Reducing Inventory by Simplifying Forecasting and Using Point of Sale Data

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Requirements for the Degree of

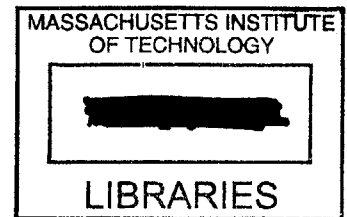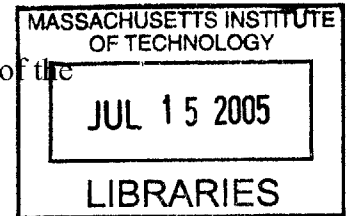## Master of Engineering in Logistics

at the

Massachusetts Institute of Technology

June, 2005

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Abstract

This thesis assesses the value to vendors of using point of sale data to predict what retailers will order from them. In particular, we look at how The Gillette Company can use point of sale data generated by two of their customers, (Wal-Mart and Target), to predict the orders of all of Gillette's customers combined. The thesis also examines the impact on forecasts of shortening and simplifying the demand planning process. By improving the forecast of orders from their customers, vendors like Gillette can reduce safety stock inventory which is held as protection against unpredictable demand.

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Acknowledgements

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1 Introduction

1.1 Research Question:

Can companies reduce inventory by simplifying demand forecasting and using point of sale information?

1.2 Definitions:

A typical retail supply chain, which has been adopted for this study, flows as follows:
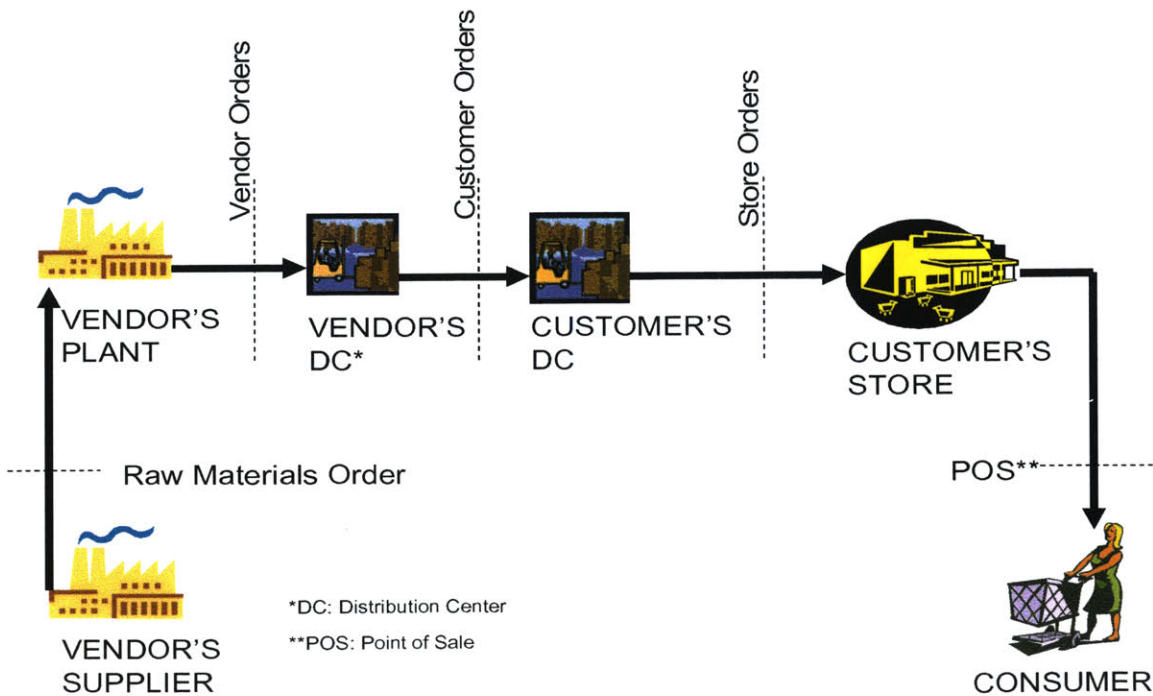
Figure 1: Typical Retail Supply Chain

A vendor's supplier is an entity who supplies raw materials and parts to a vendor. A vendor (such as Gillette) is an entity who manufactures, distributes and sells a product (such as shaving cream). The customer (of the vendor) is defined as a retailer (such as Wal-Mart) who sells the product to the consumer.

When a consumer purchases a product from a customer's store, an electronic record may be kept of the transaction. We call the collection of all such records "point of sale data" (POS). The customer's store replaces the products which were sold by placing "store orders" with the customer's distribution center (DC). The customer's DC replaces the products it sends to the customer's store by placing "customer orders" with the vendor's DC. (In cases where vendor managed inventory (VMI) or co-managed inventory (CMI) are practiced, the order may actually be placed either by representatives of the vendor or the supplier. Regardless of who places the order to replenish the customer DC or how it is placed, we define it as a "customer order".) The vendor's DC then replenishes itself by placing "vendor orders" upon the vendor's plant. Finally, the vendor replenishes materials used in production by placing a "raw materials" order with the vendor's supplier.

1.3 Brief Overview:

This thesis is written from the standpoint of the vendor. The vendor we focused on for our study was The Gillette Company. The basic challenge is to reduce the inventory which Gillette must keep at the Gillette DC (vendor DC) while maintaining the same customer service level.

Refer to Figure 2 for a better understanding of the road map we now provide and the nomenclature used throughout:

Vendor DC   Customer DC   Customer Store   Consumer
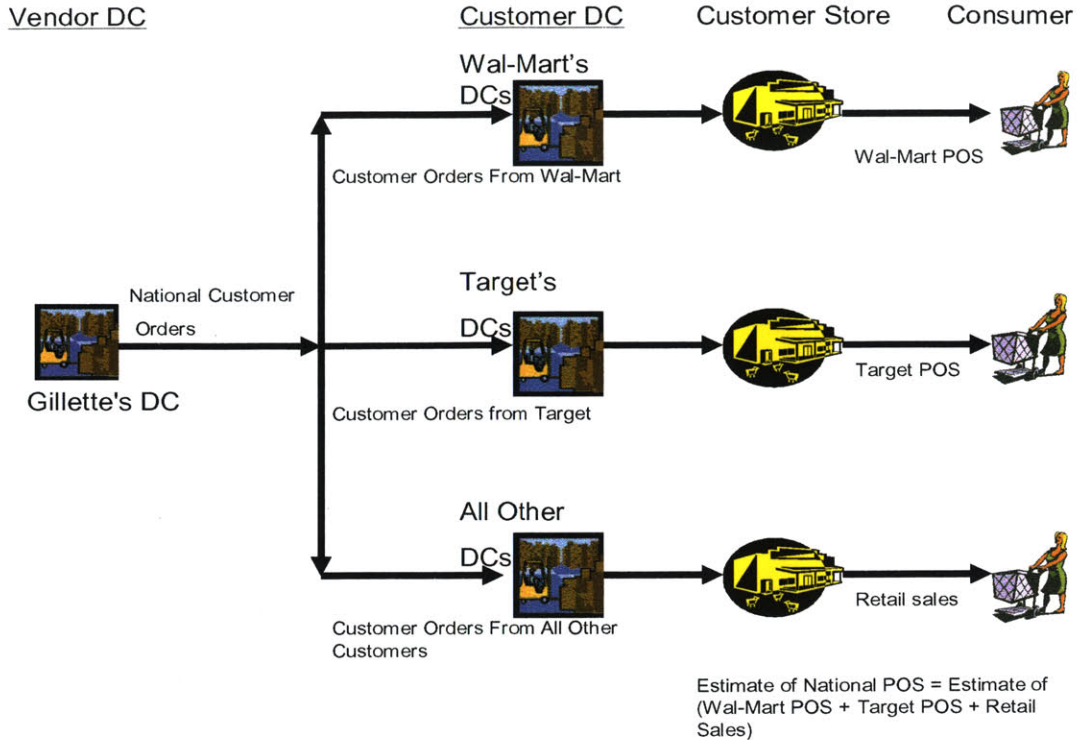
Figure 2: Supply Chain Roadmap

In Chapter III, we examine Gillette's current system and identify two potential problems which result in poor forecasts and high inventory than necessary at its DC. The first problem is that the demand forecasting process is overly complex and produces a new forecast of national customer orders only once a month. The second problem is that Gillette's forecasts of national customer orders are based on historical patterns of national customer orders. This exposes them to the well documented bullwhip effect. The bullwhip effect (which we describe in more detail in the literature review of Chapter II) basically results in small variations in the demand pattern at the POS level being amplified into large variations at higher echelons in the supply chain such as the customer order level.

We demonstrate in Chapter IV that by using a simpler weekly forecasting technique, Gillette can enjoy more accurate forecasts of national customer orders with less effort. This

method is designed to answer the first problem of Gillette's current process being long and complex.

In Chapter V we begin to address the second problem of Gillette being subject to the bullwhip effect. We start by exploring the option of Gillette incorporating the forecast of Wal-Mart POS which Wal-Mart currently generates for Gillette's use. This forecast is inaccurate and we recommend not using it. We then show that if Gillette bases its forecasts of customer orders from Wal-Mart on Wal-Mart POS (the actual data, not the forecast made by Wal-Mart), Gillette will mitigate the bullwhip effect and achieve more accurate, less variable forecasts of customer orders from Wal-Mart. Unfortunately, this alone would not solve the problem of reducing inventory at the Gillette DC since they serve all customers, not just Wal-Mart.

In Chapter VI, we try to solve this problem and still get the benefits of using POS by using the POS from Wal-Mart and Target to make an estimate of national POS. (That is, an estimate of what the POS would have been if all of Gillette's customers were capable of providing POS). Then it is a simple matter of creating a POS based forecast in the same manner as with Wal-Mart, except on a national level. We also explore simply adding the POS based forecast of Wal-Mart customer orders to standard forecasts of the non-Wal-Mart customers.

Chapter VII discusses four ideas which are often proposed as the solution to the problem of improving forecast accuracy and reducing inventory. Our goal in this chapter is to show that while these potential solutions may have some merit, their usefulness with respect to our problem is minimal.

Chapter VIII discusses the possibility of reducing the length of Gillette's manufacturing firm period. This is being worked on by Gillette experts and our thesis is unrelated to that effort. Our purpose in this section is merely to show the benefits which a reduced manufacturing firm period would have on safety stock, given the use of the forecasting techniques we describe.

The above solutions to the two key problems result in forecasts which are more accurate. Improved forecast accuracy leads to reduced inventory and therefore we emphasize the importance of improving forecasts. By holding less inventory, Gillette frees up capital to be used elsewhere and avoids the costs associated with carrying inventory such as warehousing, taxes, insurance and obsolescence.

1.4 Pilot Project:

The Gillette Company is a consumer packaged goods company which is best known for its dominance of the razor blade market. However, Gillette is organized into five major business units and only one of them focuses on this area. The five business units are "Blades and Razors", "Batteries" (Duracell), "Appliances" (Braun electric shavers), "Oral Care" (Oral B toothbrushes) and "Personal Care" (Deodorant, Shaving Cream).

Gillette will soon begin a pilot project which draws heavily on the results of this thesis. The pilot project will implement the forecasting techniques we recommend for 14 SKUs in the Personal Care business unit. In addition, inventory levels will be drawn down slowly to levels which are commensurate with the accuracy of the new techniques. The 14 pilot SKUs were deliberately chosen to be all produced on the same manufacturing line. This ensures that any new techniques which are adopted are forced to deal with the realities of manufacturing capacity. The 14 SKUs are all either men's or women's shaving gels. They are called "shave prep" SKUs.

If the pilot is successful, Gillette will scale the project first to the rest of the Personal Care business unit, then to all of Gillette's business units. In short, a successful implementation might ultimately reduce Gillette's inventory company wide.

2 Literature Review

Forrester (1958) in his paper on Industrial Dynamics was clearly far ahead of his time. He showed how a small variation in consumer demand led to large fluctuations upstream in the supply chain. This phenomenon was later defined as the now famous "Bullwhip Effect" by Lee et al (1997). This has two effects as the information flows upstream into the supply chain:

a) Demand oscillations

b) Amplification of the above oscillation

Both of the above have a detrimental effect on Supply Chain response, cost and customer service. In addition, Forrester (ibid) has shown that the bullwhip effect has significant impact on the business cycle as managers often take surge in factory demand as a corresponding increase in consumer demand and start planning for manufacturing capacity, advertisement and product development.
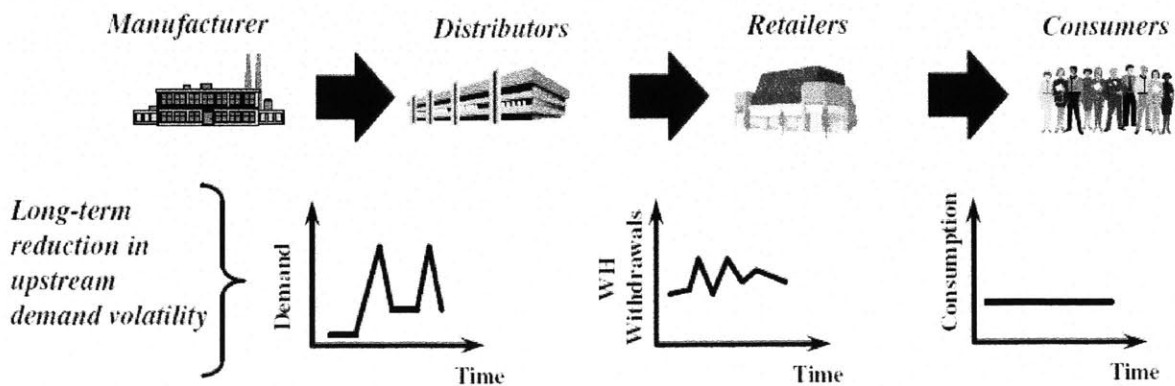
Picture source: Lapide (2004)

Figure 3: Bullwhip Effect

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Sterman (1989) has shown that the primary reason for such an oscillation is a time delay between material order and delivery. This coupled with constant managerial action to correct the supply gap leads to volatile oscillations. Furthermore, each entity overreacts to customer demand and at the same time under-reacts to the stocks it has already placed on order. This is evident in numerous real-life studies of supply chains and beer game (for an elaborate discussion on the game, refer Sterman, 2000) simulations. The problem is significantly increased as the number of entities in a supply chain increases. The effect is profoundly experienced by the entity that is farthest from the consumer.

Lee et al (ibid) makes a case that the bullwhip effect is due to rational decisions made by entities in the supply chain infrastructure and has classified them in four broad buckets as follows:

a) Demand Forecasting Update: Future orders are often reactions to downstream signals of demand. Typically, managers use statistical methods, such as exponential smoothing, to convert signals into order forecasts. The order that is sent to the supplier represents stocks required to replenish future demands and safety stocks. Long lead times can accentuate safety stocks and as a result, the order signal sent upstream is amplified. The orders sent upwards into the chain are demand signals for the next entity and if, for instance, exponential smoothing is deployed again to determine future demand, a larger oscillation takes place. Hence, a combination of lead times and demand forecasting causes signal oscillations.

b) Order Batching: A customer will often order materials in batches in accordance with inventory guidelines. Orders are often batched on a fixed period (say monthly, fortnightly or weekly) or when the inventory hits a preset value. Often orders are batched to avail full truck load transportation rates. As a result, a supplier sees a sudden spike of demand

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followed by none at all. If the demand were to be uniform the oscillations would be minimal.

c) Price Fluctuations: Trade discounts and off season deals lead to artificial demand spikes. Most companies also "forward buy" to get volume discounts or full truckload transport costs which often may be advantageous if the inventory carrying cost is lower than the price savings, but for most part this plays havoc in the supply chain. As a result of demand spikes, companies expedite suppliers, use premium transportation and pay overtime in factories.

d) Rationing and Shortage Gaming: When demand outstrips supply, the natural tendency of the supply chain entities is to ration the supply. In reaction, the customers over order in the hope that the fraction supplied to them would meet their requirements. When supply catches up with demand, customers scale down their orders to normal levels. As a result, the supply chain faces volatile shocks disturbing the normal flow of materials and information.

The bull whip effect can be significantly mellowed down by eliminating multiple layers of demand planning. This is indeed the main purpose of Collaborative Planning, Forecast and Replenishment (CPFR) where there would be one plan across the supply chain. The other solution is information sharing where demand data, for example POS numbers, is made visible to the upstream members of the supply chain. Similarly, demand batching can be improved by reducing the fixed costs of ordering. EDI and now XML offer electronic platforms where orders and its replenishment can be automated reducing transaction costs. Batching to avail of low transportation rates still remains a challenge and some multi product companies are proposing that their customers consolidate orders to utilize the advantages of a full truckload. Recognizing

the impact of pricing on supply chain volatility, some large suppliers and retailers are now moving to concepts such as Every Day Low Price (EDLP). This smoothens the oscillations significantly. Finally, in times of shortages demand signals can be dampened by supplies triggered by historical trends rather than by rationing the orders.

Croson and Donohue (2003) have studied the impact of POS data sharing on Supply Chains through the beer game. The beer game was drawn in teams of four each representing a manufacturer, a distributor, a wholesaler and a retailer. The game was run in two settings: A: The team members were aware of the demand distribution but not the actual demand per se' and B: The POS demand was visible across the supply chain. There were 11 teams in setting A and 10 teams in setting B. The authors drew three hypotheses:

1) Magnitude of order oscillations will be reduced across the supply chain if the POS information is shared

2) The magnitude of amplification of oscillation will be reduced across the supply chain if the POS information is shared especially between:

   a. Retailer and Wholesaler

   b. Wholesaler and Distributor

   c. Distributor and Manufacturer

3) The manufacturers and the wholesalers will witness larger reductions in order oscillation than would the retailer and the wholesaler.

The conclusions were both interesting and relevant to our study. The experiments indicated that there was significant reduction in order oscillations across the supply chain. The magnitude of

amplification of oscillations also witnessed a reduction but only between the wholesaler and the distributor. And, finally the upper echelons i.e. distributor and the manufacturer saw a larger reduction in oscillation than did the wholesaler and the retailer. Another, interesting fallout of POS visibility is the increase in vendor's push to manage the inventory replenishment process as against reliance on the customer's order decisions. This motivates the upper echelons to build a Vendor Managed Inventory (VMI) relationship with the retailer.

In contrast to Donohue and Croson (ibid), Steckel et al (2004) contends that Supply Chain efficiency improvement due to Shared Point of Sale Information is a function of pattern of the demand function. A step function (as described by Sternman 1989) is quite disruptive and sharing of POS information does lead to significant improvement in efficiency. However, for S shaped demand function, which is more realistic, the POS information has ambivalent impact.

Interestingly, Steckel et al contends that supply chain lag time (the time gap between order and supply) has a more profound impact on supply chain efficiency both in the case of a step and S shaped demand function and more focus on this aspect is warranted.

Lapide (2004) highlights the virtue of integrating the supply chain with the end consumer demand signal. This will help reduce variability upstream in the supply chain and will therefore significantly improve demand forecasting.

Further, Lapide (1999) has professed the use of multi tier forecasting in addressing issues of a mismatch between forecasted and actual demand. For example, a company forecasting solely on the basis of its shipments to its customers could simply end up stuffing the product pipeline

without realizing the fact that there is hardly any movement at the end consumer level. This essentially means that a company should factor in the following while building an integrated demand forecast:

1. Manufacturer Shipments

2. Wholesaler warehouse shipments and inventories

3. Retailer distribution center withdrawals and inventories

4. Retail store point of sale data and inventories

Lapide (ibid) also outlines a detailed framework for creating a multi tier forecasting tool for the company as follows:

1. Assemble Data: This implies collecting data from downstream supply chain partners- a daunting task by any standards. Most retailers are either not prepared to share data or do not have the information technology infrastructure to do so. However, sophisticated retailers such as Wal-Mart and Target share consumer sale information almost real time through advanced tools such as Retail Link [TM] and Partners-on-Line [TM] respectively.

2. Model Supply Chain: This essentially entails building a quantitative framework of using downstream signals to forecast demand. This will help to develop an understanding as to how various demand signals in the supply chain relate to each other and to examine if there were any opportunities in creating an efficient forecast model.

3. Forecasting Supply Chain Sales and Inventories: This is the key focus of our thesis to search for an ideal way to creatively and simplistically forecast demand using various signals generated at various echelons of the supply chain.

Romanow et al of AMR Research (2004) outlines the use of POS data in creating business value. The author suggests that three key functions in an organization can benefit immensely:

1) Supply Chain/ Logistics:

    a. Forecast accuracy can be improved by infusing POS data in demand planning

    b. Production schedules can be planned closer to real time

    c. Collaboration between various supply chain tiers can be improved through sharing of POS information.

2) Sales:

    a. Price Analysis: POS data can provide valuable and timely information on the impact pricing strategies have had on sales

    b. Store Level Planning: POS data facilitates information desimination by store enabling sales accounts managers to formulate strategies.

    c. Customer service: is significantly ramped up as sales information is readily available.

3) Marketing:

    a. Category Management: POS data can facilitate analysis of product platform to determine its performance on categories segregated, for example, by size, flavor, mix and type.

    b. Segmented Channel Management: POS data allows marketers to segment the market by product on the basis of sales information so generated.

    c. Promotion Performance: POS can help marketers to track performance of ongoing promotions.

Kiely (1999) runs an interesting discussion on how supply chains can be turned efficient and responsive by synchronizing it with consumer demand. POS data being unrelated to the forces of the supply chain are termed as independent data. As against order signals from the customer's store, customer's DC and the vendor's DC are dependent data as these are often masked by supply chain noise such as inventory, order push, price reductions etc.. Forecasting future demand on independent data has significant value as it represents true demand. By definition dependent data such as dispatches from various supply chain echelons can be developed using the POS data and the Distribution Resource Planning (DRP) or Materials Resource Planning (MRP) tools as the case may be. With major customers (notably WalMart and Target) adopting EDI (Electronic Data Interchange) or other systems of online information exchange such as XML (Extensible Markup Language), vendors can now create demand forecasts using independent data. In addition to visibility of POS information across supply chains, customers also develop POS forecast by product and by SKU. This can significantly reduce bullwhip effect.

One interesting implementation of use of POS signals in customer order forecasting and replenishment has been observed at The Scotts Company. Scotts is a leading manufacturer and marketer of consumer branded products for lawn and garden care, professional turf care and professional horticulture business. Scotts customers include mass merchandisers, home improvement centers, wholesale clubs, hardware chains, drug chains, hardware stores, nurseries and garden centers. Sales are highly seasonal and therefore the end consumer signal has high variability. Unlike the Consumer Packaged Goods industry (such as Gillette) where the end demand is fairly stable, the Garden care industry is extremely seasonal. Scott's supply chain was characterized by high stock outs despite large inventory, ineffective trade promotions owing to poor timing, poor collaboration with customers, and therefore poor returns on investment. The

company successfully implemented a consumer based replenishment system by generating a multi tier forecast using POS information. This significantly improved its supply chain and also helped it to gain control of its product replenishment at the store level.

We also examined the use of POS signal in a large movie entertainment business. This company is engaged in manufacture and distribution of movie videos, CD and DVDs. The company has over 10,000 SKUs with each selling 15000-30000 pieces a week, The supply chain of this organization is fairly simple with the factory and distribution center housed at one location supplying directly to the retail stores (such as Wal-Mart, Target, etc.) completely skipping retailer distribution centers. The manufacturing planning lead time is one day as is the manufacturing time. Each morning the company gets POS information from the stores and runs this through the Vendor Managed Inventory System. This helps them determine the inventory position for each store and forms the basis on which the company prepares orders on behalf of the retailer. This order is executed and the product is distributed through standard overnight couriers.

Demand is forecasted through a multi tier forecasting technique wherein the company builds the outlook by factoring in both the history of shipments to all the company's forecasts and the POS actual data. The POS data is available for only 70% of the customers. Therefore the National estimate of the end consumer demand is built by extrapolating the available POS information. The company has developed its own heuristics to determine the right technique to combine the two estimates to build the final demand forecast. Since the manufacturing total lead time is 2 days the company builds the forecast every week leading to an accurate estimate due to the short planning horizon. The forecast is highly accurate on an aggregate basis but has poor accuracy at

the store level. As a result the stores generally have a high inventory and since the company has a buy back policy, the retailers are not really worried about excess inventory. The total pipeline inventory is a staggering 10 weeks. This company is an interesting application of the use of POS signal in demand forecasting but there is perhaps an opportunity in reducing the high in-store inventory.

Our research suggests that in situations of highly variable end consumer demand, integrating the POS signal into the supply chain can have dramatic improvements. However, where the consumer signal is fairly stable there could be simpler and smarter ways to plan and execute demand forecasting.

3 Gillette's Current Process

In this chapter we try to identify the causes of inaccuracy in Gillette's forecasts. This requires a deeper look into Gillette's entire process. We first overview Gillette's supply chain. After that, we describe Gillette's demand planning process. This should make it obvious that one of Gillette's problems is the complex nature of the system which creates its forecasts. Next, we look at how Gillette's supply planners order from manufacturing. The whole reason we need a short term demand forecast is to assist supply planning in sending the right order to manufacturing. In the following section we measure Gillette's current performance using a set of metrics which we will apply throughout the thesis. Last, we demonstrate that the second potential problem for Gillette is the fact that it is subject to the bullwhip effect.

3.1 Gillette's Supply Chain:

Gillette's supply chain is large, complex, and global (see figure 4). Here we focus only on the parts of it which affect the pilot project.
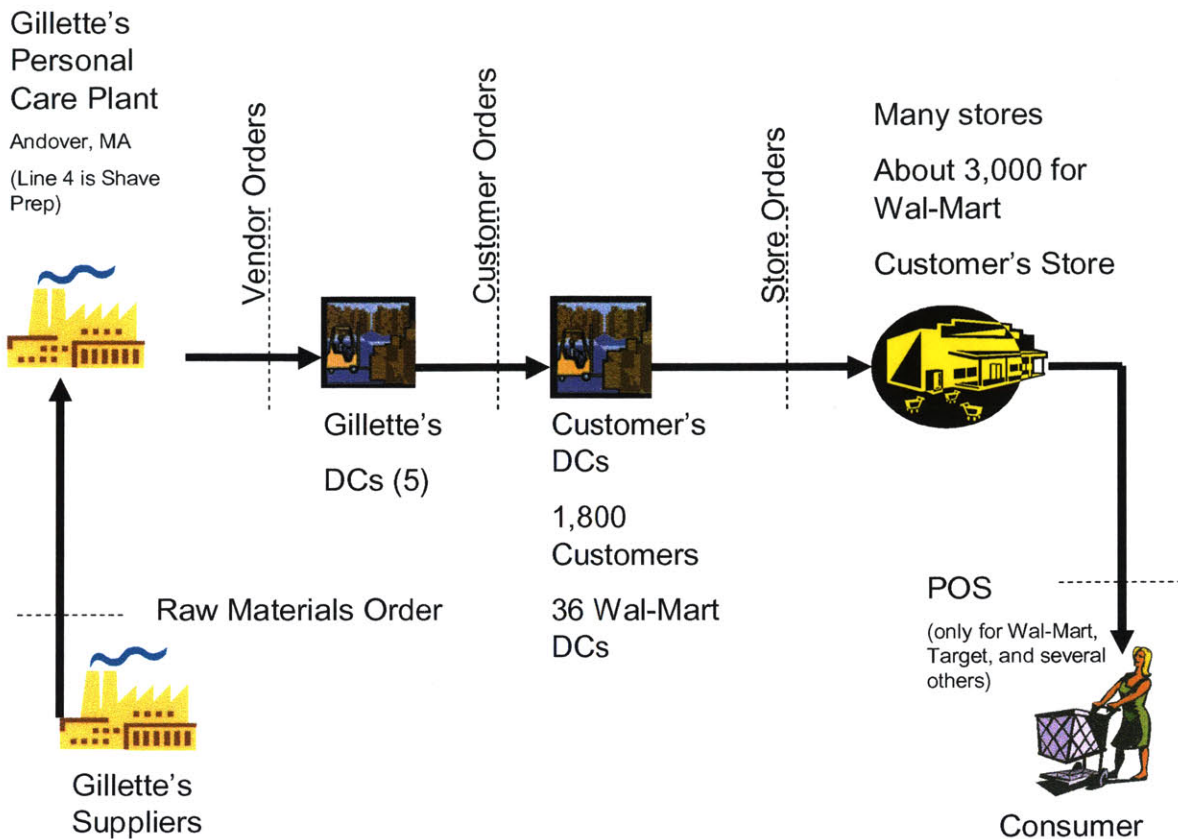
Figure 4: Gillette's Supply Chain

All pilot SKUs are manufactured in one plant, on one line, in Andover, Massachusetts. After

passing through Gillette's DCs they spread across 1,800 Gillette customers. Each of these

customers generates customer orders. The goal of the Gillette DC's is to meet these orders

97.5% of the time. (The service type used by Gillette is type I, cycle service level. This means

that in 97.5% of weeks, Gillette will meet 100% of orders.) After leaving the customer DCs the

product moves on to the customer stores and finally, the consumer purchases the product. In the

case of Wal-Mart, Target, and several other customers, this last transaction is recorded as POS.

The historical POS is sent to Gillette weekly, but at present Gillette makes only informal, limited

use of this data.

Andover, MA

Line 4 is Shave Prep

All pilot SKUs on line 4

Lead Time Plant to
Supply Warehouse = 3
weeks

Supply Warehouse

Devons, MA

Lead Time Supply
Warehouse to Regional
DCs = 1-4 Days

Canadian Regional DC

Toronto, Canada

Western Regional DC

Ontario, California

Central Regional DC

Romeoville, IL

Eastern Regional DC

Devons, MA
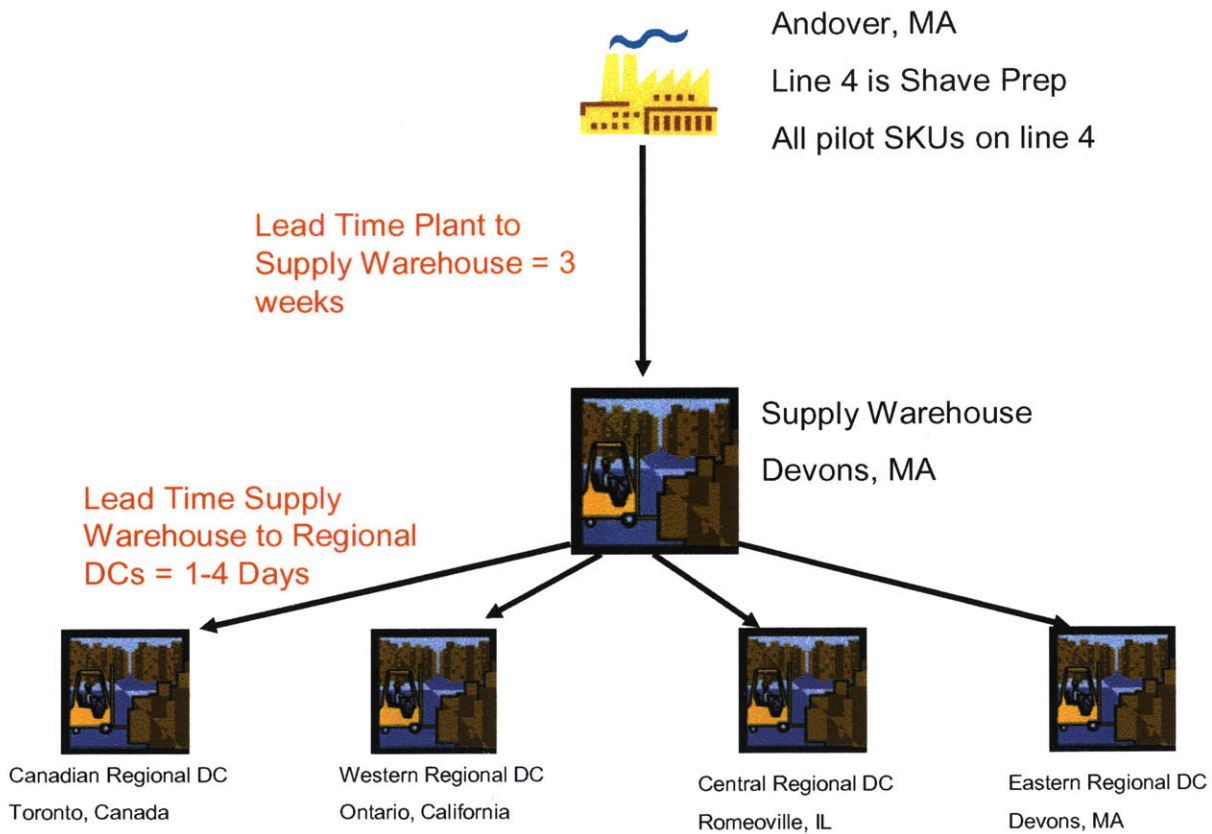
Figure 5: Gillette's DC Network

Gillette's DC network is depicted in Figure 5 above. It is important to note that there is

no inventory held at the factory and that the lead time between the factory and the supply

warehouse includes manufacturing time. The actual time required to make each product is not 3

weeks. 3 weeks is the time from when a vendor order is placed on the factory to when it arrives

in the supply warehouse. In some cases it might only take one day to manufacture a product, but

since the SKUs are all made on one line and that line is close to 100% utilization, the vendor

order must "wait in line" before being produced.

The lead time between the supply warehouse and the regional DCs is only 1-4 days. This

DC network is essentially an echelon inventory system where each regional DC keeps enough

inventory on hand to account for demand over that short lead time and the supply warehouse keeps enough inventory so that the whole system has enough inventory to account for demand over the lead time from factory to customer (3 weeks plus 1-4 days). Thus, the supply warehouse has by far the most inventory.

If the system has enough total inventory, (defined as inventory on order from the plant, in transit from the plant, at the supply warehouse, in transit to the regional DCs or at the regional DCs) then it is a simple matter to push the appropriate amount of inventory from the supply warehouse to the regional DCs. (There is no decision making authority at the regional DCs who requests inventory. Centralized supply planners order product from the factory and distribute it among the DCs). The question, then, is how much inventory should be injected into the whole system each period, and it is an afterthought to calculate how much inventory should be pushed to the regional DCs. When stock outs occur it is usually because there is not enough inventory in the system as opposed to it being in the wrong DC. Obviously this stems from the fact that the lead time from factory to supply warehouse dwarfs the lead time from the supply warehouse to the regional DCs. As a result, we treat the Gillette DC network in our research as one DC. From here on, we will refer to "the Gillette DC" meaning the whole network.

3.2 Demand Planning: The Long Journey

The process kicks off with a demand plan prepared by Gillette which is a forecast of future shipments from its DC based on historical dispatches (see figure 6). Gillette deploys a method within Manugistics® known as the Lewandowski technique to pick the best forecasting methodology from a suite of tools. The plan is a 24 month rolling plan and represents what the customer expects to receive in a particular month. This demand plan is integrated into a national plan and forms the basis for the Unconstrained Demand Plan for the company.

As is Demand Planning Cycle for Pilot SKUs
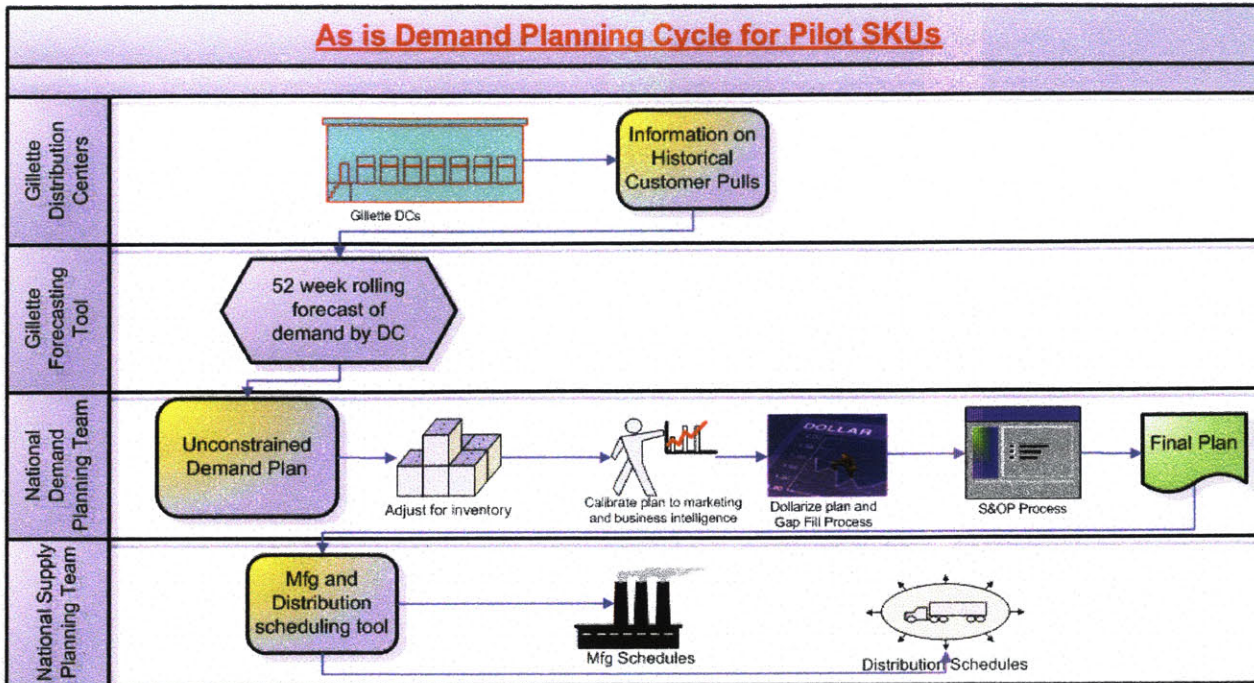
Figure 6: As is Demand Planning Cycle for Pilot SKUs

As a next step, the plan is adjusted for any marketing and business insights that could impact the demand volume. This includes promotions, roll backs, competitive activity, etc. As the company's financial goals for the planning period could be different from that represented in the unconstrained demand, a process called a Gap Fill Meeting is carried out which essentially compares the dollar value of the demand plan with that of the annual operating financial goals. An action plan is developed and executed to mitigate any gaps.

Final agreement of the plans is obtained in Sales and Operations Planning (S&OP) meeting and the output is released to supply planning for building the manufacturing and dispatch schedules.

A typical Gantt chart indicating how the activities map in time is indicated in Figure 7 below. This is a typical sample chart and is the authors' approximate adaptation of the actual process.

As one can see in the example, the planning cycle for the month of March begins on 31st January 2005. The critical pre month activity of material resource planning ends on 18th of

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February leaving about 2 weeks for the materials to arrive. For materials that have longer than 2 weeks lead time an inventory build up will be required and the quantities can be planned by picking up the numbers from the previous month's rolling plan for March 2005.
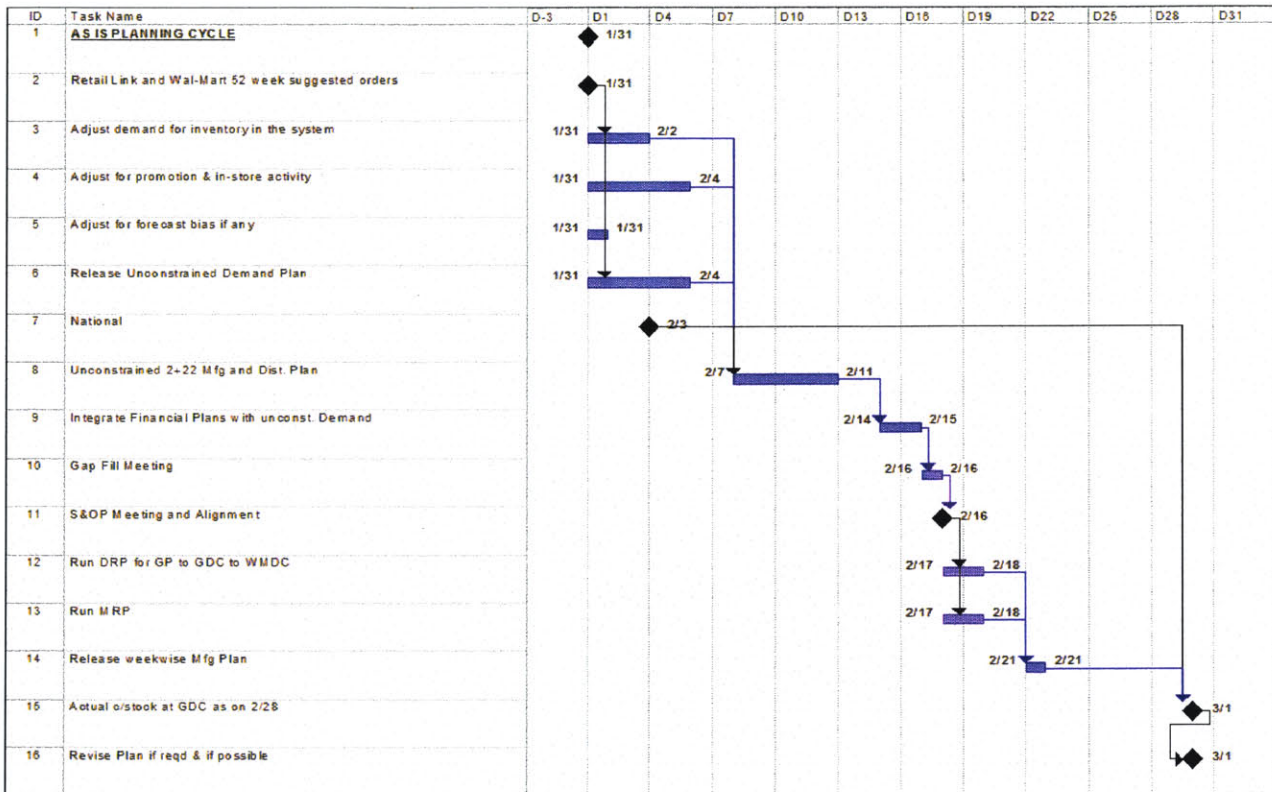
Figure 7: As-Is Planning Cycle- Gantt Chart

The current demand planning cycle has a profound impact on Gillette's supply chain in the following three ways:

1) Planning lead time: The intense planning cycle activities take about 4 weeks to accomplish.

2) Freshness of data: Owing to this turnaround time, the demand planning group operates with data that is one month old compared to the actual month it is intended for. In addition, as we will see later, manufacturing planning has a firm planning lead time of 3

weeks which leads to the actual use of data that is two months old. In other words, planning for, say, June 2005 will be based on data up until March 2005.

3) Gillette business processes: As discussed in the planning cycle, Gillette's business rules, superimposed upon the unconstrained demand plan, modify the demand signal considerably.

So in summary, the length and complexity of the demand planning process result in forecasts which are based on data that is 4-8 weeks old and subject to erroneous influence.

3.3 Supply Planning: Where the Rubber Meets the Road

As mentioned before, Supply Planners in Gillette are responsible for determining how much inventory to put into the distribution system. They do this by placing a vendor order on the plant. Due to manufacturing constraints, this is not a simple process of asking for product and getting it the next day. All pilot SKUs are produced on one line and each time that line switches to a different type of product there is a significant set up time. In addition, manufacturing needs to know ahead of time what its work load will be so it can pull the necessary raw materials and schedule sufficient labor. All of these constraints are represented by a 3-week firm period for manufacturing (Figure 8). This means that no changes can be made to the production schedule for 3 weeks out. The 3-week firm period is what causes the 3-week lead time. If supply planning wishes to order something, it basically slots it into the fourth week out of the production schedule.

3 week firm period
No changes allowed
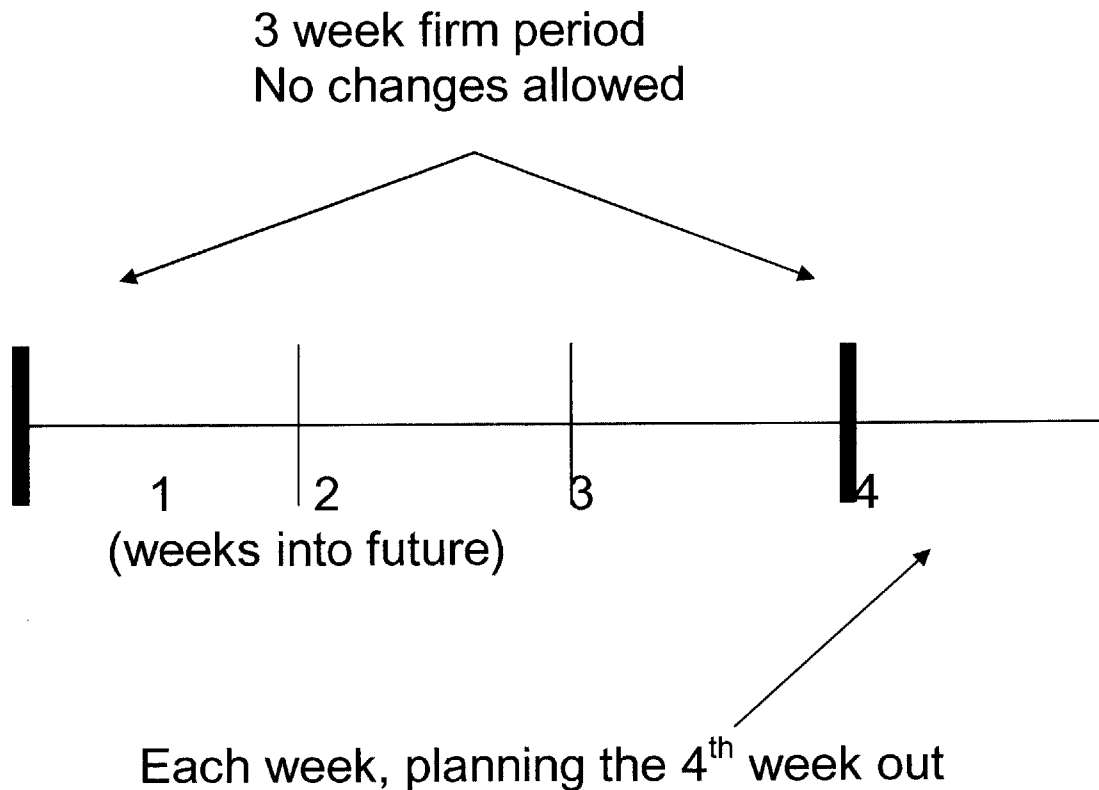
Figure 8: Manufacturing Planning Lead Time

Each week, supply planning must decide what to order for that fourth week out. By next week, that week will have become part of the firm period and there will be nothing they can do to change it. We emphasize that this inability to change is due to real manufacturing constraints and not randomly applied planning times. (There are efforts underway to improve Gillette's manufacturing flexibility which might reduce this firm period. The benefits of this to inventory are described in Chapter VII). If Supply Planning orders too much here, they will be stuck with excess inventory. If they don't order enough they will suffer stock outs. As a result, the decision of what to order for the fourth week out is truly where the rubber meets the road.

Supply Planners armed with a logistics software tool from Manugistics® use the following three inputs to determine what to order: Target inventory level (TI), current inventory on hand (OH), and Inventory on Order (OO). OH is simply the inventory that's already in the

system while OO is the inventory which has already been ordered and is locked into the 3-week firm period.

TI is the "order up to" inventory level. This is much more complex and requires detailed explanation. Gillette is essentially using a standard periodic review inventory system where the review period is 1 week, and the base stock (order up to level) is the calculated safety stock plus the expected demand for the next 4 weeks (4 weeks = 3 week lead time plus 1 week review period).

So the order which will be input into the fourth week out of the schedule is:

Order = TI − OO − OH. That is,

Order =   (Safety Stock) + (Forecasted Demand next 4 weeks) − OO − OH.

Each week, then, Supply Planning must have an estimate of demand for the next 4 weeks. This estimate is basically a combination of the monthly forecasts which we described in the demand planning section. If it is the last week of January, for example, the estimate will be ¼ of January's forecast plus ¾ of February's forecast. Unfortunately, the monthly forecast of demand only becomes available on the 5th of each month at the earliest. This means that if planning the four weeks beginning the first week of January, the forecast for January which was released on the 5th of December must be used. Therefore, it will be a little more out of date and the forecast a little less accurate. How does this inaccuracy come into play?

Safety stock accounts for the fact that it's impossible to exactly predict what the demand will be over the next 4 weeks. If the forecast of the next 4 weeks was always perfect, safety stock could be set to 0. In truth, the forecast has some inaccuracy, and the greater the inaccuracy, the higher the safety stock the system carries.

The actual level of safety stock (in number of days forward coverage) is pre-determined about every 6 months using a planning tool from Optiant®. The key input to the Optiant®

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software is the coefficient of variation (CV) of the error of the forecasts used over the past 6 months. (This measure of forecast error will be described in more detail later). This is how the inaccuracy of the forecasting system actually gets accounted for. The less accurate the forecast, higher will be the coefficient of variation and hence higher the safety stock.

It's not a simple matter in the case of shave prep SKUs to determine safety stock based on coefficient of variation. Normally, we could use the simple formula of (safety factor)*(standard deviation of forecast error over lead time). However, shave prep SKUs are made in large batches due to the nature of the manufacturing process (Mixing chemicals in a large vat). This means that there are fewer chances to stock out since products arrive at the DC in larger batches than needed and ends up having fewer cycles per year. So while batching has the unfortunate consequence of creating batch stock inventory, it also has the small counter-benefit of reducing safety stock needs. This makes the usual safety stock formula inaccurate. So Gillette determines safety stock by running an Optiant software calculation which accounts for various practical issues including batching.

In our later analysis we compare the effect of various forecasting techniques' on safety stock. To do this, we compare the CV for forecast errors of the various techniques. If calculating safety stock were a simple matter of applying the aforementioned formula, we could easily say that since standard deviation is proportional to CV, and safety stock is proportional to standard deviation, a forecasting technique that yields a CV which is 10% lower will generate a safety stock requirement which is also 10% lower. Due to the batching issue, we can't say this yet. Fortunately, it turns out that this relationship holds in spite of batching issues. We had a Gillette supply planner conduct a sensitivity analysis using the Optiant system to estimate the safety stocks that result from various CVs. The results shown in the Appendix IV confirm that the linear relationship between CV and safety stock holds even considering batching and any

other practical issues for shave prep SKUs. This means that we can compare various forecasting methods by comparing their CVs and assuming that the safety stocks thus generated are proportional.

So to sum up Supply Planning, each week they must decide what to order for the fourth week out. A key element of this order is the forecast of demand over the next four weeks. The accuracy of this forecast drives the level of required safety stock. More precisely, the amount of safety stock necessary is proportional to the CV of the error of the forecast of the next 4 weeks.

3.4 Gillette's Current Forecast Accuracy, CV, and Inventory:

Gillette's current demand planning process generates a forecast whose accuracy can be measured in many ways. One method would be to measure the accuracy of each month's forecast against the actual demand for that month. This figure would be interesting but irrelevant to the problem of determining safety stock generated by the forecast. In truth, the safety stock required depends on the forecast's ability to predict the next 4 weeks, every week. This means figuring out each week what the estimate of the next 4 weeks made by Supply Planning would have been, based on the given monthly forecasts. (Recall that the next 4 week's demand is estimated by supply planning to be a combination of different monthly forecasts.) Now we simply compared the 4-week forecast each week to the 4-week total of actual demand each week. We did this for each SKU over almost two years of data. (June 2003 to March 2005). This resulted in testing 91 weeks worth of forecasts for 11 SKUs, for a total of 1,001 forecasts. After doing this, we calculated the forecast accuracy as 1 minus the mean absolute percent error (MAPE) for each SKU and then took an average weighted by retail units. (In other words, volume). The reason for weighting by retail units is that Gillette uses this technique and we wish

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to be consistent for purposes of comparison. In addition, the dollar value of the pilot SKUs aren't very different so weighting by dollar-volume would give a similar answer.

The result was that Gillette's forecast accuracy for these SKUs over the past 2 years (the time span of our available data) was 74.6%. Had Gillette's demand planners simply used the naïve method of forecasting (this technique predicts that future orders will simply equal whatever the most recent order was), the forecast accuracy would have been 69.8%. Thus, the current method adds less than 5 percentage points to Gillette's forecast accuracy.

More important than forecast accuracy, however, is the CV of error which results from the forecast. This is what will determine safety stock. The daily CV which resulted from the current demand planning process was 1.82. This number means nothing on its own but when related to a safety stock will be used as our base case for determining the safety stock which results from other techniques.

Gillette's inventory for the pilot SKUs is reflected in Table 1. This table is in days of finished goods inventory which are either in a Gillette DC or in transit to a Gillette DC. Cycle stock for transportation results from the fact that although trucks leave the plant for the DC every day, for a given SKU there is typically one load per week since that's about how often a batch of a SKU will come off line 4. So if about a week's worth arrive at the DC and it gets consumed over the week, that averages out to just over three days on hand. Manufacturing cycle stock reflects the large batch quantities. 8 days implies that a typical batch is 16 days of inventory.

Table 1: Current Inventory in Days

Inventory Component	Current
Safety Stock	21
Early Arrival Stock	0
Transportation Stock	6
Quarantine Stock	5
Cycle Stock – Manufacturing	8
Cycle Stock – Transportation	3
Total Stock	43

The 21 days of safety stock is what results from the current daily CV of 1.82. Thus, if another technique yielded a CV of 1.64 (10% off), then we would conclude that that techniques resulting safety stock would be 18.9 days worth (also 10% off).

It's important to note that Gillette uses a non-standard technique to calculate daily CV. We will use the same technique since the number calculated in that manner is what will actually determine safety stock for Gillette and we wish to gauge the effect of our results on their inventory. A Gillette supply planner has conducted an analysis to prove that the difference between the Gillette technique and the standard technique is negligible in terms of its long run effect on safety stock (Both techniques are outlined in the Appendix II).

We only tested 11 of the 14 pilot SKU's. This is because one of the SKUs had missing data, and two of the SKUs were new and so had zero data for about half of the trial period. This is important since it means that the results of our study are not applicable to new SKUs. Even if these SKUs had been launched at the beginning of our test period, the results would not apply since the behavior of customer orders for new SKUs is radically different from mature product SKUs. For example, in the case of one new SKU, the Gillette forecasts of customer orders started at around 10,000 units per week while demand was hovering around 500. About one month in, retailers started to fill in safety stock for the new SKUs and orders were upwards of 90,000 units per week. Eventually orders settled down to something closer to the Gillette forecasts. This behavior is perhaps predictable and worth studying but our thesis is not on new SKU management so we dropped these from the test.

Table 2 summarizes the performance of the present forecasting method, and will be used for comparison later. From here on we call the current process "As-Is":

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Table 2: As-Is Forecasting Performance

Method	Forecast accuracy of national customer orders	Daily CV of error of 4-week forecast	Resulting Safety Stock
As-Is	74.6%	1.82	21 days

3.5   Bullwhip Effect for Gillette:

As discussed in the literature review, variability in the demand signal increases as one moves upstream from the customer's store to the vendor in the supply chain. We also examined the reasons for this phenomenon and the adverse impact this has on the supply chain.   In building the forecasting strategy for Gillette, we examined in depth the signal across echelons in the supply chain. The results for two of the samples SKUs are indicated below in Figure 9
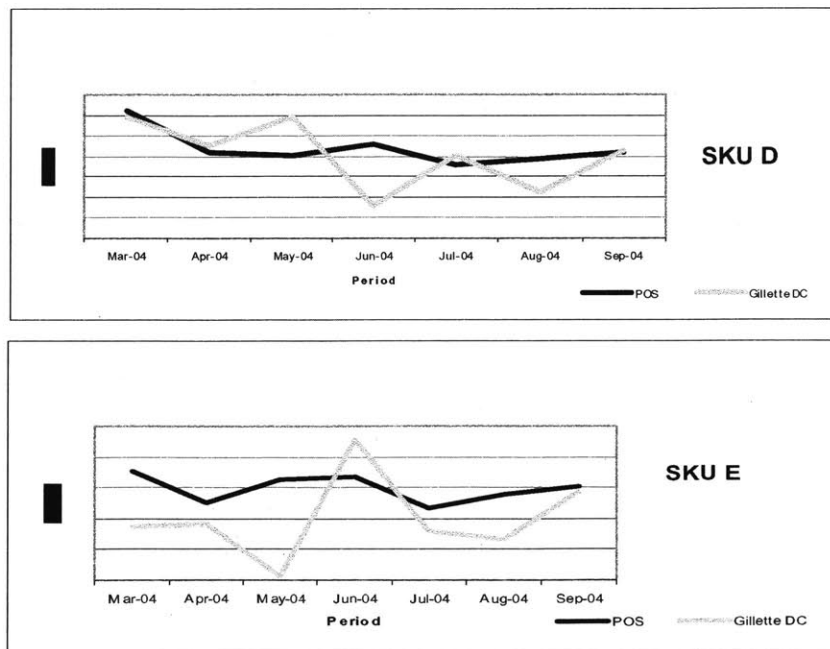
Figure 9: Sample Bullwhip Effect

The grey line represents historical customer orders from Wal-Mart while the black line represents the signal at the POS. Therefore, the grey line is the signal two echelons upstream.

Next, we evaluated the bullwhip effect for 10 of the 14 pilot SKU and measured variability as the Coefficient of Variation (CV). The signal was measured for one retailer in relation to Gillette. The results are displayed in Figure 10. As is evident from the graph, the CV is a very stable around 0.20 for the signal at the POS level and becomes fairly variable at the Gillette DC which services customer orders from Wal-M art. For one SKU H, the COV at the DC is a very high 0.80. This implies that this SKU either faces frequent stock-outs or requires a high safety stock to maintain desired service levels.
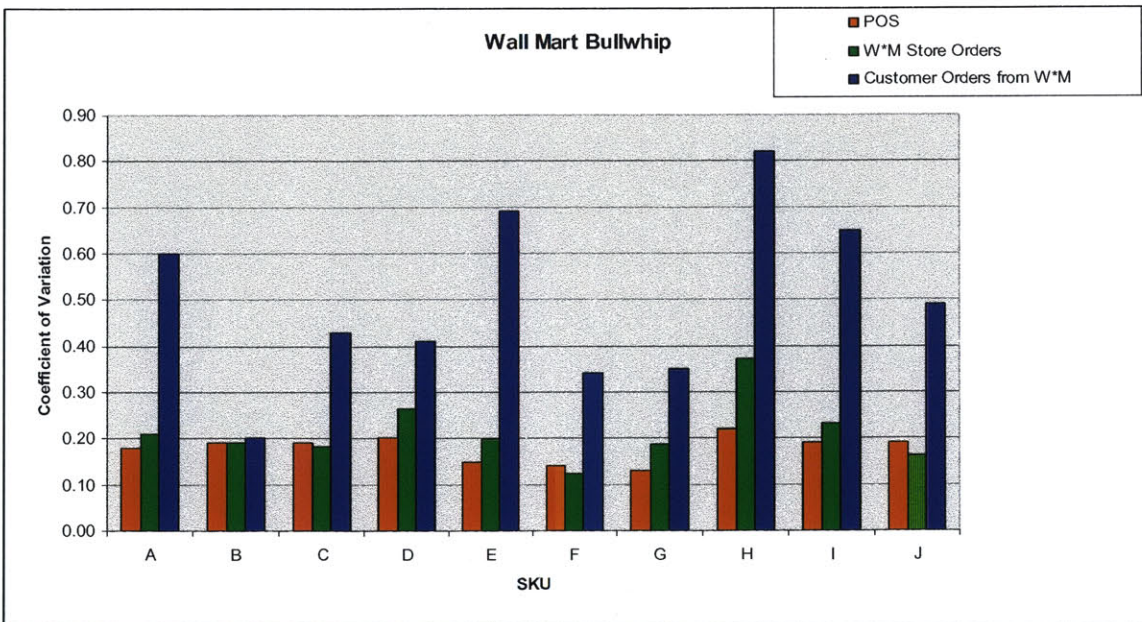
Figure 10: Wal-Mart Bullwhip Effect

Developing further, we also measured the demand variability across the supply chain for the ships to all Gillette customers (national Customer Orders) in relation to the POS information for Wal-Mart and Target combined. The results are displayed in Figure 11.
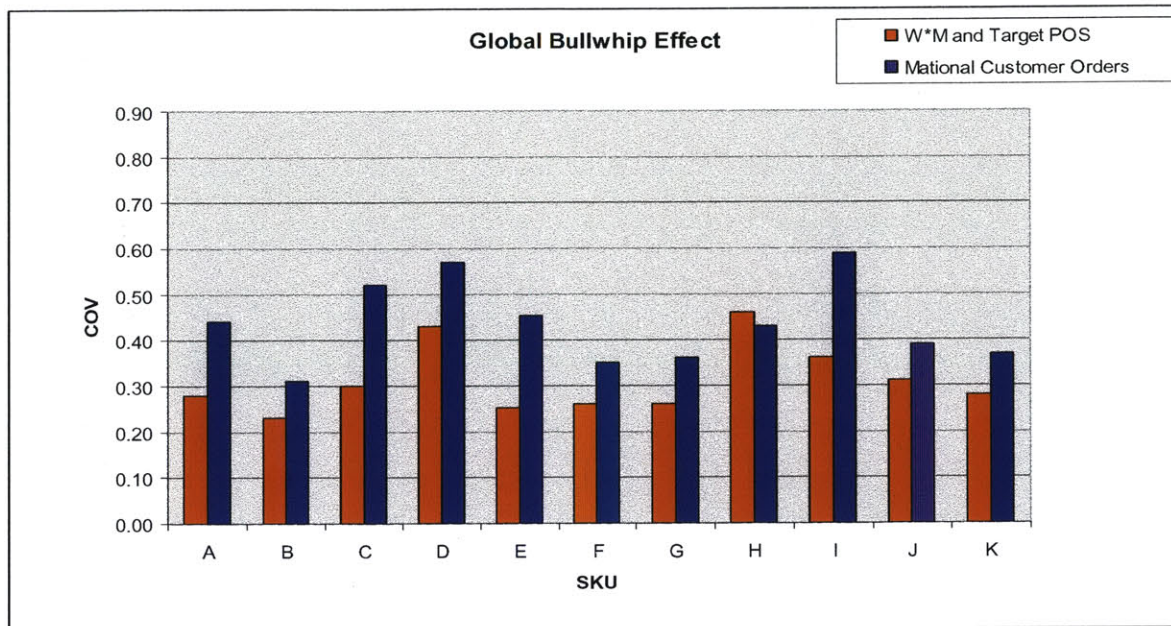
Figure 11: Global Bullwhip Effect

National Customer Orders are more variable than POS, but the difference in variability between POS and national customer orders is not as great as that between Wal-Mart POS and customer orders from Wal-Mart. This is a key point which will come into play later.

It is important to note here that even though the signal shows increasing variability as one moves up the supply chain, the mean demand over a reasonable period of time remains same. This seemingly obvious "conservation of mass" is a critical input to our thesis (Figure 12).

Gillette Plant   Gillette DC   Wa ' Mart DC   POS Actuals

Average demand

Demand Signal
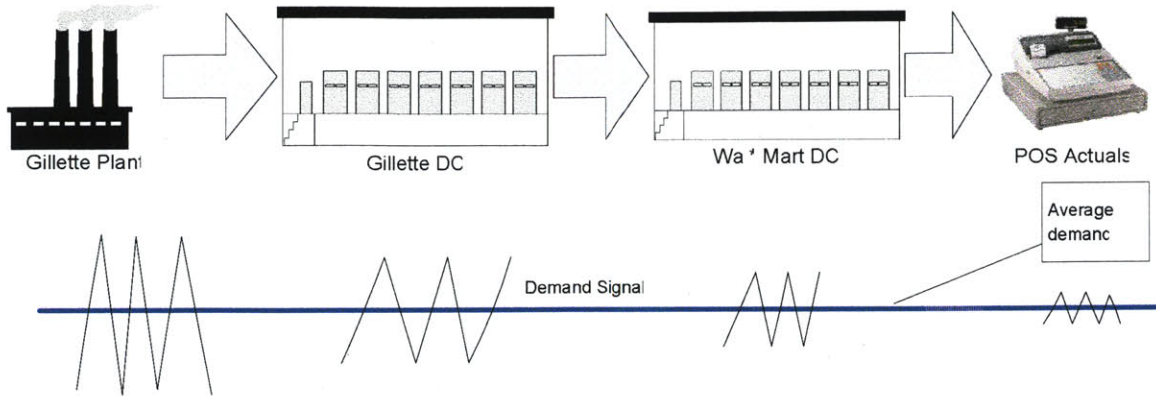
Over a reasonably large period of time average demand remains
approximately same

Figure 12: Bullwhip Insights

In summary, Gillette suffers from a long and complex demand planning process and it is

exposed to the bullwhip effect.

4 Simple Weekly Forecasting Based On Historical Customer Orders

In this chapter we propose a simple forecasting technique which could be updated weekly. Based on the fact that one of Gillette's problems is the length and complexity of it's forecasting system, it follows naturally that we should consider a basic, easy to update technique. After showing how we came up with the technique, we test it against the same data we used to test the As-Is method and compare the results.

4.1 How long should the new forecasting cycle be?

Supply planning estimates the next 4 weeks of demand every week. If they receive a forecast which comes out in any longer interval (such as 1 month in the As-Is), they simply make an estimate based on that forecast of what the in-between week's forecasts would have been. This is obviously less accurate than a method which refreshes itself at least once a week so that the forecast for each week is as fresh as possible. So we conclude that the interval of our method should be no longer than 1 week.

On the other hand, is there a benefit in having an even shorter process such as several days, one day, or real time? It would be easy to collect order data and POS on a daily basis, so perhaps we can use this data to gain even more accuracy in our forecasts. But we must relate back again to the real problem, which is to forecast every week what the next 4 weeks demand

will be so that Supply Planning can make the correct order. The review period for Supply Planning is 1 week, so using daily information would simply generate 7 forecasts per week, of which only one would be used.

Someone could argue that the weak link here is the 1-week review period. But actually the nature of the large batches and high set up times makes supply planning an art of arranging a week's worth of desired production around several different SKU's which will have a batch run that week. Adding to this is the fact that set up time is dependent on which SKU was made last. Producing a bland men's shave gel such as the Gillette Series Gel right after making an odiferous women's shave gel such as Satin Care Wild Berry requires the vats to be cleaned, otherwise the men's shave gel will retain the feminine scent. Harder still to cope with is changing from one bottle size to another. (Switching line 4 from flavor to flavor takes a few hours while switching between bottle sizes takes 14-16 hours.) The point is that even if continuous updates to the forecast were made, the benefits could not be realized since it's not practical to plan manufacturing in less than weekly buckets. (Not to mention, the benefits of shorter horizon forecasts are similar to the benefits of compounding interest in smaller and smaller periods. Going from annual interest to monthly is a large benefit, monthly to weekly is a medium benefit, weekly to daily is negligible.)

So to answer the question of this section, our planning cycle should be no longer than 1 week, and no shorter than 1 week. Therefore, it should be 1 week.

4.2 What forecasting technique should we use?

Choosing a forecasting technique is a science (as much it is an art) in its own right and our goal isn't to demonstrate our forecasting prowess. In this section we simply wish to show that it's possible for Gillette to improve their forecast accuracy by using a basic technique, and updating that technique every week. We are presently only considering techniques which use historical customer orders as the input. Another option is to use POS as the input and we will address that later.

We tested several simple techniques such as exponential smoothing and moving average using the same method as that applied to the As-Is process. Numerous methods produced good results, the best one being a 12-period moving average. (For a discussion on why 12 and not some other number of periods, see Appendix III). This simply means taking an average of the last 12 weeks of customer orders to predict the next week of customer orders. To get a 4-week forecast, you simply multiply by 4 which basically means you are forecasting that demand in the 2nd, 3rd, and 4th week will equal demand in the 1st week. This technique is extremely simple and requires very little effort to update weekly. The results of the test of this forecast against the same data as before (11 SKUs from June 2003 – March 2005) are outlined in Table 3.

Table 3: Forecasting Performance

Method	Forecast Accuracy	Daily CV of error of 4 week forecast	Resulting Safety Stock
As-Is	74.6%	1.82	21.0 days
12-period moving average of Historical Orders	77.9%	1.29	14.9 days

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The improvement of 3.3% forecast accuracy is significant, but the large drop in CV of forecast error is far more important. This improvement in daily CV would allow Gillette to reduce their safety stock from 21 days to 14.9 days, a savings of about 6 days

We feel that the essence of the benefit of this method is not the technique itself. Several other simple forecasting techniques gave results which were almost as good. In addition, we know that the Lewandowski method which Gillette uses has proven its worth and is certainly much better at picking a forecasting technique than the authors of this thesis do. The benefit of this method comes from the fact that it is updated weekly and fed immediately into supply planning. Therefore it is based on data which is only a week old instead of 4-8 weeks old as we showed was the case with the As-Is process. In addition, it's not subject to the various inaccurate human influences which we alluded to in Chapter III.

One advantage to this method is that unlike the current complex process, it can be executed simply.

5 Forecasting Wal-Mart Orders from Gillette Using Point Of Sale Data

In the last chapter we tried a simple technique based on customer orders which addressed the problem of Gillette's current process being long and complex. We now attack the other major problem, the bullwhip effect, by considering the possibility of basing forecasts on POS.

Our goal is to, forecast once a week the sum of all customer orders for the next 4 weeks. This chapter tries to do this by first forecasting what Wal-Mart will order using a POS based method, then adding this to a customer orders based forecast of the remaining customers. The results of this chapter also establish some building blocks which will be used in Chapter VI, where we forecast all of Gillette's customer orders using POS.

5.1 Using Wal-Mart's POS Based Forecast of POS

An established method to mitigate the effects of the bullwhip is for each echelon in the supply chain to use the forecast of average demand made by the customer. The benefit of this is that one avoids falling into the trap of having estimate of average demand get incorrectly adjusted upwards when a customer is replenishing to backfill a small spike in consumer demand and simultaneously ordering more to get to a new, higher target inventory. If the customer's real

estimate of demand is known, then you know that the recent large increase in his order is not representative of a long term increase in demand. Your target inventory level might adjust upwards, but not as much as if your estimate was based solely on the customer's orders. (This effect also works the same way in reverse, for a downward spike.)

Wal-Mart issues a forecast of demand to Gillette every week which forecasts what the demand at Wal-Mart stores will be for Gillette products. The idea is that Gillette would use this forecast as described above, and thus mitigate the bullwhip effect. Before relying on this forecast, we tested its accuracy for Wal-Mart for weeks 6 to 32 of 2004. (These are the only weeks for which we had data on Wal-Mart's forecasts). For the pilot SKUs, the Wal-Mart generated POS based forecast of future POS had an accuracy of 70% when predicting one week into the horizon. For example, the forecast made in week 6 of week 7 was 70% accurate. 6 weeks into the horizon, the accuracy decreased to about 57%. (The forecast made in week 6 of week 12).
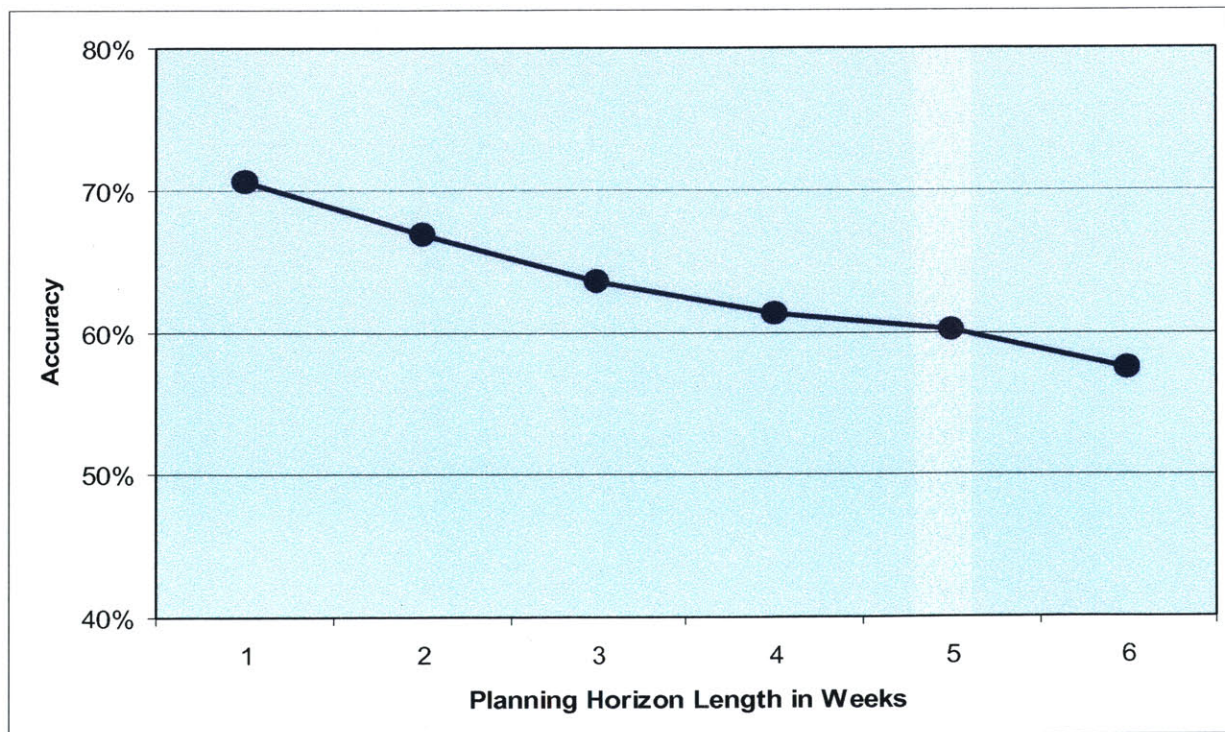
Figure 13: Weighted Average Forecast Accuracy

We also tested another 180 SKU's from all business units to draw conclusions about the Wal-Mart forecast in general. The results were close, with the 1-week horizon accuracy being 70% and the 6-week accuracy being 60%. We were surprised at these relatively low accuracies. It should be easier to predict POS than customer orders since there are fewer echelons of bullwhip effect present. This stimulated us to check out other measures of the forecast. The most important result of this investigation was the discovery that 95% of the forecasts made by Wal-Mart were higher than the actual! On average, the forecast was 28% higher than the actual! (30% for the pilot SKU's).

For our purposes, we briefly considered using the Wal-Mart forecast with a bias correction. This improved forecast accuracy but we found that we could get an even better forecast of POS by creating our own, based on the actual POS. So the recommendation as far as the Wal-Mart generated forecast of POS goes, is that we will simply not use it.

5.2 Creating a New POS Based Forecast of POS

In this section we propose a method to predict future Wal-Mart POS based on actual Wal-Mart POS. Later, we will use this forecast of POS to predict Wal-Mart customer orders.

Table 4 below outlines the results of various periods of moving average. This means we average the last n periods of historical POS and use that as our forecast for the next weeks of POS. The accuracy measures the ability to predict 1 week into the future.

Table 4: Weighted Forecast Accuracy of POS Moving Average

Periods of Moving Average	Weighted Forecast Accuracy (by retail units)	Low Range	High Range	Bias
1	93.2	90.4	95.2	-1.10%
2	92.7	89.4	94.3	-1.80%
3	91.5	87.8	93.4	-2.10%
4	90.6	86.5	93.0	-2.10%
5	90.5	86.4	92.8	-2.30%
6	89.2	84.3	92.4	-3.10%
12	85.7	81.7	88.8	-5.40%

Interestingly, the naive forecast (just taking last week's actual POS and using that as your future forecast) performed the best. In addition, as one moves away from the naive forecast (more and more periods of moving average), the forecasts get worse. How can this be, given the well known idea that a moving average with too few periods will suffer heavily from random noise in the data? Well consider the fact that we're talking about Wal-Mart, the largest retailer in the world, who lives by an every day low price strategy. The size of Wal-Mart (3,000 stores in North America) means we're aggregating demand over a large number of consumers. Arbitrarily high demand in one store will likely be cancelled out by low demand in another store due to the law of large numbers. The every day low pricing prevents any random spikes in demand due to pricing strategy. In addition, the product (shave gels) is the type of product which gets consumed in roughly regular time intervals. Considering all of this, it's not surprising that the demand at Wal-Mart for shave gels has very little random noise. As a result, we have the opportunity to avoid any error due to long term growth by taking the shortest possible period.

We also tested the ability to predict up to 2, 3, and 4 weeks into the future, and the order of the results was exactly the same with the naïve forecast being the most accurate. As expected,

the accuracy going into the horizon drops steadily with the naïve forecast accuracy being 86% at four weeks out.

Exponential smoothing simply resulted in figures which approximated the period moving averages. The more weight given to the recent data points, the closer the method approximated the 1-period naive forecast, and the more accurate the result. No gains were made by using exponential smoothing.

Compare these results to the accuracy of the Wal-Mart generated forecast which was 70% at 1 week and 62% at 4 weeks. Clearly, it is more effective for Gillette to generate its own forecasts than to rely on those of Wal-Mart.

5.3 Predicting Wal-Mart orders based on forecast of POS

In the long run, customer orders will approximately equal POS. Similar to a river, supply chains are subject to a conservation of flow. The only major difference being that echelons of the supply chain can build or reduce inventory which will create a difference between POS and customer orders. But aside from exceptions such as obsolescence or theft, whatever is sold to the customer, is eventually sold to the consumer. This suggests a very simple forecasting technique. We forecast that whatever was sold at the POS level last week, will be the forecast for each week for the next four weeks. (And we are not concerned here with forecasts beyond that).

This forecasting technique will have an error which roughly matches the difference between Wal-Mart's ordering pattern and the POS demand pattern. However, we predict that this error will be smaller than the error generated by bullwhip-inspired attempts to forecast what

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Wal-Mart will order. Due to conservation of inventory in a supply chain, the forecast can only be so wrong for so long.

Table 5 details the results of a test of this forecasting technique over the same time frame as the As-Is test of Chapter III. Included are results of a test of the As-Is forecast of just the Wal-Mart orders and a test of test of a twelve-period moving average forecast based on orders. (These are not the same tests as Chapters III and IV. Those tests looked at the nationwide demand on Gillette while these tests focus on Wal-Mart alone.)

Table 5: Forecasting Performance- Wal-Mart Alone

Forecast of Wal-Mart Orders	Forecast Accuracy	Daily CV
As-Is	59.0%	3.17
12-period moving average	63.4%	2.29
Naive POS	70.1%	1.98

The naïve POS based forecast is clearly more effective. If Wal-Mart were Gillette's only customer, switching from the As-Is to the naive POS-based order forecast would reduce safety stock by over a third. Note that the As-Is and 12-period moving average methods both have far lower accuracies than they did in predicting national demand. (74.6% and 77.9% respectively for national). This is expected since the national demand is so much larger and there are greater aggregation benefits. It does not mean that these techniques are inherently less capable of forecasting Wal-Mart's demand. (We also tested using a moving average of the last n weeks of POS to estimate customer orders but accuracy declined with increasing n just as it did for forecasting POS with POS.)

These results support the theory that the bullwhip effect can be mitigated by using POS data. More specifically, in the case of Gillette's products being sold through Wal-Mart, the best

forecasting technique of customer orders is to simply forecast that future customer orders will equal last week's POS.

Unfortunately, Wal-Mart is not Gillette's only customer and the question Gillette must answer each week is how much will the nation order, not just Wal-Mart. All the customers are served by the same DC network, and there is no separate pile of inventory dedicated to Wal-Mart. So improving predictions of Wal-Mart's orders is only useful if it helps to predict national orders. In the next Chapter we look at how the results of this Chapter can be used to get a better national forecast.

One might ask why Gillette doesn't separate Wal-Mart's inventory and thus get the benefits of these accurate forecasts. The answer is that Gillette gets huge aggregation benefits by serving all of their customers from one DC network. The accuracy benefits gained by separating out Wal-Mart or any other customer's inventory would pale in comparison to the aggregation benefits they would give up. By pooling all customer's inventory, Gillette can serve randomly high demand from one customer when they have an excess due to randomly low demand from another customer. This allows them to keep a significantly lower safety stock since the law of large numbers makes it unlikely that a large number of customers order randomly high or low at the same time.

6 Forecasting Orders from All Gillette's Customers Using Wal-Mart and Target Point of Sale Data

In this Chapter we look at two other ways to forecast nation-wide customer orders. First we will simply add the Wal-Mart POS based forecast made in the last chapter to a customer orders based forecast. Then we will develop a technique which attempts to estimate national POS, then forecast using the same idea as the last chapter.

6.1 Hybrid Forecast

We showed in the last chapter that we can significantly improve the forecast of Wal-Mart's orders by using POS. How can we use this to improve the national forecast? At the very least, we expect improvement if we forecast Wal-Mart demand based on POS and then add in the standard forecast for the rest of the nation. We call this the Hybrid As-Is forecast.

To further improve, we will combine the Wal-Mart POS based forecast with the 12 period moving average forecast (which was shown in Chapter IV to be superior to the As-Is). We call this the Hybrid 12-period.

Recall that we chose a 12-period moving average empirically and reasoned that the low number of periods was driven by the steady nature of the underlying demand. The demand for the nation minus Wal-Mart might be less steady since Wal-Mart's demand is so constant. If so, a larger number of periods would be appropriate to account for the greater random noise. Thus, we ran another empirical test and found that a 20-period moving average yielded the best forecast of the non-Wal-Mart customer orders. We then combined this forecast with the Wal-Mart POS based forecast and called it the Hybrid-20-period.

In Table 6 are the results with the tests from previous chapters included:

Table 6: Forecasting Performance- Hybrid

Method	Forecast accuracy of national customer orders	Daily CV of error of 4-week forecast	Resulting Safety Stock
As-Is	74.6%	1.82	21.0 days
12-period moving average of Historical Orders	77.9%	1.29	14.9 days
Hybrid As-Is	76.3%	1.63	18.8 days
Hybrid 12- period	78.0%	1.36	15.7 days
Hybrid-20-period	78.2%	1.32	15.2 days

As expected, the Hybrid As-Is is an improvement upon the As-Is and the Hybrid-12 and 20-periods are improvements on the Hybrid As-Is. But the results of the Hybrid-12 and 20 and the straight 12-period moving average are not significantly different. All are within less than 1% of each other in forecast accuracy and the difference in their resulting safety stocks is negligible.

Thus, we can't get the benefits of POS use merely by adding a Wal-Mart based POS forecast to another forecast. What we would really like is POS for all of the customers. Since this is not given to us, we will estimate it.

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6.2 Estimate of National POS

Wal-Mart represents about 20% of Gillette's business and 35% for the pilot SKUs. When Target is added in, 47% of the pilot SKU business is accounted for. Both Target and Wal-Mart send POS to Gillette which means that Gillette has POS for 47% of its business within the pilot SKUs. If we assume that national demand is well represented by Wal-Mart and Target, we can manufacture an estimate of the national weekly sales (national POS estimate) by dividing the POS of Wal-Mart and Target by the percent of Gillette's business that goes through Wal-Mart and Target. For example, if a particular SKU has POS for a week of 200 units and Wal-Marts and Target represent 25% of the national volume, the our national POS estimate would be 200/0.25 = 800 units.

The greatest source of inaccuracy in this method comes in estimating each week what % of the business belongs to Wal-Mart and Target. This figure varies from week to week and also has steady growth trends. First we estimated the percent by dividing the last 6 months of customer orders from Wal-Mart and Target by the last 6 months of national customer orders. We then considered time periods other than 6 months and once again faced the trade off between a short period suffering from random noise and a long period suffering from growth trends. It turned out that using a one year average yielded the best accuracy, but anything between two years and one quarter (13 weeks) was in the same range of accuracy. Less than 13 weeks, the figure jumped around randomly in reaction to week to week noise. We chose to use one quarter since it gave us the maximum flexibility in testing data and suffered no significant loss in accuracy.

So our estimate of national POS for a week is (Wal-Mart/Target POS for last week)/(% of business), where % of business = Wal-Mart/Target customer orders for the last 13 weeks divided by national customer orders for the last 13 weeks.

Similar to Chapter V, we reason that since customer orders must equal POS in the long run, a good forecast of customer orders will be to just use last week's national POS estimate. In addition we tried a sort of moving average method. Here we averaged the last n weeks of national POS estimates. 12 weeks worked the best (Coincidence?). In the results below we call these techniques Artificial naive and Artificial 12-period.

Table 7: Forecasting Performance- Estimate of National POS

Method	Forecast Accuracy	Daily CV of error of 4 week forecast	Resulting Safety Stock
As-Is	74.6%	1.82	21.0 days
12-period moving average of Historical Orders	77.9%	1.29	14.9 days
Hybrid As-Is	76.3%	1.63	18.8 days
Hybrid 12-period	78.0%	1.36	15.7 days
Hybrid-20-period	78.2%	1.32	15.2 days
National POS Estimate	75.3%	1.49	17.2 days
National POS Estimate 12-period	77.1%	1.33	15.3 days

The national POS estimate is only a small improvement over the As-Is. We feel that this method requires an accurate estimate of the percent of business each week that belongs to the POS donors. While using one quarter's worth of data resulted in a final forecast accuracy of orders that was almost as good as 6 months or 1 year, we can't quantify how any of these techniques are performing in terms of actually estimating the percent of business. We will never have a way to quantify the accuracy of our national POS estimate since national POS doesn't

really exist. (Gillette has 1,800 customers most of whom don't have the ability to electronically record and transmit sales on a weekly basis). Therefore the only way to test this method is to test its final performance in predicting customer orders. As you can see this final performance is adequate but not a major improvement.

The National POS Estimate 12-period, by contrast, is in the same range as the Hybrid-20-period and the 12-period moving average of historical orders. This was initial encouraging since it gave hope to the method of artificially creating national POS. But since POS approximates customer orders over long periods, an average of the last 12 estimates of national POS approximates an average of the last 12 customer orders. (For a detailed explanation of this see Appendix III). The accuracy of the Artificial methods grew steadily as we increased the periods from 1 (naïve = 75.3%) to 12 (Artificial 12 = 77.1%) The larger the number of periods, the more the artificial method is approximating a simple moving average of customer orders. So by the time we reach 12 periods, the Artificial 12 and the 12-period moving average of customer orders are almost the same technique. We feel that this is why both methods resulted in the same ideal number of periods. (So it was not a coincidence). This has negative implications for the national POS Estimate method. It means that the National POS Estimate method is really not an improvement over a simple moving average and that the further the National POS Estimate method strays from the simple moving average (in terms of number of periods used), the worse its accuracy gets.

Therefore, we conclude that of the two main methods of incorporating POS into a national forecast, the Hybrid is the better. Within the Hybrid, the Hybrid-20 is the best. To reiterate, this technique involves adding the POS based forecast of Wal-Mart orders to a 20-period moving average of the non-Wal-Mart orders. However, none of these POS based methods beat the 12-period moving average of historical orders.

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7 Dismissal of Some Suggestions for Improvement

We will now address four possible improvements to Gillette's system which are sure to be suggested as solutions. We feel that none of these suggestions has much real value with respect to our problem and we will explain why. We will recommend that Gillette focus on implementing a simple weekly customer orders based forecast immediately rather than delving into one of these tangents, which offer false promises.

7.1 Getting more POS Data

One obvious way to improve on the above methods is to get a larger percent of the business measured by POS. For example, we tested the Hybrid-20 using POS only from Wal-Mart. The more POS we get, the greater the percent of the Hybrid forecast will be made using the more accurate POS based technique. Unfortunately, the data we have for customer orders from Target is incomplete even though our Target POS data is accurate. We couldn't add Target to the Hybrid model since we couldn't determine non-Wal-Mart/non-Target customer orders without knowing Target customer orders. However, the Target data exists somewhere within Gillette and there is nothing preventing them from using Target in a Hybrid model. We can estimate the benefit of using Target. If we assume that Target's forecast has a similar

improvement in forecast as Wal-Mart's did due to basing on POS, then the CV of error of the national forecast would improve form 1.32 to 1.30 once Target were added to the Hybrid method. (See Appendix V for this calculation.) This would only reduce safety stock by 1.5%.

What if even more customers donated POS? To gauge the highest potential benefit of using POS based estimates, we assume that all customers give POS and they all show the same forecast improvement as Wal-Mart did. Under these conditions the national forecast would result solely from POS based forecasts and the resulting CV of forecast error would be 1.21 (See Appendix I for this calculation). This is far superior to the As-Is CV of 1.82 and would result in a 34% reduction in safety stock. However, using the simple 12-period moving average of customer orders already brought us to a CV 1.29. Thus, in a perfect POS world we would still be only improving from 1.29 to 1.21, a 6% drop. This calls into question the worth of POS.

7.2 Vendor Managed Inventory (VMI)

We will not attempt in this thesis to define VMI or detail its implications. For our purposes we simply want to describe how VMI might affect our methods. In a perfectly functioning VMI system, the vendor has complete visibility of and control over the customer orders and store orders. This means there is no unpredictability resulting from the echelon of the customer. The only unpredictability will be in the consumer POS pattern. This will drive some variation in the customer ordering pattern (even though the vendor is controlling it). If all of the vendor's customers were on such a VMI system, then the vendor would only need to hold enough safety stock to meet the unpredictability generated by the consumer POS pattern.

In reality, not all of Gillette's customers are on a VMI system. In fact, even Wal-Mart is currently only practicing a Co-Managed Inventory system with Gillette, wherein Gillette has

some ability to influence customer orders. One school of thought within Gillette argues that the best way to reduce safety stock is to focus effort on improving Gillette's relationship with Wal-Mart. The goal would be to establish a full VMI system at least at the customer order level. (In CMI, Gillette can influence customer orders, but does not have complete control. This means Wal-Mart can make orders which Gillette did not expect which results in the need for safety stock).

Clearly, if all of Gillette's customers were on a functioning VMI system, Gillette would reap huge benefits. But given the fact that Gillette has 1,800 customers, most of whom are much smaller than Wal-Mart and Target it's unrealistic to think that Gillette can count on having a VMI relationship with all of its customers any time soon. However, it is possible for them develop their relationship with Wal-Mart in the near future and we now attempt to quantify the potential benefits of this.

We will give VMI the benefit of the doubt and assume that not only customer orders for Wal-Mart but also store orders are completely under the control of Gillette. If everything worked perfectly, the CV of the forecast error of customer orders would be driven solely by the unpredictability of the POS. To measure this, we note from our analysis of POS forecasts in Chapter V that the daily CV of the POS forecast using the technique we recommended is 0.398. (As expected, this is very small compared to the CV of customer order forecast errors we have seen so far which range from 1 to 3). Assuming Gillette forecasts Wal-Mart orders with a CV of 0.398, the total CV will be

(WM is 37.5% of the business of the pilot SKUs, or 0.375. All others combined are 0.625).

In the following equations,

CV = coefficient of variation

$CV_{Wal-Mart}$ = Coefficient of Variation of forecast errors of Wal-Mart orders

CV_{Other} = Coefficient of Variation of Forecast Errors from other Non Wal-Mart customers

CV_{Total} = Coefficient of Variation of the forecast of National Customer Orders (This drives safety stock)

$$CV_{Total} = \sqrt{(CV_{Wal-mart} \times 0.375)^2 + (CV_{Other} \times 0.625)^2}$$

CV_{Other} is dependent on the ability of Gillette to forecast all the other customers. We will assume the best case scenario which is that they are using a 20-period moving average of customer orders. The resulting CV can be derived as shown in Appendix V on the benefit of adding Target.

$CV_{Other} = 1.729$

$CV_{Wal-Mart} = 0.398$

After subbing in,

$CV_{Total} = 1.19$

Thus, VMI with Wal-Mart would bring the CV down from 1.29 (which we could gain by implementing a simple 12-period moving average with no effort) to 1.19. This would generate a safety stock savings of 7.7%. Perhaps this isn't worth the effort and risk involved with managing several billion dollars worth of inventory and restructuring a large network of information systems.

7.3 Improving the Forecast of POS

Perhaps the use methods which use POS would benefit from a better forecast of the POS than that achieved by the naïve method. By incorporating seasonality and promotions, and by having employees dedicated to anticipating predictable spikes in POS, it's conceivable that accuracy of the POS forecast could be improved beyond its current level of 86%-93%. For sake of argument, we assume that Gillette can find a way to predict POS with 100% accuracy. How would this impact their ability to forecast customer orders?

To test this we simply use the POS actual data for a given week as the "forecast" for that week. We then tested the naïve POS based forecast of customer orders using this perfect forecast. Recall that the forecast accuracy of this method when using a naïve forecast of POS was 75.3%. When using a perfect POS forecast, the accuracy of the customer orders forecast went up to 78.3%. Therefore, no matter how good Gillette gets at predicting future POS, it can only improve their customer orders forecast by at most 3%. This is due to the fact that most of the error in the customer orders forecast results from the large variability of customer orders relative to POS. The point of this section is to show that investments in improving the accuracy of forecasts of POS are probably not fruitful.

7.4 Accounting for Seasonality

Seasonality can have a very beneficial effect on long term forecasts. Since sales of women's shave gel usually rise in Spring, a forecast of May made in November could improve by adjusting high to account for the expected increase of sales which usually comes in May.

Unfortunately, this does nothing to help us predict the next 4 weeks which is all that matters in the decision of what Supply Planning will order. The only way seasonality could help us, is if there were something about certain times of the year which made it easier to predict a rise or fall in demand in the coming four weeks.

We explored many possibilities in this area and came to the conclusion that there is no significant seasonality of this type. Even Christmas, known to be a high volume week, did not create a situation where seasonality would be beneficial. The weeks surrounding Christmas tend to spike high and very low with no particular pattern. As a result, the demand over any 4-week span covering Christmas is still unpredictable. It's possible that further study by Gillette analysts more familiar with their products would reveal some seasonality which would be useful for predicting the next 4 weeks. However, there was nothing obvious.

A Gillette analyst did show us a clear weekly pattern in the customer orders of Wal-Mart within a month. Week 2 tended to have much lower average orders and the last week of the month tended to be slightly higher. This is also useless to predicting the next 4 weeks, since each 4-week period would have the same mix of weeks 1 through 4. 5-week months might provide an exception. When the 4-week period covers weeks 3,4,5, and 1, the demand might be predictably higher since the usually low week 2 would be left out. This seasonality within a month would become very important if Gillette's manufacturing firm period were reduced. We discuss this in the next chapter. The point here is that due to firm period reduction, Gillette's forecast horizon could shrink from 4 weeks to 3 or 2 weeks. Then it would clearly matter which number weeks were in the forecast window and this seasonality could be applied.

8 Reducing the Manufacturing Firm Period

This chapter looks at the effect on safety stock of reducing the manufacturing lead time.

Recall that the firm period for manufacturing is three weeks, and that this is the main factor in lead time between Supply Planning making an order and product arriving at the DC. Gillette is currently undergoing efforts to reduce this firm period. This would have a variety of benefits and in this section we will estimate the effect on safety stock of a firm period reduction.

At present Gillette must keep safety stock which can cover unpredictable demand over 4 weeks. (3 week lead time plus a one week review period). Reducing the firm period by say, 1 week, would reduce the exposure period to 3 weeks and thus reduce safety stock. On the other hand, Gillette would now be forecasting over a shorter interval and therefore see a decrease in accuracy and in increase in CV which would take away some of the benefits of the firm period reduction. Nonetheless, there would be a net benefit as shown below. We retested the As-Is and the naive artificial methods using a 3 and two week firm period. The resulting safety stock for a method is calculated as:

$$Safety\ Stock = 21\,days \times \frac{Method\ CV}{As-Is\ 4\ week\ forecast\ CV} \times \sqrt{\frac{As-is\ Lead\ Time + REVIEW\ Period}{Method\ Lead\ Time + REVIEW\ Period}}$$

Table 8: Forecasting Performance- Firm Period Reduction

Method	Forecast Accuracy	Daily CV of error of 4 week forecast	Resulting Safety Stock
As-Is 3 week firm period (so 4 week exposure period when review period of 1 week is added)	74.6%	1.82	21.0 days
As-Is 2 week firm period	73.2%	1.92	19.2 days
As-Is 1 week firm period	71.0%	2.09	17.1 days
Artificial naïve 3 week firm period	75.3%	1.49	17.2 days
Artificial naïve 2 week firm period	74.0%	1.57	15.7 days
Artificial naïve 1 week firm period	71.4%	1.71	14.0 days

As shown in Table 8 each week of firm period reduction will reduce safety stock by about 10%.

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9 Results, Recommendations, and Future Research

In our analysis of Gillette's current process we identified two major problems: a long and complex demand planning cycle and an exposure to the bullwhip effect due to reliance on customer orders.

9.1 Planning Cycle Recommendation

The remedy for the first problem is to shorten the demand planning cycle from one month to one week and to use a simple, easy to update forecasting technique. We recommend using a 12-week moving average of customer orders updated weekly to forecast national customer orders. This simple technique requires no investment and no improvement of relationships with customers. If Gillette were to apply the Lewandowski method or any other automated forecasting system on a weekly basis, they could probably achieve the same or more benefits. In other words, while the technique we recommend is the best of those we tested, there are probably numerous other techniques which could perform as well or better if applied weekly. We estimate that using our method would reduce Gillette's safety stock from 21 days to 14.9 days.

9.2 Bullwhip Effect

The other problem Gillette has is its exposure to the bullwhip effect. Gillette's forecasting system is based on customer orders and this leaves them subject to the escalation of variability in orders up the supply chain. Our analysis of Gillette's ability to predict Wal-Mart

orders showed that the bullwhip effect can certainly be mitigated by incorporating POS into forecasts. Viewed in isolation, the Wal-Mart case demonstrates the potential benefit to companies of recognizing the bullwhip effect and using POS to lessen its impact.

However, like many other vendors, Gillette aggregates the demand of all of its customers and reaps the reward of risk pooling. Because of this, improving the forecast accuracy of a single customer (even one as large as Wal-Mart), does not have a very large impact on safety stock. Combining the POS based forecast of Wal-Mart orders with a simple moving average forecast of all non-Wal-Mart orders (Hybrid-20) did not make any improvements on just using a simple moving average across all of Gillette's customers.

The next thought was to see if forecasting for all Gillette customers based on an estimated national POS would make improvements. We used POS from Wal-Mart and Target to estimate national POS, and then made a forecast of national customer orders using the same technique which we used to forecast Wal-Mart orders in the hopes that we would see the same improvements. The result was a much better forecast than the As-Is process, but it was still not as good as a 12-period moving average of customer orders. This could be due to the fact that national POS simply doesn't rise and fall with Wal-Mart and Target POS, or that our ability to estimate the percentage of retail sales which belonged to Wal-Mart and Target was inaccurate. (There is no way to gauge this). So we do not recommend attempting to estimate national POS.

We next considered the potential benefit of getting POS from more customers. We tested what the benefit would be if every customer gave POS to Gillette, and if the forecasts of these customer's orders all showed the same positive response to POS based forecasting. The result was that Gillette could achieve a 6% safety stock savings beyond that which came from using a 12-period moving average of customer orders. This is not much considering the effort that would be required to get all of Gillette's 1,800 customers to send POS. Even if Gillette were to

get it from its top ten customers (about 70% of the business) they would still not realize a large gain. Thus, we recommend that Gillette not bother switching to a POS based forecasting system even though there seems to be large potential benefits.

How can it be that studies such as the Wal-Mart case demonstrate huge potential for POS based forecasts, yet we see no significant benefit? The bullwhip effect within one specific customer is easy to demonstrate and we believe that it is a real phenomenon. The benefits of switching to a POS based forecast system are equally real. However, consider the case where numerous customers are undergoing a bullwhip effect which causes them to make excessively large orders for a time period, followed by excessively small orders. If all these customers' bullwhips were in-phase, then the national ordering pattern would suffer the bullwhip effect to the same degree as a specific customer ordering pattern. Then the benefits of POS based forecasting at the national level would equal those at the customer level. In reality, however, one customer may be in a high cycle of the bullwhip while another is in a low cycle, thus canceling each other out. This makes the effect of the bullwhip less profound at the national level, and hence the benefits of POS based forecasting less significant.

If all of Gillette's customers were randomly in some part of a bullwhip cycle then there should be no bullwhip effect at all at the national level, although there would still be significant variability in orders. Because of the fact that some spikes in consumer demand affect all of Gillette's customers at the same time, there is still some phased bullwhip effect, but not as much as if only one customer were being forecasted. Thus, we expect that POS based forecasting at the national level with 100% POS would have some positive benefit, but not as much as at the customer level. The result we mentioned before confirms this. Gillette could achieve about a 6% reduction in CV with 100% POS use which is better than 0 but not as good as the 13.5% CV improvement in the isolated Wal-Mart case.

<u>In general, we feel that the usefulness of POS for vendors with customer ordering</u>

<u>patterns similar to those of Gillette is very small.</u> In particular, if a vendor's customer orders don't display the bullwhip effect in-phase with each other, then the value of using POS will be small. Gillette has a large number of customers which tends to cause the bullwhip cycles of individual customers to cancel each other out, thus mitigating the effect when demand is aggregated. If, for any reason, the customer's bullwhip cycles are in-phase, then the bullwhip effect will be seen at the aggregated national level and POS may be of more use. Possible causes of in-phase bullwhip effects are national promotions and seasonality which affects demand within a vendor's exposure period. (For example, if a vendor has a lead time of 1 week and they manufacture candy, then the seasonal spike at Halloween might generate an in-phase bullwhip effect). In the case of Gillette, they manufacture a daily use product and serve 1,800 customers. In addition, their promotions are usually customer focused, rather than national. The results of this thesis might only apply to vendors with similar circumstances. Vendor's with fewer customers or customers with in-phase bullwhip cycles may or may not have more use for POS. This is a subject for future research.

Vendor Managed Inventory is another subject which receives a lot of attention but we don't feel would benefit Gillette. If you have aggregated demand, reducing the variability of one of your customer's orders to close to zero is not as useful as reducing all of them by a small percentage. The all-powerful square root sign renders major improvements to one source of variability insignificant. In the case of Gillette and Wal-Mart, perfect VMI would only result in a 7.7% savings of nationwide safety stock. However, if a large enough percentage of Gillette's business were to come under VMI at the same time, they could realize huge gains. The benefit of bringing one customer under VMI may not outweigh the cost. (Increased responsibilities, information systems investment, supply chain integration etc.). A subject for future research is

how many customers or what percent of your business must come under VMI before the benefits of reduced safety stock outweigh the costs associated with VMI.

Gillette estimates the annual carrying cost of holding a day's worth of inventory of the whole Personal Care business unit to be $100,000. Thus, in Personal Care alone, Gillette can save $610,000 {=$100,000*(21-14.9)} each year. The pilot project which Gillette is about to start has already received pressure from higher management to expand into other business units. The goal is to prove significant improvement within a few months, then to scale the program up. Personal Care annual net sales are $961 million while all of Gillette is $10,447 million. Using this to approximate the total benefit to Gillette, we foresee a savings of ($10,447/$961)*$610,000 = $6.6 million per year in inventory carrying costs. An alternate estimation is to note that 1 day of Personal Care sales = $961 million/365 = $2.63 million. So a savings of 21 − 14.9 = 6.1 days equates to 6.1*2.63 million = $16.0 million reduced inventory. An estimate received from Gillette of their carrying cost for inventory was 10%. Thus, they can save $1.6 million per year in Personal care and $17.4 million per year Gillette wide according to this estimate. There are many considerations which would lower this estimate (such as the need to carry higher inventory for new products) and many which would raise this estimate (such as the fact that our accuracy figures are a worst case scenario since we've done nothing to improve them with promotional considerations or use of techniques such as Lewandowski).

9.3 Conclusion

In conclusion, the vast majority of the potential gain for Gillette comes from reducing the planning cycle from one month to one week. When this is done, the value of POS to vendors with customer ordering patterns similar to those of Gillette is minimal. There are benefits to

switching to a POS based forecasting system but they cannot be significant until the majority of Gillette's customers are sending POS. Even if in the future, 100% of Gillette's demand were recorded in POS, a POS based system would result in only a 6% reduction in safety stock. While a 6% reduction might seem important, it pales in comparison to the savings which Gillette can achieve today by simply using a basic forecasting technique and updating it weekly. By employing a 12-period moving average and updating it weekly, Gillette can reduce its safety stock from 21.0 days to 14.9 days. If this is implemented in all of Gillette's business units, we estimate that they could save about $6.6 million a year in carrying costs.

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Appendix I: Using 100% POS

Assume national demand =1

Let, a, b, ...,c represent the fractions of Gillette's business for each customer.

So, $a+b+.....+c=1$

C_{Total} : Coefficient of Variance (CV) of forecast error

C_1, C_2 ... C_3, represent the Coefficient of Variance (CV) of forecast error for each customer.

$$C_{Total} = \sqrt{(a \times C_1)^2 + (b \times C_2)^2 + \ldots\ldots + (c \times C_3)^2}$$

Due to aggregation or disaggregation of demand,

$$C_2 = C_1 \times \sqrt{\frac{a}{b}}; \; C_3 = C_1 \times \sqrt{\frac{a}{c}}$$

$$C_{Total} = \sqrt{C_1^2 \times a^2 + \frac{a}{b} \times C_1^2 \times b^2 + \ldots\ldots + \frac{a}{c} \times C_1^2 \times c^2}$$

$$= \sqrt{C_1^2 \times (a^2 + a \times b + \ldots\ldots + a \times c}$$

$$= \sqrt{C_1^2 \times a \times (a + b + \ldots\ldots + c}$$

$$= C_1 \sqrt{a \times (a + b + \ldots\ldots + c)}$$

$$C_{Total} = C_1 \times \sqrt{a}$$

$$CV_{Total} = (CV_{Wal\,Mart} \times \sqrt{a}) = 1.98 \times \sqrt{3.75} = 1.21$$

Appendix II Calculation method for Coefficient of Variation of error

Standard Method:

$$error \text{ "} e \text{"} = Actual\,Demand - Forecast\,Demand$$

$$Root\,Mean\,Square\,of\,Errors\,(RMSE) = \sqrt{\frac{\sum_{t=1}^{n} e_t^2}{n}}$$

$$Coeff.\,of\,Variation\,(CV)\,of\,Forecast\,Errors = \frac{RMSE}{Average\,of\,Actual\,Demand}$$

Gillette's Method:

$$error \text{ "} e \text{"} = Actual\,Demand - Forecast\,Demand$$

$$Mean\,Absolute\,Deviation\,(MAD) = \frac{\sum_{t=1}^{n} |e_t|}{n}$$

$$Coeff.\,of\,Variation\,(CV)\,of\,Forecast\,Errors = \frac{1.25 \times MAD}{Average\,of\,Forecast\,Demand}$$

The non-standard part of the Gillette formula is dividing by the average forecast instead of the average actual. This often leads to a high forecast bias and can often mislead with a erroneously high forecast accuracy. For small samples this could make a big difference but over long periods (such as 6 months) the average forecast should approximate the average actual even if the forecast isn't very accurate (Unless, there is a significant bias). A simulation was carried out by Gillette's supply planner over a large enough sample size and there was no significant difference between the standard and the Gillette method to determine the Coefficient of Variation of Error.

The Gillette method also uses the approximation 1.25*MAD in lieu of standard deviation. This is a bit less effective than using standard deviation since it doesn't punish very bad forecasts by squaring the error. (And those are the forecasts that cause stock outs!) But regardless, the important aspect is that we use the same method as Gillette.

An additional transformation is necessary to switch between 4-week CV (this is what is actually measured) and daily CV (which is how Gillette expresses it, and how they input it into the Optiant software to calculate safety stock). This is simply:

$$4\,week\,CV \times \sqrt{28\,days} = Daily\,CV$$

Appendix III: Using a 12-period moving average in forecasting based on customer orders:

Common wisdom suggests using between a 13 and a 20-period moving average, emphasizing that anything less than 13 periods will subject you to the random noise in the data, while anything greater than 20 periods will create a long enough lag time that you will suffer errors due to long term trends. (A moving average is always giving you an average that lags the present by half the number of periods. For example, a 20-period moving average takes all the data points surrounding ten periods back and gives you a figure which would be most fitting for 10 periods back. So, the greater your number of periods, the worse your error due to this lag, since the further from the present your estimate goes.)

Our intuitive argument against this is that the ideal number of periods depends on the data set you are working with. If the data has no long term trends you could use an infinitely large number of periods. If the data had very little random noise you could use shorter and shorter periods. The products in our pilot project (shave gels) tend to be purchased in regular intervals. Unless everybody decides to stop shaving in the same week there won't be much random noise from week to week in the consumer buying pattern. The customer orders will, of course, still have random noise, but the total random noise resulting from customer orders based on a fairly stable POS will be less than for customer orders based on a more variable product. Thus, we feel that the underlying demand pattern for shave prep results in a customer ordering pattern which can be modeled by a relatively short, 12-period moving average.

But feelings and intuition aside, we tested each possible period length and found that a 12-period gave the best forecast accuracy. It's important to note that 11 periods was better than 10 periods which was better than 9 periods etc. Similarly 13 periods was better than 14 etc. This implies that 12 periods represents an optimal in terms of solving the trade off between random noise in a small number of periods, and error from growth in a large number of periods.

The idea of ignoring the recommendation of 13-20 periods due to the specific nature of a demand signal will be applied to the extreme in Chapter V.

Appendix IV: Establishing linear relationship between CV and safety stock

The table contains the results of a sensitivity analysis conducted by a Gillette supply planner. It uses Optiant software® to calculate the safety stock based on a given CV. The value of this analysis is that it accounts for practical factors in Gillette's system such as batch stock and its effect on safety stock. Note that as Daily CV% rises, safety stock days of supply rises. Figure 15 shows that there is a linear relationship between the two. Thus, a 20% reduction in daily CV, results in a 20% reduction in safety stock.
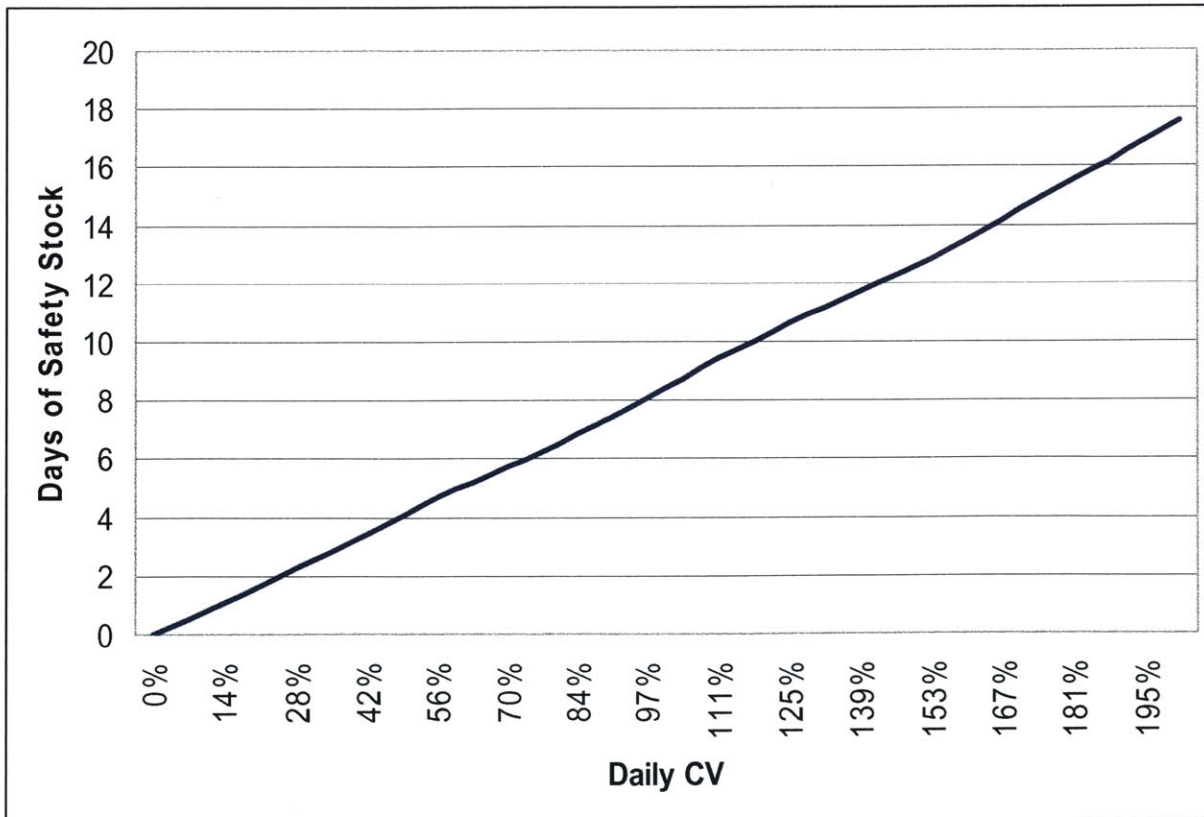

Figure 14: CV- Days Safety Stock Correlation

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Table 9: Safety Stock Sensitivity Analysis

Daily CV%	Equivalent Forecast Accuracy	Average Inventory $	Safety Stock $	Safety Stock DOS
0%	100%	1,062,879.83	0	0
7%	99%	1,094,129.31	31,249.48	0.48
14%	98%	1,132,223.22	69,343.39	1.06
21%	97%	1,172,811.88	109,932.05	1.68
28%	96%	1,210,089.80	147,209.98	2.25
35%	95%	1,248,011.75	185,131.92	2.83
42%	94%	1,286,239.16	223,359.33	3.42
49%	93%	1,325,134.77	262,254.95	4.02
56%	92%	1,367,947.95	305,068.12	4.67
63%	91%	1,403,712.87	340,833.04	5.22
70%	90%	1,436,983.32	374,103.49	5.73
77%	89%	1,472,147.53	409,267.70	6.27
84%	88%	1,510,021.27	447,141.45	6.85
90%	87%	1,547,957.93	485,078.10	7.43
97%	86%	1,591,039.10	528,159.27	8.09
104%	85%	1,634,417.33	571,537.50	8.75
111%	84%	1,678,063.01	615,183.18	9.42
118%	83%	1,716,871.87	653,992.04	10.01
125%	82%	1,760,735.25	697,855.42	10.69
132%	81%	1,790,993.69	728,113.86	11.15
139%	80%	1,827,182.02	764,302.19	11.7
146%	79%	1,863,429.09	800,549.26	12.26
153%	78%	1,899,766.05	836,886.22	12.81
160%	77%	1,943,621.31	880,741.48	13.49
167%	76%	1,987,635.81	924,755.99	14.16
174%	75%	2,031,798.19	968,918.36	14.84
181%	74%	2,076,097.25	1,013,217.42	15.51
188%	73%	2,120,524.51	1,057,644.69	16.19
195%	72%	2,165,070.40	1,102,190.57	16.88
202%	71%	2,209,726.64	1,146,846.81	17.56

Appendix V: Adding Target's POS

We wish to find the daily CV when Target is added.

Assume an average daily demand of 1:

$\sigma_{Wal-Mart}$ = Standard Deviation of the forecast error of customer orders from Wal-Mart

σ_{TARGET} = Standard Deviation of the forecast error of customer orders from Target

σ_{Other} = Standard Deviation of the forecast error of customer orders from other non Wal-Mart and Target customers

Similarly, we designate the Coefficient of Variation of errors (CV) as follows:

$CV_{Wal-Mart}$ = Coefficient of variation of errors of Wal-Mart

CV_{TARGET} = Coefficient of variation of errors of Target

CV_{Other} = Coefficient of Variation from other non Wal-Mart and Target customers

CV_{Other1} = Coefficient of Variation of forecast errors of Non Wal-Mart/ Target customers when Target POS based forecast is not present (This is different from the CV with Target)

$$\sigma_{Total} = \sqrt{\sigma^2_{Wal-Mart} + \sigma^2_{TARGET} + \sigma^2_{Other}}$$

Since Standard Deviation, $\sigma = Average\ Demand \times CV$

And, since Wal-Mart is 37.5% of the business and Target is 9.5%, then

$$CV_{Total} = \sqrt{(CV_{wal-Mart} \times 0.375)^2 + (CV_{TARGET} \times 0.095)^2 + (CV_{Other} \times 0.53)^2}$$

Since, $CV_{Wal-Mart} = 1.98$ and assume that Target's accuracy in predicting POS is similar to that of

Wal-Mart.

This implies,

$$CV_{TARGET} = CV_{Wal-Mart} \times \sqrt{\frac{\%\ of\ WAL-MART\ BUSINESS}{\%\ of\ TARGET\ BUSINESS}} = 1.98 \times \sqrt{\frac{37.5\%}{9.5\%}} = 3.93$$

Now, CV_{Other} remains to be determined, which can be derived from Hybrid-20 (recall that

Hybrid-20 is the case where Wal-Mart's POS forecast is added to a 20-period moving average of

the balance customer orders)

For a Hybrid-20-period moving average, the daily CV = 1.32

Using the same logic developed above:

$$CV_{Hybrid\,20} = 1.32 = \sqrt{(CV_{Wal-Mart} \times 0.375)^2 + (CV_{Other1} \times 0.625)^2}$$

Solving the above equation we get: $CV_{Other1} = 1.746$

It should come as no surprise that CV_{Other1} in this case is lower than that of Wal-Mart CV since

its forecasting over a much larger volume (benefits of aggregation one again).

Since $CV_{Other1} = 1.746$ when forecasting 62.5% of demand, we can calculate CV_{Other} which

represents 53% of the demand as follows:

$$CV_{Other} = CV_{Other1} \times \sqrt{\frac{62.5\%}{53\%}} = 1.746 \times \sqrt{\frac{62.5\%}{53\%}} = 1.896$$

Now, we have all the information to calculate the CV of Hybrid-20 when Target POS is thrown

in as follows:

$$CV_{Total} = \sqrt{(CV_{Wal-Mart} \times 0.375)^2 + (CV_{TARGET} \times 0.095)^2 + (CV_{Other} \times 0.53)^2}$$

$$= \sqrt{(1.98 \times 0.375)^2 + (3.93 \times 0.095)^2 + (1.896 \times 0.53)^2}$$
$$= 1.30$$

So, adding Target POS into the Hybrid-20 dropped the CV from 1.32 to 1.30, a safety stock

savings of 1.5% which is not significant.