A Short-range Forecasting and Inventory Strategy for New Product Launches

By

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Submitted to the Sloan School of Management and the Department of Chemical Engineering in partial fulfillment of the Requirements for the Degrees of

Master of Business Administration
and
Master of Science in Chemical Engineering

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ABSTRACT

Companies like Procter & Gamble that operate on a make-to-stock strategy use forecasts to drive their manufacturing, selling, and buying processes. Because forecasting future demand is not an exact science, inventory management models have been developed to accommodate these uncertainties. There has been a significant improvement in inventory management of base products, where forecasts are based on historical sales information. Because the bulk of forecasting methods depend on this use of historical data, little effort to date has been focused on inventory management of a new product. The use of traditional time-series forecasting methods is not realistic and companies typically resort to using judgmental or analogous (e.g. curve-fitting) means, which are less applicable in making short-range production and inventory decisions.

The lack of a new product forecasting method poses a significant problem in the cosmetic industry, which faces an increasing dependence on the introduction of new products for sales growth. Inventory and supply chain management is made even more difficult by the short product-life cycle, long lead times, and complexity and number of SKUs. As the industry trends toward increasing the pace of new product launches, forecast accuracy of a new product in its initial launch stages becomes more critical to manage the supply network’s inventory and capacity.

This document outlines a supply strategy for new product introductions that improves information management in the forecasting process to optimize supply and inventory planning. This method is designed to improve product pipeline forecasts as well as basic replenishment forecasts in the first few months of a product’s launch. The model was tested and validated by historical simulations on a cosmetic product line. Results showed significant inventory reductions compared to current inventory management policies.

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CHAPTER 1 - INTRODUCTION

The objective of this thesis is to describe a forecast and inventory management strategy for new product launches. It includes a quantitative model that provides weekly consumption and inventory forecasts, a discussion of internal and external supply chain requirements, and an assessment of organizational and strategic needs. This research is based on a six-month study that was conducted at Procter & Gamble's Product Supply group in their Cosmetic Business Unit.

1.1 BUSINESS NEED

The cosmetic industry has long been characterized by long, inventory- and obsolescence-laden supply chains. This has generally been accepted as the price of playing in what is a highly complex, fashion business – thousands of different products and variants, constantly changing trends and consumer preferences, highly segmented markets, tens of thousands of retail outlets. Procter & Gamble (P&G) has been focused on changing this cosmetic supply chain paradigm by looking to turn its supply chain into a competitive advantage. Not only have they optimized internal logistic processes, but the company has also sought to build collaborative partnerships with suppliers and their retail customers. Results have been significant. Over the last four years, its supply chain initiatives have cut inventories by over 60%, lead times by 80%, overall time through the supply chain by 65%, and costs by 20%. In turn, this has contributed to 5+% in net sales growth through improved capabilities.¹

This move to a more holistic, integrative supply chain, which includes suppliers, manufacturers, retailers, and end consumers, have allowed for collaborative projects that

¹ Based on initial internship description written by William Tarlton, Procter & Gamble, 2004.
were not possible in the past. One advantage is the increased availability and willingness to share information. This leads to a major opportunity to further supply chain effectiveness through the real-time integration, and leverage, of retailer point-of-sale (POS) data.

P&G currently operates on a make-to-stock model, using shipment information from the retailer to make demand forecasts. As long as a product exhibits a relatively stable demand profile without significant unplanned demand distortions, visibility at the retailer shipment level is often sufficient to make accurate production decisions. It is much harder to maintain this same level of forecast accuracy for a new item being introduced into the market. Yet, it is also one of the stages in a product’s life cycle where forecast accuracy is most important. The ability to use POS data to increase forecast accuracy at the new product introduction stage provides significant opportunity to reduce costs by inventory management while providing real demand information that could be used to improve product marketing and sales strategy.

Furthermore, the landscape is changing as retailers work with manufacturers like P&G to make a move towards a more vendor-managed approach, where P&G would have control in managing inventory and ensuring that stocks are appropriately stocked. Having the ability to manage their new product portfolio through accurate forecasts will be a major advantage when this transition occurs.

1.2 P&G’S COSMETIC BUSINESS UNIT

P&G currently markets their cosmetic products under two major brands, CoverGirl and Max Factor. Combined, these two brands make up over 1500 stock-keeping-units (SKUs) and comprise over a billion dollars in sales. These products are sold
primarily through the retail channel, including the drug market, food chains, dollar stores, and mass merchandisers.

1.3 OVERVIEW OF P&G'S COSMETIC SUPPLY CHAIN

The majority of P&G's cosmetic products are developed and manufactured in-house, with a minority outsourced to other contract manufacturers. P&G produces to a target inventory level, which is determined for each SKU by using historical shipment information and projected forecasts. Orders placed by retailers are filled by this inventory, with triggers set in place for production to replenish the inventory stock once a lower limit is reached. Targeted inventory of raw material stock is also ordered in a similar fashion, although many suppliers have transitioned to a vendor-managed strategy. Shipped products are stored in the retailer distribution centers, where they will eventually be distributed to individual stores and sold to the end consumers. Some retailers have adopted a cross-docking strategy, in which inventory is kept at the store level, eliminating the need for customer distribution centers. Figure 1 illustrates P&G's cosmetic supply chain.

Figure 1. P&G's cosmetic supply chain.

Major efforts in the recent years have focused on improving manufacturing and distribution operations, including lean initiatives, reduction in batch sizes, and reducing retailer's minimum order quantities. Most recently, P&G has begun efforts to improve their new product launch strategies through micro-marketing efforts, improved customer
and supplier relationships, and understanding of inventory and supply chain inefficiencies.

### 1.4 THE NEW PRODUCT LAUNCH PROCESS

New products are defined to mean any SKU offering that has been on the market selling on the wall shelf less than three months. Products that have been on the market longer than three months are defined as base products.

New products are introduced to consumers by the retailer twice a year, with one major launch occurring in Jan/Feb and another smaller one occurring in the summer. The launch of a new product line can occur in either one or two stages. The primary launch stage is the wall reset, when the old wall design is removed and a new wall is installed based off of a planogram designed with space for new products. A planogram is a graphic map which depicts the location and number of products on a shelf or wall. While a national launch date is usually planned, it may take a retailer up to a month or more to fully reset all of their store walls to the new planogram, depending on the complexity and changes required of the new wall design. The majority of retailers will carry the entire product line on the new wall, although some will choose to selectively carry shades that are predicted to sell more. This is especially common for color cosmetics, where a product line may include 40-60 different shades. Oftentimes, smaller stores are not physically able to carry all of the offerings in a product line.

In some cases, new products will be offered to consumers by retailers before the wall is reset. This is done by selling these products on counter and/or end-cap display stands. Display stands may hold the entire product line, multiple product lines, or a select SKU offering and are typically in stores for five to eight weeks prior to the wall reset.
date. This is an opportunity for the retailer to gain sales of new products before the wall reset and, because displays are usually colorful and aesthetically pleasing, they also serve as self-advertising agents for the products they hold. A display stand typically will be taken down when the walls are reset; products that were not sold will be removed from the displays and placed on the wall pegs or slot.

To follow the retailer’s launch strategy, P&G bundles the introduction of new products into one of the two major launch times. The products intended to sell off of counter or end-cap displays need to be shipped and at the retailer’s site approximately three or four weeks before the start of the display period. Products that will be used as wall stock usually is ordered about two months before the wall reset date. And finally, production planning for the first batch of replenishment stock (to replace consumption from the wall units) must begin early enough to cover the projected lead time (typically three or four weeks). Typically, customer order turnaround time (the time from when a customer places an order to the time when a customer receives the order) is approximately one week. Figure 2 describes when and what types of activities take place during the new product launch period.
Because of long lead times and capacity constraints, P&G must often make
production decisions well in advance of receipt of a customer’s order to ensure that
product is available when the order does arrive. As a result, forecasting must play a very
large role in ensuring that both the retailer order quantities are appropriately matched to
future consumption and that production scheduling matches actual retailer order
quantities.

1.5 P&G’S MOVE TO IMPROVE LAUNCH PROCESS

P&G has spent the last several years directly addressing the issues surrounding
new product launches as described above. A supply chain assessment performed in 2000
revealed that significant inventory existed at both the manufacturer and the retailer stages. The time for a product to move through the supply chain (from supplier to end consumer) was almost two years! Excess inventory, relatively low volumes, and short product life cycles meant obsolescence costs were a significant component of total costs.

This assessment also identified many of the inefficiencies in the current new product launch process. The root cause of excess inventory could often be pinpointed to the very first order placed by retailers. Without better information about the potential performance of the product, retailer placed initial order quantities based on sales projections from the sales and marketing arm of P&G. These estimates typically ended up being higher than actual. Order quantities were also based on a strategic decision to prevent product stock-outs – the cost of a lost sale was significantly higher than that of keeping more inventory. In historical cases, retailers have purchased over a year’s worth of products in the first initial order.

Excess inventory at P&G could also be traced back to the new product launch period. With limited information about retailer orders, excess inventory was necessary to buffer against potential variation from projected shipment quantities. P&G also tended to make blanket production decisions at the product level without rationalizing production quantities at the SKU level. Within a product line, P&G would produce the same quantity for a popular lipstick color (such as a berry/pink shade) as they would a more unique color, such as a trendy blue lipstick color. Furthermore, few resources were in place to specifically monitor new product launches both during the launch and after the first critical months immediately following. As a result, production decisions continued to be made from assumptions created
As a result, a “Go-to-Market” strategy was developed to enhance P&G’s cosmetic supply chain and better equip the company to handle the inherent issues with new product launches. Potential savings were enormous, both in terms of cost reductions in inventory as well as potential increases in revenue through in-stock improvements and improved customer service. The research described in this thesis serves to elaborate on the forecasting and inventory control component that was touched upon in this strategy.

1.6 THESIS OUTLINE

The next chapter provides an introduction to supply and demand collaboration with a focus on new product introductions. The business case for new product forecasting and applications to improve current business practices is also presented. Chapter 3 provides a detailed analysis of the forecast model. Chapter 4 provides evidence of the model’s abilities through the success of a case studies conducted using historical sales data. Chapter 5 provides an overview of the organizational and supply chain requirements needed to successfully implement such a strategy. Finally, Chapter 6 presents some key conclusions and insights.
CHAPTER 2: BALANCING THE SUPPLY AND DEMAND OF NEW PRODUCTS

Successful collaboration between supply and demand planning allows companies to operate with less inventory, better customer service, and higher profit margins. In this section, we provide an overview of research and methods currently being investigated or employed to balance the supply and demand equations during the new product launch phase.

2.1 TRADITIONAL PARADIGMS OF SUPPLY AND DEMAND MANAGEMENT

Supply chain management (SCM) is the management of manufacturing, sourcing, and distributing product from the raw material to the end consumer. Traditionally, the scope of management attention has been focused internally on the supply side. Companies focused on internal manufacturing and distribution improvements, such as the implementation of lean manufacturing principles, warehouse and distribution centers management, and making sourcing decisions based on cost. Decisions were made based on cost optimization at the local level.

The bulk of supply-chain solutions are developed for products that are exhibiting steady-state behavior. Often, it is difficult to apply these same principles and theories to products in the introduction stage. Some of the challenges that are specific to or made more prominent due to the transitional nature of new products is described.

2.1.1 The Bull-whip Effect

One of the more significant issues that companies face is the development of a response towards supply and demand variability. Both retailers and manufacturers face inherent uncertainties and variability within the supply chain due to a number of internal
and external factors. These unplanned distortions oscillate through the supply chain and are amplified as they propagate back through the different stages. For example, a retailer who increases their standard order quantity to address a temporary stock-out is perceived by the manufacturer as an overall increase in demand. This causes production to reschedule and expedite orders to meet this perceived demand, which may not have even been real. This then results in a supply chain laden with excess inventory, making upstream processes even more disconnected to what the real demand is. This phenomenon is known as the bullwhip effect.

The bullwhip effect can be even more prevalent during the launch of a new product. Real demand at the end-consumer point is furthered masked by pipeline shipments, distorted by transitional behavior as retailers seek to make the product available to consumers, and faced with temporary demand peaks induced by heavy promotional activity. Inefficiencies during the new product launch phase caused by the bullwhip effect have traditionally been accepted as an unfortunate need to do business. Although processes are in place to mitigate these effects once the product launch phase is over, the damage is already done. In an industry like the cosmetic business which is known for slow inventory turns, these initial distortions may result in production of over a year’s worth of inventory before the product is even launched!

2.1.2 Lack of internal collaboration

Demand and supply decisions have traditionally been made independently by the marketing/sales and product supply organizational groups, respectively. In most companies, manufacturing is planned based on production capacity and asset utilization.
Resulting production is then “pushed” from manufacturing through the value chain to the end consumers.

For market-driven companies like P&G, the marketing arm plays a major role in shaping demand, using levers such as promotional schedules, pricing, the number of SKUs within a product line, packaging and product aesthetics, and the timing of when a product is launched. This information flows back to the product supply groups, which then determine how to best meet this demand at minimal cost through capacity planning, inventory needs, and distribution schedules. In effect, marketing is determining a strategy to optimize revenue generation and product supply then looks at implementing that strategy at minimum cost.

Figure 3 qualitatively describes the effect that various marketing levers such as placing promotions or adjusting SKU variety within a product line have on revenue, cost to supply the product, and profit from the product line.
There is a point where increasing marketing levers actually result in a decrease in overall net profits due to the exponential increase in manufacturing and distribution costs to support the marketing efforts. While we can argue where P&G’s operations lie along this curve, what is clear is that there are greater probabilities of suboptimal behavior for companies that do not operate with effective collaboration between the supply and demand functions.

Making demand decisions independently of supply constraints can lead to suboptimal solutions, including lost sales and unnecessarily high supply chain costs.
There are many case study examples at P&G that highlight this. One classic example would be a new product that had significantly higher-than-expected sales at the launch onset. While the company certainly benefited from this blockbuster seller, it created a strain on the manufacturing resources. Since P&G had designed their manufacturing system to the original forecast, there was a lack of capacity to fulfill this additional demand and manufacturing was forced to go to contingency plans (overtime, external manufacturers, etc) to ensure that all orders could be met.

When a promotional coupon (planned months in advance) was released to the market after the first month, consumer demand soared even further for this product. With manufacturing already stretched to capacity, P&G had to resort to allocating products and setting limits on the amount that certain retailers could order. Not only did this cause lost sales due to high stock-outs in many stores, but it hurt retailer relationships and frustrated consumers looking to find a product that was being heavily promoted. This also placed a significant strain on P&G’s suppliers, who had to also find alternate means to provide the upsurge in demand for their raw materials. Ultimately, it was questionable whether the increased revenue generated from coupon promotion outweighed the significant cost incurred to maintain supply.

2.1.3 Misaligned incentives

Typical to trend-driven markets, the cosmetic industry is based on a consignment model, where unsold products can be returned by retailers to the manufacturer for a partial refund. This incentive created by manufacturers is necessary to persuade retailers to carry the many new products with little risk. While this principle may help to convince retailers to carry the product, it does little to ensure that they hold the
appropriate amount of inventory. Especially at the beginning of the launch, many retailers tend to carry more inventory than necessary, since the cost of a potential lost sale far outweighs the cost of inventory.

The situation is compounded by internal P&G incentives. Sales executives are measured on the amount of volume that retailers order, but are not currently accountable for consumption of the product to the end-consumer. Products that do not get sold to consumers at the end of its life cycle are returned to P&G at the company’s cost. Therefore, a contradiction between what P&G wants to do conflicts with the existing incentive structure. On one hand, P&G sells to retailers – the more they can push onto the retailer, the higher the revenue (and the higher the salespeople’s bonuses). On the other hand, unsold products get purchased back, increasing obsolescence costs.

Both the consignment policy and the internal sales incentives result in the retailers placing higher-than-needed initial orders, which later become excess inventory in the system.

2.2 THE NEED FOR SUPPLY AND DEMAND COLLABORATION

While traditional SCM has the power to deliver incremental cost improvement and allow companies to obtain a certain level of operational excellence, requires a shift from a localized cost-based approach to a holistic value-added way of thinking. To achieve breakthrough performance in both cost reductions and revenue growth, the supply, demand, and product development decisions need to be made collectively by internal production and marketing functional groups, as well as collaboratively with raw material suppliers, retail customers, and end consumers. This collaborative response to demand is known as the Demand-Driven Supply Network (DDSN), which is a system of
coordinated processes that designed to improve operational efficiency, streamline the new product development launch process, and optimize profit margins and revenues\(^\text{2}\).

An effective DDSN requires integration both within the “four walls” of the company as well as with external partners, including upstream suppliers and downstream customers. A process must be in place to generate and transmit real demand information and use that information to coordinate supply, demand, and product development decisions. The potential benefits to a company who can truly embrace and effectively implement DDSN are great. Because manufacturers would know exactly how much product was sold to the end consumer, they could make better planning and supply decisions. They could use their production capacity more effectively, shortening lead times while reducing inventories that were needed to hedge against demand uncertainty. Retailers would see a reduction in stock-out and lost sales situations, because the correct mix of products would be manufactured at the right time. Overall, this means a reduction in manufacturing costs and an increase in sales and revenues.

One major objective of a DDSN strategy is to reduce inventory used to hedge against distortions caused by the bullwhip effects. One of the most effective ways to moderate uncertainties which cause the bullwhip effect is through improved information sharing between the different processes within a supply chain. This information includes the amount of product available at each stage as well as a consumption demand forecast based on point of sales information. Retailers who have access to true consumption sales share this information with upstream supply chain players. Manufacturers can use this undistorted demand information and compare it with their own forecasts to make adjustments in supply scheduling and production. Suppliers with access to point of sales

information can also make better planning decisions. In effect, the supply chain is replacing inventory that was needed to buffer distortions with real demand information. Effective information sharing also requires that the right data is received by the necessary parties in a timely, ongoing manner. Timeliness is important so that parties within the supply chain can react appropriately and make the required adjustments to demand or supply needs.

2.3 THE ROLE OF FORECASTING IN SUPPLY-DEMAND COLLABORATION

One of the critical inputs to successful implementation of a DDSN strategy is an accurate forecasting methodology. In the absence of an accurate forecasting method, companies are forced to make judgmental predictions of sales. Typically, this may mean a top-down approach where sales and marketing would develop quarterly strategy to meet corporate revenue objectives. Manufacturing would produce to these sales objectives to ensure that customer service requirements would be met assuming those sales materialized. The company would then push the products onto retailer, using incentives and other means to convince retailers to buy and stock their products. In effect, this is a push-based model. This approach usually resulted in one of two things. For the items where the internal predictions exceed actual consumption sales performance, the company or the retailer would be saddled with excess inventory and high obsolescence costs from the inventory that did not sell. For items which were under-forecasted, retailers would experience high stock-out levels and potential lost sales as the manufacturer struggled to adjust production capacity to fulfill orders. In an effort to resolve this issue, a company may investigate the options of using inventory control and production planning software to control supply chain costs. Unfortunately, the bulk of
these software programs require accurate forecasts as an input. In the absence of a good forecasting method, these information technology solutions simply add more complexity to the problem.

With accurate forecasting methods, companies have the ability to implement processes and strategies to balance supply and demand. For base products where historical sales information already exists, simulations could be performed to use inputs such as demand-pricing correlations, production capacity and costs, and current inventories in the field to determine the optimal supply and demand strategy. For new products, a lack of historical sales information makes it harder for a company to use simulations. In this case, a more iterative approach may be necessary. Initial forecasts would be based on judgmental expertise or analogous product history. As information about the product’s sales performance is known, actual sales is compared to the initial forecast and a new estimate is created. Dynamic adjustments to both demand and supply behavior could be made accordingly to minimize costs and inventory while maximizing revenue.

The major issue is how quickly accurate information can be obtained and whether processes can be established to decrease the time before accurate forecasts can be obtained. In an industry where a product’s life cycle is short, lead times are long, and overall volumes are small, it is pertinent that accurate forecasts be available very quickly after a product is launched as even a small volume of over-production can mean many months (or years) of inventory. Developing a working model during the new product launch phase is especially difficult given the transient nature of any product during the
product launch phase and the product’s natural volatility due to the “trend-driven” nature of cosmetics.

2.4 APPLICATIONS OF DEMAND-DRIVEN SUPPLY NETWORKS

In the next two sections, we discuss applications of using forecasting within a DDSN framework in making supply side decisions regarding production and inventory control. Specifically, we will look at ways that P&G makes two production and inventory decisions. The first decision is reserving production capacity for wall stock units. The second is making ongoing production decisions for replenishment stock and managing optimal safety stock inventory.

2.4.1 Production of Wall Stock Units

Machine capacity decisions, which are often needed far in advanced of a product launch, are determined based on projected sales and a risk-mitigating factor to account for potential demand variability. Prior to the official launch of a new product, a pipeline quantity must be fulfilled. This pipeline order includes wall stock, initial replenishment, and warehouse safety stock needs, and the total quantity needed usually far exceeds the weekly capacity of the production machine. Therefore, it may be necessary to begin production up to six months prior to the actual launch date to ensure enough capacity to fulfill these pipeline orders.

Manufacturers like P&G must therefore make production decisions as to when to start producing for the pipeline orders and which items to produce first. On one hand, P&G will want to begin production as early as possible to ensure that they have enough capacity and mitigate risk of under-forecasting demand and disruptions to production, including quality and start-up concerns inherent in any new product launch. On the other
hand, waiting to produce until closer to the shipment order receipt date may give P&G more information as to the actual quantity needed.

Many companies have developed means to collect early sales information and use it to help improve their production scheduling and better manage their inventory. A classic example is of Sport Obermeyer, a large apparel company\(^3\). This company was plagued with many problems as a result of poor up-front production planning, including an increase in costs due to product obsolescence costs and missed revenue opportunities due to lack of supply of their more popular items. In facing these challenges, the company developed a new planning paradigm termed as Accurate Response, which uses forecasting methodologies and inventory planning algorithms. Prior to any sales information, the company found average forecast error to range from 50% to 100%. But, by extrapolating even a small amount of early sales information, they were able to improve the average forecast error to 8%! By using optimal inventory hedging strategies to reduce out-of-stock and lost sales, they were also able to increase their sales by 3.5%. Although initial production was based on forecasts from expert opinions, remaining production was determined using demand forecasts based on early sales information, which was many times more accurate than those based on the judgment. Decisions were based on the expected volume and volatility of the SKUs – higher volume, lower volatility SKUs were more likely to be produced in the initial production schedule, while lower volume, higher volatility SKUs would benefit from early sales indicator to help predict actual needed production.

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Similarly, P&G should develop a process to incorporate the use of early forecasts to make production decisions and minimize inventory while maintaining customer service and ensuring stocked shelves. This is especially applicable in making decisions of the wall stock quantity, which provide aesthetic appearance to the selling space and act as a place to hold inventory. Typically, the wall stock order quantity for a SKU is determined by multiplying the number of wall facings by a minimum pc/wall value. The calculation becomes more difficult when display quantities are considered. If the SKU was part of a counter or end-cap display, any pieces that did not sell during the display period would be transferred to the wall as unfortunate excess inventory. The ideal wall stock order quantity should therefore consider the unsold display units to optimize inventory at the store level. Unfortunately, the bulk of wall stock orders do not take this into account because the orders must be placed and production begun before the display period is over. Figure 4. describes a typical sequence of events that may occur.

**Figure 4. Timeline of events – Current Wall Stock Ordering Process**

Ideally, retailers would wait until the completion of display period, count the number of unsold pieces, and make shipment orders accordingly. Unfortunately, long lead times in production and distribution require that wall stock is shipped many weeks in advance before the completion of the display period.
In understanding the planning process behind production of the wall stock units, the first step would be to determine the portion of this quantity that can be produced independent of knowing the sales from the display period. This is best explained by looking at a typical item at the store level. Typically, the ideal wall stock is three pieces. Assuming that the display holds two pieces, a store would know with certainty that it would need to order at least one piece for the wall stock; P&G should produce that quantity prior to the onset of the test period. A subsequent decision is made regarding whether P&G should produce one, two, or no additional pieces. This portion of the wall stock orders, which we will call the reactive component, would depend on how many pieces from the display were sold prior to the actual launch of the product. For example, if both pieces were sold, the retailer would need to order an additional two pieces to ensure that there would be an ideal quantity at the wall. In other words, there is benefit in waiting to produce the reactive component of an order.

Typically, the reactive portion of the wall stock units represents 10-15% of the total wall stock quantity. In allocating production time for the wall stock units, P&G should first produce the wall stock order quantity that does not benefit from having early display sales input. Production capacity should then be reserved for the reactive portion. Figure 5 describes this timeline of events.

**Figure 5. Timeline of events – Reactive wall stock production**
It would be almost impossible to use any sales information to help improve the accuracy of the reactive wall stock quantity because the overlap between the time that a retailer places the wall stock order and the display period is so small and there would not be enough time to appropriately react. One way to get sales information earlier would be to implement a test market prior to the display period. In this way, P&G would be able to obtain some early information on projected sales to help determine their wall stock production. Figure 6 shows a potential timeline of events with the incorporation of a test period lasting 8 weeks.

Figure 6. Timeline of events – Test and Display Period

![Timeline of events – Test and Display Period](image)

There are two main components of scheduling that need to occur on a weekly basis. First, on an aggregate level, P&G must know how many total units of a product line they must produce for a given week. Second, on a line item level, manufacturing must which SKUs within the product line and how much of that SKU to produce.

Assuming a weekly timeframe, production for the week can be determined by comparing the total forecasted amount needed with the number of production weeks remaining before the target ship date, the total aggregate production capacity, and the cumulative production so far. A determination factor, DF, is calculated.

\[
DF = \left( \frac{\text{Total forecasted} - \text{Cumulative Production}}{\text{Production weeks remaining}} \right) \left( \frac{1}{\text{Capacity}} \right)
\]
Production = \begin{cases} 
0 & \text{if } DF < \alpha \\
DF \times \text{Capacity} & \text{if } \alpha < DF < \beta \\
\text{Capacity} & \text{if } DF > \beta 
\end{cases}

Where alpha and beta are lower and upper constraints between 0 and 1. The values of alpha and beta are chosen to balance the risk of running out of production capacity with over-producing unnecessary units. The value \( \alpha \) is dependent on the minimum run size on the machine. Companies that are more risk-adverse will tend to want to produce more than the determination factor calculates and thus, \( \beta \) will be larger.

Once a decision to produce is made, production needs at the SKU level could be determined by a simple proportional rule based on the SKU-level forecast, \( \text{Forecast}_i \).

\[
\text{Production}_i = \text{Production} \times \frac{(\text{Forecast}_i - \text{Cumulative}_i)}{(\text{Total forecasted} - \text{Cumulative Production})}
\]

More complicated algorithms could be developed to take into account minimum production quantities, set-up times, and forecasted demand variability.

2.4.2 Production of Replenishment and Safety Stock Units

The other production decision that P&G needs to make is the ongoing production decisions for replenishment stock and managing optimal safety stock inventory once the product has been launched. Retailers are typically on a drumbeat schedule, placing ongoing weekly orders to maintain safety stocks levels and cover upcoming demand. As highlighted in Figure 7, long production lead times (LT) and short turnaround times of orders (TT) means that P&G must actually begin production of an order prior to receipt of the order.
Typically, retailers expect turnaround of orders within one week (e.g. orders placed on a Sunday should be received by the following Sunday), while production and transportation lead times may exceed a month. In other words, P&G does not have the luxury to wait for receipt of the order before beginning the production process on that order. It is important for P&G to be able to forecast with some accuracy what the order quantity placed by the retailer will be. This is because P&G is producing in week t what will be requested by retailers during week t+LT.

Production is determined by extrapolating the projected inventory to determine the expected inventory level at the time the retailer makes the order and comparing that to the forecasted amount needed at t+LT weeks

\[
\text{Production} = \begin{cases} 
0 & \text{, if forecasted need < expected inventory at t + LT} \\
[\text{Need} - \text{Expected}], & \text{if forecasted need > expected inventory at t +LT}
\end{cases}
\]

Where

Expected inventory level =

Actual Inventory @ T = t + LT = Inventory @ t - \( \sum_{x=t+1}^{LT} (\text{forecasted}_x - \text{orders}_x) \)

- Forecasted Consumption @ T = t + LT

Forecasted need = Safety Stock + Forecasted\(_{t+LT+1}\)
Where safety stock is equal to four weeks of expected demand and forecasted,\textsuperscript{t+LT+1} is the forecasted replenishment need for the week (t+LT+1). Safety stock could also be determined by using more traditional periodic review methods based on the average and standard deviation of weekly demand.
In this section, we describe the process in developing a new product forecasting method. We also provide a description of the current methods employed by P&G and show benefits in incorporating new product demand forecasting methods into current processes. Finally, a forecasting method designed to contend with issues relevant to the cosmetic industry is described.

### 3.1 THE CASE FOR NEW PRODUCT FORECASTING

A typical product evolves through a sequence of stages from introduction to growth, maturity, and decline. Figure 8 graphs a typical product and the relative sales volume at each stage. While the scale and slope of the graph may be different, the general shape of the curve is applicable to most products, including trend-driven ones such as cosmetics.

**Figure 8. Product Life Cycle**

![Product Life Cycle](http://www.quickmba.com/marketing/product/lifecycle/)

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Each stage may require a different marketing, supply chain, and operation strategy to induce maximum sales and minimize costs. For example, product branding and heavy promotion is usually necessary in the introduction stage to build awareness of the product and grab market share. As the product progresses to the maturity and declining stage, a greater focus is placed on reducing costs through improved distribution or pricing adjustments.

While forecasting is important throughout the product’s life cycle, it is especially important in the introduction phase, when companies want to exert the maximum influence to drive sales and recognition of the new product. This is especially critical in the cosmetic industry, where purchases are often spontaneous and times between purchases are long. If a consumer makes a substitute purchase, it may be many months before she makes another similar purchase.

3.2 OVERVIEW OF FORECASTING TECHNIQUES

There are primarily four general categories of forecast techniques. The type of forecasting technique used depends on the type and amount of information available as well as the use of the forecast.

- Judgmental models rely on intuition, probabilities, and opinions of field experts. It usually involves either an expert panel making consensus agreements on forecasts or aggregating individual opinions independently until consensus is met. This type of forecasting is useful in situations where no quantitative information exists or where historical data can not be used due to a significant change in the selling environment.

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• *Technological forecasting techniques* are long-range, exploratory methods based on fitting forecasts to an expected growth patterns. For example, in forecasting a new product, a technological forecast can be created using historical sales information from a similar product that is currently on the market. This type of forecast is best used for long-range decisions at the product line aggregate level.

• *Time series models* use past historical information to make predictions about the future. They are based on past data patterns and include moving averages, exponential smoothing, and other methods to predict patterns, trends, and product changes. These forecasts are most relevant for making ongoing consumption predictions on a short-range level.

• *Causal forecasts* are created based on relationships between predictable factors and outcomes. It assumes that the variable in question, such as sales for a new product, is associated with other factors that can be forecasted. By forecasting the secondary factors, the sales for a new product can be also be forecasted. Methods such as regression analysis and leading indicators are commonly used.

3.2.1 The Test Market

The use of test markets as an input to a forecast is not new – many firms utilize a form of the traditional test markets to obtain both product marketability and projected sales forecast prior to full market launch of a new item. The viability of using test panel data was first documented by Fourt and Woodlock in 1960 where companies used diary entries from consumers to generate forecasts for long-term sales projection.

In order to be effective, a test market must reflect real market conditions. A keen understanding of the demographics and shopping habits of the test market is needed to
help understand the relevance of the results. For example, if a competitor introduces a similar product at the same time as the display period, display sales velocity are expected to be lower than those during the test period. Other factors that may affect forecast accuracy may be differences in where the product is located in a store, change in weather or economic conditions, and merchandising activity. One way to account for these differences is to assign a correlation factor between test and display sales velocity:

\[
\text{Display sales velocity} = C \times \text{[Test sales velocity]}
\]

Where \( C \) is a numerical factor that is based on differences observed between the two periods (\( C = 1 \) for no observable differences).

The ability to correlate test market behavior with real market demand also depends on a number of factors regarding the implementation of the test market, including size and length of trial. Advances in technology have also allowed companies to understand the demographics and behaviors of potential consumers and to strategically place test market to capture a representative real market situations. With the advent of advanced technologies such as POS systems, more accurate and timely forecasts could be reproduced. Fader and etc. in 2003 describe the use of test markets to forecast trial, first repeat, and additional repeat purchases. In most cases, a test market of 3-6 months is required to fully capture true repeat purchasing behaviors.

The cosmetic industry is different from others in that the long cycles between purchases and the short product-life cycle cause the majority of purchases to be trial-based. A P&G internal study conducted in 2001 found that trial volume made up 80-100% of the total consumption volume for the first year after launch. Even after the first year, trial purchases make up an average of 86% of total purchases. If we can assume
that all purchases made within the first three months of launch are primarily trial-based, it is possible to have a shorter test market period that only serves to capture trial-based consumption behavior.

3.3 CURRENT P&G FORECASTING METHODS AND MODELS

There are a number of forecast methods and processes that P&G employs during all stages of a product’s life cycle. Technological forecasts are developed by the market research group based primarily on existing market trends and availability of analogous (clone products) information. This method is relevant for long-range forecasts (e.g. annual volumes at a sub-brand level) and is used to assess financial viability of a new product and to make upstream manufacturing decisions such as capacity planning and other design criteria.

P&G also utilizes time-series techniques that are then subjected to qualitative and judgmental methods. This method is used primarily for forecasting replenishment orders and is most effective for their base product portfolio, where enough historical shipment information exists.

Replenishment forecast of new products needed for production and inventory management poses a problem for P&G in that sufficient information is not available to use time-series techniques, while technological forecasts do not offer the resolution necessary to make these types of decisions. Initial production decisions are based more on a “no-stock-out” philosophy, with attempts to re-level inventory back to target once adequate shipment information is available.

In addition to the traditional replenishment orders, retailers must make a pipeline order which goes towards stocking empty wall slots and filling warehouses with safety
stock. P&G must predict this order quantity as well. Initial safety stocks are determined based off of the initial replenishment forecasts and re-adjusted as consumption information is obtained.

The forecast model presented in this thesis serves to address the white-space opportunity within P&G to improve their short-range forecasts during the introductory phase of a new product. It is not meant to replace existing processes already in place for long-range decisions and base business production scheduling. It is meant to complement these existing forecasting techniques and can be layered on top of current methods.

3.4 ESTABLISHMENT OF DATA REQUIREMENTS

The first stage in the creation of a forecasting strategy is to understand what exactly you want to forecast. If the objective of the forecast is to determine financial viability of a brand, an annual sales estimate of the aggregate product lines could be used. On the other hand, if the purpose is to create a production schedule in anticipation of future customer orders, a different analysis at the customer and SKU level needs to be conducted.

3.4.1. Defining the data level

Understanding the level and type of data that will be used as an input to a forecast is important in ensuring that your forecast’s output is useful for the original purposes. Examples of the level of data to be measured could be the production output of a manufacturing plant, inventory turns at a DC, or point of sales at the retailer and consumer level. As your information source gets closer to the end consumer, your level
of detail into the system is magnified. At the same time, more collaboration is needed to manage information flow between external parties such as a retailer and a manufacturer. Therefore, a balance between management of information and the need for information is required.

To understand the appropriate level needed, a company should look at the general behavior of the products in their portfolio. Products can be categorized on their demand velocity (sales movement) and on their volatility (how steady the movement is between time periods).

High-volume, low-volatility products are typically seen as the easiest to manage and forecast. Products that are typically considered in this category include baby diapers and toilet paper. Forecasts are based on a “steady flow” approach, where replenishment orders are replaced based on inventory levels at the manufacturer or retailer’s distribution centers. Having the additional insight at the point of sales level may not provide additional significance. Low-volume, low-volatility products can also follow a basic replenishment approach with less dependence on point of sales information. While the low-volatility products may have lower inventory levels than their high-volatility counterpart, both types of products could use inventory turns at the DC level to make replenishment forecasts.

Detailed-level forecasts at the store and consumer level become more necessary with products that experience high volatility in sales between time periods. Products that are high volume with high volatility are more prone to bull-whip effects that make it harder to manage without point of sales information.
Cosmetic products fall into the hardest category to manage – the low-volume, high-volatility group. Inventory turns are extremely slow and would not give upstream processes an indication of when more production is needed. In the cosmetic industry, the minimum shipment quantity to a store may be equal to over 6 months worth of inventory. Watching inventory turns in a DC would not be able to provide a forecaster with the appropriate level of resolution. In these cases, point of sales would be more appropriate to obtain useful and accurate information.

For new products that have not been launched in the market yet, it may be helpful to use point of sales information regardless of the product categorization. This is because, during the new product introduction phase, many factors cloud actual retailer shipment behavior and DC inventory movement, such as pipeline shipment orders, additional buffers against potential demand, and an increase in promotional activities. Having the true sales information allows production to clearly see what end consumer demand is.

### 3.4.2 Segregation of a forecast market

P&G primarily sells their cosmetics to retailers. These retailers have traditionally been classified into four main segments – drug, mass merchandiser, dollar, and food stores. For P&G, the bulk of sales come from the drug and mass merchandising market, which comprises 30% and 45%, respectively, of total sales of cosmetic products.

A mass merchandiser is a large, self-service general store. Examples of mass merchandisers include Wal-mart and Target. They tend to compete on cost and convenience, allowing the consumer to do the bulk of their shopping in one location. Many mass merchandisers such as Wal-Mart and Target are moving to become super-
centers, which is a combination of both a complete mass merchandiser store and a complete grocery store.

A drug retailer is more specialized, offering a range of prescription and over-the-counter (OTC) products, as well as health and beauty supplies, which includes cosmetics, toiletry items, and vitamins. Retailers in this bucket include Walgreen’s, CVS, and Rite-Aid. They are typically smaller in size and bring in less traffic than the larger mass merchandisers, although drug chains make up for this by having more stores. For example, there are approximately 1500 Target Centers and Super-centers in the US, while Walgreen’s boasts more than 4500 stores nationwide.

Because of the difference in foot traffic, a significant difference in sales velocity is observed. Sales velocity can be defined as the number of items sold per store in a given time period. A mass merchandiser store can move products up to five times faster than a drug store. Figure 9 shows the difference in sales velocity between the drug and mass market for specific product lines that were launched in January, 2004.

**Figure 9. Comparison of Sales Velocity between Drug Market and Mass Market**

![Comparison of sales velocity between drug market and mass market](image)

- Lipstick
- Mascara
- Face

Product Line
Another difference between the drug and mass markets is the timing of new product launches. Drug stores, in an effort to compete against the low costs that a mass merchandiser can offer, have improved their organizational efficiency to allow them to introduce new products earlier to the consumers and capture early sales.

In determining the market level at which to forecast at, one option is to ignore these differences and simply create an aggregate forecast for all the different types of retailers. The potential problem is that the true behavior of the product may be masked. For example, a new product which is offered a few weeks earlier in a drug retailer before will exhibit a jump in sales velocity once the product is introduced through the mass merchandisers. This forecast may be misinterpreted as an increase in actual demand for the product.

A better option may be to create and use a forecast, \( F(m) \), for a selectively chosen market, \( m \). Forecasts for the entire product line, \( F_T \), can be determined by aggregating the sub-forecasts for all the markets.

\[
F_T = \sum_{m=1}^{M} F(m)
\]

Segmenting the marketing into the appropriately sized groups can be done based on looking at similar consumer demographics, the type of retailer, or other factors.

To date, P&G can not easily extrapolate POS data beyond the retail account level. In other words, one can measure weekly sales for Retailer A’s, but could not look at individual store sales. Therefore, for this thesis, we looked at grouping all retailers classified as drug stores into one market group and classifying mass merchandisers in another group. P&G has previous researched customizing marketing efforts at the individual store level, grouping subsets of stores for which the demand of the customer
base is similar. Retailers have or are developing micro-marketing databases which allow
them to track behavioral and demographic data on their customers. In the future, there
is opportunity to create forecasts based on markets segmented by real consumer behavior
and demographics. Forecasting at this level will help to further improve accuracy. For
example, a small Target store located in a rural community may behave more like a
typical drugstore, although the current model counts it in the mass merchandiser bucket.

3.5 A FORECAST MODEL FOR NEW PRODUCT LAUNCHES

The new product forecast model developed for P&G’s new cosmetic product
introductions has two main objectives – first, it seeks to predict the amount of wall stock
needed, assuming that this stock includes the transfer of unsold pieces from the display
period. Second, it seeks to predict basic replenishment and safety stock orders made
during the first three months after a launch. The key concern was the ability to
extrapolate information from limited data to make short-term weekly/daily production
and inventory planning decisions at the SKU level.

The final forecasting method is a combination of causal and time-series methods
that can be used both to make inventory build-up and planning decisions prior to the
official product launch date and to monitor the product in the first few critical months as
customers make adjustments in safety stock and replenishment orders according to actual
demand. There is also future opportunity to integrate the information into demand
decision planning, such as developing promotional marketing strategies or deciding
product placement.
3.5.1. SKU-level forecasting of wall stock units

In the most simplistic sense, the wall stock order, which provide aesthetic appearance to the selling space and act as a place to hold inventory, can be calculated by the following:

\[
\text{Wall stock order} = \# \text{ of walls} \times \text{presentation pieces/wall}
\]

Typical values for the presentation pieces/wall are usually 2-3 pieces.

The calculation becomes more difficult for products which were on a promotional display prior to the wall reset. Generally, display pieces that did not sell during the display period are transferred to the wall as additional inventory. Ideally, a retailer would like to know how many display pieces were not sold and adjust the wall stock order accordingly:

\[
\text{Wall stock order} = (\# \text{ of walls} \times \text{presentation pieces/wall}) - (D_{\text{ini}} + D_{\text{rep}}) \times (1 - \text{PLV})
\]

Where \(D_{\text{ini}}\) are the pieces that are used to fill the displays, \(D_{\text{rep}}\) are any additional pieces that customers order to replenish anticipated demand during the display period, and PLV is the percentage display lift, or the percentage of pieces that were sold relative to the total number of pieces available for the display period.

The initial PLV can be determined based on historical lift values or by judgmental forecasts. Subsequent values can be determined by multiplying the item’s sales velocity – the average pieces sold per store per week – by the number of displays available and dividing that by the total number of display pieces available.

\[
PLV = \frac{\sum_{i=1}^{D} (\text{sales velocity})_D \times (\# \text{ of displays})_D}{D_{\text{ini}} + D_{\text{rep}}}
\]

Where \(D\) is the number of weeks that a display period is available to consumers.
Because retailers usually require the wall stock units to be ordered up to six weeks in advance, the placement of orders occurs before any accurate information on the sales velocity or PLV from the display period is available. Therefore, a forecast of SKU-level sales velocity is needed.

The forecasted SKU-leveled velocity is calculated using traditional exponential smoothing technique, which is described by the following equation:

\[
t_i u_i = S(t, v_i) + (1 - S)(t_{i-1} u_i)
\]

Where

- \( t_i u_i \) = velocity forecast of SKU \( i \) for future periods
- \( t_i v_i \) = current sales velocity of SKU \( i \)
- \( t_{i-1} u_i \) = previously forecasted velocity of SKU \( i \) for current period
- \( S \) = smoothing constant with values between 0 and 1

Information on the current sales velocity is obtained from sales during a test period, which occurs prior to the display phase. For SKUs that are not represented in the test phase, the average velocity of the entire product line (if it is part of the test period) or historical sales information from a like-product that is on the market could be used.

Determining the smoothing constant that provides the most optimal results requires more thought. Training of the model could be done using a data set from analogous products and the constant could be set accordingly. Where no training sets exist, it is often sufficient to set the constant for the first forecast week as \( S = 1 \). The smoothing constant for subsequent weeks can be calculated by comparing the coefficient of variation (weighted standard deviation) of the entire product line against the specific SKU and make an adjustment depending on the level of deviation.
SKU-level forecasting of replenishment and safety stock units

Retailers make replenishment orders to replace product that has been sold. If the product faces long lead times, retailers often must place orders for projected sales over the lead time. Replenishment can be determined by

\[
\text{Forecasted replenishment} = \# \text{ of stores} \times SV_T
\]

Where \(SV_T\), the total sales velocity per store, is:

\[
SV_T = SV_B + SV_P
\]

Where \(SV_B\) is base sales and \(SV_P\) is sales velocity induced by promotional and marketing activity.

\(SV_B\), which is the amount of sales activity that is attributed to normal demand, can be thought of as the aggregation of four components. The trend is the overall upward or downward tendency of the data. Seasonality is the periodic fluctuation that occurs due to seasonal factors throughout the year. Cyclical factors are variations that may occur over a long period of time due to economic trends. And finally, a random factor is noise variations that are inherent in a dynamic system. Random factors are usually not predictable and are assumed to be insignificant for our purposes. For forecasting of new products during the first three months of the launch, seasonal and cyclical factors are not applicable. The trend fact, on the other hand, is likely a significant contributor to the base sales velocity and needs to be considered. In that case, the \(SV_B\) for the time period over the lead time is

\[
SV_B = t_u_i + TF*(\text{lead time})
\]

Where \(t_u_i\) is calculated using an exponential smoothing method discussed in the previous section and \(TF\) is a moving trend factor that is calculated by looking at the slope of the
actual sales velocity from previous weeks. Once again, smoothing constants to determine \( \text{SV}_t \), need to be determined using a training set or pre-defining a value based on historical or known information.

SV\(_p\), promotional sales velocity, is the increase over base sales velocity induced by promotional activity, such as coupons, rebates, or in-store specials. One method for estimating this is by assuming an increase as a percentage of base sales velocity. This percentage increase should be determined by looking at effects of similar historical promotional activities and should take into account the percentage of stores that the promotion will affect.

Safety stock is needed to buffer supply and demand uncertainties that result from network inefficiencies and inherent variability in the system. Typically, retailers hold 30 days of safety stock, although a number of approaches could be used to calculate levels based on the forecasted demand and deviation. A common approach is to use a basic period replenishment model where safety stock levels are replenished on a scheduled timeframe. The forecasted safety stock levels needed is therefore

\[
SS = z\sigma \sqrt{I + r}
\]

Where \( \mu \) is the forecasted demand, \( r \) is the reorder interval, \( \sigma \) is the forecasted deviation, \( I \) is the lead time, and \( z \) is a value associated with the service level, which is either pre-determined based on customer service requirements or optimized by comparing the cost of inventory to the cost of understocking.
The new product forecasting methodology described in the previous chapter was developed and benchmarked against traditional forecasting methods using historical data. In this section, we will discuss the results of this case study.

4.1 CASE STUDY INTRODUCTION

The purpose of the case study was to assess the following:

1. Determine the ability to forecast items that are assumed to be highly volatile (in terms of sales) and generally perceived within the organization to be “non-forecastable”
2. Develop a forecasting methodology designed to predict the ideal wall stock production and order quantity as well as dynamic replenishment and safety stock needs.
3. Compare supply chain inventory results from a DDSN strategy incorporating this forecasting methodology with inventory results due to traditional SCM.

The forecast model was tested using a historical product launch. In choosing the appropriate product line to measure and the market level to forecast, we felt it was important to pick products and markets that would be more difficult to forecast. This would allow us to measure the robustness of the model in forecasting complex scenarios. The product launch that was studied was a color product that included 46 SKUs. A color product line was chosen for its complexity, as both production scheduling and inventory management becomes more difficult to manage as the number of SKUs increase. We chose to forecast demand for four customers classified in the drug store market segment, which represents approximately 20% of total volume sales. Because of the low per-store
volume and high number of stores, we felt that the drug channel would be more challenging to forecast due its higher volatility (over the mass merchandisers channel).

Weekly sales consumption from four drug retail customers was collected by ACNielsen. Information about shipments from P&G to the retailers was collected using internal shipment databases.

The display period lasted 8 weeks occurring right before the official launch of the product. A test period was simulated based on sales information from approximately 430 stores that were part of a small regional drugstore chain. This chain was not one of the four included in the case study. We assumed that this test period occurred prior to the display period and lasted 5 weeks.

The analysis conducted on this data sample provides some measure of proof that even the sales of the most trend-driven, highly volatile SKUs can be forecasted to an reasonable degree of accuracy over the three month period after a product is launched, which is defined from company standards as having a forecast error ± 30%. From the case study, we also present some initial conclusions on how new product forecasting could be used to supplement current practices and provide benefit to both P&G and their retail customers.

4.2 PRELIMINARY ANALYSIS

The forecast methodology presented in Chapter 3 was run against the historical sales information for the color product line. The forecast for the sales velocity of the 46 SKUs were aggregated and compared to the actual sales velocity. Aggregate forecast error was calculated as followed:

\[
\text{Aggregate Forecast Error} = \frac{\sum_{i=1}^{N} (\text{Forecast} - \text{Actual})}{\text{Actual}}
\]
The results are shown in Figure 10, where week 0 is assumed to be the launch week of the new product.

**Figure 10. Aggregate forecast error**

A four week production leadtime was assumed, which means that a forecast created on week \( t \) is actually for four weeks out \((t+4)\). Therefore, the forecast from the first four weeks is based on sales information from the test and display period. Subsequent weeks are based on real sales information after the new product launched.

The aggregate forecast error was within current target specs of ±30% of actual sales velocity within six weeks after product launch. At a product-line level, forecasts can accurately predict actual sales.

At the SKU level, results are also within target specs. Figure 11 shows the number of SKUs within the product line that were forecasted within the ±30% target.
On average, 75% of SKUs were within the targeted forecast error of ±30%. Of that 75%, approximately 80% of those were consistently within the targets – in other words, an item’s forecast error was within specs for multiple weeks. If we were to examine all of the SKUs, 95% of them were within ±60%. SKUs that were not within the target specs typically had higher volatility, making them more difficult to forecast.

4.3 SKU-LEVEL CHARACTERIZATION

Different SKUs exhibit different consumption patterns and we can compare how the forecast model reacts to these differences. Figure 12 shows forecast error for three different SKUs within this product line. Figure 13 shows the relative sales velocity between the three SKUs.
Figure 12. Forecast error for three different SKUs

SKU 1 – “Fast Mover”

SKU 2 – “Slow Mover”

SKU 3 – “Trend Mover”
SKU 1 is characterized as a “fast mover”, or one that exhibits stable, but higher than average sales (relative to the average of the product line). The forecast model was able to very accurately predict sales velocity of these SKU types. These SKUs are easier to manage from a production and inventory planning perspective.

SKU 2 is characterized as a “slow mover”, or one that exhibits relatively low, stable sales. Initial forecasts, which were determined from the display period, were higher than expected. These are one of the hardest SKUs to manage from a forecasting perspective as lower volume items tend to see a bigger impact of percentage forecast error as a function of absolute error. Yet, even with a slow moving SKU, we see that the forecast was mostly within target by the 3rd month. From an inventory standpoint, the cost to manage the slow movers at the same customer service level as a larger mover is higher. An analysis could be performed to determine the optimal service level for these items based on minimizing overall cost.

SKU 3 is characterized as a “trend mover”, or one that exhibits an upward trend in sales with time. Although initial forecasts were slightly above actual performance, the
forecast accuracy was within target specs by the end of the 2\textsuperscript{nd} month. In the forecast method, trend was not entered into the forecasting equation until the fourth week to allow for sufficient data. This may account for some of the fluctuation seen in the first two months. These SKUs can also be difficult to manage, especially if the trend is not observed immediately. With potentially long lead times and miscommunications, a bullwhip type effect can occur, causing oscillations up the value chain as manufacturing and suppliers respond.

One benefit from a forecasting tool would be the ability to provide early characterization of which items fell into which category. The forecasting model shows potential in being able to predict characterization:

**Figure 14. Early Characterization of SKUs from Display Period**

![Figure 14. Early Characterization of SKUs from Display Period](image)

Each point in Figure 14 represents one of the 46 SKUs tested in the case study and is based on information obtained during the display period. By examining this figure, P&G could make some generalizations regarding the nature of the SKUs. Although it may be difficult to ascertain whether an item will have a tendency to trend, we can look at overall magnitude and see that both SKU 1 and SKU 2 would be classified
as fast and slow movers, respectively. From examining display period information, SKU 3 seemed to be a high performer and, indeed, actual performance by the 3rd month after launch placed its sale velocity in a position that was higher than SKU 1.

We can also use the volatility to help understand how valid the data is. Forecasted items that exhibited high volatility should be monitored closely and safety stocks adjusted accordingly to account for the higher variation.

For both SKU 2 and SKU 3, the initial forecasts, which were created based on information from the display sales, were significantly higher than actual wall sales. This is because the model assumed a 1-to-1 correlation between sales velocity during the display period and sales velocity after the product was transferred to the wall. In real life, displays are more eye-catching and tend to attract more spontaneous purchases. By using a correlation factor, this over-estimation of slow and trend movers could be reduced without significantly affecting the large mover groups (we found that a display:wall sales ratio of 0.8 was the optimal value for this case study).

**4.4 Retailer Inventory Comparisons**

Unfortunately, because P&G did not forecast consumption sales of this product line, we are not able to compare the model’s output to current practices.

What can be compared are inventory levels using the described forecasting methodology and actual inventory levels that retailers held for this new product launch. Figure 15 compares the actual inventory held by the retailer prior to the launch date with the inventory that the retailer would have held had they used a sales-based forecasting method.
Each point on the graph represents one of the 46 SKUs tested in the case study. Excess inventory is defined as the remaining inventory after minimum wall presentation and safety stock units are accounted for. The straight diagonal line represents same performance between actual and model results. The model used test market and display period sales information to forecast wall stock, first replenishment, and initial safety stock ordering quantities. In contrast, actual performance was determined by the retailer using sales information based off of clone products or predictions based off of expert opinions within P&G and the retailer. SKUs that fall above the diagonal represent items where customers held more inventory than needed than what the model would have determined. As an example, if a customer was carrying 95% more inventory than needed, the model performance would have been 75% more than needed. Through the
use of improved forecasting, customer inventory can be reduced overall by 20% prior to the onset of the launch.

What can also be compared is the amount of aggregate inventory that retailers held during the first three months after a product launch. Figure 16 compares the amount of inventory held by the retailers over the 14 week period after a new product launch with inventory results from the model simulation.

**Figure 16. Retailer Inventory Comparison**

In the figure, week 1 denotes the first week of launch when the product is moved to the wall. The model uses the demand forecasting techniques described in Chapter 3, with order quantities determined using the equations described in Chapter 2.4.2.

At the onset of the launch, the model shows 200% less excess inventory at the retailer than actual performance. This is consistent with the findings described in Figure 15, which shows that, at the SKU-level, the amount of product retailers order prior to the launch is more than that which the forecast model suggests.

For the model, the first four orders (week 1-4) were actually placed prior to the wall launch and were based off of test and display sales information. This is due to the assumed four week lead time. By the 5th week, the model is able to use real sales
information and begin to correct itself, with the bulk of excess inventory eliminated within two months of the product launch.

One of the weaknesses of the model is its inability to capture inventory that is due to network inefficiencies. Some network inefficiencies include the need for minimum quantity purchases as well as behavior inefficiencies such as localized hoarding of products in anticipation of potential stock-outs. For example, while the model may determine a retailer ordering quantity of X, the retailer may actually need to order more than that if they have policies or cost reasons to fill a truckload or if the manufacture has minimum order quantities greater than X. Retailers may also increase orders above ideal order quantities, especially if they have experienced problems in the past in getting product. The model does not factor in minimum quantity purchases or consider local behavior patterns that may induce retailer hoarding of some products.

Nevertheless, even in the most conservative manner, this reduction in inventory can be translated to significant financial benefits, which have been estimated at close to $4 million annually, shared between retailer customers (40%) and P&G’s cosmetic business unit (60%). If we were to include other indirect benefits such as better management of production as well as potential revenue increases as retailers faced less stock-outs, potential annual savings exceed $5 million. With an increasing importance placed on new products and a growing percentage of new products in the company’s product portfolio, these savings may be even more in future years.
In this section, we discuss the requirements and impacts on organizational and supply chain processes to successfully implement the proposed forecasting and inventory management strategy.

5.1 THE ROAD TO IMPLEMENTATION

For a long time now, retail supply chain has struggled with the balance of supplying the right amount of product at the right time to the right customers and demand. The new product launch process adds complexity to this equation. On the demand side, there is limited (if any) demand information available and more than usual promotional push. On the supply side, production must begin far in advance of the launch date to ensure sufficient capacity to produce the needed wall, safety, and replenishment stock. An ideal future state of the new product launch process would be a perfect supply of product being received at the right time and right location and demand being controlled through marketing levers to best optimize revenue and cost.

Full implementation will be significantly challenging as it requires both a paradigm shift in the way P&G manages their supply and demand strategies as well as a strategic shift in the way new products launches are managed. A change of this scale needs to be established in increments, ensuring buy-in first from the internal function groups, including marketing, product supply, and product development, as well as getting collaboration with external partners including suppliers and retail customers. Some of the key considerations are listed below.
5.1.1 Establish metrics to determine forecasting portfolio.

While it may be nice to forecast all of the new products that are introduced, resources may not make this a feasible option. At any given time, P&G’s product portfolio is composed of more 1500 SKUs, with up to 30% considered in the new product category. This percentage is likely to increase in the future as well, as new products play a more dominant role in maintaining sales growth. Because of the large number of SKUs, metrics and decision criteria’s should be established to determine which items would benefit most from new product forecasting.

Before a decision on which SKUs should be included is made, P&G needs to look at which SKUs are capable of being forecasted. Intuitively, we could expect forecast error to increase as the leadtime over which the forecast is needed increases. Weather forecasts for the next 24 hours are more accurate than a forecast for 10 days out. Analogously, forecasts for next week’s consumption are typically more accurate than forecasts for consumption four week’s out. Figure 17 compares the forecast error for six different forecasts that were made at the same time (t = Week 0).

Figure 17. Forecasts Error

<table>
<thead>
<tr>
<th>Forecast for:</th>
<th>Forecast Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>Week 1</td>
<td>8%</td>
</tr>
<tr>
<td>Week 2</td>
<td>1%</td>
</tr>
<tr>
<td>Week 3</td>
<td>8%</td>
</tr>
<tr>
<td>Week 4</td>
<td>20%</td>
</tr>
<tr>
<td>Week 5</td>
<td>31%</td>
</tr>
<tr>
<td>Week 6</td>
<td>30%</td>
</tr>
</tbody>
</table>

We can see that forecast error increases for those forecasts made for weeks that were further in the future. The appropriate lead time over which a forecast is accurate varies depending on the forecast inputs. A forecast created during the first week of launch that uses very little information will have limited ability to accurately forecast past a few
weeks. On the other hand, a forecast created at end of the new product launch phase (t = 3 months), can be accurate over a longer time period (up to 6-10 weeks).

To assess whether a product is capable of being forecasted, we need to compare the product’s manufacturing lead time with the forecast model’s ability to forecast over that lead time. For the bulk of P&G’s cosmetic products manufactured in-house, this is not an issue. Typical manufacturing lead times are 3-4 weeks and the model is capable of creating forecasts out through those lead times. On the other hand, products that are outsourced to contract manufacturers (CM) usually have significant lead times (up to four times longer than internally produced items). This makes it very difficult or impossible to use forecasting as an input in making production quantity decisions for those products.

Once a list of feasible SKUs are determined, decisions on which SKUs to include in a new product forecasting process can be made based on a cost-benefit metric. Color cosmetic product lines tend to be more difficult to manage and expect to have the largest benefits in terms of inventory savings.

5.1.2 Determine criteria of success for forecast output.

In this case study, forecast error was based on measuring the error relative to a perfect forecast. This provides a basic idea of potential forecasting bias, but may not be the most appropriate in understanding how the forecast error impacts top or bottom line results. For example, what is the impact on revenue or cost if SKU 1 is inaccurately forecasted compared to the revenue impact of SKU 2 if it is equally forecasted inaccurately? To perform such an analysis, the forecast error should be weighted on either a volume or revenue basis.
Forecast targets should also be examined on a SKU-by-SKU basis. The case study used an accuracy target of ±30% because of the current metrics used within P&G. While this may be good from a reporting standpoint and a means to make a high-level judgment on the forecast process’s validity, it may not be an appropriate measure to reflect SKU level performance of the forecast. This is because target specifications should be determined based on the natural volatility of the SKU. It would be impossible, even with the most high-tech forecasting model, to predict a highly volatile SKU within target limits that are less than the SKU’s natural random fluctuations.

This is especially relevant if forecast error is being used to make judgments on the performance of a forecast or demand planning group. A very stable product with low volatility that easily met large-spread targets would become a favorite amongst forecasters to own in their portfolio. In this case, targets should be adjusted accordingly depending on the expected volume. A weighted forecast error may also be applicable.

5.1.3 Develop a system of accountability

While the need for a method to measure forecast error throughout the product launch period is understood, without a stable system in place, the cultural attitude is to take a “no-stock-out” policy and make adjustments once more consumption sales and shipment information is available. Currently, this information isn’t unavailable until 3-6 months into the launch. Inaccurate forecasts made during the introductory phase of a product are seen as unfortunate, but necessary. Individuals and groups that play a part throughout the launch process, including demand forecasting, sales, marketing, and product supply, need to be held accountable for behavior that goes against the new paradigm.
Implementation of a system to monitor accountability is not designed to specifically blame someone; rather, it allows the company to reflect on and improve the forecast process. This could be controlled by documenting any changes that is made to a new product forecast, including keeping a record of the person or group making the change, and the reasons for the change. Shipment information to retailers should also be documented in a similar way to understand where, if any, excess inventory is introduced in the system. In this way, the process involving the evolution of the forecast could be reflected upon to improve the process.

5.1.4 Obtain display lift values through test market

As was mentioned previously, wall stock orders should be adjusted to account for unsold display products. Because wall stock orders are made before the end of the display period, a test market is used to make estimations on the display lift. Technical organization is needed to ensure that product and promotional counter displays are available and on retailer countertops or walls in time. This means that preparation for a test market must be incorporated in the current P&G new product launch process.

One potential issue that arises with the initiation of a test market is managing retailer relationships. Because of the complexity of implementing such a market, it may not be possible to offer test product through all retail customers or channels. This can be a problem if one retailer feels that they are at a competitive disadvantage because they receive the new product line later than another.

Implementation of the test market will also need to be monitored closely to ensure that retail customers have correctly. Oftentimes, due to limited counter-top space in the retail stores, displays are not always set up at the requested time. Some retailers may
wait for an existing display unit to completely sell out before bringing out another to replace it, while others may bring out new displays but place them in non-ideal locations (behind a wall beam, behind other displays, etc). All these factors will affect the data obtained and must be considered.

The incorporation of product stock-out must also be considered. A typical display unit will hold 2-6 pieces/SKU. While some retailers may order replenishment display units should the initial units completely sell, many do not replenish as it may be time-consuming to continuously monitor something that is only on counters for 5-8 weeks. For a product that has stocked-out, we must realize that the actual sales of the product may not necessarily represent the true demand. In this case, more complex algorithms that look to extrapolate real demand from sales information could be used for a more accurate test market output.

Finally, while no research was conducted in this area, it is possible to simulate a test market in an on-line setting, especially with advances in technology and the rise of internet capabilities. If testing through retailers is not possible, traditional methods such as focus groups may also help to understand sales, although these methods tend to be more qualitative and provide only an indication of which items may be more popular.

5.1.5 Apply lean principals to marketing process

Unlike the manufacturing and supply side of P&G, there has not been significant “leaning” of the marketing processes. Typically, marketing activity for a product launch takes 3-6 months to design and implement. This is because of the long lead times in obtaining acceptable graphics, collaborating with outside vendors, and reserving needed ad space or commercial time slots. This long lead time means that promotions for new
products are actually set long before the product is sold and information about the product’s sales are known. An ill-timed advertisement campaign may actually cost the company more than the revenues generated from the promotion if supply chain resources are already constrained.

While there are many cost-saving benefits of a new product forecasting strategy, the potential to optimize revenues may be even more significant. Early indications of a product’s performance can allow marketing to strategically making promotional decisions that would have maximum impact. Having accurate sales information would also allow the sales units to understand the true gap between production capacity and demand and promote the product accordingly.

In order to successfully achieve this, marketing needs to have the ability to make dynamic adjustments as more information about a product is known. Rather than having marketing determine a strategy months in advance, they could create multiple avenues that could be used depending on the product’s performance. For example, if a product is performing significantly better than expected and straining production resources, marketing may re-allocate potential resources for a coupon campaign to another product where sales have been less than expected.

In addition to dynamic determination of promotions, other levers such as product placement and distribution can be adjusted as product performance is known. Currently, regardless of how a product is performing, it will remain on the retailer wall until the next re-launch period, which may be up to six months to a year later. This means that poor selling items may be taking up valuable retail shelf space while “hot” selling items may not be selling in the maximum number of retail stores. There is benefit to both the
retailer and to P&G if dynamic adjustments can be made based off of new product forecasts.

Ultimately, this will mean a paradigm shift in marketing, where decisions for new products are based somewhat on the holistic analysis and not just on experience. Having contingency plans in place to consider possibilities of product that performs higher than, at, or lower than expected allow marketing to truly optimize their budget for maximum return.

5.1.6 Integrate forecast process into current business practices

From a technological standpoint, the ideal future state is a new product forecasting methodology that can complement the current forecasting methods for base products and be integrated with the current production and inventory control planning systems. To ensure a smooth transition of this new process, it may be practical to implement in stages. In the first stage, it is important to prove the concept and show benefits in terms of inventory savings for the retailer. Selecting the retailers in the first stage should be based on the existing relationship and how advanced they are with their supply chain. Forecasting should be conducted on a small selection of the entire new product portfolio. As success is proven out, the number of retailers and the number of products to incorporate in this method should be expanded accordingly. Forecasting for these select products will be done using a new product forecast tool such as the one described in Chapter 3. This will need to be done on a weekly basis (vs. the current monthly basis of base products) to be able to capture deviations that are inherent in the transitional nature of new products. As new product forecasting is adopted as the “way
of doing business”, integration of POS information between retailers and P&G should be considered to eliminate human error and further reduce lead time.

It may be necessary or beneficial to conduct the first stage as an offline simulation that was parallel to actual operations but which would be observed in real time. In this way, P&G could convey potential benefits to a retailer by comparing actual inventories with potential inventories had the system been implemented. At the same time, there is minimal risk to the retailer should there be problems in the transition.

**5.1.7 Create joint-value with retailers**

The current value chain is one where P&G sells to end consumers but ships product through retailers. This means that ultimately the retailer has the power in deciding the final order quantity. For some, the retailer may depend on P&G to provide them with forecasts and information to help them determine order quantities. For others, the retailer may have their own system in deciding new product order quantities.

One major assumption that forecast model follows is that retailer behavior and ordering patterns are determined based on standard inventory rules. It does not assume external behavior factors such as hoarding (when retailers order more than they actually think they need) to hedge against risk of future supply allocation. Having an accurate forecast is moot if a retailer chooses to place an order based on their own system. Yet, as the case study shows, using sales-based forecasts can improve inventory for both retailer and P&G. This is real cost savings that can be invested back into the business, creating more profit for everyone. Therefore, it is crucial to have an established relationship with the retailer where both parties are interested in creating joint value by working together.
5.2 CULTURAL BARRIERS TO IMPLEMENTATION

Like most large companies, P&G has developed a distinct culture. One of the most prevalent components of the culture is the corporate belief that “P&G lives and breathes their consumers”. One of the primary drivers of this culture is the importance of the end consumer. This is stated in their corporate mission statement and is one of the major driving forces in all strategic decisions that are made. As a result, the groups that interface most with the consumer (marketing and sales) are seen as the powerful force within the company. Other groups, including product supply, are designed to support the marketing and sales groups. As a result, it is difficult to gain exposure and company buy-in without support from these groups. Implementation will require involvement and collaborative effort between marketing and product supply, where the basis of the work initiated.

Another strong cultural element within the cosmetic group in particular is their focus on holistic value chain improvement, especially as the company looks to find a competitive advantage through partnering with the increasingly powerful retailers. This has promoted the increase in information flow between retailers and P&G and allowed for the creation of initiatives such as this project. Unfortunately, while P&G’s strategy is moving towards holistic solutions, historical infrastructures and incentive systems still prevail. Sales performance is still judged on how much P&G ships to retailers, regardless of whether that product is sold to the consumer or returned later through P&G’s buy-back program. During new product launches, the manufacturing group is applauded in its ability to produce to a target production level, even though that level itself may be inaccurate and highly overestimated, causing excessive inventory and problems.
throughout the product’s life cycle. A deep look at organizational infrastructure may be necessary to ensure that incentives and accountability are designed to enhance the company’s behavior towards holistic objectives and not towards traditional, local benefit.

Perhaps the strongest influence that culture plays is the perception that the cosmetic industry is like the stock market. It is perceived that you can make best guesses on how a particular SKU will perform, but ultimately, it is “impossible” to forecast in such a trend-driven industry. Often, in meeting with individuals outside of product supply, I heard comments such as, “I understand the concepts behind your project, and maybe if this was [the] diapers or toilet paper [business unit], it would work. But you can’t ever forecast cosmetics”. Even with data disproving this theory, it has been difficult to change people’s mindsets. Training on how forecasts are developed and what they can and can not accomplish will help the company better understand what role such a process could play in improving business.

The management of changing a cultural paradigm requires top-level support from both the manufacturer as well as their collaborative retail and supplier partners. The strategic vision of how a collaborative DDSN strategy would benefit all parties must first be agreed upon by everyone. Once the mutual goal is determined, expectations, expected financial benefits, and an executable implementation plan to roll-out the new initiative can then be planned out.
Figure 18. Business Focus on Demand Collaboration

Business Focus on Demand Collaboration

Joint Business Plan: Define Mutual Expectations and Financial Results

Senior Executive Level

Manager Level

Define Demand and Inventory Information That Will Be Shared

Manager Level

Agree on Relationship Parameters and Rules (e.g. What is a Forecast, a Commitment to Buy, and a Commitment to Supply)

Manager Level

Performance Measurement and Reviews

Senior Executive and Manager Level

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This thesis serves to advocate a paradigm shift needed in the company - one from independent demand and supply planning to a more collaborative approach which will maximize the benefits of a new product forecasting process. This represents a move to true management of new product launches. In the words of one employee, “P&G currently has no information on a product’s success or failure out in the market for the first three months. Yet, we have to keep producing to hedge against stock-outs. When information starts to become more available after the 3rd month, we reassess any damage and adjust our production and forecast accordingly.” This reactive approach can mean significant inventory; in some cases, the inventory produced in the first few months exceed that which will be needed for the product’s entire life cycle. With a forecasting strategy to capture early demand, P&G can take a proactive approach to optimizing overall profits by reducing costs due to excess inventory and optimizing revenue by appropriately allocating promotional support.

The bulk of the project work conducted at this internship focused on the development of a forecast model that could be used in parallel with existing business practices to improve demand planning and inventory management for new product launches at both the retailer and at P&G. An effective and accurate forecast methodology is a critical input for a successful DDSN strategy. This forecast model was tested against historical data and proved to be effective in reducing excess inventory at the retailer, improving production planning at P&G, and providing early indicators (within 6 weeks of launch) to help marketing adjust promotional levers to improve sales.
Effective implementation will require high-level management support to drive this paradigm shift, continuation of building retailer relationships where information can be shared for mutual benefit, and an integration of this process and system into current practices. While such an implementation may be substantial, the benefits that such a process can bring are enormous and P&G has the ability to turn their supply chain into a true competitive advantage.
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