecast accuracy. Table 7.3 shows the final model selections for each variety and region, as well as MAPEs and other measures of fit.

Value Wine: West, Northeast, and Southeast Regions

The models for value wines in the West, Northeast, and Southeast regions required further attention. Figure 7.6 shows the autocorrelation chart for the Western region (with the holdout sample):

The autocorrelation charts in Figure 7.6 show a significant spike at Lag 1 in the partial autocorrelation function (PACF) and the autocorrelation function appears to have exponentially decreasing values. These are characteristics that indicate a likely ARIMA

Table 7.3 Final Model Fit Statistics

			Holdout		Training + Holdout	All Data		
Region	Type	Final Model	MAPE	R-Squared	MAPE	MAPE	Reconciled MAPE	R-Squared
Overall	All	ARIMAX (Intercept)	6.39	0.60	15.13	6.46	6.25	0.88
Central (4)	All	ARIMAX (012) (100)	0.19	0.93	0.52	0.27	0.27	0.96
Central (4)	Vintage	ARIMAX (012) (100)	0.55	0.91	1.12	0.51	0.74	0.93
Central (4)	Table White	ARIMAX (012)(100)	1.62	–0.18	1.73	1.79	1.35	0.74
Central (4)	Table Red	ARIMAX (012) (100)	1.63	–0.18	1.80	1.84	1.39	0.73
Central (4)	Value	ARIMAX (1,1,1)	2.06	–0.01	2.80	2.50	2.78	0.26
North East (2)	All	ARIMAX (Intercept)	6.61	0.53	14.41	7.71	7.71	0.83
North East (2)	Vintage	UCM	7.72	0.73	12.74	10.09	14.52	–0.78
North East (2)	Table Red	Smoothing (Winters' Additive)	12.81	0.03	13.63	10.83	9.56	0.85
North East (2)	Table White	Smoothing (Winters' Additive)	12.99	0.02	13.86	10.79	9.38	0.85
North East (2)	Value	ARIMAX (1,1,1)	13.47	0.03	22.77	20.04	22.34	0.11
South East (3)	All	ARIMAX (100) (000)	6.22	0.62	15.73	6.61	6.61	0.88
South East (3)	Vintage	ARIMAX (Intercept)	6.70	0.73	15.13	7.59	13.50	0.63
South East (3)	Table Red	ARIMAX (1,1,1)	14.26	0.04	16.77	17.46	8.41	0.86
South East (3)	Table White	ARIMAX (1,1,1)	14.26	0.04	16.77	17.46	8.41	0.86
South East (3)	Value	ARIMAX (1,1,1)	14.95	0.03	22.92	20.13	33.01	–0.72
West (1)	All	ARIMAX (100)	6.18	0.61	16.38	6.46	6.46	0.89
West (1)	Vintage	UCM	9.23	0.39	16.81	7.63	11.43	0.67
West (1)	Table Red	ARIMAX (1,1,1)	14.26	0.15	16.00	17.50	8.96	0.85
West (1)	Table White	ARIMAX (1,1,1)	14.26	0.04	16.77	17.46	9.02	0.85
West (1)	Value	ARIMAX (1,1,1)	14.95	0.02	22.82	20.13	32.16	0.65

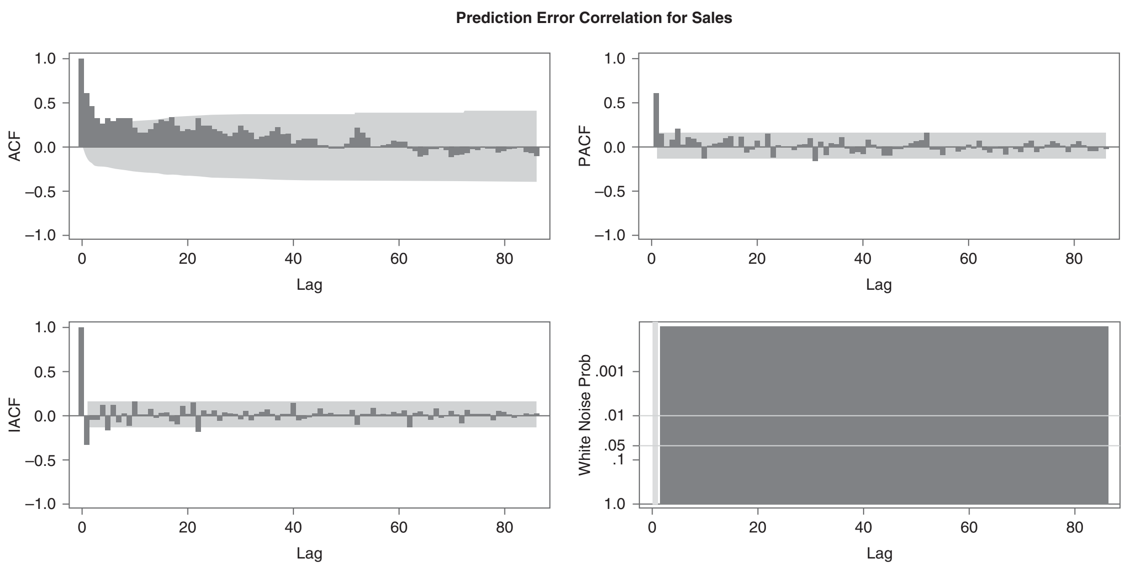


Figure 7.6 Autocorrelation panel for value wines in Western region.

(1,1,0) model. We added the price variable, which reflects the price of a case of value wine, to test if this affects the number of cases purchased. However, even with the price variable, there still remained an upward/downward trend and so differencing of the demand history was taken to capture (account) for the trend effects. After running the model, the residual errors were checked to verify if any seasonality remained or if there were any outliers. After careful study of the output, it was determined that the residual errors were inflated on the weeks of December 24, 2013, and December 30, 2014, which coincide with our promotions. Interestingly, the promotion had a positive effect on sales demand, which indicates that the promotion led to added incremental demand. With each of these factors included into the model, the overall MAPE based on the holdout sample decreased to 13.49 percent.

Multiple models were tested to verify that the holdout MAPE had been minimized, but we were ultimately unable to beat the aforementioned model. Exponential smoothing models were generated but have a minimum MAPE of over 14.95 percent. Other ARIMAs such as (0,1,1) and (0,1,2) were tested, but they did not predict the holdout sample as accurately. Much effort was spent on building multiple regression models due to the increased interpretability available via such modeling techniques. However, this increased interpretability was not significant enough to offset the large increase in MAPE.

The MAPEs for value wine forecasts in the Northeast and Southeast regions also fell outside of the filtering threshold. It was quickly apparent that the autocorrelation charts were very similar to the Western region. The same modeling methodology was used to build models for these regions, but the ARIMA (1,1,1) model with the December sales promotion (intervention variable) causal variable offered the lowest MAPE.

Table Red Wine: West and Southeast Region

For both of these regions, exponential smoothing models were automatically selected, but the MAPEs fell outside of the cutoff level. Using similar methods to above, various models were built to best fit the data. It was again noted that both of these regions' autocorrelation charts were very similar, implying that similar models could be employed for both regions. An ARIMA (1,1,1) model with the December sales promotion causal variable offered the best predictive power over the holdout sample period bringing MAPE under the 14 percent threshold.

Table White Wine: West and Southeast Region

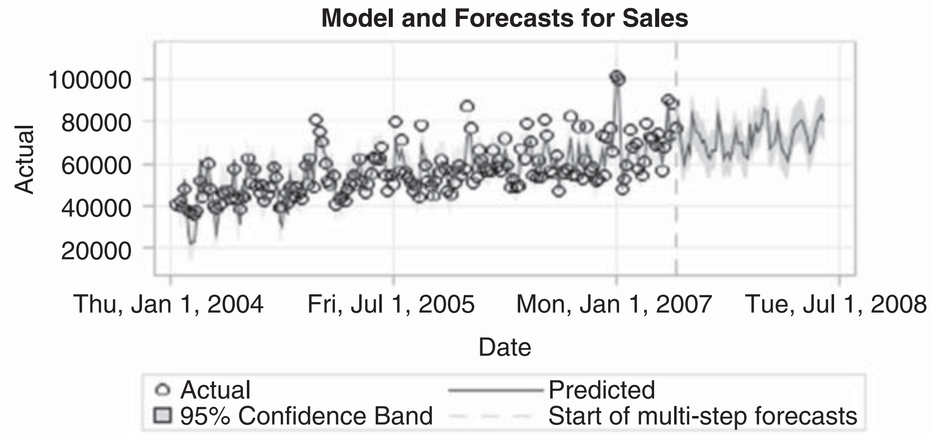
Table white wines in the West and Southeast regions had MAPEs over the cutoff level under the automatic model selection. As with each of the earlier sets of models, the autocorrelation charts for these two levels of the hierarchy were very similar, and thus similar models were likely to minimize both MAPEs. Models were built manually using similar methods to those used on the earlier levels, and again the ARIMA (1,1,1) model with the December sales promotion causal variable proved the most accurate. This model decreased the holdout MAPE for both models to 13.98 percent.

The original exponential smoothing model offered a relatively similar holdout MAPE. However, the ARIMA (1,1,1) model had a substantially higher Adjusted *R*-squared value of 0.784 versus 0.346 for the ESM. Additionally, the increased interpretability of the ARIMA model and the ability to add event variables made the decision straightforward. ESM models offer limited interpretation, and are primarily used to maximize forecast accuracy when interpretation of other factors like sales promotions is not needed.

Overall Model

The overall model was autogenerated with the middle-out hierarchical settings and selected an ARIMA model with a holdout MAPE of 5.91 percent, well below our cutoff level. Additional analysis was not necessary due to the strong predictive strength of the model. The final model selected was reconciled, which included the base price, the December sales promotions, the May sales promotion, and an outlier variable for the week of December 18, 2013.

Figure 7.7 shows the parameter estimates for the final overall model. There appears to be trend and seasonality associated with wine sales. The estimate for base price implies that for each dollar increase



ARIMA (1,1,1)(0,0,1)					
Component	**Parameter**	**Estimate**	**Standard Error**	**t-Value**	**Appox Pr>|t|**
Sales	Constant	137523.80	3485.90	39.45	0.0001
Sales	MA_52	–0.16	0.10	–1.66	0.0993
Sales	AR_1	0.31	0.07	4.15	0.0001
BasePrice	Scale	–1926.60	81.43	–23.66	0.0001
December Promo	Scale	24091.80	4995.10	4.82	0.0001
December Promo	Num1_1	–24568.80	4838.50	–5.08	0.0001
May Promo	Scale	12850.80	4560.40	3.49	0.0006

Figure 7.7 Parameter estimates for overall model.

in price, with all else held constant, sales would decrease by approximately 1,926.6 cases per week. The December sales promotion, which offered 10 percent off every purchase during the last week of 2013 and 2014, increased weekly sales on average by 24,091.8 units. However, there was a negative effect that occurred the week after the December sales promotion, which decreases sales by 24,568.8 units. These lower sales could be a result of customers' pantry loading additional wine anticipating the holiday with family and friends visiting and for gifting purposes. The May sales promotion, on the other hand, increased weekly sales by approximately 12,850.8 cases on average with little if any pantry load effects.

SCENARIO ANALYSIS

The Implications of a 5 Percent Price Increase

An across-the-board price increase of 5 percent per case would result in an estimated 4.47 percent drop in sales for the XWZ Winery as a whole, while raising total revenues by an estimated 0.3 percent because the effects of this price increase are not uniform across all regions and products, it is believed that a more targeted price increase would have a stronger positive effect on revenues. Figure 7.8 shows the drop in sales after a 5 percent increase in price.

As Table 7.4 shows, the Northeast region has the largest projected loss of sales, with an estimated reduction of 63,511 cases sold, a loss of 6.54 percent of regional sales volume. Since this results in a projected revenue loss of 1.86 percent once the price increase is also taken into effect, a price increase in Northeast is not recommended. In contrast, the Central region shows a strong projected revenue increase, with the price increase more than making up for the slight loss of sales. The Southeastern region shows a slight increase in projected revenue, but the difference is small enough that other business considerations should be taken into account when deciding whether to take a price increase.

On the face of it, the Western region appears similar to Southeast. But when further subdivided by type of wine, as shown in Table 7.5, only red wine sales in the Western region cannot sustain the price increase. An increase in price for the other types of wine would result in a stronger projected growth of revenues.

Final Recommendations

Given these results and analysis, our final recommendation related to whether to proceed with a 5 percent price increase across regions/types is as follows:

- **Increase prices in the Central region, but not for the other types of wine as it would result in a stronger projected growth of revenues.**

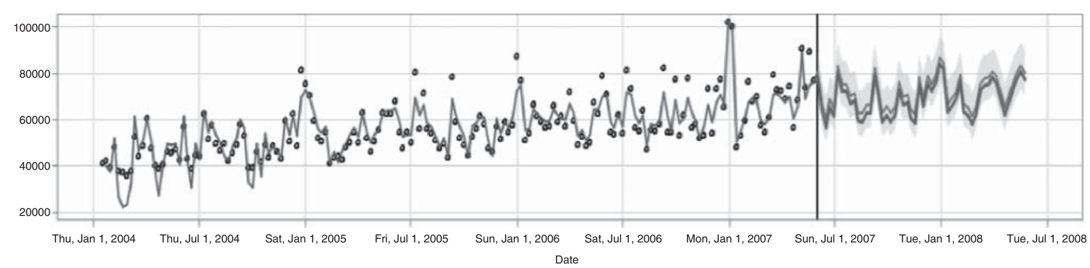


Figure 7.8 Nationwide sales projections for 2015, with and without a price increase.

Table 7.4 Projected Change Due to 5% Price Increase

Projected Change in Remaining 2007 Sales Due to 5% Price Increase					
	Overall	**West (1)**	**Northeast (2)**	**Southeast (3)**	**Central (4)**
Total Change/ Volume	−96652	−42596	−63511	−5477	−430
Percent Change/ Volume	−4.47%	−4.59%	−6.54%	−3.91%	−0.40%
Percent Change/ Income	0.30%	0.18%	−1.86%	0.90%	4.58%
Recommendation		Limited Increase	Do Not Increase	Possible Increase	Increase

Table 7.5 West Region Projected Change in Sales Volume & Income by Type

Western Region Projected Change in Remaining 2007 Sales Due to 5% Price Increase				
	Vintage	**Red**	**White**	**Value**
Percent Change/Volume	−1.78%	−7.79%	0.20%	−1.04%
Percent Change/Income	0.18%	−3.18%	3.13%	5.21%
Recommendation	Possible Increase	Do Not Increase	Increase	Increase

Pros

- **Lower unit loss:** Total units loss, under our recommended scenario, will be **2,082 units** (compared to a potential 44,964 unit loss if prices were increased across all regions).
- **Substantial additional profits for the Central region**: Given that the expected decrease in units for Central region is very low (only 0.2 percent), we believe that the price increase will turn out beneficial for XYZ Wines in terms of profit. To support this insight, we conducted a hypothetical P&L analysis (see Table 7.6) under the following assumptions for the Central region.

Another final assumption, not shown in Table 7.6, is related to the cost structure of the Central region. We assumed a cost structure of 80 percent fixed costs, and 20 percent variable costs.

Table 7.6 P&L Analysis Assumptions

Variable	Assumption	Source
Average Price, Region 2	$54	WineData
Units (June–December, 2007)	971,679	Forecast Model for Region 2
Profit Margin (%)	17%	Industry Benchmark: Beverages – Wineries & Distillers, Yahoo! Finance (http://biz.yahoo.com/p/347mktd .html)

P&L Analysis: Actual versus Scenario

Overall, XYZ Winery will potentially add **$2,530,765** to its bottom line by increasing prices 5 percent in the Central region. Bear in mind that the Central region (Region 2) is the most influential region for the company, as it accounts for 45 percent of total sales. These figures could be subject to significant improvement by the financial department, but we believe they signal the potential for increasing profits for the company if we were to make this move.

Cons/Risks

- **Unexpected decrease in units for Region 2, Central:** Our price/volume sensitivity analysis was performed under the assumption that the past relationship between price and volume holds for our demand forecast in Region 2 (Central). See Table 7.7. To assess the risk of a volume decrease different from the forecasted 0.2 percent, we used the same financial model of the previous section. Based on this model, we established a maximum unit decrease **threshold of 5.7 percent**. This

Table 7.7 What-If Analysis for 5% Price Increase in Region 2

	Actual	Scenario	Change
Price	$54	$57	5%
Units	971,679	969,736	–0.2%
Revenue	$52,470,666	$54,984,011	4.8%
Profit	$8,920,013.22	$11,450,778.38	28.4%
Profit Mrg.	17.0%	20.8%	3.8%

is, if demand in Region 2-Central decreases above this level, then the price increase will be detrimental for the region in terms of profit (less profit than the expected under the no price increase scenario). This threshold, we believe, could be used to monitor the demand response for the first few weeks of the price increase and dampen the risk of an unexpected variation in volume.

In an attempt to analyze the effects of known sales promotions, interventions were created and applied up and down the hierarchy for the three events outlined by senior management. These events were as follows:

1. **May sales promotion:** Buy a case and get a 15 percent discount.
   a. The sales promotion started the week of May 5, 2015, and ran for four weeks.
2. **December sales promotion:** Buy one case and get a 10 percent discount.
   a. The sales promotion was a test promotion the week of December 31, 2013 and 2014, and ran one week.

In addition to the sales promotion events, we also selected pre-defined holiday events from the event repository to run against our models. It is important to note that only one of the sales promotions was used in the final models to help explain variation in the data. The December 31, 2013, promotion appears in five of the forecasting models as either a pulse or temporary change event. Additionally, a few highly significant outlier events were detected and applied to the appropriate models to account for additional variation in the wine sales demand data. We are currently working closely with the sales and marketing teams to uncover any local events run by retailers during those times.

Cons/Risks

- The December sales promotion, which offered 10 percent off every purchase during the last week of 2013 and 2014, increased weekly sales on average by 24,091.8 units. However, there was a negative effect that occurred the week after the December sales promotion, which decreased sales by 24,568.8 units. This sales promotion on the surface does not appear very effective when applied across all regions and products as consumers appear to be pantry loading due to the holiday in anticipation for additional consumption during the holiday, and gifting. However, running this promotion multiple times (four times) over the year could significantly increase volume, thus reducing pantry loading.

- We are interested in investigating further with senior management the possibility of running the December sales promotion during the weeks prior to and during Valentine's Day as we found two outlier events were significant in the weeks of February 21 and February 28 in 2004. The spike in sales demand during these two weeks accounts for around 30,000 cases of wine sales.
- In the Southeast region, a highly significant outlier event was detected during the week of August 14, 2012. This spike accounts for 17,350 cases of wine sold in the Northeast region of the United States. Perhaps there was a back to school sales promotion? Or perhaps this surge in sales is directly correlated with Hurricane Sandy, which made landfall in South/North Carolina and in the next day moved up the east coast. Maybe people in the Northeast stocked up on wine for the storm. Either way, further investigation is needed to understand this event.

Final Recommendation

Based on our analysis, although the December promotion was the more effective for any given week, the depth of the promotion and seasonal timing encourage consumers to pantry load. This situation actually decreases sales over the two-week period. The larger percent discount (15 percent) proved better for the company's bottom line in May 2015, and weekly incremental sales rose by a larger amount overall (12,850.8 units). The May event did last longer (three weeks) than the December event, thus increasing total demand more than the shorter event, but we believe there may be an opportunity to

Table 7.8 Estimated Change in Sales due to Promotions

Estimated Change in Sales Due to Promotions					
	Overall	West (1)	Northeast (2)	Southeast (3)	Central (4)
Estimated Weekly Increase During December Promotion	23500	10513.3	10615.6	1565.2	Not significant[1]
Estimated Weekly Percent Increase During December Promotion	24.39%	24.94%	30.59%	30.34%	Not significant
Estimated Weekly Increase During May Promotion	12850.8	6231.2	5570.5	906.6	Not significant
Estimated Weekly Percent Increase During May Promotion	15.55%	17.02%	14.92%	16.50%	Not significant

offset these effects by having 4 one-week 10 percent discount events spaced throughout the year, realizing the higher weekly benefit of the December event with similar benefits to the longer duration of the May event. We also do not recommend running any promotions in the Western region. See Table 7.8.

Giving a 10 percent-off, one-week, December-style promotion spaced throughout the year could be the vehicle for generating additional sales. The increased sales from the sale promotion could be enough to counteract any sales lost due to the price increase. It was found that instituting a 5 percent price increase across the board together with a quarterly one-week 10 percent-off promotion would result in an estimated 1.21 percent reduction in sales by volume and a corresponding 2.10 percent increase in revenues. On the other hand, by instituting the price increase only for those regions and types of wine recommended in the previous section, and offering the quarterly discount only in the Central, Northeast, and Southeast regions, significantly higher revenues would be expected.

SUMMARY

The monthly demand planning brief allows companies to continuously look ahead and plan based on sales tactics and marketing investment strategies. It contains the details and actions taken by the demand forecasting and planning team working closely with the sales and marketing organizations using feedback from actual execution to final demand response. This tight collaboration in maintaining this document between the demand forecasting and planning and sales and marketing organizations creates trust, accountability, and ownership.

As seen through the winery example, the next generation demand management process is more than just creating an accurate demand forecast. It is a business analytics function embedded downstream in the sales and marketing organization providing analytics support to drive demand generation. As such, demand analysts working closely with sales and marketing provide predictive analytics support to validate and justify sales tactics and marketing strategies that impact the final demand response.

Demand sensing and shaping capabilities not only provide the ability to predict demand more accurately, but also can uncover deep insights into customer/consumer behavior by identifying those key performance indicators that influence consumer demand and replenishment polices. These factors can be quantified (measured) and used to shape future demand based on sales and marketing tactics and strategies. As such, those tactics and strategies need to be tested and validated using predictive analytics and documented to maintain accountability and ownership.

Implementing a monthly demand planning brief is the best way to build accountability and ownership of the unconstrained demand forecast through sound testing using analytics and documentation of the assumptions (tactics and strategies) that were used to justify the demand forecast. Then, get sign-off by the sales and marketing senior management team prior to the S&OP meeting. The monthly *demand planning brief* outlines in detail what tactics and strategies were tested to validate the assumptions using data and analytics versus gut feelings.

KEY LEARNINGS

- Implementing a monthly demand planning brief is the best way to build accountability and ownership.
- The monthly demand planning brief outlines in detail what tactics and strategies were used to create the final demand response.
- Demand sensing and shaping capabilities provide the ability to not only predict demand more accurately, but also uncover insights that influence future demand. Those insights are driven through the use of downstream data and collaboration between demand planning and sales and marketing.
- The next generation demand management process will require new analytics skills and the hiring of demand analysts (data scientists) who need to be embedded in sales and marketing closer to the customer/consumer to support demand generation.

CHAPTER 8

The Strategic Roadmap