Quantifying the Value of Reduced Lead Time and Increased Delivery Frequency

by

Joseph Sean Walkenhorst

B.S. Chemical Engineering
Brigham Young University, 1998

Submitted to the Engineering Systems Division in Partial Fulfillment of the Requirements for the Degree of

Master of Engineering in Logistics

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Signature of Author

Engineering Systems Division
May 11, 2007

Certified by

Stephen C. Graves
Abraham J. Siegel Professor of Management Science
Thesis Supervisor

Accepted by

Professor of Engineering Systems
Professor of Civil and Environmental Engineering
Director, MIT Center for Transportation and Logistics
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Abstract

A large consumer package goods company would like to know the answer to the following question. What is the value to its customers of increased delivery frequency or reduced lead time? To answer this question, we collected shipment and inventory data for three customers: a mass merchandiser, a grocery store chain, and a drug store chain in the US. We examined the shipment histories to the customers’ Distribution Centers (DCs) in the West, the Midwest, and the East for SKUs from three product families. We developed a continuous review QR inventory model to calculate the theoretical inventories for these high volume SKUs. We used this model to assess the theoretical inventory requirements for multiple scenarios entailing some form of increased frequency or decreased lead time.

Some companies run heavy promotions during which time the majority of sales occur. If such a company is to benefit from reduced lead time from its supplier to their DCs, shipments from their DCs to stores must be frequent enough to respond to their stores’ needs during a promotion. If this is not the case, the main opportunity to reduce inventory will be through better promotional planning.

The data showed that there was a great amount of variability in the average inventory levels at the customers’ DCs, which suggested that some DCs have large excesses of inventory for some SKUs. If customers could simply match their best in class inventory levels across all other products and locations, possibly $120 million could be saved annually in inventory carrying costs across all of this company’s customers. The model also suggested that increasing delivery frequency provides a greater value than decreasing lead time. The methodology used to calculate the value of potential savings to customers could be applied to other locations or other industries.

Thesis Supervisor: Stephen C. Graves
Title: Abraham J. Siegel Professor of Management Science
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Finally, I would like to offer a heartfelt thanks to my wife April who has been such a wonderful support throughout the length of this project. I truly could not have accomplished all that I did without her loving support.
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1 Introduction

Companies seek to improve their profitability by removing costs from their supply chains, but they can only go so far by looking at just their own costs. They must also look at costs and systems of other companies within their supply chain in order to optimally reduce total costs including their own. Some changes that increase one company’s costs may actually reduce costs for the overall supply chain. Once opportunities like this have been identified, negotiations between the companies can occur to share the savings so that each company has an incentive to embrace the change.

1.1 Problem Statement

A large consumer package goods company, SupplierCo, has made changes over its history to optimize its part of the supply chain for its products and to minimize its costs. As the company considers other options to improve its supply chain, it has identified options that might improve its overall supply chain, but would add internal costs. These costs might actually be less than the benefit to its customers; however, to see whether or not the options do improve the total supply chain, SupplierCo needs to be able to estimate the potential benefits to its customers.
For example, if SupplierCo built more distribution centers (DCs) around the country, then the lead time to ship products to retailers would be shorter. That shorter lead time could benefit its customers through lower inventory levels, lower handling or storage costs, or fewer out of stocks. But it also would translate into higher costs for SupplierCo. Similarly, if SupplierCo ships more frequently to the retailer, the retailer could also achieve lower inventory levels, lower handling or storage costs, or fewer out of stocks, but SupplierCo would incur increased freight costs. So, the purpose of this thesis is to evaluate the potential savings for the retailers of possible network changes that SupplierCo could implement. In particular, it addresses the question – What is the value to the customer of increased delivery frequency or reduced lead time?

This question was studied for SupplierCo by looking at three national retailers in the United States – a mass merchandiser (MassCo), a grocery store chain (GroceryCo), and a drug store chain (DrugCo). These different retailers provide an opportunity to examine different retail channels that attract different types of customers and also see different levels of shipment frequency and demand volumes. For instance, MassCo has a high frequency of shipments from its DCs to its large stores while DrugCo has a much lower frequency from its DCs to its small stores.

Three products were chosen to focus the research; Big&Fast that ships frequently to customer DCs and has short lead times from customer order to delivery; Big&Slow that ships frequently to customer DCs but has long lead times, and Small&Slow that
ships infrequently to customer DCs and has long lead times. Finally, for each retailer we selected three of its DCs— one in the East, one in the Midwest, and one in the West. This will allow us to examine whether there are differences due to geography, primarily when it comes to lead time. Since SupplierCo’s distribution points are located mostly in the Midwest, shipments to the West Coast take several more days. The retailers, products, and DC locations were selected to reveal as much information as possible in the time available.

1.2 Description of Network

SupplierCo has a variety of products which are produced in manufacturing plants across the world, and these products can vary greatly in their frequency of shipments to customers and lead time to customers. For each of the three products in this study, the distribution network is described below.

Big&Fast ships frequently to retailers and has six main distribution points in the US in the Midwest, the South, and the West. Big&Slow has a similar shipment frequency as Big&Fast and has two distribution points in the Midwest, one serving the northern part of the country and the other serving the southern part. Small&Slow has a much lower shipment frequency and has only one distribution point in the Midwest. For Big&Slow and Small&Slow, we saw longer lead times to the West because the distribution points in the Midwest were so much farther away.
1.3 Opportunities

There are several possible methods SupplierCo could use to reduce its lead time. One option would be to use a DC in the West Coast to ship products to customers. Big&Slow and Small&Slow take an average of five days longer to reach the West Coast than the East and Midwest. Having goods already in the West could reduce five days of lead time from shipments going there. This would reduce inventories at customer locations in the West, but the majority of consumption and inventory is in the East and Midwest. The benefit to SupplierCo’s customers may be large enough to justify the additional cost, but the cost of this option must be weighed against the benefit to only about 20% of SupplierCo’s customer base in the United States.

Another option that could reduce lead time throughout SupplierCo’s network would be if SupplierCo could speed up its average response time to an order. Right now SupplierCo commits to a maximum of three days from when an order is submitted to when it is shipped to a customer. The actual time for this varies by customer but is often higher as many orders are submitted early and have request dates as far as two months in the future. This long lead time might seem surprising but is due to promotional planning. For instance DrugCo regularly promotes SupplierCo products and the majority of these sales occur during promotions. Because of this, the majority of orders to SupplierCo are submitted well in advance as part of DrugCo’s promotional planning process which begins 18 weeks before each scheduled promotion. Their
planning process results in orders being submitted 10 weeks before the promotion with a requested delivery date in their DCs in 8 weeks to allow time to ship product from their DCs to their stores. Additional orders are sometimes submitted as well if demand forecasts increase.

For orders submitted early like this, no benefit would be expected from SupplierCo improving its response time as the customer did not ask for a quick response. An opportunity would exist to provide a benefit to customers for orders that were requested within a few days. If SupplierCo could reduce their response time from three days to two days or even to one day, how much might that benefit their customers?

In order to increase the frequency of shipments, SupplierCo could ship smaller amounts of more SKUs together on a truck. This could occur by shipping some product from one manufacturing plant to another so that only a fraction of the material would have to be shipped twice, once within SupplierCo’s network, and a second time to the customer. Alternatively, products could be shipped to a regional distribution center from which customers could order all products together, rather than shipping directly from the factory. Finally, products could be shipped LTL (less than truck load) to achieve greater frequency. Some of these options may be better than others, and this could vary by geography and by customer. This study will focus on trying to quantify
the benefit that could be realized from improved frequency regardless of how it is actually achieved.
In determining what to focus on in the subsequent analysis, it was first important to identify the areas of potential cost savings. Possible areas of cost reduction for SupplierCo customers are:

1. Reduced inventories in their DCs
2. Reduced handling costs in DCs resulting from reduced inventories
3. Reduced storage costs in facilities outside of main DCs resulting from reduced inventories
4. Improved service levels at their retail stores resulting in fewer out of stocks and increased sales

In discussing these possible savings with representatives of each customer, their feedback was that the primary cost reductions they would realize would be reduced inventories and some reduced out of stocks. One customer mentioned that another retailer who is not part of this study uses an activity based costing system that would have seen savings from reduced handling, but that they were the exception of most retailers. Quantifying such a savings for other customers would be difficult and fairly minimal as SupplierCo products in customer DCs represented only 5-10% of their total
inventory. Since SupplierCo’s products were a small fraction of the overall sales for each customer, even a large reduction in SupplierCo inventory would not be a sizable inventory reduction for the customer DC. Therefore, no reduction in storage area requirements would be expected either.

With that feedback in mind, the analysis focused on inventory reduction in the DCs. First, a theoretical inventory level was calculated for each product in each DC for each customer. This value was compared with actual inventories to determine the effectiveness and accuracy of the model.

Further, theoretical inventories could then be calculated to examine the potential improvement over the initially calculated theoretical inventory. Eleven scenarios were evaluated by varying frequency, lead time, or planned days of inventory in customer’s DCs. A percent improvement over the theoretical inventory could be calculated for each, and they could be compared with one another to see which options would deliver the greatest value to SupplierCo’s customers. These eleven scenarios were specified by:

1. Identifying the product in a DC for each retailer with the fewest days of inventory and assuming that each product in each DC for that customer could reach that best in class inventory level. The difference from the actual inventory to the best in class inventory represented the potential savings. Due to large differences in demand volume and frequency, to achieve the best
in class would be quite challenging but perhaps represents an upper bound
on possible customer benefits.

2. Combining multiple product families together on the same truck to achieve a
daily shipment frequency.

3. Increasing the frequency of shipments to what it would be if these SKUs went
out on each shipment of product from the manufacturing plants. Some
shipments were sent with a few SKUs but not the high volume SKUs being
studied. Thus, there was sometimes a sizable difference in the overall
frequency on a particular lane from the frequency of a particular SKU even if
it was a high volume SKU. Increasing the delivery frequency could reduce
the need for cycle stock and total inventory. Once the delivery frequency
improved to daily shipments, further improvements were ignored as we
assumed that the planning systems at the DCs would not allow for further
inventory improvements.

4. Increasing the frequency of shipments to what it would be if Big&Slow and
Small&Slow SKUs shipped together. If these products could ship together,
both would ship more frequently, and the DCs would need less cycle stock of
each.

5. Eliminating lead time variability. If shipments were to arrive exactly when
expected, the DCs would not need to carry as much safety stock.
6. Reducing lead time variability by 50%. Since completely eliminating lead time variability is not likely, this scenario is perhaps more realistic and will tell us how much of the total benefit might be achievable.

7. Reducing the replenishment lead time by two days for all shipments. This could most likely be accomplished if SupplierCo were to improve its response time to orders. This could reduce the amount of safety stock needed in the DCs.

8. Reducing the lead time by one day for all shipments.

9. Limiting the lead time to no more than four days for all products and locations. This would require SupplierCo to have more inventory in more locations but could examine the potential inventory reduction at customer DCs due to all products having a short lead time.

10. Examining the effect of having a DC in the West Coast that would allow the lead time to the West Coast to be the same as it was to the Midwest and the East Coast.

11. Examining the effect of just moving Small&Slow to an existing SupplierCo DC on the West Coast since Small&Slow had the lowest frequency of the three products being studied.
3 Data

There were a number of different pieces of data collected and analyzed to answer the question of what is the value to the customer of increased shipment frequency or decreased lead time. While the scope of the project had been clearly defined, there were still dozens of unique SKUs for the three products to be studied. Therefore the first step was to identify specific SKU numbers of high volume products within the three product families. This had to be done for each of the three customers.

3.1 Types and Sources of Data

Once the SKU numbers to study had been identified, shipment data from SupplierCo DCs to customer DCs could be collected from SupplierCo’s data systems. This data showed each shipment containing these SKUs over the past three to eight months and listed the SKU, shipping locations, order quantity, order date, processing date, shipping date, actual arrival date, and requested arrival date. Due to changes in the distribution network for MassCo, accurate data was only available for three months while for GroceryCo and DrugCo, eight months of data was available.

As SupplierCo received an order, planners would have to process the order in their system and release it to manufacturing, who could then begin to assemble the
order and load it onto a truck. The time from order date to processing date was the
time it took Planning to process the order, and the time from the processing date to the
ship date was the time it took the order to get filled and shipped.

This shipment data provided a picture of the demand from the customer DCs to
SupplierCo, but it was also important to see what the demand was from the customer
stores to their DCs. The shipments to the stores better reflected actual customer
demand and the variability of that demand. From this data we calculated an average
and standard deviation of demand for each product in each customer’s DC.

Inventory data at SupplierCo’s manufacturing plants was collected to determine
out of stock levels to see how often SupplierCo’s lack of inventory resulted in late
shipments that could cause customers to keep additional safety stock on hand. Eight
months of data was collected for each SKU.

Inventory data at customer DCs and customer stores was also collected to see
how often out of stocks occurred at either location. The time frame of available data
varied by customer.

- MassCo had 20 weeks of DC inventory data but only 4 weeks of store data
  available.
- GroceryCo had 2 years of DC inventory data and 2 years of store data.
- DrugCo had 35 weeks of DC inventory data available but no store data
  available.
This also provided an opportunity to see how often out of stocks at one point in the supply chain caused out of stocks at another point in the supply chain. It turned out to be rare for customer DCs and stores to be out of stock at the same time.

### 3.2 Current frequencies and travel times

The current delivery frequency per week of all SKUs of the three product types to the three retailers is summarized in the tables below.

#### Table 1 - Shipments Per Week of all SKUs in a Product Family to Customers

<table>
<thead>
<tr>
<th></th>
<th>MassCo</th>
<th>GroceryCo</th>
<th>DrugCo</th>
</tr>
</thead>
<tbody>
<tr>
<td>Big&amp;Fast</td>
<td>WA 13.8, IL 34.8, PA 29.8</td>
<td>CA 13.7, IN 5.9, VA 5.3</td>
<td>CA 5.7, IN 5.6, RI 10.7</td>
</tr>
<tr>
<td>Big&amp;Slow</td>
<td>WA 14.1, IL 30.0, PA 26.5</td>
<td>CA 12.8, IN 6.5, VA 4.4</td>
<td>CA 4.8, IN 5.1, RI 8.0</td>
</tr>
<tr>
<td>Small&amp;Slow</td>
<td>WA 1.3, IL 2.5, PA 2.4</td>
<td>CA 1.3, IN 1.5, VA 0.8</td>
<td>CA 0.3, IN 0.3, RI 0.4</td>
</tr>
</tbody>
</table>

In contrast, the delivery frequency per week of the individual SKUs is summarized in the tables below.

#### Table 2 - Shipments Per Week of Individual High Volume SKUs to Customers

<table>
<thead>
<tr>
<th></th>
<th>MassCo</th>
<th>GroceryCo</th>
<th>DrugCo</th>
</tr>
</thead>
<tbody>
<tr>
<td>Big&amp;Fast</td>
<td>WA 4.3, IL 4.6, PA 4.3</td>
<td>CA 3.0, IN 2.2, VA 2.7</td>
<td>CA 1.3, IN 1.8, RI 3.4</td>
</tr>
<tr>
<td>Big&amp;Slow</td>
<td>WA 2.7, IL 4.0, PA 3.6</td>
<td>CA 2.1, IN 2.8, VA 2.3</td>
<td>CA 1.1, IN 1.1, RI 1.8</td>
</tr>
<tr>
<td>Small&amp;Slow</td>
<td>WA 0.6, IL 1.1, PA 1.3</td>
<td>CA 0.8, IN 1.1, VA 0.4</td>
<td>CA 0.3, IN 0.2, RI 0.3</td>
</tr>
</tbody>
</table>

This shows that the shipment frequency of an individual SKU even when it is a high volume SKU can be quite different than the shipment frequency of an entire product family. Some SKUs ship out on almost every truck, but this appears to be the
case only for Small&Slow going to DrugCo, which only ships about once a month. Products that ship several times per week have the high volume SKUs going out much less frequently. For instance, a high volume SKU for MassCo on average only ships out on 1 of every 7-8 trucks.

Additionally, the current lead time (average and standard deviation) to the three retailers is summarized in the tables below.

**Table 3 - Travel Time in Days (average) to Customers**

<table>
<thead>
<tr>
<th>DC Location</th>
<th>WA</th>
<th>IL</th>
<th>PA</th>
</tr>
</thead>
<tbody>
<tr>
<td>Big&amp;Fast</td>
<td>5.0</td>
<td>1.6</td>
<td>1.0</td>
</tr>
<tr>
<td>Big&amp;Slow</td>
<td>5.4</td>
<td>1.0</td>
<td>1.1</td>
</tr>
<tr>
<td>Small&amp;Slow</td>
<td>7.0</td>
<td>1.3</td>
<td>2.1</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>DC Location</th>
<th>CA</th>
<th>IN</th>
<th>VA</th>
</tr>
</thead>
<tbody>
<tr>
<td>Big&amp;Fast</td>
<td>1.0</td>
<td>1.1</td>
<td>1.5</td>
</tr>
<tr>
<td>Big&amp;Slow</td>
<td>7.4</td>
<td>0.7</td>
<td>1.9</td>
</tr>
<tr>
<td>Small&amp;Slow</td>
<td>7.9</td>
<td>1.7</td>
<td>2.5</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>DC Location</th>
<th>CA</th>
<th>IN</th>
<th>RI</th>
</tr>
</thead>
<tbody>
<tr>
<td>Big&amp;Fast</td>
<td>1.6</td>
<td>1.8</td>
<td>1.7</td>
</tr>
<tr>
<td>Big&amp;Slow</td>
<td>6.7</td>
<td>0.7</td>
<td>5.7</td>
</tr>
<tr>
<td>Small&amp;Slow</td>
<td>6.5</td>
<td>2.0</td>
<td>3.6</td>
</tr>
</tbody>
</table>

**Table 4 - Travel Time in Days (standard deviation) to Customers**

<table>
<thead>
<tr>
<th>DC Location</th>
<th>WA</th>
<th>IL</th>
<th>PA</th>
</tr>
</thead>
<tbody>
<tr>
<td>Big&amp;Fast</td>
<td>1.0</td>
<td>0.8</td>
<td>1.0</td>
</tr>
<tr>
<td>Big&amp;Slow</td>
<td>1.5</td>
<td>0.8</td>
<td>1.0</td>
</tr>
<tr>
<td>Small&amp;Slow</td>
<td>1.9</td>
<td>1.1</td>
<td>1.1</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>DC Location</th>
<th>CA</th>
<th>IN</th>
<th>VA</th>
</tr>
</thead>
<tbody>
<tr>
<td>Big&amp;Fast</td>
<td>0.7</td>
<td>0.5</td>
<td>0.8</td>
</tr>
<tr>
<td>Big&amp;Slow</td>
<td>1.7</td>
<td>0.2</td>
<td>0.6</td>
</tr>
<tr>
<td>Small&amp;Slow</td>
<td>1.0</td>
<td>0.5</td>
<td>1.0</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>DC Location</th>
<th>CA</th>
<th>IN</th>
<th>RI</th>
</tr>
</thead>
<tbody>
<tr>
<td>Big&amp;Fast</td>
<td>3.2</td>
<td>1.4</td>
<td>1.2</td>
</tr>
<tr>
<td>Big&amp;Slow</td>
<td>1.7</td>
<td>0.2</td>
<td>1.8</td>
</tr>
<tr>
<td>Small&amp;Slow</td>
<td>1.9</td>
<td>1.8</td>
<td>0.6</td>
</tr>
</tbody>
</table>

A general observation about the lead time data is that travel times to the West Coast are typically the longest. The exception to this is that Big&Fast shipments to California are short as there is a Big&Fast manufacturing plant in California. However, shipments to MassCo's DC in Washington are much longer as they come from the Midwest.
Some assumptions had to be made when data was not available. Big&Slow shipments to GroceryCo's DC in Indiana did not have carrier arrival dates recorded; we assumed that the travel time to GroceryCo would be the same as DrugCo since the two DCs are near one another and receive shipments of Big&Slow from the same nearby manufacturing facility. A similar assumption had to be made for Big&Fast shipments to GroceryCo's DC in California as carrier arrival dates also were not recorded. We assumed that the average travel time would be similar to DrugCo since the two DCs are also near one another and receive shipments of Big&Fast from the same nearby manufacturing facility. However, the DrugCo DC is new to their network and has been known to have problems that have sometimes dramatically delayed shipments. Therefore, out of 185 shipments, the 9 with travel times greater than 7 days were excluded from the travel time calculations for GroceryCo. This resulted in a travel time of $1.0 \pm 0.7$ days for GroceryCo compared to $1.6 \pm 3.2$ days for DrugCo.
3.3 DC Inventories and Best in Class Levels

The customer DC inventory levels are shown below in Table 5.

Table 5 - Customer DC Average Days of Inventory with Best in Class Highlighted

<table>
<thead>
<tr>
<th>DC Location</th>
<th>DC Location</th>
<th>DC Location</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>WA</td>
<td>IL</td>
</tr>
<tr>
<td>Big&amp;Fast</td>
<td>3.9</td>
<td>5.1</td>
</tr>
<tr>
<td>Big&amp;Slow</td>
<td>4.8</td>
<td>4.2</td>
</tr>
<tr>
<td>Small&amp;Slow</td>
<td>22.8</td>
<td>14.0</td>
</tr>
</tbody>
</table>

Data was not available for GroceryCo's DC in VA. From these values we can see that the best in class inventory level for MassCo is 3.9 days. If MassCo were to achieve best in class inventory levels, each product in each DC must also reach this level – no small task especially considering how infrequently Small&Slow ships to customers.

However, this may represent an upper bound of what is possible from a combination of changes in customer's ordering patterns and SupplierCo's network to allow for improved frequency and lead time. The best in class inventory is 7.6 days for GroceryCo and 10.7 days for DrugCo. These customers appear to have a greater opportunity to examine their ordering practices to better achieve their own best in class inventory levels at each DC.
4 Analysis

The analysis will first compare the overall lead time distributions for each of the three customers as there were some significant differences. The effect of heavy promotions will then be discussed as DrugCo primarily sells products during promotions while MassCo rarely runs promotions. The creation of the model will then be presented, and the appropriateness of the model for each customer based on their use of promotions will be examined.

4.1 Overall Lead Time Distributions

The current lead times from when orders were submitted until product was delivered at the customer’s DC varied by customer. The lead time distributions for MassCo and GroceryCo were somewhat similar, but the distribution for DrugCo was very different as shown in Figures 1, 2, and 3 below. These distributions show all shipments on all lanes. There appears to be a bimodal or trimodal distribution for MassCo and GroceryCo, but this is merely the result of showing together shipments on lanes which average one, two, five or seven days of travel time.
Figure 1 - Lead Time from SupplierCo to MassCo

Figure 2 - Lead Time from SupplierCo to GroceryCo
4.2 Effect of Heavy Promotions

The large difference with DrugCo stems from its promotional planning process. Many orders are submitted weeks ahead of time while additional orders could follow as plans for the promotion change. In between promotions, some product is sold, but about 75% of sales of SupplierCo products happen during promotions which typically occur every 4-6 weeks. With promotions occurring about 18% of the time, the sales rate during promotions is about 14 times greater than during non-promotional periods. This type of business model requires a large focus on promotional planning to focus on
the key driver of sales. As a result of this business model, the demand pattern is very erratic as shown in Figure 4 below.

Figure 4 - Weekly Shipments of Big&Slow to DrugCo's DC in RI
This can be contrasted with the shipments of Big&Slow going to MassCo on the East Coast in Figure 5 below. The same product is going to the same part of the country but with a very different demand signal. MassCo does very few promotions and only has 5% of sales occur during promotions compared to the 75% for DrugCo.

![Weekly Shipments of Big&Slow to MassCo's DC in PA](chart)

*Figure 5 - Weekly Shipments of Big&Slow to MassCo's DC in PA*

While there is still some variation in the rate of shipments (coefficient of variation = 0.68), it is much more stable than the demand of DrugCo (coefficient of variation = 1.43).

MassCo and DrugCo are the two extremes when it comes to promotions while GroceryCo is in the middle with about 40% of sales coming from promotions.

Shipments of the same product going to the East Coast are shown below in Figure 6.
The demand is fairly stable except for a promotional period in weeks 26-28, and the resulting coefficient of variation is 0.73, similar to that of MassCo.

### 4.3 Calculation of Theoretical Inventory

When attempting to calculate the theoretical inventory for each product at each customer’s DC, the key factors affecting this were

- demand mean and variability
- lead time mean and variability
- target service level
- current frequency of shipments
Both the Base Stock model and the Continuous Review QR model were examined, but neither model fit exactly. The Base Stock model assumes a fixed time between orders and that the order would bring inventory up a target inventory level. Time between orders for all customers varied so this assumption did not hold well. The QR model assumes a fixed order quantity that is ordered when inventory on hand and on order drops to or below a target inventory level. The order quantity also was not fixed, but that is partly because the analysis is focused on only a few individual SKU’s. Almost all orders made to SupplierCo are made in full truckload quantities so while quantities could be different, volume would be fairly constant. Given that and that these customers ordered once inventory dropped to a certain level, the QR model was selected to calculate theoretical inventory.

The theoretical inventory level is composed of two parts – cycle stock and safety stock which are shown in Figure 7 below.

Figure 7 - Cycle Stock vs Safety Stock
Cycle stock represents the changing inventory levels between shipments while the safety stock is a buffer to prevent running out in case of higher than expected demand or shipments delays. The average cycle stock inventory is simply the order quantity \( Q \) divided by 2.

\[
\text{Cycle stock} = \frac{Q}{2} \quad \text{where} \quad Q = \frac{\text{Demand (units per week)}}{\text{Frequency (shipments per week)}}
\]  

(Eq. 1)

The cycle stock is a function of the order quantity and is therefore a function of frequency. If half as much of a product is ordered but is ordered twice as often, the fluctuation in inventory levels will also be cut in half as illustrated in Figure 8 below.

![Figure 8 - Cycle Stock Reduction with Greater Frequency](image-url)
To minimize transportation costs, SupplierCo offers a discount when purchasing a full truckload of product. Rather than shipping just one product on a truck, if two products of equal size and demand were to be shipped together each could be ordered twice as often resulting in a 50% reduction in cycle stock for both products. In relation to this study, if products which are not shipped very frequently, like Small&Slow, could be shipped more frequently in smaller quantities, the customer DCs would not have nearly as much cycle stock. Products like Big&Fast which are already shipped quite frequently would not see much benefit from increasing their frequency. In fact, any frequency improvement beyond once a day was assumed to have no improvement as the customer's planning systems could not respond more frequently than that to realize a potential benefit.

The next component of the theoretical inventory is the safety stock. Safety stock was calculated using the following equations:

\[
\text{Safety Stock} = z\sigma(D_{st}), \quad \text{(Eq. 2)}^3
\]

where

- \(Z\) is statistical z value based on target service level and
- \(\sigma(D_{st})\) is standard deviation of demand over the lead time.

\[
\sigma(D_{st}) = \sqrt{E(L)\sigma_D^2 + (E(D))^2 \sigma_l^2}, \quad \text{(Eq. 3)}^4
\]

where

- \(E(L)\) is expected lead time,
- \(\sigma_D\) is standard deviation of the demand,
- \(E(D)\) is expected demand,
- \(\sigma_l\) is standard deviation of the lead time.

---

3 MIT course lecture notes, ESD.267, Lecture 2, February 2007
An example of this calculation for Big&Slow going to MassCo’s DC in Pennsylvania is as follows:

\[
\text{Demand} = 3296 \text{ units/week;}
\]

\[
\text{Frequency} = 3.8 \text{ shipments/week} \quad \text{(There are actually 26.5 shipments of Big&Fast per week, but only 3.8 shipments/week contained this SKU.)}
\]

\[
\text{Cycle stock} = \frac{\text{Demand}}{\text{Frequency} \times 2} = \frac{3296}{3.8 \times 2} = 438 \text{ units}
\]

\[
Z = 2.05 \text{ when service level is at 98%}.
\]

\[
E(L) = 1.1 \text{ days}
\]

\[
\sigma_L = 1.0 \text{ days}
\]

\[
E(D) = 471 \text{ units/day}
\]

\[
\sigma_D = 149 \text{ units/day}
\]

\[
\sigma(D_L) = \sqrt{E(L)\sigma_L^2 + (E(D))^2 \sigma_D^2} = \sqrt{4.1 \times 149^2 + (471)^2 \times 1.0^2} = 554
\]

\[
\text{Safety stock} = z\sigma(D_L) = 2.05 \times 554 = 1138 \text{ units}
\]

### 4.4 Appropriateness of the Model

An assumption that goes into these calculations is that the data is normally distributed. Several published articles discussed using a gamma distribution rather than a normal distribution to model demand when the lead time and demand per unit time are both stochastic. But even as Mark Keaton suggests this, he acknowledges that a normal distribution “may be a reasonable approximation for fast moving ‘Type A’ items, but it is not suitable for slower moving items.”

Since this study only focused on fast moving items, the normal distribution was deemed to be appropriate. This was

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5 Keaton, Mark, Using the gamma distribution to model demand when lead time is stochastic, *Journal of Business Logistics*; 1995; 16, 1; ABI/INFORM Global, pg. 107
further suggested to be reasonable by John E. Tyworth and Liam O’Neill who said that “the normal approximation is robust with respect to both cost and service for seven major industry groups.”6 As further practical evidence of this, a Program Manager from HP named Barrett Crane commented during a presentation on supply chain improvements at HP over the past six years that they have always used the normal approximation and found it to work very well.7

In the instance calculated above of Big&Slow going to MassCo’s DC in PA, safety stock is 72% of total theoretical inventory. However, theoretical inventory is only 67% of actual inventory which raises the question of whether MassCo is operating optimally or whether the theoretical inventory calculation is missing some additional variability that would require additional safety stock. For instance, the model assumes a fixed time of three days for SupplierCo to ship an order after the order was initially sent. If there was additional variability in this time, additional safety stock would be needed to cover that variability. However, since some orders are submitted early for all customers and are submitted early most of the time for DrugCo, it is impossible to determine how much of this time is the variability in SupplierCo’s internal processes to fill orders.

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6 Tyworth, John E., O’Neill, Liam, Robustness of the Normal Approximation of Lead-Time Demand in a Distribution Setting, Naval Research Logistics Vol 44, 1997, pg 165-186

7 Crane, Barrett, personal conversation
The model calculates theoretical inventories for MassCo that are on average 74% of actual inventory but there was some variation from one product and DC combination to another. The theoretical inventory for Big&Fast going to Pennsylvania was only 55% of actual inventory while the theoretical inventory for Big&Slow going to Washington was 117% of actual inventory. Seven of the nine values were within a range of 55-68% lower with two additional values at 92% and 133%.

Values where theoretical inventory was lower than actual could perhaps be explained by the model not taking into account some additional type of variation or by the DC keeping additional buffer inventory and not acting in an optimal manner. However, two of the nine values stood out from the rest and showed theoretical inventories as 92% and 133% of actual inventory. A possibility here is that there were some unusual outliers in the transportation data that would not cause MassCo to carry safety stock to cover. For instance, out of 298 shipments, there were 5 shipments that made it there in 2-3 days to cover ~2200 miles while 12 other shipments took 8-11 days to make the trip. Removing unusually short or long shipment times caused the travel time variation to drop which caused the calculated theoretical inventory to drop from 133% to 116% of actual inventory. If demand variability also happened to be higher than normal during this 20 week period, this product inventory might not be too different than the other product inventories although both demand and lead time variability would need to be reduced by about 60% to achieve this.
In talking with SupplierCo employees who managed shipments to MassCo or shipments to DrugCo, we learned that MassCo does not directly take into account lead time variability while DrugCo does. In calculating target inventory levels, MassCo takes a fixed value of three days for SupplierCo to process their order, adds the average travel time committed by carriers, and adds a fixed number of days of safety stock. This value of safety stock could indirectly be accounting for lead time variability, but further details of how they determine inventory set points were not available.

By contrast, DrugCo’s inventory management system calculates the average and variation of lead time for the past 10 shipments and uses that data to determine the inventory set point for all products. Excessive variability can dramatically increase this target inventory level so consistency in delivery is a larger focus for them than reducing lead time. We found that the requested lead time in their system was 13-16 days which is much longer than the travel time plus the 3 days for SupplierCo to process the order. This longer lead time is observed in Figure 3 presented above that shows much longer lead times for DrugCo than for MassCo or GroceryCo.

By removing variability from the calculation, the calculated theoretical inventory for MassCo decreased causing it to diverge further from actual inventory; however, the offset from actual inventory was then much more consistent from product to product. If additional data was available on how MassCo determined days of safety stock, the
model could be adjusted to this way of calculating inventory, and this could be the focus of a follow up project.

The ratio of theoretical inventory to actual inventory for each product and customer DC is listed in the tables below.

**Table 6 - Ratio of Theoretical Inventory to Actual Inventory**

<table>
<thead>
<tr>
<th></th>
<th>MassCo</th>
<th>GroceryCo</th>
<th>DrugCo</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>DC Location</td>
<td>DC Location</td>
<td>DC Location</td>
</tr>
<tr>
<td></td>
<td>WA</td>
<td>IL</td>
<td>PA</td>
</tr>
<tr>
<td>Big&amp;Fast</td>
<td>92%</td>
<td>57%</td>
<td>55%</td>
</tr>
<tr>
<td>Big&amp;Slow</td>
<td>116%</td>
<td>67%</td>
<td>67%</td>
</tr>
<tr>
<td>Small&amp;Slow</td>
<td>61%</td>
<td>65%</td>
<td>68%</td>
</tr>
</tbody>
</table>

The model predicts actual inventory levels most closely for MassCo where demand is fairly stable. The model is not as predictive of inventory levels at GroceryCo and DrugCo where so much of the demand is driven by periodic promotions.

However, since many of the products were fairly consistent with one another, the calculations presented above, which take both demand variability and lead time variability into account, were used to try to answer the question of how much value would the customer realize from increased frequency or decreased lead time. By modifying the frequency or lead time by varying amounts the value to each customer of each potential change can be estimated.

Another concern about the model was that it assumes normally distributed consumption and demand, but 75% of the sales for DrugCo and 40% of the sales for GroceryCo occur during promotional periods. Calculating the standard deviation of
demand variability influenced by heavy promotions produces a very high variability which then predicts a high level of safety stock. DrugCo was able to provide data that distinguished promotional orders from non-promotional orders, but the data showed long periods of no orders after some promotions which did not sell as much as expected. DrugCo confirmed that while the DCs initially store inventory as either promotional or turn business, they will often move excess inventory from one category to another so the order data provided was not an accurate representation of the promotional versus non-promotional customer demand.

Given this challenge to determine how to effectively model a business which relies so heavily on promotions, a further assumption was made to allow the calculations to try to predict potential benefits to these customers as well. The assumption was that the demand variation GroceryCo and DrugCo saw would be similar to MassCo, although somewhat higher because of greater uncertainty with high promotional demand. Since promotions are planned well in advance, the need to keep safety stock would not be based upon the deviation from total average demand but deviation from forecasted demand. Forecast data was not available, but it seems reasonable to assume that a well planned promotion will be able to use past promotions and sales data to effectively plan for expected demand similar to how MassCo could plan for fairly steady demand. Variability will exist for both, but assuming that customer demand variability is roughly equivalent for all companies seems reasonable
given advance promotional planning efforts. Changing demand variability of GroceryCo to 150% of MassCo and of DrugCo to 200% of MassCo allows us to reflect that the higher a company’s promotional sales are, the harder it is to accurately forecast demand. This assumption allows the model to more accurately predict theoretical inventory for GroceryCo and DrugCo and to then calculate potential savings.
5 Results and Potential Savings

The eleven scenarios described in Chapter 2 represent possible ways to increase shipping frequency or reduce lead time. We evaluated each scenario for each product at each customer’s DC. The results were then summarized by grouping results first by customer and then by product type. When combining the calculated savings from different locations, the following assumption was made: 20% of total company sales and inventory was from the West, 40% from the Midwest, and 40% from the East so customer DCs from those areas of the country were weighted accordingly. Also, we assumed that 20% of sales came from products like Big&Fast, 50% of sales came from products like Big&Slow, & 30% of sales came from products like Small&Slow. The potential savings for each customer will be discussed individually below and then compared to one another. Finally the calculations that had been reported as percentage savings will then be converted to potential dollar savings and examined.

5.1 Potential Savings for MassCo

When the SKUs were identified, the highest volume SKUs were selected, and an initial assumption was made that this SKU would be part of every shipment. This turned out to be a bad assumption for MassCo as there were 2-8 times as many
shipments on these lanes as shipments containing the SKUs of interest. This may be specific to MassCo as the calculated frequencies for GroceryCo and DrugCo seemed about right to them while MassCo had realized that the initially calculated values were too low. If frequency were to increase by always having the high volume SKUs on a truck up to the point of daily shipments, a reduction in cycle stock could be expected. In the case of MassCo, the model predicts a 13.2% reduction in overall inventory with almost half of that coming from Small&Slow.

A further improvement in frequency could occur if product families were shipped together. Enabling this would first require some internal shipments for SupplierCo to move product from one manufacturing plant to another or ship products from multiple manufacturing plants to regional DCs. These options would chiefly help the low frequency products like Small&Slow, which could go from shipments once a week or once a month to daily shipments allowing for a huge reduction in cycle stock. For this option the model predicts a 17.1% reduction in inventory with the additional 4% benefit coming completely from increased frequency of Small&Slow shipments.

In examining benefits of reduced cycle time, the model calculates the potential benefit of reducing the lead time of all shipments by two days and then by one day. This could most likely be accomplished by SupplierCo reducing their order to ship time from three days to one or two days. This may not be possible though as SupplierCo commits to filling an order within three days but often does so more quickly than that.
With MassCo, about 25% of shipments were prepared within one day and another 45% were prepared within two days; thus, a total of 70% of shipments to MassCo were already beating the three day commitment. This makes a reduction of one day in SupplierCo’s response to orders pretty difficult and a reduction of two days impossible in some cases where the response time is already less than two days. Even if reducing SupplierCo’s processing time was not feasible, lead time improvements could also come from having product located closer to customers to reduce travel time so the potential inventory reduction of this option may still have merit. With customers being able to get a quicker response to orders placed with SupplierCo, customers should be able to reduce their safety stock. For MassCo, reducing the lead time for all shipments by two days would allow inventory to be reduced by an estimated 7.6% and reducing lead time by one day would allow a reduction of 3.7%.

Instead of reducing lead time for all products the model also explores the potential value of decreasing lead time to 4 days or fewer. This could be accomplished by shipping product from manufacturing plants which were far away from customers to regional DCs which could then ship to customers. If the value to the customer for this option would be greater than SupplierCo’s cost, SupplierCo could consider negotiating with customers and revising its pricing policies. The model predicts a potential inventory reduction of 3.9% for MassCo.
Since most lead times to the West Coast are so much longer, another scenario to evaluate is the potential benefit of just having a DC on the West Coast to reduce lead times there. The expected value of having all products moved to this DC is a 2.4% reduction in inventory for MassCo. If only Small&Slow were moved, the benefit is expected to be a 1.1% reduction.

Finally, in looking at each of the product and DC combinations, the one with the fewest days of inventory was identified. This turned out to be Big&Fast in Washington which had 3.9 days of inventory. If all other products could reach and sustain this inventory level the expected inventory reduction would be 38.4% compared to today’s levels. This is clearly the largest potential benefit but also has the least concrete methods for achieving those results. A combination of scenarios discussed above could help achieve that but even if frequency was increased to daily shipments and the lead time was reduced by 2 days, the potential improvement is less than 25% which is still less than the best in class potential savings.
A summary of these potential savings is shown in Figure 9 below.

**Theoretical inventory reduction possible - MassCo**

*Lead time = order to delivery time*

*matching best in class days of inventory*
*increasing frequency to achieve daily shipments*
*increasing frequency by having high volume SKUs on every truck*
*increasing frequency by shipping Big&Slow & Small&Slow together*
*eliminating lead time variability*
*reducing lead time variability by 50%*
*reducing lead time by 2 days*
*reducing lead time by 1 day*
*reducing lead time to 4 day max for all products & locations*
*reducing lead time on the West Coast with a new DC*
*reducing lead time by moving Small&Slow to a West Coast DC*

*Big&Fast*  |  *Big&Slow*  |  *Small&Slow*  
---|---|---
0% | 10% | 20% | 30% | 40% | 50% | 60% | 70% | 80% 

**Figure 9 - Potential Savings for MassCo from 11 Scenarios**

Since the scenario matching best in class days of inventory is so large and skews the scale on the y axis, Figure 10 displays the same information without this scenario to provide greater clarity on the benefits of the other 10 scenarios.
5.2 Potential Savings for GroceryCo

The same calculations of potential savings for MassCo were done for GroceryCo. The only difference was that the demand variability was assumed to be 150% of the demand variability for MassCo. Promotions caused the available demand data to be much more variable and unexpected than reality since forecasts are used to better predict promotional demand. Unfortunately, forecast data was not available. A summary of the potential savings is listed below in Figure 11.
Theoretical inventory reduction possible - GroceryCo

Lead time = order to delivery time

Since the scenario matching best in class days of inventory skews the scale on the y axis, Figure 12 displays the same information without this scenario to provide greater clarity on the benefits of the other 10 scenarios.
The theoretical inventory reduction possible - GroceryCo

Lead time = order to delivery time

- Increasing frequency to achieve daily shipments
- Increasing frequency by having high volume SKUs on every truck
- Increasing frequency by shipping Big&Slow & Small&Slow together
- Eliminating lead time variability
- Reducing lead time variability by 50%
- Reducing lead time by 2 days
- Reducing lead time by 1 day
- Reducing lead time to 4 day max for all products & locations
- Reducing lead time on the West Coast with a new DC
- Reducing lead time by moving Small&Slow to a West Coast DC

Figure 12 - Potential Savings for GroceryCo from 10 Scenarios

The DC inventory data did suggest some opportunities for inventory improvements where ordering appeared to be far from optimal. An example of this type of problem is shown in Figure 13 below.
One Big&Fast SKU at the DC in California had many weeks of inventory in late 2006 that was slowly consumed, but then very large orders were made in early 2007 that far exceeded demand. It appears that about $400K of excess inventory was held for 5 weeks, $200K for 7 weeks, and $100K for 4 more weeks. At a 15% inventory carrying cost this represents a $11K loss as well as tying up space at the DC. This would be a good case to explore in more detail with the planners making the orders to understand how the inventory management system works and why such orders were made.
5.3 Potential Savings for DrugCo

The same calculations were also performed for DrugCo although the demand variability was assumed to be 200% of the demand variability of MassCo. Since DrugCo runs even more promotions than GroceryCo, it was assumed that the forecast accuracy would be lower. A summary of the potential savings is listed below in Figure 14.

Theoretical inventory reduction possible - DrugCo

Figure 14 - Potential Savings for DrugCo from 11 Scenarios
Since the scenario matching best in class days of inventory skews the scale on the y axis, Figure 15 displays the same information without this scenario to provide greater clarity on the benefits of the other 10 scenarios.

**Figure 15 - Potential Savings for DrugCo from 10 Scenarios**

However, in talking with DrugCo, we discovered that because of its smaller stores, their DCs only replenished their stores about once a week. Since this customer also sells so much of their product during promotions and orders weeks in advance, a lead time reduction for them would be of limited value because of their business processes. If their business processes were more typical of MassCo and GroceryCo then
the calculated inventory reductions for reduced lead times listed above might be valid. As further evidence of this, we computed the correlation between inventory levels and travel times to see if shorter lead times leads to lower inventory levels; we found no correlation for any of the eight SKUs studied. Savings from improved frequency might also be somewhat overstated because frequency during promotional orders is so much higher.

For a company like DrugCo, this model given by equations 1, 2, and 3 may not be appropriate for estimating their inventory. The DC inventory data did suggest some opportunities for inventory improvements although it had more to do with improving forecast accuracy to avoid ordering too much inventory that would then be held until the next promotion. An example of this type of problem is shown in Figure 16 below.
Inventory was ordered and arrived in week 24 in preparation for a promotion in week 26, but the promotion consumed less than half of the inventory. For some unknown reason more inventory was ordered and arrived in week 28. This inventory remained on hand until another promotion occurred in week 36. In the meantime $400K of inventory was tied up for 12 weeks. At a 15% inventory carrying cost this represents a $10K loss as well as tying up space at the DC. This would also be a good case to explore in more detail with the planners making the orders to understand how the inventory management system works and why such orders were made.
5.4 Potential Savings Comparison by Company and Brand

In using the model for all three customers, we can compare the potential benefits of each side by side. To better visualize the possible inventory reduction for each customer the Figure 17 compares the eleven scenarios.

![Theoretical inventory reduction possible graph](image)

**Figure 17** - Potential Inventory Reduction of 11 Scenarios, Grouped by Customer

The final scenario of matching best in class days of inventory has by far the largest values. To better see how the other scenarios compare to one another, this option is removed from Figure 18 below.
This shows that all customers will benefit more from improving frequency than by reducing lead time. It should be noted that this result for GroceryCo and DrugCo is due to the assumption about eliminating variability. While it is not correct to calculate safety stock using the extremely high standard deviation of demand, when this was calculated initially, frequency improvements provided a much lower benefit while lead time reductions provided a larger benefit. Therefore, a closer study of the forecast accuracy for companies with high demand variability might be warranted. It is possible that for highly variable demands, a lead time reduction could be more beneficial than is portrayed on these graphs.
Instead of adding up the savings of each product by company, the savings by product can be calculated by adding up the savings of each company for each product. This is displayed in Figure 19 below.

**Theoretical inventory reduction possible - all customers**

*Lead time = order to delivery time*

![Graph showing theoretical inventory reduction possible for all customers.](image)

Figure 19 - Potential Inventory Reduction of 11 Scenarios, Grouped by Brand

Once again the potential savings of the best in class days of inventory dwarfs those of the other scenarios so the graph is presented again below without this option as Figure 20.
Figure 20 - Potential Inventory Reduction of 10 Scenarios, Grouped by Brand

This graph shows that frequency improvements could dramatically decrease inventories of Small&Slow and provide a sizable reduction for Big&Slow while doing very little for Big&Fast.
5.5 **Potential Savings for All Customers**

We then used the data above to estimate potential total dollar savings. Some assumptions that went into this calculation were that 50% of SupplierCo’s business is in the US and that the inventory carrying cost was 15%. We also assumed that 50% of SupplierCo’s business went to companies like MassCo, 25% to companies like GroceryCo, and 25% to companies like DrugCo.

SupplierCo works especially closely with MassCo, and in the past has identified potential savings and negotiated additional promotions or SKUs in return for delivering the potential savings to MassCo. The additional promotions and SKUs help increase sales for both companies but deliver an estimated $5 of profit to SupplierCo for every $1 of savings provided. This makes potential savings for MassCo that much more valuable. After weighting potential savings from MassCo five times the initial value, potential cost savings for each of the eleven scenarios are shown in Figure 21 below.
Theoretical benefit of making the following changes
Lead time = order to delivery time

- MassCo & SupplierCo often negotiate joint value creation that results in a 5x benefit that may be a one-time benefit (additional merchandising event) or continuous (additional SKUs).

- DrugCo currently won't benefit from lead time improvements but other similar customers might.

Figure 21 - Potential Inventory Savings of 11 Scenarios, Grouped by Customer

Like before, removing the best in class data helps to better see the data from the other scenarios as shown in Figure 22 below.
Theoretical benefit of making the following changes
Lead time = order to delivery time

MassCo & SupplierCo often negotiate joint value creation that results in a 5x benefit that may be a one-time benefit (additional merchandising event) or continuous (additional SKUs) - not reflected below.

DrugCo currently won't benefit from lead time improvements but other similar customers might.

Figure 22 - Potential Inventory Savings of 10 Scenarios, Grouped by Customer

This shows that increasing shipment frequency can deliver greater savings than reductions in lead time. Intuitively this makes sense as large improvements in shipment frequency are possible while only incremental improvements in lead time are possible.
6 Conclusions

Making any changes to a large supply chain network like SupplierCo’s will surely be costly, but the potential benefits to customers are also quite large. The modeling done through this project estimated the potential value of a number of possible changes to their supply chain in the United States including the following:

1. Improve inventory performance for all products and DCs to match the best in class inventory for each customer

2. Increasing frequency by combining products to achieve daily shipments to customer’s DCs

3. Increasing frequency by ensuring that high volume SKUs were part of every shipment

4. Increasing frequency by shipping Big&Slow and Small&Slow together

5. Eliminating lead time variability

6. Reducing lead time variability by 50%

7. Decreasing lead time by 2 days for all shipments

8. Decreasing lead time by 1 day for all shipments

9. Decreasing lead time to a maximum of 4 days for all shipments
10. Decreasing lead time to the West Coast by having products in a DC somewhere on the West Coast

11. Decreasing lead time to the West Coast for Small&Slow by having Small&Slow in a DC on the West Coast

Of all these possible improvements, matching best in class inventory performance offers the greatest potential opportunity. With an estimated opportunity of over $120 million, focusing some resources to understand how this could be achieved could provide benefits and improved profitability for SupplierCo and its customers. Some of this amount may not represent achievable opportunities as inventory levels could have been operating leaner than normal for a period of time when data was available. However, even if half of this opportunity were real, it represents a very sizable opportunity worth exploring.

Further research could be done to understand exactly how target inventory levels are set at each customer and then work with those planners who create orders for the best in class products and DCs to understand how they achieve the low levels observed and what could be different with other products and other DCs. Once that is clearly understood, opportunities to close those performance gaps could be brainstormed and discussed with the planners for confirmation. The potential value of those changes could be estimated to determine whether the benefits of such changes would be worth the cost.
Increasing the frequency of shipments by making sure high volume SKUs are on each shipment to a DC seems like a relatively simple and inexpensive change to make that could also yield a large benefit. All three customers in this study could stand to benefit from this. To confirm whether other customers could also see this benefit, shipment frequencies for the highest volume SKU of each product family could be compared to the shipment frequency of the entire product family. All that should be required is either 1) increased management by the planners, 2) a modification of the company's inventory management system to either reduce the economic order quantity or include some amount of each high volume SKU on each shipment, or 3) possibly a reduction in Customer A's required minimum order quantity.

Further improvements in frequency could also be focused on low frequency products like Small&Slow. Shipping Small&Slow or other low frequency products to manufacturing facilities producing high frequency products would be ideal so that products like Small&Slow could be shipped with those high frequency products.

Reductions in the lead time variability have a large potential improvement for some customers and products but much less for others. Reducing lead time variability has the greatest opportunity to reduce inventory for products which have stable demand and are not low frequency shipments. If demand is highly variable, that variability will be the key driver of safety stock inventories; if demand is stable the lead time variability will be the key driver of safety stock inventories. If a product does not
ship very frequently, it will have a high cycle stock which may make reductions in
safety stock less significant.

Finally, reductions in average lead time also have the potential to help drive
inventories down some but not as much as increasing the frequency of shipments. This
aligns with feedback one of SupplierCo’s managers received from many SupplierCo
logistics managers who were speaking from their experience. It is encouraging that the
theoretical calculations done with this project agree with the voice of experience.

An exception to this is for companies with high promotional sales which can
replenish their stores in the middle of a promotion to meet higher than expected
demand. These companies would benefit more from reducing average lead time to
reduce lost sales. GroceryCo could benefit from reducing average lead time, but
DrugCo would not. The amount of sales going to customers that have this capability
compared to those who do not should be taken into account to determine how much
benefit could be expected for the supply chain from reducing average lead time.

After having done a lot of calculations and modeling, one final point worth
mentioning is that the point of doing mathematical modeling is the generation of
insight, not exact numbers. A number of data sources went into the modeling, and
some data points or time frames may be outliers from normal behavior. This may help
explain how some products seemed to have an inventory even better than what the
model calculated as optimal. Additionally, a number of assumptions went into calculating the results presented, and the accuracy of those assumptions will obviously affect the accuracy of the model's output. Therefore, the key insights drawn from this exercise are the main points which should be taken away. There should not be an expectation that $25 million of benefit could be realized if Small&Slow were shipped to another distribution point where it could be shipped to customers more often.

This same methodology of calculating theoretical inventory and then comparing possible improvements to the original theoretical inventory could be followed to estimate the supply chain value in other parts of the world or in other industries. A key consideration would be to determine how much of the business was promotional. If a significant percentage of sales occur during promotions, forecast data could be used to determine forecast errors which could be used to determine the required safety stocks. If forecast data was not available like in this study, the assumption could be made that demand variability will be similar to but a little higher than that of another company which does not use promotions much. Using the inputs of demand, lead time, and frequency, theoretical inventories could be calculated for any number of scenarios to assess potential inventory savings.

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