THE PENNSYLVANIA STATE UNIVERSITY
SCHREYER HONORS COLLEGE

DEPARTMENT OF SUPPLY CHAIN AND INFORMATION SYSTEMS

THE BENEFIT OF IMPROVING FORECAST ACCURACY ON CUSTOMER SERVICE

JADE ADAMS

SPRING 2014

A thesis
submitted in partial fulfillment
of the requirements
for a baccalaureate degree
in Supply Chain & Information Systems
with honors in Supply Chain & Information Systems

Reviewed and approved* by the following:

Robert A. Novack
Associate Professor of Business Logistics
Thesis Supervisor

John C. Spychalski
Professor Emeritus of Supply Chain Management
Honors Advisor

***Signatures are on file in the Schreyer Honors College**

ABSTRACT

The purpose of this thesis is to analyze the effectiveness of a consumer packaged goods (CPG) company's current demand forecasting practices and provide recommendations for future improvement. Using three years of bias and mean absolute percent error (MAPE) data for two prominent compromised skin brands, overarching trends between lag and forecast error were be identified. A quick cost analysis revealed the cost of over and under forecasting in terms of holding cost and the cost of lost revenue and how this relates to lag. This thesis concluded that although there is a correlation between MAPE and the number of months prior to the shipment the forecast was made (lag), there is no correlation between lowest MAPE and lowest total cost.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

ACKNOWLEDGEMENTS

I would like to thank my thesis supervisor Dr. Novack and Dr. Bansal for their unwavering help and support. I would also like to thank the company, who is the subject of this thesis, for the opportunity to work on this project and for all of their help throughout the process.

Introduction:

Balancing supply and demand is the underpinning of any successful supply chain, and is the essence of demand management. According to Michael Shea, the President of Griffin Strategic Advisors LLC, “The ability to see customer demand and align it with your supply chain has become a truly crucial capability. But many supply chain managers still struggle with building this capability into their organizations” (Cecere, 2013). An essential element of the demand management process is forecasting, which determines the amount and when product will be shipped. Although all forecasts will ultimately be wrong, the key to successful forecasting is reducing the difference between what was actually demanded and what was predicted to be demanded. Despite sounding like a simple concept, there are many factors that contribute to derailing demand away from what was anticipated. Predicting and adjusting to all of these potential factors is something that companies throughout all industries struggle with.

This thesis will help a consumer packaged goods company get a detailed overview of the effectiveness of their current forecasting practices for two of their major brands and assess how much the current level of error is costing them. The company currently forecasts on a twenty-four month rolling basis in order to effectively plan for capacity, in terms of the labor required and components needed for production. With proper allocation of resources riding on accurate forecasting by stock-keeping unit (SKU), it is vital that demand plans are as accurate and timely as possible. In order to track its accuracy, this company uses a six lag horizon and measures both MAPE, which is mean absolute percent error, and bias.

Having a six lag horizon means that the actual shipment of a SKU is measured against what was forecasted for that SKU up to six months prior. For example, consider a SKU that was delivered in December. Looking at the forecast accuracy of that item at a lag 1 would show the difference between what was actually demanded in December and what was predicted to be demanded, one month prior, in November. Furthermore, looking at the forecast accuracy of that item at a lag 2 would show the difference between what was actually demanded in December and what was predicted to be demanded, two months prior, in October. This logic continues all the way up to lag 6, with the number of the lag corresponding to the number of months prior to the shipment month that the forecast being assessed was made. For this company, the performance of their demand planners is based on their lag 3 forecast accuracy since their average manufacturing lead time is over thirty days. It is important for their forecast to be as accurate as it can be three months out, as changes to predicted demand made after that date may not be easy to adjust for and may ultimately lead to further supply imbalance.

Understanding the accuracy of the forecast is just as important as developing it as this is the first step to driving continuous improvement. A survey conducted by Griffin Strategic Advisors garnered responses from one hundred ninety companies and found that the majority used recognized statistical measures to measure their forecast accuracy. Mean Absolute Percent Error (MAPE) ranked as the most popular measure, followed by Mean Absolute Deviation (MAD), bias, and Weighted Absolute Percent Error (WAPE) (Shea and Gilleon, 2011). The company featured in this thesis primarily tracked MAPE and bias as a percent so their measures were scale independent and thus easily comparable across data sets. MAPE, or mean absolute percent error, takes the absolute value of the difference between product shipped and forecasted and divides it by the number shipped. By relating the forecast error to the level of demand, the magnitude of the error can be determined (Gilliland, 2010). Traditionally, bias is calculated as the sum of the differences between the forecast and the actual demand. However, this company turns that number into a percent by taking the difference between shipped and forecasted and dividing it by the number of units shipped. The advantage of using bias is that you can tell the directionality of the error. The disadvantage is that an overall low error total can result even if forecasts were much lower or higher in individual periods due to the negative and positive errors (Coyle, et.al., 2009). Negative bias means an over-forecast or, put simply, too much supply, and positive bias means an under forecast, or too little supply.

Using the data generated using these two performance metrics, this thesis will identify trends in the forecast accuracy of two prominent compromised skin brands, analyze the cost associated with the current level of error, and ultimately give recommendations to improve the current forecast process. All product brand names used in this thesis are disguised.

Background:

In order to stay competitive, companies are constantly looking at what they can do to drive increased efficiencies into their processes and ultimately increase profitability. Since improving demand planning accuracy can eliminate waste and improve service, it is no wonder so much attention has been focused on its improvement. Prior to 2013, this consumer packaged goods company measured its demand planners on their lag 1 performance. The problem with this strategy was that most manufacturing lead times for their products are greater than thirty days. This meant that the accuracy of lag 1 had no actionable relevance since it did not provide time for the upstream supply chain to react. For instance, if the planner predicted fifty units in September for delivery in December and the supply planner schedules production thirty days out, they are going to take those fifty units as the input into their scheduling. This means that even if the planner changes the schedule in November, say to add ten more units, it may not be feasible for the manufacturer to now produce an additional ten units at such short notice. Although it is virtually impossible for a company of this magnitude to consider the lead time of each individual SKU when planning, the company did decide to change its focus from lag 1 performance to lag 3, to better accommodate average lead time.

At this consumer packaged goods company the demand planning process is done on a monthly basis. In the first week the planning team reviews the MAPE results of lag 1 and lag 3 for the month prior. During this meeting the top SKUs driving the forecast error are identified and reasons are assigned to them to explain why the forecast was so misaligned with demand. In addition to this meeting, in the first week SAP runs a statistical forecast and the demand planners review it, making any necessary adjustments. In the second week, demand planners lead meetings with the relevant supply planning, marketing, sales, and finance teams to review the results of the previous month and discuss any upcoming changes to demand. For example, marketing and sales will mention any promotions and displays that are in the pipeline that will alter the current forecast. In the third week, demand planners meet with a cross functional team to review market consumption trends. In addition to this, the demand planners and marketing team review the latest operational forecast and the sales forecast to address any significant gaps between the two. In the final week of the process, week four, the demand planners host a sales and operations planning meeting (S&OP), to review any issues, project updates, and ensure alignment on the forecast. After this meeting, the forecast is locked into the system. When doing this, special attention is taken with the forecast for product that will be shipped three months out since the accuracy of this forecast is what demand planners are currently measured against. Throughout this whole process shipment trends are continuously monitored to mitigate the risk of substantial under- and overages of supply occurring.

Literature Review:

Although never perfect, forecasting is an essential element in the successful functioning of an efficient supply chain. Aligning supply with demand as accurately as possible is something companies from all industries struggle with. Lora Cecere (2013) has cited research conducted by her research and advisory firm, Supply Chain Insights, which found that (1) demand planning is the most misunderstood and frustrating piece of the supply chain planning process, and (2) supply chain planning had the greatest gap between performance and satisfaction, with demand planning ranking the lowest within the planning umbrella. This frustration can be attributed to the fact that, even after over twenty years of process refinement, excellence in the realm of demand management still eludes supply chain teams who are still unclear on how best to improve (Cecere, 2013). Despite this pessimistic outlook, many companies realize the potential profit that can be sought from improvement in this area and continue to strive to reduce the error in their demand planning processes.

Before delving into improving forecast accuracy, it is essential to understand the concerns associated with the effectiveness of a company's forecasting capabilities. According to a study published in Supply Chain Management Review, respondents put the challenges of long lead times, stock-outs, and excess inventory at the top of their list of concerns. Of these challenges, both stock-outs and excess inventory present a direct financial impact, in terms of inefficient use of capital and the potential loss of business. On the other hand, lead times present more of a cause for the inaccuracies because long lead times worsen the problems inherent in demand management (Shea and Gilleon, 2011).

Inaccurate alignment of information can lead to numerous supply chain inefficiencies such as: holding excessive inventory, poorly planning capacity, ineffectively scheduling transportation, and ultimately losing revenues. Overestimating the amount of product needed to satisfy demand will cause a surge in inventory, while underestimating demand can cause valued customers to be shorted supply and stock outs to ensue. As can be seen in Figure 1, either instance is not favorable and reducing these costs, regardless of which way it tips the scale, is key to increasing profitability.

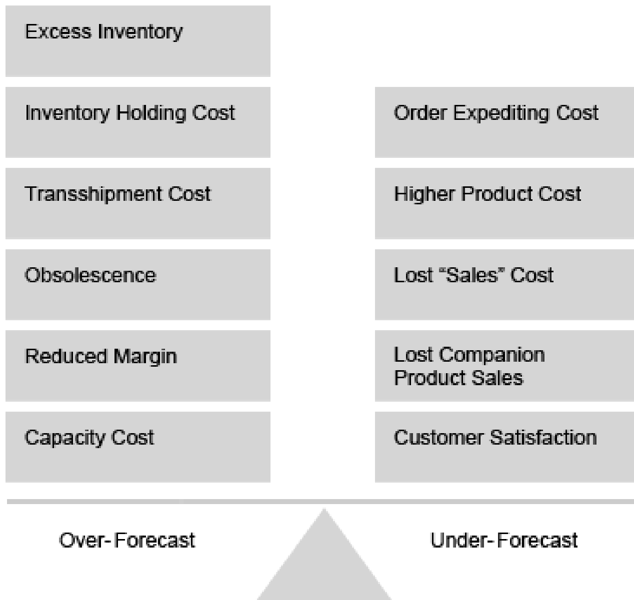

Figure 1: Costs associated with striking a balance between supply and demand

The consumer packaged goods, or CPG, industry has revenue of about $250 billion per year globally and about $41 billion per year in the United States. The competitive landscape in the United States is incredibly concentrated, with only fifty companies accounting for eighty-five percent of that $41 billion (Hoover's, 2014). In order to stay competitive in this industry, companies must rely on a constant influx of new products and line extensions. These constant additions, although great for sales, make demand even more challenging to plan for and mean that companies must place constant focus on driving out inefficiencies in their operations. With such a wide variety of product offerings, it is a constant challenge for companies to accommodate for varying production complexity, and therefore differing lead times, when forecasting.

Furthermore, the sales of products in this industry are usually seasonal so this provides an additional challenge for the planning and production process to overcome. According to Lora Cecere, “As products proliferate, the organizational design, process design, and how the data is used in demand processes all play a major role in defining the differences between leaders and laggards” (Cecere, 2013).

The improvement of forecast accuracy is not a problem that can be fixed by investing in technology or systems. No matter the system implemented to help with forecasting, improvement comes down to integration, consistent performance measurement, and a focus on continuous improvement. In *The Powerful Potential of Demand Management,* featured in Supply Chain Management Review, one of the key recommendations for improving demand management was to create incentives around key metrics. The thought here is that employees will be more inclined to put effort into further reducing error as much as possible (Shea and Gilleon, 2011). The company in this case saw benefit from this best practice which will be proven in the analysis below.

Methodology:

In order to analyze the current state of forecasting at this large consumer goods company, bias and MAPE data for 2011, 2012, and 2013 was provided for two well-known compromised skin brands. This data was cleaned and put into a pivot table so that only relevant data was available. For example, some of the SKUs had a forecast but had zero shipments associated with them. As Figure 2 illustrates, these data points created significant skew in the graphical representations of the data so were treated as outliers and excluded.

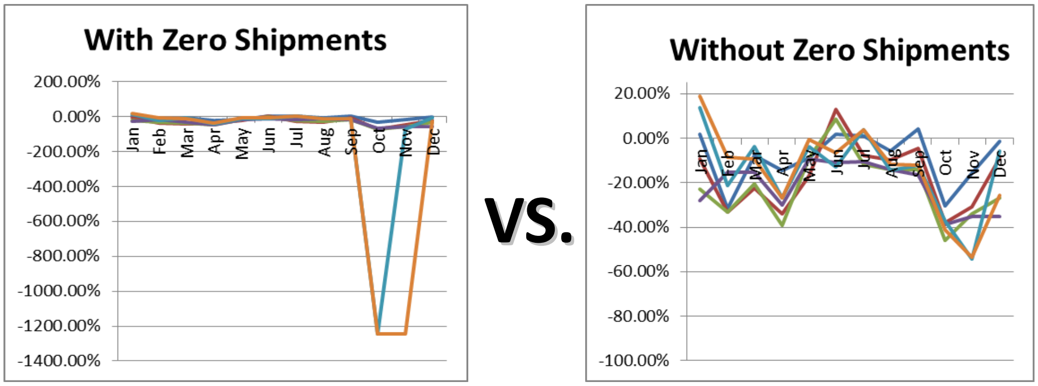

Figure 2: Justification for Data Removal

After this data was removed, bias was pulled by lag for each month for each of the three years. From here, the raw data was filtered in different sub groupings to see if any trends emerged. The data was analyzed by sub-brand, meaning the different brands underneath the umbrella brand; by DP classification, meaning the type of customer the SKU was going to, and by ABC classification, meaning the level of volume. The breakdown of the ABC classification is listed below in Table 1.

Next, MAPE was analyzed in the same way. However, in order to have a more objective measure, the average MAPE for the 12 month period was taken and compared by lag to find the optimal lag, meaning the lag with the lowest forecast error. To put a dollar amount to the amount of forecast error present, a quick cost analysis was performed. First, the number of units by which demand was greater than forecast was determined to show the amount of shortage. This number was then multiplied by the average list price for the brand to show the cost of lost revenue. Then, the number of units by which forecast was greater than demand was calculated to find the amount of surplus product. This total was multiplied by the manufacturing cost and then multiplied by the average industry holding cost, which is thirty percent. Calculating this gave an estimate of the additional cost the company must endure to hold the extra inventory associated with over forecasting.

Product Priority "Grade"	Cumulative % of Products	Cumulative % of Gross Sales	Approximate GTS Range ($MM)
A	4.1 %	25%	$12+
B	14.6%	50%	$6 to $12
C	33.0%	75%	$3 to $6
D	67.8%	95%	$1 to $3
F	Rest (32.2%)	Rest (5%)	< $1

Table 1. Breakdown of ABC Classification

Analysis:

To analyze the current state of forecasting at this large consumer goods company, a high-level overview of brand performance by lag was generated. By taking the total number of units forecasted by month for each lag and the total number of units actually demanded by month for each lag, a monthly bias for each lag was generated. Figure 3 shows the graphical representation of this data for one of the brands in 2013. From the graphs of both brands it was apparent that forecast accuracy is more closely related to seasonality than it is to lag.

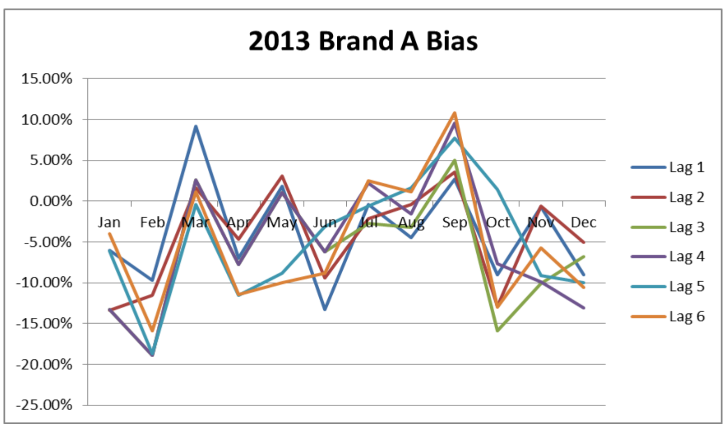

Figure 3: 2013 Brand A Bias by Month and Lag

Taking this observation into consideration, it was important to see how lag impacts forecast accuracy by using a more objective measure that would discount seasonality. Mean Absolute Percent Error (MAPE) was calculated for each month and then the average of the twelve month period was taken for each lag. Figures 4 and 5 show how the forecast accuracy of 2013 was much improved for both brands when compared to previous years. Considering the 2011 change to how the performance of the demand planners was measured, it is interesting to observe the dramatic improvement not only to the lag 3 MAPE, but also to the overall MAPE trend.

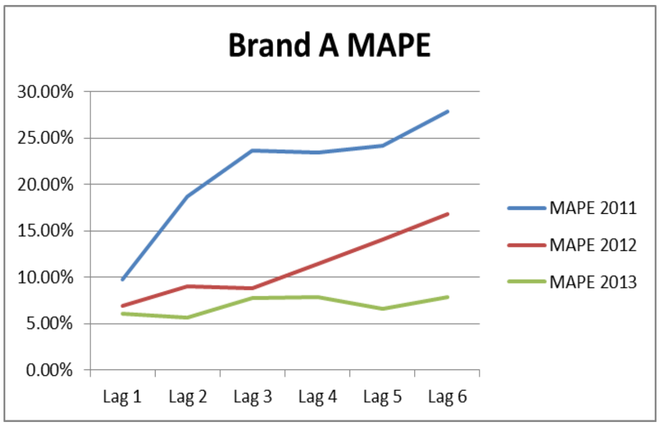

Figure 4. Brand A MAPE by Year

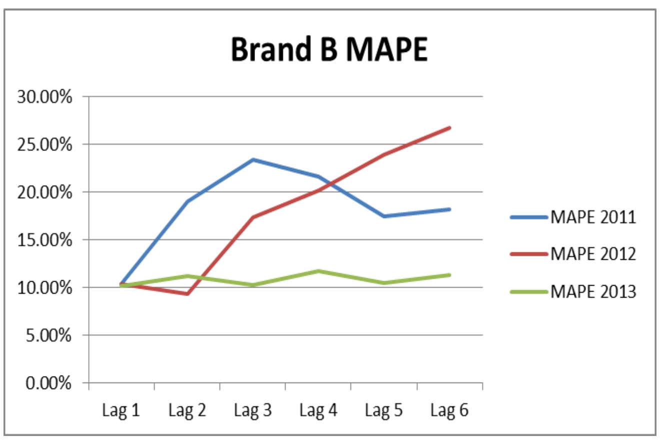

Figure 5. Brand B MAPE by Year

In order to see how different breakdowns of the SKUs affected the error trends, the data was manipulated to show how different sub-brands perform, how different classifications of product types, such as promotional, perform, and how different volume thresholds perform. Within the sub-brands, there was an obvious similarity between the two sub-brands which were planned entirely through a statistical model in SAP. Both sub-brands, were the only two to have consistent positive bias, whereas a consistent negative bias was evident throughout the other sub-brands of both brands. Figure 6 shows an example of the comparison between the sub-brands modeled by the statistical model, as represented by sub-brand A, and the sub-brands planned through the traditional process, as represented by sub-brand B. From this comparison, it can be inferred that the computer generated forecast is much more willing to risk a shortage than demand planners, who generally tend to over forecast thus buffer with inventory.

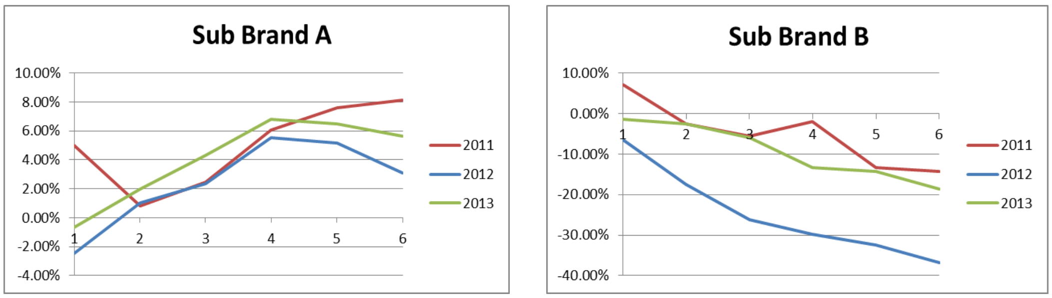

Figure 6. Strictly Statistical Modeling v. Traditional Planning Technique

When looking at the data broken by product type, it was clear that for promotional and made to order items the projections beyond two months were not reliable. Since promotional and made to order stock are not usually forecasted until two months out, there is an obvious drop off in forecast accuracy after lag 2. When looking at Figure 7 it is important to note the extremely large range of biases on the Y axis, which emphasize just how unreliable these projections are.

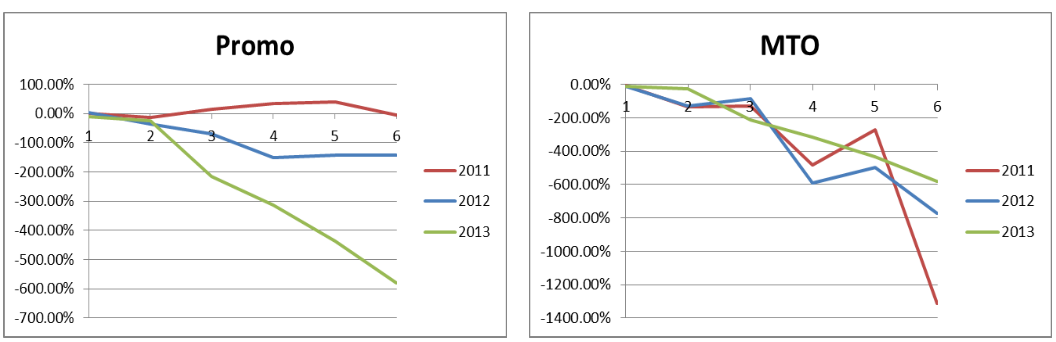

Figure 7. Promotional and Made to Order Bias Trends

Not surprisingly, volume has a significant impact on forecast accuracy. As illustrated in Figure 8, when comparing A classification items to F classification items there is a substantial decrease in forecast accuracy regardless of brand. This implies that perhaps more focus needs to be awarded to lower volume products which may be pulling down overall performance.

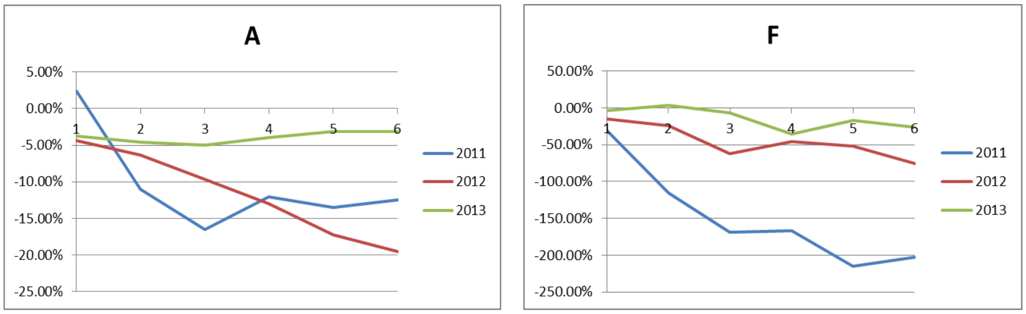

Figure 8. Impact of ABC Classification on Bias Trend

In order to get a sense of what this mismatch between supply and demand is costing the company, a quick cost analysis was performed. A shortage was calculated as the number of units short of demand the forecast was multiplied by the average list price of the brand. This gave a quick estimate of what the cost of lost revenue would be, in the worst case scenario. A surplus was calculated as the number of units in excess of demand, multiplied by the manufacturing cost, multiplied by the percent holding cost. This gave a rough estimate of how much holding excess inventory costs the company. Upon completion of this analysis it was apparent that lowest total cost does not correspond to lowest MAPE, which can be seen in Figure 9.Furthermore, there is no consistent optimal lag throughout all forecasts. However, for two out of the three years for brand A lag 2 was the optimal lag.

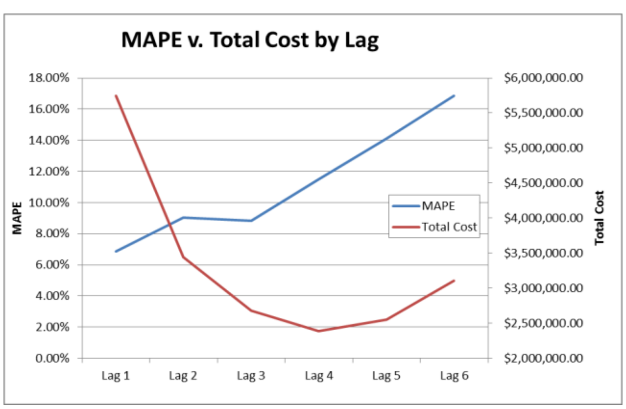

Figure 9. MAPE v. Total Cost by Lag

Conclusion:

Looking at the overall trends in the accuracy of the forecast some key observations are apparent. First, it is clear that bias follows seasonality more closely than lag, which indicates there is some inherent bias in the forecast. One specific example of this can be seen at the beginning of the year, year over year. Knowing this reoccurring trend, demand planners can make a concerted effort to counter this historical pattern and ultimately improve their forecast accuracy for those beginning few months. This inherent bias is also visible when looking at the data broken into sub-brands. According to an article published in the *Supply Chain Management Review*, persistent under- or over- forecasting is a common problem for demand managers and it is most often caused by company culture and expectations (Shea and Gilleon, 2011). In the case of this company, there is a deep rooted pattern of over-forecasting, also known as a tendency to be overly optimistic about actual demand. The result of this tendency is that excess inventory is repeatedly produced leading to increased inventory carrying costs and ultimately waste.

There is a consistent trend for both brands between MAPE and lag. As the lag increased, denoting the forecasting month getting further from the actual shipment month, the Mean Absolute Percent Error (MAPE) increased, meaning the misalignment between what was predicted and what was demanded worsened. Similarly, as the volume size denoted by ABC classification got less, Mean Absolute Percent Error (MAPE) increased. Noting this correlation and the fact that there is no consistent lag that delivers the lowest forecast error, determining the optimal lag should be made based on ABC classification or by brand. Furthermore, since there is no one-to-one correspondence between the lowest MAPE and the lowest total cost, it is not wise to judge forecasting performance on MAPE alone. For instance, MAPE could be the exact same for two different lags but have completely different cost implications.

Since the company started tracking lag 3 performance in addition to lag 1 there has been a significant improvement in the bias trend no matter how the data is sliced. This finding strongly supports the established best practice that higher performance can be driven by increasing focus on areas in need of improvement, for instance through the use of tracking related metrics. In two out of the three years for one of the brands the optimal lag was lag 2. However, on average this was only around a ten percent cost saving when compared to utilizing lag 3. This means if the company wished to take advantage of this average cost saving they would have to assess whether it outweighs the cost and feasibility of shortening lead time.

Limitations and Future Research:

The conclusions that were reached in this thesis are limited to the two brands and company featured. The reason they are limited is because the data used throughout was company specific. However, these findings could easily be tested by broadening the research to include data applicable to one or more additional companies.

In the future, the company involved in this study intends to conduct research into overcoming the inherent bias in their data, particularly in the persistent over-forecasting at the beginning of each year. Furthermore, the company is going to use the lag 6 data collected through this research to aid with their efforts to reduce slow moving and obsolete goods. By correlating SKUs with large negative lag 6 bias and SKUs with long lead times, the company will be able to identify and hopefully reduce the quantity of these slow movers. If the supply chain teams are aware of the excess product coming down the supply chain there will be a higher likelihood that they will be able to avoid waste and heavy discounting.

BIBLIOGRAPHY

Cecere, Lora. "A Practitioner's Guide to Demand Planning." *Supply Chain Management Review* Mar.-Apr. 2013: 40-46. Print.

Coyle, John J., John Langley, Brian J. Gibson, Robert A. Novack, and Edward J. Bardi. "Chapter 7/Demand Management." *Supply Chain Management: A Logistics Perspective*. 8e ed. South-Western.: Cengage, 2009. N. pag. Print.

Gilliland, Michael. *The Business Forecasting Deal: Exposing Myths, Eliminating Bad Practices, Providing Practical Solutions*. Hoboken, NJ: Wiley, 2010. Print.

"Industry Information: Personal Care Products Manufacturing." *Hoovers: A D&B Company*. Hoover's, Inc, n.d. Web. 25 Mar. 2014.

Lapide, Dr. "Demand-shaping With Supply in Mind." *Supply Chain Management Review* Nov. 2013: 4-5. Print.

Shea, Michael, and Berry Gilleon. "The Powerful Potential of Demand Management." *Supply Chain Management Review* May-June 2011: 18-27. Print.

"Why Accurate Forecasts?" *Thought Leadership Resource Center*. Terra Technology, n.d. Web. 28 Mar. 2014.

Academic Vita

EDUCATION:
The Pennsylvania State University, The Smeal College of Business
University Park, PA
Schreyer Honors College
Bachelor of Science in Supply Chain and Information Systems
Deans List: 5 Semesters
Terry Priest Scholarship

WORK EXPERIENCE:
Unilever
Operational Excellence Intern

- Championed a kaizen by leading cross functional meetings to determine the root cause and next steps of a service issue.
- Identified opportunities to reduce variable lead times for the import process of Knorr Latin.
- Created a new SharePoint site for the OpEx team to streamline current reporting process and improve communication.

Johnson and Johnson
External Supplier Integration Co-op

- Maintained and created key performance metrics that aided both the planning team and the external site managers to ensure efficiency in the supply chain
- Managed a project to remove blister perforations at the packaging site which were causing an ergonomic and aesthetic issue. Led conference calls, recorded meeting minutes, and authored a change control to resolve this challenge.
- Organized a gifts of the season drive on behalf of the United Way which provided presents to over 150 families in need.
- Cycled 28 miles and raised over $1,000 for multiple sclerosis in the Bike MS: City to Shore Ride with Team J&J

ACTIVITIES
Sapphire Leadership Program
Community Service Chair

- Recruited to apply and accepted to an 80 member cohort representing top 8% academically of incoming smeal class
- Organized student run blood drives by collaborating with the Red Cross, attended biweekly chair board meetings, and planned community service opportunities for Sapphire members to participate in.
- Responsible for completing professional development, leadership development, fundraising events, and attended general biweekly meetings

Women in Business

- Actively participated by attending involvement nights, book symposiums, corporate lunch events, and by fundraising for THON
- Accepted to be a member of the Raffle Basket Committee which is in charge of organizing and recruiting sponsors for the baskets that will be won as part of the women in business “Powerful Women Paving the Way” conference.

SKILLS

- Experienced in excel and SAP